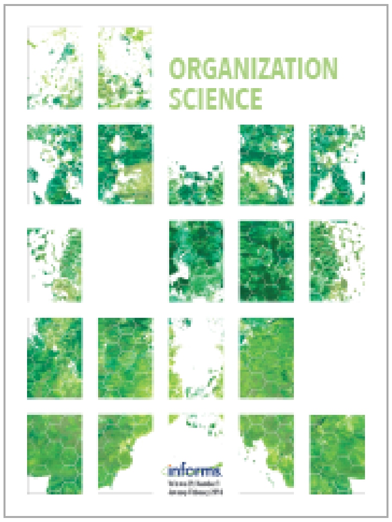

Organization Science

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http://pubsonline.informs.org/journal/orsc
ORGANIZATION SCIENCE
Vol. 31, No. 2, March–April 2020, pp. 378–414
ISSN 1047-7039 (print), ISSN 1526-5455 (online)

Do Accelerators Work? If So, How?

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Received: July 10, 2016
Revised: December 30, 2017; September 25, 2018; April 3, 2019
Accepted: April 20, 2019
Published Online in Articles in Advance: February 24, 2020

https://doi.org/10.1287/orsc.2019.1304

Abstract. Accelerators are entrepreneurial programs that attempt to help ventures learn, often utilizing extensive consultation with mentors, program directors, customers, guest speakers, alumni, and peers. Although accelerators have rapidly emerged as prominent players in the entrepreneurial ecosystem, entrepreneurs, policy makers, and academics continue to raise questions about their efficacy. Moreover, relevant organizational literature suggests that, even if accelerators are associated with better venture outcomes, results could be due to mechanisms other than learning, such as sorting or signaling. Drawing on mixed empirical methods that include proprietary data on the ventures accepted and "almost accepted" to a set of top accelerators, we find evidence that some, but not all, of the early accelerators we study substantially aid and accelerate venture development. We also find some evidence of sorting dynamics. These findings are corroborated using an auxiliary quantitative data set constructed from publicly observable data. Complementary qualitative fieldwork suggests a key driver of these accelerator effects is a novel learning mechanism we label broad, intensive, and paced consultation. The implication of these insights is that the practices of early accelerators represent a beneficial and likely replicable form of intervention that may also have relevance for independent entrepreneurs, educational programs, and corporate innovation.

Funding: The authors thank the London Business School's Deloitte Institute of Innovation and Entrepreneurship and RAMD fund, the University of Washington Faculty Development Fund, the Ewing Marion Kauffman Foundation, and the Batten Institute at the Darden School of Business for their generous funding of this project. The contents of this publication are solely the responsibility of the authors.

Keywords: entrepreneurship • accelerators • venture finance • organizational learning

Introduction

Over the last decade, accelerators have emerged as a prominent feature of the entrepreneurial landscape. They provide cohorts of ventures with mentoring and education during fixed-length programs that usually last three months. Notable accelerators include Y Combinator (Silicon Valley), Techstars (originally in Boulder, Colorado, now with 50 franchises globally), and Seedcamp (London). The industry began in 2005, and an estimated 6,000 startups—including Drobpox, SendGrid, and AirBnB—have since participated in one of hundreds of programs across the world (Cohen et al. 2019b). Collectively, these startups raised more than $30 billion in capital, and in 2015, a third of all ventures raising "Series A" venture capital in the United States had graduated from an accelerator (Tom 2016, SeedDB 2017). Although accelerators often advertise to entrepreneurs that they can "accelerate your business" (Techstars 2016), there is surprisingly little research on their ability to do so. Consequentially, the press and policy reports frequently request such research. For example, a *Wall Street Journal* article stated, "We actually know very little about the impacts they are having on the companies that they are trying to accelerate" (Kempner and Roberts 2015), and a recent academic policy report similarly posited, "efficacy of these programs is scant at best" (Hochberg 2016, p. 3). Amplifying such uncertainty is the limited theoretical understanding as to how the mechanisms in accelerators might be similar to or different than the various mechanisms previously examined by researchers.

The purpose of this paper is to address this gap. We ask if accelerators aid venture development, and if so, how? Accelerators themselves have long claimed they benefit ventures and that a key driver is a set of learning-oriented practices that include mentorship, guidance from program staff, guest speakers, and interactions with other ventures. Thus, if accelerator participation is associated with greater venture development, one potential mechanism could be learning. We follow Huber (1991) and define learning as the processing of information that changes an organizations' cognition or range of potential behaviors.[1] Yet, even if accelerators do aid entrepreneurs by facilitating learning, there is a well-developed body of literature on interorganizational learning, and it is unclear how learning within accelerators may be theoretically distinct. Moreover, besides learning, literature on venture development suggests two compelling mechanisms that might alternatively drive any relationship between accelerator participation and venture outcomes: *sorting* and *signaling* (Stuart et al. 1999, Sørensen 2007, Mindruta et al. 2016). Overall, empirical research is needed to understand whether and how accelerators aid venture development.

We answer these research questions using mixed methods across three data sets, combining the rigor of quantitative methods with the rich understanding afforded by qualitative fieldwork (Hall and Ziedonis 2001, Edmondson and McManus 2007, Small 2011, Kaplan 2015). Mixed methods are especially suited for questions such as ours that are forensic in nature with both applied and theory-driven aims (McFarland et al. 2016). We first present analyses exploring whether accelerators indeed meaningfully effect venture development. These analyses utilize proprietary quantitative data on accelerator participants and entrepreneurs "almost accepted" to the same accelerator cohorts. By allowing us to compare ventures of highly similar quality that were all interested in accelerator participation, this sample is well suited for estimating the presence and magnitude of any accelerator treatment effects. These quantitative analyses suggest that accelerators causally affect participating ventures. Data reveal that ventures participating in select accelerators enjoyed superior long-term outcomes across several dimensions—funding, web traffic, and employee growth—relative to highly similar ventures almost accepted to these same accelerators. For instance, in three of the four studied cohorts, accelerator participants raised 47%–171% more funds in the subsequent two to three years than almost accepted applicants. We also see evidence of these accelerators accelerating the speed with which ventures raise funding. Such positive effects, however, were not universal, and some accelerators had no effect or even negatively affected some outcomes. Our results also reveal that accelerators often complement (versus substitute for) founder pre-entry experience. Consistent with accelerators' own claims, analyses of contingencies and mediating effects suggest that learning is likely a key mechanism though we also find evidence of a complementary sorting mechanism as well as accelerator participants increasing effort (quitting outside jobs). We corroborate these findings in an auxiliary quantitative data set constructed from publicly available data on ventures that raised venture capital, examining how accelerator participation is correlated with speed to funding and reaching particular levels of web traffic among otherwise similar ventures.

Following our quantitative analyses, we present the results of rich, complementary fieldwork that draws on a nested, multiple-case design involving the participating ventures, directors, and mentors of eight of the original U.S. accelerators. Relying on site visits and 70 semistructured interviews, we first validate the mechanism of learning. We then inductively build theory that explicates how the learning mechanisms within accelerators are similar to and distinct from previously studied forms of interorganizational learning. Specifically, we reveal how learning within accelerators appears to be driven by a novel combination of broad, intensive, and paced consultations with many others outside of the venture. Overall, our blending of rigorous statistical analysis with rich qualitative data provides external and internal validity and a fuller understanding than any single method would allow. Together these complementary analyses help us unpack to what extent accelerators aid the development of new ventures and how this might occur.

Collectively, our findings offer several important contributions. First, given the increasingly prevalent role of accelerators in the entrepreneurial landscape, our research provides compelling evidence for entrepreneurs, policy makers, and entrepreneurship educators that many accelerators indeed work. Second, our research brings to light a unique mechanism for learning used within accelerators. Thus, whereas research and practice generally stress the importance of internal trial-and-error for entrepreneurial ventures (e.g., such as the lean startup methodology; McGrath and MacMillan 1995, Gavetti and Rivkin 2007, Ries 2011, Camuffo et al. 2019, McDonald and Eisenhardt 2019), our research suggests that early ventures also substantially benefit from broad, intensive, and paced consultation with external parties as this can both expand search and prevent exploration of opportunities that should remain unexplored. Third, we contribute to the literature on pre-entry knowledge (Agarwal et al. 2004, Gruber et al. 2008, Dencker et al. 2009) as we find that even founders with substantial human capital benefit from accelerator participation, suggesting fundamental limitations of knowledge inheritance for entrepreneurs that may be addressed through consultative learning. We conclude with a discussion of the potential generalizability of our findings to the growing and evolving population of accelerators as well as the generalizability of accelerators' practices to university programs looking to accelerate student development or large, established organizations looking to accelerate innovative initiatives. Overall, we validate the efficacy of accelerators, unpack how they work, and spotlight why the organizational form is deserving of greater consideration by practitioners and researchers alike.

Research Context: Accelerators

The Emergence of Accelerators

We begin with a brief overview of the emergence of accelerators (sometimes called seed or startup accelerators) and compare them to three other types of organizational sponsors that also seek to aid early venture development: incubators, angel investors, and venture capital firms. Following industry reports and our field interviews with accelerator participants, directors, and mentors, we define accelerators as learning-oriented, fixed-length programs that provide cohorts of ventures with mentoring and education (Stross 2012, Cohen 2013). Participating ventures are typically early stage, often either having recently launched or being about to launch their product or service, and pursuing a high-potential opportunity that may eventually facilitate an acquisition or IPO.

The accelerator form began with Y Combinator, founded in 2005 by Paul Graham (a successful entrepreneur with a vast online following), Jessica Livingston (a marketer and author working on a book about founders), Robert Morris (a Massachusetts Institute of Technology computer science professor and former entrepreneur), and Trevor Blackwell (a serial entrepreneur) (Miller and Bound 2011, Stross 2012). Although the emergence of new industries and organizational forms often exhibits an extended period of exploration (Agarwal and Tripsas 2008), the emergence of the accelerator form is striking in that the first recognized accelerator achieved early success and was widely and quickly imitated.

Y Combinator arose from questions about building a startup that Graham received while giving a talk to the Harvard undergraduate computer club (Graham 2012, 2014, 2016). Initially focused on working with undergraduate entrepreneurs, the founders batched the startups over summer break. Batching, a key feature that would become a hallmark of accelerators, had the unpredicted benefit of also accelerating their own learning curve as angel investors. Because the founders wanted to learn more about angel investing, they invited experienced investors and entrepreneurs to speak to the venture teams. Other elements of the initial program were borrowed from Graham's experiences as a former computer science PhD student, including providing a similar level of funding to what graduate students received as summer stipends. The program culminated in a "demo day" at which founders delivered short presentations to an audience of potential investors. The initial Y Combinator cohort included eight firms and several early successes, including Reddit and Loopt. In reflecting back on many of the early decisions, Graham notes, "We got lucky in that the length and structure of a summer program turns out to be perfect for what we do. The structure of the YC cycle is still almost identical to what it was that first summer" (Graham 2012).

The first competitor, Techstars, was founded in Boulder, Colorado, in 2007 by David Cohen (a serial entrepreneur), Brad Feld (a venture capitalist and former entrepreneur), Jared Polis (a serial entrepreneur), and David Brown (a serial entrepreneur). Cohen was seeking to improve the local entrepreneurial ecosystem, and Feld suggested he look to Y Combinator. Techstars adapted many features from Y Combinator and added the use of extensive mentoring by local entrepreneurs, investors, and professionals. Other accelerators followed soon after, including Dreamit in Philadelphia, Seedcamp in London later in 2007, and Launchbox Digital in Washington, DC, in 2008. Most based their core feature set off either Y Combinator or Techstars, though often with some local variation. As of September 2018, Crunchbase estimates that upward of 750 accelerators have subsequently been founded in the United States alone. Some are privately funded, and others are backed by governments, corporations, or universities. Given their focus on high-potential ventures requiring minimal initial capital, many of the original accelerators centered on information technology ventures though a growing number specialize in other industries, such as energy or healthcare.

Accelerators typically select ventures by having an open call for applications. According to our primary sources, top programs were receiving 1,000–2,000 applications per cohort at the time of our study. Ventures submit a written application and often a video providing information about the founders, business idea, and progress to date. A small percentage of applicants are then interviewed, often initially via Skype and later in person. Among the accelerators we studied, interviews at both stages were restricted to 10–30 minutes and fewer than 15%–20% of initial applications made it to the final interview stages. The level of due diligence given to teams prior to admission was, thus, substantially limited relative to that of angels or venture capital firms. Between 6 and 125 venture applicants were then accepted into each accelerator cohort. Although selection practices varied, most accelerators accepted ventures holistically (versus scoring and ranking them). Accepted ventures typically agree to receiving a small equity investment from the accelerator; at the time of our study, the typical accelerator invested \$15,000 to \$20,000 in exchange for 6% to 8% equity[2] with such capital intended to help cover living expenses during the accelerator.

Focus on Learning and Distinctions from Incubators, Angels, and Venture Capitalists

Accelerators' focus on learning was reflected in the early language used by accelerators and those describing them. For instance, a 2007 *Denver Post* article written just before the start of the first Techstars cohort used the analogy of a university, describing the accelerators' founders as "professors" and emphasizing that participating entrepreneurs would have "unfettered access to about 40 mentors to help guide them through the strategy, implementation, funding, marketing and legal obstacles every startup faces" (Johnson 2007). Likewise, in their initial call for applicants to what they then called their "Summer Founders Program," Y Combinator's founders described the program:

> We'll have some smart people who are willing to talk over your plans with you, and suggest pitfalls and new ideas. We may also have connections to companies you'd like to do deals with. But how much you want to take advantage of our advice and connections is up to you.
>
> We'll organize some kind of dinner once a week for all the Summer Founders, so you can meet one another and compare notes. We'll try to get some expert in technology, business, or law to speak at each dinner. (ycombinator.com 2005)

This focus on learning distinguishes accelerators from incubators, an earlier form of organizational sponsor that also seeks to aid the development of early stage ventures that have either recently launched or are about to launch their product or service. In contrast to many accelerators' strong emphasis on learning, traditional incubators help ventures conserve scarce resources by providing physical infrastructure (office space, internet connection, printers, administrative support) and professional services (legal, accounting, etc.) at discounted rates to venture tenants (Hackett and Dilts 2004, Rothaermel and Thursby 2005). In other words, learning is generally not the primary focus of incubators. Additionally, whereas different ventures start and exit at different times and spend varying lengths of time in the same incubator (Rothaermel and Thursby 2005), accelerators have a cohort of ventures that start and end together and stay for a fixed period of time (typically three months). Thus, although research indicates that incubators do positively aid venture survival (Amezcua et al. 2013, Dutt et al. 2016), accelerators differ from such programs and may have quite different impacts.

At the outset of our research, it was also clear that accelerators' approach to learning distinguished them from angel investors and venture capital firms, other key entrepreneurial sponsors, in a few important ways. Many angel and venture capital firms positively impact venture development. For instance, angel investor groups have been associated with improved survival, additional funding, and growth (Kerr et al. 2014) and venture capital firms with professionalization (Hellmann and Puri 2002), strategy development (Garg and Eisenhardt 2017), and innovation (Pahnke et al. 2015). Yet, although some angel investors may provide funding similar to that provided by an accelerator, angel investments lack the formal structure, planned activities, and batching of ventures common in accelerators (Huang and Pearce 2015). Also, unlike venture capitalists that typically assign a representative member to handle advising and interactions with each venture in which they invest, accelerators often encourage consultation from many different types of parties beyond just internal program directors, including mentors, peer ventures, alumni, and industry experts. Venture capital firms further differ from accelerators in having relationships lasting several years (versus three months), taking substantial equity ownership (versus 6%–8%), employing legal protections that provide further control (e.g., liquidation preferences, right of first refusal), and restricting investments to those in their social networks (versus having an open call for applications). Thus, as accelerators appear different than incubators, angels, and venture capital firms, it is unclear whether any positive causal effects associated with these sponsors also extend to accelerators. It is also unclear what mechanisms might drive any accelerator effects.

Nonlearning Mechanisms That May Also Manifest in Accelerators

Although accelerators themselves emphasize learning, literature on venture capital and other forms of early organizational sponsorship suggests two compelling nonlearning mechanisms that might alternatively drive any positive relationship between accelerator participation and improved venture outcomes.

First, any observed relationship might be due to sorting (Roth and Sotomayor 1990, Mindruta et al. 2016). Sorting is a two-sided, often iterative process by which matches emerge based on the consent of both parties and accounting for the competition for partners. Sorting is frequently driven by actors seeking partners with whom they may maximize value capture (often as a result of improved joint value creation) (Mitsuhashi and Greve 2009, Mindruta et al. 2016) or from a tendency of high-status organizations to partner with each other to preserve their own status (Podolny 1993). When there are limits in actors' abilities to form additional ties and matching is primarily on the basis of perceived quality, sorting yields a dynamic whereby highly desirable partners are most likely to exclusively partner with one another, leaving less desirable partners to partner with others who are also less desirable. Such sorting has been observed in the venture investment context in the form of entrepreneurial ventures being more likely to ultimately receive investments from venture capital firms of similar relative quality and status[3] (Hallen 2008) and appears to drive about two-thirds of the performance differences among venture capital firms (Sørensen 2007, Fitza et al. 2009). Critical for our purposes, sorting's relationship to venture development is not causal and merely correlational; if found that there is only a sorting dynamic and no other accelerator effects, this would suggest that entrepreneurs gain little from accelerator participation and that policy makers seeking to advance venture development should avoid supporting accelerators.

Second, even if accelerators have a causal treatment effect, it might be due to signaling. Signals are observable information that is correlated with otherwise hard-to-observe attributes, often because the difficulty of obtaining the signal is inversely related to an actor's quality (Spence 1973). When high-status firms are perceived as having a capability for identifying high-quality partners, formed partnerships are a credible signal of a partnering organization's quality (Podolny 1993, Gulati 1995). Affiliations with higher-status venture capital firms, for instance, serve as effective signals to other investors and to the public market (Hsu 2004, Hallen 2008, Lee et al. 2011). Signals are especially important in contexts such as early-stage entrepreneurship when information about a venture's quality and history is often limited (Podolny 1994, Stuart et al. 1999). We also include in signaling the idea that accelerators may provide network connections to other resource providers and that these connections may act as information pipes that efficiently disseminate information about a venture's quality[4] (Podolny 2001). Although signaling would aid entrepreneurs, replicating such an effect for new accelerators would be difficult without first achieving a degree of prominence, status, and embeddedness. Moreover, if the accelerators' effect is largely a result of signaling, the internal activities of accelerators would be inconsequential. Overall, although these nonlearning mechanisms might influence the relationship between accelerator participation and venture outcomes, sorting and signaling are unlikely to arise independent of accelerators having (or being perceived as having) a direct and substantive effect on venture development; thus, it is still unclear whether accelerators aid venture development, and if so, how.

Mixed Methodology and Samples

We use mixed methods that combine a proprietary quantitative sample, a second quantitative sample gathered from publicly observable data, and rich qualitative fieldwork. This enables triangulation that helps overcome the limitations of individual research methods (Hall and Ziedonis 2001, Edmondson and McManus 2007, Kaplan 2015). Mixed methods are especially well suited for questions such as ours that merge applied and theory-driven aims (McFarland et al. 2016). In particular, our research is motivated by an applied question of "Do accelerators aid venture development?" and a theoretical question around how mechanisms driving any observed accelerator effect may be unique.

Our first set of analyses utilize proprietary, highly confidential quantitative data from four top accelerator cohorts to contrast ventures that were accepted with ventures that applied to and were almost accepted in those same cohorts (sample A). The strength of these proprietary data is that they allow especially close comparison of ventures of highly similar quality and interest in accelerator participation, but only some of the ventures ultimately received the treatment effect of accelerator participation. Such an approach to estimating the presence and magnitude of any accelerator effect is especially attractive given the challenges of performing a random control trial in our context (e.g., convincing high-potential entrepreneurs, accelerator programs, and mentors to participate in what might be a control group). We further unpack the mechanisms likely underlying any observed effect as well as the presence of sorting and signaling dynamics through analyses that examine potential moderating and mediating effects. These analyses indicate that accelerators do aid and accelerate venture development and that learning appears likely to be a primary mechanism. We further validate these findings in an auxiliary quantitative sample that draws on publicly available data to match accelerator and nonaccelerator participants that raised venture capital in a similar manner, contrasting the extent to which accelerator participation is correlated with speed to raising such funding or reaching other key milestones.

Second, we draw on extensive qualitative fieldwork in the form of more than 70 interviews with participants, program directors, and mentors at eight of the original U.S. accelerators as well as site visits and conference attendance (sample B). We utilize this qualitative fieldwork both to further validate the mechanism of learning and to build theory that explicates how this mechanism differs from previously studied interorganizational learning mechanisms (e.g., embedded partnerships, employee mobility, peer networks, remote observation, and crowdsourcing). It is through this qualitative fieldwork that we explicate broad, intensive, and paced consultation as a key and distinct theoretical mechanism that distinguishes accelerators from other early organizational sponsors.

Selection of Accelerators in the Samples

Although the number of accelerators continues to grow rapidly, we focus our research on the impact of accelerator cohorts that ran in 2011–2012. It was at this point that accelerators were gaining prominence in the entrepreneurial landscape, capturing scholarly and practitioner attention. By this time the accelerator form had emerged from its nascent stage, with Y Combinator and Techstars both having multiple years of cohorts and a number of other accelerators having entered around the world. Overall, although the accelerator form and the impact of accelerators may continue to evolve, we believe this period strikes a balance between ensuring the form had settled on common features and also allowing us to examine long-term outcomes for participating ventures.

Across all samples, we chose to focus on relatively top U.S. accelerators located in major metropolitan areas or entrepreneurial hubs as these accelerators were both likely to be imitated by new accelerators and be more attractive to entrepreneurs. As part of obtaining the proprietary data for both samples, we agreed to mask accelerator identities and refer to sampled accelerator using letters (i.e., "A" or "B"). Our samples include some particularly prominent accelerators now viewed as "beacons" of the accelerator form (Bermiss et al. 2017, Younger and Fisher 2020) as well as some that were well-regarded at the time but who later struggled or even failed. Following early industry reports, we restricted our focus to fixed-length programs that worked with batches of ventures and provided mentorship and education[5] (Miller and Bound 2011). For clarity of interpretation, we introduce sequentially the data, methodology, and results of each sample, utilizing consistent accelerator labels between the two confidential samples.

Do Accelerators Work?

Almost Accepted Sample and Methods (Sample A)

Our first analyses draw on sample A, a sample of confidential quantitative data on the accepted and almost accepted applicant pools at four different accelerator cohorts associated with three different accelerators—three cohorts drawn from two accelerators that are also in our qualitative fieldwork (accelerators B and E) and one unique to sample A (accelerator X). All sampled accelerators are in the United States and generally regarded as "top tier" by interviewed entrepreneurs and subsequent public rankings (Cohen et al. 2019b). All cohorts come from the 2011–2012 period. As a condition of the data access, we agreed not to contact any of these entrepreneurs.

These data allow an approach stylistically similar to a regression discontinuity design. We begin with the top portions of the applicant pools to these accelerators. We can then most heavily weight in our regressions those ventures that, based on other observables, appear closest to the cutoff, that is, barely accepted and barely rejected ventures; we do so using inverse probability of treatment weights (IPTW) (Hirano and Imbens 2001, Azoulay et al. 2009, Elfenbein et al. 2010). We could not, however, utilize a traditional regression discontinuity as these particular accelerators selected ventures holistically and did not explicitly rank order almost accepted ventures.

The almost accepted set was identified for each accelerator cohort as follows. As is common with accelerators, each accelerator had an open and well-publicized call for applications with a fixed submission deadline. After this deadline, each accelerator utilized a multistage process of filtering down the applicant pool. The almost accepted sets were identified as the ventures that made it to the round before last in this filtering process. Such applicants generally participated in one or more Skype conversations with the accelerator staff and visited the accelerator to interview in person. Our discussions with accelerator leaders suggest that the experienced directors overseeing selections for these accelerators regarded the almost accepted set as nearly indistinguishable to the selected set prior to the program. Indeed, a managing director of one cohort told us he and his partners had a "7.5 hour meeting till 3:00 in the morning trying to select the companies."

Across the four applicant pools, our confidential data include a total of 45 accepted ventures and 217 almost accepted ventures out of more than 3,100 applicants. Thus, the combination of the accepted and almost accepted ventures represent about the top 7% of applicants to each of these accelerators. Out of this top 7%, roughly 17% were accepted and participated in the accelerators (i.e., roughly 1.5% of the initial applicant pools). Program directors generously provided access to these confidential data.[6] We refer to these applicant pools by their accelerator pseudonym and year: B-2012, E-2012, X-2012, and E-2011.

We identified the founders and gathered complete founder biographies for 44 of the accepted ventures and 191 of the almost accepted ventures.[7] The data set also included five ventures that applied to multiple of the sampled cohorts. Consistent with the almost accepted nature of the data, three of these ventures were ultimately accepted by one of the cohorts.[8] We gathered data on venture outcomes and entrepreneur backgrounds from websites of ventures, internet searches, LinkedIn, Amazon Web Services, AngelList, and Crunchbase.

Measures

Dependent Variables. As entrepreneurs have different aims and some metrics are more relevant for certain business strategies than others, we triangulate accelerator impact by considering four different venture outcomes. Our first dependent variable is *currently ongoing*, a binary measure indicating that a venture is either an ongoing operational concern or has been acquired (versus having been shut down) at the time of data gathering (Hochberg et al. 2007). We identified ongoing activity by examining the websites and social media presences of ventures.[9] Second, for the subset of ventures still alive and not acquired, we measured whether the venture had *11 or more employees*. This binary measure is attractive as it reflects the extent to which ventures have achieved a revenue stream or funding to support hiring (Piezunka and Dahlander 2015). We obtained the size of companies from LinkedIn.[10] Third, we examined the *subsequent funding* of the venture in millions raised from investors after the accelerator graduation. We drew investment data from both the Crunchbase database and AngelList and excluded any capital raised from the focal accelerator or investments guaranteed to all accelerator participants.[11] Fourth, to examine customer traction, we measured *web traffic after one year* (Rindova and Kotha 2001, Goldfarb et al. 2007). We measured it as the average number of daily page views (in thousands) of a venture's website for the month one year after the accelerator's demo day. These data came from Amazon's Alexa service. Outcome data collection was completed in the summer of 2014. We note that, although each outcome captures a different element of venture success, venture fundraising was the primary metric utilized by accelerator program directors.

Accelerator Measures. We include four dummy variables indicating if ventures participated in one of the focal four accelerator cohorts. We also include corresponding dummy variables for each venture's application pool; cohort E-2011 applicants were the omitted category. We also control for the 32 ventures that were rejected from the focal cohort but later participated in another accelerator.

Founder and Venture Measures. We also gathered founding team and venture measures to control for remaining founder differences between the accepted and almost accepted sets in both regressions and weighting. We also control for *prior web traffic* in the month leading up to the start of the accelerator,[12] measured in a manner consistent with the web traffic outcome.

We follow prior literature and include a range of measures to capture the founding team's human and social capital (Eisenhardt and Schoonhoven 1990, Beckman et al. 2007, Hsu 2007, Hallen 2008, Eesley and Roberts 2012). We include *number of founders* to account for the greater human and social capital of larger teams. Consistent with recent literature on hybrid entrepreneurship (Raffiee and Feng 2014), we include *full time at application* as the percentage of founders working full time on the venture when they applied to the accelerator. We hand-collected data using LinkedIn to examine if each entrepreneur had another full-time job or was in school (e.g., completing an MBA) at each date. We also include dummy variables indicating if any of a venture's founders had an MBA, JD (a law degree), technical masters, or technical PhD. We include *university prominence* to measure the maximum prestige of the universities from which the founders received their undergraduate degrees. We followed Rider (2012) and use *U.S. News & World Report*'s 2012 worldwide ranking of the top 400 global universities, which assigns scores ranging from 29.2 to 100.[13]

We also control for founders' prior work experience because some employers may provide founders with technical insights and networks beneficial to the starting of a new venture (Agarwal et al. 2004). We follow Burton et al. (2002) and control for *prior employer prominence* by measuring the number of startups in the overall sample that shared the same prior employer as one of the venture's founders.[14] To account for the depth of experience, we include *years work experience* as the average number of years between founders receiving their undergraduate degree and founding the venture, logged to reduce skew.[15] We also include dummy variables indicating if one or more founders had former entrepreneurial experience (*serial entrepreneur*) or had previously raised venture capital (*previously raised VC*).

Do Accelerators Aid Venture Development? (i.e., Is There a Treatment Effect?)

Table 1 reports descriptive statistics and correlations for sample A. All pairwise correlations between independent variables and controls are below 0.7, suggesting that our estimates are unlikely to be biased by multicollinearity. Table 2 reports regression estimates of four outcomes—(1) currently ongoing, (2) 11 or more employees, (3) subsequent funding, and (4) web traffic—across the four applicant pools. All models control for founder characteristics and to which accelerator a venture applied. Although currently ongoing and 11 or more employees are binary outcomes, we use linear probability models rather than logit estimates for ease of interpretation and because participation in certain accelerators perfectly predicted venture outcomes (logit estimates did, however, yield broadly similar results). We logged the continuous outcome variables, funding, and web traffic to correct for skew before using least squares regressions. Across all models, robust standard errors clustered at

Table 1. Descriptive Statistics and Pairwise Correlations

	Measure	Mean	Standard Deviation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Currently ongoing	0.562	0.497											
(2)	11 or more employees[a]	0.237	0.427	*NA*										
(3)	Subsequent funding (ln(M$))	0.174	0.463	0.32	0.45									
(4)	Web traffic in one year (ln(thousand views))	1.527	2.190	0.34	0.18	0.40								
(5)	Cohort B-2012 participant	0.051	0.221	0.13	0.37	0.41	0.19							
(6)	Cohort E-2012 participant	0.043	0.202	0.06	0.03	0.14	0.10	−0.05						
(7)	Cohort X-2012 participant	0.051	0.221	0.20	0.14	0.25	0.11	−0.05	−0.05					
(8)	Cohort E-2011 participant	0.043	0.202	0.06	0.04	0.10	0.04	−0.05	−0.04	−0.05				
(9)	Eventually other accelerator	0.132	0.339	0.04	−0.06	0.03	0.08	−0.09	−0.08	−0.09	−0.08			
(10)	Cohort B-2012 applicant	0.268	0.444	0.09	0.11	0.09	0.06	0.38	−0.13	−0.14	−0.13	0.02		
(11)	Cohort E-2012 applicant	0.226	0.419	−0.10	−0.19	−0.09	−0.12	−0.13	0.39	−0.13	−0.11	−0.12	−0.33	
(12)	Cohort X-2012 applicant	0.268	0.444	0.13	0.13	0.05	0.09	−0.14	−0.13	0.38	−0.13	0.05	−0.37	−0.33
(13)	Prior web traffic	1.325	1.914	0.15	0.04	0.17	0.71	0.00	−0.01	0.12	0.10	0.09	−0.04	−0.14
(14)	Number of founders	2.098	0.967	0.16	0.10	0.24	0.17	0.08	0.04	0.14	0.00	0.18	0.00	−0.10
(15)	Full time at application	0.529	0.431	0.20	0.04	0.13	0.13	0.08	0.04	0.15	0.02	0.04	0.19	−0.06
(16)	Years work experience (L)	1.853	0.900	0.19	−0.02	0.11	0.06	0.13	0.06	0.09	0.02	−0.01	0.05	0.06
(17)	Years work experience missing	0.089	0.286	−0.05	−0.07	−0.12	−0.04	−0.07	−0.07	−0.07	0.01	−0.03	−0.05	−0.03
(18)	Prior employer prominence	0.145	0.573	−0.03	0.04	0.02	0.03	0.12	0.15	−0.01	0.09	0.05	0.12	−0.01
(19)	University prominence	50.402	22.833	−0.03	−0.03	0.01	0.04	−0.05	−0.08	0.02	−0.01	−0.01	−0.04	−0.04
(20)	MBA	0.345	0.476	0.05	−0.20	−0.04	−0.14	−0.05	−0.06	−0.09	0.11	−0.04	−0.05	0.04
(21)	JD	0.026	0.158	0.09	0.08	0.02	−0.08	−0.04	0.10	0.09	−0.03	−0.06	−0.04	0.11
(22)	Technical masters	0.243	0.430	0.06	0.13	0.03	−0.02	0.00	0.08	−0.04	0.03	0.07	0.06	−0.04
(23)	Technical PhD	0.068	0.252	0.14	0.01	−0.02	0.00	0.01	0.03	0.17	−0.06	−0.01	−0.09	−0.02
(24)	Serial entrepreneurs	0.502	0.501	0.25	0.20	0.24	0.23	0.08	−0.09	0.19	0.04	0.01	0.14	−0.09
(25)	Previously raised VC	0.034	0.182	0.17	0.17	0.22	0.07	0.28	0.08	0.17	−0.04	−0.07	0.05	−0.05

		(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(13)	Prior web traffic	0.13												
(14)	Number of founders	0.23	0.18											
(15)	Ful ltime at application	0.08	0.16	−0.04										
(16)	Years work experience (L)	−0.01	−0.01	0.05	0.19									
(17)	Years work experience missing	−0.12	0.02	−0.20	−0.18	−0.65								
(18)	Prior employer prominence	−0.05	−0.03	0.04	0.10	0.06	−0.08							
(19)	University prominence	0.05	0.05	0.02	−0.06	−0.02	−0.11	0.11						
(20)	MBA	−0.05	−0.13	0.01	−0.01	0.20	−0.04	0.06	0.04					
(21)	JD	−0.04	−0.05	−0.04	−0.02	0.09	−0.05	0.09	0.05	−0.06				
(22)	Technical masters	−0.01	−0.03	0.16	−0.08	0.06	−0.04	0.16	0.01	0.07	−0.03			
(23)	Technical PhD	0.10	−0.03	0.08	0.04	0.00	0.09	0.14	−0.04	0.02	−0.04	0.24		
(24)	Serial entrepreneurs	0.16	0.24	0.30	0.20	0.20	−0.17	−0.06	0.05	−0.07	0.05	0.03	0.07	
(25)	Previously raised VC	0.10	−0.01	0.30	0.07	0.10	−0.06	0.07	0.00	0.01	−0.03	0.06	0.14	0.19

Note. N = 235 for all measures, except for 11 or more employees (N = 118), subsequent funding (N = 231), and web traffic in one year (N = 227).
[a]Note that "11 or more employees" only takes on values for ventures that are both currently ongoing and have not been acquired (and, thus, has no correlation value with currently ongoing/acquired).

Table 2. Venture Outcomes in Almost Accepted Data (Sample A)

	Currently ongoing (alive/acquired vs. shut down)	11 or more employees	Funding	Web traffic
Nature of outcome	Binary	Binary	Ln(M$)	Ln(thousands daily page views)
Accelerator participation				
Cohort B-2012 participant	0.261***	0.754***	0.997***	2.320***
	(0.028)	(0.050)	(0.029)	(0.209)
Cohort E-2012 participant	0.315***	0.305***	0.385***	2.086***
	(0.047)	(0.066)	(0.044)	(0.279)
Cohort X-2012 participant	0.345***	0.006	0.382***	0.631**
	(0.036)	(0.061)	(0.032)	(0.234)
Cohort E-2011 participant	0.208**	0.120	0.083	–0.400***
	(0.060)	(0.161)	(0.062)	(0.103)
Eventually other accelerator	0.098**	–0.007	0.109	0.377
	(0.041)	(0.119)	(0.069)	(0.429)
Applicant pool (E-2011 omitted)				
Cohort B-2012 applicant	0.186***	0.031	–0.132*	0.248
	(0.047)	(0.078)	(0.067)	(0.229)
Cohort E-2012 applicant	0.023	–0.116**	–0.089**	–0.158
	(0.022)	(0.044)	(0.032)	(0.166)
Cohort X-2012 applicant	0.189***	0.166*	–0.094	0.076
	(0.028)	(0.078)	(0.055)	(0.147)
Controls				
Prior web traffic	0.020	0.018	0.024	0.758***
	(0.014)	(0.064)	(0.019)	(0.075)
Number of founders	0.012	–0.030	0.102	–0.034
	(0.029)	(0.058)	(0.063)	(0.170)
Full time at application	0.082	–0.012	0.038	–0.289
	(0.073)	(0.073)	(0.067)	(0.508)
Years work experience[a] (L)	0.108**	–0.048	0.028	0.126
	(0.040)	(0.068)	(0.049)	(0.298)
Years work experience missing[a]	0.375**	–0.117	–0.027	–0.104
	(0.134)	(0.122)	(0.070)	(0.642)
Prior employer prominence	–0.101**	–0.046	–0.044	–0.063
	(0.041)	(0.134)	(0.076)	(0.302)
University prominence	0.002	–0.001	0.001	0.010
	(0.001)	(0.001)	(0.001)	(0.008)
MBA	0.131	–0.079	–0.034	0.418
	(0.085)	(0.137)	(0.088)	(0.430)
JD	0.306*	0.329	0.107	–0.890
	(0.134)	(0.323)	(0.129)	(0.829)
Technical masters	0.081	0.060	0.001	–0.026
	(0.081)	(0.143)	(0.072)	(0.403)
Technical PhD	0.132	–0.103	–0.146*	0.010
	(0.124)	(0.142)	(0.074)	(0.431)
Serial entrepreneurs	0.148**	0.125	0.225*	0.375*
	(0.050)	(0.132)	(0.111)	(0.189)
Previously raised VC	0.149	0.075	–0.041	0.099
	(0.144)	(0.209)	(0.209)	(0.787)
Intercept	–0.192	0.267	–0.332	–0.596
	(0.149)	(0.190)	(0.189)	(1.013)
Estimation model	Linear probability model	Linear probability model	Least squares	Least squares
Weighting	IPTW	IPTW	IPTW	IPTW
N[b]	235	118	231	227

Table 2. (Continued)

	Currently ongoing (alive/acquired vs. shut down)	11 or more employees	Funding	Web traffic
Nature of outcome	Binary	Binary	Ln(M$)	Ln(thousands daily page views)
Log likelihood	−112.224	−52.202	−140.443	−411.665
R^2	0.318	0.381	0.420	0.577

Notes. Robust standard errors clustered at the level of the accelerator cohort/applicant pool. All models are weighted using inverse probability of treatment weights, calculated using logit estimates of the likelihood of acceptance into the focal cohort.

[a]The founders of 42 ventures did not list graduation years; these were assigned years work experience (L) = 1, and the dummy years work experience missing was set to one.

[b]Sample size varies across estimates based on differences in the availability of data on certain outcomes for some ventures.

**p* < 0.10; ***p* < 0.05; ****p* < 0.01; two-tailed tests.

the level of the participant cohort/almost accepted pool (e.g., all almost accepted applicants to cohort B-2012 were in one cluster).

We utilize inverse probability of treatment weights calculated at the venture level to dampen the influence of any sorting dynamics based on observable attributes (Hirano and Imbens 2001, Azoulay et al. 2009, Elfenbein et al. 2010). We calculated these weights using a logistic regression of each venture's likelihood of participating in the accelerator to which it applied, estimated using all control variables. We discuss this logistic regression in detail later when exploring the extent to which *sorting dynamics* exist in the data. We calculate inverse probability of treatment weights for ventures participating in the accelerators as $1/p$ (where p is the estimated probability of participation) and weights for almost accepted ventures as $1/(1-p)$.

We present estimates of accelerators' effects on venture outcomes in Table 2. For the outcome currently ongoing, we find that all four cohorts have a positive and statistically significant effect. Cohort B-2012 participation increased the likelihood of being alive or acquired by 26.1% ($p < 0.01$), cohort E-2012 by 31.5% ($p < 0.01$), cohort X-2012 by 34.5% ($p < 0.01$), and cohort E-2011 by 20.8% ($p < 0.05$). Wald tests did not reveal any significant differences between these effects.

For 11 or more employees and conditional on the venture still being ongoing and not acquired, we find that cohort B-2012 participation increased the likelihood of reaching 11 or more employees by 75.4% ($p < 0.01$) and cohort E-2012 by 30.5% ($p < 0.01$). We do not observe statistically significant effects for cohort X-2012 or cohort E-2011. Wald tests reveal that the effect of cohort B-2012 was statistically different from that of cohort E-2012.

For raising additional capital, we find that accelerator participation increases funds raised: 171% (cohort B-2012; $p < 0.01$), 47% (cohort E-2012; $p < 0.01$), and 47% (cohort X-2012; $p < 0.01$); cohort E-2011 did not show a statistically significant effect. Wald tests reveal the effect of cohort B-2012 was statistically different from those of cohorts E-2012 and X-2012 though these two were not statistically different from each other.

For web traffic (a measure of prominence and customer traction), we find that accelerator participation increased traffic by +917% for cohort B-2012 ($p < 0.01$), +705% for cohort E-2012 ($p < 0.01$), and +88% for cohort X-2012 ($p < 0.05$). Unexpectedly, cohort E-2011 shows a *decrease* in web traffic of 33% ($p < 0.01$). We note the program directors of accelerator E retrospectively viewed the program getting stronger over time, which is consistent with these results. With the exception of cohorts B-2012 and E-2012, all of these effects were significantly different from each other.

Taken as a whole, our results indicate that *some, but not all,* accelerators likely causally benefit participating ventures. Our results also indicate, though, that, even among these relatively well-regarded accelerators, there are differences in treatment effects. We see some accelerators are better at aiding certain outcomes; for example, cohort X-2012 saw improvements in currently ongoing, funding, and web traffic, and cohort B-2012 saw improvements in these dimensions and number of employees. Finally, the differences between cohorts E-2012 and E-2011 indicate individual accelerator performance may shift and possibly improve over time.

Do Accelerators Accelerate Venture Development?

The analyses presented here indicate many of these accelerators have a positive and meaningful treatment effect on the long-term outcomes of ventures. Yet the name "accelerators" implies that these programs do not simply enhance the likelihood of reaching key outcomes, but also the speed of reaching these outcomes. Understanding how accelerators impact the speed with which ventures reach key outcomes is theoretically important because the additional time spent on accelerator activities comes with high opportunity costs, and it could be that accelerators improve long-term outcomes at the expense of slower times to key milestones.

We therefore analyze the question of accelerators' impact on the speed to reaching key funding milestones of raising $500,000 (reached by 35 ventures in our sample), $1 million (reached by 26 ventures), or $2 million (reached by 15 ventures) in aggregate funding. We only examine speed to these funding milestones as the other outcomes we examined in Table 2 were not available longitudinally.[16] We analyze the speed to reaching these outcomes for the 231 ventures for which we could find complete data on the size of rounds. Following prior studies of time to venture funding, we use event history methods in the form of piecewise constant models (Shane and Stuart 2002). This model is attractive in that it does not make strong parametric assumptions about the functional form of age dependence in the baseline hazard. We construct the sample for our event history analyses as monthly spells beginning at the starting month of each accelerator program. The focal transitions were whether a venture raised a round in the focal month that brought their aggregate funding to one of the three milestone levels. The ventures not reaching these funding milestones by the end of the data-collection period in the summer of 2014 were treated as right censored. We include in the analyses the same independent and control variables as before. After inspecting life tables of hazard rates to identify periods in which hazard rates were relatively constant, we chose duration period effects of 0–5 months, 6–11 months, 12–17 months, 18–23 months, and 24+ months. We also added year fixed effects to account for the fundraising climate over time. These analyses also utilized inverse probability of treatment weights though estimates without these weights yielded highly similar results.

Table 3 presents the results of our piecewise constant event history analyses. We find that accepted participants in cohorts B-2012, E-2012, and X-2012 reach each of the three focal funding levels faster than the almost accepted applicants to these same cohorts. The magnitude of these effects is also quite substantial. For instance, the smallest statistically significant accelerator participation coefficient for speed to reaching $500,000 in funding is 1.863 for cohort X-2012. This corresponds to a 544% increase in likelihood of reaching this funding level each month. As with the overall amount of capital raised, we do not see a statistically significant effect for accelerator participation in cohort E-2011. Taken as a whole, results indicate most of the focal accelerators likely increase the speed to raising different levels of funding.

How Do Accelerators Work? Learning, Signaling, or Other Potential Mechanisms?

The almost accepted research design helps identify the presence and magnitude of any accelerator treatment effects above and beyond any sorting dynamics that might be present. Yet this leaves the question as to whether these observed effects are primarily driven by learning, as emphasized by accelerators, or instead by signaling. We conducted several follow-on analyses to gain insight into which mechanism might be more likely to be the primary driver of the observed accelerator effects.

First, we follow a classic approach used in the signaling literature to disentangle signaling from other effects (e.g., learning or sorting in our context). This approach relies on the logic that signals matter more when there is greater uncertainty about underlying and otherwise unobservable quality (Spence 1973). By this same logic, when other information about underlying quality is available such that there is less uncertainty, signals should matter less.[17] In our context, this suggests that any signaling effect of accelerators would be dampened when there is more data about a venture's quality. Here we consider two available sources of data that provide information about a ventures' underlying quality and, thus, might reduce the additional value of any accelerator signaling effect. The first of these is ventures having one or more founders who were serial entrepreneurs. Having serial entrepreneurs on a team may be suggestive of a venture's potential because such founders are presumed to have learned from their past experiences about evaluating opportunities and launching a venture. The second source of data is a venture's level of prior web traffic. Although investors and other potential partners may not attend to web traffic directly, it is a metric that ventures are likely to mention in meetings and one likely to determine the extent to which the venture attracts attention from relevant media.

We argue that, if any accelerator effect is driven primarily by signaling, such effects should be dampened for founding teams that include a serial entrepreneur or ventures having greater prior web traffic and that there would be negative and significant interactions between these variables and accelerator participation.[18] Table 4 explores the effect of serial entrepreneur and prior web traffic for the outcomes of future funding raised and future web traffic; we focused on these outcomes as they involve audiences (funders, potential customers) to whom any accelerator signal might be particularly relevant. We increase our predictive power by combining the effects of cohorts B-2012, E-2012, and X-2012 (which all had significant effects in Table 2). For the outcome of subsequent funding, we observe positive interactions

Table 3. Time to Key Fundraising Outcomes in Almost Accepted Data: Piecewise Constant Analyses with IPTW (Sample A)

Time to raising	\$500k	\$1M	\$2M
Accelerator participation			
Cohort B-2012 participant	4.525***	4.482***	5.055***
	(0.679)	(0.777)	(0.798)
Cohort E-2012 participant	17.256***	15.782***	19.042***
	(1.146)	(1.216)	(1.199)
Cohort X-2012 participant	1.863***	1.826***	3.918***
	(0.537)	(0.382)	(0.718)
Cohort E-2011 participant	1.259	–1.201	–1.890
	(1.770)	(1.035)	(1.209)
Eventually other accelerator	0.700	0.378	1.396*
	(0.858)	(0.549)	(0.778)
Applicant pool (E-2011 omitted)			
Cohort B-2012 applicant	0.171	–2.673***	–3.118***
	(2.384)	(0.664)	(0.691)
Cohort E-2012 applicant	–14.353***	–15.746***	–18.731***
	(3.058)	(1.337)	(1.501)
Cohort X-2012 applicant	1.397	–1.123	–3.373***
	(2.312)	(0.809)	(1.006)
Controls			
Prior web traffic	0.220	0.047	0.095
	(0.247)	(0.216)	(0.221)
Number of founders	0.013	–0.498	–0.333
	(0.244)	(0.378)	(0.420)
Full time at application	–1.134***	–1.112	–1.451***
	(0.386)	(0.716)	(0.512)
Years work experience[a] (L)	0.483	–0.795**	–0.855***
	(1.328)	(0.310)	(0.306)
Years work experience missing[a]	–14.752***	–16.620***	–19.072***
	(3.615)	(0.516)	(0.877)
Prior employer prominence	–0.193	–0.236	–11.478***
	(0.350)	(0.690)	(0.861)
University prominence	0.013	–0.016***	–0.013
	(0.021)	(0.006)	(0.012)
MBA	0.707	0.427	–0.930
	(0.665)	(0.502)	(1.144)
JD	0.967*	0.431	–18.039***
	(0.570)	(1.051)	(0.611)
Technical masters	0.427	0.463	–0.538
	(0.714)	(0.378)	(0.907)
Technical PhD	–0.191	0.259	–16.404***
	(0.672)	(1.341)	(0.864)
Serial entrepreneurs	1.151**	1.509**	1.735**
	(0.560)	(0.657)	(0.881)
Previously raised VC	–0.691	0.228	–0.299
	(1.101)	(1.174)	(0.830)
Year fixed effects	Y	Y	Y
Age period effects	Y	Y	Y
Weighting	IPTW	IPTW	IPTW
Number of ventures	231	231	231
Log likelihood	–245.468	–276.611	–169.564

Notes. Robust standard errors clustered at the level of the accelerator cohort/applicant pool. Spells are venture-months. All models are weighted using inverse probability of treatment weights, calculated using logit estimates of the likelihood of acceptance into the focal cohort.

[a]The founders of 42 ventures did not list graduation years; these were assigned years work experience (L) = 1, and the dummy years work experience missing was set to one.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$; two-tailed tests.

Table 4. Contingencies in Outcomes for Almost Accepted Data (Sample A)

	Funding contingencies (Least squares estimate of Ln(M$) with IPTW)			Web traffic contingencies (Least squares estimate of Ln(thousands daily page views) with IPTW)		
Accelerator participation						
Cohort B-2012, E-2012, or X-2012 participant	0.600***	0.244**	0.444**	1.616***	1.698***	1.985***
	(0.126)	(0.092)	(0.168)	(0.388)	(0.319)	(0.309)
Cohort E-2011 participant	0.091	0.151***	0.124**	−0.384***	−0.397***	−0.457***
	(0.059)	(0.021)	(0.050)	(0.088)	(0.104)	(0.119)
Eventually other accelerator	0.092	0.096	0.109	0.401	0.396	0.338
	(0.077)	(0.070)	(0.073)	(0.422)	(0.426)	(0.424)
Interactions						
Cohort B-2012, E-2012, or X-2012 participant × serial entrepreneurs		0.635***			−0.147	
		(0.131)			(0.234)	
Cohort B-2012, E-2012, or X-2012 participant × prior web traffic			0.110**			−0.260
			(0.036)			(0.147)
Applicant pool (E-2011 omitted)						
Cohort B-2012 applicant	0.080	0.106	0.092	0.606	0.601	0.586
	(0.142)	(0.141)	(0.140)	(0.352)	(0.352)	(0.346)
Cohort E-2012 applicant	−0.169	−0.095	−0.172	0.051	0.034	0.063
	(0.100)	(0.063)	(0.095)	(0.216)	(0.221)	(0.194)
Cohort X-2012 applicant	−0.177	−0.164	−0.179	−0.345	−0.348	−0.343
	(0.123)	(0.128)	(0.130)	(0.442)	(0.439)	(0.407)
Controls						
Prior web traffic	0.025	0.012	−0.002	0.767***	0.770***	0.829***
	(0.019)	(0.017)	(0.013)	(0.070)	(0.067)	(0.034)
Number of founders	0.101	0.088	0.096	0.001	0.004	0.012
	(0.066)	(0.060)	(0.060)	(0.159)	(0.165)	(0.163)
Full time at application	−0.040	0.013	−0.045	−0.453	−0.465	−0.445
	(0.069)	(0.063)	(0.079)	(0.504)	(0.497)	(0.472)
Years work experience[a] (L)	0.044	0.027	0.049	0.178	0.181	0.158
	(0.053)	(0.057)	(0.057)	(0.297)	(0.296)	(0.299)
Years work experience missing[a]	−0.022	−0.081	−0.024	−0.094	−0.082	−0.103
	(0.085)	(0.086)	(0.092)	(0.647)	(0.641)	(0.647)
Prior employer prominence	−0.048	−0.047	−0.039	−0.039	−0.040	−0.059
	(0.076)	(0.060)	(0.072)	(0.311)	(0.315)	(0.326)
University prominence	0.001	0.000	0.000	0.007	0.007	0.008
	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)	(0.008)
MBA	−0.011	−0.022	−0.001	0.391	0.395	0.378
	(0.089)	(0.090)	(0.093)	(0.421)	(0.420)	(0.420)
JD	0.022	0.080	0.090	−1.001	−1.014	−1.160
	(0.130)	(0.143)	(0.163)	(0.761)	(0.768)	(0.686)
Technical masters	−0.011	0.071	−0.012	0.044	0.023	0.040
	(0.075)	(0.072)	(0.066)	(0.368)	(0.350)	(0.336)
Technical PhD	−0.133	−0.177**	−0.143	−0.074	−0.063	−0.046
	(0.079)	(0.072)	(0.084)	(0.384)	(0.388)	(0.409)
Serial entrepreneurs	0.214*	0.012	0.169	0.266	0.313*	0.369*
	(0.099)	(0.032)	(0.100)	(0.145)	(0.143)	(0.175)
Previously raised VC	0.050	0.016	0.067	0.378	0.385	0.337
	(0.203)	(0.251)	(0.198)	(0.719)	(0.713)	(0.715)
Intercept	−0.301	−0.170	−0.229	−0.495	−0.523	−0.660
	(0.202)	(0.190)	(0.197)	(1.032)	(1.051)	(1.045)
N[b]	231	231	231	227	227	227
Log likelihood	−148.522	−137.106	−144.303	−416.506	−416.454	−414.366
R^2	0.378	0.437	0.401	0.558	0.558	0.566

Notes. Robust standard errors clustered at the level of the accelerator cohort/applicant pool. All models are weighted using inverse probability of treatment weights, calculated using logit estimates of the likelihood of acceptance into the focal cohort.

[a]The founders of 42 ventures did not list graduation years; these were assigned years work experience (L) = 1, and the dummy years work experience missing was set to one.

[b]Sample size varies across estimates based on differences in the availability of data on certain outcomes for some ventures.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$; two-tailed tests.

Table 5. Contingencies for Time to Key Fundraising Outcomes in Almost Accepted Data: Piecewise Constant Analyses with IPTW (Sample A)

Time to raising	$500k	$500k	$500k	$1M	$1M	$1M	$2M	$2M	$2M
Accelerator Participation									
Cohort B-2012, E-2012, or X-2012 participant	3.187***	2.414**	2.552**	3.118***	1.697**	2.388*	4.726***	2.466**	3.907***
	(1.235)	(1.109)	(1.225)	(1.008)	(0.729)	(1.384)	(0.615)	(0.980)	(1.057)
Cohort E-2011 participant	1.353	1.542	1.533	−1.145	−0.404	−0.319	−1.886	−1.003	−1.662
	(1.868)	(1.862)	(1.596)	(1.014)	(0.869)	(0.972)	(1.197)	(0.898)	(1.102)
Eventually other accelerator	0.703	0.716	0.894	0.369	0.374	0.816*	1.425*	1.313*	1.560*
	(0.971)	(0.975)	(0.914)	(0.469)	(0.482)	(0.482)	(0.763)	(0.777)	(0.808)
Interactions									
Cohort B-2012, E-2012, or X-2012 participant × serial entrepreneurs		1.137			2.185**			2.832*	
		(0.879)			(1.088)			(1.552)	
Cohort B-2012, E-2012, or X-2012 participant × prior web traffic			0.494*			0.609			0.403
			(0.262)			(0.536)			(0.356)
Applicant pool (E-2011 omitted)									
Cohort B-2012 applicant	1.343	1.506	1.280	−1.505*	−0.863	−1.377	−2.795***	−2.047***	−2.581***
	(2.082)	(2.082)	(1.795)	(0.815)	(0.714)	(0.918)	(0.728)	(0.621)	(0.914)
Cohort E-2012 applicant	−0.331	−0.211	−0.562	−3.241***	−2.645***	−3.180***	−4.412***	−3.747***	−4.215***
	(1.875)	(1.817)	(1.529)	(1.012)	(0.797)	(1.212)	(1.020)	(0.770)	(1.147)
Cohort X-2012 applicant	0.451	0.522	0.499	−2.120*	−1.749*	−1.925	−4.106***	−3.656***	−3.976***
	(1.564)	(1.558)	(1.242)	(1.116)	(0.913)	(1.224)	(0.833)	(0.695)	(1.028)
Controls									
Prior web traffic	0.240	0.231	0.033	0.074	0.045	−0.306	0.101	0.083	−0.137
	(0.202)	(0.214)	(0.105)	(0.192)	(0.194)	(0.377)	(0.219)	(0.210)	(0.274)
Number of founders	0.054	0.040	−0.075	−0.401	−0.388	−0.479	−0.295	−0.402	−0.364
	(0.220)	(0.211)	(0.207)	(0.385)	(0.354)	(0.437)	(0.404)	(0.403)	(0.434)
Full time at application	−1.358***	−1.311***	−1.638***	−1.335*	−1.158*	−1.439**	−1.516***	−1.089**	−1.537***
	(0.294)	(0.374)	(0.353)	(0.733)	(0.638)	(0.608)	(0.516)	(0.442)	(0.523)
Years work experience[a] (L)	0.541	0.518	0.626	−0.675***	−0.704***	−0.486	−0.856***	−0.750***	−0.680**
	(1.271)	(1.233)	(1.125)	(0.249)	(0.250)	(0.318)	(0.299)	(0.229)	(0.318)
Years work experience missing[a]	−14.370***	−14.234***	−15.257***	−16.287***	−17.113***	−16.331***	−19.705***	−20.035***	−17.720***
	(3.334)	(3.313)	(2.749)	(0.520)	(0.592)	(0.538)	(0.881)	(0.768)	(0.803)
Prior employer prominence	−0.172	−0.181	−0.144	−0.201	−0.154	−0.133	−12.551***	−12.999***	−11.364***
	(0.351)	(0.325)	(0.310)	(0.668)	(0.697)	(0.662)	(0.870)	(0.721)	(0.881)
University prominence	0.011	0.011	0.010	−0.016***	−0.016**	−0.017***	−0.013	−0.013	−0.015
	(0.021)	(0.022)	(0.020)	(0.005)	(0.007)	(0.006)	(0.012)	(0.015)	(0.012)
MBA	0.597	0.566	0.825*	0.367	0.240	0.276	−0.946	−1.052	−1.076
	(0.551)	(0.504)	(0.490)	(0.480)	(0.502)	(0.497)	(1.144)	(1.001)	(1.008)
JD	0.769	0.824	1.030*	0.275	0.597	0.660	−18.745***	−17.590***	−16.773***
	(0.527)	(0.546)	(0.619)	(1.117)	(1.227)	(1.388)	(0.593)	(0.825)	(0.630)
Technical masters	0.386	0.576	0.420	0.374	0.736	0.562	−0.591	−0.085	−0.446
	(0.618)	(0.718)	(0.632)	(0.371)	(0.566)	(0.461)	(0.876)	(0.724)	(0.855)

Table 5. (Continued)

Time to raising	\$500k	\$500k	\$500k	\$1M	\$1M	\$1M	\$2M	\$2M	\$2M
Technical PhD	−0.322	−0.294	−0.405	0.186	0.131	0.101	−17.550***	−17.116***	−15.410***
	(0.729)	(0.736)	(0.730)	(1.216)	(1.264)	(1.154)	(0.889)	(0.775)	(0.857)
Serial entrepreneurs	0.867**	0.120	0.699	1.164*	−0.196	0.998	1.663*	0.066	1.581*
	(0.402)	(0.637)	(0.516)	(0.610)	(0.618)	(0.737)	(0.879)	(0.814)	(0.919)
Previously raised VC	−0.484	−0.591	−0.406	0.465	0.029	0.568	−0.252	−0.719	−0.240
	(1.310)	(1.313)	(1.232)	(1.221)	(1.343)	(1.377)	(0.852)	(0.941)	(0.910)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Age period effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of ventures	231	231	231	231	231	231	231	231	231
Log likelihood	−255.715	−253.384	−247.286	−283.350	−276.321	−275.679	−170.035	−163.862	−167.153

Notes. Robust standard errors clustered at the level of the accelerator cohort/applicant pool. Spells are venture-months. All models are weighted using inverse probability of treatment weights, calculated using logit estimates of the likelihood of acceptance into the focal cohort.

[a]The founders of 42 ventures did not list graduation years; these were assigned years work experience (L) = 1, and the dummy years work experience missing was set to one.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$; two-tailed tests.

between accelerator participation and having a serial entrepreneur on the team (+88.7% increase; $p < 0.01$) and having more web traffic (a one standard deviation increase in web traffic is associated with a 23.4% increase in subsequent funding; $p \approx 0.018$). In the estimates of future web traffic, neither interaction is statistically significant at the $p < 0.05$ level. Table 5 presents similar interactions for the event history estimates of time to the focal funding levels. Here too the interactions of accelerator participation with these founder and venture variables are either positive or nonsignificant. Thus, although we would expect negative and significant interactions if signaling were a primary driver of the observed accelerator effects, we find no evidence of this. The positive or nonsignificant interactions, however, are consistent with the learning mechanisms emphasized by accelerators themselves though, of course, such tests do not rule out other mechanisms, and care must obviously be taken in the interpretation of any nonsignificant effects.

We also sought to unpack the mechanisms driving the observed accelerator effects by examining two potential mediating measures: changes to ventures' websites (which would suggest learning how to market to customers) and founders shifting from part-time to full-time work (which would suggest a form of "Hawthorne effect" and accepted founders working harder).[19] See Appendix A for a description of these mediation tests. In short, we find that website change generally does not mediate the effect of accelerators improving venture development outcomes. Likewise, although we do find evidence that these accelerators generally increase the percentage of founders working full time on their ventures, this does not appear to mediate the observed accelerator effects. Together these tests indicate the impact of accelerators is unlikely to be primarily driven by accelerators changing which customers are targeted/messaging to those customers nor by simply inducing founders to work harder.

Is There Sorting in the Accelerator Context? (Noncausal Effects)

Our almost accepted data also offers insight into sorting dynamics that may occur prior to any causal treatment effect of accelerators (see Table 6). Although our data are restricted to ventures that applied to accelerators and that made it to the almost accepted rounds (and, thus, some differences could be due to differences in accelerator selection and not applications), they do allow us to examine sorting at two different points in the overall venture–accelerator matchmaking process.

First, we examine "between-applicant pool sorting" by estimating a multinomial logit model of the likelihood of a given venture applying and being accepted to one cohort's final round applicant pool

Table 6. Sorting Dynamics in Almost Accepted Data (Sample A)

	Between-applicant pool sorting (Multinomial logit with cohort E-2011 as omitted category)			Within-applicant pool sorting
	Cohort B-2012 applicant	Cohort E-2012 applicant	Cohort X-2012 applicant	(Logit estimate of accelerator participant)
Applicant pool (E-2011 omitted)				
Cohort B-2012 applicant				–0.732
				(2.243)
Cohort E-2012 applicant				–0.222
				(2.152)
Cohort X-2012 applicant				–0.706
				(2.289)
Controls				
Prior web traffic	–0.265**	–0.310**	–0.097	0.126***
	(0.123)	(0.133)	(0.109)	(0.035)
Number of founders	0.096	0.064	0.455*	0.216
	(0.307)	(0.274)	(0.260)	(0.142)
Full time at application	1.731***	0.748	1.242**	0.898**
	(0.491)	(0.490)	(0.482)	(0.387)
Years work experience[a] (L)	–0.262	–0.101	–0.504	0.433
	(0.358)	(0.335)	(0.321)	(0.282)
Years work experience missing[a]	–0.977	–1.030	–2.327**	–0.315
	(1.155)	(0.993)	(1.003)	(0.238)
Prior employer prominence	0.501	0.093	–0.156	0.672***
	(0.340)	(0.375)	(0.419)	(0.203)
University prominence	–0.008	–0.007	–0.001	–0.013
	(0.009)	(0.009)	(0.009)	(0.011)
MBA	–0.596	–0.240	–0.415	–0.479
	(0.461)	(0.436)	(0.450)	(0.450)
JD	–0.969	0.852	–0.199	0.754
	(1.421)	(1.303)	(1.787)	(0.618)
Technical masters	0.438	–0.171	–0.110	0.008
	(0.523)	(0.522)	(0.525)	(0.372)
Technical PhD	–1.760*	–0.284	0.417	0.210
	(1.038)	(0.838)	(0.819)	(0.628)
Serial entrepreneurs	1.395***	0.540	1.009**	0.211
	(0.500)	(0.472)	(0.461)	(0.572)
Previously raised VC	12.844***	12.419***	12.844***	2.348***
	(0.867)	(1.111)	(0.654)	(0.854)
Intercept	–0.168	0.426	–0.462	–2.717
	(1.232)	(1.150)	(1.083)	(1.881)
N	235			235
Chi[2]	1,392.452			
Log likelihood	–287.661			–94.860

Notes. Robust standard errors clustered at the level of the accelerator cohort/applicant pool. The "between-applicant pool sorting" multinomial logit estimates the likelihood of a given venture applying and being accepted to one cohort's final round applicant pool versus another cohort's. The "within-applicant pool sorting" logit estimates the likelihood that a given venture that has made it to the almost accepted set of a given applicant pool is offered admission to an accelerator and chooses to attend.

[a]The founders of 42 ventures did not list graduation years; these were assigned years work experience (L) = 1, and the dummy years work experience missing was set to one.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$; two-tailed tests.

versus that of another cohort. Applicants to cohort E-2011 were the omitted category. If we find evidence of such sorting, it would arise from a combination of entrepreneurs' decisions to apply to a given accelerator at that time in a venture's life and the decisions of an accelerator to continue to consider a venture up through the final selection round. We present results of this model in the first three columns of Table 6. Ventures with more web traffic were less likely to be in the B-2012 and E-2012 applicant pools, ventures whose founders were full time at the time of application or serial entrepreneurs were more likely to be in the B-2012 and X-2012 applicant pools, and entrepreneurs previously raising venture capital were less likely to be in the E-2011 applicant pool.

Second, we also examined sorting in the form of "within-applicant pool sorting" by estimating a logit regression of whether a venture that made it to the final round of a given applicant pool ultimately participated in that cohort (see the final column in Table 6). We use estimated probabilities from this model as the basis for the inverse probability of treatment weights for the estimates presented in Tables 2–5. We find ventures are more likely to be accepted and participate if the venture has more web traffic, more full-time founders, prior employers are more prominent in producing startups, and if one or more of the founders has previously raised venture capital[20]—findings largely consistent with our qualitative fieldwork and prior literature on how investors choose ventures in which to invest (Franke et al. 2008, Petty and Gruber 2011, Huang and Pearce 2015). We note, though, that many of the coefficients are insignificant, and other effects are modest, suggesting that any sorting effect is likely to primarily happen prior to the final selection round.

Third, we also examined sorting by examining the extent to which ventures not participating in the focal cohort ultimately participated in another accelerator. This occurred with 32 (15%) of the ventures that did not participate in the focal cohorts. About one third of these ultimately participated in a similarly ranked accelerator, including three that ultimately participated in the focal accelerator at a later date. The rest ultimately participated in lower ranked accelerators. In no cases did we observe a venture participating in a competing accelerator soon after its application to the focal cohort, suggesting that the within-applicant pool sorting was driven primarily by accelerator selection and not entrepreneurs choosing from among multiple acceptances. We also note that we found only limited evidence of ventures simultaneously engaging multiple accelerators to find the best match.[21] We suspect, however, that this dynamic has changed as the accelerator field has become more established.

Establishing External Validity of Sample A Analyses

Two limitations of our almost accepted sample A are that it only includes four accelerator cohorts, and each of the sampled accelerators' identities is masked to preserve the confidentiality of our sources. To help better understand how the patterns observed in our sampled accelerators may relate to the broader population of accelerators, we also examine an auxiliary quantitative data set constructed from publicly observable data on high-potential ventures (see Appendix B for a description of these data and their analysis). This data set was constructed by matching accelerator participants that raised venture capital with ventures that did not participate in an accelerator but raised venture capital in a similar manner (same time period, same caliber of investors, same sector, etc.). We focused on eight early accelerators—500 Startups, AngelPad, Dreamit Ventures, Excelerate Labs, LaunchBox Digital, Seedcamp, Techstars, and Y Combinator—and cohorts from 2006 through 2011. These data were collected parallel to our fieldwork and were used to help develop trust with accelerator directors to obtain access to the almost accepted data in sample A. Although these data are less able to identify the causal impact of accelerators, they do allow for the examination of correlational patterns between participation in publicly identifiable accelerators and speed to key milestones and also enable us to reveal accelerator names because they do not rely on proprietary data. As described in Appendix B, we examine the speed to the outcomes of (1) raising an initial round of venture capital, (2) reaching a moderate level of web traffic (250,000 daily page views), (3) a high level of web traffic (2 million daily page views), and (4) being acquired.

Relative to matched ventures that also raised a similar amount of venture capital in a similar manner around the same time, we find that participants of most of these accelerators have statistically significant coefficients for faster times to raise their initial round of venture capital; the exception are participants in Excelerate Labs. Although emphasizing that we are less able to draw causal conclusions in this sample, we find accelerator participation's relationship to the likelihood of raising venture capital each month ranges from 135% more likely (AngelPad) to 204% more likely (500 Startups). Similarly, nearly all of these accelerators are associated with a faster time to reaching a moderate level of web traffic (250k daily page views) with the exceptions being Excelerate Labs and Seedcamp. The magnitude of this relationship ranges from 69% more likely each month (AngelPad) to 518% more likely (500 Startups). Fewer accelerators are associated with faster times to the less frequent milestones of a high level of web traffic (just Techstars and Y Combinator) or being acquired (just Excelerate Labs and Techstars). We also observe statistically significant negative coefficients for these outcomes for a number of accelerators though we interpret these cautiously as indicating that ventures in such accelerators were simply less likely to reach the focal milestones during the period of observation or may have not prioritized such outcomes. For example, more ventures may have been pursuing business-to-business opportunities less reliant on website traffic or may not be interested in selling via acquisition.

As a whole, the correlational patterns in this auxiliary data corroborates the patterns in the almost accepted data and that such accelerator effects may exist among not only the most famous accelerators (e.g., Techstars and Y Combinator), but also other well-regarded (but less prominent) accelerators.

How Do Accelerators Work?

Qualitative Fieldwork Sample and Methods (Sample B)

Our quantitative analyses provide compelling evidence that some accelerators work and that their effect is unlikely to be driven primarily by sorting or signaling. This suggests some accelerators have a causal impact on venture learning though our quantitative data does not directly capture such learning. Hence, it remains unclear how the learning mechanisms within accelerators are theoretically similar to or distinct from other long-studied interorganizational learning mechanisms. We, therefore, draw on in-depth qualitative data to establish the face validity of the learning mechanism specifically by examining whether and what entrepreneurs learn through accelerator participation. We also use the qualitative data for *inductive theory-building* purposes, developing theory around how the learning mechanisms within accelerators are theoretically distinct (if at all) from other interorganizational learning mechanisms. Our fieldwork began as part of a larger research initiative using accelerators to understand entrepreneurial learning and how accelerators help entrepreneurs overcome the challenges of their bounded rationality (Cohen et al. 2019a). As is common with qualitative research, we constructed this sample with the objective of generating theoretical insights versus being able to make more conclusive statements of causality (Eisenhardt 1989, Gehman et al. 2017).

We sampled eight accelerators primarily from the 2011 seed rankings and the Techgox and Seed-DB online databases, focusing on pioneers of the organizational form and the set of well-regarded accelerators likely to be attractive to entrepreneurs. This focus on pioneers and well-regarded accelerators ensured that all sampled accelerators were homogenous in possessing particular theoretically relevant antecedents (Miles et al. 2013). At the time, nearly all accelerators operated independently (e.g., were not part of an incubator nor founded by a university or corporation).Within the set of well-regarded accelerators, we sampled eight that allowed variation in geography (west coast, midwest, and east coast) and in venture cohort size (<8, 9–15, >50). At the time of sampling, it was not clear which programs would ultimately become industry leaders though such quality differences did become more apparent in subsequent years.

We gathered retrospective and real-time data, including 70 semistructured interviews (which were transcribed) with entrepreneurs, program directors, mentors, and investors; observations from site visits; email correspondence for clarification; and archival data from accelerator and startup websites and blogs. Entrepreneurs within accelerators were sampled in a polar manner (Elsbach and Kramer 2003), allowing us to explore whether ventures with better or worse performance described their accelerator experiences differently. We have replaced accelerator names with letters to ensure informant anonymity though where there is overlap with the almost accepted sample A, we have utilized the same letters. We follow Graebner and Eisenhardt (2004) and utilize a replication logic to build theory based on patterns of learning broadly common across the eight accelerators (while also explicating the pervasiveness of such patterns). In doing so, we iterated between the case histories, our emergent theory, and extant literature (Eisenhardt 1989, Yin 2003).

Validating the Presence of Entrepreneurial Learning

As reported in Table 7, our qualitative data provides more direct observation of the venture learning inferred in our quantitative analyses. Entrepreneurs in many of the sampled accelerators reported substantial learning, which took two general forms. First, accelerator participants reported learning processes and skills that improved the execution of their business model, that is, procedural knowledge about *how to do things*. For example, a founder at accelerator A, who attended the accelerator the summer after his junior year and eventually dropped out of college to purse his venture, said, "We were certainly nerds that can code, but we didn't know a lot about product and customer development and that was immensely helpful." He explained that the accelerator's managing directors pushed him and his cofounder to think about customers in a new way, and his cohort peers helped his team find solutions to technical problems that enabled them to capture the opportunity.

Although managing directors or program alumni frequently led sessions on how to pitch, most accelerators brought in professional investment experts, such as venture capitalists and lawyers to teach ventures about term sheets from both negotiation and legal perspectives. An accelerator B founder explained how the managing director of his program provided initial guidelines on how to develop his pitch, but meetings with professional investors supplemented her advice. He said, "I had never gone through the fundraising process before. So, in the third month, I was trying to consume as much information as possible and talk to as many people [including the managing director and external mentors] as possible about what terms actually mean, whether it's equity or convertible debt and how that affects the company over time." Entrepreneurs also frequently reported learning technical skills, including how to overcome technical obstacles. For example, several teams reported needing to learn how to get unblocked

Table 7. What Accelerator Participants Learned from Accelerator Participation[28] (Sample B)

Accelerator	"How" to do particular tasks/entrepreneurial skills	"What" to do in this venture/expected payoffs and risks of planned activities and awareness of alternatives
Accelerator A: Western United States, 9–15 ventures, 10 weeks. Six interviews with participants, program directors, and mentors.	• "We were certainly nerds that can code, but we didn't know a lot about product and customer development, and that was immensely helpful." • "A lot of it is basic fundraising knowledge."	• "The core of the business stayed constant, and to this day, we're still based on a [product]. Yet our vision with that became much, much, much bigger."
Accelerator B: Middle United States, 9–15 ventures, three months. Twelve interviews with participants, program directors, and mentors.	• "We learned so much—how to start a business, learned how to raise money, learned how to function in a company." • "What terms actually mean whether it's equity or convertible debt and how that affects the company over time."	• "We heard over and over and over that we can't raise money while being in higher education and that was something that we changed."
Accelerator C: Western United States, >50 ventures, three months. Seven interviews with participants, program directors, and mentors.	• "We learned how to build a product, to know what the steps are, how you balance quality with speed and experimentation, and we learned how to do sales." • "We got blocked on Facebook earlier on because we didn't really understand some of the policies, and we were able to get help figuring out how we can get unblocked.	• "We learned that just making money by itself is not as powerful of a motivator [for our customers] as we thought. So we needed to add a lot of other things—it had to be beautiful, people wanted to be proud of what they were sharing, and [we added] an aspect of social rewards that were not monetary."
Accelerator D: Western United States, <8 ventures, three months. Four interviews with participants, program directors, and mentors.	• "Learned how to tell a story." • "So we tend to learn from other people what they do process-wise."	• Limited evidence among informant ventures
Accelerator E: Middle United States, 9–15 ventures, three months. Eight interviews with participants, program directors, and mentors.	• "How to get that right product market fit, how to manage your process much better." • "I started understanding how people make money in startups. . .how you can use other people's money to leverage your equity and make more money."	• "Figuring out how to price it, and shall we charge for software? We ended up saying no, we sell product."
Accelerator F: Eastern United States, 9–15 ventures, three months. Six interviews with participants, program directors, and mentors.	• "[I learned] focus on the product standpoint is not trying to do too much or build too many features of the business." • "The peer group is where you could actually exchange best practices in real time."	• "[The process helped] us decide which industry and which go-to-market strategy were the most appropriate."
Accelerator G: Eastern United States, <8 ventures, three months. Five interviews with participants, program directors, and mentors.	• Limited evidence among informant ventures • "I didn't learn anything about e-commerce even though e-commerce is picking up, and I think that would have been an easy move for us."	• Limited evidence among informant ventures • "At the end of the day, the accelerator doesn't provide you with where you want to go." • "I discovered that we just didn't have the best idea."
Accelerator H: Eastern United States, >50 ventures, four months. Eight interviews with participants, program directors, and mentors.	• "[Before Accelerator H], I didn't know what a business was or how to pitch something. I didn't know any of that stuff. I think if I had done an MBA I wouldn't have learned as much as I learned at (accelerator)."	• Limited evidence among informant ventures

from social media providers. Technical knowledge most frequently came from cohort peers who were often facing similar challenges. As a whole, such how-to knowledge improved understanding of action–outcome relationships that we would expect to be especially beneficial for first-time entrepreneurs.

Second, accelerator participants also learned declarative knowledge about *what to do* in their current ventures. This learning reflected shifts in beliefs regarding the expected payoff and risks of planned activities and greater awareness of alternative activities. One accelerator B venture entered the cohort unsure about its target market. One founder wanted to pursue the higher education market, and the other wanted to focus on corporations instead. They entered mentor meetings with investors and other entrepreneurs seeking guidance to this critical decision. One founder explained, "We heard over and over and over that we can't raise money while being in higher education, and that was something we changed." The firm eventually pivoted away from the education market toward corporations, and one of the founders left the venture as a result. Another founder, this one in accelerator F, explained how his team used meetings with mentors to narrow his venture's scope, "so instead of saying we're going after everyone, [meetings with mentors] helped us decide which industry and which go-to market would be most appropriate." In this case, mentors provided introductions to potential customers in various industry verticals, which allowed the venture to go through an iterative process of eliminating and prioritizing potential markets until they eventually identified the most promising ones. Although such early "pivots" are increasingly viewed as a critical part of entrepreneurship, striking here is that these business model and strategy changes largely were a result of external mentors versus the internal trial and error often emphasized in academic theories and the lean startup methodology (Gavetti and Levinthal 2000, Ries 2011, Camuffo et al. 2019, McDonald and Eisenhardt 2019). Also, whereas prior work on organizational learning often focuses on process improvements and getting better at existing tasks (e.g., moving down a current learning curve; Argote and Epple 1990, Haunschild and Miner 1997, Beckman and Haunschild 2002), such learning about *what to do* is often about the redirection of where the organization needs to head (i.e., moving to a new learning curve)—something we would expect to be especially critical in all new ventures regardless of an entrepreneur's prior experience and knowledge.

Unpacking learning in accelerators also offers further insight into findings from our quantitative analyses. In particular, our quantitative analyses indicated that accelerator participation generally has a positive or nonsignificant interaction with measures of founder entrepreneurial experience or venture progress. Coupled with our qualitative data, this suggests that the estimated accelerator effects are unlikely to be primarily driven by the learning of general entrepreneurial skills because serial entrepreneurs would be more likely to have garnered such skills previously. Accordingly, it may be that much of the estimated effect of accelerators is driven by learning what to do in the form of declarative knowledge around the expected payoffs of planned activities for this specific venture and awareness of alternative activities. This also suggests that even experienced entrepreneurs with substantial preentry knowledge (Agarwal et al. 2004, Gruber et al. 2008, Dencker et al. 2009) may benefit from additional learning, such as that provided in accelerators, perhaps because many entrepreneurial opportunities involve a critical level of novelty.

Distinguishing Accelerators' Mechanisms: Broad, Intensive, and Paced (BIP) Consultation

Beyond establishing the validity of ventures learning from others through accelerator participation, a primary motivation of our qualitative fieldwork was to better understand how such interorganizational learning differs from other forms of interorganizational learning highlighted in the literature. We define interorganizational learning as learning based on the knowledge and experience of other parties (March and Simon 1958, Cohen and Levinthal 1990, Lane and Lubatkin 1998, Bingham and Davis 2012). To explore the potential distinctiveness of the interorganizational learning mechanisms in accelerators, we focus on contrasting accelerators' practices against five commonly cited interorganizational learning mechanisms emphasized in the literature: embedded partnerships, employee mobility, peer networks, remote observation, and crowdsourcing. Learning via embedded partnerships occurs when relationships with high mutual interdependence, such as venture capital investments and R&D alliances, foster frequent interaction, familiarity, trust, affect, and influence that facilitate the flow of otherwise private information between organizations (Powell et al. 1996, Hellmann and Puri 2002, Uzzi and Lancaster 2003, Rothaermel and Deeds 2004, Pahnke et al. 2015). Learning via employee mobility occurs when the founders, employees, or board members of a venture have relevant past professional experience; this can include knowledge inherited from both other firms or prior experience as end users (Agarwal et al. 2004, Dencker et al. 2009, Chen et al. 2012, Eesley et al. 2014, Katila et al. 2017). Learning via peer networks occurs via the social connections of entrepreneurs to other entrepreneurs in their same industry, either via formal groups like the "young president's organization" that gather similarly staged entrepreneurs or via informal connections arising from industry events, prior employment, or prior education (Zuckerman and Sgourev 2006, Stam 2010, Cai and Szeidl 2017, Chatterji et al. 2019). Learning via remote observation occurs through the monitoring of public information revealed about other organizations through media coverage, public statements, and analyst reports (Strang and Macy 2001, Denrell 2003, Kim and Miner 2007). Finally, learning via crowdsourcing revolves around open calls for assistance from a large set of external parties around a stated problem, thus enabling particularly broad and distant search (Jeppesen and Lakhani 2010, Afuah and Tucci 2012, Piezunka and Dahlander 2015).

As we iterated between our data and the literature, we used an inductive process to identify and distinguish the mechanisms accelerators use to facilitate interorganizational learning. What emerged from our analysis is a mechanism we label *BIP consultation*.[22] Table 8 provides evidence for this mechanism. The label "BIP consultation" is ours though it encapsulates a logic expressed by many of our informants. Consistent with our goal of understanding the theoretical distinctness of learning in accelerators, we focus on practices that were common in most of the

Table 8. Broad, Intense, and Paced Consultation in Focal Accelerators (Qualitative Fieldwork, Sample B)

Accelerator	Breadth of consultation	Intensity of consultation[1]	Pacing of consultation
Accelerator A	**Mentors:** 10 intimately involved per venture and another 40–50 available. **Customers:** Accelerator encouraged as many as possible, often 100–150. **Accelerator directors:** Frequent multihour meetings with each venture challenged core assumptions, initially about idea and then execution. **Cohort:** Daily and weekly sharing. **Seminars:** Weekly with IP lawyers, fundraising, customer interviews, customer acquisition, etc.	**High intensity** High volume of customer interactions, other interactions spread over program. "[The time in the accelerator is] really helping them think through things for this very intense freeze time in the company's history."	**High-level pacing:** First three weeks focus on idea validation. Second three weeks focus on gaining customers. Final four weeks focus on seeking investments. Each transition demarked with a pitch event. **Weekly pacing**: Cohort-wide weekly dinners. Seminars with IP lawyers, fundraising, customer interviews, customer acquisition, etc.
Accelerator B	**Mentors:** Accelerator setup large number of initial meetings (75 on average per a venture). **Customers:** Accelerator manager gives an assignment to speak to 200 customers. Cohort-mates often used each others' products. **Accelerator directors:** Weekly progress report and continuous frank feedback on business model and progress. **Cohort:** Daily sharing, weekly key metric updates. **Seminars:** Lunch and learns with experts in product development, fundraising, customer development, etc.	**High intensity** 4–6 mentor meetings per day and hundreds of customer interactions during the first month. "[We were] dedicated to knocking on doors and physically going into offices." "Doing a lot of Skype calls and a lot of just emails in getting feedback that way, doing a lot of Q&A stuff with people. So we got a lot of feedback."	**High-level pacing:** Three sections. First month is mentor dating and interviews with potential customers. Second month is product development and getting it into hands of users. Third month is preparation for demo day and plan after accelerator. **Weekly pacing**: Key metrics update with cohort, publically state goal for next week and then report progress to the group. Also met weekly with accelerator director (on a different day than cohort meeting).
Accelerator C	**Mentors:** Requested by ventures and setup by well-connected accelerator managers. Average of five per venture. (Instead emphasized accelerator managers and customer consultation). **Customers:** Encouraged to "get out of the building" to learn about customer needs and preferences and to get product into the hands of customers early. Alumni and cohort-mates were often potential customers and willing to provide feedback. **Accelerator directors:** Several managers with various background hosted office hours, and ventures selected which ones to meet with throughout the program. Managers offered advice and connections. **Cohort:** Most ventures arrive at weekly seminars several hours early and stay afterward to interact with each other. Active social media network in which ventures broadcasted problems. **Seminars:** Weekly with industry luminaries; inspirational.	**High intensity** Focus on soliciting customer feedback for part of each day, especially in the beginning. Customer feedback was intense. "We talked to a lot of customers." Frequent peer-to-peer feedback, used each others' prototypes, asked for help. "They really pushed us to just get something out there and get feedback, and we found we didn't know anything." "The partners were giving real-time feedback [on each venture's pitch]." *Note: In contrast to other accelerators, consultation was more venture-directed in Accelerator C. Thus, although it was high-intensity for many ventures (which anecdotally performed better), it was lower intensity for others.*	**High-level pacing:** Has "prototype day" after first two weeks; believe helps force entrepreneur commitment and get initial traction. A week prior to demo day has a rehearsal for all ventures to practice their pitch, which triggers ventures to shift gears and work on their pitch. **Weekly pacing**: Cohort gathers hours prior to weekly dinner with featured guest speaker. Norm of discussing progress to peers (e.g., new features, additional customers, etc.). Also often met with accelerator managers prior to speaker.

Table 8. (Continued)

Accelerator	Breadth of consultation	Intensity of consultation[1]	Pacing of consultation
Accelerator D	**Mentors:** Ventures able to search long list of potential mentors and schedule meetings; 15 meetings per venture on average, also met with seminar speakers. **Customers:** Accelerator encouraged as many as possible, also encouraged profiling and surveying potential customers. **Accelerator directors:** Two full- and two part-time, former founders, product focused. Weekly scheduled meetings with each team. **Cohort:** Daily stand-up meetings to help each other and share what they are working on. **Seminars:** Several a week. Operationally focused: user acquisition, social acquisition, morality, SEO, legal, back office, investors.	**Moderate intensity** Interactions for a short time of most days. These interactions often drove how used rest of the day. "We had to talk to as many people as we can and try to see whether or not what we're developing is actually useful." "We had guest speakers every day."	**High-level pacing:** *None. "It really all depends...it's really hard to say like formulaically or programmatically like every company does this or that the first week or the first month."* **Weekly pacing**: Each team privately meets with accelerator manager. All cohorts meet weekly.
Accelerator E	**Mentors:** Accelerator setup around 60 initial meetings. Entrepreneurs met with small subset of these repeatedly. **Customers:** Accelerator pushed ventures to get customer feedback. Cohort-mates often used each others' products and provided customer feedback. **Accelerator directors**: VC and CEO backgrounds. Daily interactions in shared space, weekly updates. Daily critical feedback on pitch last month. **Cohort:** Daily sharing, weekly key metric updates, weekly pitches. Shared office space made it easy to share advice. **Seminars:** Daily lunch sessions covered a broad array of topics, including, unit economics, term sheets, search engine optimization, positioning, public relations, etc. Middle month a "mini-MBA" with even more frequent speakers.	**High intensity** 4–6 mentor meetings per day coupled with hundreds of customer interactions for the first month, occupied ventures all day for first month and periodic consultations throughout. "A lot of feedback [from mentors]: great feedback, mediocre feedback, and informed feedback; was the whole gamut." "[The mentor feedback is] quite overwhelming." "They got no work done in June. They were in meetings [with mentors] all day." "Huge push to get customer feedback on product, because that is going to help refine the business model."	**High-level pacing:** Three sections. June is mentor dating month. July is the "entrepreneurs' MBA." August is preparing for demo day. **Weekly pacing**: Key metrics updates with cohort and accelerator manager.
Accelerator F	**Mentors:** Accelerator had nearly 250 mentors on list. Mentors came to the office. Ventures met with 25–50 on average. **Customers:** No specific advice given. **Accelerator directors**: Three distinct backgrounds (engineer, VC, CEO). Available to answer questions, mostly tactical. **Cohort:** Weekly CTO roundtables and separate weekly whole venture meetings. **Seminars:** Frequent, with engineers, product managers, VCs, entrepreneurs, PR, etc., "a big name once a week."	**High intensity** Multiple interactions with mentors, directors and peers most days. Some days fully booked. Periodic consultations throughout. "Felt like drinking water from a fire hose." "We got a lot of feedback."	**High-level pacing:** Three sections. First month of mentorship focuses more on product. Second month focuses more on marketing and distribution strategy. Final month is about meeting with investors. **Weekly pacing**: Weekly cohort-wide updates and CTO meetings.

Organization Science, 2020, vol. 31, no. 2, pp. 378–414, © 2020 INFORMS

Table 8. (Continued)

Accelerator	Breadth of consultation	Intensity of consultation[1]	Pacing of consultation
Accelerator G	**Mentors:** <10. One assigned mentor (mentors choose firms that they want to work with) and others selected from list. **Customers:** Mentors were often potential customers. **Accelerator directors**: Weekly formal updates, limited involvement or availability. **Cohort:** Weekly pitches to each other prior to seminars. **Seminars:** Two to three per week investors, attorneys, tax, business development and sales, SEO marketing.	**Low intensity** Advice spread evenly throughout the program and mixed with other forms of learning.	**High-level pacing:** *None. Topics were covered based on speaker availability versus intentional sequence.* **Weekly pacing**: Meetings with the group and managing director. Weekly meetings for CTOs. Weekly seminars.
Accelerator H	**Mentors:** Speed dating the first week (~20 mentors), and then a handful of mentors were matched to each venture based on mutual preferences. Many ventures researched hundreds of mentors to find matches. **Customers:** Varied by venture. **Accelerator directors:** Limited prior experience. Primarily connected ventures with others (versus helping directly). **Cohort:** Regular cohort-wide, optional events. Mostly social in nature. **Seminars:** 200 seminars, learning activities, and workshops with external professionals. (Attendance is optional.)	**First week: High intensity** "Boot camp" and mentor speed dating that was all encompassing. **Rest of program: Low intensity** Most reported spreading a few meetings with mentors across the program.	**High-level pacing:** Start with an intensive boot camp. Then work with mentors to set goals and learn about the available resources. Rest of program is self-directed. **Weekly pacing**: *None.*

Note. We defined "high intensity" as either several weeks in which consultation consumed more than 40+ hours a week, or several days/half days were spent every week throughout on consultation. Italics indicate an accelerator that did not exhibit a given practice (e.g., did not exhibit high-level or weekly pacing).

sampled accelerators although employed to a varying degree.[23] We observed what we consider full BIP consultation in five of the eight informant accelerators; in contrast, accelerator D exhibited consultation that was broad and paced but of moderate intensity, and accelerators G and H exhibited consultation that was broad, paced, and of low intensity. Overall, BIP consultation has four attributes that collectively distinguish it from embedded partnerships: employee mobility, peer networks, remote observation, and crowdsourcing.

First, the learning happens via consultation, which we define as knowledge exchanges in which the knowledge source is actively involved in relaying its cumulative experiences and translating those experiences to the entrepreneurs' specific situation and plans. We observed consultation in the form of entrepreneurs receiving mentoring from domain experts, having interviews with customers, private meetings with program directors, check-ins with other ventures in the same cohort, and discussions with seminar speakers. Such consultation helps entrepreneurs conduct cognitive search by drawing on the experiences of others and may be a valuable precursor to trial-and-error learning (Gavetti and Levinthal 2000). Beyond helping entrepreneurs consider a broader set of solutions to known problems, the rich dialog enabled by consultation helped knowledge sources to identify other potential problems in entrepreneurs' current plans or activities as well as other opportunities. Such consultation distinguishes learning in accelerators from learning via remote observation as it actively involves the party that previously had the experiences and conveys private information about failed activities and causal relationships (Ingram and Baum 1997, Denrell 2003, Kim and Miner 2007). It is also different from interorganizational learning facilitated by crowdsourcing, which generally involves only limited bilateral dialog and focuses on the solicitation of solutions to identified problems (Afuah and Tucci 2012, Piezunka and Dahlander 2015), whereas BIP consultation typically involves repeated back-and-forth discussions and the knowledge source identifying potential problems for entrepreneurs to address as well as potential solutions.

The second distinguishing attribute we observe in BIP consultation is broad—in both the different types and numbers of individuals consulted. We define "broad" as a large number of learning interactions with a variety of different types of knowledge sources. In contrast to embedded partnerships, such as venture capital investments and R&D alliances, which might create a handful of consultative relationships for ventures with a small number of sources, accelerators typically help ventures develop a set of consultative relationships that numbered between the mid-double digits and low hundreds and which involved many different types of sources. At accelerator B, for instance, participating entrepreneurs typically met with up to 75 mentors with a range of backgrounds; had daily and weekly interactions with their cohort peers and the program directors; had weekly interactive seminars with experts on topics, such as IP law, fundraising, and customer interviews; and simultaneously met with hundreds of potential customers. Theoretically, such breadth is likely to be beneficial as it further expands the alternatives entrepreneurs may cognitively consider (Gavetti and Levinthal 2000). For instance, Gruber et al. (2008) found that entrepreneurs identifying more market opportunities prior to entry (i.e., cognitively searching more broadly) are likely to have greater revenue postentry. The variety of knowledge sources involved in accelerators is also much greater that what is commonly seen in work on learning within peer networks (Zuckerman and Sgourev 2006, Chatterji et al. 2019). We further note that, although the breadth seen in accelerators was generally lower than in crowdsourcing, the high volume of inbound information in crowdsourcing has been shown to narrow the attention of the learning organization (Piezunka and Dahlander 2015). Thus, it may be that accelerators hit a sweet spot of providing sufficient breadth while also allowing more interactive and cumulative consultation with each knowledge source.

The third distinguishing attribute of learning in accelerators was the *intensity* of the consultations, which we define as entrepreneurs devoting a substantial portion of their attention, including both time and effort, toward interorganizational learning. Such intensity was a key differentiator from the consultation highlighted in prior literature on entrepreneurs learning from embedded partners (e.g., venture capitalists) or peer networks (Gorman and Sahlman 1989, Hellmann and Puri 2002, Zuckerman and Sgourev 2006, Garg and Eisenhardt 2017), in which consultation may take only a few hours a week or a month. In many accelerators, for instance, we observed that entrepreneurs were spending 40+ hours a week in consultation-related learning.[24] For example, a participating entrepreneur in one accelerator told us that he began the program with "six meetings a day, six days a week, for six weeks." Several of the accelerators had entrepreneurs meet individually with more than 40 mentors, often toward the beginning of the accelerator program. This was often in parallel with entrepreneurs being encouraged to meet with a large number of potential customers.[25] Entrepreneurs' time was also consumed by weekly or daily check-ins with the other teams, daily or weekly meetings with program directors, and a frequent speaker series with relevant experts. Theoretically, we believe such intensity was a by-product of entrepreneurs engaging a large breadth of consultative sources and trying to give adequate time and attention to each. This often required, however, that entrepreneurs temporarily slow down trial-and-error experimentation or product implementation. As one program director noted, "Rather than have entrepreneurs spend all that time going down dead ends, we try to slow them down [and focus on gathering advice]."

The fourth and final attribute we observed that distinguished BIP consultation from other forms of interorganizational learning was that accelerators *paced* learning. By paced, we mean providing temporal structures that encouraged entrepreneurs to periodically transform consultation into decisions and actions. Many of the observed accelerators facilitated microtemporal pacing by having regular check-ins between all entrepreneurs in a cohort and meetings between each entrepreneurial team and the program director. Nearly all of the accelerators also provided a higher level of temporal pacing. For example, accelerator E structured the first month for mentor dating and interviews with potential customers; the second month for product development, getting the product into the hands of users, and learning business essentials; and the third month for demo day presentation preparation. As a whole, pacing is important as it provides a rhythm between consultation and decision making. It encourages entrepreneurs to periodically make decisions leveraging existing information but also to gather new information about other aspects of their ventures. In prior literature, such temporal pacing has been argued to be valuable in uncertain settings as it encourages the transition between activities and avoids escalation of commitment to any one (Gersick 1988, 1994; Brown and Eisenhardt 1997).[26] Overall, our qualitative data helps bring to light BIP consultation as a distinct mechanism for interorganizational learning (see Table 9 for summary). Combining both qualitative and quantitative analyses, our data collectively indicate that BIP consultation may have a substantial impact on venture development and that such effects are often either independent of or complementary to prior founder experience or venture progress.

Discussion

In this paper, we ask if accelerators aid and accelerate participating ventures, and if so, how? Using mixed methods involving proprietary and confidential quantitative data, publicly available quantitative data, and extensive qualitative fieldwork, we find many of the studied accelerators *do* indeed benefit ventures, increasing both their likelihood and the speed of reaching key outcomes. Although some emerging research on a government-run ecosystem accelerator[27] (Gonzalez-Uribe and Leatherbee 2017) also suggests a treatment effect (though only for the ventures in the startup school), we find that the treatment effect appears uneven as different accelerators aid and accelerate different outcomes, some accelerators have a greater effect than others, and one examined accelerator even seems to have inhibited venture development along some dimensions. Our empirical support for such positive accelerator performance effects also complements recent research that finds accelerators may help entrepreneurs more quickly and efficiently decide to shut down ventures (Yu 2019).

Our analyses also indicate that learning appears to be a key mechanism by which accelerators affect ventures. Because they do not depend as much on an accelerator's prominence and reputation, learning-driven accelerator effects are especially intriguing as they are more likely to be replicable than sorting or signaling. Moreover, our results also indicate that a venture's learning is largely independent or complementary to its founding team's pre-entry experience. Our qualitative data help unpack the drivers of this learning, spotlighting the relevance of BIP consultation with many parties outside of the venture. Collectively, these attributes distinguish BIP consultation from other interorganizational learning mechanisms, including embedded partnerships, employee mobility, peer networks, remote observation, and crowdsourcing. Our findings offer several important contributions to both theory and practice.

Implications for Understanding Learning in New Ventures and Established Organizations

We offer insights to the literature on organizational learning, including learning via founder pre-entry knowledge (Eisenhardt and Schoonhoven 1990, Agarwal et al. 2004, Beckman 2006, Chatterji 2009, Eesley and Roberts 2012). For many outcomes, we observe positive or independent interactions among accelerator participation and whether founders were serial entrepreneurs or their ventures had more web traction. Our findings contribute by suggesting that there are likely fundamental limitations to pre-entry knowledge for even very experienced entrepreneurs but that participation in certain accelerators may efficiently help address such limitations.

Perhaps more importantly, our study contributes by revealing that accelerators offer substantial learning benefits early in a venture's life. Existing scholarship holds trial and error to be especially critical for new ventures because it allows learning about truly novel opportunities (McGrath and MacMillan 1995, Ries 2011, Camuffo et al. 2019, McDonald and Eisenhardt 2019). Yet our results indicate that accelerator participation—even though it temporarily slows down trial-and-error learning—often aids and accelerates venture development overall. This may be because broad, intensive, and paced consultation helps entrepreneurs prevent exploring opportunities

Table 9. Contrasting Venture Interorganizational Learning Mechanisms (Sample B)

	Accelerators and BIP consultation	Embedded partnerships	Employee mobility	Peer networks	Remote observation	Crowdsourcing
Source of learning	Mentors, program directors, peers, alumni, and accelerator networks	Long-term, mutually interdependent partners, such as equity investors (VCs and angels) or alliance partners	Prior professional experience of founders, employees, and independent board members	Noncompeting peer entrepreneurs in same industry	Media coverage, public statements, and analyst reports	"Crowd" outside of firm
Nature of interactions	Iterative dialogs and small-group presentations in which knowledge source actively involved in relaying and translating their experiences	Iterative dialogs and formal meetings (including board meetings). Generally high familiarity, trust, and affect	No direct formal interaction between the source organization and the venture. Knowledge flow mediated through the employee or board member	Small group meetings. Norm of transparency and trust created by broader organization	No direct interactions	Often websites where firms post problems and crowds submit solutions.
Number of different knowledge sources involved (typically)	50 to 150	Single digits	Varies. May increases as venture scales	Typically 20 or fewer	Varies; Often shaped by competition and geography	Often several hundreds or thousands
Intensity of entrepreneurs' attention toward learning from sources	Generally high	For investments, a few hours every week. Alliances vary based on current firm goals	Varies based on current firm goals	Face-to-face meetings a few times a year	Varies, but typically limited	Often delegated to other managers (Note: typically conducted in larger firms)
Explicit temporal structures to guide and shift attention?	Common	Regularly scheduled coordination meetings; often monthly	No	Often different themes for each meeting	No	Contests typically have deadlines, but not necessarily broader temporal structures
Representative papers	*Our focus*	Powell et al. (1996) Sapienza (1992) Hellmann and Puri (2002) Rothaermel and Deeds (2004) Pahnke et al. (2015)	Agarwal et al. (2004) Dencker et al. (2009) Katila et al. (2017)	Zuckerman and Sgourev (2006) Stam (2010) Cai and Szeidl (2017) Chatterji et al. (2019)	Baum et al. (2000) Kim and Miner (2007)	Afuah and Tucci (2012) Jeppesen and Lakhani (2010) Piezunka and Dahlander (2015)

that should remain unexplored. BIP consultation also lets entrepreneurs better decide what experiments to run, which alternatives to consider, and how to interpret the results of experiments. This is because BIP consultation acts as a forcing mechanism to keep search open and so mitigates the common bias found in many entrepreneurs to prematurely close search for novel solutions (Cohen et al. 2019). Thus, although accelerators continue to be an intriguing area for future research, their unique practices for stimulating learning may be generalizable beyond their original context. That is, BIP consultation may be generalizable and so provide utility for educators and university programs looking to accelerate student entrepreneurship projects or even for large, established organizations seeking to accelerate their innovative initiatives.

More broadly, our findings also contribute to the literature on interorganizational learning. Prior literature has often portrayed interorganizational learning as beneficial yet prone to error and inappropriate mimicry (Ingram and Baum 1997, Strang and Macy 2001, Denrell 2003, Kim and Miner 2007). This literature, though, has often examined interorganizational learning occurring through the media or indirect network connections. In such situations, the knowledge source is not actively involved in the relaying of experiences and the flow of information is often one way. In contrast, we focus on BIP consultation: learning in which the knowledge source is actively involved in the knowledge transfer. Learning, thus, involves a close interactive discussion, not distant observation and imitation. The result is that the knowledge source is often (but not always) involved in identifying the connections between their prior experiences and the learner's current situation.

Likewise, learning in accelerators typically involves a greater number of embedded knowledge sources than in venture capital investments or alliances (Rothaermel and Deeds 2004, Pahnke et al. 2015) and a greater diversity of knowledge sources than peer networks (Zuckerman and Sgourev 2006, Cai and Szeidl 2017). So, although the amount and diversity of experience is important in learning, so are the amount and diversity of knowledge sources. The amount and diversity of knowledge sources appears consequential because they help founders in different aspects of entrepreneurship: discovery, evaluation, and exploitation. For example, our data suggest that learning from mentors may be more useful earlier in the entrepreneurship process as founders seek to clarify their value proposition, and learning from peers may be more useful later as founders seek to capture value in the marketplace. A key managerial implication is that skilled entrepreneurs should source learning from mentors for discovery, highly experienced external advisors during evaluation, and peers for exploitation. Our work, thus, suggests a more refined and accurate description of interorganizational learning. More specifically, our work suggests that interorganizational learning may not be the result of efficiently leveraging one well-grooved learning mechanism (i.e., observation and imitation). Rather, it may be the result of blending several sources of interorganizational learning (e.g., from mentors, from peers, from directors). This blending of several sources is effective because it permits leaders to maintain speed and accuracy in learning while sidestepping expensive internal trial and error. It also creates a pattern that propels new firms forward as they shift focus from one type of interorganizational learning to the next. Overall, our data suggest that firms may learn different things from different others at different times.

Implications for Entrepreneurs and Policy Makers

Our findings also offer important implications for entrepreneurs, venture investors, policy makers, and educators. To entrepreneurs, our findings offer insight around the question of whether accelerators are beneficial and how they impact entrepreneurs. Our results provide compelling evidence that select accelerators aid and accelerate venture performance. Unexpectedly, we also observed that accelerator effects were, in most cases, independent of or complementary to founder and venture experience. For entrepreneurs, this indicates that participating in accelerators such as those we studied (i.e., at least moderately prominent and experienced) may be broadly beneficial and worth pursuing while also suggesting caution about new and unproven accelerators.

For policy makers and would-be accelerator founders, our results offer more guarded guidance. Although we see that accelerators can be an effective entrepreneurial intervention and observe that they can be beneficial outside of the strongest entrepreneurial hubs (i.e., Silicon Valley, Boston, New York City), we did not find a universal acceleration effect even though we focused on a generally well-regarded set of accelerators. Moreover, given that the differences in acceleration did not cleanly correspond to ecosystem differences, designing an effective accelerator may be difficult and dependent on many interdependent activities. For policy makers or investors considering funding accelerators, our findings suggest that they too should be cautious about rapidly expanding the accelerator form, particularly when available mentors and program directors may lack the depth of entrepreneurial and industry experience common to the accelerators in our samples. Moreover, the observed sorting dynamics in our samples are likely to be amplified over time as certain accelerators become even more prominent and well regarded (Merton 1968). As the accelerator form continues to propagate, our study, thus, suggests an increasing bifurcation between a top tier of accelerators that have an effect, attract the best ventures, and provide a strong signal and a second tier that provide beneficial learning but attract weaker ventures and provide a more limited signal of quality.

Directions for Future Research

Finally, our findings around the efficacy of accelerators and the fact that different accelerators are associated with faster times to different outcomes suggests opportunities for researchers to explore the potential effects of various program configurations. Although the core attributes of the accelerator form appeared relatively stable by the time of our study, accelerators are likely to continue to evolve, and their impact may change further. Thus, additional research is needed to examine the consistency of our findings in newer generations of accelerators. We believe that a stream of studies periodically revisiting similar questions is an intriguing broader opportunity for reflexive awareness of how organizational forms evolve.

Further explicating the boundary conditions of the effects we observe in *some* accelerators is also an important direction for future inquiry. We focused on a prominent and moderately prominent set of accelerators that were likely to be attractive to entrepreneurs and widely imitated by other accelerators and located in major metropolitan areas or entrepreneurial hubs in the United States. Yet, given the relatively low financial resources required to start up, the accelerator form is being widely imitated in ecosystems as diverse as Katmandu, Doha, and Nairobi. Our theoretical framework would suggest that, contingent on having a local ecosystem sufficiently rich in entrepreneurial knowledge and knowledge of customer needs, accelerators and BIP consultation would be effective though follow-on research is clearly needed.

Another intriguing area for future research is the efficacy of accelerator practices and BIP consultation for innovation within large and established corporations. Again, our theoretical framework would suggest that such approaches would likely be beneficial though any application may introduce complexity about how to balance consultation within and external to the organization and challenges that may arise when initiatives are led by internal employees and not independent entrepreneurs. Related to this, a key opportunity is to further explicate and test the boundary conditions of BIP consultation. A key benefit of BIP consultation appears to be helping entrepreneurs identify and select among multiple potential business models or strategic paths forward. This does raise questions about the value of BIP consultation when such paths are more limited and the primary uncertainty is technical—a dynamic that might be the case for many pharmaceutical or other startups rooted in hard science.

There also remains an empirical opportunity to more conclusively test the efficacy of accelerators. Although our access to data on almost accepted ventures, coupled with our use of inverse probability of treatment weights, allowed us to compare ventures perceived as highly similar in potential and interests, such methods do not perfectly rule out underlying quality differences. Thus, an opportunity remains to further validate the efficacy of accelerators using methods such as random control trials or instrumental variables.

In conclusion, our study offers compelling evidence that many accelerators have a positive treatment effect on venture development and that this effect appears likely to be primarily driven by a novel form of interorganizational learning grounded in broad, intensive, and paced consultation.

Acknowledgments

The authors gratefully acknowledge the support of the (anonymous) informant accelerators and entrepreneurs. They are also especially grateful to Senior Editor Rajshree Agarwal and the anonymous reviewers as well as for the thoughtful feedback and suggestions of Brad Bernthal, Kathy Eisenhardt, Nathan Furr, Siobhan O'Mahony, Rebecca Karp, Emily Cox Pahnke, David Tan, Anu Wadhwa, and Henning Piezunka; as well as seminar participants at the University of Warwick, University of Colorado Boulder, University of Tennessee, the AOM BPS Executive Committee Meeting, the Emory 2015 Social Enterprise Colloquium, the INSEAD Doriot Entrepreneurship Conference, University of California Berkeley, National University of Singapore, University of Michigan, University of Georgia, and Boston University. They also recognize the invaluable research assistance of Grant Durando, Will Glasscock, Donovan Ferguson, Katrina LaHair, Kristin Mednick, and Jessica Schuster. This paper received the Best Paper Award at the 2014 Academy of Management from the Technology and Innovation Management Division.

Appendix A. Potential Mediation in Almost Accepted Sample

To further examine the mechanisms of any observed accelerator effect, we also considered two potential mediating measures. To try and capture one aspect of accelerator-related learning, we examined mediation in the form of changes in the content of ventures' websites from the time of application to the graduation date of each accelerator. We accessed archived web pages via the internet archive, ultimately finding data for 181 ventures (websites have to reach a certain level of prominence to be archived). We measured changes using natural language processing techniques from machine learning[29] (Bird et al. 2009, Teodorescu 2017). In particular, we extracted the visible text from each venture's home page; dropped punctuation and commonly used stop words, such as "and," "that," and "this," which serve grammatical purposes but have little semantic meaning;

Table A.1. Potential Mediation by Venture Website Change (Sample A)

		Indirect effects of accelerator on outcome via mediation path of web content change		
Accelerator	Direct effect on web content change	Currently ongoing	Subsequent funding	Future web traffic
Cohort B-2012	0.312 (CI –0.113 to 0.716)	0.021 (CI: –0.005 to 0.118)	0.028 (CI: –0.010 to 0.198)	0.303 (CI: 0.014 to 0.869)*
Cohort E-2012	–0.200 (CI: –0.576 to 0.139)	–0.014 (CI: –0.090 to 0.003)	–0.018 (CI: –0.170 to 0.006)	–0.199 (CI: –0.866 to 0.003)
Cohort X-2012	–0.0545 (CI: –0.309 to 0.199)	–0.004 (CI: –0.059 to 0.07)	–0.005 (CI: –0.067 to 0.010)	–0.055 (CI: –0.378 to 0.103)
Cohort E-2011	–0.200 (CI: –0.404 to –0.005)*	–0.014 (CI –0.015 to 0.630)	–0.018 (CI: –0.101 to 0.005)	–0.201 (CI: –0.654 to –0.050)*

Notes. CI: 90% confidence interval estimated using bootstrapping, 1,000 replications with replacement, and bias correction. Sample comprised of the 181 ventures for which archived web pages were available for the focal dates.

*Significance at the $p < 0.10$ level.

and constructed word-count vectors. We measured change in a venture's website between the two points in time as one minus the cosine similarity of the two word vectors; higher values, thus, indicate more change.

Following best practices, we tested for potential mediation using bootstrapping procedures (a nonparametric approach) to estimate the indirect effects of the predictor variable on the outcome via the mediator (Shrout and Bolger 2002, Gulati and Sytch 2007, Vissa 2012). We did so using the *bootstrap* and *sem* commands in Stata, determining the 90% confidence interval of the indirect effect (i.e., accelerator × mediator) based on the distribution of 1,000 replications of the estimates (we use a 90% confidence interval to be conservative in our estimates). In contrast to the more traditional Baron and Kenny (1986) causal steps approach, bootstrapping better accounts for skew in the distribution of indirect paths and has an improved power to detect mediation. For clarity of interpretation, we focused on outcomes estimated in Table 2 using linear regression: currently ongoing, subsequent funding, and web traffic. All models utilized the same independent variables and controls as used in Table 2.

As shown in Table A.1, we surprisingly see that the negative effect of cohort E-2011 on web traffic is mediated by that accelerator reducing the amount of web content change engaged in by participants. We do not see evidence for website changes mediating the effects of either cohort E-2012 or cohort X-2012. For cohort B-2012, we see ambiguous results as the bootstrapped and bias-corrected confidence intervals indicate that the indirect path is marginally significant but the direct effect of cohort B-2012 participation on web content change is not significant.[30] As a whole, these results indicate that the primary impact of accelerators is unlikely to be driven by accelerators changing which customers are targeted or messaging to those customers.

Changes in Founders Working Full Time on the Venture

We also explored whether any effect of accelerators might be due to a Hawthorne effect and accepted founders working harder. Although our agreement with the informant accelerator programs stipulated that we not contact any of the ventures directly, we proxy for this effect by examining the percentage of founders that were full time at the venture when the accelerator concluded versus the time of application. As with our control variable of *full time at application*, we measured this by manually reviewing the LinkedIn profile of each entrepreneur. We again estimated mediation using bootstrap methods. We also restrict the sample to the 145 ventures in which at least some founders were not yet full time at the time of application, and a treatment effect was, thus, possible.

Table A.2 reports the bootstrapped direct effects of the accelerators on an increase in the percentage of full time. We find that cohorts B-2012, E-2012, and X-2012 are all associated with positive and significant increases in the number of founders working full time on ventures by the time of the accelerator's conclusion. Yet, other than the indirect effect of cohort E-2011 on subsequent funding, we do not see other statistically significant indirect effects in Table A.2. This indicates that, although most of the accelerators are indeed more likely to result in founders dedicating more time to their ventures, it appears unlikely such additional effort is driving the observed accelerator effects. Moreover, if our results were driven purely by a Hawthorne effect, we would expect the effect size to be fairly constant across accelerators, and it is not.

Table A.2. Potential Mediation by Entrepreneurs Working Full Time on Venture (Sample A)

		Indirect effects of accelerator on outcome via mediation path of working full time		
Accelerator	Direct effect on working full time	Currently ongoing	Subsequent funding	Future web traffic
Cohort B-2012	0.584 (CI: 0.229 to 0.784)*	0.036 (CI: –0.103 to 0.203)	0.088 (CI: –0.060 to 0.304)	0.404 (CI: –0.145 to 1.128)
Cohort E-2012	0.381 (CI: 0.180 to 0.569)*	0.024 (CI: –0.064 to 0.144)	0.060 (CI: –0.045 to 0.220)	0.260 (CI: –0.108 to 0.735)
Cohort X-2012	0.342 (CI: 0.124 to 0.526)*	0.021 (CI: –0.087 to 0.118)	0.054 (CI: –0.061 to 0.204)	0.234 (CI: –0.129 to 0.701)
Cohort E-2011	0.237 (CI: –0.057 to 0.473)	0.015 (CI: –0.048 to 0.106)	0.037 (CI: 0.020 to 0.201)*	0.158 (CI: v0.064 to 0.610)

Notes. CI: 90% confidence interval estimated using bootstrapping and 1,000 replications with replacement. Sample comprised of the 145 ventures in which at least one founder was not full time at the time of application.

*$p < 0.10$.

Appendix B. Establishing External Validity Using Publicly Matched Data (Sample C)

To help better understand how the patterns observed in our sampled accelerators may relate to the broader population of accelerators, we also examined a data set constructed from publicly observable data on high-potential ventures. This data set was constructed by matching accelerator participants that ultimately raised venture capital with ventures that had not participated in an accelerator but did raise venture capital in a similar manner (same time period, same caliber of investors, same sector, etc.). These data were originally collected parallel to our fieldwork and were used to help develop trust with accelerator directors to obtain access to the almost accepted data.

In restricting the sample to ventures that ultimately raise venture capital and in contrast to our almost accepted data, these publicly available data are less able to disentangle accelerators' causal treatment effect from sorting dynamics. This arises from an inherent limitation of many publicly available samples of high-potential ventures in that it is difficult to predict with high accuracy the potential and growth intentions of very early stage ventures. Moreover, absent data on applications to accelerators such as that we obtained for our almost accepted sample, reliable and representative directories of such ventures are unfortunately not available in sectors such as web ventures (to our knowledge). Recognizing these limitations, our approach in this supplemental analysis is to narrow our focus to the speed of raising venture capital among ventures that ultimately reach this quality milestone. We are explicit, though, in that these data cannot speak to the impact of accelerators on the likelihood of reaching this outcome and that the resulting evidence is correlational (and not causal).

At the time of data collection, our primary focus was on the speed to reaching the outcome of raising venture capital. Early venture capital rounds, however, can vary on a number of attributes, including their size, the stage of the venture, and the status of the investors (Kaplan and Strömberg 2004, Feld and Mendelson 2012). We thus included such attributes as control variables to better equalize the focal milestone. Likewise, while recognizing that it would not fully rule out potential sorting dynamics, we also sought to control for differences in founder and venture attributes. A limitation to doing so, though, is that much of these data were not easily observable in the source databases and required expensive hand collection. Given that such costs required limiting our sample size, we chose to focus the data collection on ventures in which the focal treatment (accelerator participation) was less confounded with the control variables observable in databases and without hand collection. We did so by using coarsened exact matching (Ho et al. 2007, Iacus et al. 2012, Pahnke et al. 2015) as a preprocessing step to guide our subsequent collection of more costly control variables. In particular, we matched accelerator and nonaccelerator ventures that were in the same industry and raised their first round of venture capital from VC firms with similar status (measured by eigenvector centrality coarsened to four buckets and matched exactly) in the same year, at the same venture stage (measured dichotomously as early: seed, angel, A; or late: B or later), and in the same broad region (United States versus Europe). In constructing the sample, we were careful to omit ventures raising only funds guaranteed to all graduates of a particular accelerator.

We restricted the analysis to accelerators that had their first cohort in 2011 or earlier and in which four or more graduating ventures raised venture capital before the end of data collection in summer 2013. This yielded seven programs in the United States (500 Startups, AngelPad, Dreamit Ventures, Excelerate Labs, LaunchBox Digital, Techstars, and Y Combinator) and one in Europe (Seedcamp). Our sample included cohorts from 2006 through 2011. We identified accelerators and their participating ventures using the Techgox database. We gathered data on nonaccelerator ventures and venture funding data from Crunchbase. Additional data were hand collected from multiple sources, such as LinkedIn, the ventures' archived web pages, the Whois domain name registry, press releases, and Alexa. Of the 176 accelerator ventures meeting our criteria, we identified 145 coarsened exact matches, yielding a final sample size of 290 ventures. We then constructed venture–month spells starting at each venture's founding and ending at the time of the focal milestones. Following our almost accepted sample and to dampen the influence of any sorting dynamics based on observable attributes, we utilized inverse probability of treatment weights. These were calculated at the venture level using a logit estimate of whether each venture participated in an accelerator and including as regressors all founder and venture controls observable at the time of founding; accelerator participants were assigned weights of $1/p$, where p is the estimated probability of accelerator participation, and weights for other ventures were calculated as: $1/(1-p)$.

Variables

Dependent Variables. We focused on four milestones that our fieldwork indicated were important to ventures' development and available longitudinally. First, we examined *months till raises venture capital*. As with the almost accepted sample, we were careful to exclude rounds driven solely by investments guaranteed to all participants in an accelerator.[31] We then examined customer traction as the speed with which ventures reached either a modest level of web traffic (250,000 daily page views) or a high level of web traffic (2 million daily page views) (Rindova and Kotha 2001, Goldfarb et al. 2007). Finally, we examined the time from founding to acquisition because such an event may represent a positive financial outcome for a venture's founders (reached by 18.3% of the sample; we did not observe any IPOs). In contrast to the almost accepted analyses, we did not examine employee growth as such data were not available longitudinally. To determine all speed measures, we assessed venture founding dates based on when ventures purchased their website domain (determined with Whois) and verified that this date was not before any other public venture activity.

Independent Variables. We include time-variant dummies indicating if a venture had begun or completed a particular accelerator; the time-varying nature of these measures helps

Table B.1. Publicly Matched Sample of Time to Key Outcomes; Piecewise Constant Analyses with IPTW (Sample C)

	VC funding	Web traffic of 250k daily views	Web traffic of 2M daily views	Venture acquisition
Accelerator participation				
500 Startups	1.112**	1.822***	0.433	–15.341***
	(0.464)	(0.235)	(0.269)	(0.990)
AngelPad	0.857*	0.522*	0.526	–0.924**
	(0.474)	(0.283)	(0.344)	(0.384)
Dreamit Ventures	1.017*	1.089***	–0.510	–15.845***
	(0.567)	(0.232)	(0.450)	(1.178)
Excelerate Labs	0.708	–0.180	–0.533***	1.312**
	(0.497)	(0.149)	(0.145)	(0.549)
LaunchBox Digital	1.094**	0.809***	–12.786***	–16.873***
	(0.557)	(0.223)	(1.188)	(1.105)
Seedcamp	1.052***	0.628	0.596	–0.461
	(0.384)	(0.382)	(0.634)	(0.520)
TechStars	0.895*	0.983***	0.714***	0.827***
	(0.460)	(0.174)	(0.106)	(0.277)
Y Combinator	0.859*	0.808***	0.697**	–1.497***
	(0.452)	(0.159)	(0.304)	(0.575)
Controls				
Number of founders	0.028	0.202**	0.190**	0.722***
	(0.071)	(0.089)	(0.087)	(0.254)
Years work experience (L)	–0.404***	–0.077**	0.605***	–0.688*
	(0.073)	(0.039)	(0.149)	(0.366)
Prior employer prominence	0.006	0.033	–0.257	0.424*
	(0.087)	(0.089)	(0.178)	(0.217)
University prominence	0.005***	–0.000	0.005	–0.012*
	(0.001)	(0.003)	(0.005)	(0.007)
MBA	0.441***	0.077	–0.981***	–0.977
	(0.137)	(0.287)	(0.359)	(0.798)
JD	0.605**	0.672***	–0.476	–16.568***
	(0.279)	(0.126)	(0.550)	(0.783)
Masters	0.172	–0.101	–0.217	0.244
	(0.208)	(0.086)	(0.293)	(0.492)
PhD	0.348**	–0.281	0.261	1.159
	(0.136)	(0.187)	(0.362)	(0.743)
Serial entrepreneurs	0.342***	–0.167	0.228	1.214***
	(0.116)	(0.167)	(0.435)	(0.139)
Previously raised VC	0.546**	0.113	–0.538**	–0.995*
	(0.247)	(0.148)	(0.268)	(0.547)
Missing Founder Biographies	0.131	0.198	1.266	–1.368
	(0.169)	(0.395)	(0.864)	(0.998)
Prior regional investments	0.017	0.073*	0.164**	0.225*
	(0.032)	(0.038)	(0.074)	(0.116)
Funding Round Controls				
Round size (L)	–0.256*			
	(0.152)			
Missing round size	–0.037			
	(0.140)			
Early stage round	0.413**			
	(0.184)			
Initial VC centrality	–0.153			
	(0.435)			
Funding year dummies	Y	N	N	N
Sector dummies	Y	Y	Y	Y
Age period effects	Y	Y	Y	Y

Table B.1. (Continued)

	VC funding	Web traffic of 250k daily views	Web traffic of 2M daily views	Venture acquisition
Number of ventures	290	249	249	290
Log likelihood	–707.857	–664.402	–457.620	–209.487

Notes. Robust standard errors clustered at the level of the accelerator/nonaccelerator set shown in parentheses. Spells are venture-months. All models are weighted using inverse probability of treatment weights, calculated using logit estimates of the likelihood of a venture being in the accelerator/nonaccelerator subsamples; these logit estimates included all founder and venture-level controls observable at the time of founding. Funding round controls are included in time to VC funding model to help equalize this outcome across ventures. Time to web traffic analyses have a smaller sample because of omitting ventures founded prior to 2007 (when complete web traffic data are not available).

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$; two-tailed tests.

further tease apart sorting versus treatment effects. Not participating in an accelerator is the omitted category.

Controls. Our controls are broadly consistent with the almost accepted sample though, given the longitudinal nature of this analysis, we focused on measures related to characteristics at the time of founding.[32] We found complete founder biographies for 86% of the ventures; accordingly, we include a dummy, *missing founder biographies*, to indicate when founders' biographies could not be identified[33] (assigning other founder measures a value of zero). Additionally, we controlled for *prior regional investments* as the logged number of venture deals in the venture's region in the year prior to the venture's accelerator graduation (or the matched year in the case of the nonaccelerator ventures); regions were based on Crunchbase's entrepreneurial regions and are broadly equivalent to metropolitan statistical areas but include regions in the United States and internationally. To account for market sector differences in the ease of attracting customers and venture capital, we include dummy variables for the 12 market categories listed in Crunchbase. Given our sampling methodology, we did not include founding year dummies.[34]

In our estimate of speed to raising venture capital, we also included further controls to equalize this milestone: round size (measured in millions and logged), missing round size (dummy with a value of one if round size unknown; here round size was set to zero), early stage round (value of one if listed as "seed," "angel," or "A" round), and initial VC centrality (the maximum eigenvector centrality of all investors in the round determined using the preceding three-year syndication network). In this model, we also included dummies for the year when a venture raised its initial round of venture capital to account for the economic climate. As the raising of venture capital might either be the result of or mediate the other focal milestones, we only included these round-level controls in the estimate of time to raising venture capital.

Results

Following our examination of acceleration effects in Sample A, we use event history methods in the form of piecewise constant models (Shane and Stuart 2002). After inspecting life tables of hazard rates to identify periods in which hazard rates were relative constant, we chose duration-period effects ranging from 0–23 months, 24–47 months, 48–71 months, and 72+ months. We regard the venture as right-censored if it had not reached the focal outcome by the end of data collection in the summer of 2013. Spells are at the level of venture-months. As with our almost accepted sample, we utilized inverse probability of treatment weights calculated at the venture level[35] (IPTW) so as to place greater emphasis on ventures that appeared most similar based on observables at the time of founding.

As shown in Table B.1, we find that many accelerators are associated with faster times to reaching some, but not all, of the focal milestones. Specifically, we consistently find positive and statistically significant relationships between accelerator participation and speed to raising venture capital or reaching a modest level of web traffic (250,000 daily page views). The exceptions are Excelerate Labs, which does not have a statistically significant relationship to either outcome, and Seedcamp, which does not have a statistically significant relationship for time to modest 250k daily page views. We also note that some of the coefficients for AngelPad, DreamIt, TechStars, and Y Combinator are only marginally statistically significant ($p < 0.10$). While, again, emphasizing that we are less able to draw causal conclusions in this sample, the relationship between accelerator participation and the likelihood of raising venture capital each month ranges from 135% more likely (Angel) to 204% more likely (500 Startups). For speed to reaching modest web traffic (250,000 daily views), the relationship ranges from 69% more likely (AngelPad) to 518% more likely (500 Startups).

For the milestones of reaching high web traffic (two million daily views) or being acquired, we see statistically significant relationships only for some accelerators, and we see both positive and negative statistically significant coefficients though we caution these estimates may be noisier given that relatively fewer ventures in our sample reach these outcomes.[36] For speed to reaching 2M daily views, we see positive statistically significant effects for Techstars (104% more likely each month) and Y Combinator (101% more likely) and negative and significant coefficients for Excelerate Labs (41% less likely) and LaunchBox Digital (99% less likely). For speed to acquisition, we only see positive coefficients for Excelerate Labs (271% more likely each months) and Techstars (129% more likely). We also see a number of negative and statistically significant effects; given that these focal events are less frequent, we interpret these cautiously as indicating only that their ventures were less likely to reach 2M in daily page views or be acquired *prior* to the end of data collection.

Overall, we see that most of the focal accelerators in this publicly identified data are associated with faster speeds to raising venture capital or reaching a modest level of web traffic. A smaller number of accelerators are associated with faster speeds to reaching very high levels of web traffic or being acquired. Again, this evidence is more correlational and less indicative of causality than our results in sample A.

Endnotes

[1] Although some studies of organizational learning focus on systemic change in behavior or performance, we believe Huber's admittedly broad definition is particularly appropriate for the entrepreneurial context as young ventures are often at the planning stage and have limited past behavior or performance.

[2] See www.seedrankings.com. Some offer more today.

[3] Specifically, entrepreneurs often approach investors they perceive as high quality and to whom they can obtain introductions (Hsu 2004, Hallen and Eisenhardt 2012), and venture capital investors often base investment offers on entrepreneur backgrounds, venture accomplishments, product/offering attributes, and industry dynamics (Franke et al. 2006, 2008; Hallen 2008; Petty and Gruber 2011). In the context of angel investors, recent research suggests angels often base investment offers on a combination of expertise-based intuition and formal analysis with intuition trumping formal analysis (Huang and Pearce 2015).

[4] We note that, although some prior research differentiates between the "pipes" and "prisms" aspects of affiliations, we collapse them here because of the similarity of their mechanisms relative to accelerator-facilitated learning. Future accelerator research, however, may seek to tease apart to what extent accelerators provide ventures with a prism that relays quality to distant audiences versus a pipe that relays quality to connected audiences.

[5] All accelerators meeting these criteria focused on high technology (especially the internet sector) and were independent (i.e., not affiliated with universities or corporations).

[6] Obtaining these data required extensive engagement with accelerators, to both establish trust around the treatment of the confidential data and convince the directors to retrieve the data as many accelerators did not keep systematic records of their evaluation processes and, thus, had to go through email archives to identify spreadsheets containing their final stage lists. We are especially grateful to these accelerators for their support of this project.

[7] For one of the accelerator participants, we could not find data on whether the founders were working full time at the time of application. Of the 26 almost accepted ventures we could not identify, 11 had generic names, no websites or media mentions could be found, and the accelerator did not provide founder information. For 15 other ventures, we could not find key founder measures (e.g., graduate degrees, dates at which founders began working full time on the venture).

[8] These ventures, thus, appear in the overall sample multiple times. We note, however, that we include venture-level controls that are measured at the time of each application. Moreover, we also note that each venture only receives one treatment (i.e., participates in a single accelerator).

[9] Our fieldwork revealed that some founders of failed ventures did not update their LinkedIn profiles until they started another job. Thus, if all but one founder had reported leaving a venture, we triangulated against other activity. If we saw signs that the venture had ceased Twitter and other social media activity, the copyright on website had not been updated for several years, or the web domain had expired, then we listed the venture as shut down and no longer active.

[10] LinkedIn reports company sizes as categorical levels, for example, 1–10 employees, 11–50 employees, and 51+ employees. As only one venture in our analysis sample reached 51+ employees by the time of data collection, we utilized a binary measure of 11 or more employees. An ordinal logit analysis utilizing three categories, however, yielded highly similar results.

[11] Around the time of our sample, some venture capital funds and angels began offering convertible notes at prespecified terms to any venture accepted into certain accelerators, such as Y Combinator or Techstars. These typically ranged from $50,000 to $150,000. We, thus, reviewed the venture investments to ensure our totals did not include these guaranteed investments. See https://techcrunch.com/2011/01/28/yuri-milner-sv-angel-offer-every-new-y-combinator-startup-150k/.

[12] We thank an anonymous reviewer for encouraging us to further account for venture-level differences at the time of application. Although we sought to measure web traffic at the time of application, the Alexa service now only provides web traffic in 2013 and later. We have, thus, utilized data we previously gathered on web traffic in the month preceding the start of each accelerator cohort; generally this comes one to three months after the original date of application but still before the time of participation.

[13] Founders who either did not attend university, did not list a university on the profile, or attended unlisted universities were assigned a ranking of 28.0, thus ensuring that unlisted universities were roughly one below the lowest listed score in the *U.S. News* ranking of 29.2 (see Rider (2012) for further discussion of this approach).

[14] As with Burton et al. (2002), we select this measure over alternatives, such as a prior employer's size or technical prominence, because it allows us to capture the impact of employers from across many industries (e.g., both Google and McKinsey) and to focus on the prior employers' entrepreneurial impact. For consistency across the two samples and to increase comparability, we use the sample described in Appendix B (which we temporally constructed first in our research) to identify the relative number of ventures coming out of each prior employer. When two founders each worked for a prominent prior employer, we took the maximum value. We logged this measure to reduce skew.

[15] If they did not graduate, we took the year they started full-time employment or, otherwise, the year they turned 22.

[16] Alexa only provides web traffic data for the most recent four years. In our original data collection, we gathered data only at key points in time for the focal ventures. We added this event history analysis a few years after the initial data collection and, thus, could not collect complete longitudinal web traffic for the few years immediately following the focal accelerator programs. Likewise, employment data were not available longitudinally.

[17] For instance, Podolny (1994) validated whether investment bank status influenced syndication through a signaling mechanism by verifying that the effect was most pronounced in the syndication of noninvestment-grade bonds versus investment grade bonds (with the logic being that investment grade is an alternative signal that reduces the need for signals such as status). See also Stuart et al. (1999), Jensen (2003), and Ozmel et al. (2013) for use of similar contingency tests to unpack signaling from alternative treatment effects.

[18] Stern et al. (2014), however, do show that founder reputation and status have complementary—and not partial substitution—effects on the formation of alliances by biotechnology ventures. The mechanisms underlying this effect, though, are not necessarily present in our context. Building on social cognition arguments (Fiske and Taylor 1991), they note that *congruent* signals have a complementary effect as they consistently support certain founders being categorized as "star scientists." Our context, though, lacks such extant socially constructed categories in which audiences would expect accelerator participants to also have certain status attributes. Additionally, we note that their constructs and measures are defined and measured

such that status is orthogonal to the reputation measures, and thus, any overlapping information has been removed. We thank an anonymous reviewer for encouraging us to clarify the distinctiveness of these predictions.

[19] We are thankful to an anonymous reviewer for the insightful suggestion of a Hawthorne effect potentially driving our observed results. As we returned to our qualitative fieldwork, we observed that several participating entrepreneurs remarked on how being accepted into the accelerator encouraged them to focus on the venture full time.

[20] Effect sizes are as follows. Greater web traffic of a one standard deviation increase from the mean shifts the probability of participation from 14.5% to 17.6% ($p < 0.01$). For founders full time, moving from half to all full time increases the probability from 14.2% to 20.6% ($p \approx 0.02$). For prior employer prominence, a one standard deviation increase from the mean increases the probability from 14.5% to 19.7% ($p < 0.01$). Having previously raised venture capital increases the probability from 13.6% to 68.5% ($p < 0.01$).

[21] Though it may be that many lower quality ventures applied to multiple accelerators but never made it to the almost accepted stage.

[22] Our initial focal construct was advice-based learning with this construct related to the organizational behavior literature on advice-based mentorship within organizations (e.g., Ashford and Cummings 1983). Iterating between our data and extant theory, however, highlighted that the learning mechanisms within the sampled accelerators were distinct from advice-based mentorship in a few critical ways. This led us to first explicate the intensive attribute and later the broad and paced attributes. Additionally, whereas advice-based mentorship generally has connotations of receiving general advice, much of the interactions we observed focused on the entrepreneurs' present venture; this led us to the term "consultation," which better highlights these distinctions. We also explored including the attribute "early" around the stage of the venture or idea. Although all of the ventures in our sample were indeed at an early stage, the theoretical logic we developed around BIP consultation suggested it might also benefit innovative initiatives within established organizations.

[23] Some variance is expected because the accelerator field was still at a nascent stage at the time of our data collection (Agarwal and Tripsas 2008).

[24] We observed the greatest variance among the sampled accelerators with regard to the attribute of intensity. For example, accelerator D exhibits moderate intensity, and accelerators H and G exhibit a lower intensity of consultation.

[25] Although consultations with mentors were generally arranged by the accelerators, entrepreneurs were often responsible for finding their own potential customers—largely out of a belief that this would also help entrepreneurs refine their customer acquisition strategy.

[26] Such pacing is also a key differentiator from many other interorganizational learning mechanisms with the closest analogies being the monthly board meetings in venture investment relationships or the regularly scheduled meetings in R&D alliances though we note that pacing in accelerators often had a more frequent component (e.g., weekly meetings) and often included elements that sequentially guided entrepreneurs' attention toward different types of decisions (e.g., marketing versus fundraising).

[27] Whereas the accelerators in our sample prioritized the return on their investment and the aiding of individual businesses, many government-run accelerators (such as Startup Chile in the Gonzalez-Uribe and Leatherbee (2017) study) aim to stimulate regional startup activity. Further, in contrast to the accelerators we studied, a notable feature of Startup Chile is that only the top ventures accepted into the program are able to participate in the internal school; the rest simply receive access to coworking space and capital.

[28] Interviews conducted in 2011–2012.

[29] We are grateful for aid on this approach from a former MBA student who worked in machine learning at Microsoft and Google.

[30] Being able to detect an indirect path even if the direct path is insignificant is one of the advantages of the bootstrap methodology. This can occur when, within the randomly generated populations, there is a strong and positive relationship between the sign of the estimated first-stage coefficients (i.e., independent variable → mediator) and the sign of the estimated second-stage coefficients (i.e., mediator → dependent variable). Thus, even though each step of the path may be insignificant (with confidence intervals including zero), the product of the two coefficients may be significant (by not including zero). That is, many of the randomly drawn populations produce two negative coefficients, which multiply to produce a positive indirect path in those same populations.

[31] As a robustness test, we also analyzed the speed to raising a seed round (e.g., at least $250,000 in funding data from AngelList) from either VCs or angels and obtained broadly similar results.

[32] We, thus, did not include in our main analyses measures of either venture web traffic or whether the founders were full time because each varies across the life span of the venture. Thus, the values of these measures postaccelerator participation might represent mediation effects.

[33] We do not omit these ventures as Kolmogorov–Smirnov tests on the other control variables indicated systematic differences between ventures in which we could find complete versus incomplete biographies. Including this dummy, therefore, helps avoid possible sample bias from omitting these ventures.

[34] If accelerator or nonaccelerator ventures were systematically older at the time of funding, then founding year dummies might pick up some of these differences (versus their being captured by the accelerator dummies). Thus, including such founding year dummies would likely either overestimate or underestimate any accelerator effects. We note, however, that our event history regression models do account for effects of venture age.

[35] These weights were calculated as logit estimates of the probability of a venture being in the accelerator/nonaccelerator subsamples. These models included all founder and venture controls as well as sector dummies. We observed that teams that included a founder with a PhD ($p < 0.10$), less work experience ($p < 0.01$), and which had not previously raised VC ($p < 0.01$) were more likely to be part of the accelerator subsample.

[36] Specifically, 111 ventures in our sample reached 2M daily page views and were founded in 2007 or later (at which point we could observe web traffic), and 53 were acquired. In contrast, all 290 raised VC funding and 237 reached 250,000 daily page views and were founded in 2007 or later.

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