How Do Accelerators Impact High-Technology Ventures?

Revise & Resubmit, Management Science

Sandy Yu *
University of California, Berkeley
sandyyu@berkeley.edu

Abstract

Accelerators aim to help nascent companies reach successful outcomes by providing capital, enabling industry connections, and increasing exposure to investors. However, it remains unclear how accelerators impact the performance of early-stage ventures. I construct a novel dataset of approximately 900 accelerator companies that participated in 13 accelerators which are then matched to 900 non-accelerator companies. Using this dataset, I establish stylized facts and propose a model to identify mechanisms through which accelerators impact funding, acquisitions, and closures. I find that through both self-selection and accelerator feedback effects, accelerator companies raise less money, close down earlier and more often, raise less money conditional on closing, and appear to be more efficient investments compared to non-accelerator companies. Additional analysis using a separate sample of rejected accelerator applicants further supports these findings. These results suggest that accelerators help resolve uncertainty around company quality sooner, allowing founders to make funding and exit decisions accordingly.

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1 Introduction

Innovation is one of the key drivers of productivity and economic growth (Romer, 1990; Acemoglu, 2008) and entrepreneurs innovate through the formation and development of new ventures (Acs and Audretsch, 1988). Entrepreneurial finance plays an important role in fueling innovations (Kortum and Lerner, 2000), and according to the National Venture Capital Association, in year 2008, venture capital-backed companies in the U.S. generated revenue equal to 21% of the GDP and created 11.9 million jobs (11% of U.S. Private Sector Employment).[1] Prior research has studied the link between various sources of finance and entrepreneurship, including venture capital (Dushnitsky and Shapira, 2010; Gompers and Lerner, 1997; Hellmann and Puri, 2000; Hsu, 2004; Kaplan and Stromberg, 2004), banking (Kerr and Nanda, 2009; Kerr and Nanda, 2010; Robb and Robinson, 2014), and credit cards (Chatterji and Seamans, 2012). Early-stage ventures often face greater challenges in securing external financing, particularly since many lack existing funding or patents that could signal higher quality (Conti, Thursby, and Rothaermel, 2013; Conti, Thursby, and Thursby, 2013; Hsu and Ziedonis, 2013). Consequently, participating in accelerators has become a popular way for entrepreneurs to distinguish themselves and potentially signal quality.

Accelerators are financial organizations that invest in cohorts of start-up companies, usually in exchange for equity (typically around $20,000 investment for 10% of the company). After selecting a cohort of companies, accelerators run limited-duration programs that offer mentorship from industry experts, weekly educational programming, and co-working space. The first accelerator, Y Combinator, was established in year 2005, and the popularity of accelerators has been boosted by famous participants such as Dropbox, Reddit, and Airbnb. Currently there are at least two hundred accelerators worldwide and their portfolio companies have raised more than $14.5 billion in funding. Furthermore, many governments are interested in using accelerators as a way to foster entrepreneurship, and in turn, stimulate the local economy (Gonzalez-Uribe and Leatherbee, 2014).[2]

However, whether and how accelerators actually benefit entrepreneurs is still an open question.

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On one hand, accelerators can provide training, rapid feedback, and industry connections for the founders, which may help them raise funding after Demo Day. On the other hand, founders often have to give up equity for a small investment from the accelerator, which may outweigh the promised benefits. Many news articles tout the success of accelerators by citing the aggregate amount of funding raised by portfolio companies, acquisition rates, and employment numbers, yet there is no indication that these outcomes would be different without the accelerators.

The goal of this paper is to better understand how accelerators affect entrepreneurial firm performance. To do this, I combine both anecdotal evidence and quantitative analysis across multiple accelerators. First, I interview founders, accelerator partners, and accelerator mentors to understand their experiences participating in or operating accelerators. These interviews also inform me of key performance metrics from both the founders and partners perspectives, and accelerator features and founder characteristics that motivate founders to apply. I then construct a dataset of approximately 900 accelerator companies from 13 different accelerators that are then matched to the same number of non-accelerator companies based on pre-accelerator characteristics. Many factors, such as the experience of the founder can impact firm performance (Chatterji, 2009; Roberts, Klepper, and Haywardy, 2011) and influence the decision to apply to an accelerator. For a founder who has prior entrepreneurial experience, it is not clear whether the benefit of accelerator participation outweighs the cost of ownership dilution. By constructing a control sample consisting of matched non-accelerator companies that are of similar company age, location, description, founder experience, and funding as the accelerator companies, I can control for the selection bias (different types of founders or companies are more likely to participate in accelerators). From here I use nonparametric analysis to establish a set of stylized fact.

I then propose a theoretical model that is motivated by the established stylized facts. The model characterizes the differences between accelerator and non-accelerator companies as the combination of self-selection and accelerator feedback effects. The self-selection affect results from the observation of a signal of the quality of the founder’s idea. As a result of this signal, founders who are more pessimistic are more likely to join an accelerator. By doing so they pay a cost but the uncertainty around the quality of their idea is resolved sooner. This faster resolution of uncertainty results from the intense feedback within the accelerator environment, which is the feedback effect. The model implies that conditional on idea quality, accelerators provide for more efficient development
decisions, both in terms of selecting projects to drop and in terms of selecting the optimal amount of effort to exert on a given project. I show that the theoretical model implies four testable implications; three of which correspond to the stylized facts obtained through nonparametric analysis. An additional implication is related to the relative efficiency of accelerators as funding vehicles.

The four main results are as follows. First, accelerator companies raise less money than non-accelerator companies. Due to the cost of dilution from participating in accelerators, the founders with the best ideas do not apply. Then, the remaining companies that do apply to accelerators have lower quality ideas. Assuming the amount of funding raised is a good proxy for the quality of an idea, accelerator companies will raise less money than non-accelerator companies. Second, accelerator companies close down earlier and more often. During the accelerator program, the accelerator companies receive intense and frequent feedback from the partners, mentors, cohort-mates, and even the alumni network. By the end of the program, accelerator companies will have a more accurate assessment of their product viability. Outside of the accelerator program, non-accelerator companies may receive some feedback from their own network, but the intensity and frequency of feedback will be much lower. Due to the faster resolution of uncertainty for accelerator companies, lower quality accelerator companies will shut down and higher quality accelerator companies will fundraise or aim for acquisitions. In contrast, after the same time frame of three to four months, there will still be uncertainty around the quality of ideas for non-accelerator companies. Therefore, lower quality non-accelerator companies may not realize they should shut down and will continue to raise money. Third, conditional on closing, accelerator companies raise less money. This arises because lower quality accelerator companies that eventually shut down do so sooner rather than later, and do not fundraise beyond the accelerator program. However, due to the lack of feedback, lower quality non-accelerator companies continue to raise money even though they eventually shut down. And fourth, accelerator companies appear to be more efficient investments than non-accelerator companies. If we consider the ratio of funding received for closed companies and funding received for acquired companies as a measure of how capital is allocated within a portfolio, this ratio is smaller for accelerator companies than non-accelerator companies. In other words, within accelerator companies, more money is allocated towards companies that are eventually acquired than companies that eventually close and offer zero returns.

Finally, I proceed to explore these testable implications with regression analyses using the
matched sample of companies. Furthermore, as an additional test of the self-selection and accelerator feedback effects implied by the model, I restrict my analysis to an additional sample of accepted accelerator applicants and rejected applicants in the final round. The prediction from the model is that the implications related to selection effects should be absent — or at least greatly reduced — in this comparison. This is particularly true for final round rejects: anecdotal evidence from interviews suggest that the final selection is not very different from a coin toss, which in turn implies the statistical comparison is as close to a randomized experiment as I can get. Consistent with the model’s predictions, I observe that the difference in funding amounts disappear, whereas the differences in closure probability and funding efficiency persist. In other words, I observe that self-selection effects disappear but accelerator feedback effects persist.

This paper has several contributions. First, this is one of the first papers to document the accelerator phenomenon. Specifically, I present both qualitative and quantitative data to document how accelerators operate. Second, I investigate accelerators as a source of entrepreneurial finance, using both theoretical and empirical analyses. There have been various industry reports and news articles about accelerators, but most focus on overall portfolio performance of select few accelerators and individual founder stories. Third, to my knowledge, I have created the largest sample of accelerator companies across 13 different accelerators, which allows me to conduct cross-cohort and cross-accelerator analysis. Lastly, by examining the effect of accelerator participation on new venture performance and the relevant mechanisms, I lend insight into the efficiency of accelerator investments, which has implications for policy aimed toward fostering innovation and building entrepreneurial communities.

2 Relevant Literature

Entrepreneurial finance plays a major role in pushing innovation and motivating would-be entrepreneurs to take risks (Kortum and Lerner, 2000; Dushnitsky and Lenox, 2005). There is a large body of literature analyzing the factors that determine whether entrepreneurs raise money from venture capital firms (Hellman and Puri, 2000) and factors that affect the terms of this financing (Gompers and Lerner, 1996; Kaplan and Stromberg, 2004). There is also previous work investigating the relationship between venture capital funding and start-up initial public offerings (IPOs),
and types of venture capital firms that have better performance. However, there is also an issue of sorting effects that may skew the distribution of good start-ups to certain venture capital firms, which creates barriers to entry for other start-ups and venture capital firms (Hochberg, Ljungqvist, and Lu, 2010). Most of the time entrepreneurial finance is synonymous with venture capital, but in fact there is an array of alternate sources of funding, including accelerators.

Accelerators are a new type of financial organization and have received little attention in the economics, finance, and management literature. There is a nascent literature examining this phenomenon (Cohen and Hochberg, 2014; Hallen, Bingham and Cohen, 2014) and its regional effects (Fehder and Hochberg, 2014; Gonzalez-Uribe and Leatherbee, 2014) but the findings vary due to heterogeneity in methodology, accelerator structure, and institutional details. Therefore, I turn to papers that pose and analyze questions for venture capital firms, angel investors, and incubators to serve as initial steps for investigating accelerators. One of the main findings in the venture capital literature is that venture capital firms offer more than monetary benefits. They also contribute value-added services such as certification, recruitment, and access to their networks (Hellmann and Puri, 2002; Hsu, 2004; Hochberg, Ljungqvist, and Lu, 2007; Nanda and Rhodes-Kropf, 2013). In terms of angel financing, Kerr, Lerner, and Schoar (2014) find a strong, positive effect of angel funding on the survival and growth of ventures, but not on access to additional financing. In contrast, ventures that work out of traditional incubators have marginally lower survival rate (Amezcua, 2010).

Given the mixed results across different sources of financing, it is unclear how accelerators should impact new ventures. This paper seeks to bridge that gap by understanding an important industry and shedding light on crucial strategic concerns of founders: fundraising and growth. By documenting and analyzing whether and how accelerators affect new venture performance, I take steps in extending the literature to include accelerators as a new source of finance. Furthermore, this paper disentangles the mechanisms to explain whether accelerator companies are good investments. In other words, whether accelerators are predictors of success or reduce the risk of uncertainty.
3 Institutional Setting

There are numerous funding sources for a start-up company, and founders decide which sources to pursue based on factors such as the stage of the company, the target funding round size, and experience and reputation of the investors. In addition to accelerators, other sources of funding include friends and family, loans, grants, angel investors, crowd-funding, and venture capital firms. Each type of funding comes with different trade-offs but here I will focus on the trade-off between mentorship and price of funding, and comparisons with angel investors and venture capital firms. First, instead of investing in companies on an ad-hoc and ongoing basis like angel investors and venture capitalists, accelerators select cohorts of companies through an application process once or twice during a year. Second, the magnitude of investment is on the order of tens of thousands of dollars for anywhere between 2 percent to 10 percent equity stake instead of the hundreds of thousands, or even millions that would be expected from institutional investors. Third, a highly attractive characteristic of being funded by an accelerator is access to mentors, strategic connections, and the accelerator alumni network. Although angel investors and venture capitalists also offer advice and introductions to their networks, the magnitude and frequency of mentorship is much higher in an accelerator. Based on conversations with investors and entrepreneurs, there is a strong sense of paying it forward within the entrepreneurial community. Even though the mentors are not compensated financially, they commit to spending time with the accelerator company founders to share their experiences, stay current with start-up trends, and foster relationships. Many mentor-mentee relationships even become investor-investee after the accelerator program ends. Alumni mentors are yet an additional source of advice and encouragement. As one participant of 500 Startup states, “the whole 500 Startups network is the real value.” Lastly, accelerators often provide physical office space for the companies, and this setting allows companies in the same cohort to work within close proximity of each other.

In Figure 1, differences between accelerators and other sources of financing are highlighted along the dimensions of mentorship and price of equity in terms of amount of funding received for equity given up. Venture capital firms offer the most funding but are relatively less hands-on than accelerators. Angel investors tend to invest less money than venture capital firms (and more than accelerators) but there is heterogeneity in terms of the degree of mentorship. Some angel
investors take a personal interest in the founders, while others may provide less mentoring than venture capitalists. Relative to venture capitalists and angel investors, accelerators are the most expensive—small amount of financial investment for a relatively large amount of equity—but offer the highest degree of involvement in terms of developing the company at an early-stage. Companies at different stages and industries require varying amounts of financing and mentoring; therefore, the source of financing is not “one size fit all” for every company. However, it seems that by choosing accelerators, a founder is prioritizing mentorship over the price of equity, which may be appropriate for earlier stage companies.

**Application Process.** Given that educational programming and mentorship are large components of an accelerator program, it is fitting that the application process for accelerators is very similar to the college application process. An accelerator posts the application online with questions related to the founder team, previous projects, product idea, funding status, and often requests videos or links to a prototype. After an initial screening, there are one or multiple rounds of phone and face-to-face interviews with the accelerator partners. Then, a final decision is made and the founders will usually be required to move to the city in which the accelerator is located for the duration of the program. Due to the popularity of accelerators, the number of applicants has increased, and there is even a common application, the Unified Seed Accelerator Application[3] which allows founders to apply to multiple accelerators with a single form. Even though there are many options for founders who want to participate in an accelerator, many founders aim for the handful of prominent accelerators that have a proven track record. The acceptance rate for the most selective accelerators is very low and continues to decrease[4] and due to the large number of applicants, founders may not get feedback on why their applications were rejected. It seems that especially for founders who make it to the final interview round, it is difficult to explain why they were eventually rejected. The following quote from Paul Graham, founding partner of Y Combinator, suggests that companies in the final round are very similar, at least based on observable characteristics: “So why don’t we tell people why we didn’t invite them to interview? Because, paradoxical as it sounds,

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3The Unified Seed Accelerator Application is used by 25 different accelerators (as of May, 2014) and can be accessed at: [https://accelerato.rs/](https://accelerato.rs/)

4According to press releases, the acceptance rate in 2012 for Y Combinator was 2 percent [http://techcrunch.com/2012/05/22/ycombinator-80-strong/](http://techcrunch.com/2012/05/22/ycombinator-80-strong/) and as low as 0.6 percent in 2013 for TechStars NYC [http://www.techstars.com/techstars-nyc-2013-class/](http://www.techstars.com/techstars-nyc-2013-class/)
there often is no reason.” In this paper I will focus on companies that applied to and participated in accelerators, and similar companies that could have applied.

**Demo Day.** The most unique characteristic of accelerators is Demo Day, which is essentially the graduation ceremony of the program. More importantly, it is a chance for all the companies in the cohort to showcase their products to a large audience of investors. Founders take turns pitching their companies, and they also specify the amount of money they are aiming to raise. After the pitches, investors have time to talk with companies they are interested in, and funding deals can be closed as quickly as in the following weeks. From the perspective of the investors, even if they do not invest in the companies immediately, they are aware of accelerator companies and can track their developments for a future financing round.

### 4 Data and Summary Statistics

This paper presents both qualitative and quantitative data to document the accelerator phenomenon. Specifically, in order to understand how accelerators operate and a founders motivations for choosing accelerators, interviews were conducted with 12 accelerator partners, industry mentors, and founders and a survey was distributed to founders (with more than 70 respondents) asking specific questions about the decision to apply to an accelerator, what the perceived and realized benefits were, and details of their ventures. The survey results were helpful for data collection, but more importantly, they revealed which accelerator characteristics were most valuable to the founders.

In order to investigate the effects of accelerators on venture formation and performance, it is necessary to obtain data on companies that have participated in accelerators (accelerator companies) and similar companies that have not participated in accelerators (non-accelerator companies). This sample is constructed by identifying a set of accelerator companies, and then matching non-accelerator companies to accelerator companies based on observable characteristics.

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5IRB #13-9648. Survey instrument available upon request.
4.1 Accelerator Selection and Accelerator Companies

Given the large number of new accelerators being created in recent years, the data is limited to participants of more established accelerators. In addition, there are several definitions of accelerators with various program structures, so I further limit the type and geographic location of the accelerator. The qualifying accelerators satisfy the following criteria: 1) located in the U.S., 2) have invested in more than 30 companies across 2 cohorts, 3) take equity in exchange for investment, and 4) are not affiliated with a university or corporation. Imposing these criteria ensure that the accelerators in the sample face similar legal and country-specific geographic constraints, have some baseline experience investing in companies, accept applications from anyone, and focus on financial incentives (rather than promoting academic entrepreneurship or specific technology platforms). According to Seed-DB, a popular website tracking accelerator activities, there are 172 active accelerators worldwide that have accelerated 2921 companies (as of October 2013). After imposing the selection criteria, I retain 13 accelerators and record the location and founding year of the accelerator, details of the program structure including program length and funding terms, the number of affiliated mentors, and its complete investment history with cohort information. These accelerator characteristics are summarized in Table 1. The accelerators are about 4 years old on average, run 14-week programs, and invest $20,846 in 15 companies for each cohort. In terms of network size, they have, on average, 102 alumni and 62 mentors that are affiliated with the accelerator at the time of data collection. The resulting sample consists of 1311 accelerator companies from 13 accelerators.

For each of the accelerator companies, I gather the founder names, employment history, founding date, founding location, funding dates and amounts, industry, description, and operational status. The main data source is Crunchbase, which is an open source database maintained by TechCrunch, the leading technology news site. CrunchBase contains profiles of companies, people, and investors, and is regarded as one of the best resources for technology companies and transactions. It has partnerships with more than four hundred venture capital firms, accelerators, incubators, and angel groups to ensure the accuracy of the data. CrunchBase tends to have more early stage transactions compared to similar databases (such as CB Insights, Dow Jones Venture-
Sources, PitchBook, and PwC MoneyTree), which makes it ideal for the companies in the sample.\(^7\)

Most importantly, existing company entries cannot be deleted from CrunchBase so there is no survivalship bias. This is particularly important because many companies (about half in the sample) are recorded in CrunchBase but never report any external funding rounds, which is another indicator that CrunchBase captures a wide range of companies, not just well-funded and well-publicized ones. One caveat to point out is that only external funding is reported. In other words, funding from friends and family or the individual wealth of the founders are not reflected in CrunchBase. However, according to interviews and surveys with the founders, financing constraints are not the main reason for applying to an accelerator, so the possibility of founder wealth driving accelerator participation is not a huge concern. In addition to CrunchBase, AngelList and CapitalIQ are used to supplement and validate company information, and LinkedIn is used to collect past founding experience of the entrepreneurs. AngelList is a platform for new venture fundraising, and often includes information about founders and funding history. Capital IQ is a division of S&P and contains financial transaction data for both private and public companies. Capital IQ obtains information from a variety of sources including press releases, media mentions, and regulatory filings, which makes it complementary to the data from CrunchBase and AngelList. One of the challenges of working with early-stage companies is that company names appear in different forms\(^8\) so extra care has been taken to reconcile company and product names to ensure consistency. To determine a founder’s employment history, a combination of founder profiles in CrunchBase and LinkedIn cross-checked with other data sources is used to see if a founder is associated with multiple ventures. When there are discrepancies in founding or funding information across the different sources, I defer to the company website or whichever source has been most recently updated.

Tables 2 through 4 contain summary statistics for the accelerator companies. From Table 2, we see that the seed investment from the accelerator was the first round of capital raised for 95.3 percent of the companies. In other words, the majority of the accelerator companies had no funding beyond their own money or from friends and family at the time of acceptance. Only less than 5 percent of the accelerator companies had raised at least one round of funding prior to acceptance.

\(^7\)A detailed comparison between CrunchBase and other industry sources, including a spreadsheet with raw numbers was featured on TechCrunch, and can be accessed at [http://techcrunch.com/2013/07/23/how-crunchbase-data-compares-to-other-industry-sources/](http://techcrunch.com/2013/07/23/how-crunchbase-data-compares-to-other-industry-sources/)

\(^8\)For example, a company listed as “ABCStartup” in once source might appear as “ABCStartup.com,” ABC-Startup.com, Inc.,” or “123Startup (formerly ABCStartup)” in other sources.
into the accelerator. In fact, the average company age at the time of acceptance into an accelerator is 17 months old. These numbers indicate that accelerator companies are generally young and are at the early stages of product development. Table 3 shows that location-wise, it is not surprising that more than half of the companies are located in Silicon Valley (including San Francisco, California) and New York, New York. The five regions with the most companies also highly correlate with where the accelerators are headquartered. In terms of industries, the first column of Table 4 shows that software-related industries still dominate, accounting for at least 55 percent of the companies.

4.2 Matched Sample

The second half of the sample consists of companies that did not participate in accelerators, “non-accelerator companies,” which are matched to accelerator companies based on founding year, founding location, company description, founder experience and “pre-accelerator” funding (based on when the corresponding accelerator company applied to an accelerator). The goal here is to control for the type and quality of company such that the matched pairs look identical right before the accelerator company enters the accelerator. The counterfactual is companies that could have participated in accelerator programs but did not. Both company characteristics and founder background can impact how companies evolve and perform (Roberts, Klepper, and Haywardy, 2011). Selecting investment targets is a complex process that is difficult to codify, and even the accelerator partners may not be able to articulate why one company was accepted and not the other.

Due to the high degree of variation in business descriptions within the same industry, matching on industry alone is insufficient. For example, a company that analyzes and synthesizes social conversations in real-time and a company that instruments and monitors your application’s performance are both categorized as software companies but represent very different business. Propensity score matching would only allow matching on the industry level and be insufficient for precise matches. Therefore, matches are identified by hand via two coders. The project details were not disclosed to the coders, and they were given detailed instructions for the matching algorithm and examples.

9The Y Combinator website has an FAQ about why founders do not get selected for interviews (http://ycombinator.com/whynot.html) The following quote by Paul Graham is particularly telling, “So the reason we can’t respond to emails about why groups were rejected is that a lot of the time there’s literally no answer. We could make one up, but we’d be lying in many cases, and the better the group, the more likely we’d be lying.”
of different types of matches. At a high level, the matching procedure is the following: the universe of companies in CrunchBase is first filtered based on founding year and location, then each of the remaining companies are examined to determine the best fit based on the description of the company. Then, the entrepreneurial experience of the founders is compared. After this first-stage matching, a second-stage match is completed based on cumulative funding raised right before a company enters an accelerator (based on cohort date to a quarter precision). For instance, if an accelerator company participates in an accelerator in year 2.25 (the 9th quarter) with $20,000 in funding, the matched non-accelerator company has also raised the same amount by year 2.25. The second-stage matching is particularly useful for comparing funding patterns post-accelerator. An example of a perfectly matched pair is the following: Company A, an accelerator company, was founded in San Francisco, CA in 2011, and specializes in “fraud technology for e-commerce stores.” The founders of Company A have no prior founding experience, and Company A had zero funding at the time of accelerator application. It is matched to Company B, a non-accelerator company, which was founded in Palo Alto, CA in 2011 and describes itself as technology services that help e-commerce businesses detect and fight fraud. The founders of Company B were all new founders, and they also did not raise any money “pre-accelerator.” Checking both company websites (see Appendix for screenshots) further confirms that the companies are similar based on observable characteristics, and therefore, Company A and Company B would be considered a perfect match. If a perfect match cannot be found, the matching criteria are relaxed in turn until a lesser match can be found. The quality of the match is recorded, and accelerator companies with no matches are also recorded. The exact algorithm for matching is included in Appendix A. One caveat here is that founders fill out lengthy applications and may disclose information, such as alumni recommendations and links to product demos, which can be pertinent to the accelerators selection process. These selection criteria are private and unobservable to the econometrician, and are therefore not accounted for in the matching process.

Once the list of non-accelerator companies is identified, company details are gathered in the same manner as company details for accelerator companies, and the two samples are combined. After excluding accelerator companies with no appropriate matches and accelerator companies that

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10Within the overlapped subsample between the two coders, both coders identified the exact same match or a match of the same quality for 70% of the subsample (17 accelerator companies were matched to different companies).
participated in multiple accelerators, the final matched sample consists of 1796 companies, including 898 accelerator companies matched to 898 non-accelerator companies. A comparison of company characteristics pre-accelerator between the accelerator companies and non-accelerator companies is presented in Table 5. We can see that on average, both accelerator companies and non-accelerator companies are 17 months old pre-accelerator, and have 2 founders that are new founders 90% of the time. The companies are also mostly clustered in Silicon Valley, New York, and Boston and focus on consumer web, software, and e-commerce. In other words, the extensive matching algorithm builds a sample of accelerator companies and non-accelerator companies that look very similar based on observable characteristics.

4.3 Variables: Measures of Performance

The performance of companies is examined through three sets of measures: 1) external financing and venture growth, 2) acquisitions, and 3) closures. The first set of measures is based on the funding amount, time-to-funding, and web traffic to the company website. Funding Amount is the amount of money raised in U.S. Dollars and Time-to-funding measures the time (in days) between when the company was founded and the current funding event. In other words, Time-to-funding is the company age at the month when a company receives a certain round of funding. Companies may choose to disclose the date they have raised a round of funding, who the investors are, and the round size on their website, on CrunchBase, or through press releases. Therefore, if this information becomes public, it is observed in at least one of the data sources, and the funding details are further cross-checked between CrunchBase and Capital IQ for accuracy. When no funding information is found, it is assumed that the company has not raised any money. In this sample, companies that have not raised any money vary across age, location, and industry, alleviating concerns that only specific types of companies are represented. To measure venture growth, web traffic data is collected via Alexa (www.Alexa.com) to capture whether users are engaged with the company websites. The first measure compares the log ratio of web views per million between August 1st of the first and third year after the company is founded, and the second measure is a binary indicator for whether the views increased at all at the end of the two-year period. To account for potentially large within-industry variations in website use, the website rank in the U.S. is also collected, and analogous measures are constructed (Kerr, Lerner, and Schoar, 2014).
To analyze performance from the perspective of acquisitions, several acquisition-related measures are created. Given that acquisition statistics are often cited when accelerators speak to the performance of their portfolio companies, it is clear that it is an important metric of success to track. Acquired is a binary variable, with 1 indicating that a company has been acquired, and 0 indicating that a company has not been acquired. Note that initial public offerings are not used as a metric here because all of the accelerator companies in the sample are still private (as of May 2015). Similar to Time-to-funding, Time-to-acquisition tracks the age of the company at the month the company is acquired. Without seeing the actual terms of the acquisition, it is difficult to evaluate whether it is successful from a financial standpoint. However, additional details of the acquisition are collected from company press releases to gain insight into the conditions under which a company is acquired. These measures include binary variables for whether there are plans to shut down the initial product, whether it is an explicit “acqui-hire” for a small group of employees, and the count of employees at the time of the acquisition. These variables are coded only if specific plans or numbers are explicitly stated in press releases or related articles.

The last set of measures concerns survival of the venture. Closed is also a binary variable, with 1 indicating that a company is no longer active, and 0 indicating that a company is still operating. A company is coded as inactive if 1) it is indicated as “closed” on any of the data sources, 2) if the company website cannot be found, or 3) the company social media accounts (e.g., Twitter) or any traces of presence on the internet have not been updated in a year. All other companies are coded as active, including companies that have been acquired, even if the original product or team no longer exists after the acquisition. It is plausible that an acquired company might have gone out of business if it had not been acquired, but there is no evidence of this in the sample. Prior research also suggests that companies that are acquired are more appropriately characterized as successful rather than unsuccessful outcomes (Coleman, Cotei, and Farhat, 2013). For companies with explicit closing dates reported in any of the databases, an additional variable, Time-to-close is calculated as the company age when it goes out of business.
5 Nonparametric Analysis

Several patterns emerge from comparing the accelerator companies and the non-accelerator companies within the matched sample on the following dimensions: funding amount, acquisition rate, and survival rate. Figure 2 shows a comparison of funding trends between the accelerator companies and non-accelerator companies, focusing on the median funding amount. Pre-accelerator, both types of companies have zero funding. There is a clear separation between the companies over time, and we see that the non-accelerator companies raise more money than accelerator companies. In the data, this funding gap persists for the 75th percentile and outliers in the 95th percentile and 99th percentile. At these levels, the difference in funding between non-accelerator and accelerator companies is even wider. For the outliers that raise minimum funds, non-accelerator companies raise zero dollars compared to accelerator companies that only receive initial funding from the accelerator. One caveat is the funding amounts alone only give us approximations of the company value since I do not have the equity terms.

Nonetheless, these trends suggest that accelerators may not help with fundraising. From Table 6 we see that 13.3% of accelerator companies have been acquired, compared to 10.7% of non-accelerator companies; and that at the time of acquisition, accelerator companies have only raised $1.99 million compared to $7.86 million for the non-accelerator companies. Furthermore, in Figure 3, the kernel density graph indicates that accelerator companies tend to get acquired in two years after the accelerator. Taking into account the low funding numbers, these figures suggest that the accelerator companies get acquired early on instead of raising additional funding. It is plausible that the product is either very promising at an early stage, or the founders are being acquired for their talent.

Turning to the companies that close down, in the second set of results in Table 6 we see that accelerator companies go out of business 11.4% of the time, compared to 4.34% of the time for non-accelerator companies. In addition, when accelerator companies shut down, they have only raised around $0.13 million dollars in funding compared to $1.81 million for non-accelerator companies. In addition, there is a spike in closures within one year after graduation, as seen in Figure 4. In fact, the majority of accelerator companies (77%) have less than $50,000 at the time of closure, which suggests that most of these companies are young, of lower quality, and likely go out of business to
cut losses early. This can actually be seen as a benefit of accelerator participation in the sense that accelerator companies learn about their own quality during the program and know when to close down instead of sinking more money into an idea that will eventually fail.

6 Model

To account for any residual heterogeneity in unobservables in the matched sample, I propose a model that explicitly allows for selection into the accelerator. The model is consistent with three main empirical stylized facts established in the previous section: 1) accelerator companies raise less money than non-accelerator companies, 2) accelerator companies shut down earlier and more often, and 3) conditional on shutting down, accelerator companies raise less money. The model also makes additional predictions, which are then further tested with data.

6.1 Mechanisms

Here I highlight the intuition and mechanisms behind the model. The timing of the model and further mathematical details are included in the Appendix. The first mechanism is a self-selection effect where founders choose to participate in an accelerator only if the signal about the quality of their idea is below a certain threshold. The second mechanism is an accelerator feedback effect where the resolution of uncertainty around the quality of the idea is faster due to feedback within the accelerator.

The self-selection threshold is a consequence of the cost of participating in an accelerator. This cost is the equity a founder must give up, but it can also be seen as the opportunity cost of joining the accelerator. These costs are higher for founders with better quality ideas. Anecdotal evidence from founders supports this. For example, one accelerator company founder said that “If your company fails, that 6-10% you gave out (to the accelerator) won’t be useful,” suggesting that the cost of participation is lower for founders with low quality ideas. On the other hand, when asked about the decision not to apply to an accelerator, a non-accelerator company founder stated that the founders “didn’t want to give up equity on unfavorable terms.” In other words, the founders thought they had a promising idea and were not willing to dilute the company for a $21,000 accelerator investment. Therefore, founders with relatively lower quality ideas will apply
to participate in accelerators whereas founders with the highest quality ideas may pursue other sources of financing. This means that there are founders with good ideas that are willing to exchange equity for the potential benefits that accelerators offer. Put differently, one advantage of joining an accelerator is that you buy a real option: instead of investing more resources in the dark, you do so with knowledge of the true quality of the idea, thus having the option of shutting down and cutting losses short. If we use cumulative funding as an indicator of company quality, then companies with lower quality ideas should raise less money. In this model, I assume that all founders who apply to the accelerator are accepted. Therefore, due to a self-selection where the best founders do not join accelerators, accelerator companies, on average, will raise less money than non-accelerator companies.[1]  

Conditional on a founder choosing to participate in an accelerator, there is an accelerator effect due to the intense feedback during the accelerator program. Accelerator company founders meet with accelerator partners and mentors frequently and also have daily interactions with other founders in their cohort. This allows founders to iterate more quickly and resolve uncertainty around the feasibility of an idea at a faster pace. In fact, in my survey of more than 70 founders, “Access to industry mentors” was listed as the most important reason for applying to an accelerator, and one accelerator company stated that the biggest gain of participating in an accelerator was “Co-working with other founders. People were very open and helpful.” In contrast, non-accelerator company founders receive very little and less frequent feedback during the same time period of the accelerator program, so there is still uncertainty around the quality of the idea when founders need to decide whether to invest further. Consequently, founders of lower quality accelerator companies know when to cut losses and do not attempt to raise more money, whereas founders of lower quality non-accelerator companies will continue to raise money until the uncertainty is resolved. Therefore, accelerator companies shut down more often and do so sooner rather than later. In addition, at the time of shutting down, accelerator companies will have raised less money, on average.  

To summarize, the model characterizes the differences between accelerator companies and non-accelerator companies as a combination of self-selection and accelerator feedback effects. The

[1] If we allow for accelerators to reject a subset of applicants, we now have three groups of companies: non-accelerator, accepted applicants, and rejected applicants. The difference in funding between non-accelerator companies and accepted applicants will persist. However, if we consider non-accelerator and rejected applicants together, the difference in funding compared to accepted applicants will depend on the threshold for rejection.
self-selection effect results from the observation of a signal about the quality of the idea before the accelerator participation decision is made. Founders who observe low quality signals choose to pay the equity cost of joining an accelerator in favor of a better signal of the true quality of the idea. This better signal, in turn, provides the feedback effect of accelerator participation. It implies that, conditional on idea quality, accelerators provide for more efficient development decisions, both in terms of selecting projects to drop and in terms of selecting the optimal amount of effort to put into a given project.

6.2 Empirical Implications

Consistent with the nonparametric analysis, the model derives the following testable implications.

**HYPOTHESIS 1.** Accelerator companies receive less funding, on average, than non-accelerator companies.

**HYPOTHESIS 2.** Accelerator companies go out of business earlier and more often than non-accelerator companies.

**HYPOTHESIS 3.** Conditional on going out of business, accelerator companies receive less funding than non-accelerator companies.

Assuming that funding is an indicator of the quality of an idea or company, *H1* is a consequence of the self-selection mechanism. Due to the cost of accelerator participation being lower for founders with lower quality ideas, founders with the best ideas will not join accelerators. Therefore, accelerator companies will raise less money than non-accelerator companies due to differences in quality and *H1* follows.

*H2* and *H3* are both consequences of the intense feedback environment during the accelerator program. Accelerators enable founders to have direct and frequent access to mentors and the alumni network who offer advice and feedback. Mentors are usually industry experts, serial entrepreneurs, or venture capitalists who want to give back to the entrepreneurial community or have previously invested in alumni companies. Based on conversations with investors and entrepreneurs, there is a strong sense of “paying it forward” within the entrepreneurial community. Even though the mentors are not compensated financially, they commit to spending time with the accelerator company.
founders to share their experiences, keep current with start-up trends, and foster relationships. While non-accelerator company founders may have other sources of mentorship, the frequency and intensity of mentorship is unlikely to be higher compared to an accelerator environment. The frequency of the meetings varies, but founders can spend numerous hours weekly or even daily meeting with mentors. There is an expectation for accelerator mentors to be available or involved to a certain degree, and sometimes the meetings are organized by the accelerator directly. For example, according to the Techstars website, “About two or three nights a week, well organize informal educational sessions with our mentors. We also expect many of the mentors to drop into Techstars at various times throughout the program.” In addition to having more frequent interactions with a given mentor, accelerator company founders will also be exposed to more mentors due to the large network associated with the accelerator. The alumni network consists of all previous participants of the same accelerator, and it grows consistently with each cohort. The founders can tap into a wealth of knowledge from alumni who had the same experiences and faced similar challenges. In addition to mentors and alumni, cohort-mates can serve as another source of feedback. Founders in the same cohort spend significant amount of time together and develop into a tight-knit community. They can then benchmark their own quality against the progress and quality of other companies in their cohort, and assess their likelihood of raising follow-on funding, getting acquired, or going out of business.\footnote{12}

Based on the feedback during the accelerator program, uncertainty around the quality of the idea is resolved much faster for accelerator companies, so founders are able to make exit decisions sooner rather than later. In particular, lower quality companies realize that their ideas may not be sustainable in the long term and choose to go out of business altogether instead of trying to fundraise later. In contrast, due to the lack of frequent feedback, this uncertainty is still unresolved for all non-accelerator companies during the same timeframe. Therefore, founders will continue to operate and fundraise until the uncertainty is resolved later. Therefore, $H2$ follows. As a result,

\footnote{12 Most accelerator company founders do not have prior entrepreneurial experience, so they are unlikely to give advice related to fundraising, go-to-market strategies, or customer acquisition, as mentors would. However, since the founders spend considerable time together and the sense of community enables information-sharing, cohort-mates can brainstorm solutions to similar problems, serve as beta-testers, or provide emotional support. While the cohort effect is not the focus of this paper, an additional way cohort-mates can help resolve uncertainty about venture quality is to provide a benchmark for the founders. More specifically, the relative quality within the cohort may be resolved. For example, if a founder sees that their performance milestones are lagging behind other cohort-mates, the founder may interpret that their own venture is low quality (even though the absolute quality may be high).}
for many accelerator companies, the last round of funding will be from the accelerator, which on average is only $21,000. Consequently, conditional on closing, accelerator companies will raise less money and $H3$ follows.

**Funding Ratio.**

An additional prediction of the model considers accelerator companies as a portfolio, specifically, outcomes of investing in all accelerator companies. Here I propose a “funding ratio,” defined as $\text{FR} \equiv \frac{\text{Average Funding}\mid\text{Closed}}{\text{Average Funding}\mid\text{Acquired}}$. Using an acquisition as a successful outcome, the funding ratio is a measure of whether companies that eventually succeed receive more funding than companies that eventually shut down. If the funding ratio is small (less than 1), investors are making better investments (higher probability of a return) than if the funding ratio is large. Due to faster exit decisions, conditional on quality, the model predicts that following:

$$HYPOTHESIS\ 4. \ The\ funding\ ratio,\ \text{FR} \equiv \frac{\text{Average Funding}\mid\text{Closed}}{\text{Average Funding}\mid\text{Acquired}}, \ is\ smaller\ for\ accelerator\ companies\ than\ non-accelerator\ companies.$$  

This is closely related to $H3$ because accelerator companies that eventually close do not raise additional development funding. Furthermore, $\text{FR}_{accelerator} < \text{FR}_{non-accelerator}$ indicates that investing in accelerator companies as a whole may be an efficient use of money because the funding allocated to acquired companies is larger. In other words, there is less funding in companies that will eventually shut down and result in zero returns.

In Table 7, we see that in the matched sample, $\text{FR}_{accelerator} = 0.07 < 0.34 = \text{FR}_{non-accelerator}$, which is consistent with the predictions of the model and $H4$ is supported. The policy implication is that there are efficiency gains from investing in accelerator accelerator companies because the quality of the companies is observed sooner and the risk of investment is mitigated. While accelerator participation has various performance implications, on an aggregate level, its role as an intermediary resolving uncertainty seems beneficial.
7 Results from Regression Analysis

7.1 Main Findings from Matched Sample

There are three parts for the empirical analysis. The first is investigating the overall effect of accelerator participation using the matched sample, the second is providing additional evidence using a separate sample of rejected accelerator applicants, and the third includes additional robustness checks. In order to isolate the effect of the accelerator, I compare the outcomes of accelerator companies and non-accelerator companies. Identification comes from variation across accelerators and across matched pairs. The necessary assumption on the accelerator companies and non-accelerator companies is that conditional on observable characteristics, the prior likelihood of acceptance into an accelerator is identical. The matched sample consists of 1796 companies, including 898 non-accelerator companies that are matched to 898 accelerator companies.

The main empirical challenge is selection bias in the sense that certain types of founders might be more likely to apply and participate in accelerators. In particular, founders with more experience, better ideas, or existing investor connections may not think it is worth giving up equity and potentially moving to a new city, just to participate in an accelerator. To alleviate this concern, I use a founder’s entrepreneurial experience as a proxy for the type of founder that may be interested in applying to an accelerator. There might also be selection in the type of companies that are more likely to be accepted into an accelerator. In order to control for observable characteristics that appear on the application, the non-accelerator companies are matched to accelerator companies based on founding year, founding location, company description, and pre-accelerator funding, in addition to founder experience. The founding year and location control for macroeconomic conditions, geographic advantages, and the company age (which may proxy for the stage of the business). More importantly, the company description accounts for the type of business that the accelerator partners are interested in funding. The funding pre-accelerator is a proxy for company quality. Taking these factors into consideration, the matched non-accelerator companies should resemble the accelerator companies at the time of application. However, accelerator partners may choose companies to invest in based on unobservable characteristics—impressive demos, charismatic founders, recommendations from accelerator alumni—but the accelerator companies and non-accelerator companies are only matched based on observable characteristics. While it is difficult to completely
control for the selection bias in the matched sample, one of the ways I alleviate this concern is by restricting the accelerator and non-accelerator companies to subsamples that have achieved certain funding thresholds. Furthermore, analysis in the next section uses a separate sample of accelerator applicants to address this issue.

To test Hypothesis 1, I use ordinary least squares to regress the performance outcome (funding amount) for company \( i \) on an accelerator company dummy variable and controls for founding year, founder experience, and industry fixed effects.

\[
\text{FundingAmount}_i = \beta_0 + \beta_1 \text{AcceleratorCompany}_i + \text{FounderExp}_i + \text{FoundingYear}_i + \text{Industry}_i + \epsilon_i
\]  
(1)

To test Hypothesis 2, I use the following logit model to regress closure event on an accelerator company dummy variable and controls for founder experience, year, and industry fixed effects.

\[
P(\text{Closed}_i = 1) = P(\beta_0 + \beta_1 \text{AcceleratorCompany}_i + \text{FounderExp}_i + \text{FoundingYear}_i + \text{Industry}_i + w_i \geq 0)
\]  
(2)

To test Hypothesis 3, I use the same specification in Equation 1 but now condition on shutting down.

\[
\text{FundingAmount}_{i|\text{Closed}} = \beta_0 + \beta_1 \text{AcceleratorCompany}_i + \text{FounderExp}_i + \text{FoundingYear}_i + \text{Industry}_i + \xi_i
\]  
(3)

The regression results of venture performance and growth of the matched sample are reported in Table 8. Column 1 of Table 8 provides estimates of the changes associated with participating in an accelerator on the amount of total money raised (in millions), controlling for founder experience, year effects to control for macroeconomic conditions, and industry effects to account for
differences across industries. Consistent with the nonparametric analysis, the coefficient on total funding amount is negative and statistically significant for accelerator companies. This suggests that the quality of accelerator companies may not be higher than non-accelerator companies. In columns 2 and 3 the number of days it takes to reach a cutoff amount of funding is used as the outcome variables. For each of the funding levels, we see accelerator participation has a positive and significant effect on lengthening the time-to-funding. Therefore, Hypothesis 1 is supported. In columns 4 and 5, the number of funding rounds and existing amounts of funding are used as proxies for company quality. The sample is limited to companies that have raised at least one round of funding and companies that have raised at least $1MM, respectively. In both regressions, participating in an accelerator contributes negatively and significantly towards total funding raised, indicating that differences in fundraising are robust to additional restrictions on company quality. It is worth noting that there may be heterogeneous effects given the wide dispersion of fundraising amounts within the sample. However, based on patterns we observe for outlier companies that have the most funding in either group, the results in Table 8 may be conservative estimates for the best-performing companies. Two additional measures of performance, changes in web traffic and web ranking are examined in columns 6 through 9. In columns 6 and 7, I use log changes in web traffic and web ranking in the U.S. and the results show that accelerator participation contributes to decreases in web traffic between the first and third year of company operation. It does not have a significant effect on changes in web ranking, though. Regression results using binary measures tracking any improvements are presented in columns 8 and 9. Similar to findings using actual differences in web traffic and web rank, we see that accelerators have a negative and significant effect on the probability that web traffic increases over a two-year period.

In Table 9 I examine the probability of acquisition using accelerator participation, founder experience, year effects, and industry effects. Although the coefficient on accelerator companies is not significant in column 1, after conditioning on the quality of the company using funding as a proxy, the coefficients are positive and significant in column 2. In column 4, we see that conditional on being acquired, accelerator companies also raise less money. To gain insight into the conditions under which companies are acquired, I regress accelerator participation on additional acquisition characteristics. In columns 5 through 7, we see that acquisition of accelerator companies are more likely to involve shutting down the initial product and there is a negative and statistically
significant effect on the number of employees at the time of acquisition. These results indicate that acquisitions involving accelerator companies are less likely for technology and more likely for the talent of employees. Moreover, accelerator companies may be better positioned as acquisition targets due to exposure to large networks and potential acquirers.

The results in Table 10 address the probability of survival of accelerator companies and non-accelerator companies. In column 1, accelerator companies are positively and significantly more likely to shut down than non-accelerator companies. Even when controlling for lower quality by conditioning on raising at most $100,000 or $5 million of funding in columns 2 and 3, the coefficients are still positive and significant. These results suggest that accelerators may help resolve uncertainty around the company quality, and consequently, accelerator companies cease to operate rather than continue to operate at a loss. Moreover, focusing on companies that shut down eventually, we see in column 5 that closed accelerator companies receive less funding than closed non-accelerator companies. Given that companies do not shut down randomly, here the analysis is limited to lower-quality outliers. The effect on closed companies is smaller in magnitude than the effect on average for all companies as seen in column 1 of Table 8, but the coefficient is statistically significant. In other words, when lower quality accelerator companies go out of business, they have raised less funding compared to lower quality non-accelerator companies that go out of business. By combining the results in Tables 9 and 10, Hypothesis 2 and Hypothesis 3 are further supported.

7.2 Additional Evidence: Rejected Applicants

In order to provide additional evidence of the main findings, a separate applicant sample consisting of rejected applicants and accepted applicants (accelerator companies) was constructed to test the hypotheses. Due to the low acceptance rates and lack of feedback for rejected applicants, many founders turn to online forums to solicit feedback on their applications and interviews. Applicants rejected by Y Combinator are particularly vocal, and one applicant even started an accelerator specifically for fellow rejects. Through Y Combinator’s own news forum, web searches, and YC Rejects (http://www.forbes.com/sites/tomiogerona/2011/04/11/start-ups-rejected-by-y-combinator-and-investors-flock-to-yc-rejects/) I was able to identify a group of applicants to Y Combinator that were rejected in the
final round of interviews.\textsuperscript{14} After excluding applicants that eventually participated in an accelerator, remaining applicants are then matched back to accepted Y Combinator accelerator companies based on cohort applied to and business descriptions, resulting in a sample of 34 companies.\textsuperscript{15} Further company details including funding milestones and operational status are then collected. Due to the small sample size and availability of data such as the date of closure, a subset of the analysis from Section 7.1 is replicated with the applicant sample.

The evidence from applicants that would be the most consistent with current findings is as follows: 1) funding amount is not different between rejected and accepted applicants, 2) the closure rate is higher for accepted applicants, and 3) the funding ratio is lower for accepted applicants than accepted applicants. If there are no differences between the rejected and accepted applicants, this would suggest that the accelerator effect is entirely one of selection. In other words, accelerators may have an effect on founders, but such effect is not reflected in funding, acquisitions, or closures. The regression results of performance outcomes of the applicant sample are reported in Table 11. Note that year and industry fixed effects are not included to leverage the available data with a smaller sample size. Since the accepted applicants and rejected applicants in the final round are already matched by the cohort they applied to and the business description, they are similar from the perspective of the accelerator and omitted variable bias becomes less of a concern here. In column 1, we see that the funding amount is not significantly different between accepted and rejected applicants. In columns 3 and 4, accepted applicants are more likely to close down, with or without a funding threshold, but the coefficients are not statistically significant. In terms of the funding ratio, $\text{FR}_{\text{accepted}} = 0.004 < 0.02 = \text{FR}_{\text{rejected}}$ in Table 7, which is a ratio of 5. Although the coefficient on closure rate is not statistically significant, it is directionally consistent and may indicate heterogeneous effects within the accelerator companies. Overall, these results support the main findings and help alleviate concerns about selection bias in the matched sample. Furthermore, they provide some evidence of both self-selection and feedback effects of the accelerator.

\textsuperscript{14}Sources include, but are not limited to, Hacker News (https://news.ycombinator.com/) and YC Universe (http://ycuniverse.com/yc-applying-interviewees)

\textsuperscript{15}All companies in this sample applied to Y Combinator across several different cohorts, and consequently, they were not necessarily evaluated by the same judges. However, applicants are evaluated by multiple judges in each round, which alleviates the concern that one particular judge may bias the results.
7.3 Robustness Checks

To test the robustness of the main results, the baseline regressions are extended with three modifications. Even though an extensive matching algorithm was used, there were varying degrees of the quality of the match. In order to account for this, Table 12 includes analysis where the observations are weighted by the quality of the match. The signs on the coefficient for accelerator participation are consistent with the main results from Tables 8 through 10 and the effect size actually increases for the probability of closing down. The next robustness checks are shown in Table 13 where additional industry*year fixed effects are added in Panel A and accelerator*treated fixed effects are added in Panel B. In Panel A, we see that the results are robust to the additional year by industry effects, which is consistent with expectations since companies are matched by founding year and business descriptions. To account for additional variation across 13 accelerators in the sample, Panel B shows analysis including accelerator by treated companies fixed effects. The signs and significance of the coefficients are robust to this specification. Overall, these results give us more confidence in the matched sample and rule out the possibility that heterogeneous characteristics of accelerators may be driving the main findings.

8 Conclusion

The recent popularity of accelerators has prompted both founders and investors to scrutinize the benefit of accelerators. This paper analyzes a matched sample of accelerator companies and non-accelerator companies, and uses a theoretical model motivated by stylized facts established by the data to investigate the effects of accelerator participation on fundraising, acquisitions, and closures. There are four sets of results. The first is that accelerator companies receive less funding than non-accelerator companies. Second, accelerator companies close earlier and at a higher rate. Third, conditional on closing, accelerator companies raise less money than non-accelerator companies. These results suggest that accelerators help resolve uncertainty around company quality faster, and that accelerator companies learn to cut losses earlier and shut down accordingly. Fourth, even though accelerator companies raise less money on average, the funding ratio is lower, meaning that more money is invested in companies that eventually get acquired than in companies that eventually close. Furthermore, it seems that accelerators provide an environment such that would-
be entrepreneurs can experiment with new ideas in a low-cost way. These results are further supported when the analysis is restricted to matched accelerator and non-accelerator companies achieving certain funding thresholds, and when using a separate sample of rejected applicants instead of matched non-accelerator companies, mitigating concerns for selection bias.

This paper provides evidence that there are both self-selection and feedback effects from accelerators. Specifically, there is self-selection in that founders with the most promising ideas do not participate in accelerators, and consequently result in differences in funding. The feedback effect is that accelerators provide better signals of the idea quality and thus allow for quicker exits and better funding efficiencies. More broadly, this paper provides evidence of specific mechanisms that can affect the exit decisions of firms. As an alternative to the cash-out mechanism proposed in Arora and Nandkumar (2011), the decision to exit either via acquisition or closure is not strategic. Rather, the revelation of quality of the company determines the longevity of the firm. It is also feasible that a high-opportunity cost entrepreneur may choose to participate in accelerators, precisely to learn faster about the potential of the venture and shut down sooner if the quality is low. More fundamentally, closures in this context are actually positive outcomes because more capital and time is not wasted. As a source of entrepreneurial finance, accelerators can fill a unique role of decreasing the barriers to entry due to founder experience and human capital. More experienced founders may be able to evaluate new ideas better and have social networks in place, whereas accelerators can give inexperienced founders the opportunity to learn and fill these gaps. From the perspective of entrepreneurs, the feedback effect may be particularly beneficial for founders who do not have the skills or resources to evaluate product ideas. Moreover, given that many accelerator companies are in less capital-intensive industries, accelerators are mostly helpful for resolving demand uncertainty. The presence of mentors and cohort-mates that provide feedback can encourage faster iteration of ideas, prototyping, and consumer testing. Consistent with the spirit of the Lean Startup method, participating in an accelerator can help entrepreneurs learn when and how to fail. Furthermore, it demonstrates that there is value in experimentation to produce optimal outcomes, even when that outcome is to shut down the company.

While the matched sample allows us to investigate the overall effect of accelerators, the main limitation is that empirically, it is difficult to disentangle additional mechanisms such as network access and cohort effects. Furthermore, non-accelerator company founders may access capital, find
mentors, and try to expand their network outside of an accelerator. Although this paper does not address network or cohort effects directly, we are able to gain some clarity around the self-selection and feedback mechanisms by leveraging the data on funding and mentorship combined with anecdotal evidence from founders. It is worth noting that positive network effects and cohort-mates providing additional sources of feedback are consistent with the main findings both in the model and empirically. Isolating the network effects and investing cohort dynamics require different sets of data and are certainly topics for future work. There are also questions related to the design of accelerators that may have implications on performance outcomes. For example, suppose accelerators charge a fixed fee rather than equity in the company.

The number of accelerators is still growing, and a topic for further research is whether accelerators impact regional economies and social welfare. In addition to providing an alternate source of financing to new ventures, can accelerators facilitate allocation of labor, increase innovative activities, or promote economic growth? Further more, is the increase in accelerators beneficial or detrimental to the entrepreneurial ecosystem? One explanation is that more accelerators is beneficial because they can share mentor resources, investor networks, and encourage more start-ups. An alternative explanation is that mentor resources are limited in a given region so the average quality of accelerators decreases as the number of accelerators increases. Consequently, there are accelerators who take equity without delivering value and instead hinder progress. These are just several questions to be answered as the industry develops and matures. Moreover, there is great potential for future work in areas related to university- and corporation-affiliated accelerators, accelerators outside of the U.S., and peer effects within accelerator cohorts.
References


Figure 1: Comparison of sources of finance along the dimensions of mentorship and price of equity

Notes: From the entrepreneurs perspective, accelerators offer the highest intensity of mentorship. However, relative to venture capitalists and angel investors, accelerators require more equity relative to the low amount of financial input. Therefore, the price of equity taken is also highest.

Figure 2: Funding comparison for accelerator companies and non-accelerator companies

Notes: This figure highlights the differences between the median accelerator and non-accelerator companies. Accelerator companies receive initial funding from accelerators, but over time non-accelerator companies raise more money.
Figure 3: Kernel density graph of acquisition time post-accelerator

Notes: The Epanechnikov kernel is used to calculate the kernel density estimate for when companies get acquired.

Figure 4: Kernel density graph of closure time post-accelerator

Notes: The Epanechnikov kernel is used to calculate the kernel density estimate for when companies go out of business.
Table 1: Accelerator summary statistics

<table>
<thead>
<tr>
<th>Accelerator Attributes</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
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</thead>
<tbody>
<tr>
<td>Accelerator age (years)</td>
<td>13</td>
<td>3.92</td>
<td>2.06</td>
<td>1.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Investment amount ($USD)</td>
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<td>20846</td>
<td>5505</td>
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<td>38000</td>
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<tr>
<td>Program length (weeks)</td>
<td>13</td>
<td>13.69</td>
<td>2.81</td>
<td>10.00</td>
<td>20.00</td>
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<tr>
<td>Cohort size</td>
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<td>14.94</td>
<td>13.59</td>
<td>5.00</td>
<td>84.00</td>
</tr>
<tr>
<td>Number of mentors</td>
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<td>62.12</td>
<td>59.99</td>
<td>1.00</td>
<td>182.00</td>
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<tr>
<td>Size of alumni network</td>
<td>13</td>
<td>101.62</td>
<td>143.12</td>
<td>30.00</td>
<td>566.00</td>
</tr>
</tbody>
</table>

Table 2: Summary of financing round in which accelerator invested in accelerator companies

<table>
<thead>
<tr>
<th>Accelerator Round</th>
<th>Freq.</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Round 1</td>
<td>1,078</td>
<td>95.31</td>
</tr>
<tr>
<td>Round 2</td>
<td>40</td>
<td>3.54</td>
</tr>
<tr>
<td>Round 3</td>
<td>10</td>
<td>0.88</td>
</tr>
<tr>
<td>Rounds 4, 5, 6</td>
<td>3</td>
<td>0.27</td>
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<tr>
<td>Total</td>
<td>1,311</td>
<td>100</td>
</tr>
</tbody>
</table>

Notes: Only publicly announced funding activity are included.

Table 3: Summary of geographic dispersion of accelerator companies

<table>
<thead>
<tr>
<th>Region</th>
<th>Freq.</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Silicon Valley, California</td>
<td>542</td>
<td>54.69</td>
</tr>
<tr>
<td>New York, New York</td>
<td>130</td>
<td>13.12</td>
</tr>
<tr>
<td>Boston/Cambridge, Massachusetts</td>
<td>64</td>
<td>6.46</td>
</tr>
<tr>
<td>Boulder, Colorado</td>
<td>60</td>
<td>6.05</td>
</tr>
<tr>
<td>Philadelphia, Pennsylvania</td>
<td>46</td>
<td>4.64</td>
</tr>
<tr>
<td>International (Canada, Europe, Russia)</td>
<td>24</td>
<td>2.42</td>
</tr>
<tr>
<td>Other</td>
<td>125</td>
<td>12.61</td>
</tr>
<tr>
<td>Total</td>
<td>991</td>
<td>100</td>
</tr>
</tbody>
</table>

Notes: The total number is less than 1311 because location information could not be confirmed for 320 companies.
Table 4: Summary of accelerator company industries (self-reported on CrunchBase)

<table>
<thead>
<tr>
<th>Industry</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer Web/Internet Software</td>
<td>24.32</td>
</tr>
<tr>
<td>Software</td>
<td>10.81</td>
</tr>
<tr>
<td>E-commerce</td>
<td>10.42</td>
</tr>
<tr>
<td>Mobile/Wireless</td>
<td>10.04</td>
</tr>
<tr>
<td>Games/Video/Entertainment</td>
<td>8.11</td>
</tr>
<tr>
<td>Enterprise</td>
<td>5.41</td>
</tr>
<tr>
<td>Advertising</td>
<td>4.25</td>
</tr>
<tr>
<td>Messaging</td>
<td>3.86</td>
</tr>
<tr>
<td>Analytics/Big Data</td>
<td>3.09</td>
</tr>
<tr>
<td>Other</td>
<td>19.69</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
</tr>
</tbody>
</table>

Notes: Other industries include Consumer Electronics/Hardware, Social Networking, Travel, Search, Education, Network/Hosting, Public Relations, Finance/Venture, Health/Fitness, Hospitality/Food, Medical, Real Estate, Biotech, Manufacturing, Music, News/Media, Photo/Video, and Security.

Table 5: Comparison of accelerator companies and non-accelerator companies pre-accelerator

<table>
<thead>
<tr>
<th>Company Characteristics</th>
<th>Accelerator (N=898)</th>
<th>Non-Accelerator (N=898)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average age (months)</td>
<td>17</td>
<td>17</td>
</tr>
<tr>
<td>Average number of founders</td>
<td>2.36</td>
<td>2.29</td>
</tr>
<tr>
<td>Percentage of companies with new founders</td>
<td>90%</td>
<td>90%</td>
</tr>
<tr>
<td>Top 3 locations</td>
<td>Silicon Valley</td>
<td>New York, NY</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Boston, MA</td>
</tr>
<tr>
<td>Top 3 industries</td>
<td>Consumer Web/Internet Software</td>
<td>Software</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ecommerce</td>
</tr>
</tbody>
</table>
Table 6: Acquisition and closure rate comparison for accelerator companies and non-accelerator companies

<table>
<thead>
<tr>
<th></th>
<th>Accelerator (N=898)</th>
<th>Non-Accelerator (N=898)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Acquisitions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of companies acquired</td>
<td>119 (13.3%)</td>
<td>96 (10.7%)</td>
</tr>
<tr>
<td>Average funding at time of acquisition ($MM)</td>
<td>1.99</td>
<td>7.86</td>
</tr>
<tr>
<td><strong>Closures</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of companies closed</td>
<td>102 (11.4%)</td>
<td>39 (4.34%)</td>
</tr>
<tr>
<td>Average funding at time of closure ($MM)</td>
<td>0.13</td>
<td>1.81</td>
</tr>
</tbody>
</table>

Notes: The number of acquisitions for non-accelerator companies includes 3 companies that have gone public. None of the accelerator companies are public or have filed for an initial public offering. The average funding at time of acquisition for non-accelerator companies, excluding public companies, is $5.47MM.

Table 7: Comparison of funding ratio between accelerator and non-accelerator companies

<table>
<thead>
<tr>
<th></th>
<th>Accelerator</th>
<th>Non-Accelerator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matched Sample</td>
<td>0.07</td>
<td>0.34</td>
</tr>
<tr>
<td>Applicant Sample (Accepted applicants)</td>
<td>0.004</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Notes: The funding ratio is defined as $FR \equiv \frac{\text{Average Funding}|\text{Closed}}{\text{Average Funding}|\text{Acquired}}$. The analytical results derived from the model are that $FR < 1$ for accelerator companies and $FR \approx 1$ for non-accelerator companies.
<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accelerator company</td>
<td>-5.062***</td>
<td>50.31*</td>
<td>106.1***</td>
<td>-11.77***</td>
<td>-5.902***</td>
<td>-0.438*</td>
<td>0.0650</td>
<td>-0.410***</td>
<td>0.099</td>
</tr>
<tr>
<td></td>
<td>(0.853)</td>
<td>(27.24)</td>
<td>(32.03)</td>
<td>(2.140)</td>
<td>(2.231)</td>
<td>(0.224)</td>
<td>(0.0837)</td>
<td>(0.130)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>Founder experience</td>
<td>-0.259</td>
<td>25.26</td>
<td>3.760</td>
<td>-1.809</td>
<td>-0.865</td>
<td>0.288</td>
<td>-0.248**</td>
<td>-0.0744</td>
<td>0.192</td>
</tr>
<tr>
<td></td>
<td>(0.830)</td>
<td>(32.55)</td>
<td>(36.60)</td>
<td>(1.947)</td>
<td>(2.036)</td>
<td>(0.306)</td>
<td>(0.123)</td>
<td>(0.164)</td>
<td>(0.144)</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>27.38</td>
<td>914.5***</td>
<td>1,736***</td>
<td>49.96***</td>
<td>3.957</td>
<td>1.149</td>
<td>-0.991***</td>
<td>0.735***</td>
<td>-0.861***</td>
</tr>
<tr>
<td></td>
<td>(18.53)</td>
<td>(109.8)</td>
<td>(439.1)</td>
<td>(4.876)</td>
<td>(2.879)</td>
<td>(1.374)</td>
<td>(0.325)</td>
<td>(0.202)</td>
<td>(0.192)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,798</td>
<td>864</td>
<td>643</td>
<td>748</td>
<td>691</td>
<td>802</td>
<td>802</td>
<td>1,649</td>
<td>1,649</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.079</td>
<td>0.252</td>
<td>0.260</td>
<td>0.138</td>
<td>0.126</td>
<td>0.067</td>
<td>0.071</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors clustered by company in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Table 9: Analysis of accelerator participation and acquisition outcomes for matched sample of accelerator companies and non-accelerator companies

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accelerator company</td>
<td>0.0742</td>
<td>0.351*</td>
<td>-47.57</td>
<td>-3.246**</td>
<td>0.630*</td>
<td>-0.0157</td>
<td>-0.998***</td>
</tr>
<tr>
<td>Founder experience</td>
<td>-0.222</td>
<td>0.149</td>
<td>95.16</td>
<td>-0.0142</td>
<td>0.659</td>
<td>0.400</td>
<td>-0.499*</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>-3.538***</td>
<td>-4.052***</td>
<td>2,779***</td>
<td>-0.114</td>
<td>-1.473</td>
<td>-1.637**</td>
<td>0.729</td>
</tr>
<tr>
<td>Observations</td>
<td>1,745</td>
<td>925</td>
<td>201</td>
<td>211</td>
<td>197</td>
<td>146</td>
<td>71</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.622</td>
<td>0.333</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors clustered by company in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Table 10: Analysis of accelerator participation and closure outcomes for matched sample of accelerator companies and non-accelerator companies

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accelerator company</td>
<td>0.921***</td>
<td>1.417***</td>
<td>0.826***</td>
<td>-779.7**</td>
<td>-1.828***</td>
</tr>
<tr>
<td>(0.208)</td>
<td>(0.305)</td>
<td>(0.220)</td>
<td>(377.4)</td>
<td>(0.494)</td>
<td></td>
</tr>
<tr>
<td>Founder experience</td>
<td>-0.130</td>
<td>-0.0185</td>
<td>-0.0863</td>
<td>-885.0**</td>
<td>-0.420</td>
</tr>
<tr>
<td>(0.262)</td>
<td>(0.333)</td>
<td>(0.273)</td>
<td>(389.2)</td>
<td>(0.328)</td>
<td></td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.787**</td>
<td>-2.772**</td>
<td>-2.837**</td>
<td>571.6</td>
<td>1.367***</td>
</tr>
<tr>
<td>(1.084)</td>
<td>(1.228)</td>
<td>(1.106)</td>
<td>(798.2)</td>
<td>(0.296)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,681</td>
<td>762</td>
<td>1,387</td>
<td>42</td>
<td>142</td>
</tr>
<tr>
<td>R-squared</td>
<td></td>
<td></td>
<td></td>
<td>0.570</td>
<td>0.401</td>
</tr>
</tbody>
</table>

Robust standard errors clustered by company in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Table 11: Analysis of accelerator participation and performance outcomes for accelerator companies and rejected applicants

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>Logit</td>
<td>Logit</td>
<td>Logit</td>
<td>Logit</td>
</tr>
<tr>
<td>Total funding ($MM)</td>
<td>Acquired</td>
<td>Closed</td>
<td>Closed if</td>
<td>Closed if</td>
</tr>
<tr>
<td>Accelerator company</td>
<td>-0.421</td>
<td>0</td>
<td>0.474</td>
<td>0.857</td>
</tr>
<tr>
<td></td>
<td>(2.590)</td>
<td>(1.109)</td>
<td>(1.030)</td>
<td>(1.092)</td>
</tr>
<tr>
<td>Constant</td>
<td>3.245</td>
<td>-2.015**</td>
<td>-2.015**</td>
<td>-1.705**</td>
</tr>
<tr>
<td></td>
<td>(2.374)</td>
<td>(0.801)</td>
<td>(0.801)</td>
<td>(0.832)</td>
</tr>
<tr>
<td>Observations</td>
<td>34</td>
<td>34</td>
<td>34</td>
<td>23</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors clustered by company in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Table 12: Analysis of accelerator participation and venture performance where sample is weighted by quality of matched company pairs

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS Total funding ($MM)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accelerator company</td>
<td>-4.858***</td>
<td>0.232</td>
<td>0.950***</td>
<td>1.467***</td>
<td>0.915***</td>
<td>-683.2*</td>
<td>-1.947***</td>
</tr>
<tr>
<td>(0.960)</td>
<td></td>
<td>(0.164)</td>
<td>(0.225)</td>
<td>(0.330)</td>
<td>(0.238)</td>
<td>(368.7)</td>
<td>(0.561)</td>
</tr>
<tr>
<td>Founder experience</td>
<td>-0.261</td>
<td>-0.262</td>
<td>-0.0870</td>
<td>0.0767</td>
<td>-0.0446</td>
<td>-906.5**</td>
<td>-0.508</td>
</tr>
<tr>
<td>(0.830)</td>
<td></td>
<td>(0.230)</td>
<td>(0.273)</td>
<td>(0.354)</td>
<td>(0.286)</td>
<td>(434.8)</td>
<td>(0.343)</td>
</tr>
<tr>
<td>Year fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>27.32</td>
<td>-3.627***</td>
<td>-3.102***</td>
<td>-3.148***</td>
<td>-3.164***</td>
<td>693.5</td>
<td>1.402***</td>
</tr>
<tr>
<td>(19.04)</td>
<td></td>
<td>(0.478)</td>
<td>(1.069)</td>
<td>(1.209)</td>
<td>(1.090)</td>
<td>(933.1)</td>
<td>(0.352)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,796</td>
<td>1,743</td>
<td>1,681</td>
<td>762</td>
<td>1,387</td>
<td>42</td>
<td>142</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.084</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors clustered by company in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Table 13: Robustness checks of main analysis using additional year*industry and accelerator*treated fixed effects

### Panel A: Base regression with additional year x industry fixed effects

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) OLS Total funding ($MM)</th>
<th>(2) Logit Acquired</th>
<th>(3) Logit Closed</th>
<th>(4) Logit Closed if funding ≤$100k</th>
<th>(5) OLS Logit Time-to-close</th>
<th>(6) OLS Total funding if closed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accelerator company</td>
<td>-4.047*** (0.611)</td>
<td>0.226 (0.169)</td>
<td>0.869*** (0.224)</td>
<td>1.482*** (0.349)</td>
<td>-996.7*** (229.8)</td>
<td>-1.679*** (0.612)</td>
</tr>
<tr>
<td>Founder experience</td>
<td>0.743 (0.757)</td>
<td>-0.287 (0.243)</td>
<td>-0.113 (0.283)</td>
<td>0.335 (0.371)</td>
<td>-1,048 (863.7)</td>
<td>-0.560 (0.372)</td>
</tr>
<tr>
<td>Year and industry fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year x industry fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>4.065*** (0.611)</td>
<td>-30.85 (18.36)</td>
<td>-30.40 (310.1)</td>
<td>3.062 (18.36)</td>
<td>2,305*** (310.1)</td>
<td>-0.583 (0.612)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,796</td>
<td>1,322</td>
<td>1,192</td>
<td>521</td>
<td>42</td>
<td>142</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.374</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Panel B: Base regression with additional accelerator x treated fixed effects

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>OLS Total funding ($MM)</th>
<th>Logit Acquired</th>
<th>Logit Closed</th>
<th>Logit Closed if funding ≤$100k</th>
<th>OLS Logit Time-to-close</th>
<th>OLS Total funding if closed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accelerator company</td>
<td>-4.782*** (1.264)</td>
<td>0.370** (0.188)</td>
<td>0.885*** (0.236)</td>
<td>0.0722*** (0.0217)</td>
<td>-1.204*** (404.4)</td>
<td>-1.370* (0.732)</td>
</tr>
<tr>
<td>Founder experience</td>
<td>-0.238 (0.840)</td>
<td>-0.234 (0.220)</td>
<td>-0.107 (0.266)</td>
<td>0.000229 (0.0132)</td>
<td>-905.0* (522.7)</td>
<td>-0.672 (0.459)</td>
</tr>
<tr>
<td>Year and industry fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Accelerator x treated fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>29.47 (18.87)</td>
<td>0.465 (1.695)</td>
<td>-0.634 (1.189)</td>
<td>-0.0309 (0.0412)</td>
<td>1,520 (1,009)</td>
<td>-1.505 (1.359)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,796</td>
<td>1,691</td>
<td>1,654</td>
<td>826</td>
<td>42</td>
<td>142</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.374</td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Robust standard errors clustered by company in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Appendix A: Matched Sample Example and Algorithm

A.1 Example of Matched Accelerator Company and Non-Accelerator Company

Figure 5: Screenshot of Company A homepage:

![Company A homepage](image)

Figure 6: Screenshot of Company B homepage:

![Company B homepage](image)
A.2 Company Matching Algorithm

The following is an overview of the matching procedure.

Step 1: Identify the company description of the accelerated company to be matched.

- For this example, suppose the accelerated company was founded in San Jose, CA, on 6/1/2011.
- Go to the company website and get a sense for what the company does. Suppose the accelerated company offers “an enterprise solution for threat detection and analytics.”

Step 2: Find a subset of potential matches based on the location and founding year of the accelerated company.

- Using the existing dataset, filter companies according to founding location and founding year of the accelerated company.
- If no matches are found, look in the S&P dataset.
- If there are still no matches, relax the restrictions in the following order to create a new subset:
  - Allow for companies founded in plus or minus one year (2010-2012 in this example).
  - Search for companies located within a radius of 50, 100, 150 miles, and then expand to the entire state (for example, Mountain View, CA; San Francisco, CA; California State).

Step 3: Research the company description and founder experience of each potential match and identify the closest match.

- Go to each company’s website to learn what it does, and based on the descriptions, identify one or several matches to the accelerated company.
- Verify that the matched companies have not participated in an accelerator. Eliminate any matches that have received accelerator investment.
• For the remaining companies, find and record the names of the founders. Research the founders backgrounds and record whether the founders have entrepreneurial experiences (have founded companies before).

• Based on the description and founder experience, identify a best match to the accelerated company. If there are multiple best matches, record all candidates.

• If there is no match based on both the company description and founder experience, relax the founder experience criteria.

• If there is still no match and neither the location nor founding year restriction has been relaxed previously, go back to Step 2 and relax the restrictions in the following order to find a new subset of potential matches:
  – Allow for companies founded in plus or minus one year (2010-2012 in this example)
  – Search for companies located within a radius of 50, 100, 150 miles, and then expand to the entire state (for example, Mountain View, CA; San Francisco, CA; California State)

• If there is no match, even with the relaxed criteria of founding year and location, find companies that are in the same industry instead of an exact match on the description.

• If a match is found, record the closeness of the match (perfect match, location non-match, founding year non-match, description non-match, founder experience non-match)

• If at this point no match is found, record that the company could not be matched.

Step 4: Search for company details for the matched company and record findings.

Using a combination of CrunchBase.com, the S&P dataset, and internet searches (media mentions, company LinkedIn profile, SEC Form D, and investor websites), find company details including number of employees, industry, total funding, dates and amounts of individual rounds of funding, investors in each round, and operational status.
Appendix B: Model Timing and Proofs

B.1 Timing

A founder’s decision to participate in an accelerator and its consequences evolve over four stages.

**Stage 1.** In Stage 1, which roughly corresponds to the first year of a new founder’s life, Nature generates the value of $\theta$, the quality of the founder’s idea. In this model, $\theta$ captures a composite quality of both the founder and the idea itself. The founder obtains initial funding $\alpha$ and observes $s = \theta + \epsilon$, where $\epsilon$ is independent of $\theta$ and $E(\epsilon) = 0$. I assume that $\theta, \epsilon$ (and thus $s$) have full support (the real line). For the time being, I assume $\alpha$ is exogenously given and the same for all founders.\(^\text{16}\)

**Stage 2.** In stage 2, the founder must decide whether to join an accelerator or not. For simplicity, I assume that all applicants are accepted.\(^\text{17}\) If the founder decides to join an accelerator, he or she gives up $(1 - \delta)$ of the company, retaining $\delta$ ownership. During the accelerator program, the founder undergoes a process of passive learning (Jovanovic, 1982), whereby interaction with other founders in the same cohort, accelerator alumni, and feedback with mentors allows the founders to learn the true value of $\theta$.\(^\text{18}\)

If the founder does not join an accelerator, then nothing happens during this period. In other words, a founder of a non-accelerator company continues to pursue his idea, but the uncertainty about the idea quality is not resolved. For simplicity of the model, I assume the extreme case that non-accelerator founders receive no feedback during this time. This assumption can be relaxed to reflect that non-accelerator founders may have other sources of feedback, but the frequency and

\(^{16}\)The base model assumes that founders do not know how noisy their signal is; that is, they do not differ in their ability to interpret the quality signal. If we assume that founders are aware of how noisy their signal is, and suppose that more experienced founders receive less noisy signals (higher degrees of faith) and less experienced founders receive more noisy signals (lower degrees of faith). The model would predict that given the same quality signal, founders with more (less) noisy signals would be more (less) likely to participate in accelerators. This also means that more experienced founders are more likely to sort correctly into accelerator and non-accelerator, whereas less experienced founders (realizing their signal is noisy) will be even more likely to participate in accelerators. Therefore, high quality ideas may still end up in accelerators and explain outliers such as Dropbox and Airbnb. The degree to which the average funding for accelerator companies changes depends on how much noisier the signals are, but we would at least expect the number of outliers to increase in the accelerator companies.

\(^{17}\)We can extend the model to assume some noise in the system, which in turn would be consistent with allowing accelerators to reject applicants based on a cutoff signal. If the cutoff signal for being admitted to an accelerator is sufficiently high, the average funding amount for accelerator companies may increase, the likelihood of closure may decrease, and the amount of funding conditional on closure may increase as well. The qualitative results will hold if we consider non-accelerator companies separately from rejected applicants.

\(^{18}\)In a more general version of the model, there is possibility of active learning, whereby the value of the founder’s idea changes from $\theta$ to $\theta' = \theta + \lambda$, where $\lambda$ is either a scalar or a random variable.
intensity of the feedback will still be lower outside of the accelerator environment. Therefore, there will still be uncertainty around the quality of the idea. In terms of calendar time, this second period corresponds to about four months, the average time a founder spends at an accelerator.  

Stage 3. Stage 3 corresponds to a development stage. Let $x$ be the level of development that the founder’s idea is subject to. The eventual value of the project is given by $x\theta$ so better ideas are worth greater effort. I assume that effort requires funding $C(x)$, which has the properties that $C'(0) > 0$, $C''(0) > 0$ and $\lim_{x \to 0^+} C(x) > 0$. In other words, there is a fixed cost of developing an idea and the cost of additional development is increasing and convex.

For accelerator companies, the value of $\theta$ is known, and so $x = x^*(\theta)$. If $\theta < 0$, then it is optimal not to develop the idea any further (that is, $x^*(\theta) = 0$) and close down the company. For non-accelerator companies, only the value of $s$ is known, and so $x = x^*(s)$.

Stage 4. The results from venture development, as well as the value of $\theta$ (for non-accelerator companies) are observed. Surviving accelerator companies get acquired. Non-accelerator companies with $\theta > 0$ get acquired, whereas non-accelerator companies with $\theta < 0$ go out of business.

B.2 Solving the Model

Consider the development stage decision for an accelerator company (case A). By now the value of $\theta$ is known. If $\theta < 0$, then the project is terminated. If $\theta > 0$, then the founder chooses development effort $x$ given by

$$x^*(\theta) = \arg \max_x x\theta - C(x)$$

This results in a value of $\theta$.

---

19In addition to equity as a cost of participation, high opportunity costs may also prevent a founder from joining an accelerator. At the same time, founders with higher opportunity costs may derive extra benefit from rapid feedback. If the founders with highest or lowest opportunity costs opt to participate in accelerators, then the main findings will hold if we believe that idea quality is not correlated with founder opportunity costs. However, if we assume that better ideas come from more founders with higher opportunity costs, higher quality companies may participate in accelerators, increasing the average funding for the accelerator sample. Empirically, how a founders educational background factors into the decision to participate in accelerators is an open question for future work.

20Strictly speaking, the value of the company is zero. However, by assuming even an infinitesimal cost of keeping the company alive, the optimal decision is strictly to close down.

21Given the vast network of alumni, investors, and mentors affiliated with the accelerator, it is possible that the network effects contribute to the probability of acquisition. If we extend the model to account for network effects in this stage, the model would predict that accelerator companies have a higher likelihood of acquisition, condition on quality. This prediction is supported by the matched sample as well.
\(v_2^A(\theta) = x^*(\theta) - C[x^*(\theta)]\)

Let \(f(\theta; s)\) be the belief about \(\theta\) following the signal \(s = \theta + \epsilon\). Before joining the accelerator (that is, before knowing the value of \(\theta\)), the expected value from joining the accelerator is given by

\[
v_1^A(s) = \delta \int_0^\infty \left( x^*(\theta) - C(x^*(\theta)) \right) f(\theta; s) \, d\theta
\]

(4)

Consider now the development stage decision for a non-accelerator company (case B). The value of \(\theta\) is not known, only the value of \(s\). When deciding on development effort, the founder chooses

\[
x^*(s) = \arg \max_x x \int_0^\infty \theta f(\theta; s) \, d\theta - C(x)
\]

The expected optimum value is given by

\[
v_1^B(s) = v_2^B(s) = x^*(s) \int_0^\infty \theta f(\theta; s) \, d\theta - C(x^*(s))
\]

(5)

where the equality \(v_1^B(s) = v_2^B(s)\) results from the fact that no news is received by non-accelerator companies during stage 2.

B.3 Equilibrium Characterization

The main point about equilibrium characterization is finding the rule whereby a founder chooses path \(A\) (accelerator) or path \(B\) (non-accelerator). Intuitively, option \(A\) trades-off higher dilution (loss of a \(1 - \delta\) fraction of firm value) in favor of a better signal of firm value (specifically, knowledge of \(\theta\)). If \(\theta < 0\), then knowledge of the value of \(\theta\) has economic value, for it saves development costs \(x^*(s)\) that are invested if \(s\) is the only information available. Since a low \(s\) implies that a negative \(\theta\) is more likely to occur, I expect that the real option value of an accelerator is higher when \(s\) is lower. The following results confirm this intuition.

**Proposition 1** There exists an \(\bar{s}\) such that, if \(s < \bar{s}\), then the founder chooses an accelerator.

**Proof:** If \(s\) is sufficiently small, then \(x^*(s) = 0\). It follows that \(v_1^B(s) = 0\). By contrast, since \(f(\theta; s) > 0\) for all \(s\), \(v_1^A(s)\) is strictly positive for all \(s\). \(\blacksquare\)
Proposition 1 only provides a partial equilibrium characterization; however, it provides a lot of intuition. By choosing path $A$ and observing the value of $\theta$, the founder and investors are able to make a more efficient funding decision. This is particularly helpful if $s$ is small, so that the probability that $\theta < 0$ is significant. To put it differently, one advantage of joining an accelerator is that you buy a real option: instead of investing $x$ (development effort) in the dark, you do so with knowledge of $\theta$, thus having the option of shutting down and cutting losses short.

The complete equilibrium characterization requires knowledge of the optimal choice for any value of $s$. Proposition 1 suggests that there is a threshold of the initial signal that separates founders between the accelerator and the alternative path; that is, a threshold value of $s$ such that $v^a_1 > v^b_1$ if and only if the initial signal is sufficiently bad. The following two results provide conditions such that this is the case.

**Proposition 2** There exists a $\bar{\delta} \in (0,1)$ such that, if $\delta < \bar{\delta}$, then there exists a $\bar{s}$ such that the founder chooses an accelerator if and only if $s < \bar{s}$.

**Proof:** By the envelope theorem,

$$\frac{dv^0_1(s)}{ds} = \frac{\partial \tilde{v}^0_1(s,x)}{\partial s}$$

and since $s = \theta + \epsilon$, it follows that if $s'' > s'$ then $f(\theta; s'')$ dominates $f(\theta; s')$ in $s$ in the sense of first-order stochastic dominance. Since there is a fixed cost of effort $x$, there exists an $\bar{s}$ such that $x^*(s) = 0$ for $s < \bar{s}$ and $x^*(s) > 0$ for $s > \bar{s}$. For $s > \bar{s}$, $f(\theta; s)$ multiplies a strictly increasing function of $\theta$ in the integral that defines $\tilde{v}^0_1(s,x)$. I thus conclude that $dv^0_1(s)/ds$ is strictly increasing in $s$ for $s > \bar{s}$ (Milgrom, 1981).

If $\delta = 0$, then $v^a_1(s) = 0$ and $dv^a_1(s)/ds = 0$. This implies that, in the neighborhood of $\delta = 0$, $v^a_1(s) > v^b_1(s)$ if and only if $s < \bar{s}$. □

Although Propositions 1–2 are limited to regions of the parameter space, together they provide credence to the more general conjecture that equilibrium has the nature of a threshold strategy\textsuperscript{22}

\textsuperscript{22}The reason why the result is not obvious is that value of knowing $\theta$ is not simply the real option of shutting down
B.4 Proofs for Predictions of the Model

**H1.** Accelerator companies receive less funding, on average, than non-accelerator companies.

**Proof:** Suppose that $\sigma = 0$. Then the initial signal $s$ provides an exact estimate of $\theta$. Let $\bar{s}$ be the lowest value of $s$ such that $v^B_1(s) = 0$. (By Proposition 2, we know $v^B_1(s)$ is strictly increasing for high enough $s$, so $\bar{s}$ exists.) Since $\sigma = 0$, in equilibrium the founder choses an accelerator if and only if $s < \bar{s}$. Moreover, no accelerator company gets funded. By continuity, as I consider infinitesimally small values of $\sigma \to 0$, I get that accelerator companies get funded with an infinitesimally small probability. Non-accelerator companies, by contrast, are funded with probability 1 and at amounts that exceed $x^*(\bar{s})$, which is strictly positive. In other words, as $\sigma \to 0$, the amount of funding received by accelerator companies converges to 0, whereas the amount of funding received by non-accelerator companies is bounded away from 0. ■

**H2.** Accelerator companies go out of business earlier and more often than non-accelerator companies.

**Proof:** The prediction that accelerator companies go out of business earlier is by construction (the extensive form considered). To show that accelerator companies close more often than non-accelerator companies, consider the proof of H1. As $\sigma \to 0$, the probability that accelerator companies close down converges to 1, whereas the probability that non-accelerator companies close down converges to 0. ■

**H3.** Conditional on closing down, accelerator companies receive less funding than non-accelerator companies.

**Proof:** Conditional on closing down, accelerator companies receive funding of $\alpha$, whereas non-accelerator companies receive

$$\alpha + \int_{\bar{s}}^{\infty} x^*(s) g(s) ds$$

where $g(s)$ is the unconditional distribution of $s$. The result follows. ■

---

when $\theta < 0$. Even if $\theta > 0$ (and thus development is the optimal strategy), the optimal value of $x$ depends on $\theta$, and thus knowledge of $\theta$ has value. In fact the information value regarding the choice of $x$ may be increasing in $s$, which goes against the conjectured “single-crossing” property.
H4. The funding ratio, \( FR \equiv \frac{Average\ Funding|Closed}{Average\ Funding|Acquired} \), is smaller for accelerator companies than non-accelerator companies.

**Proof:** If \( \sigma_\epsilon \) is sufficiently large, then

\[
x^*(s) \approx \bar{x}^*
\]

It follows that all non-accelerator companies received approximately the same amount of funding. As a result, \( FR \) for non-accelerator companies is approximately 1. On the other hand, for accelerator companies,

\[
FR \approx \frac{\alpha}{\alpha + E(x^*(\theta)|x^*(\theta) > 0)} < 1
\]

The result follows. \( \blacksquare \)