# Business Accelerators: Evidence from Start-Up Chile[1]

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This paper investigates whether government funded business accelerators create value for start-ups. We focus on the case of Start-Up Chile (SUP), an accelerator sponsored by the Chilean government, which provides participants with 40,000 USD (equity free) in seed capital, a work visa, and free office space, as well as the option to be selected into in the Highway: the mentoring arm of the programme where start-ups can access top mentors. Selection into the accelerator follows a rules-based approach: the top 100 applicants are selected every 4 months based on a ranking by external judges. We analyse start-up performance using web-based metrics for applicants that marginally rank above or below the 100th threshold. This analysis provides a clean causal estimate that deals with potential selection bias from heterogeneity in growth opportunities across start-ups. Our results do not allow us to rule out the possibility that participation in the accelerator has no impact on subsequent start-up performance. However, we find evidence, albeit weak, of differences in performance across participants in and out of the mentoring arm. These additional results provide new insights about the selection skills of government-sponsored programmes, and the potential value added role of mentoring for start-ups.

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Encouraging entrepreneurship is nowadays a major policy objective. The rationale for public intervention in entrepreneurship is that while it is crucial to generate economic growth and job creation, there is rampant underinvestment in new businesses and ideas, either because a funding gap exists (i.e., potential entrepreneurs with positive NPV projects do not get funded) or because stigma of failure is prevalent (i.e., risky but positive NPV entrepreneurial projects are forgone, because market's beliefs on individual's abilities negatively overweight failure). Government-sponsored programmes to spur entrepreneurship are now, as a consequence, common place. However, academic analysis about these programmes remains relatively scant, and the little existing evidence is quite glum (e.g., Brander et. al (2008), Lerner(2009)).

In this paper we take a careful look at whether government sponsored programmes to encourage entrepreneurship add-value to participants. We focus on a type of programme which has increasingly gained participation not only in the public, but also in the private sector: business accelerators. Accelerators are early stage financiers of high technology start-ups. In contrast to the investment practices of other early stage financiers, accelerators are structured as fixed-term and cohort-based programmes, which include mentorship and educational components, and offer shared-office space to participants (Cohen and Hochberg, 2014). From only one business acelerator in 2005, Y Combinator in Silicon Valley, there are now thousands worldwide, including Techstars which operates in several cities in the U.S., and Seedcamp, originally London-based and currently pan-European (e.g., Cohen and Hochberg, 2014).

In spite of their prominence, business accelerators remain understudied in the economics literature due to data- and methodology-related challenges (see Cohen and Hochberg, 2014). Because participants are early-stage start-ups, they are often not legally incorporated, and are thus missing from standard business data sources. In addition, the probability that these early stage start-ups "pivot" is so large, that is challenging to even define, let alone adequately measure, post-application performance. Finally, because simple comparisons across participants and non-participants confound the effect of the programme with the higher growth opportunities of teams that succeed in the competitive application processes, researchers are prevented from more in-depth analysis, unless selection processes are random or rules-based. Establishing empirically how business accelerators affect start-up value and what type of accelerator services have greater effects, thus, while essential for welfare and policy design is challenging.

Our analysis overcomes several of these data and measurement challenges and provides the first formal analysis of an accelerator programme: Start-up Chile (SUP), an accelerator promoted by the Chilean government since late 2010. Participants in SUP receive a grant for U$40,000 (equity free), a one year work visa (i.e., the programme is open to Chilean and non-Chilean teams), shared office space for six months in Santiago de Chile, and the option to be selected into the Highway: the mentoring arm of the programme where participants are given additional access to top mentors. Every four months approximately 650 start-ups compete for the 100 coveted spots in SUP.[4]

One of the advantages of focusing on the case of SUP is that selection follows a rules-based approach. Each round, applications are scored and subsequently ranked by external judges using three criteria: the quality of the founding team, the merits of the project, and the expected impact of the project on Chile's entrepreneurial environment. Chilean government officials then use this external ranking to select from the pool of applicants (circa 650 every four months) the participants: roughly, the first 100 ranking start-ups.[5] We argue that a

[4] The 100 scale of the programme is based on budgetary restrictions. SUP has an annual budget of 15 million dollars and 100 start-ups every four months is the capacity of that budget.

[5] Except in generation 2 were the SUP decided before the application round was opened to accept 150 participants.

regression discontinuity design on start-up performance based on this exogenous selection rule allows overcoming the endogeneity limitations of simple comparisons across participants and non-participants. The empirical strategy essentially compares performance of start-ups that rank marginally above and marginally below the $100^{th}$ company threshold. For these close-call applicants, selection is akin to an independent random event (it is “locally” exogenous) and therefore uncorrelated to start-up growth opportunities. Intuitively, the average growth opportunities of start-ups that rank 97 are similar to those that rank 103. However, this small difference in rank leads to a discrete change in the probability that the start-up is accelerated: start-ups ranking below $100^{th}$ are 14.5% more likely to participate in the accelerator.

Our estimate captures the effect of this discrete change in selection at the $100^{th}$ ranked company threshold, and this estimate does not incorporate any observed or unobserved confounding factors as long as their effects are continuous around the threshold. We show that indeed, for start-ups that ranked closed to the $100^{th}$ company threshold, selection is uncorrelated with observed start-up and founder characteristics. Hence, by focusing on these start-ups, we can plausibly estimate a casual effect. We present an analytical framework that shows how start-up performance should be affected by acceleration and how one can recover the value of acceleration from the outcomes of start-ups ranking near the $100^{th}$ company threshold.

Our analysis exploits hand-collected data at the applicant level for start-ups that applied to the accelerator during the 2010-2013 period. The accelerator provided us access to confidential records of the companies that applied to the programme, the evaluation scores from the panel of judges, and the selection decisions made. Based on these records, we collected information on subsequent start-up performance using surveys and extensive web-searches on the businesses and the teams' leaders in fund raising sites such as AngeList, Techcrunch, social media sites like Facebook, Linkedin, and in web-page tracking sites like Google Insights and Alexa.

The results do not allow us to reject the null hypothesis that the basic services offered by the government-sponsored accelerator, i.e., cash infusions and shared office space add no value to participant start-ups. However, the effect that we identify pertains, by definition, only to participants that have observations around the discontinuity, which affects the degree to which one can extrapolate the results of our analysis to others. In future versions of the paper we plan to explore this point further, by comparing the observable quality of applicants close and far from the 100$^{th}$ company threshold.

We then exploit detailed data on the mentoring arm of SUP (i.e., The Highway) to analyse the importance of mentoring as part of the services traditionally offered by business accelerators. In SUP, two months into the accelerator, participants have the choice to apply for participation into the mentoring arm. The application process consists of a "pitch-day" in which start-ups do a formal presentation of their businesses to judges, both external (i.e., staff at other private accelerators in Chile such as Telefonica's Wayra) and internal (i.e. staff at SUP). The judges independently score the start-ups, and then based on that score the staff at the accelerator selects roughly 20% of the participants into the mentoring arm. The accelerator provided us access to the additional confidential records detailing the scores of participants during the pitch-day and the selection decisions made. Using this information, we show that start-ups in the mentoring arm outperform their peers in the accelerator programme. This additional result is consistent with both, selection skills of government-sponsored programmes, and the potential value added role of mentoring for start-ups.

To provide further suggestive evidence of the potential role of mentoring for start-ups we exploit an implicit selection rule into the mentoring arm. While selection into the Highway is not based on such an exogenous rules-based procedure as selection into the accelerator (i.e., there is no clear cut-off), there is evidence of an implicit selection rule: we find a discrete jump in the probability of selection into the mentoring arm of 40% if the start-up scores at least 3.6/5 during the pitch-day. Following a methodology akin to a regression discontinuity approach, we compare start-up performance for applicants near the 3.6 score threshold, and find evidence, albeit weak, that mentoring has a positive causal impact of start-up performance.

In future versions of the paper we plan to: 1. explore the real effects of acceleration beyond start-up performance, by focusing on the potential effects on founders, 2. include results from a detailed survey on applicants regarding their experience in SUP, and their opinion on the most useful aspects of the programme. Finally, we will also present suggestive evidence of the more general impact of SUP on the Chilean entrepreneurial ecosystem, by comparing registering rates of start-ups in Chile across industries targeted and not targeted by SUP.

Our paper contributes to the more general literature assessing the impact of early stage financiers on firms (e.g., Hellman and Puri (2000); Sorensen (2007) Kortum and Lerner (2000)) in two ways. First, we focus on a neglected type of investor: business accelerators. Second, our methodology allows us to uncover casual estimates; in contrast, the estimates in most pre-existing studies may be biased because of the non-random nature of selection process by early stage financers. For example, if better start-ups (e.g., those with unobservable better growth opportunities) are also more likely to be selected by an early stage financier, this would cause regression coefficients to be biased upwards.

Our paper also contributes to our understanding on what types of services to start-ups appear to add more value, especially when imparted by government-sponsored programmes. Our results point to an important role of mentorship which complements studies in other fields such as subsistence businesses in developed economies (McKenzie and Woodruff (2008), De Mel et al. (2014)).

Our paper has policy implications, in particular regarding design of policies to sponsor entrepreneurship. Our results suggest both that government-funded programmes can develop valuable selection skills, and also that mentoring is potentially an important policy lever. Both these results are important. Business accelerators are becoming more frequent as policy tools to sponsor entrepreneurship: the SUP model has already been adapted in several countries such as the U.S., Brazil and Peru, and is in the process of being adapted to several other countries (e.g., Canada, Denmark and Spain, among others). Our findings can help policy makers understand how to adapt more successfully this type of programs to the idiosyncrasies of their countries, by understanding which is the crucial policy element.

The rest of this paper is as follows. In Section 1 we describe the SUP programme and its selection process. In Section 2 we explain the analytical framework and in Section 3 the identification strategy. In Section 4 we present the estimates of the value-added of acceleration, and in Section 5 we present the estimates of the value added of mentoring. We conclude in Section 6.

## 1. START-UP CHILE

SUP is a government-sponsored program launched in August 2010 to attract early-stage, high-potential entrepreneurs to bootstrap their ventures in Chile. The programme is run by the Ministry of Economy and is executed by the Chilean Economic Development Agency (CORFO), the leading organization for promoting innovation and entrepreneurship in the country. Its main long-term goal is to convert Chile into an innovation and entrepreneurial hub in Latin America not only by bringing in more entrepreneurs, but also by creating a much better-developed ecosystem of supporting institutions—including venture capital firms and angel investors.

SUP offers four main benefits to participants. First, SUP provides selected start-ups with $40,000 equity-free seed capital. The capital is staged: 50% is delivered at the beginning of the programme, and the remaining 50%, 3 months after. The second instalment is conditional on pre-determined performance milestones.[6] The staging of capital provides incentives to entrepreneurs to provide effort, and accountability of participants' expenditures.

Second, SUP sponsors a temporary one-year work visa for accepted participants in order to attract foreign entrepreneurs. The programme also helps participants settle in Chile through a "buddy system". The buddy-system pairs entrepreneurs with local members of the Santiago business community based on background interests and language. Local buddies advice participants on opening Chilean bank accounts, registering with the police, obtaining a local ID, and securing housing and mobile phones, in addition to checking in with participants once or twice a month throughout the entrepreneurs' stay in the country.

Third, SUP provides free, shared office space in downtown Santiago, equipped with WiFi, for all start-ups. Workshops on think-tanking and pitch-training based on peer to- peer teaching are held on-site. Start-ups also have access to SUP's network of mentors.

Starting in 2012, SUP expanded its programme to include more accelerator-type activities such as national and international pitch competitions. It created a mentoring arm within the accelerator known as the Highway, which provides additional resources to

[6] In the inception of the programme, capital disbursements were neither pre-expense nor staged. This system was implemented in the first semester of 2013.

participants including access to the most renowned mentors and frequent monitoring by the SUP staff. Participants are carefully selected into the Highway after a pitch competition, in which external and internal judges rank participants. Roughly 20% of participants in each generation have classified into the Highway since SUP's fourth generation.

The SUP program, in turn, requires accepted entrepreneurs to stay in Chile for the six-month duration of the program, and contribute to the building of an entrepreneurial culture in Chile. During their stay, entrepreneurs have to accumulate 4,000 in "Return Value Agenda" (RVA) points, a system to measure the social contribution of participants in the Chilean entrepreneurial ecosystem. Participants have the option to attend, organize or innovate in social-related activities. Attendance refers to participation in local events, such as meetings and conferences at which entrepreneurs make themselves available to share knowledge and to network with locals. Organization can include giving a talk at a school, presenting a pitch to a local investor, or mentoring a local entrepreneur or student. Innovation refers to initiatives that actively engage the Chilean business community, such as starting a new business with a Chilean partner or patenting a product in Chile.

## 1.1. SELECTION INTO THE ACCELERATOR

Selection into SUP is a two-part process that takes place every four months. First, entrepreneurs apply to the programme and their applications are ranked by external judges. SUP outsources this first part to Younoodle, a consulting start-up in California, which provides and objective evaluation of the merit of the start-ups outside the particular context of the Chilean economy.

Entrepreneurs fill in their applications through an open surve, and then Younoodle resorts to Silicon Valley experts (3-4 judges per application) who evaluate applications using three criteria: the quality of the founding team, the merits of the project, and the impact that it is likely to have on Chile's entrepreneurial environment. Using the experts' judging sheets, applicants are ranked. No ties are permitted; if companies tie in their judges' score they are randomly ranked.

The second part of the selection process is handled by CORFO, which makes the final decision based on Younnodle's ranking. A threshold is pre-specified each round (normally 100), and roughly, only companies that rank above the threshold are selected.[7] The threshold is decided on by the government before the application process begins and is a function of government's budget.

The start-ups cannot precisely manipulate their ranking. Because start-ups do not know the judges' scoring rules, and are unlikely to learn about these rules from past SUP participants, it is improbable that start-ups have room for manipulating their scores around the 100-th company cut-off. In addition, the judges are unlikely to manipulate the scores, as no judge evaluates all applications and only observe the very few he/she is asked to score.

As it is common in government-sponsored programmes, however, the selection committee at CORFO does not strictly follow the selection rule and thus not all participants who rank above the 100$^{th}$ company threshold end up participating in the programme. Indeed, of the top 100 ranked applicants, about 75% of them are selected into SUP. The remaining 25% are selected by a committee among applicants ranked between 101 and 300 based on qualitative attributes of the applications. The setting, thus, is akin to a fuzzy RD design (Van der Klauw, 2008), where, although there is no 100% compliance of the selection rule, there is nonetheless a discrete jump in the probability of selection. In section 3 we explain in detail how we exploit this selection rule to identify the causal effect of SUP.

[7] The threshold has been 100 in every generation, except the second generation where the threshold was set at 150.

### 1.2 SELECTION INTO THE MENTOR ARM

Participants in SUP have the option to participate in the Highway: the mentoring arm of the programme where participants are given additional access to top mentors. Two months into the participants have the choice to apply for participation into the mentoring arm. The application process consists of a "pitch-day" in which start-ups do a formal presentation of their businesses to judges, both external (i.e., staff at other private accelerators in Chile such as Telefonica's Wayra) and internal (i.e. staff at SUP). The judges independently score the start-ups, and then based on that score the staff at the accelerator selects roughly 20% of the participants into the mentoring arm. In section 4, we document how we exploit this selection process into the mentoring arm to explore whether mentorship adds value to the participant start-ups.

## 2. DATA AND ANALYTICAL FRAMEWORK

### 2.1 DATA

We were given access to applicant records for seven generations of SUP. In total we have information on 3,258 applicants, 616 and 2,642 participants and non-participants, respectively. Panel A of Table 1 displays the number of applications judged per generation (i.e., not all applications are judged by YouNoodle as some are incomplete), the number of applications selected (e.g., and offer is extended by the accelerator to the start-up) and the number of applications that are formalized (e.g., the start-up accepts offer and reallocates to Chile for the 6 month duration of the programme).[8] Panels B through D, and E through G,

[8] Results from the Global Entrepreneurship Monitor (GEM) report provide a basis for comparison between the entrepreneurs that apply to SUP, and the average Chilean entrepreneur. According to the latest GEM (2012), the average Chilean entrepreneur is 37.5 years old, is twice as likely to be male than female, has studies beyond those that are compulsory, and has a business that serves the consumer sector. The survey on micro entrepreneurship (EME) also provides a basis of comparison for the composition of Chilean SUP entrepreneurs. According to the EME of 2012 the average Chilean micro entrepreneur is male (69%), has between 45 and 59 years of age (39%), is responsible for a home (74%), has basic to mid-level education (67%) and its business

describe the composition of the sample by start-up and lead founder characteristics, respectively. For the empirical analysis, we bundle together all generations. While the average quality of start-ups on the accelerator is likely to change over time (e.g., as the accelerator gains recognition better start-ups may apply), we are unable to analyse generations separately due to power considerations. We address this concern in our empirical strategy including generation fixed effects throughout.

For the 3,258 start-ups that constitute our sample we hand-collect performance measures using extensive web-searches. Table A1. in the Appendix has a list of the performance measures and their sources. Table 2 displays the summary statistics of these web-based performance measures.

### 2.2. ANALYTICAL FRAMEWORK

In this section, we present an analytical framework that shows how to recover the value of acceleration by focusing on applicants ranking close to the 100th company threshold. We show that a discontinuity analysis is a simple way to deal with heterogeneity in unobserved growth opportunities across applicants.

Denote as $r$ the ranking of the applicant and $V(r)$ the added-value of government-funded accelerator services. For simplicity, we assume throughout that the outcome of the selection process is binding, that the threshold for selection is $r \leq 100$, and that the value of acceleration to the start-up is fixed (i.e. is independent of $r$), such that $V(r) = \bar{V}$ if $r \leq 100$ and 0 otherwise. The objective of the empirical analysis is to estimate $\bar{V}$, the value of acceleration, which is not directly observable. Further assume that the underlying growth opportunities of the applicants can be represented by a function of the ranking $r$, $G(r)$, that is

belongs to the sectors: retail, restaurant and hotel (34%), agriculture and fishing (24%) and manufacturing (13%).

continuous around the 100th company threshold. For highly ranked applicants, growth opportunities are likely very high. Around the threshold, growth opportunities may not be as high, but most importantly, are comparable across participants in either side of the threshold.

Since $G(r)$ is a continuous function of $r$, but $V(r)$ is discontinuous at the 100th company threshold, the performance of the applicant that one observes after participation is also discontinuous at the 100th company threshold. This implies that the difference in the performance at the 100th company threshold, VA, between a start-up that barely ranks above the 100th company and one that barely ranks below is exactly the value added of acceleration. Under the assumptions outlined before, $VA = \left(\bar{V} - G(r)\right) - \left(0 - G(r)\right) = \bar{V}$. Therefore, one can recover the value of acceleration form the difference in performance across start-ups that rank close to the discontinuity. The only two crucial identification assumptions are that the distribution of start-up characteristics and growth opportunities is similar on both sides of the discontinuity, and that the probability of selection changes discretely when the company ranks below 100.

We made a number of additional assumptions in our example, some of which do not necessarily hold in reality but are not crucial for identification. For example, as explained, the government committee sometimes decides to accept start-ups that fail to rank below 100. Hence, in this case one should expect $V(r)$ to be slightly positive to the right of the threshold and thus, the average performance to the right of the threshold will be less negative than if the selection rule were strictly binding. At the same time, start-ups may decide last minute to reject the offer; thus, $V(r)$ will be below the effective value of acceleration to the left of the threshold, and the average performance of start-ups in the left will be less positive than if selection were binding. Still, provided that $G(r)$ is continuous and the probability of selection is discontinuous around the threshold, $VA$ can be used as a measure of the value of acceleration to the start-up. In this case, the value estimated at the discontinuity, $VA$, is not equal to $\bar{V}$, as in the previous example. However, as Lee and Lemieux (2010) discuss the identification strategy is still valid as long as there is a discrete jump in the probability of selection at the 100th company threshold (this is the fuzzy regression discontinuity setting). The estimate recovered is the average effect of acceleration for start-ups ranking close to the threshold. An important issue, thus, is that the degree to which we can make generalizations based on our results, will depend on how different are the applicants ranking close to the threshold from other applicants. We return to this point in the next section when we discuss the results.

Another important question that arises when trying to infer the value of government-funded acceleration from differences in performance at the discontinuity is whether we should expect any effect of acceleration on start-ups that are barely rank below or above the threshold. If there are no frictions in the economy all projects with positive NPV should be funded and thus, as long as the assumption that start-ups in either side of the threshold have the same distribution of growth opportunities, then they will likely funded elsewhere, possibly by a different accelerator. Thus, (as long as added value from early stage investors is constant across accelerators) we should likely observe no differences in performance. However, if there is underinvestment in entrepreneurship because there is a funding gap, or because there is stigma of failure (i.e., applicants would only be willing to apply to the accelerator, but if not accepted would rather stop pursuing the project for aversion to further rejection and potential failure), then the founders of start-ups that are not selected will likely not pursue the project. We will return to this point in the next section when we discuss the interpretation of results.

### 2.3 START-UP SURVIVAL AND ACCELERATION: GRAPHICAL EVIDENCE

Figure 1 shows the impact of ranking below the 100th company on various measures of performance. The x-axis reflects the margin of selection (the ranking minus the threshold). The interpretation of the first plot in Panel A is as follows: applicants that rank above the 100th company threshold appear to be weakly more likely to survive as measured by having a listing in AngeList. The same Figure, however, shows that this weak positive evidence is either reversed or continues to be weakly positive when using alternative performance measures. The figure is an intuitive representation of the main finding of the paper: we cannot reject the hypothesis that applicants ranking closely above the threshold do not perform differently to those ranking closely below the threshold. Before showing regression results (In Section 4), over the next two sections we describe the methodology that uses all the data efficiently and we test the validity and generality of our identification approach.

## 3. METHODOLOGY AND IDENTIFICATION STRATEGY

Suppose start-up $s$ applies to the accelerator and is ranked at $r_s$ relative to all other start-ups in its generation. We code the indicator for accepted into the accelerator as $A_s$ =1.

We are interested in the effect of acceleration on the performance of start-up $s$, $y_s$. We can write

$$(1)\ \ y_s = \alpha + \beta A_s + \varepsilon_s,$$

where the coefficient $\beta$ that we are interested in is the effect of acceleration on the performance measure, for example, survival, and $\varepsilon_s$ represents all other determinants of performance $(E(\varepsilon_s) = 0)$. The problem with estimating a regression such as (1) directly is that acceptance into the accelerator is a highly endogenous outcome, and $A_s$ is unlikely to be independent of the error term $(E(A_s\,, \varepsilon_s) \neq 0)$, in which case the estimate of $\beta$ will be biased.

To get a consistent estimate, we would ideally want acceptance into the accelerator to be a randomly assigned variable. The regression discontinuity framework that exploits the ranking by external judges helps us approximate this ideal setup because ranking in an arbitrarily small interval around the discontinuity (i.e., $s^*$ the 100th company threshold), is random, however, the probability of acceptance is dramatically different in either side of the threshold in that small window. This implies that our estimate of $\beta$ using the regression discontinuity design is not affected by omitted variables, such as differences in growth opportunities, even if they are correlated with acceptance, as long as their effect is continuous around the threshold. Therefore, by comparing the outcome $y_s$ of startups that barely ranked above the 100th ranking threshold to the ones that barely ranked below the 100th threshold, we get a consistent estimate of acceleration.

To use all our data and improve efficiency we follow the standard approach (see Lee and Lemiueux (2010)) and assume that we can approximate the continuous underlying relationship between $y_s$ and $r_s$ with a polynomial in the ranking. This polynomial flexibly captures the underlying relationship between any variable that is continuously affected by the ranking and the outcome variable. Only the discontinuous effects at the threshold are captured by $\hat{\beta}$. Allowing for a different polynomial for observations on the right-hand side of the threshold $P_r(r_s, \gamma^r)$ and on the left-hand side of the threshold $P_l(r_s, \gamma^l)$ gives

$$y_s = \beta A_s + P_r(r_s, \gamma^r) + P_l(r_s, \gamma^l) + \varepsilon_s,$$

The estimate, $\hat{\beta}$, is precisely the estimate of VA from section 2.2.

## 4. RANKING AS A QUASI-EXPERIMENT: ACCEPTANCE DISTRIBUTION AND PRE-EXISTING DIFFERENCES

There are two basic assumptions of the regression discontinuity design. First, that there is a discrete jump in the probability of selection around the threshold. Second, that around the 100th company threshold acceptance into the accelerator is as good as random assignment. Here, we provide standard tests of these assumptions.

Panel A in Figure shows the probability of participation in the accelerator programme by rank-bins (6 participants per bin) in dots. Panel B presents polynomial smoothing using 6 participant bins and a $4^{th}$ degree polynomial to the left and $5^{th}$ degree polynomial to the right. The Figure shows a discrete jump in the probability of selection around the threshold. Table 3 provides the corresponding regression analysis. Across all specifications there is a significant jump in the probability of participation around the $100^{th}$ company threshold. The results continue to hold when we include generation fixed effects and several controls.

We now turn to the second assumption that participation in the accelerator around the threshold is as good as random assignment. There are two standard tests. The first is to look at the distribution of applicants around the threshold. Because the selection mechanism is based on ranking, however, by definition, our sample is uniformly distributed along the forcing variable, of a visual tests as suggested by McCrary (2008) is not very informative.

The second test is to evaluate whether at the time of application there were any systematic differences in characteristics of start-ups of founders in either side of the $100^{th}$ company threshold. The main assumption of the design is that there are no systematic differences in the characteristics across applicants that fall arbitrarily close to either side of the $100^{th}$ company threshold. Table 4 evaluates this assumption. Panel A presents simple comparisons across applicants in either side of the threshold. Panel B focuses on differences around the discontinuity by including the polynomials in the raking on both sides of the threshold. We see that that there are no significant differences in the characteristics mention panel by panel.

## 4.1 RESULTS: BASIC ACCELERATION SERVICES AND START-UP PERFORMANCE

Table 5 reports estimates of the difference in performance between applicants ranking above versus below of the threshold for increasingly small intervals around the selection threshold by December 2013 (standard errors are heterosedasticity robust).[9]

Column 1 in Panel A estimates the difference in the probability of having a listing on AngeList on the whole sample. On average, participants above the threshold are more likely to have a listing in AngeList. Columns 3, 4 and 5 restrict the sample to proposals that fall within 30, 10, 6 and 3 rankings of the threshold. In these windows we see that the coefficient falls close to 0 and is no longer significant. For companies within 3 ranks of the 100th threshold, the likelihood of a page in AngeList is only a marginal and statistically insignificant 0.071 higher for those ranking above the threshold. Column 6 makes use of all the data in the sample (as described in Section 3) and introduces two polynomials one of order four on the left side of the threshold and one of order five on the right hand side of the threshold. Finally, Column 7 scales the coefficient by the estimated increase in acceptance into the accelerator using an instrumental variables framework. Using this model we confirm that we cannot reject the null hypothesis that the basic services offered by the government-sponsored accelerator, i.e., cash infusions and shared office space add no value to participant start-up, which is consistent with the findings of the unrestricted models of columns 3-6.

The rest of the Panels in Table 5 and Tables 6-7 replicate the analysis for the rest of the performance measures, divided into survival, growth and employment and fundraising. Results are similar across the different performance measures.

We argue that the regression discontinuity allows us to obtain a causal estimate that is not driven by omitted variables or unobserved applicant characteristics. The standard

[9] In unreported regressions we repeat the analysis clustering standard errors by generation and results continue to hold. Consistent with potential small cluster bias (there are only 7 generations) we find that standard errors are most conservative without clustering.

interpretation is that the positive estimates from simple differences across participants and non-participants are driven by selection. However, the regression discontinuity estimate is the weighted average effect across all participants, where more weight is given to those participants very near the 100$^{th}$ company threshold. However, the effect that we identify pertains, by definition, only to participants that have observations around the discontinuity, which affects the degree to which one can extrapolate the results of our analysis to others. In future versions of the paper we plan to explore this point further, by comparing the observable quality of applicants close and far from the 100$^{th}$ company threshold.

## 5. MENTORING AND START-UP PERFORMANCE

We now focus on explore differences in performance across participants in the mentor arm. Table 8 shows that start-ups in the mentoring arm outperform their peers in the accelerator programme, as reflected in the positive and significant estimates of several of the performance measures. These additional results are consistent with both, selection skills of government-sponsored programmes, and the potential value added role of mentoring for start-ups.

To provide further suggestive evidence of the potential role of mentoring for start-ups we exploit an implicit selection rule into the mentoring arm. While selection into the Highway is not based on such an exogenous rules-based procedure as selection into the accelerator (i.e., there is no clear cut-off), there is evidence of an implicit selection rule: we find a discrete jump in the probability of selection into the mentoring arm of 40% if the start-up scores at least 3.6/5 during the pitch-day, as shown in Figure 3. Following a methodology akin to the regression discontinuity approach used in the previous section, we can approximate the value-added of mentoring. In detail, we compare start-up performance for applicants near the 3.6 score threshold. Table 9 shows that participants at either side of the

3.6 score cut-off are similar. Table 10 summarizes results, which provide evidence, albeit weak, that mentoring has a positive causal impact of start-up performance.

In future versions of the paper we plan to: 1. explore the real effects of acceleration beyond start-up performance, by focusing on the potential effects on founders, 2. include results from a detailed survey on applicants regarding their experience in SUP, and their opinion on the most useful aspects of the programme. Finally, we will also present suggestive evidence of the more general impact of SUP on the Chilean entrepreneurial ecosystem, by comparing registering rates of start-ups in Chile across industries targeted and not targeted by SUP.

## 6. CONCLUSIONS

In this paper we provide new evidence performance of government sponsored programmes that sponsor entrepreneurship. We focus on business accelerates a neglected yet increasingly popular type of early stage financiers both in the public and the private sectors. We quantify the causal impact of a government-funded accelerator in Chile, SUP, by simultaneously exploiting novel, rich micro-data and addressing concerns about unobserved heterogeneity. We find that we cannot rule out that the government-sponsored accelerator has an impact on start-up performance. Using additional data from the mentor arm of the accelerator, however, we find stronger evidence that accelerator services related to mentorship positively impact start-up performance.

In future versions of the paper we plan to contemplate several explanations for the findings. Including potential value-added reflected in founders' income or regional spillovers.

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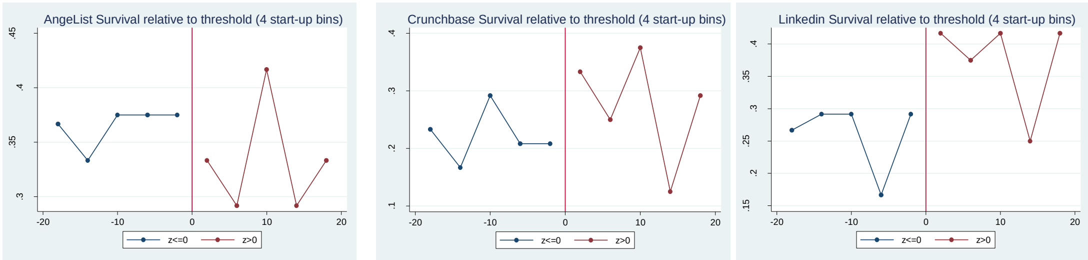
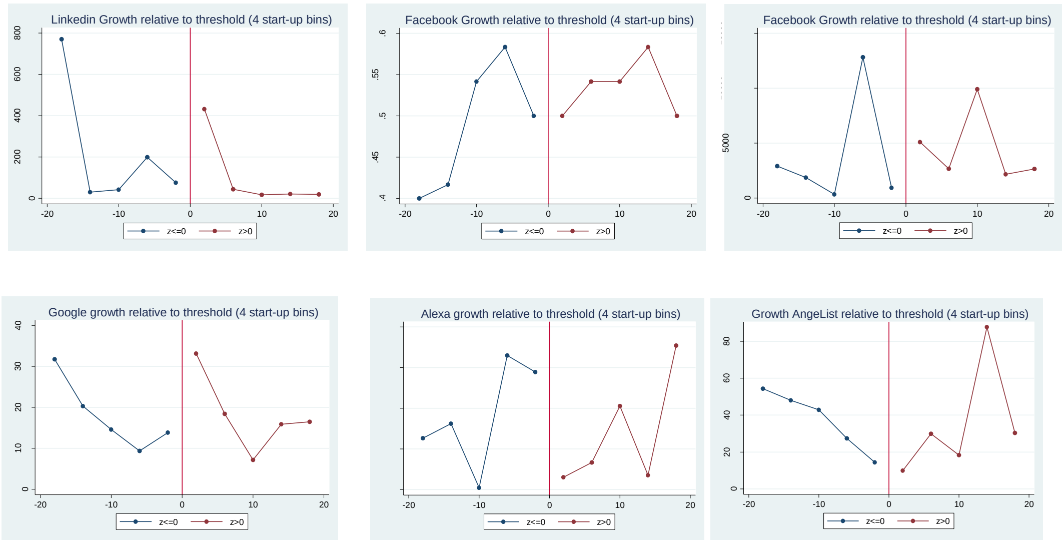
**Figure 1 - Performance by rank-bins around the rank threshold**

The figure shows average performance as measured in December 2013 by normalized ranking (i.e., 0 equals 100 (150) for generations 1 and 3-7 (2)). Start-ups are grouped into bins of 6 applicants and results are shown for applicants with normalized ranking between -20 and 20.

**Panel A. Survival**




**Panel B. Growth**




**Panel C. Fundraising and employment**

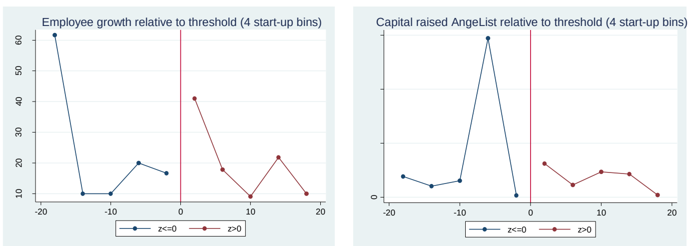
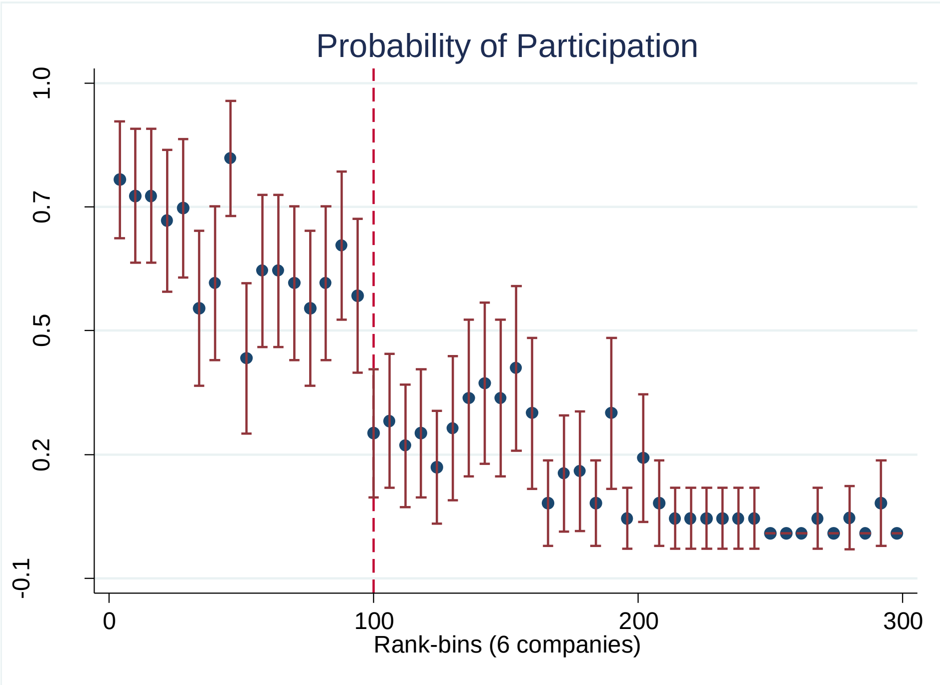


**Figure 2 – Assumptions Regression Discontinuity Approach**

Panel A shows the probability of participation in the accelerator by rank-bins(each bin includes 6 applicants). Panel B plots local polynomial smoothing of the probability of selection using a 5th degree polynomial of the ranking for observations to the right of the threshold (Rank>100) and a 4th degree polynomial on the ranking for observations to the left of the threshold (Rank<=100), around a local window of 6 applicants.

**Panel A – Probability of Participation by rank-bins**




**Panel B- Local polynomial smoothing**

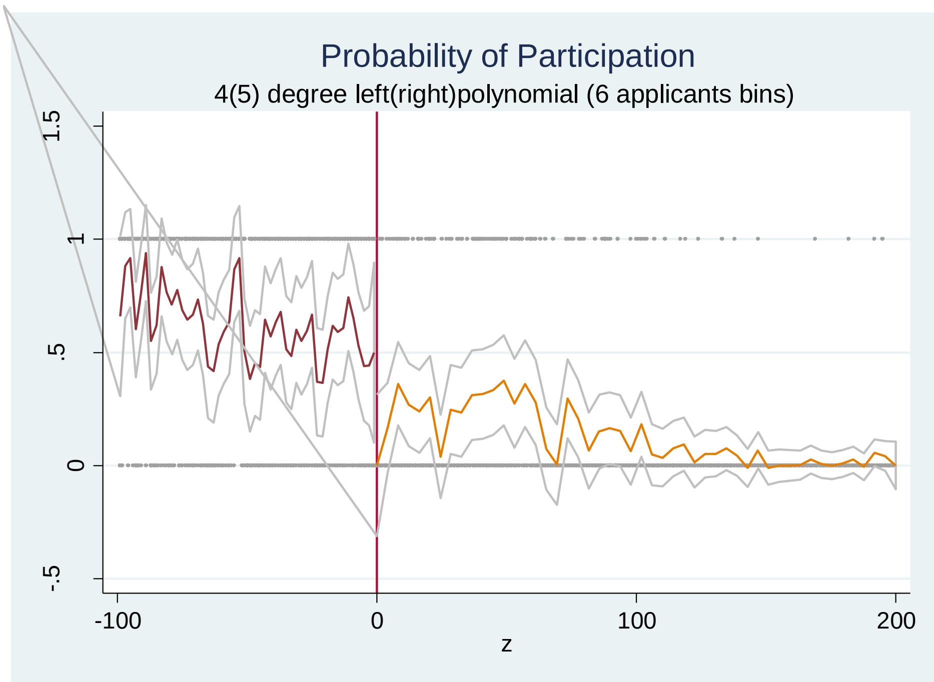


**Figure 3 – Probability of Participation in Mentor Arm**

The plots the probability of selection into the mentor arm of the accelerator program as a function of the score for the applicant during the pitch-day.

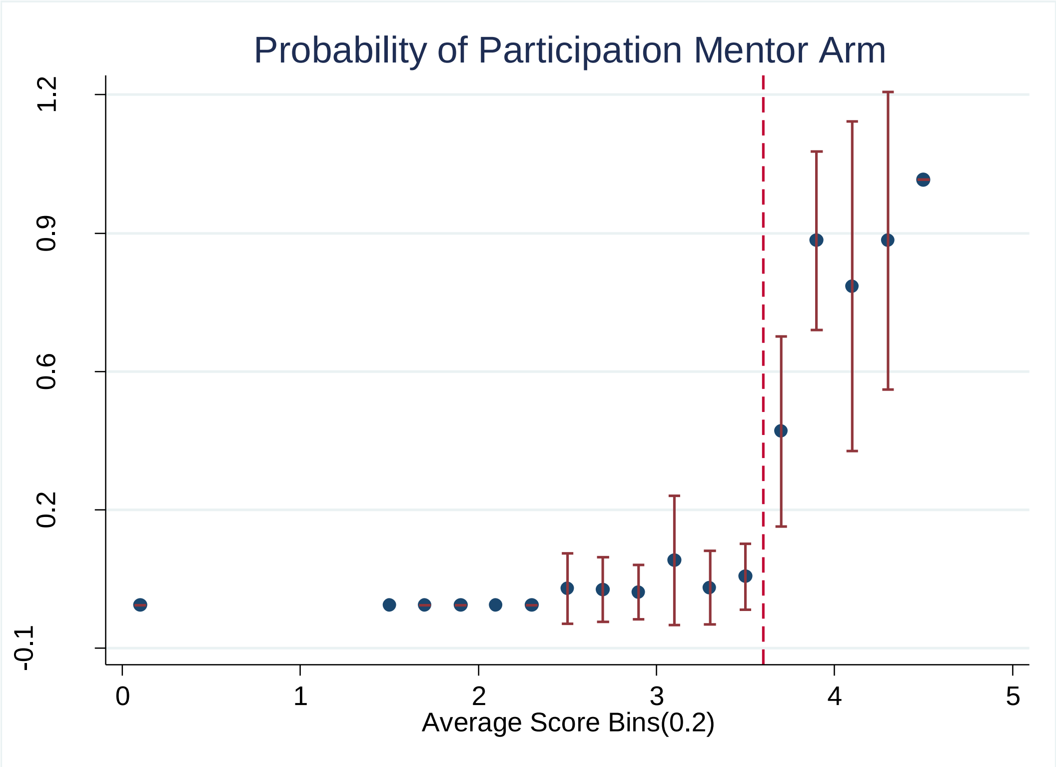


**Table 1 - Composition sample**

Table 1 describes the composition of the sample. The full sample includes 3,258 observations. Panel A shows the composition of the sample including the fraction of selected and final participants in the program. Panels B-E (F-I) describe the composition of the sample across characteristics of the applicant start-ups (founders).

**Panel A: Selected and formalized start-ups by generation**

| Generation | Selected | | | Participated | | | Total |
|---|---|---|---|---|---|---|---|
| | Obs. | Mean | Std. Dev. | Obs. | Mean | Std. Dev. | |
| 1 | 86 | 0.68 | 0.47 | 64 | 0.51 | 0.50 | 126 |
| 2 | 150 | 0.32 | 0.47 | 125 | 0.26 | 0.44 | 474 |
| 3 | 99 | 0.25 | 0.43 | 85 | 0.22 | 0.41 | 394 |
| 4 | 98 | 0.21 | 0.41 | 74 | 0.16 | 0.36 | 472 |
| 5 | 101 | 0.15 | 0.36 | 90 | 0.14 | 0.34 | 655 |
| 6 | 105 | 0.18 | 0.39 | 95 | 0.16 | 0.37 | 581 |
| 7 | 100 | 0.18 | 0.38 | 83 | 0.15 | 0.36 | 556 |
| Total | 739 | 0.23 | 0.42 | 616 | 0.19 | 0.39 | 3,258 |

**Panel B: Capital raised before application by generation**

| | Generation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Total |
| - | 1 | 462 | 3 | 13 | 0 | 0 | 0 | 479 |
| No (Bootsrapped) | 107 | 10 | 290 | 354 | 492 | 450 | 357 | 2,060 |
| < 50K | 10 | 1 | 72 | 72 | 116 | 92 | 134 | 497 |
| 50 K to 100K | 3 | 1 | 20 | 15 | 24 | 24 | 50 | 137 |
| 100K to 500K | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 5 |
| 500K to 1 M | 0 | 0 | 7 | 13 | 19 | 11 | 14 | 64 |
| <5M | 0 | 0 | 2 | 5 | 4 | 4 | 1 | 16 |
| Total | 126 | 474 | 394 | 472 | 655 | 581 | 556 | 3,258 |

**Panel C: Industry of start-up at application by generation**

| | Generation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Total |
| - | 5 | 95 | 64 | 135 | 206 | 83 | 347 | 935 |
| Consulting | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 3 |
| E-commerce | 32 | 81 | 54 | 57 | 73 | 95 | 35 | 427 |
| Education | 0 | 0 | 36 | 26 | 45 | 32 | 25 | 164 |
| Energy & Clean Technology | 6 | 24 | 10 | 4 | 13 | 10 | 9 | 76 |
| Finance | 6 | 12 | 10 | 7 | 5 | 12 | 5 | 57 |
| Healthcare & Biotechnology | 5 | 0 | 12 | 16 | 15 | 21 | 12 | 81 |
| IT & Enterprise Software | 29 | 97 | 59 | 48 | 57 | 67 | 30 | 387 |
| Media | 0 | 0 | 17 | 22 | 15 | 33 | 7 | 94 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Mobile & Wireless | 12 | 53 | 24 | 25 | 42 | 36 | 20 | 212 |
| Natural Resources - mining, food, lumber, etc. | 0 | 0 | 6 | 4 | 13 | 10 | 2 | 35 |
| Other | 22 | 82 | 32 | 35 | 40 | 48 | 21 | 280 |
| Social Enterprise | 9 | 30 | 14 | 15 | 20 | 21 | 8 | 117 |
| Industry | 0 | 0 | 40 | 55 | 81 | 79 | 28 | 283 |
| Social Media/Social Network | 0 | 0 | 16 | 23 | 27 | 34 | 7 | 107 |
| Total | 126 | 474 | 394 | 472 | 655 | 581 | 556 | 3,258 |

**Panel C: Stage of start-up at application by generation**

| | Generation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Total |
| - | 126 | 14 | 2 | 2 | 5 | 0 | 0 | 149 |
| Concept | 0 | 118 | 100 | 124 | 155 | 137 | 53 | 687 |
| Functional Product with users | 0 | 83 | 69 | 87 | 140 | 126 | 195 | 700 |
| Scaling Sales | 0 | 21 | 11 | 24 | 19 | 18 | 35 | 128 |
| Working Prototype in Development | 0 | 238 | 212 | 235 | 336 | 300 | 273 | 1,594 |
| Total | 126 | 474 | 394 | 472 | 655 | 581 | 556 | 3,258 |

**Panel D: Start-up age at application by generation**

| | Generation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Total |
| - | 0 | 2 | 0 | 9 | 6 | 1 | 0 | 18 |
| 12-24 months | 19 | 51 | 33 | 52 | 56 | 54 | 73 | 338 |
| 6-12 months | 30 | 119 | 108 | 135 | 204 | 174 | 250 | 1,020 |
| Less than 6 months | 66 | 276 | 231 | 276 | 389 | 352 | 233 | 1,823 |
| More than 2 years | 11 | 26 | 22 | 0 | 0 | 0 | 0 | 59 |
| Total | 126 | 474 | 394 | 472 | 655 | 581 | 556 | 3,258 |

**Panel E: Continent of leader by generation**

| | Generation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Total |
| - | 4 | 82 | 1 | 4 | 3 | 0 | 0 | 94 |
| Africa | 2 | 4 | 0 | 2 | 7 | 4 | 2 | 21 |
| Asia | 10 | 23 | 22 | 40 | 47 | 51 | 80 | 273 |
| Europe | 26 | 81 | 79 | 82 | 94 | 110 | 101 | 573 |
| North America | 56 | 142 | 118 | 122 | 112 | 106 | 103 | 759 |
| Oceania | 2 | 8 | 6 | 6 | 12 | 6 | 5 | 45 |
| South America | 26 | 134 | 168 | 216 | 380 | 304 | 265 | 1,493 |
| Total | 126 | 474 | 394 | 472 | 655 | 581 | 556 | 3,258 |

**Panel F: Gender leader by generation**

| | Generation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Total |
| - | 5 | 97 | 76 | 305 | 439 | 83 | 347 | 1,352 |
| Female | 8 | 49 | 47 | 24 | 27 | 78 | 28 | 261 |
| Male | 113 | 328 | 271 | 143 | 189 | 420 | 181 | 1,645 |
| Total | 126 | 474 | 394 | 472 | 655 | 581 | 556 | 3,258 |

**Panel G: Education leader by generation**

| | Generation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Total |
| - | 7 | 191 | 66 | 136 | 133 | 83 | 348 | 964 |
| Bachelor | 78 | 177 | 230 | 226 | 370 | 350 | 170 | 1,601 |
| High School | 2 | 3 | 2 | 1 | 1 | 3 | 0 | 12 |
| Master | 35 | 90 | 87 | 97 | 144 | 132 | 36 | 621 |
| Ph.D. | 4 | 13 | 9 | 12 | 7 | 13 | 2 | 60 |
| Total | 126 | 474 | 394 | 472 | 655 | 581 | 556 | 3,258 |

**Panel H: Background studies leader by generation**

| | Generation | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Total |
| - | 16 | 198 | 77 | 149 | 152 | 94 | 355 | 1,041 |
| Arts and Humanities | 11 | 32 | 61 | 55 | 94 | 90 | 36 | 379 |
| Business | 29 | 104 | 95 | 115 | 152 | 146 | 62 | 703 |
| Engineering | 45 | 84 | 121 | 97 | 198 | 173 | 68 | 786 |
| Law | 3 | 6 | 5 | 9 | 7 | 6 | 5 | 41 |
| Natural Science | 13 | 34 | 15 | 19 | 24 | 34 | 14 | 153 |
| Social Science | 9 | 16 | 20 | 28 | 28 | 38 | 16 | 155 |
| Total | 126 | 474 | 394 | 472 | 655 | 581 | 556 | 3,258 |

**Table 2- Summary Statistics**

Table 2 presents the summary statistics of the main variables used in the empirical strategy. The full sample includes 3,258 observations.

| Variable | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Chilean | 3,258 | 0.21 | 0.41 | 0 | 1 |
| Age | 1,582 | 30.33 | 6.76 | 19 | 84 |
| Gender (male) | 3,258 | 0.50 | 0.50 | 0 | 1 |
| Start-up has a working prototype | 3,258 | 0.49 | 0.50 | 0 | 1 |
| Money raised before program | 2,779 | 0.26 | 0.44 | 0 | 1 |
| Listing in AngeList | 3,258 | 0.2 | 0.4 | 0 | 1 |
| Listing in Crunchbase | 3,258 | 0.14 | 0.35 | 0 | 1 |
| Listing in Linkedin | 3,258 | 0.25 | 0.43 | 0 | 1 |
| Listing in Facebook | 3,258 | 0.35 | 0.48 | 0 | 1 |
| Followers in Linkedin | 814 | 68.96 | 279.46 | 0 | 4,001 |
| Likes in Facebook (K) | 1,151 | 0.65 | 5.36 | 0 | 118 |
| Searches in Google | 3,258 | 13.96 | 27.57 | 0 | 95 |
| Global Ranking Alexa | 3,258 | 2.03 | 5.74 | 0 | 186 |
| Followers in AngeList | 662 | 31.54 | 76.17 | 0 | 1,120 |

**Table 3- Discrete jump probability of participation**

This table presents regressions estimates from OLS regressions. The dependent variable is a dummy indicates if the applicant participated in the accelerator. The main explanatory variable is a dummy that equals one if the company ranked above the 100th company threshold (except generation 2 where the cutoff is 150 as explained in Section 1.1). All regressions include two polynomials of the ranking (the degrees are specified in the bottom of each column), one for observations in each side of the threshold. Panel B includes generation fixed effects and panel C includes other covariates in the regression such as indicators for: Chilean founders, male founders, start-ups with working prototype at application, and start-ups that have raised funds at application. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A. Estimates using no covariates**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Rank<=100 | 0.291*** | 0.186*** | 0.146** | 0.161** | 0.211*** | 0.152* |
| | (0.036) | (0.052) | (0.068) | (0.071) | (0.075) | (0.085) |
| Constant | 0.181*** | 0.281*** | 0.324*** | 0.310*** | 0.260*** | 0.260*** |
| | (0.013) | (0.021) | (0.028) | (0.034) | (0.041) | (0.041) |
| Observations | 3,258 | 3,258 | 3,258 | 3,258 | 3,258 | 3,258 |
| R-squared | 0.383 | 0.397 | 0.399 | 0.399 | 0.400 | 0.401 |
| Degree Polynomial left of thresh. | 1 | 2 | 3 | 3 | 3 | 4 |
| Degree Polynomial right of thresh. | 1 | 2 | 3 | 4 | 5 | 5 |

**Panel B. Estimates including generation fixed effects**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Rank<=100 | 0.291*** | 0.189*** | 0.149** | 0.160** | 0.210*** | 0.153* |
| | (0.037) | (0.052) | (0.068) | (0.071) | (0.074) | (0.085) |
| Constant | 0.148*** | 0.230*** | 0.269*** | 0.259*** | 0.214*** | 0.214*** |
| | (0.038) | (0.041) | (0.044) | (0.046) | (0.050) | (0.050) |
| Observations | 3,258 | 3,258 | 3,258 | 3,258 | 3,258 | 3,258 |
| R-squared | 0.386 | 0.399 | 0.401 | 0.401 | 0.402 | 0.403 |
| Degree Polynomial left of thresh. | 1 | 2 | 3 | 3 | 3 | 4 |
| Degree Polynomial right of thresh. | 1 | 2 | 3 | 4 | 5 | 5 |

**Panel C. Estimates including generation fixed effects and covariates**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Rank<=100 | 0.296*** | 0.221*** | 0.229*** | 0.234*** | 0.281*** | 0.183** |
| | (0.041) | (0.062) | (0.075) | (0.077) | (0.080) | (0.091) |
| Constant | 0.162*** | 0.234*** | 0.266*** | 0.261*** | 0.218*** | 0.220*** |
| | (0.039) | (0.041) | (0.043) | (0.046) | (0.049) | (0.049) |
| Observations | 2,779 | 2,779 | 2,779 | 2,779 | 2,779 | 2,779 |
| R-squared | 0.415 | 0.426 | 0.427 | 0.427 | 0.429 | 0.431 |
| Degree Polynomial left of thresh. | 1 | 2 | 3 | 3 | 3 | 4 |
| Degree Polynomial right of thresh. | 1 | 2 | 3 | 4 | 5 | 5 |

**Table 4- Comparison of covariates**

This table presents regressions estimates from OLS regressions. The dependent variables are specified on top of each column. The main explanatory variable is a dummy that equals one if the company ranked above the 100$^{th}$ company threshold (except generation 2 where the cutoff is 150 as explained in Section 1.1). Panel B includes in the regressions two polynomials of the ranking (the degrees are specified in the bottom of each column), one for observations in each side of the threshold. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A – Simple comparison above and below 100$^{th}$ company threshold**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Chilean | Age | Male | Working Prototype | Money raised before |
| Rank<=100 | -0.038** | 0.497 | -0.222*** | -0.064*** | 0.061*** |
| | (0.016) | (0.422) | (0.020) | (0.021) | (0.021) |
| Constant | 0.216*** | 30.246*** | 0.546*** | 0.504*** | 0.246*** |
| | (0.008) | (0.190) | (0.010) | (0.010) | (0.009) |
| Observations | 3,258 | 1,582 | 3,258 | 3,258 | 2,779 |
| R-squared | 0.002 | 0.001 | 0.035 | 0.003 | 0.003 |

**Panel B – Comparison at the discontinuity**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Chilean | Age | Male | Working Prototype | Money raised |
| Rank<=100 | 0.003 | -2.566 | 0.017 | -0.014 | 0.054 |
| | (0.075) | (1.993) | (0.088) | (0.092) | (0.094) |
| Constant | 0.187*** | 31.207*** | 0.358*** | 0.450*** | 0.231*** |
| | (0.040) | (1.323) | (0.050) | (0.051) | (0.049) |
| Observations | 3,258 | 1,582 | 3,258 | 3,258 | 2,779 |
| R-squared | 0.009 | 0.004 | 0.058 | 0.007 | 0.011 |
| Degree Polynomial left of thresh. | 4 | 4 | 4 | 4 | 4 |
| Degree Polynomial right of thresh. | 5 | 5 | 5 | 5 | 5 |

**Table 5- Accelerators and start-up survival**

This table presents regressions estimates from OLS regressions. The dependent variables are specified in the title of each panel. The main explanatory variable is a dummy that equals one if the company ranked above the $100^{th}$ company threshold (except generation 2 where the cutoff is 150 as explained in Section 1.1). The model and sample used is specified on top of each column. Columns (2)-(5) use only observations that fall within the window around the $100^{th}$ company threshold specified on top of the column. Column (6) includes in the regressions a $5^{th}$ degree polynomial of the ranking for observations to the right of the threshold (Rank>100) and a $4^{th}$ degree polynomial on the ranking for observations to the left of the threshold (Rank<=100). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: Listing in AngeList**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | All applicants | -30;+30 | -10;+10 | -6;+6 | -3;+3 | Full model | IV |
| Above | 0.260*** | 0.054 | 0.104 | 0.037 | 0.071 | 0.024 | 0.200 |
| | (0.019) | (0.045) | (0.078) | (0.100) | (0.137) | (0.086) | (0.532) |
| Constant | 0.148*** | 0.278*** | 0.286*** | 0.310*** | 0.286*** | 0.318*** | 0.279* |
| | (0.007) | (0.031) | (0.054) | (0.072) | (0.101) | (0.045) | (0.165) |
| Observations | 3,258 | 422 | 147 | 91 | 49 | 3,258 | 3,258 |
| R-squared | 0.073 | 0.003 | 0.012 | 0.002 | 0.006 | 0.090 | 0.154 |

**Panel B: Listing in Crunchbase**

| | (1) | (2) | (3) | (4) | (5) | (6) | IV |
|---|---|---|---|---|---|---|---|
| | All applicants | -30;+30 | -10;+10 | -6;+6 | -3;+3 | Full model | |
| Above | 0.202*** | -0.013 | 0.001 | -0.058 | -0.024 | -0.096 | -0.627 |
| | (0.018) | (0.042) | (0.074) | (0.090) | (0.124) | (0.080) | (0.728) |
| Constant | 0.103*** | 0.244*** | 0.271*** | 0.262*** | 0.238** | 0.303*** | 0.466** |
| | (0.006) | (0.030) | (0.054) | (0.069) | (0.095) | (0.043) | (0.224) |
| Observations | 3,258 | 422 | 147 | 91 | 49 | 3,258 | 3,258 |
| R-squared | 0.057 | 0.000 | 0.000 | 0.005 | 0.001 | 0.082 | 0.082 |

**Panel C: Listing in Linkedin**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | All applicants | -30;+30 | -10;+10 | -6;+6 | -3;+3 | Full model | IV |
| Above | 0.187*** | -0.023 | -0.058 | -0.116 | -0.060 | -0.126 | -0.827 |
| | (0.020) | (0.046) | (0.078) | (0.099) | (0.141) | (0.086) | (0.800) |
| Constant | 0.215*** | 0.332*** | 0.357*** | 0.381*** | 0.381*** | 0.379*** | 0.594** |
| | (0.008) | (0.033) | (0.058) | (0.076) | (0.108) | (0.048) | (0.248) |
| Observations | 3,258 | 422 | 147 | 91 | 49 | 3,258 | 3,258 |
| R-squared | 0.032 | 0.001 | 0.004 | 0.015 | 0.004 | 0.046 | 0.046 |

**Table 6- Accelerators and start-up growth**

This table presents regressions estimates from OLS regressions. The dependent variables are specified in the title of each panel. The main explanatory variable is a dummy that equals one if the company ranked above the 100th company threshold (except generation 2 where the cutoff is 150 as explained in Section 1.1). The model and sample used is specified on top of each column. Columns (2)-(5) use only observations that fall within the window around the 100th company threshold specified on top of the column. Column (6) includes in the regressions a 5th degree polynomial of the ranking for observations to the right of the threshold (Rank>100) and a 4th degree polynomial on the ranking for observations to the left of the threshold (Rank<=100). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: Followers in Linkedin**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | All applicants | -30;+30 | -10;+10 | -6;+6 | -3;+3 | Full model | IV |
| Above | 29.358 | 85.791 | -113.482 | -200.327 | -445.319 | -32.852 | -162.786 |
| | (21.809) | (93.511) | (160.981) | (250.545) | (495.648) | (126.588) | (646.420) |
| Constant | 58.320*** | 89.588 | 191.960 | 284.250 | 525.875 | 136.712 | 196.661 |
| | (11.008) | (58.627) | (159.075) | (248.855) | (494.637) | (115.928) | (351.325) |
| Observations | 814 | 134 | 48 | 29 | 17 | 814 | 814 |
| R-squared | 0.003 | 0.006 | 0.010 | 0.019 | 0.057 | 0.016 | 0.016 |

**Panel B: Listing in Facebook**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | All applicants | -30;+30 | -10;+10 | -6;+6 | -3;+3 | Full model | IV |
| Above | 0.185*** | 0.013 | 0.064 | 0.061 | 0.048 | -0.047 | -0.306 |
| | (0.020) | (0.048) | (0.083) | (0.106) | (0.144) | (0.092) | (0.680) |
| Constant | 0.311*** | 0.434*** | 0.443*** | 0.429*** | 0.381*** | 0.488*** | 0.568*** |
| | (0.009) | (0.035) | (0.060) | (0.077) | (0.108) | (0.051) | (0.211) |
| Observations | 3,258 | 422 | 147 | 91 | 49 | 3,258 | 3,258 |
| R-squared | 0.027 | 0.000 | 0.004 | 0.004 | 0.002 | 0.037 | |

**Panel C: Likes Facebook**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | All applicants | -30;+30 | -10;+10 | -6;+6 | -3;+3 | Full model | IV |
| Above | 0.590 | -0.070 | 0.219 | -0.227 | 0.102 | -1.451 | -5.739 |
| | (0.422) | (0.222) | (0.483) | (0.285) | (0.112) | (1.014) | (4.935) |
| Constant | 0.461*** | 0.434*** | 0.344* | 0.394 | 0.070 | 0.445** | 2.606 |
| | (0.133) | (0.124) | (0.178) | (0.278) | (0.059) | (0.190) | (2.044) |
| Observations | 1,151 | 186 | 70 | 42 | 20 | 1,151 | 1,151 |
| R-squared | 0.003 | 0.001 | 0.003 | 0.020 | 0.035 | 0.022 | |

**Panel D: Google searches**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | All applicants | -30;+30 | -10;+10 | -6;+6 | -3;+3 | Full model | IV |
| Above | -0.368 | -2.424 | -7.996* | -16.453*** | -3.544 | -9.894** | -64.911 |
| | (1.123) | (2.733) | (4.169) | (6.066) | (7.497) | (4.650) | (46.836) |
| Constant | 14.040*** | 16.235*** | 15.225*** | 23.530*** | 12.946** | 17.020*** | 33.888** |
| | (0.555) | (2.040) | (3.451) | (5.281) | (5.953) | (2.961) | (14.728) |
| Observations | 3,258 | 422 | 147 | 91 | 49 | 3,258 | 3,258 |
| R-squared | 0.000 | 0.002 | 0.026 | 0.081 | 0.005 | 0.004 | 0.00 |

**Panel D: Ranking Alexa**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | All applicants | -30;+30 | -10;+10 | -6;+6 | -3;+3 | Full model | IV |
| Above | 0.800*** | 0.154 | 1.711** | 2.131** | 1.823 | 1.123 | 7.369 |
| | (0.222) | (0.484) | (0.704) | (1.025) | (1.259) | (0.997) | (6.883) |
| Constant | 1.845*** | 2.082*** | 1.222*** | 1.600*** | 1.234** | 2.009*** | 0.095 |
| | (0.118) | (0.337) | (0.320) | (0.476) | (0.525) | (0.452) | (2.075) |
| Observations | 3,258 | 422 | 147 | 91 | 49 | 3,258 | 3,258 |
| R-squared | 0.003 | 0.000 | 0.037 | 0.042 | 0.035 | 0.007 | 0.007 |

**Panel E: Followers AngeList**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | All applicants | -30;+30 | -10;+10 | -6;+6 | -3;+3 | Full model | IV |
| Above | 24.548*** | 7.885 | 13.019 | 3.082 | 9.778 | 4.216 | 14.324 |
| | (6.198) | (12.370) | (10.292) | (5.888) | (6.308) | (16.399) | (54.840) |
| Constant | 20.306*** | 28.509*** | 16.050*** | 12.231*** | 4.667** | 25.994** | 18.499 |
| | (2.436) | (10.622) | (5.978) | (3.871) | (1.972) | (12.017) | (38.340) |
| Observations | 662 | 126 | 49 | 29 | 15 | 662 | 662 |
| R-squared | 0.026 | 0.004 | 0.028 | 0.010 | 0.115 | 0.044 | 0.040 |

**Table 7- Accelerators and start-up employment and fund-raising**

This table presents regressions estimates from OLS regressions. The dependent variables are specified in the title of each panel. The main explanatory variable is a dummy that equals one if the company ranked above the 100$^{th}$ company threshold (except generation 2 where the cutoff is 150 as explained in Section 1.1). The model and sample used is specified on top of each column. Columns (2)-(5) use only observations that fall within the window around the 100$^{th}$ company threshold specified on top of the column. Column (6) includes in the regressions a 5$^{th}$ degree polynomial of the ranking for observations to the right of the threshold (Rank>100) and a 4$^{th}$ degree polynomial on the ranking for observations to the left of the threshold (Rank<=100). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: Employees Linkedin**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | All applicants | -30;+30 | -10;+10 | -6;+6 | -3;+3 | Full model | IV |
| Above | -32.585 | 6.462 | -11.542 | -17.102 | -18.750 | 21.421 | 76.403 |
| | (23.061) | (9.741) | (8.973) | (13.012) | (24.454) | (25.227) | (101.580) |
| Constant | 53.764** | 21.297*** | 27.542*** | 34.375*** | 38.750 | -8.331 | -37.161 |
| | (22.925) | (3.543) | (8.357) | (12.081) | (23.561) | (24.136) | (61.764) |
| Observations | 767 | 122 | 44 | 27 | 16 | 767 | 767 |
| R-squared | 0.002 | 0.004 | 0.033 | 0.049 | 0.040 | 0.006 | 0.000 |

**Panel B: Capital raised AngeList**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | All applicants | -30;+30 | -10;+10 | -6;+6 | -3;+3 | Full model | IV |
| Above | 0.088 | 0.027 | 0.127 | 0.229 | -0.160 | 0.045 | 0.172 |
| | (0.075) | (0.082) | (0.174) | (0.304) | (0.163) | (0.250) | (0.985) |
| Constant | 0.123*** | 0.086** | 0.068 | 0.086 | 0.167 | 0.020 | -0.068 |
| | (0.044) | (0.041) | (0.050) | (0.076) | (0.163) | (0.091) | (0.541) |
| Observations | 676 | 129 | 50 | 30 | 16 | 676 | 676 |
| R-squared | 0.002 | 0.001 | 0.008 | 0.016 | 0.103 | 0.005 | 0.000 |

**Table 8- Comparison of performance across participants in and out of the mentor arm**

This table presents regressions estimates from OLS regressions. The dependent variables are specified on top of each column. The main explanatory variable is a dummy that equals one if the company was accepted into the mentoring arm. All regressions include covariates and generation fixed effects. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A – Survival**

| | (1) | (2) |
|---|---|---|
| Dependent variable | Listing in Crunchbase | Listing in Linkedin |
| Mentor arm | 0.292*** | 0.283*** |
| | (0.080) | (0.072) |
| Constant | 0.274*** | 0.478*** |
| | (0.032) | (0.035) |
| Observations | 247 | 247 |
| R-squared | 0.058 | 0.049 |

**Panel B – Growth Social media**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent variable | Followers Linkedin | Listing Facebook | Likes in Facebook | Google Searches | Alexa Global Rank |
| Mentor arm | -9.704 | 0.154** | 0.997* | 9.269** | -1.324 |
| | (36.467) | (0.065) | (0.566) | (4.551) | (0.860) |
| Constant | 76.875** | 0.672*** | 0.163*** | 12.870*** | 3.768*** |
| | (31.701) | (0.033) | (0.035) | (1.884) | (0.403) |
| Observations | 131 | 247 | 173 | 247 | 247 |
| R-squared | 0.000 | 0.017 | 0.058 | 0.018 | 0.008 |

**Panel D – Employment and Fundraising**

| | (1) | (3) | (5) |
|---|---|---|---|
| Dependent variable | Employees Linkedin | Capital AngeList | Capital Crunchbase |
| Mentor arm | -1.546 | 0.179 | 0.115 |
| | (3.412) | (0.148) | (0.153) |
| Constant | 16.824*** | 0.074*** | 0.152** |
| | (2.465) | (0.022) | (0.067) |
| Observations | 127 | 171 | 48 |
| R-squared | 0.001 | 0.025 | 0.013 |

**Table 9-Comparison of covariates for selection into mentor arm**

This table presents regressions estimates from OLS regressions. The dependent variables are specified on top of each column. The main explanatory variable is a dummy that equals one if the company scored above 3.6 in the pitch-day. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A. All participants in the Pitch-Day**

| | (1) Chilean | (2) Age | (3) Male | (4) Working Prototype | (5) Money raised before |
|---|---|---|---|---|---|
| Score>=3.6 | -0.092 | 0.264 | -0.003 | -0.124 | 0.033 |
| | (0.059) | (1.254) | (0.057) | (0.076) | (0.069) |
| Constant | 0.255*** | 30.604*** | 0.167*** | 0.578*** | 0.258*** |
| | (0.032) | (0.566) | (0.027) | (0.036) | (0.032) |
| Observations | 247 | 182 | 247 | 247 | 245 |
| R-squared | 0.008 | 0.000 | 0.000 | 0.011 | 0.001 |

**Panel B. Participants in the pitch-day with scores between 3 and 4**

| | (1) Chilean | (2) Age | (3) Male | (4) Working Prototype | (5) Money raised before |
|---|---|---|---|---|---|
| Score>=3.6 | -0.040 | 1.693 | 0.052 | -0.112 | 0.177* |
| | (0.076) | (1.670) | (0.071) | (0.099) | (0.093) |
| Constant | 0.207*** | 29.947*** | 0.115*** | 0.529*** | 0.212*** |
| | (0.044) | (0.729) | (0.034) | (0.054) | (0.045) |
| Observations | 123 | 82 | 123 | 123 | 121 |
| R-squared | 0.002 | 0.016 | 0.005 | 0.010 | 0.034 |

**Table 10- Mentoring and start-up performance**

This table presents regressions estimates from OLS regressions. The dependent variables are specified on top of each column. The main explanatory variable is a dummy that equals one if the company scored above 3.6 in the pitch-day. The sample used is specified on top of each column. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

**Panel A – Survival**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable | Listing in Crunchbase | Listing in Crunchbase | Listing in Linkedin | Listing in Linkedin |
| Sample | Pitch-day | Score [3-4] | Pitch-day | Score [3-4] |
| Above 3.6 | 0.210*** | 0.185* | 0.136* | -0.014 |
| | (0.075) | (0.097) | (0.075) | (0.098) |
| Constant | 0.281*** | 0.287*** | 0.500*** | 0.598*** |
| | (0.033) | (0.049) | (0.036) | (0.053) |
| Observations | 247 | 123 | 247 | 123 |
| R-squared | 0.035 | 0.031 | 0.013 | 0.000 |

**Panel B – Growth Social media**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Depedent variable | Followers Linkedin | Followers Linkedin | Listing Facebook | Listing Facebook | Likes in Facebook | Likes in Facebook |
| Sample | Pitch-day | Score [3-4] | Pitch-day | Score [3-4] | Pitch-day | Score [3-4] |
| Above 3.6 | -30.991 | 20.049 | 0.081 | -0.053 | 0.416 | 0.972* |
| | (34.787) | (23.485) | (0.067) | (0.091) | (0.351) | (0.532) |
| Constant | 82.563** | 39.904*** | 0.682*** | 0.747*** | 0.281** | 0.083*** |
| | (31.945) | (9.626) | (0.034) | (0.047) | (0.137) | (0.023) |
| Observations | 131 | 73 | 247 | 123 | 173 | 90 |
| R-squared | 0.003 | 0.013 | 0.005 | 0.003 | 0.011 | 0.089 |

**Panel C – Growth Web Traffic**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable | Google Searches | Google Searches | Alexa Global Rank | Alexa Global Rank |
| Sample | Pitch-day | Score [3-4] | Pitch-day | Score [3-4] |
| Above 3.6 | 0.210*** | 0.185* | 0.136* | -0.014 |
| | (0.075) | (0.097) | (0.075) | (0.098) |
| Constant | 0.281*** | 0.287*** | 0.500*** | 0.598*** |
| | (0.033) | (0.049) | (0.036) | (0.053) |
| Observations | 247 | 123 | 247 | 123 |
| R-squared | 0.035 | 0.031 | 0.013 | 0.000 |

**Panel D – Employment and Fundraising**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable | Employees Linkedin | Employees Linkedin | Capital AngeList | Capital AngeList | Capital Crunchbase | Capital Crunchbase |
| Sample | Pitch-day | Score [3-4] | Pitch-day | Score [3-4] | Pitch-day | Score [3-4] |
| Above 3.6 | 0.004 | 8.636** | 0.149 | 0.099* | -0.086 | 0.045 |
| | (3.521) | (3.705) | (0.130) | (0.051) | (0.091) | (0.067) |
| Constant | 16.385*** | 10.000 | 0.075*** | 0.035* | 0.198** | 0.071*** |
| | (2.439) | (0.000) | (0.023) | (0.019) | (0.079) | (0.024) |
| Observations | 127 | 72 | 171 | 83 | 48 | 24 |
| R-squared | 0.000 | 0.150 | 0.019 | 0.063 | 0.008 | 0.029 |

**Table AI. Definition of Variables**

**Add a column were we have a short name for the variable. Make sure that all tables have the same notation.**

| Name of variable | Definition |
|---|---|
| | Covariates |
| Age | Leader’s age of startups before SUP. |
| Money Raised | Dummy variable equals 1 if startup has money raised before SUP. |
| Gender | Dummy variable equals 1 if startup leader is female before SUP. |
| Incorporated | Dummy variable equals 1 if startup is incorporated before SUP. |
| Continent | Category variable indicates the continent of startup belongs to. |
| Industry | Category variable indicates the industry of startup. |
| Field of leader | Category variable indicates the leader of startup degree field. |
| | Outcome variables |
| Listed in AngelList | Dummy variable equals 1 if startup is listed in AngelList. |
| Listed in Crunchbase | Dummy variable equals 1 if startup is listed in Crunchbase . |
| Listed in LinkedIn | Dummy variable equals 1 if startup is listed in LinkedIn. |
| Num of startups AngelList | Number of startups listd in AngelList. |
| Num of startups Crunchbase | Number of startups listd in Crunchbase . |
| Num of startups LinkedIn | Number of startups listd in LinkedIn. |
| Num of Followers in AngelList | Number of followers in AngelList |
| Num of Followers in LinkedIn | Number of followers in LinkedIn. |
| Num of Facebook Likes | Number of Facebook likes. |
| Google Search | Google search times by 07/12/2013 |
| Alexa global rank | Global rank on Alexa |
| Alexa US Rank | US rank on Alexa |
| Num of Alexa Site Link | Number of Alexa Site Links |
| AngelList Funding | Capital raised via AngelList |
| Crunchbase Funding | Capital raised via Crunchbase |
| LinkedIn Company Size | Company size shows in LinkedIn |
| Webpage | Dummy variable equals 1 if we find a webpage of the startup. |