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The Bachman Belson Dilemma

How corporate and traditional accelerators impact startup trajectory through funding

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How corporate and traditional accelerators impact startup trajectory through funding

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Abstract

This paper tackles differences between startup accelerators that has previously been left unattended in research: How do corporate and traditional accelerators differ in the way they affect a startup's trajectory in terms of funding? By using transactional data, on a startup-level, we examine how the two different accelerator types play a role in startups' access to funding. Our paper points to substantial differences, in total follow-on funding, when comparing the two groups. Startups accelerated by a corporate accelerator receive less funding after acceleration than traditionally accelerated startups, but the sources of funding are not significantly different. We also find that startups are more mature when accepted into a corporate accelerator, than a traditional accelerator, which may point to a difference in strategic rationale for establishing an accelerator program.

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Introduction

Similar to the fictional character Richard Hendricks in the HBO show Silicon Valley, we believe startups have to make difficult choices, i.e., with whom to partner. For Richard Hendricks the choice was between the independent incubator owner Erlich Bachman, on one side, and Gavin Belson, who was the somewhat evil CEO of a large Silicon Valley tech company, on the other. For real life startups, the choice may come down to traditional accelerator (TA) vs. corporate accelerator (CA). Hopefully and realistically, the choice of accelerator has far less extreme and evil options than Richard Hendricks' but we believe the choice is too important to not be dealt with in research.

This master thesis is targeting gaps within strategic management literature regarding corporate innovation and startup success. As disruptive innovations often emerge from startups, there is an increase in various types of interaction between startups and large corporations looking to access innovation and cutting-edge technologies. More established methods include corporate venture capital (CVC), joint ventures and strategic alliances. In the last decade there has been an increased interest in new approaches to innovation which has led to the formation of several CAs (Hochberg, 2016), both on their own or in partnership with a TA.

A startup accelerator, according to Miller & Bound (2011), consists of five main features: an open, yet highly competitive, application process; pre-seed investment (equity); focus on small teams instead of individual founders; it is time limited and consist of cohorts or classes of startups. This sets the startup accelerators apart from both incubators and general investments. While the terms incubator and accelerator are often used interchangeably, in the literature, there is a distinction. An incubator is primarily set up to make ideas into startups, while accelerators take already existing startups and accelerate their growth. An accelerator can be set up as a TA program like Y Combinator and Techstars, or it can be a CA program with a corporate sponsor such as Techstars Energy, a cooperation between Equinor and Techstars.

CAs are becoming increasingly popular within the large corporations, often with the influence of or in cooperation with TAs with a global footprint. Techstars Energy is an example of a Norwegian giant Equinor using this approach to access disruptive technological innovations connected to their core business and value chain.

Given the novelty of this approach, there is a limited amount of research looking at the effects of accelerators. Within the strategic management literature, the effects for the corporation, or the accelerator itself, is to a larger extent documented, but effects related to the startups and startup performance is insufficiently researched in empirical settings. Are there any significant differences between startups graduating from TAs and startups graduating from CAs? Does it affect access to funding and its attractiveness as an investment object? Does it affect the type of investors interested in investing in the ventures? We aim to answer these questions primarily in terms of funding in order to contribute to the information basis for managers and stakeholder's decision making.

Research question and aim

This thesis investigates the impact TAs and CAs have on the startups that are accepted into the programs. By investigating both CAs and TAs, we aim to shed light on the differences between the two and distinguish how they influence the trajectory of participating firms. The complexity surrounding the interactions between accelerators and startups make it a very interesting subject for further research. One interesting effect is how the participation in such programs might have consequences on the startup's interactions with other important actors, especially investors such as venture capitalists (VC).

Within this field of research, we want to provide a more nuanced view of the impact of different types of accelerators on startups when focusing on the funding the startup is able to attract. Our research question is therefore:

How do corporate and traditional accelerators differ in the way they affect a startup's trajectory in terms of funding?

The main aim of the research is to contribute to the knowledge base for the startups, corporate innovators and policymakers on the use and impact of accelerators. We believe that startups in general have limited information regarding their alternative choices at important crossroads, and that the choice of accelerator might influence their trajectory. We aim to increase the information basis for these decisions and decrease any information asymmetries that may exist.

Trajectory is here defined as the path of a startup after receiving the accelerator treatment at either a CA or TA. The trajectory of a startup is highly affected by the funding it has access to. Empirical evidence indicates that funding, often through VC, is an important explanatory factor when looking at differences between startups (Hellmann & Puri, 2000). Evans and Leighton's (1991) research supports the notion that access to financial capital is of the essence when making the decision to exploit entrepreneurial opportunities, which makes funding an interesting measure when investigating differences in the early stages of development. Better access to funding is one of the key advantages of acceleration, where the startups often pitch their businesses in front of potential investors on demo-day.

The thesis is investigating questions which are not well covered in previous research. Implications of this is that this thesis will be exploratory in its nature and previous literature will be used to motivate and give direction to hypotheses and guide data sampling. Existing research has compared accelerated startups to non-accelerated startups (Smith et al., 2013; Hallen et al. 2020), but so far research towards the different types of accelerators has been scarce. As accelerator-activity gains momentum and increases in diversity both in the US and elsewhere, the value and importance of understanding their impact on startups increase. We position our research to extend the field of research into accelerators and startups on a deeper level and at the same time create a basis for new research to increase the knowledge for decision making within a startups' management.

Theory and hypotheses

Drivers of startup performance

Research on startups has been aimed towards identifying and explaining factors that seem to determine success and failure through different lenses and several theoretical perspectives. Baum, Calabrese & Silverman (2000) look at the effect alliances and network have on early stage performance of startups in the Canadian biotech industry and find that there are significant differences in performance. The findings indicate that some alliances positively affected performance, while alliances with potential competitors seemed to have little or negative effect. While this study is not investigating accelerators, it still tells us that choosing the right network is important, and network access is a large part of the reason to enroll in an accelerator (Cohen & Hochberg, 2014).

Others have looked at the human and social capital of the new ventures and found positive causal relationships with startup performance (Bosma, Van Praag, Thurik & De Wit, 2004). Relevant industry experience of the founder has been found to significantly enhance performance in new ventures (Bosma et al., 2004). Startups run by a shared leadership style within top management seems to be outperforming the ventures where the management is deploying a more vertical leadership style (Ensley, Hmieleski & Pearce, 2006).

The degree of involvement of the founder in combination with startup capital and perceived market risk have also been found to impact performance (Van Gelderen, Thurik & Bosma, 2005). High degree of founder involvement, little required startup capital and low perceived market risk are seen to serve as positive indicators for establishing a startup. These findings are evident in the pre-startup phase and are not suitable to predict startup performance in a longer perspective. However, it is beneficial to understand the structure and drivers of the startups that get going, when investigating external factors impacting them at later stages of development.

Supplementing the internal factors there are also external factors that are interesting for understanding the rise and downfall of startups. Investors such as venture capital firms function as *scouts* and *coaches* to startups (Baum & Silvermann, 2004). The term «scout» refers to the role VCs have as a dominant force in analyzing and selecting startups (Anderson, 1999). VCs often provide more than the capital needed in that they work actively with the startups providing management expertise and access to other capabilities (Hellmann & Puri, 2002), taking more of a coaching role (Hellmann, 2000). Several papers have identified that VC-backed firms outperform comparable non-VC-backed firms (Megginson & Weiss, 1991; Sandberg, 1987; Timmons, Spinelli & Tan 2004). Startups with VCs represented at the board level outperform on metrics such as funding, annual sales and centrality in formal networks (Hadley, Gloor, Woerner & Zhou, 2018). Access to funding and resources in initial phases is found to be key for the development of startups.

Startup funding

Startups are generally funded on a “piecemeal basis over several stages” (Talmor & Cuny, 2005), the stages being either milestone or round financing, or a combination of both. The stages are mitigating the information asymmetry between funder and founder as well as the overall uncertainty tied to new ventures (Krohmer, Lauterbach & Calanog 2009). Milestone financing is an upfront commitment from the venture capitalist to the startup (Talmor & Cuny, 2005) where the startup has to reach certain goals in order to unlock the next portion of cash.

The coarser and less committed version of milestone funding is staged funding where the venture capitalist only commits to a lump sum with no future commitments (Talmor & Cuny, 2005). In this case, the startup is still reliant on achieving goals to prove their worthiness of future investments to the broader group of investors with no commitments going forward.

Staging, in any case, lets venture capitalists abandon projects they no longer have faith in and therefore lets them sort good projects from bad on a continuous basis (Dahiya & Ray, 2012). Rounds may therefore point to a startup’s progress in a dynamic per-project way, where, if there is progress the startup will attract consecutive rounds, but if the investors perceive a halted project, they may shy away from future commitments.

Accelerators impact on startup trajectory

For a startup, there are several ways of getting access to the right type of funding and capabilities. Data from Pitchbook (2019) presented in Cohen, Fehder, Hochberg & Murray (2019) show that a third of all startups that received VC funding in 2015 had graduated from an accelerator program. Several recent papers find positive impacts of acceleration treatment of startups (Smith, Hannigan & Gasiorowski, 2013; Hallen, Cohen & Bingham, 2020).

Smith et al. (2013) present results suggesting that startups going through accelerator programs are able to get follow-on funding significantly sooner and are more likely to either be acquired or fail. Through analyzing recent data, Smith (2018, Working paper) offers continued support to the notion that accelerated startups are faster to either being acquired or closed down. The paper nuances the view of the accelerated effect of getting follow-on funding where it states that in the short run, startups going through accelerators receive follow-on VC-funding faster. However, when looking at a longer period, the relationship is reversed and the startups going through angel groups are faster to receive follow on VC-investments (Smith, 2018, working paper). Indicating that accelerated startups receive the initial follow-on faster than startups that have gone through angel groups, and that the angel-backed startups catch up after some time has passed.

The investor type has impact on performance of the investee when looking at post funding timing. Accelerated startups obtained shorter post funding timing, meaning that the startups receiving investments from accelerators received the next round faster than startups engaged with only angel investors or venture capital firms (Choi & Kim, 2018).

Hallen et al. (2020) take into account the opportunity cost of spending time in the accelerator programs and investigates if the startups graduating from accelerators actually get the benefit of an accelerated process. The evidence shows that the accelerators, in general, significantly reduces the time to reach certain milestones compared with those that almost got accepted into the program.

Even though there is empirical evidence of the positive impact of accelerators, the large variety of startups, type of accelerators and other influential factors seem to somewhat cloud the image as other researchers are not as conclusive on the directions of their findings. Yu (2020) finds that accelerated startups close down more often and raise less capital before closing, which could be an indication of the accelerators ability to reduce uncertainty and allows investors and founders to make more efficient investments. This could be linked to the same effect that Smith et al. (2013) finds regarding accelerated startups closing down more often and sooner. Gonzalez-Uribe & Leatherbee (2018) investigate the effect of the accelerator offering the bundle of entrepreneurial schooling and basic services, such as covering living expenses and offering co-working spaces. The effect of the bundle seems to be positive, yet the effect of basic services alone is not confirmed.

Choi & Kim (2018) find that seven years on, after initial investment rounds, accelerated startups experienced a lower survival rate compared to angel investments and venture capital investments (Choi & Kim, 2018), indicating a temporal aspect of the findings. The complexities surrounding the decision to enroll a startup in an accelerator or working together with an angel or VC might have unknown impacts on the startup's trajectory and access to future funding. We are aiming to provide a more nuanced view of what impact a TA or CA has on the funding of startups enrolled.

Signaling effects

Within the strategic management literature, the focus has mostly been limited to market signals, which is by Porter (2008) defined as "any action by a competitor that provides a direct or indirect indication of its intentions, motives, goals or internal situation" (p. 75). A similar definition, from Ndofor & Levitas (2004), defines signals to be "conduct and observable attributes that alter the beliefs of, or convey information to, other individuals in the market about unobservable attributes and intentions" (p. 688).

Signaling effects are, for most purposes, to be interpreted as a mechanism that reduces the information asymmetry that are present between actors in a market. This information asymmetry functions as a barrier when startups compete for external funding with competitors that seem to be similar. For the investors, the success is dependent on the ability to evaluate information correctly and invest at fair prices (Pfeffer & Salancik, 1978). To enable investors to do so, firms provide critical information through signaling mechanisms that the outside investors perceive to be credible (Spence, 1978).

Elitzur & Gavious (2003) investigate the signaling effects of angel investments at an early stage. They find a significant effect of the signal of attracting angel investors. The signal is interpreted by venture capitalists to be a proof of intent, and that the startup is on a trajectory that will create positive financial returns for the investors. Which, on the contrary, means that the entrepreneurs are not there to collect a quick cash payout and leave the startup as soon as the VC investment is secured.

Islam, Fremeth & Marcus (2018) support the findings in Elitzur & Gavious (2003) when they show that startups that receive research grants from public agencies positively impact the ability to attract VC investments. Islam et al. (2018) finds the same effect of winning research awards. Even though this effect could lead to a large payoff, it turned out to be short lived as VC investors appeared to focus on more recent indicators of quality. The value of a research award should not be underestimated, but in the long run other factors prove to be more important for attracting funding.

Janney & Folta (2006), point towards the same conclusion when examining the effect of private placements of equity, signaling and follow-on funding. They find a positive signaling effect of attracting subsequent funding for the startups where the information asymmetry is significant and has the ability to disclose prominent investors at an earlier stage.

Research into signaling effects have revealed positive effects related to funding for startups aligning with prominent investors at earlier stages, as well as positive effects related to founder's education and previous entrepreneurial experience (Ko & McKelvie, 2018). In the initial phases, when attracting first-round financing, the founder's education and experience show the greatest effect, but over time only the educational factor remains significant.

Kim & Wagman (2014) examines the position the accelerator has as the provider of information on the quality of the startups. They find proof that the incentive accelerators might have to only provide positive signals in order to maximize their profits. As the accelerators gain a return on their capital invested and as their portfolio companies get follow-on funding, there exists a risk of them only partially disclosing relevant information as market signals and actively withhold negative signals.

Signaling effects are important due to the aforementioned information asymmetries and uncertainties tied to investing in startups, but these effects have shown to be short lived. Hoenen, Kolympiris, Schoenmakers & Kalaitzandonakes (2014) studied the effects of patents between rounds and found a positive but diminishing effect. Ko & McKelvie (2018) find that the effect of experience is short-lived. Islam et al. (2018) find that research grants are positive, but that the effect wears off and that investors tend to focus on recent measures of success rather than a startup's history in its entirety.

Corporate rationale

CAs and TAs are inherently different in numerous ways. They are set up for different reasons, with different structures and with differing goals. The basis for these differences may stem from differing primary business foci. A TA's reason to exist is to find valuable startups and accelerate them, and by growing the value of their equity stake, they generate returns for their shareholders at exit. A typical CA, on the other hand, have entirely different business models where value creation in the corporation as a whole is not primarily tied to the increasing value of a startup's share value. Based on this, we find it central to look further into the corporate rationale for engaging in startup activity and the goal misalignment it may result in.

Goal alignment

Due to the difference in value creation between TAs and their corporate counterparts, there may be a significant difference in goal alignment between a startup and the corporation accelerating it. Crichton (2014) points to this difference in calling CAs an oxymoron in that CAs have to meet the needs of corporate objectives; unlike the TAs whose goals are more linked to a startup's success.

Crichton (2014) further cautions that care is needed in order to ensure that the CA programs accelerate the startups and their potential, rather than only accelerating the corporation. This view is shared by Kohler (2016) who stresses design consideration in order to bridge the needs of startups and the corporate objectives. One of the design aspects Kohler (2016) points to is the question of equity stakes. Kohler (2016) claims that the answer depends on whether the accelerator is driven by strategic or investment goals. Most CAs do not take equity stakes as their goals are strategic, but the few who do, argue that "they align their incentives with the startups" (Kohler 2016, 352). This is, however, an argument that is hard to swallow, both because of the signaling effects stated earlier in that the corporate funding may limit the startup's attractiveness towards future investors and that it may also limit the "entrepreneurial drive" (Kohler 2016, 352).

Lindener (2019), the global head of Airbus' BizLabs, argues in a series of articles that corporations should be careful when establishing an accelerator. Lindener comments on the goals of the accelerators and especially the ones that are financially motivated such as the ones Crichton (2014) divides from the strategically motivated. Lindener argues that the financial arguments from the CA point of view is extremely thin in that startup equity stakes will not matter on the “P&L of several billion Euros” (Lindener, 2019). This leaves us with strategic motivation to engage in CAs, in which the goals may not be aligned in a way where the startups are free to pursue their product’s potentials and possibilities for wider market application. Smith (2020) finds that the CA portfolios are less diverse than that of CVC, which again may point to strategic motivations underlying CA.

Marval & Kupp (2016) conducted a qualitative study on CAs and found two distinct groups: the complement seeker accelerator and the campaigner accelerator. The former describes a corporation which engages in startup activity to “indentify partners that potentially enhance or complement the parent corporation’ offering to its client” (Marval & Kupp, 2016) and the latter describes the corporations whose “primary objective is to extend the use of the corporations products and services in the startup audience” (Marval & Kupp, 2016). Both groups are strategically motivated, although drastically different. The complement seeking CAs are typically looking to improve their vertical value chain, which seem to be the most common strategic goal, also in our data set. The campaigner accelerator’s goals are even harder to align with the startups’ as it is closer to a marketing strategy for the corporation utilizing it.

An accelerator program will, in all cases, alter the startups enrolled. This is the way they reach their objectives, but in order for it to be meaningful for the startups, they have to fulfill multiple goals.

Corporate accelerators

The change in how large corporations engage with the startup world through CAs is examined in Weiblen & Chesbrough (2015). They find an increased use of lightweight interaction models such as the CA as compared to the more financially involved CVC. This allows for an increase in startup interactions as well as an increased independence among the startups that cooperate with the corporations. Kanbach & Stubner (2016) conducted case studies to assess objectives and design choices made by corporations with accelerator programs. Contrary to previous studies, they find that CAs exist for reasons broader than to insource innovation. Kanbach & Stubner (2016) also find that in order for a program to be successful, it must deliver real value for startups. Otherwise the program will be short-lived and attract sub-par startups. They strongly advise against engaging in CAs for reasons related to public relations and conclude that programs need to be beneficial for both startup and the corporate host.

Moschner & Herstatt (2017) have investigated the underlying motives for engaging in knowledge sourcing through accelerators and how corporations have adopted the model of the accelerator programs. Moschner & Herstatt (2017) find that the motives are highly varying and that the established firms seem to use CAs as a way of "entrepreneurial washing", much like companies that engage in green-washing or sport-washing activities.

Based on interviews with CA and participating startups, Kohler (2016) has developed a framework of four dimensions that needs to be considered when designing and constructing an efficient CA. The aim is to leverage the startup's innovations and innovative capabilities effectively and simultaneously support the startup in a suitable manner. The four dimensions are: *proposition* i.e. what the program offers; *process* i.e. how the program is run; *people* i.e. who is involved and *place* i.e. where the accelerator is hosted (Kohler, 2016).

Heinemann (2015) provides a definition of the CAs and compares them to TAs along several parameters. He offers several interesting reflections regarding their differences. One is that there seems to be a difference in selection criteria, where the CAs are more open and might also be targeting more developed startups, whereas TAs might accept startups closer to idea stage. Another is that some CAs keep the demo day internal. Usually this is an event where external investors and other potential stakeholders are invited. This might be a reflection of the differing goals and motivation behind the CA, which is not solely financial, but should, for instance, support their own products, services or supply chain.

Literature on CAs combined with the research on different alternatives of knowledge sourcing, make the foundation for well documented insights on what these CAs do for the large corporations, but how they affect the startups trajectory and structure is yet to be examined in an empirical setting. Through our literature review it becomes clear that numerous considerations must be made in order for both parties to benefit. Early-stage ventures that may choose to apply for an accelerator make important decisions that may greatly impact their trajectory and future options without fully knowing if they are being used as window-dressing or if they are applying for a program that is beneficial for all parties involved.

Traditional accelerators

Previous research done on TAs includes, among others, Miller & Bound (2011) and Cohen & Hochberg (2014), providing an extensive mapping of their characteristics. Cohen & Hochberg (2014) found the activities of an accelerator to include helping ventures to define and build product, perform market research, secure resources, provide capital and employees. This is done within a limited timeframe, most often a three-month program. The program ends with a grand event called a "demo day", where the startups get exposure to possible important collaborators within distribution, further development, investors, employees and also marketing for their product (Cohen, 2013).

There is previous research on which types of startups and entrepreneurs, accelerators are more suited to work with. The research indicates that accelerator programs are a good fit for firms that have surpassed the first phase of development and have a high growth potential, need a short term process, operate within a sector with relatively short time to market, and, startups that focus on growth and return on investment (Isabelle, 2013).

Yu (2015) found that through the feedback loops, facilitated by the accelerator, the startups close down earlier and more often, raise less capital prior to exiting, and stand out as more efficient investments than non-accelerated startups. The effect may be caused by the startups holding off on funding until demo-day. Contrary to Yu (2015), other findings suggest that startups graduating from an accelerator had a 23% higher survival rate than other startups (Regmi, Ahmed & Quinn, 2015). The lower mortality rate of firms graduating from an accelerator is further supported by Sharma, Joshi & Shukla (2014). The last two are not completely in line with Yu (2015), which demonstrates the complexity and need for further research within the field. This may point to a direction where the effect is stronger for CAs, as they are more likely to have cohorts close to their core business. Different from the CAs, a TA could have a wider scope in the industrial background or presence of the startups they accept into their cohorts.

Hypotheses

Hypothesis 1

When forming the first hypothesis, we build on signaling theory as laid out in the literature review. There is reason to believe that signaling effects can impact funding in at least two ways: either act as a negative signal to industry competitors or it may act as a proof of industry relevance.

One potential impact due to signaling effects in startup investments is a proof of relevance for competing corporate investors. If Techstars Energy, in collaboration with Equinor, accepts a startup into its cohort, it may tell the competing energy companies that the startup has valuable technology with potential for industry-wide application. In this scenario, the signals may be positive for a startup as the signal acts as a “proof of concept” towards other potential investors. These positive signals are, however, not necessarily in keeping with the strategic motivations behind a CA.

TA programs may offer a more open selection in terms of investors willing to co-invest or invest in following rounds. Where early corporate investors may limit further funding or at least exclude competing corporations from co-funding the same startup, TAs do not scare off investors, as they are not operating in the same market as the corporations viewed as potential investors. CAs might have more to gain from clouding the signals on the quality of the startup towards potential investors leading to increased uncertainty. Similarly, the TA has a strong incentive to only give out positive signals on the quality of the accelerated firms, increasing the value of their investment. We therefore test the following hypothesis:

H1: Startups in the CA group receive less follow-on funding as a separate entity than the ones in the TA group.

Hypothesis 2

In addition to testing for a generally lower amount of total follow-on funding received, as in H1, we also test whether the type of accelerator affects the ability to attract follow-on funding from CVC investors.

Heinemann (2015) finds that CAs occasionally keep the demo-day as an internal event as opposed to the TAs. This could be an indication that there is a willingness to cloud signals of the startups quality to outside investors inhibiting subsequent funding for the startups. This could especially be the case towards other corporate investors as these could represent the biggest threat to the focal corporation.

We hypothesize that the startups graduating from CAs will, due to the underlying strategic motivation of the CAs, reduce their attractiveness toward CVC investors. We test the following hypothesis:

H2: Startups graduating from CA are less likely to receive CVC follow-on investments, than startups graduating from TA.

Hypothesis 3

Combining the strategic goals motivating CAs with the funding structure typically used in our dataset, we aim to test if startups enrolled in CAs are more mature at the stage of acceleration. This logic is backed by Heinemann (2015) which finds that the CAs generally accept startups that are closer to market than the ones enrolled in TAs. Heinemann (2015) has, however, not tested this with transactional data. We test this hypothesis using measures of both pre-accelerator funding and time from founding to acceleration:

H3: Startups accelerated by CA are more mature at the time of enrollment, than the startups accelerated by TA.

Data collection and sampling

Data collection

For this study, we have collected transactional data from Refinitiv's SDC Platinum VentureXpert database. Our raw data consists of 18.589 transactions received by

1483 accelerated startups. 640 of these are from CAs and 843 from TAs. Our choices as to what accelerator to include in our search is mainly decided by availability of data. Our initial accelerator search input comes from online accelerator lists and publicly available information on top TA and CA. These lists were reduced due to availability of information in VentureXpert and after cleaning and structuring, we ended up with 12 CA and 53 TA, not counting multiple locations like Techstars or 500 Startups programs, which are among the ones that have multiple locations.

Data structuring and cleaning

In order to conduct meaningful research using VentureXpert data, we had to structure the outputs. VentureXpert data is structured in a way where all the information on a startup is lumped together in single cells and difficult to work with. In order to be able to make descriptive statistics and to use it for regressions, we had to structure it so that we have it on a startup level, meaning that each row is containing data on only one startup. We structured it by using Microsoft Excel and, thereafter, exported it and ran statistics and analyses using Stata.

The first step in our cleaning process was to systematically remove startups that are not registered with any monetary investments, startups that are founded before 2005 and startups that received their first investment before 2007. The reason we decided to systematically exclude these startups is that VentureXpert includes data on VC deals that falls outside our scope. We therefore, drastically reduced the size of the dataset to ensure that our sample is more precise. We decided to include startups founded in 2005 and onwards to focus on startups receiving investments in a time period where accelerators were active and where the mechanisms investigated in previous research are present. For instance, Y Combinator and Techstars were not operative prior (Cohen & Hochberg, 2014) and the general accelerator activity was far lower and less defined. Following this, we excluded startups that received their initial round of funding before 2007 in order to exclude any old (2+ years) startups that may have been accelerated at a later stage, resulting in a dataset where all startups are both founded and have received the first rounds of funding within the relevant time period. The data was extracted from VentureXpert in March 2020, which marks the end of the time period where potential investments could be registered in time to be included in the dataset.

Due to some inconsistencies and partially missing data, we deemed it necessary to exclude startups with founding dates exceeding their first rounds of investments, due to concerns regarding the quality of data from that specific startup.

A somewhat negative result of the necessary data cleaning process is that we have drastically reduced the number of CA startups. This is due to under-reporting of CAs in VentureXpert. The reason some of these startups were included in the initial data gathering is because the same corporations also have CVC investments outside their accelerator and, for our purpose, these startups are not representative for the research. The result of this cleaning is that our dataset contains more startups from TAs than CAs which is also what the real world looks like (Heinemann, 2015). Due to CA more often than TA operating with soft funding rather than equity stakes, many of the CA startups are not present in VentureXpert at all, leaving us with a starting point that may be lower than what is actual.

As we were only able to search for investor names in VentureXpert, we had to cross check the data to secure that our dataset consists of accelerated startups. In other words, there was a chance that the search would include startups that have received investments from a company that has an accelerator but has not been through the accelerator. An example of this is Boeing which has a CA program (HorizonX), but which has also invested separately from the accelerator. We, therefore, gathered lists of startups from the accelerators to ensure that the sample is, in fact, consisting of startups that have been enrolled in an accelerator program.

In addition to this, we manually gathered data through searches on startup websites and crunchbase.com on each investor in the dataset and categorized them into CA, TA, VC and CVC. By doing this, we have been able to ensure that every startup left in the final sample has been through either a CA or TA. We also get the added information of what type of investors the startups have been receiving investments from, both before and after graduating from an accelerator. Based on this, we were able to conclude that the accelerators in our sample mostly invest in startups in their own cohorts and to a low degree, engage in external VC or seed investment.

VentureXpert

Our primary source of data is VentureXpert which contains rich transactional data that can be accessed through Refinitiv SDC Platinum. It is one of the longest serving databases for venture capital investments and have collected data since 1961 (Kaplan & Lerner, 2016). The database is seen as being wider and more informational regarding investment rounds than the other comparable databases but has the downside of being less accurate than Venture Source (Maats, Metrick, Yasuda, Hinkes & Vershovski, 2011). VentureXpert, as a source for research, is also becoming increasingly difficult to use as a result of lower reporting in more recent years, something that may limit its potential as a source for research. In addition, there are a number of investments marked “Unspecified fund” which in a few cases makes it difficult to pinpoint what type of investors have invested in a startup.

VentureXpert does not contain information on accelerators beyond their investor ID, meaning that one cannot search for accelerators without specifying also their investor ID. VentureXpert data on the public status of a startup has been severely underreported in recent years (Maats et al., 2011), making that particular part of the data hard to use for research which looks at IPOs and changes in company status beyond funding rounds.

Using VentureXpert also makes it difficult to account for how the data is being collected. The database collects information from the US venture capital association in collaboration with Price Waterhouse Coopers, neither of whom offer information on the collection of data or why the database contains blank investor IDs. This leads to an uncertainty regarding whether or not this data is self-reported such as is the case with Venture One and Venture Economics (Kaplan, Strömberg, & Sensoy, 2002) which has resulted in underreporting of roughly 15% of deals.

While VentureXpert is not without faults, as is the case with most databases, we have been able to deal with the limitations and structured our research in a way that lets us shed light on meaningful aspects of both venture research and accelerators.

Empirical setting and sample

The final sample consists of n=896 startups. 80 startups have graduated from a CA and 816 have graduated from a TA. 654 of the startups have been accelerated in their first round of investments, while 242 have entered and graduated at a later stage. These 896 startups make for an interesting sample to research as they have collectively, received investments that form a total of 3541 different investors, including the accelerators, resulting in 10604 investments made. The temporal range of investments span from 2007 to 2020. The startups represent a wide variety of industries such as medical and healthcare; internet specific; communication and media and consumer products to mention a few. The number of rounds a startup has received range from 1 round to 15. In terms of nationality of the startups, the majority of the sample is based in the United States of America, while other countries with a considerable amount of startups in the sample is Canada, United Kingdom and Germany, with an additional 37 countries with fewer startups.

Accelerators

Given the plethora of opportunities for new ventures and the similarities between the programs in existence, we based our selection criterion on Cohen & Hochberg (2014). They divide between accelerators, business incubators and angel investors in eight different categories. Based on this, we only included accelerators that have open application processes, are cohort-based and work with early-stage ventures. See table 1 for an overview of which accelerators most of the startups have graduated. This approach to selection allows us to better guarantee that the sample is in fact accelerators and not somewhat similar angel groups or business incubators.

Table 1: Top accelerator overview

Corporate Accelerator	Number of startups	Traditional Accelerator	Number of startups
Samsung NEXT	29	500 Startups	398
MuckerLab	27	Y Combinator	326
Boeing HorizonX Ventures	17	Techstars	149
Wayra	8	Investment Accelerator (MaRS IAF)	70
Other	19	Other	263

**sums does not match sample size because of repeat investments*

Variables

Dependent variables

The thesis is targeting three hypotheses aimed at the effects of the interactions between startups and the two different types of accelerators. The three dependent variables are FOFUNDING, FOFCVC and ACCTYPE. In the first and second hypotheses, ACCTYPE will be the focal independent variable.

FOFUNDING is the main dependent variable regarding startup trajectory post accelerator treatment. It consists of the total amount of follow-on funding a startup has received in its post acceleration investment rounds. The numbers are inflation adjusted to 2020-USD. Inflation coefficients are gathered from Statista.com (O'Neill, 2020). The funding amount in FOFUNDING has been transformed using a natural logarithm. A factor M=1 is used when transforming the variable in order to account for the startups with zero follow-on funding.

FOFCVC is the dependent variable aimed at the type of investors participating in the following rounds of investments. It is structured as a binary variable, with the value "1" if a startup has received follow-on funding from a CVC investor and "0" otherwise.

ACCTYPE is the main explanatory variable that indicates which type of accelerator the startup has enrolled in. It is constructed as a dichotomous variable returning the value "1" for CA accelerated startups and "0" for TA accelerated startups. ACCTYPE serves as the focal independent variable in hypotheses 1 and 2, but as the dependent variable in hypothesis 3.

Independent variables

B2A controls for the age of the startups as they are entering the accelerator and is a count of the days from founding date (birth) to being enrolled in an accelerator program, transformed with the natural logarithm. A factor M=1 is used when transforming the variable in order to account for the startups with zero days from founding to accelerator treatment.

PREACCFUNDING is a variable aimed at controlling for funding received prior to accelerator treatment. It contains funding amounts summarized from the relevant rounds. The values are denominated in USD and is inflation adjusted using 2020-dollars. The funding amount in PREACCFUNDING has been transformed using a natural logarithm. A factor M=1 is used when transforming the variable in order to account for the startups with zero funding in the relevant rounds.

PREACCROUNDS is an independent variable aimed at identifying a possible difference in selection criteria among the two types of accelerators. Number of investments rounds received is a measure of how developed the startup is when going into the accelerator. The variable represents a count of all investment rounds prior to getting investment from the accelerator the startups later enroll in. The range of the variable spans from the ones that engage with an accelerator without any investment rounds prior, to the ones with up to nine rounds pre acceleration.

IND controls for the type of industry the startup is operating within or aiming to operate within. There may be inter-industry variations tied to funding which may affect our findings. We control for industry in order to isolate any differences in funding that may be tied to the different industries rather than accelerator. This may be especially important as some industries are more involved in CA or CVC. The variable is a categorical variable and takes on 10 different values.

At a more aggregated level, we have made a control variable called CSSnonCSS only distinguishing between startups from the industry of Computer Software and Services and those who are not in this industry. The variable takes only these two values and is therefore dichotomous.

YEAR is a control variable allowing us to check for cyclicality in the data. Macroeconomic factors, financial crisis or procyclical effects could be impacting our data and subsequently the findings. The variable contains the year each startup enrolled in an accelerator program. The variable has a starting point in 2007 and ends at 2020. We included a string variable named YCODE which contains a coded input of each year.

COUNTRY controls for the nationality of the startup. Due to the US activity within accelerators and VC and the nature of the data collected from VentureXpert, the US startups are somewhat overrepresented in the final sample indicating the need for a country specific control variable. The COUNTRY variable takes on 41 different values.

The REGION variable is the aggregated variable of the geographical data. It is made on region level with values such as «Europe» and «North America». It is dived into a total of 7 different regions.

ACCID controls for the potential impact a specific accelerator might have on the dependent variable. The accelerator a startup has enrolled in is an encoded string variable in our data.

Methodology

Coarsened exact matching

In order to deal with the imbalance in our dataset between CA and TA startups, we do coarsened exact matching (CEM) (Blackwell, Iacus, King & Porro, 2009). We match and create strata based on geographical location, industry and year of acceleration. We set the accelerator dummy variable as treatment to ensure that each stratum contains both TA and CA startups and, thereby, alleviate some of the issues tied to the imbalance between the two groups. We apply this matching technique to all hypotheses.

Heckman correction

In order to deal with selection bias, we do a two-step Heckman correction (Heckman, 1979). The first step consists of making a selection criterion, with CEM, in the form of a probit regression with one variable that is not included in the outcome model, and a variable that is not the same as the dependent variable in the outcome regression. We then use the output from the probit regression to create the inverse mills ratio (IMR) and include IMR in the outcome regression.

When applying this method, we are able to better control for the potentially uneven acceptance into the accelerators, which makes is easier to assign an unbiased effect to the focal explanatory variable.

Robust standard errors

When including the robust option for the regressions we are able to better control for potential issues regarding observations with large residuals and heteroscedasticity. The difference between the robust and classical standard errors, in our analyses, are relatively small which does not motivate any further actions (King & Roberts, 2015).

Regression design

Hypothesis 1

Hypothesis 1 has a continuous dependent variable (FOFUNDING) and both categorical (ACCTYPE, CSSnonCSS, REGION, YCODE, ACCID) and continuous (PREACCFUNDING, B2A) independent variables. We use an OLS regression with log transformation. Log transformation allows us to deal with the somewhat high dispersion in our continuous variables.

After CEM, we are left with a total of 557 observations (Table 3). The startups were matched on year of acceleration, industry they operate within, country of origin and the type of accelerator they go into. The sample includes 73 startups from the corporate group and 484 from the traditional group.

For the selection model in the Heckman correction, we use ACCTYPE as the dependent variable. The output of the selection model is used to calculate the IMR to be included in the final regression. In the second step we run the final OLS regression to test the hypothesis.

The correlation matrix (Table 2) showed overall low internal correlation between the independent variables, however there was an issue with the correlation between PREACCFUNDING and PREACCROUNDS at 0,78, and PREACCROUNDS was removed from the equation to avoid potential problems with multicollinearity. Due to several explanatory and control variables there is a need to check for multicollinearity. Using Variance-inflation factors (VIF), we test for this. The mean VIF is 1,24, which is well within tolerable levels (Mean VIF < 5) and shows no sign of multicollinearity (Gujarati, 2015). We performed a Breusch-Pagan test to control for heteroscedasticity. It turned out insignificant with a Prob > Chi2 of 0,7931, allowing us to reject the alternative hypothesis assuming heteroscedasticity (Gujarati, 2015). Hence, heteroscedasticity is not an issue. We still, due to reasons related to common practice, run the regression with robust standard errors.

The final regression equation we use to test Hypothesis 1:

$$FOFUNDING = b_0 + b_1ACCTYPE + b_2PREACCFUNDING + b_3ACCID + b_4REGION + b_5YCODE + b_6CSSnonCSS + b_7IMR + e$$

Hypothesis 2

The dependent variable (FOFCVC) in this hypothesis is binary, allowing us to make use of a probit regression model, with a Heckman two step correction. In order to investigate the effects on FOFCVC we include type of accelerator (ACCTYPE), region (REGION), industry (CSSnonCSS), year of acceleration (YCODE), the accelerator enrolled in (ACCID) and IMR.

In order to deal with the imbalance in the data we do CEM and end up with a sample of 557 startups, when matching on the same criteria as in the first hypothesis. Further, we include a two-step Heckman correction where we select based on whether or not a startup has been accepted into a CA. Based on the output from the selection equation, we calculate IMR. We include IMR in the outcome equation. As the dependent variable is binary, we make use of a probit regression model.

The output from the correlation matrix shows only tolerable levels of correlation between the independent variables. With the highest being a 7,15% correlation between ACCTYPE and YCODE.

The final outcome equation to test Hypothesis 2:

$$FOFCVC = b_0 + b_1ACCTYPE + b_2CSSnonCSS + b_3REGION + b_4YCODE + b_5ACCID + b_6IMR + e$$

Hypothesis 3

The third hypothesis has a binary dependent variable (ACCTYPE) and two explanatory independent variables. One of which is a count variable measuring the number of rounds pre-acceleration (PREACCFUNDING) and one continuous for the time between founding to acceleration (B2A). We control for year of acceleration (YCODE), industry (CSSnonCSS) and region (REGION).

We continue with the same CEM criteria as in the previous hypotheses and therefore test a sample of 557 matched startups. Unlike the two previous hypotheses we are not doing a Heckman correction for the third. This is because we use the accelerator variable as dependent variable, and we are therefore not able to create a meaningful selection equation. We run the model with robust standard errors and control for high correlation among the independent variables.

The model for testing Hypothesis 3 is as follows:

$$ACCTYPE = b_0 + b_1PREACCFUNDING + b_2B2A + b_3YCODE + b_4CSSnonCSS + b_5REGION + e$$

Results

Hypothesis 1

With a $F(7,549) = 7{,}97$ and a Prob > F = 0,000 the combined model turned out significant at a 1% significance level. An R^2 of 10,26% indicates a good explanatory power.

$$FOFUNDING = -5{,}490 - 1{,}284(ACCTYPE) + 0{,}212(PREACCFUNDING) + 1{,}020(CSSnonCSS) + 0{,}722(REGION) + e$$

We get a significant coefficient for accelerator type on the dependent variable: follow-on funding. With a Prob > t = 0,033 and a coefficient of –1,284, Hypothesis 1 is confirmed with the predicted directionality. When transforming the coefficient from the logarithmic form, using Euler's number ($e \approx 2{,}718$), we observe a strong effect of the accelerator type. The CA startups are predicted to receive 72,3% less follow-on funding compared to startups graduating from TA, when keeping all other variables constant.

As a secondary finding we observe that PREACCFUNDING yields a positive, and significant (Prob > t = 0,005), coefficient at 0,212. This finding is significant at a 1%-level. Transforming the coefficient, we find that 10% increase in the PREACCFUNDING variable estimates a ≈ 1% increase in the level of follow-on funding for a startup, *ceteris paribus*. In comparison, a 50% increase in PREACCFUNDING estimates as ≈ 4% increase in follow-on funding.

As for the other control variables, we see that CSSnonCSS is significant with a Prob > t = 0,012. With the coefficient of 1,020, we are able to estimate that startups in the computer software and services industry tend to get more follow-on funding compared with those that are not. When interpreting the coefficient we see that startups in this particular industry are estimated to get 177% more follow-on funding that in other industries, *ceteris paribus*. The model yields a significant result at the 1%-level for the REGION. Compared to other regions, we see that North America is estimated to raise 105% more follow-on funding, all else unchanged. The coefficient for ACCID turns out to be significant with a low coefficient which further supports the independent variable in explaining the variance in FOFUNDING.

The model returns a significant IMR (Prob > t = 0,000) and a positive coefficient (5,007). The positive coefficient indicates a positive selection bias. Without the Heckman correction it would have positively skewed the coefficients of the other independent variables, as interpreted by Irfan (2011), in line with Heckman (1979).

Hypothesis 2

The regression outputs (Table 5) shows no significance for any variables other than IMR. We therefore reject Hypothesis 2. The significant (Prob > z = 0,000) IMR, with a positive coefficient (0.772), confirms the need to include the Heckman correction, to adjust for a positively skewed selection bias. IMR in itself does, however, not provide any meaningful insights towards understanding the determinants of CVC follow-on funding.

Hypothesis 3

With a Prob > chi2 of 0,0005 the estimated probabilities are not significantly different from the observed ones and the model, as a whole, fits the data. Our model outputs the following significant estimation model:

$$ACCTYPE = -2,837 + 0,032(PREACCFUNDING) + 0,261(B2A) + e$$

We get significant results for both PREACCFUND and B2A. PREACCFUND has a coefficient of 0.032 with a Prob > z = 0,106 and B2A has a coefficient of 0,261 with a Prob > z = 0,017. We therefore confirm Hypothesis 3 at a somewhat roomy 10% significance level. When transforming the results and interpreting the marginal effects table (Table 7) we see that for every unit increase in mean PREACCFUND, the probability of going into a CA, rather than a TA, increases by 0,63%, *ceteris paribus*. Similarly, for B2A also has a positive effect on CA entrance, where a one unit increase on the mean B2A increases the probability of going into CA as opposed to TA by 5,31%, *ceteris paribus.* The, seemingly "extreme", effects are marginal effects on changes in mean and cannot be interpreted on a startup level per se. The effects we present here are best interpreted as directionalities, rather than rules on a per-startup basis.

The control variables for Hypothesis 3 are all insignificant, assigning the variation, in the dependent variable, to the focal independent variables.

Discussion

This thesis, which has investigated how CAs and TAs differ in the way they affect a startup's trajectory in terms of funding, was motivated by a desire to increase the knowledge surrounding the different alternatives a new venture has. As our literature review indicated, there is no prior research looking at the differences between CAs and TAs from this point of view. Hopefully, our research will contribute to the expansion of knowledge within the field and may lead to startups, CA and TA being able to make better informed decisions. By taking this point of view we are able to shed light on how new ventures' access to funding differ, and the ramifications that follow for all parties involved.

Prior to testing the hypotheses, we predicted that startups enrolling in CA would have lower post accelerator funding, have significantly fewer corporate follow-on investors and have a significantly higher number of rounds prior to accelerator treatment.

Hypothesis 1

Our analysis provides significant support for Hypothesis 1 (Table 4) and we see that startups enrolled in CAs receive significantly less funding after acceleration than the ones enrolled in a TA. This is in keeping with theories regarding the strategic goals and characteristics of CA.

Startups graduating from CAs are receiving less follow-on funding which can be caused by a number of factors. They may be faster to exit either by acquisition or closing. The lower funding may be caused by negative signals to other potential investors. Given the nature of our data, we are unable to concretely prove anything beyond the fact that they receive less funding, which in and of itself is an interesting finding that lets startups be aware of how they will be affected by enrolling in different accelerators.

Our dependent variable in Hypothesis 1 is funding and it shows a large part of the picture, but far from all. We are able to mostly inform startups that need funding and have an ambition to stay as an active separate entity. Other goals may include being acquired or simply continue without raising any more funding. We, however, find it difficult to argue that startups in CA receive less funding than TA because they, on a general basis, need less funding to realize their ideas. Yet, in addition to funding, there is often a need for resources beyond funding that only the larger corporations possess.

Some of the CAs have demo day internally and therefore not open to the same degree of external investors as the TAs. The internal demo days might be part of the reasoning why CA graduated startups receive less follow-on funding. The impact of this seems very clear, limited access to external investors will likely lead to less follow-on funding.

Previous findings indicate that startups that are in need of corporate resources often are more willing to partner up with corporates, more so than the ones that can go on without. When looking at how new ventures interact with established corporate investors, in the case of a CVC for example, Katila, Rosenberger & Eisenhardt (2008) state that “firms swim with sharks rather than safer partners when they need the unique resources that sharks possess” (p.322). In our dataset, the startups may be even “younger” in that they may have both less alternatives and less information on the programs they choose to enroll in.

Whether the accelerator case is a case of sharks or not is hard to determine as we are not able to comment on the goals of the individual startups in our data. Yet for any startups that are looking to remain a separate entity, have broad market application and attract funding, TA is the clear choice if the startup can go on without the corporate resources. In many situations, there may not be a choice as the startup is reliant on the corporate in order to develop their product. In other cases, the startups may plan on being acquired by a larger corporation. Regardless of the individual startups' plans for the future, we find it valuable to contribute that there is a significantly lower amount of funding going to startups after having finished a CA.

The other findings are in line with relevant literature and expectations pre-regression. A higher level of funding pre acceleration has a positive effect on follow-on funding, which fits well with the logic that more funding informs potential investors on the quality of the startup. Higher levels of funding could also indicate a higher degree of development, which is backed by the reasoning that rounds follow a certain progress in development from, for instance, seed to series A and B funding (Crunchbase, 2020).

The control variables provide interesting information and verifies the need to include them. Structuring the predicative model, we expected there to be variations in the follow-on funding between geographical regions and industries that we needed to control for. The region of North America is home to many of the innovative frontrunners and it is also where most of the startups and accelerators, in our data, are located.

Startups within computer software has been a major interest for the larger corporations and accelerators for some time now, and has experienced a tremendous pace of development. Hence, it is no surprise that the rapid growth has caught the attention of competent investors wanting a piece of the pie.

Hypothesis 2

Wanting to investigate further, we looked at whether or not the startups differed in their ability to attract follow-on funding from CVC-investors. Our second hypothesis shows no sign of any significant differences between the two groups.

Previously, we provided support to state that the startups graduating from CAs in general receive less follow-on funding, but the type of investors investing is not affected. This might point to less of a signaling effect from CAs than first anticipated.

Part of our reasoning, for this particular hypothesis, was tied to the protection of proprietary knowledge, technology and other know-how from influential industry players. There might be unfavorable spillovers from the startup to the corporation behind the accelerator that we anticipated to be an inhibitor for co-investment between rivaling CAs and CVCs. On the other side there may also be startups motivated to enroll in CA because of a higher likelihood for CVC. Our data shows no support for either direction.

As we are not able to conclude in any direction on this matter, we believe it to be of interest for future research to have the hypothesis tested with new and other types of data. As the binary variable, of receiving follow-on CVC-investments, did not yield significant results, one alternative measure could be to test for average amount invested by the different investor types, a measure we were unable to test for in our data.

Hypothesis 3

Our analysis provides significant support for both measures of maturity tested (Table 6). We found that startups with more funding pre-acceleration and more time elapsed from founding to acceleration are more likely to end up in a CA. We therefore confirm that CAs accept startups that are significantly more mature than TAs.

These findings are aligned with the expectations derived from the literature review and the explanation may be tied to the difference in rationale underlying CAs and TAs. Where the TAs accept younger, less funded startups, the CAs are accepting, what we interpret as, startups closer to market.

Accepting more developed startups may be due to a higher degree of risk aversion. More pre-accelerator funding will likely, act as a proof of quality and thus, alleviate some of the risks tied to novel businesses. The strategic reasoning for engaging in accelerators, for a corporation, may also explain why the CA group are generally more mature. This can either be explained by CAs being less equipped to recognize future worth, at an early stage, or because potential future parts of the corporation's value chain are simply not evident to the corporations when the startup is at an early age.

Conclusion

Our findings indicate that startups should be careful when choosing who to get in bed with. As stated in our discussion: not in terms of which investors are willing to follow corporate investors, but the negative impact a CA has on a startup's follow-on funding. This is of course an implication with many sides to it. As stated above, it may be essential and desirable to enroll in a CA because of the resources that reside there and only there. In any other case, the goals may be to raise more funding as a separate entity, which according to our findings, is more in line with the impact of TAs.

For the accelerator programs, and especially the corporate ones, it is worthwhile to look into the impact the CA has on the startups. A successful accelerator program has a positive impact on all parties involved if design considerations have been taken into account. A reputable CA should deliver resources and education that is necessary for the enrolled startup. In the same way, a startup should be aware that the goals of CAs are, of course, in line with the corporation's.

A startup's choice of whom to partner with are rarely as extreme as Richard Hendricks' in "Silicon Valley", but on a broad level there are definitely differences worth considering.

Limitations

In our research we have dealt with secondary data. Where possible we have crosschecked and found no mismatches when using supplementary secondary sources. What makes the data less rich, or potentially creates uncertainty, is that we are unable to identify the investors categorized as "Undisclosed". This limitation is to an extent dealt with, as we use round amounts in our research, but it may still cause our findings to be limited if one type of investor is consistently underreported.

Given the open-ended nature of our data we are also unable to determine the reason why CA startups receive less follow-on funding. We have had to treat startups that close, get acquired or has raised sufficient funding or stopped looking for funding the same way, simply because they do not appear beyond a certain point in our data. This is not something that limits our findings, yet, including “status” in future research may help shed light on the reason why CA startups raise less funding.

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Appendix

Table 2: Correlation matrix

	ACCTYPE	FOFUNDING	PREACCFUDNING	B2A	FOFCVC	PREACCROUNDS	ACCID	CSSnonCSS	REGION	YCODE
ACCTYPE	1									
FOFUNDING	-0,1274	1								
PREACCFUDNING	0,1574	-0,0329	1							
B2A	0,1547	-0,1463	0,4148	1						
FOFCVC	-0,0431	0,45	-0,0171	-0,1324	1					
PREACCROUNDS	0,1124	-0,0175	0,7867	0,3801	-0,0372	1				
ACCID	0,0087	-0,073	-0,0036	0,0289	-0,0588	-0,0034	1			
CSSnonCSS	-0,0638	-0,0108	-0,1022	-0,0978	0,009	-0,0947	-0,0919	1		
REGION	0,0305	0,1304	0,0185	-0,0368	0,0462	0,0397	-0,0079	0,0114	1	
YCODE	-0,0715	0,0774	-0,0826	-0,0508	0,0343	-0,0386	0,0106	-0,0515	0,0521	1

Table 3: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ACCTYPE	557	0,131	0,338	0	1
FOFUNDING	557	5,984	4,781	0	14,414
PREACCFUNDING	557	2,051	3,671	0	12,560
B2A	557	6,620	0,861	0	8,442
FOFCVC	557	0,224	0,418	0	1
PREACCROUNDS	557	0,510	1,126	0	8
ACCID	557	30,393	15,462	1	48
CSSnonCSS	557	1,424	0,495	1	2
REGION	557	6,630	1,047	2	7
YCODE	557	7,355	4,091	2	14

Table 4: Regression output – H1

(Statacode)

reg FOFUNDING ACCTYPE PREACCFUNDING ACCID CSSnonCSS REGION YCODE imr if cem_matched==1, robust

Linear regression robust

Number of obs = 557

F(7, 549) = 7.97

Prob > F = 0.0000

R-squared = 0.1026

Root MSE = 4.558

FOFUNDING	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
ACCTYPE	-1,284347	0,6023244	-2,13	0,033	-2,467489	-0,1012041
PREACCFUNDING	0,211978	0,0743554	2,85	0,005	0,065922	0,3580339
ACCID	-0,0206114	0,0126169	-1,63	0,103	-0,0453947	0,0041718
CSSnonCSS						
CSS	1,020692	0,4058698	2,51	0,012	0,2234441	1,81794
REGION	0,7222546	0,1929547	3,74	0,000	0,3432349	1,101274
YCODE	0,0015265	0,0497653	0,03	0,976	-0,0962272	0,0992802
imr	5,006672	0,9790774	5,11	0,000	3,083476	6,929869
_cons	-7,532252	2,269188	-3,32	0,001	-11,9896	-3,074899

Table 5: Regression output – H2

(Statacode)

probit FOFCVCBINARY CA RCODE CSSCODE YCODE AXCODE imr if cem_matched==1, robust

Iteration 0: log pseudolikelihood = -296,56977

Iteration 1: log pseudolikelihood = -287,27059

Iteration 2: log pseudolikelihood = -287,24695

Iteration 3: log pseudolikelihood = -287,24695

Probit regression robust

Number of obs = 557

Wald chi2(6) = 17,55

Prob > chi2 = 0,0075

Log pseudolikelihood = -287.24695 Pseudo R2 = 0,0314

FOFCVC	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ACCTYPE	-0,0537617	0,1863777	-0,29	0,773	-0,4190553	0,3115319
REGION	0,0858146	0,0608245	1,41	0,158	-0,0333994	0,2050285
CSSnonCSS	-0,1379306	0,1265599	-1,09	0,276	-0,3859834	0,1101223
YCODE	-0,0022806	0,0146632	-0,16	0,876	-0,03102	0,0264588
ACCID	-0,0051391	0,0039041	-1,32	0,188	-0,0127909	0,0025127
imr	0,7719487	0,2144477	3,60	0,000	0,351639	1,192258
_cons	-2,283032	0,5853849	-3,90	0,000	-3,430365	-1,135699

Table 6: Regression output – H3

(Statcode)

probit ACCTYPE PREACCFUNDING B2A REGION CSSnonCSS YCODE if cem_matched==1, robust

Iteration 0: log pseudolikelihood = -216.3362

Iteration 1: log pseudolikelihood = -205.09074

Iteration 2: log pseudolikelihood = -204.84708

Iteration 3: log pseudolikelihood = -204.84658

Iteration 4: log pseudolikelihood = -204.84658

Probit regression robust

Number of obs = 557

Wald chi2(5) = 22.05

Prob > chi2 = 0.0005

Log pseudolikelihood = -204.84658 Pseudo R2 = 0.0531

ACCTYPE	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
PREACCFUNDI	0,0315488	0,0195315	1,62	0,106	-0,0067322	0,0698297
B2A	0,2609815	0,1095311	2,38	0,017	0,0463045	0,4756585
REGION	0,0468245	0,0716369	0,65	0,513	-0,0935812	0,1872303
CSSnonCSS	-0,1840391	0,1436955	-1,28	0,200	-0,4656771	0,097599
YCODE	-0,0254168	0,0174319	-1,46	0,145	-0,0595828	0,0087491
_cons	-2,837209	0,9973051	-2,84	0,004	-4,791891	-0,882527

Table 7: Margins output – H3

(Statacode)

margins, dydx(*) atmeans FOR PROBIT

Conditional marginal effects Number of obs = 557

Model VCE : Robust

Expression : Pr(CA), predict()

dy/dx w.r.t. : PREACCFUNDING B2A REGION CSSnonCSS YCODE

at : PREACCFUNDING = 2.050967 (mean)

LB2A = 6.619837 (mean)

REGION = 6.630162 (mean)

CSSnonCSS = 1.423698 (mean)

YCODE = 7.355476 (mean)

		Delta-method				
	dy/dx	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
PREACCFUNDING	0,006249	0,0038846	1,61	0,108	-0,0013646	0,0138626
B2A	0,0516937	0,0211983	2,44	0,015	0,0101459	0,0932416
REGION	0,0092747	0,0140959	0,66	0,511	-0,0183528	0,0369022
CSSnonCSS	-0,0364534	0,0285873	-1,28	0,202	-0,0924835	0,0195767
YCODE	-0,0050344	0,0034266	-1,47	0,142	-0,0117504	0,0016815