Success factors of accelerator backed ventures

Insights from the case of TechStars Accelerator Program
Acknowledgments

The authors of this paper truly appreciate the support and encouragement that have been received when writing this thesis.

We especially want to thank our supervisors Michael Olsson and Pingjing Bo for the guidance and inspiration we have received throughout the process of this thesis.

We also want to show our gratitude to our seminar colleagues for their support and continuous feedback that has helped us improve this paper.
Abstract

Different types of business incubators have been established worldwide in the last decade. As the latest generation of incubation models, the accelerator provides a mix of services including mentorship, office space, access to the latest technology and a network of investors, with an aim to help ventures survive in the market. Meanwhile, startups are important to the society because they help balance the labor market and make contributions to the economic growth.

The aim of this paper is to find the factors which best predict the success of new ventures based on characteristics of entrepreneurs and ventures. This research utilizes a case study of TechStars Accelerator and includes 640 startups from all industries and geographical regions which participated in the programs between 2007 and 2015. The analysis employs two statistical models, namely the Logit Model and the Ordinary Least Squares (OLS) Model.

This study finds that technology intensive ventures founded by a team of entrepreneurs are more likely to succeed. Also, other variables such as the amount of funding, previous industry experience and location have a positive effect on the success of accelerator backed startups.
Figures
Figure 1: Statistics of global accelerators and startups, 2015 ..................................................6
Figure 2: Key success factors of ventures ..................................................................................34

Tables
Table 1: Comparison between different sources of equity funding ..............................................10
Table 2: Descriptive statistics ........................................................................................................27
Table 3: Logistic regression results ..............................................................................................29
Table 4: OLS regression results .....................................................................................................30

Appendix
Appendix 1: Correlation matrix of independent variables .........................................................42
Appendix 2: Result of Logit Model ...............................................................................................43
Appendix 3: Result of OLS Model .................................................................................................44
1. Introduction

This chapter aims to familiarize the reader with the current situation regarding new ventures, introduce the accelerator model and present the problems and purpose, as well as delimitations of this thesis.

Ventures play an important role in the health and stability of any economy – job creation, economic growth and poverty reduction, so it becomes crucial to analyze and understand the factors that make a new venture succeed or fail (Gaskill, Van Auken, & Manning, 1993), not only for the entrepreneurs but for their mentors, investors and policy makers as well.

1.1 Background

Over the last decades, private investors, universities, corporations and policy makers have explored different systems to nurture and encourage the growth of new ventures, and to transform entrepreneurs’ creative ideas into reality. The process of starting a new business evolved from providing only financial support, to providing mentorship, working spaces, access to an entire network of professionals and entrepreneurs, in different combinations. After that, incubation models continue to evolve as new models arise to address the shortcomings of the previous ones (Bruneel, et al., 2012). In the past years, scholars have studied different variations of business nurtures, trying to build models to understand which of their characteristics have an influence on a new venture’s survival in the market. However, in the Information Age, the speed at which consumers’ behavior changes and the way the market replies to those changes increases even more.

Recent statistics show that there is still a lot of unknown regarding the factors that contribute to a business’ success. According to the latest US Bureau of Labour and Statistics (2016) data, the number of establishments that started up in 2007 was 918,000 and the number of startups which exited during the same year was 854,000. Also, the number of newly established firms and the number of exited firms were 860,000 and 788,000 respectively in 2013, which is the latest year the Bureau provided statistics for all four quarters. Even that the numbers of newly established ventures oscillated throughout the years, the ratio of new ventures divided by the number of startups which failed in their first year remains the same, around 1.07. It seems that even if the number of new ventures
has decreased during the past ten years, the findings of what determines the survival of startups in long term are still not enough to help new ventures succeed.

Therefore, it is important to create new approaches to the classical models used in the entrepreneurship literature and gain insights into the specific characteristics of each incubation model, rather than assuming that their characteristics are similar.

The first incubation model appeared through the nineties and has evolved into science parks, innovation centers and more recently, accelerators. The accelerator arises in the last ten years, aiming to address the shortcomings of its predecessor — business incubator. The accelerator programs offer selected ventures intense mentorship, office space, and help them get access to a network of investors, all while participating in intensive training sessions over a short period of time (Cohen & Hochberg, 2014; Hoffman & Radojevich-Kelley, 2012).

As a new-born in the business market, but despite the growth and success, there is scarce knowledge related to accelerator programs. However, there is extensive literature, both qualitative and quantitative, about the business incubator, which is the predecessor of the accelerator. These studies, together with the descriptive studies on accelerators, provide the theoretical background for our study.

1.2 Problem discussion

Our motivation to study this topic is the importance of new ventures. After the Global Financial Crisis, the world’s employment problem became much more serious. The data Smerdon (2015) provides in his article shows there were around 290,000 people losing their jobs in Australia in 2015, and this number is 50 percent higher than it was in 2008. Fortunately, new ventures can relieve the pressure of employment. Becoming an entrepreneur can not only benefit oneself but also create more occupations for others. According to the International Labor Organization (2016), the rate of young people working in small and medium enterprises was 46 percent globally in 2016. Besides, new ventures can increase the competition and productivity while preventing monopolies and oligopolies in the business market (Sappin, 2016). Due to enterprises’ positive impact on economy, most countries’ governments are now encouraging and supporting individuals to build up their own businesses.

As a result, we think it is necessary to find the success factors of startups especially those participating in accelerator programs.
1.3 Purpose

This thesis aims to find the variables that increase a startup’s likelihood of success after participating in a fast-paced training and mentoring program, while being surrounded by fellow entrepreneurs. Hence, the research question of this paper is:

“What are the factors behind an accelerator backed venture’s success?”

In order to find an answer, we combine the factors that previous researchers found as determinants of startup’s success and apply them on the current case study based on TechStars Accelerator. Besides, we use two different models to analyze the success factors. For the Logit Model, we define the success of startups as a binary outcome: whether they receive further funding from investors or not. For the Ordinary Least Squares (OLS) Model, we use the total funding amount that the startups received throughout the program as the dependent variable and test the chosen independent variables from a different angle. Furthermore, the ultimate goal of this paper is to find the success drivers of accelerator backed startups and establish a theoretical and empirical framework. We expect to provide some useful information to help entrepreneurs achieve the long-term survival of their new ventures, as well as comments regarding investors and other stakeholders.

1.4 Perspective

The entrepreneurship literature studied over the years the process of creation of new ventures, what makes them succeed in the long term, compared the impact of different types of investors on the fate of new ventures and analyzed the characteristics of successful entrepreneurs. Nonetheless, we found there is little research regarding the accelerator programs, and most of the existing one aims to define the concepts behind accelerators or discuss the promising future of accelerators. In view of the accelerator being a special kind of incubation model which provides ventures with necessary technological equipment, work space and business network, rather than just providing funding as venture capitalist and angel investors do, we believe the success factors of accelerator backed startups are also different from other types of equity investments. But, we noticed there are not enough quantitative studies to explain what makes a startup successful after enrolling in this type of program. Therefore, we apply the factors that have been previously accounted for the success of a new venture, into our case study based on TechStars Accelerator, to provide some insight regarding which accelerator features contribute to new venture’s success in the long term.
1.5 Delimitations

This paper chooses case study as the research method, and expects to find the factors that affect the success of accelerator backed startups by using the TechStars Accelerator as an example. However, the case study has its limitations. According to Gust’s report (Brunet, et al., 2016), there are 387 accelerator programs operating by the end of 2015. Although TechStars is one of the biggest accelerator networks, it is hard to say that TechStars can represent the whole accelerator industry. Moreover, for the convenience of data access, we use second-hand information collected from several websites as our data source. The websites are all considered as reliable sources; nevertheless, we cannot rule out the possibility that the information may be different with first-hand data collected by researchers’ questionnaires and interviews. Consequently, this paper can only be used as a reference and further studies are needed to prove the accuracy of its results.
2. Literature Review

The current chapter presents the theoretical background for accelerators and other equity investment structures, together with some previous studies on the characteristics of entrepreneur and startup.

2.1 Accelerators – history and definitions

An accelerator is an organization that helps the entrepreneurs develop their ideas and create the product in beta, provides mentorship and access to a large network of individuals in different industries (Cohen & Hochberg, 2014). An accelerator program usually lasts several months (between six weeks and three months), operates on a set schedule, provides a small amount of capital and for a company to “graduate”, it needs to present its product in front of an audience of investors (so-called demo day).

Accelerator programs started in the early 2000’s, previous literature mentioning different reasons behind their emergence. On one hand, most of the studies state that accelerators were meant to overcome the shortcomings of incubators (Pawels, et al., 2016), while others believe that they emerged to fill a gap left by angel investors and venture capitalists (VC), which reduced their investments in high-risk companies after the Internet bubble from 2000 (Hoffman & Radojevich-Kelley, 2012). Regardless of the reasons behind the constitution of accelerators, the literature agrees on their goal: to nurture startups and guide entrepreneurs with the intention of reducing the high failure rates.

The first accelerator, Y Combinator, was founded in the US in 2005. Currently, the number of business accelerators is around 2,000 and growing rapidly. At the beginning, all the accelerators were generalists, accepting applicants from various industries (Cohen & Hochberg, 2014). Today, only the biggest ones are generalists (TechStars and Y Combinator), while many have chosen to focus on a specific industry: health, energy, financial technology, educational technology and so on.

According to the latest Accelerator Report, the total funding amount invested in startups by accelerators is 191,999,757 dollars globally, with USA and Canada investing the highest amount. Figure 1 presents the global statistics of accelerators and startups. It is shown that, apart from North America and Canada, other regions from South America, Middle East and Asia also develop accelerator programs. A report from Guss and Fundacity (2015)
shows that in 2015, nearly 50 percent of newly launched accelerators in Middle East were non-profit, making Middle East the region with the highest number of non-profit accelerators worldwide. On the contrast, Asia and Oceania have the highest number of for-profit accelerators in the world, 76 percent of the region’s total number of accelerators (Gust, 2015).

The TechStars founders stated, in one of the interviews (Gazdik, 2014) they gave to the media, that the reason behind founding the Accelerator Program was because, when they wanted to start their own business, they could not find the assistance needed. The first TechStars Accelerator was founded in Boulder, Colorado, in 2007, to give back to the entrepreneurship community. The program offers 100,000 dollars convertible note and 20,000 dollars in exchange for 6 percent of equity to the companies accepted. In addition to that, the founding teams also have access to a large network of founders, alumni, and mentors, office space and supplies, access to the latest technologies and programs. This boot-camp style environment is meant to help nascent entrepreneurs grow their business and prepare it to survive and grow in the market.

The 90-day TechStars program ends with a Demo Day, where the companies present their products in front of a large number of investors. All the companies that have graduated from each batch become TechStars Alumni.
2.2 Other sources of financing for startups

In the earliest stages, one of the most crucial issues for an entrepreneur and its startup’s success is fundraising. The closest funding sources to the founder, apart from its own capital, are the contributions from private individuals such as family and friends (Morrissette, 2007). Previous research (Bannock, 2005) suggests that it might be difficult for startups to raise money in their very early stages, and especially for high-technology firms, which have costly expenditures. Some governments also grant funds that do not need to be repaid, but due to their strict application guidelines, they are not so commonly used (Crampton, 2016). Another way to raise equity capital is for the entrepreneur to pitch his idea or product to different types of early stage investors. There are several different external equity investment sources other than accelerators which are willing to invest time, money and resources in the development of a new company, namely incubators, angel investors and venture capitalists.

2.2.1 Incubators

According to the National Business Incubation Association, the first incubator was established in the United States in 1595. The association’s website also clarifies the meaning and main characteristics of an incubator. It provides seed, level A or level B capital, mentorship, office space, legal advice and access to accounting consultants in exchange for a part of equity.

In their first years, the incubators only focused on providing small amounts of capital at different time intervals and little physical resources, most commonly office spaces, to potential ventures (Phan, Siegel, & Wright, 2005). Over time, incubators began to provide more intangible services. These included: prospects of different markets and industries, product development support, access to networks of entrepreneurs and finance providers, among others (Soetanto & Jack, 2013).

Unlike accelerators, incubator programs last somewhere between one and five years. Another difference is that, where incubators are sheltering and protecting the startup from external market influences until it is ready, the accelerator speeds up the growth by forcing the startup to interact with the market (Dumitru, 2017). As for the amount and type of funding provided, both programs can be for profit or non-profit. An incubator can provide the space and technology either for free, being subsidized by a university or municipality, or in exchange for a monthly rent. On the other hand, an accelerator provides a small,
fixed investment for each startup in the program, in return for a certain percentage of equity. For example, Y Combinator invests 120,000 dollars for seven percent in equity and Alchemist Accelerator invests 36,000 dollars for an average of five percent in equity.

### 2.2.2 Business angels

A more formal type of funding is angel investment, which has expanded very rapidly in recent years and it can improve the survival rate of startups. Kerr, Lerner and Schoar (2010) noted that “Startups funded by angel investors are 14 percent to 23 percent more likely to survive for the next year and a half to three years and grow their employment by 40 percent relative to non-angel funded startups”.

Angel investors are wealthy individuals who invest their own money into very early stage startups, usually having previous experience in seed investing or who might have started a few businesses on their own before (Wiltbank, Read, Dew, & Sarasvathy, 2009). The average age of angels tends to be between 47 and 50, they are predominantly male and their net worth exceeds on average, one million dollars. They come from many different backgrounds, but almost all of them are entrepreneurs (Morrissette, 2007). In respect to their level of education, the same paper finds that more than sixty percent of them have a college degree and almost half of them have graduate degrees.

### 2.2.3 Venture capitalists

The most formal and corporate funding type is the venture capital investment, provided by VC funds in companies which present high growth, but also high risk, and are often within technology intensive industries (Black & Gilson, 1998).

Venture capital is defined as a multiple stages equity investment in privately held ventures by a company that acts as a financial intermediary, in order to take advantage of profitable opportunities (Li, 2008). There are two types of venture capital funds: private and corporate. A private venture capital fund is a company in which several wealthy individuals employ their money to be invested by the fund managers. A corporate venture capital fund has direct ties with a parent company and builds investment portfolios using corporate funds, usually within or in connection with the company’s industry.

In addition to money, venture capitalists also assist entrepreneurs in their management decisions, holding a similar role with management consultants, track their performance intensively and give the venture better chances in the market due to their reputation (Black & Gilson, 1998).
2.3 Comparison between different funding sources

The next table presents a brief comparison between the previously mentioned equity funding sources, to provide a better understanding of their offerings and demands from the venture. As it can be seen in Table 1, the amount of funding increases from accelerators and venture capitalists, and so does the rate of return. Investing in startup companies entails different degrees of risk, and for taking that risk, investors demand more equity in return.

Even if they seem to have the same goal, to help a new venture succeed, success is defined different for each entity, and this can be linked with the differences in the length of holding period. Angel investors do not have an exact holding period, but they exit from their investments when they can get the highest return on it (Wiltbank & Boeker, 2007). Most of the times, the investment is considered successful if the venture goes public, is sold to another company or if the angels consider their returns to be maximized if they sell their shares to the other shareholders (Collewaert, 2012). Venture capitalists remain involved in a venture until it raises an IPO or is sold to a larger company, which they try to push even if the venture is not fully prepared (Ibrahim, 2012).

At last, Table 1 is made to compare the difference of key features between each source of funding. One of the main differences is the type of funding these sources offer: while accelerators and incubators offer a small, fixed amount of capital, angel investors and venture capitalists offer up to 5,000,000 dollars, but for this additional risk they take, they require also a higher part of the venture’s equity. Another difference is the level of involvement in a startup: in an accelerator or incubator, the entrepreneur has more freedom and control over his company, but angel investors and venture capitalists require to be part of the startup’s board and most of the times they have veto rights. The length of the holding period differs significantly between accelerators (several weeks) and the other equity financing sources (several years). Also, as it was mentioned previously in this chapter, each capital provider offers different kinds of support, alongside with money.
Table 1: Comparison between different sources of equity funding

<table>
<thead>
<tr>
<th>Key features</th>
<th>Accelerators</th>
<th>Incubators</th>
<th>Angel investors</th>
<th>Venture capitalists</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investors</td>
<td>Various investors from the network</td>
<td>Various investors from the network</td>
<td>Wealthy individuals</td>
<td>Professional managers</td>
</tr>
<tr>
<td>Type of funding</td>
<td>Small, fixed investments</td>
<td>Small, fixed investments</td>
<td>100,000–500,000 dollars</td>
<td>50,000 – 5,000,000 dollars</td>
</tr>
<tr>
<td>Rate of return</td>
<td>5% - 8% of equity</td>
<td>5% - 8% of equity</td>
<td>30% - 35% of equity</td>
<td>25% - 45% of equity</td>
</tr>
<tr>
<td>Investment stage</td>
<td>Seed, level A</td>
<td>Seed, level A, Level B</td>
<td>Seed</td>
<td>Series A, Series B, Series C</td>
</tr>
<tr>
<td>Level of involvement in the startup</td>
<td>Offer advice</td>
<td>Offer advice</td>
<td>Part of the startup's board, with veto rights</td>
<td>Part of the startup's board, with veto rights</td>
</tr>
<tr>
<td>Length of holding period</td>
<td>6 – 13 weeks</td>
<td>1 – 5 years</td>
<td>around 5.8 years</td>
<td>Several years, until IPO or other exits</td>
</tr>
<tr>
<td>What they offer</td>
<td>Mentorship, office space, technological support, business seminars and more</td>
<td>Mentorship, office space, legal advice, accounting consultants</td>
<td>Advice</td>
<td>Mentorship</td>
</tr>
</tbody>
</table>

Source: (Stiles, et al., 2016)

2.4 Common characteristics of successful startup alumni

2.4.1 Characteristics of the entrepreneur(s)

The existing entrepreneurship literature analyzed over the years the predictive value of the venture’s resources on its success and the stakeholders’. Firstly, the entrepreneur's ability to acquire capital and human resources has an immediate, direct effect on the organization’s success (Barringer, Jones, & Neubaum, 2005). Secondly, the founders of a company have a lasting impact on that company’s values, culture, and behavior. For example, the values of Walt Disney are so deeply rooted in the company that even after a long time from his death, executives are still taking decisions based on what would Walt do (Collins & Porras, 1995). Because accelerators help companies that are mostly in their pre-seed and seed stages, when entrepreneurs can only pitch their ideas but do not have an actual product to show, the board decides which startups to enroll in the program and which not, based on the entrepreneur’s traits and history.
Entrepreneurship scholars believe that the discrepancy between an entrepreneur’s intention and his actual behavior is influenced by different push and pull factors (Baluku, Kikooma, & Kibanja, 2016). For example, the Equilibrium Model of the Labor Market suggests that there are three reasons behind people’s decision to start their own company. The first hypothesis mentions a person’s talent: highly talented individuals will eventually start new ventures, while the not so talented individuals work for someone else. The second hypothesis was presented by Parker (2005), and states that individuals choose entrepreneurship according to their level of risk aversion: the least risk averse individuals choose to either start their own firms or run the largest firms in the industry, while the others choose more secure and comfortable roles. The last assumption is that “pull” entrepreneurs seek to earn income by realizing their own ideas, while the “push” entrepreneurs manage businesses created by others (Startiene, Remeikiene, & Dumciuviene, 2010). While these assumptions indicate why someone is likely to become an entrepreneur, they do not mention what it takes to succeed in this field.

Due to the central role of entrepreneurs, there is an extensive literature that studies their strengths and weaknesses (Bates, 2005; Cooper, Gimeno-Gascon & Woo, 1994; Roure & Keeley, 1990). Some of those variables are also included in our model. The following paragraphs provide a summary of each variable, together with the literature that supports it.

2.4.1.1 Gender

Many papers in the entrepreneurship literature studied the likelihood of success of a new venture based on the entrepreneur’s gender. The literature is often presented within a masculine gender framework. In one of her papers, Ahl (2006) discusses the reasons why the entrepreneur and entrepreneurship are male-gendered and compares the words describing masculinity and femininity with the words used to describe an entrepreneur in various texts. On one hand, the words used to describe masculinity are similar with those used to describe entrepreneurs, such as self-reliant, assertive and competitive. On the other hand, the words used to describe femininity are direct opposites of those used to describe entrepreneurs, such as gentle, loyal and shy.

Other studies find that despite differences in men and women’ characteristics, there is no difference in the survival duration of male and female-founded firms (Robb & Watson, 2012; Kalleberg & Leicht, 1991).
In today’s world, there are still present concepts like “occupations for men” and “occupations constructed as appropriate for women”, due to a social constructionism perspective. A social constructionism perspective does not focus on the differences in skills and characteristics of men and women, but on how people’s expectation in the gender system affects their perception (Kalnins & Williams, 2014). Moreover, this gender inequality has different forms in different countries. Thailand for example has been a matriarchal society since ancient times, and women are always active in a variety of economic activities (Harriford & Thompson, 2010). But this does not mean that women get better treatment in labor market. According to Darity and Mason (1998), women usually receive less salary than men and tend to participate in low-skilled occupations.

H1: The probability of success is higher for male entrepreneurs.

2.4.1.2 Size of founding team

The entrepreneurship literature agrees that there is a direct correlation between the size of the founding team and the venture’s success (Barringer, et al., 2005; Cooper, et al., 1994; Roure & Keeley, 1990). Firstly, more partners have access to a broader area of knowledge and expertise, because most of the times they come from different industries (Barkham, 1994). Secondly, partners act as moral and psychological support for each other. Lastly, the presence of a team can influence an investor’s decision to invest capital (Eisenhardt & Schoonhoven, 1990).

H2: The probability of success is higher for ventures with a team of founders.

2.4.1.3 Level of education

It is expected that higher levels of education account for higher chances of successfully surviving in the market. The field in which the entrepreneur graduates is not as important as the skills accumulated through a Bachelor, Masters or Ph.D. program: communication and IT skills, analytical and research skills and creativity (Sapienza & Grimm, 1997).

H3: The probability of success is higher for ventures whose founders completed higher levels of education.

2.4.1.4 Previous industry experience

Studies find that entrepreneurs with relevant prior experience to the new venture they’re founding have a higher chance of successfully launching their product on the market. This affirmation is supported by previous research in the automobile (Carroll, et al, 1996; Klepper S., 2002) and shipping industries (Thompson, 2005).
The lack of this industry-specific experience results in higher costs and efforts for the entrepreneurs who have to build everything from scratch, from knowledge of the product and industry to relationships with suppliers and consumers (Cooper, Gimeno-Gascon, & Woo, 1994).

Although, for this case study, we expect that the lack of industry experience from the entrepreneurs’ part to be compensated with the experience of the accelerator’s network. During the three months period and after, entrepreneurs are expected to gain all the knowledge necessary to grow their business by observing and learning from their mentors and not only.

There are several papers that study learning modes that provide the highest return for companies, which include learning from previous experience (Lieberman, 1984), learning from others (Haunschild & Miner, 1997; Haunschild, 1993; DiMaggio & Powell, 1983), from experiments (Miller & Shamsie, 2001; Pisano, 1994) and by trial-and-error (Miner, Bassoff, & Moorman, 2001). Learning from others, also called vicarious learning, has several advantages: the information is available, if one knows where to search for it (Baum, Li, & Usher, 2000), bears a lower cost than the learning-by-doing method (Miner & Haunschild, 1995), and offers the possibility to gather heterogenous information, by observing multiple companies and people (Bingham & Davis, 2012). From all the learning methods mentioned in the beginning, vicarious learning is the best one to be employed by ventures in their early stages, prior to entering the market (Bingham & Davis, 2012; Haunschild & Miner, 1997).

Several previous research found that the more knowledge a venture has accumulated prior entering the market, the longer its chances for survival and overall good performance in the long run (Delmar & Shane, 2006; Klepper & Simmons, 2000; Mitchell, 1989).

In a qualitative study conducted by Hamel (1991) on nine international alliances between firms, he found out that firms that plan to learn from others learn more than the ones which do not have learning as an explicit goal.

\[ H_4: \text{The probability of success is higher for entrepreneurs with related industry experience.} \]

2.4.1.5 Entrepreneurial experience

In this case, however, skills like grit, perseverance and initiative that are developed mostly through prior entrepreneurial experience cannot be learned from observing others, only by trial-and-error. Studies find this to be one of the most expected factors of entrepreneurial
success (Singer, 1995). Founders with prior experience are more likely to avoid costly mistakes and are more familiar with the process of starting a new venture.

\( H_5 \): The probability of success is higher for ventures whose founders have prior entrepreneurial experience.

### 2.4.2 Characteristics of the firm

Another set of variables that the entrepreneurship researchers have been studying in relationship with a venture’s success or failure are its characteristics, including both new ventures and old ventures, such as capital available, age of the firm, geographic location, industry of operation and innovation, among others (Battistella, et al., 2017; Barringer, et al., 2005; Bates, 2005; Roure & Keeley, 1990). On one side, researchers put most of the weight behind a venture’s failure on firm specific factors (Zacharakis, Meyer, & De Castro, 1999), while, on the other side, others attribute higher importance to industry dynamics (Teal & Hofer, 2003).

#### 2.4.2.1 Amount of funding throughout the program

An important factor to consider when investigating a company’s success is the financial detail, such as the amount of money it raises from various investors throughout the program. Apart from acquiring knowledge from a large network of mentors and entrepreneurs, the most important characteristic of an accelerator is its network of investors, which many of the newly formed ventures could not have reached otherwise.

The amount of initial capital is also related to the strategy being pursued by entrepreneurs (Cooper, Gimeno-Gascon, & Woo, 1994), and we believe it to be a direct indication of the confidence business people and industry experts have that a certain product will be well received by the consumers.

Also, early stage companies are often highly dependent on external capital to help them overcome the costs, since they are too young to generate capital on their own (Cooper, Gimeno-Gascon, & Woo, 1994).

\( H_6 \): The probability of success is higher for ventures which raise a higher amount of initial financial capital.

#### 2.4.2.2 Age of firm

In some previous papers the firm’s age is also introduced as a dependent variable to study the success of the ventures. With the increase of firms’ operating time, the venture will accumulate more business experience and expand the network of business partners (Zahra,
Matherne, & Carleton, 2003). These changes can influence the probability of the venture’s success.

Song et al. (2008) find the age of firm is a success factor of new ventures and denote that with the age increasing, firms are more likely to succeed. Another study defines the firm’s age as the duration in years between a venture’s foundation and the year that its first international sale is obtained by other ventures (Głowik & Sadowski, 2014). The result is significant and the firm’s age can be considered a success factor for new, international ventures. If a firm expands internationally within its first three years, the firm will speed up its internationalization and succeed in the long run.

H7: The probability of success is higher for ventures of older age when participating in the accelerator program.

2.4.2.3 Geographic location

Another variable studied by scholars of the entrepreneurship literature is the location of startups. It has demonstrated that there are certain clusters, such as Silicon Valley, Cambridge Region or Singapore that facilitate the absorption of external knowledge (Barringer, Jones, & Neubaum, 2005) and create “knowledge spillovers” (Jaffe, Trajtenberg, & Henderson, 1993).

Clusters are “geographic concentrations of interconnected companies and institutions in a particular field” (Porter, 1998). They include a mix of various suppliers, providers of infrastructure, complementary products, supportive governmental policies, and universities.

This friendly environment nurtures the company and sometimes protects it, but there are also startups which participate in an accelerator program and then move their headquarters back to the entrepreneurs’ country. We assume that those companies have a higher failure rate due to the fact that the fate of a venture is highly influenced by the quality of the local government and business environment.

H8: The probability of success is higher for ventures which are established in the same geographic location as the accelerator.

2.4.2.4 Industry

In addition to the three characteristics of firms presented above, this study also considers the industry sector to be an influential variable. Previous research has found that a venture’s performance is very different across industries (Gimeno, et al., 1997; Roure & Keeley, 1990; Reynolds, 1987), stating reasons such as resource dependency, economics,
regulations, but most importantly, competition. One way in which entrepreneurs can address these issues is if they locate market niches with few competitors, sense a change in customers' expectations and jump ahead of the curve or use technological innovation to create new niches (Roure & Keeley, 1990).

*H*$_1$: *The probability of success is different for different industries.*

2.4.2.5 Technology intensive

Several entrepreneurial studies find that a venture’s survival and growth is highly correlated with the degree of innovation that its product entails (Deeds, et al., 2000; Schoonhover, et al., 1990). A firm’s competitive advantage is constructed around those skills and capabilities which are rare and difficult to copy (Barney, 1991). We expect the technology-intensive ventures to have a higher probability of success in the market.

*H*$_{10}$: *The probability of success is higher for ventures which are technology-intensive.*

In summary, the literature cited above provides a list of factors that may lead to a high successful rate for ventures. According to it, we assume new ventures backed by accelerators to be more likely to succeed if they are founded by a team of male entrepreneurs with high education level, prior related industry experience and entrepreneurial experience; also, the ventures are likely to be technology intensive set up in the same location with the accelerator program, to join the program at an older age and are able to receive high amount of capital. The sum of hypotheses is as followed:

*H*$_1$: The probability of success is higher for male entrepreneurs.

*H*$_2$: The probability of success is higher for ventures with a team of founders.

*H*$_3$: The probability of success is higher for ventures whose founders completed higher levels of education.

*H*$_4$: The probability of success is higher for entrepreneurs with related industry experience.

*H*$_5$: The probability of success is higher for ventures whose founders have prior entrepreneurial experience.

*H*$_6$: The probability of success is higher for ventures which raise a higher amount of initial financial capital.

*H*$_7$: The probability of success is higher for ventures of older age when participating in the accelerator program.
H₈: The probability of success is higher for ventures which are established in the same geographic location as the accelerator.

H₉: The probability of success is different for different industries.

H₁₀: The probability of success is higher for ventures which are technology-intensive.
3. Data

This chapter aims to clarify the statistical method of data collection and define all the variables used in the analysis. Then, it proceeds with explanations for the analysis method and models.

3.1 Case study

A case study research, probably the most used method in business research, is used in this paper because it involves investigating one entity – one accelerator, using multiple data sources when conducting an iterative research process (Easton, 2010). Usually, the case studies are applied when the phenomena are too complicated and cannot be solved by single factor analyses (Yin, 1981). The advantages of case studies are its capability to examine the outcome of several objectives in a series of activities over time and no limitation to qualitative or quantitative data (Yin, 1992). Thus, case studies allow researchers to study their phenomena of interest in a real-life environment without any background constraints (Stake, 1995).

Previous research on accelerators is limited, especially studies on the success drivers of startups backed by accelerators. Hence, in this paper, we did a case study on one of the most famous accelerator operators – TechStars, to fill the gap in the entrepreneurial literature. We intend to find some explanatory factors which can affect the success of accelerator backed startups and provide some suggestions not only for startups’ founders but for accelerator boards and investors alike.

3.2 Data collection

Different from most previous researchers who used questionnaires and face-to-face interviews to collect the data, this study uses second-hand data from some external sources such as TechStars’s company website, CrunchBase and LinkedIn.

TechStars is a worldwide entrepreneurial network who was established to help companies succeed. Founded in 2006, the US based entity has helped over one thousand companies through its accelerators programs and raised 2.95 billion dollars in 2016. (Techstars, 2017) The TechStars accelerator programs last 90 days and provide each venture 20,000 dollars in funding together with intense mentorship from 200 mentors globally. In return, the companies give TechStars 6 percent common stock. Apart from TechStars’ website,
CrunchBase is the main source of information about the startup companies and their founders. CrunchBase is an entrepreneurial database supported by TechCrunch from 2007. It provides information on industry trends, investments, and news about firms worldwide. We choose it as our main data source because it offers information concerning almost every startup, the founders, the number of funding rounds and other important data. LinkedIn is a social network launched in 2003 which focuses on connecting employers and job hunters. It is usually used for posting resumes. (Lemann, 2015) Therefore, we consider LinkedIn as a good data source for the founders’ working experiences and previous education.

Our data consists of 640 companies which participated in the TechStars Accelerator Programs from 2007 to 2015. From the 1,023 ventures shown on TechStars’s company website, we excluded those which lacked sufficient information and those which joined the programs from 2016 on. The companies that enrolled in 2016 are excluded because it is too early to make a conclusion whether the companies are successful or not, after a few months of completing the programs.

3.3 Variable description

3.3.1 Dependent variables

The purpose of this study is to find the success drivers of accelerator backed startups, thus the dependent variable is the success of startups. However, based on the literature surveyed, there are several ways to define the success: the personal perception of an entrepreneur over his venture’s overall performance, regardless if the venture was closed or not (Bates, 2005), or if the startup meets certain criteria such as sales level, after tax-profits greater than 5 percent, etc. (Roure & Maidique, 1986).

In this paper, we use two regression models to examine the success determinants and set different standards for each model.

The Logit model is usually applied when the outcome variable is binary. In this case, we use receiving further funding as an event to distinguish success and failure (Hoffman & Kelley, 2012). We define a venture as successful if it continued to raise money after participating in the program and unsuccessful if it failed to raise additional money until the time of the study or it has closed. The outcome of this event can only be yes (receiving further funding) or no (not receiving further funding and closed). We use 1 to represent success and 0 to represent failure when running the logistic regression.
Another measurement of startups’ success is the total amount of funding they have received through the program from the day the startup entered the accelerator to the day we collect the data. For this dependent variable, we use the Ordinary Least Squares (OLS) model to examine the influence of each independent variable brings to the success of startups.

### 3.3.2 Independent variables

According to previous research which studied the relationship between funding factors and venture success, there are usually more than 25 indicators for over 1,000 data in the model (Podoynitsyna, et al., 2008; Bates, 2005; Song, et al., 2005). However, considering the sample size of our study only have 640 observations, we choose 19 indicators for 10 factors and divide them into two groups of characteristics. Almost every indicator is presented as a dummy in order to run the logistic regression.

**Entrepreneurs’ characteristics**

- **Gender**: As in many countries, the social status of men and women is not entirely equal. We suppose the opportunity and difficulty that men and women faced in the entrepreneurial process may be different. Hence, we divide the gender factors into 3 indicators.
  - **Male**: If founders are all male, this variable = 1, otherwise = 0
  - **Female**: If the founders are all female, this variable = 1, otherwise = 0
  - **Mixed**: If there are both male and female in the founding group, this variable = 1, otherwise = 0

- **Number of founders (FOUNDERS)**: Sometimes the individual entrepreneur may receive less support and funding than an entrepreneurial team (Barkham, 1994). Thus, we consider the number of founders as an explanatory variable.

- **Education level**: Education is a wildly used factor in the success drivers’ studies. Some prior researchers believe that entrepreneurs with higher education level have developed more skills necessary to make the firm survive and grow in the long run (Watson, et al., 2003). We also set three levels for this factor.
  - **High school (HS)**: If the highest education level completed by the entrepreneur or entrepreneurial team is high school, then this variable = 1, otherwise = 0
  - **Bachelor’s degree (B.A)**: If the highest education level completed by the entrepreneur or entrepreneurial team is Bachelor, then this variable = 1, otherwise = 0
Higher education (HIGHER): If the entrepreneur or at least one of the entrepreneurs in the team received a master or doctorate degree, then this variable = 1, otherwise = 0

- Industry experiences (IND_EXP): If the entrepreneur or any entrepreneur in the team has prior working experiences in the same field as the startup, this variable = 1, otherwise = 0

- Entrepreneurial experiences (ENT_EXP): According to Barringer et al. (2005), the founders with prior entrepreneurial experience have an advantage over the first-time entrepreneurs. Therefore, if the founder or at least one of the members of the founding team has previously founded other companies, this variable = 1, otherwise = 0

Companies’ characteristics

- Amount of funding (FUNDING): This is the total current funding that the venture has received from TechStars and other investors. In a previous study conducted by Cooper and Gascon (1992), they reported that firms usually have a better performance when they have more capital. As mentioned before, funding amount is the dependent variable we use in the OLS model, but for the Logit model, we also take it as an independent variable.

- Startup's age (AGE): Based on previous studies and the accelerator’s feature, we define the startups’ age as the number of years between the startup’s founding year and the year they joined the accelerator program. We assume the startup’s business experience before it participates in the program can affect its probability of success.

- Location: The accelerator’s worldwide popularity makes thousands of new ventures to apply for each batch. Companies all over the world can apply for the program and the only condition is to be able to relocate for three months in the city where they applied. As mentioned previously in the literature review, this has certain advantages and disadvantages, and an influence on the startup’s survival. Therefore, this variable is included in the model. If the company’s headquarters are in the same country as the accelerator program, this variable = 1, otherwise = 0.

- Industry of operation: Different industries have different business risks and opportunities; these differences may have an influence over the success of a new
venture. The 640 startups we collected are classified in the following industry categories:

Retail: If the startup is part of the retail industry, this variable = 1, otherwise = 0
Finance: If the startup is part of the finance industry, this variable = 1, otherwise = 0
Media: If the startup is part of the media industry, this variable = 1, otherwise = 0
Education (EDU): If the startup is part of the education industry, this variable = 1, otherwise = 0
Information Technology (IT): If the startup is part of the IT industry, this variable = 1, otherwise = 0
Health: If the startup is part of the health industry, this variable =1, otherwise=0

- **Technology intensive (TECH):** TechStars founders claim they are interested in technology oriented companies, but they also accept companies with world influence even if they don’t meet the standard. If the startup uses advanced technologies, this variable = 1, otherwise = 0

### 3.4 Methodology

In order to find the success factors of startups supported by the accelerator, we choose to run both Logistic regression and Ordinary Least Squares (OLS) regression on the 640 observations. All the regressions are run in Eviews — a statistical software mainly used for econometric analysis.

#### 3.4.1 The Logit Model

The Logit model is applicable when the dependent variable is binary. The Logistic regression examines the independent variables that can make the best prediction of the dependent variable’s value by estimating the coefficients of the model. If the coefficient of the explanatory variable is positive, it increases the probability of the outcome, while the negative coefficient reduces the probability (Hair, et al., 1995).

The logistic distribution function is defined as:

\[
P_i = \frac{1}{1 + e^{-Z_i}}
\]

where: \(Z_i = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_i\)
$P_i = \text{the probability of the dependent variable, which is the probability of startups' success in our study. As a binary outcome, } P_i \text{ ranges between 0 and 1 and it is non-linearly related to } Z_i$

$X_i = \text{the set of independent variables, which is the 19 variables in our study}$

$\beta_0 = \text{the intercept term}$

$\beta_n = \text{the set of parameters for each independent variable}$

$e = \text{the base of natural logarithm, which equals to 2.71828}$

In addition, another concept called the odds ratio is introduced to represent the ratio of the probability that a startup is successful against the probability that a startup fails (Gujarati and Porter, 2009). Unlike chi-square, the odds ratio gives us a direction of the association.

The equation of the odds ratio is:

$$\frac{P_i}{1 - P_i} = e^{Z_i}$$

However, because we use a sample of 640 observations to estimate the success factors of all accelerator backed startups, the sampling distribution of the odds ratio can be skewed (Taylor, 2016). In order to reduce the numerical precision errors, the log likelihood function will be used. Taking the natural log of the equation above we obtain the log of the odds ratio, namely,

$$L_i = \ln \left( \frac{P_i}{1 - P_i} \right) = Z_i$$

After taking the log, $L_i$ is not only linear in $X_i$, but also linear in the parameters $\beta_n$ (Gujarati and Porter, 2009).

Moreover, unlike the OLS Model, when interpreting the regression results, we need to calculate the marginal effect of each variable by using the formula below:

$$\bar{\beta}_n \bar{Y} (1 - \bar{Y})$$

where $\bar{\beta}_n = \text{the coefficient of each independent variable}$

$\bar{Y} = \text{the ratio of the number of observations with value of 1 to the number of sample size}$
Furthermore, the goodness of fit, $R^2$, should be mentioned here. The goodness of fit is used to present how well the model fits the observations. Its value ranges from 0 to 1. If the value is 1, the fitted regression perfectly explains the changes in observations. On the contrary, if the value is 0, the model cannot explain any change in the observations. Therefore, the closer to 1 means the better the model fits the data (Gujarati and Porter, 2009). The measurement of $R^2$ is various, many different $R^2$ statistics have been proposed in the past thirty years. According to Allison (2013), the McFadden $R^2$ is a better choice and it is also the one measured in Eviews. The McFadden $R^2$ is defined as:

$$R^2_{MCF} = 1 - \left( \frac{LLF_{ur}}{LLF_r} \right)$$

where $LLF_{ur}$ = the unrestricted log likelihood function where all regressors are included in the model

$LLF_r$ = the restricted log likelihood function where only the intercept is included in the model

However, since the value of observations in Logit Model is either 0 or 1, the goodness of fit is almost always low. Hence, it is not particularly meaningful to focus on the $R^2$ in binary models (Hosmer, et al., 1997).

### 3.4.2 The Ordinary Least Squares (OLS) Model

The OLS model can find the data that best fits the model by minimizing the sum of squares of the error between the actual value of observed data and the value predicted by a linear function of a set of explanatory variables (Fortmann-Roe, 2012).

The function of the OLS model is as follows (Gujarati and Porter, 2009):

$$Y_i = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \cdots + \hat{\beta}_n X_i + \hat{u}_i$$

where $Y_i$ = the value of the dependent variable, which is the amount of funding of the startups studied in our case

$\hat{\beta}_0$ = the intercept term

$\hat{\beta}_n$ = the set of parameters which shows the influence each independent variable brings to the dependent variable

$\hat{u}_i$ = the residual term, the estimated value of the stochastic disturbance term $u_i$
Furthermore, in our case, the unit of measurement for the dependent variable is different than the unit for the independent variables. Therefore, we need to standardize the OLS regression variables using the following formula (Giles, 2013):

\[ Y_i^* = \frac{Y_i - \bar{Y}}{StDev(Y)} \]

where \( \bar{Y} = \frac{1}{n} \sum Y_i \)

\( Y_i = \) original data

\( Y_i^* = \) standardized data

Additionally, even if it has been ensured that the model best fits the sample observations by using the ordinary least squares estimation method, due to the influence of residuals, we still need to test the goodness of fit. The measurement of goodness of fit in OLS regression is defined as:

\[ R^2 = \frac{ESS}{TSS} = \frac{\sum(Y_i - \bar{Y})^2}{\sum(Y_i - \bar{Y})^2} \]

or

\[ R^2 = 1 - \frac{RSS}{TSS} = \frac{\sum(Y_i - \bar{Y})^2}{\sum(Y_i - \bar{Y})^2} \]

where 

\( ESS = \) explained sum of squares

\( RSS = \) residual sum of squares

\( TSS = \) total sum of squares

\( Y_i = \) the observed dependent variable

\( \bar{Y}_i = \) the estimated value of dependent variable

\( \bar{Y} = \) the mean of dependent variable

Apart from this, since the independent variables contained in the model do not all affect the dependent variable, in order to correct the results, another statistic called the adjusted R squared is proposed. The adjusted R squared only takes those independent variables which actually affect the dependent variable into account (Frost, 2013).
The equation of adjusted R squared is denoted as:

$$\bar{R}^2 = 1 - \frac{\sum(Y_i - \bar{Y}_i)^2}{\sum(Y_i - \bar{Y})^2} \frac{(n - k)}{(n - 1)}$$

where \( n = \) the total number of observations in the sample

\( k = \) the number of parameters in the model including the intercept term
4. Results

This chapter presents the empirical results of the analyses applied to our case study. We present a descriptive statistics comparison between successful and unsuccessful startups, followed by the results of the Logistic regression and OLS regression.

4.1 Descriptive statistics

First of all, we group the 640 observations into successful and unsuccessful based on whether they have received further funding. Then we summarize the traits of the entrepreneurs and startups and compare all these traits between each case. As the data shows in Table 2, successful startups have a higher percentage in entrepreneurs’ higher education background, related industry experience and prior entrepreneurial experience than unsuccessful startups. Besides, the average funding amount that successful startups received is $6,548,599.16 dollars, which is around 15 times more than the $429,197.53 dollars that unsuccessful startups received.

Table 2: Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Successful startups</th>
<th>Unsuccessful startups</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Entrepreneur traits:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male (%)</td>
<td>78</td>
<td>77</td>
</tr>
<tr>
<td>Female (%)</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Mixed (%)</td>
<td>17</td>
<td>19</td>
</tr>
<tr>
<td>Number of founders (mean)</td>
<td>2.4958</td>
<td>2.2284</td>
</tr>
<tr>
<td>Education level:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school (%)</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Bachelor degree (%)</td>
<td>43</td>
<td>49</td>
</tr>
<tr>
<td>Higher education (%)</td>
<td>56</td>
<td>48</td>
</tr>
<tr>
<td>Industry experience (%)</td>
<td>82</td>
<td>73</td>
</tr>
<tr>
<td>Entrepreneurial experience (%)</td>
<td>62</td>
<td>50</td>
</tr>
<tr>
<td><strong>Startups’ traits:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amount of funding (mean)</td>
<td>$6,548,599.16</td>
<td>$429,197.53</td>
</tr>
<tr>
<td>Startups’ age (mean)</td>
<td>1.0272</td>
<td>1.1975</td>
</tr>
<tr>
<td>Location (%)</td>
<td>88</td>
<td>86</td>
</tr>
<tr>
<td>Industry of operation:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Retail (%)</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td>Finance (%)</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Media (%)</td>
<td>25</td>
<td>28</td>
</tr>
<tr>
<td>Education (%)</td>
<td>8</td>
<td>6</td>
</tr>
<tr>
<td>Information technology (%)</td>
<td>38</td>
<td>38</td>
</tr>
<tr>
<td>Health (%)</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>Technology intensive (%)</td>
<td>68</td>
<td>49</td>
</tr>
</tbody>
</table>
In addition, 68 percent of the startups in the successful group are technology intensive, while the unsuccessful group only has 49 percent. Therefore, we should pay attention to these different characteristics in the following regression analyses, since they are more likely to be the success drivers.

4.2 Regression analysis

Before running the regressions, we first perform a correlation analysis to study the relationship between the independent variables and assess the presence of multicollinearity. The correlation matrix is presented in Appendix 1. According to the result, we can find that the correlation between male and mixed variables is -0.8455, while the correlation between bachelor degree and higher education variables is -0.9690. This means that the mentioned variables are strongly correlated, the value of one variable can be predicted by the value of the other one. Hence, we deleted the variables male and bachelor degree when running the regressions. Apart from this, there is no issue of multicollinearity between the remaining variables and we can proceed to run the Logit regression. However, the indicators under the gender, education level and industry of operation factors are defined as a dummy, and according to the rule of dummy variables, we should delete the variables with the highest occurrence in each category (Princeton University Library, 2007).

4.2.1 Logistic regression

Table 3 shows the result of the Logistic regression. According to the data, the variable amount of funding is significant at 5 percent level while three other variables are significant at 10 percent level, namely number of founders, female and technology intensive. The corresponding marginal effects imply that the four independent variables are positively related to the dependent variable. If the number of founders increases with 1 person, the probability of success will increase by 0.0388 percent, and if the entrepreneur is female, the probability of success will increase with 0.1628 percent. When looking into the amount of funding variable, it indicates that an increase with 1 dollar will increase the probability of success with 2.65E-07 percent. Also, if the startup is technology intensive, its probability of success will increase by 0.0919 percent.
Table 3: Logistic regression results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Marginal effect</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of founders</td>
<td>0.0388</td>
<td>0.0818**</td>
</tr>
<tr>
<td>Female</td>
<td>0.1628</td>
<td>0.0808**</td>
</tr>
<tr>
<td>Mixed</td>
<td>-0.0373</td>
<td>0.5087</td>
</tr>
<tr>
<td>High school</td>
<td>0.0210</td>
<td>0.8864</td>
</tr>
<tr>
<td>Higher education</td>
<td>0.0475</td>
<td>0.2782</td>
</tr>
<tr>
<td>Industry experience</td>
<td>0.0653</td>
<td>0.2175</td>
</tr>
<tr>
<td>Entrepreneurial experience</td>
<td>0.0348</td>
<td>0.4090</td>
</tr>
<tr>
<td>Amount of funding</td>
<td>2.65E-07</td>
<td>0.0000***</td>
</tr>
<tr>
<td>Startups’ age</td>
<td>-0.0028</td>
<td>0.8419</td>
</tr>
<tr>
<td>Location</td>
<td>-0.0403</td>
<td>0.5046</td>
</tr>
<tr>
<td>Retail</td>
<td>0.0579</td>
<td>0.4507</td>
</tr>
<tr>
<td>Finance</td>
<td>0.0420</td>
<td>0.5948</td>
</tr>
<tr>
<td>Media</td>
<td>0.0188</td>
<td>0.7571</td>
</tr>
<tr>
<td>Education</td>
<td>0.1071</td>
<td>0.2129</td>
</tr>
<tr>
<td>Health</td>
<td>0.0286</td>
<td>0.7154</td>
</tr>
<tr>
<td>Technology intensive</td>
<td>0.0919</td>
<td>0.0547**</td>
</tr>
</tbody>
</table>

Note: The independent variables with a statistical significance of 5%, 10%, and 15% are marked with ***, ** and *, respectively.

Apart from this, from the original Eviews output presented in Appendix 2 we can see that the value of McFadden R squared is 0.3115. The result shows that the goodness of fit of our Logit model is relatively low. But unfortunately, we did not see any discussions of the R squared in previous studies. Hence, we cannot evaluate how good or bad our model is compared to other models. However, the goodness of fit in binary regression models is not as important as it in other regression models. What really matters is the variables’ coefficients and statistical significance.

4.2.2 Ordinary Least Squares (OLS) regression

For the second regression, we take the amount of funding as the dependent variable. As it can be seen from Table 4, there are two variables significant at 5 percent level, one significant at 10 percent level and four significant at 15 percent level. Looking at the variables that describe an entrepreneur’s characteristics, the coefficient indicates that an increase in the number of founders will lead to 0.125 percent increase in the funding amount. Meanwhile, if an entrepreneur has related industry experience, the amount of funding will increase with 0.0658 percent. Second, among variables that describe a startup’s characteristics, if the startup is located in the same country as the accelerator program, it will increase the startups’ funding amount by 0.0889 percent. Also, if the startup is technology intensive and if it operates in the health industry, the amount of funding will increase by 0.0695 percent and 0.0765 percent, respectively. Thirdly, according to our study, the higher education and startups’ age variables have a negative effect on the amount of
funding. If the entrepreneurs with a higher education background increase with 1 people, this will lead to a decrease in the amount of funding by 0.064. Almost the same effect can be seen for a one year increase in the age of startup, which leads to a decrease in the amount of capital raised by 0.0612 percent.

Table 4: OLS regression results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of founders</td>
<td>0.1250</td>
<td>0.0027***</td>
</tr>
<tr>
<td>Female</td>
<td>-0.0417</td>
<td>0.3079</td>
</tr>
<tr>
<td>Mixed</td>
<td>-0.0152</td>
<td>0.7090</td>
</tr>
<tr>
<td>High school</td>
<td>-0.0211</td>
<td>0.59761</td>
</tr>
<tr>
<td>Higher education</td>
<td>-0.0640</td>
<td>0.1170*</td>
</tr>
<tr>
<td>Industry experience</td>
<td>0.0658</td>
<td>0.1137*</td>
</tr>
<tr>
<td>Entrepreneurial experience</td>
<td>-0.0220</td>
<td>0.5800</td>
</tr>
<tr>
<td>Startups' age</td>
<td>-0.0612</td>
<td>0.1271*</td>
</tr>
<tr>
<td>Location</td>
<td>0.0889</td>
<td>0.0274***</td>
</tr>
<tr>
<td>Retail</td>
<td>-0.0171</td>
<td>0.7005</td>
</tr>
<tr>
<td>Finance</td>
<td>0.0018</td>
<td>0.9657</td>
</tr>
<tr>
<td>Media</td>
<td>-0.0322</td>
<td>0.5084</td>
</tr>
<tr>
<td>Education</td>
<td>-0.0248</td>
<td>0.5610</td>
</tr>
<tr>
<td>Health</td>
<td>0.0765</td>
<td>0.0822**</td>
</tr>
<tr>
<td>Technology intensive</td>
<td>0.0695</td>
<td>0.1143*</td>
</tr>
</tbody>
</table>

Note: The independent variables with a statistical significance of 5%, 10%, and 15% are marked with ***, ** and *, respectively.

As it shows in Appendix 3, the adjusted R squared is 0.0279, which is very low. This means that the residuals have a strong effect on the regression line, the estimated regression line may be biased to the true regression line. Therefore, the model does not ideally fit the observations and this can be considered as one of the limitations of our study.
5. Analysis

The purpose of this chapter is to present the analysis around the presented results obtained from the Logit and OLS models and to present a discussion about the models' accuracy and performance.

Based on our results, the hypotheses we proposed before have their answers.

\(H_1\): Reject. Ventures founded by female entrepreneurs have a higher probability of success.

\(H_2\): Do not reject. The probability of success is higher for ventures with a team of founders.

\(H_3\): Reject. Founders with higher education levels have a lower probability of success.

\(H_4\): Do not reject. The probability of success is higher for entrepreneurs with related industry experience.

\(H_5\): Reject. Prior entrepreneurial experience is not significant in both models.

\(H_6\): Do not reject. The probability of success is higher for ventures which raise a higher amount of initial financial capital.

\(H_7\): Reject. Ventures participating in the accelerator program at a younger age have a higher probability of success.

\(H_8\): Do not reject. The probability of success is higher for ventures which are established in the same geographic location as the accelerator.

\(H_9\): Do not reject. The probability of success is different for different industries and the health industry has a higher probability of success.

\(H_{10}\): Do not reject. Technology-intensive ventures have a higher probability of success.

Further analysis regarding the significant factors follows.

Overall, each statistical analysis performed in this study finds similar variables at different levels of significance to explain the success of new ventures. The number of members of the founding team and the intensity of technology appears to be significant in the descriptive statistics and both models, thus, we consider them to be the best explanatory variables for startup's success. In addition, there are other variables, such as the amount of funding, previous industry experience, the age and location of startups when they joined
the accelerator program, which are significant in at least one of the models, at different levels of significance.

The number of founders has a positive relationship with the probability of a startup’s success, consistent with our initial hypothesis. Results show that the higher the number of members in the founding team, the higher the probability that the venture will be successful in the long-run. Furthermore, our findings are compatible with the entrepreneurial literature, which has previously found that teams of entrepreneurs can provide more ideas, diverse background, and psychological support to each other (Watson, et al., 2003; Cooper & Woo, 1989).

The analyses imply that most of the successful companies are technology intensive as we expected. The firms which developed high technology products have a higher chance to survive in the market because their products are more difficult to be copied and have fewer competitors (Barney, 1991). In addition, Barringer et al. (2005) also find that young firms with high growth such as eBay and Cisco Systems have created new niches with their innovative, high technology products.

The result of the logistic regression indicates that with the increase of the funding amount, the probability of success increases for a new venture. On one hand, if investors are willing to invest more money in a startup, they are confident that the startup will survive and grow in the long run. On the other hand, studies show that if the entrepreneurs receive more funding, they can take more risk and pursue bigger projects (Cooper, Gimeno-Gascon, & Woo, 1994).

The industry experience is also a success factor of new ventures. If entrepreneurs have prior experience in the same industry as their startups, they can avoid novice errors because they have more knowledge in this area (Bruderl, Preisendorfer, & Ziegler, 1992). Apart from this, the entrepreneurs already have a reputation in that industry, a network of suppliers and customers (Cooper, Gimeno-Gascon, & Woo, 1994).

Another variable that is significant in the OLS regression is the location of startups. It is more likely for a startup to succeed in the long-run and receive more funding if its headquarter is located in the same country as the accelerator program, which is the same as the hypothesis we made before. Moreover, the entrepreneurial literature reveals that if a venture is situated in a cluster that facilitates knowledge, with a competent workforce and
government supports, it has a higher possibility of grow in the future (Porter, 1998; Pouder & St. John, 1996).

Moreover, the health industry is found to be a success factor in the OLS regression. If the venture operates in the health industry, it may have a higher probability of success. According to the literature (Roure & Keeley, 1990), this might be because of lack of competitors in this industry. As it is shown in the descriptive statistics table, only 9 percent of the successful startups from TechStars Accelerator operate in the health industry, which is the lowest compared to 38 percent for IT industry and 25 percent for media industry.

The variable that we introduced in this analysis, the age of the startup, appears to be significant in the OLS regression. It shows that there is a negative correlation between the age of the startup when it joined the accelerator program and its funding amount. This result is contrary to our hypothesis, an explanation might be that the accelerator specializes in helping early-stage ventures, and the resources used to help these companies are not entirely suitable for later stage ventures.

Surprisingly, this study reveals that female entrepreneurs are more likely to operate successful ventures than male entrepreneurs or gender mixed teams. Thus, we have to reject our initial hypothesis which states that male-owned ventures have a higher probability of success.

According to the correlation matrix, female entrepreneurs are more likely to start a business in a different industry, without having any entrepreneurial experience and receive less capital. These findings are also supported by Cooper et al. (1994). However, as mentioned before, industry experience and the funding amount are success factors of accelerator backed ventures. These contradictions suggest that more in-depth research is needed to clarify the relationship between female entrepreneurs and the success of their new ventures.

Last but not least, the variable of higher education level has turned out to be an explanatory factor of venture’s success in OLS regression. Nonetheless, the negative coefficient indicates the higher the education background the entrepreneur has, the less funding amount the startup is likely to receive. This finding is different from our expectations, but in Broström and Baltzopoulo’s paper (2013), they point out that a negative relationship between high education and enterprise’s performance can exist.
Entrepreneurs may spend too much time on education rather than accumulating working experience. Moreover, another paper also reports that highly educated entrepreneurs are more likely to have opportunities to start their own business, but not to found viable active ventures (Delmar, Davids, & Gartner, 2003).

In view of the limitation of the case study, the results of TechStars Accelerator cannot represent the results of all accelerator programs. Thus, further studies can be designed to expand the sample size and give more accurate results.

In order to compare the results of this paper with previous literature, we create Figure 2 to present the success factors of ventures identified in previous studies and the variables considered as success drivers of accelerator backed startups in our paper.

<table>
<thead>
<tr>
<th>Entrepreneurs’ characteristics</th>
<th>Startups’ characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big number of entrepreneurs</td>
<td>High amount of funding</td>
</tr>
<tr>
<td>Female entrepreneurs</td>
<td>Technology intensive</td>
</tr>
<tr>
<td>Previous industry experience</td>
<td>Young age of startups</td>
</tr>
<tr>
<td>High education background</td>
<td>Same location as the program</td>
</tr>
<tr>
<td>Young age of founders</td>
<td>Health industry</td>
</tr>
<tr>
<td>Less working hours</td>
<td>Low-capitalization</td>
</tr>
<tr>
<td>Perceived business stress</td>
<td>Less working hours</td>
</tr>
<tr>
<td>Perceived level of family support</td>
<td>Good product at a competitive price</td>
</tr>
<tr>
<td>IT knowledge</td>
<td>Employees’ IT/e-business knowledge</td>
</tr>
<tr>
<td>Positive attitude towards innovation</td>
<td>Governmental support</td>
</tr>
<tr>
<td>Non – minority race</td>
<td>Nongovernmental financial support</td>
</tr>
<tr>
<td>Parents had owned business</td>
<td>Big firm size</td>
</tr>
<tr>
<td>Previous marketing experience</td>
<td>Patent Protection</td>
</tr>
<tr>
<td></td>
<td>Supply Chain Integration</td>
</tr>
</tbody>
</table>

Key:
- **Normal font** = significant success factors found in previous studies
- **Bold** = significant variables in this paper

**Figure 2: Key success factors of ventures**
6. Conclusions and Future Research

This final chapter provides a summary of the findings of this paper, some economic implications and ideas for future research.

New ventures are critical for the evolution of society and growth of economy. They can create more job positions for people who face employment pressure, increase the diversity of marketplace, and help eradicate poverty in least developed areas. Entrepreneurs want to bring new ideas into the market to meet consumers’ expectations and they need help to develop their ideas into reality.

There are different entities such as governments, universities and investors encouraging the development of new ventures. However, they lack a complete support system to nurture the entities in their earliest stages. This gap is filled by incubators and accelerators. In this study, we chose to focus on accelerators because there is not enough quantitative research regarding such programs.

This paper aimed to find the success factors of the accelerator backed ventures. In order to fulfill this purpose, we conducted a case study focus on TechStars Accelerator Programs. We analyzed 640 startups which participated in the programs between 2007 and 2015, using the Logit Model and the OLS Model.

Our study shows that a venture is more likely to succeed if it is a technology intensive venture founded by a team of entrepreneurs with previous industry experience and a sufficient amount of capital. Also, the OLS regression finds location and startup’s age to be significant determinants of a startup’s success. If the startup joins the accelerator program soon after it was founded, and it is located in the same region as the program, it has a higher chance to survive and grow in the long term. Despite the findings of previous research, this study finds that female entrepreneurs are more likely to establish successful ventures.

These findings give an insight to the success factors of accelerator backed ventures. The accelerators can take these features into account when selecting the startups which apply for their programs. Apart from this, other investors such as venture capitalists, governments and universities can also focus on supporting enterprises which have participated in such programs and have the characteristics found in this study. If our study
can help more startups to succeed, then these startups can provide more job positions, create diverse products and promote economic development worldwide.

However, because this is a case study focusing only on TechStars startups, its findings should not be extrapolated to the entire pool of accelerator backed ventures, and limit itself to a hypothetical base that can be further investigated by the authors or others. For future studies, we suggest researchers to increase the sample size, take more accelerators into account, and get more convincing results. Besides, if the time allows, they can use face-to-face interview or questionnaire to obtain more personal and accurate data. Researchers can also include more variables such as government support, company’s size and entrepreneur’s race, conducting a cross-section analysis to compare the operating differences in each country.
7. References


---

39


### Appendix 1: Correlation matrix of independent variables

<table>
<thead>
<tr>
<th></th>
<th>FOUNDERS</th>
<th>MALE</th>
<th>FEMALE</th>
<th>MIXED</th>
<th>HS</th>
<th>BA</th>
<th>HIGHER</th>
<th>IND_EXP</th>
<th>ENT_EXP</th>
<th>FUNDING</th>
<th>AGE</th>
<th>LOCATION</th>
<th>RETAIL</th>
<th>FINANCE</th>
<th>MEDIA</th>
<th>EDU</th>
<th>IT</th>
<th>HEALTH</th>
<th>TECH</th>
</tr>
</thead>
<tbody>
<tr>
<td>FOUNDERS</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MALE</td>
<td>-0.0678</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FEMALE</td>
<td>-0.1778</td>
<td>-0.4335</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MIXED</td>
<td>0.1836</td>
<td>-0.8455</td>
<td>-0.1064</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HS</td>
<td>-0.1030</td>
<td>0.0377</td>
<td>0.0244</td>
<td>-0.0574</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BA</td>
<td>-0.1379</td>
<td>0.0252</td>
<td>0.0719</td>
<td>-0.0763</td>
<td>-0.1132</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HIGHER</td>
<td>0.1631</td>
<td>-0.0345</td>
<td>-0.0778</td>
<td>0.0903</td>
<td>-0.1358</td>
<td>-0.9690</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IND_EXP</td>
<td>-0.0201</td>
<td>0.0954</td>
<td>-0.0167</td>
<td>-0.0932</td>
<td>0.0315</td>
<td>-0.1163</td>
<td>0.1081</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ENT_EXP</td>
<td>0.1467</td>
<td>0.0249</td>
<td>-0.0778</td>
<td>0.0157</td>
<td>-0.0236</td>
<td>-0.0215</td>
<td>0.0273</td>
<td>0.0223</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FUNDING</td>
<td>0.1187</td>
<td>0.0335</td>
<td>-0.0563</td>
<td>-0.0034</td>
<td>-0.0232</td>
<td>0.0295</td>
<td>-0.0237</td>
<td>0.0630</td>
<td>0.0018</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AGE</td>
<td>-0.0773</td>
<td>-0.0326</td>
<td>0.0132</td>
<td>0.0190</td>
<td>0.1322</td>
<td>0.0021</td>
<td>-0.0349</td>
<td>-0.0315</td>
<td>-0.0529</td>
<td>-0.0761</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOCATION</td>
<td>-0.0783</td>
<td>0.0623</td>
<td>-0.0150</td>
<td>-0.0582</td>
<td>0.0469</td>
<td>0.0178</td>
<td>-0.0295</td>
<td>0.0525</td>
<td>-0.0370</td>
<td>0.0879</td>
<td>-0.1035</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RETAIL</td>
<td>-0.0236</td>
<td>-0.1457</td>
<td>0.1163</td>
<td>0.0877</td>
<td>0.0392</td>
<td>0.0199</td>
<td>-0.0206</td>
<td>-0.0204</td>
<td>-0.0278</td>
<td>-0.0367</td>
<td>0.0198</td>
<td>0.0338</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FINANCE</td>
<td>-0.0334</td>
<td>0.0812</td>
<td>-0.0052</td>
<td>-0.0736</td>
<td>-0.0401</td>
<td>-0.0366</td>
<td>0.0464</td>
<td>-0.0837</td>
<td>0.0007</td>
<td>-0.0048</td>
<td>-0.0680</td>
<td>-0.0629</td>
<td>-0.1090</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MEDIA</td>
<td>0.0255</td>
<td>0.0402</td>
<td>-0.0140</td>
<td>-0.0382</td>
<td>-0.0158</td>
<td>0.0949</td>
<td>-0.0907</td>
<td>-0.0484</td>
<td>0.0326</td>
<td>-0.0449</td>
<td>0.0093</td>
<td>0.1301</td>
<td>-0.1882</td>
<td>-0.1863</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EDU</td>
<td>-0.0023</td>
<td>-0.0802</td>
<td>0.0563</td>
<td>0.0526</td>
<td>0.0367</td>
<td>-0.0626</td>
<td>0.0715</td>
<td>-0.0873</td>
<td>0.0402</td>
<td>-0.0429</td>
<td>-0.0150</td>
<td>-0.0517</td>
<td>-0.0995</td>
<td>-0.0928</td>
<td>-0.1072</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IT</td>
<td>0.0026</td>
<td>0.1253</td>
<td>-0.1402</td>
<td>-0.0549</td>
<td>0.0061</td>
<td>-0.0434</td>
<td>0.0418</td>
<td>0.2677</td>
<td>-0.0375</td>
<td>0.0496</td>
<td>-0.0377</td>
<td>-0.0555</td>
<td>-0.2658</td>
<td>-0.2477</td>
<td>-0.4543</td>
<td>-0.2262</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HEALTH</td>
<td>0.0099</td>
<td>-0.1309</td>
<td>0.1060</td>
<td>0.0778</td>
<td>0.0449</td>
<td>0.0186</td>
<td>-0.0297</td>
<td>-0.1836</td>
<td>0.0095</td>
<td>0.0659</td>
<td>0.1043</td>
<td>-0.0255</td>
<td>-0.1110</td>
<td>-0.1034</td>
<td>-0.1897</td>
<td>-0.0945</td>
<td>-0.2523</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>TECH</td>
<td>0.0539</td>
<td>0.0422</td>
<td>-0.0136</td>
<td>-0.0351</td>
<td>-0.0073</td>
<td>-0.1407</td>
<td>0.1422</td>
<td>0.1326</td>
<td>0.0457</td>
<td>0.0960</td>
<td>-0.0078</td>
<td>0.0197</td>
<td>-0.1699</td>
<td>0.0440</td>
<td>-0.3293</td>
<td>-0.0049</td>
<td>0.3511</td>
<td>0.0516</td>
<td>1.0000</td>
</tr>
</tbody>
</table>
### Appendix 2: Result of Logit Model

Dependent Variable: SUCCESS  
Method: ML - Binary Logit (Newton-Raphson / Marquardt steps)  
Date: 07/20/17   Time: 12:05  
Sample: 1 640  
Included observations: 640  
Convergence achieved after 9 iterations  
Coefficient covariance computed using observed Hessian

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-1.5547</td>
<td>0.5447</td>
<td>-2.8542</td>
<td>0.0043</td>
</tr>
<tr>
<td>FOUNDERS</td>
<td>0.2050</td>
<td>0.1178</td>
<td>1.7402</td>
<td>0.0818</td>
</tr>
<tr>
<td>FEMALE</td>
<td>0.8610</td>
<td>0.4930</td>
<td>1.7463</td>
<td>0.0808</td>
</tr>
<tr>
<td>MIXED</td>
<td>-0.1974</td>
<td>0.2987</td>
<td>-0.6608</td>
<td>0.5087</td>
</tr>
<tr>
<td>HS</td>
<td>0.1112</td>
<td>0.7780</td>
<td>0.1429</td>
<td>0.8864</td>
</tr>
<tr>
<td>HIGHER</td>
<td>0.2512</td>
<td>0.2317</td>
<td>1.0844</td>
<td>0.2782</td>
</tr>
<tr>
<td>IND.EXP.</td>
<td>0.3454</td>
<td>0.2800</td>
<td>1.2333</td>
<td>0.2175</td>
</tr>
<tr>
<td>ENT.EXP.</td>
<td>0.1843</td>
<td>0.2232</td>
<td>0.8256</td>
<td>0.4090</td>
</tr>
<tr>
<td>FUNDING</td>
<td>1.40E-06</td>
<td>1.75E-07</td>
<td>7.9850</td>
<td>0.0000</td>
</tr>
<tr>
<td>AGE</td>
<td>-0.0148</td>
<td>0.0744</td>
<td>-0.1995</td>
<td>0.8419</td>
</tr>
<tr>
<td>LOCATION</td>
<td>-0.2134</td>
<td>0.3198</td>
<td>-0.6673</td>
<td>0.5046</td>
</tr>
<tr>
<td>RETAIL</td>
<td>0.3063</td>
<td>0.4060</td>
<td>0.7543</td>
<td>0.4507</td>
</tr>
<tr>
<td>FINANCE</td>
<td>0.2222</td>
<td>0.4177</td>
<td>0.5319</td>
<td>0.5948</td>
</tr>
<tr>
<td>MEDIA</td>
<td>0.0997</td>
<td>0.3223</td>
<td>0.3093</td>
<td>0.7571</td>
</tr>
<tr>
<td>EDU</td>
<td>0.5667</td>
<td>0.4549</td>
<td>1.2457</td>
<td>0.2129</td>
</tr>
<tr>
<td>HEALTH</td>
<td>0.1513</td>
<td>0.4148</td>
<td>0.3647</td>
<td>0.7154</td>
</tr>
<tr>
<td>TECH</td>
<td>0.4862</td>
<td>0.2530</td>
<td>1.9216</td>
<td>0.0547</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>McFadden R-squared</td>
<td>0.3115</td>
<td>Mean dependent var</td>
</tr>
<tr>
<td>S.D. dependent var</td>
<td>0.4351</td>
<td>S.E. of regression</td>
</tr>
<tr>
<td>Akaike info criterion</td>
<td>0.8321</td>
<td>Sum squared resid</td>
</tr>
<tr>
<td>Schwarz criterion</td>
<td>0.9506</td>
<td>Log likelihood</td>
</tr>
<tr>
<td>Hannan-Quinn criter.</td>
<td>0.8781</td>
<td>Deviance</td>
</tr>
<tr>
<td>Restricted deviance</td>
<td>724.1502</td>
<td>Restricted log likelihood</td>
</tr>
<tr>
<td>LR statistic</td>
<td>225.6016</td>
<td>Avg. log likelihood</td>
</tr>
<tr>
<td>Prob(LR statistic)</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Obs with Dep=0</td>
<td>162</td>
<td>Total obs</td>
</tr>
<tr>
<td>Obs with Dep=1</td>
<td>478</td>
<td></td>
</tr>
</tbody>
</table>
Appendix 3: Result of OLS Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.0000</td>
<td>0.0390</td>
<td>0.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>FOUNDERS_STAR</td>
<td>0.1250</td>
<td>0.0414</td>
<td>3.0169</td>
<td>0.0027</td>
</tr>
<tr>
<td>FEMALE_STAR</td>
<td>-0.0417</td>
<td>0.0409</td>
<td>-1.0205</td>
<td>0.3079</td>
</tr>
<tr>
<td>MIXED_STAR</td>
<td>-0.0152</td>
<td>0.0407</td>
<td>-0.3734</td>
<td>0.7090</td>
</tr>
<tr>
<td>HS_STAR</td>
<td>-0.0211</td>
<td>0.0400</td>
<td>-0.5281</td>
<td>0.5976</td>
</tr>
<tr>
<td>HIGHER_STAR</td>
<td>-0.0640</td>
<td>0.0408</td>
<td>-1.5697</td>
<td>0.1170</td>
</tr>
<tr>
<td>IND_EXP__STAR</td>
<td>0.0658</td>
<td>0.0415</td>
<td>1.5842</td>
<td>0.1137</td>
</tr>
<tr>
<td>ENT_EXP_STAR</td>
<td>-0.0220</td>
<td>0.0398</td>
<td>-0.5537</td>
<td>0.5800</td>
</tr>
<tr>
<td>AGE_STAR</td>
<td>-0.0612</td>
<td>0.0401</td>
<td>-1.5277</td>
<td>0.1271</td>
</tr>
<tr>
<td>LOCATION_STAR</td>
<td>0.0889</td>
<td>0.0402</td>
<td>2.2104</td>
<td>0.0274</td>
</tr>
<tr>
<td>RETAIL_STAR</td>
<td>-0.0171</td>
<td>0.0445</td>
<td>-0.3848</td>
<td>0.7005</td>
</tr>
<tr>
<td>FINANCE_STAR</td>
<td>0.0018</td>
<td>0.0425</td>
<td>0.0431</td>
<td>0.9657</td>
</tr>
<tr>
<td>MEDIA_STAR</td>
<td>-0.0322</td>
<td>0.0487</td>
<td>-0.6617</td>
<td>0.5084</td>
</tr>
<tr>
<td>EDU_STAR</td>
<td>-0.0248</td>
<td>0.0426</td>
<td>-0.5817</td>
<td>0.5610</td>
</tr>
<tr>
<td>HEALTH_STAR</td>
<td>0.0765</td>
<td>0.0439</td>
<td>1.7411</td>
<td>0.0822</td>
</tr>
<tr>
<td>TECH_STAR</td>
<td>0.0695</td>
<td>0.0440</td>
<td>1.5814</td>
<td>0.1143</td>
</tr>
</tbody>
</table>

R-squared          | 0.0507      | Mean dependent var | 0.0000      |
Adjusted R-squared | 0.0279      | S.D. dependent var  | 1.0000      |
S.E. of regression | 0.9860      | Akaike info criterion | 2.8343     |
Sum squared resid   | 606.6158    | Schwarz criterion   | 2.9458      |
Log likelihood      | -890.9774   | Hannan-Quinn criter. | 2.8776     |
F-statistic         | 2.2208      | Durbin-Watson stat  | 1.8939      |
Prob(F-statistic)   | 0.0050      |                     |             |