LUISS

Department of Impresa e Management

Course of Advanced Corporate Finance

A Multifactor Model to Improve Start-up Valuation

Prof. Raffaele Oriani

SUPERVISOR

Prof. Pierluigi Murro

CO-SUPERVISOR

Lorenzo Calanca

CANDIDATE

Academic Year 2019/2020

Page intentionally left blank

Table of Contents

Introduction

Venture capitalists are entities that provide capital to small and new enterprises, characterized by high risk-return trade-off. Given that 92% of start-ups fail, we can assume that the remaining 8% that survives need to ‘’hit it big” for an investor to make a considerable profit. Nevertheless start-ups, as private economic initiatives, are becoming increasingly important, not only for venture capitalists. Considering the relevance dedicated to this matter by both Governments and investors, there is a clear need to expand this research field. The start-up valuation area of expertise is still unclear. The analytical process of start-up valuation needs to take into account a huge variety of parameters, and usually the standard valuation approaches (as Income approach, Cost approach and Market approach) are either complex or ineffective in the first stages of this process. In fact, the reliability of the standard approaches grows progressively with the successful ageing of the start-up, when more historical data becomes available.

In this context, the main research questions that this thesis aims to answer is to identify the elements that drove Fintech start-up success between 2000 and 2018 in Europe and United States. Specifically, this research’s objective is to develop a multi-factor model to understand and predict the probability of success, which is essential for the robustness of the start-up valuation outcome. In conclusion, based on the findings of this work, I will be able to give some advice on how to employ the probability of success to improve the valuation of a start-up. The main purpose of this research is to help investors making better and more conscious investment decisions.

Performing an analysis of the literature provides interesting highlights concerning the elements that drive start-up success and their valuation. To begin with, Kohn (2018) reviewed the current state of the literature concerning the determinants of start-up valuation in the Venture Capital (VC) context. He provided evidences that start-up valuation is determined by the interaction of a) Start-Up; b) Venture Capital and c) External environment characteristics. Kohn’s observations shape the gap researchers need to fill in future studies. He highlighted the need to expand the geographical scope of the research field, involving other countries apart from the US. Furthermore, he pointed out how important would be, in future research, to analyse the determinants of start-up valuation and success considering all the aforementioned classes. In his conclusions, Kohn recognized that research so far "only scratched the surface" when we talk about determinants of start-up valuation and success.

Following that, Sanders and Boivie (2004) highlighted the importance of second-hand indicators of firm quality to evaluate a firm in new emerging sectors. Specifically, they found evidence that investors often use such indicators to make investment decisions under uncertainty conditions. Just to mention some of them: Corporate governance is linked to efficient organizations; the ability to tie business relationships with prestigious parties increases the chances of getting a higher valuation at IPO; an higher quality company will more likely be able to attract and retain talents on its board. What is important to highlight, is that investors will rely more on second-hand indicators of firm quality when uncertainty is stronger. As a result, we should trust more sophisticated tools to assess a company's value and potential performance as the industry/company matures.

Lastly, it is crucial to discuss the risk-return trade-off for investors when evaluating a new venture. To begin with, Cochrane (2005) examined whether VC investments behave in the same way as publicly traded securities. Next, Korteweg and Sorensen (2010), supporting the evidence of Cochrane (2005), built an asset pricing model that accounts for sample selection of observed returns. Specifically, they argued that when an asset is scarcely traded we observe a sporadic valuation of that asset. This sporadicness creates the so called "stale price" problem (the price of an asset does not reflect the latest available information), which biases the estimated price of the asset, its risk and return measures.

This study will focus on which parameters define success for a start-up and to what extent these parameters predict success on a reliable basis. According to this thesis a start-up is *a company which started its operations with a skeletal business plan, product, or service and may, or may not, have reached more mature stages*. Moreover I recognize success "when a start-up has experienced a liquidity event and so when is either: 1) acquired through an M&A deal; b) listed on the market through an IPO; c) achieved a target return." Cochrane (2005). My sample consists of 153 start-ups either alive, dead, acquired or public founded in Europe or United States. The sample period is from 2000 to 2018 and the main database used is CB Insight, provided by LUISS

Guido Carli University. However, this research topic required me to construct a database from different sources (e.g. LinkedIn, Crunchbase, Capital IQ, Bloomberg etc.). Relevant data was hand-collected from multiple origins to create the final database used for the purpose of this study. I chose to develop my model based on a logistic regression because of its desirable properties. Specifically, this econometric tool allowed me to restrict the probability outcome of start-up success between 0 and 1 by means of a non-linear transformation.

This study is structured as follows. In this section I gave a brief introduction of the topic and the relevance of the problem. Subsequently, chapter 1 provides an overview of the analogies and differences between start-ups and more mature companies. Subsequently, chapter 2 will present the current state of the literature; after that, chapter 3 gives a detailed and structured description of how the empirical analysis was conducted. Specifically, how the database was constructed, the definition of the relevant variables, some interviews as a robustness check, the inference findings from my analysis and the prediction model. Then, in chapter 4, I give some recommendations on how to employ the probability of start-up success to increase the robustness of its valuation. Next, I analyse the main limitations of my thesis and finally, I draw the main conclusions of my study.

Chapter I - An overview on Start-ups and their valuation challenges

In this chapter I introduce the main differences between start-ups and mature companies concerning different elements: financing, capital raising and dividends. Lastly, I point out the main issues concerning start-up valuation and the importance that success factors may play in achieving a more robust valuation result.

1.1 Start-ups and mature companies: analogies and differences

Academics have studied organizations for decades. Unfortunately, not much attention has been given to start-ups, even if almost all mature and public corporations started their activity from a start-up phase. The aim of this chapter is to understand the importance of start-ups and the main differences with respect to more mature companies.

If every business starts with an idea, there are many shades that characterize start-ups, depending on their current stage of development (Figure I). Usually a start-up begins with an idea from a founding team, which tries to fill an identified gap in the market. After that, this idea develops towards a more mature stage, where it is implemented in practice by realizing a new product or service. The latest stage is the one where the company is actually offering the product/service to the market and have the potential to achieve some profits in the future.

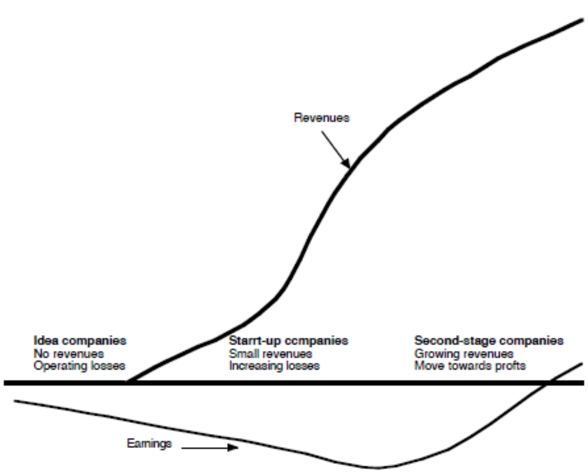

Figure I: The Early Stages of Start-ups Life Cycle, Damodaran (2009)

One of the main characteristics of start-ups is that they represent, from a value perspective, just a small portion of the overall economy. However, the impact they have on the economy is huge. Starting from an employment perspective, according to Forbes "between 1977 and 2009 start-ups contributed nearly all the roughly two million to three million new jobs created every year. Big companies contributed to no net new jobs.". This helps substantially Governments to achieve growth. Following that, start-ups are important to generate innovation. According to Christensen (1990), start-ups disrupt the market by developing new technologies and innovation. As the Harvard professor states, "it is impossible to achieve this level of innovation and disruption in an already established firm. Big companies have too much to lose from developing new innovative products or services, while start-ups have very little to lose". This is the reason why the retail disruption was led by Amazon.com, rather than an already established firm operating in that sector. Then, start-ups are essential to achieve economic growth. Specifically, according to Da Rin and Hellmann (2020) the "countries that grow the most are the one that have the highest number of newly founded businesses. That is how the US was able to grow constantly and maintain its role of western economic superpower." Moreover, nowadays start-up environment is positive thanks to national and local Governments. This implies that in the future we will probably register an increasing number of newly founded companies. Next, start-ups are important for investors to realize higher returns. In the current economic cycle, it is very complex to earn the high returns investors are looking for. One way to achieve this goal might be investing in start-ups. In conclusion, even if most of start-ups fail, the ones that survive may turn in successful company and contribute to the growth of the economy.

Start-up companies may be very different to each other. Many characteristics will be driven by both the industry in which the company operates and the condition of the market. However, according to Da Rin and Hellmann (2020) they share some common features. First of all, they have little or no history. When we try to evaluate a newly born venture, we have just few years of data (if we are lucky). This creates a wide range of problems. As Da Rin and Hellmann (2020) highlight "one common issue for investors is that standard valuation approaches (cost approach, income approach, market approach) are complex to apply". Then, start-ups generate small or no revenues (leading to frequent operating losses). Specifically, the first phase of a company is characterized by high cash-burning rates and low revenues. Moreover, initial costs are attributed to setting up the business, so are not very informative anyway. This implies that even if we have few years of data available, these data will not be very handy to understand the value of the company. Compared to more mature firms, almost all newly born ventures rely heavily on private equity financing. Initially, the founders and his network will fund the start-up. Afterwards, the company will need to get additional financing from private investors (VC and PE). Another element that characterize all start-ups is the high percentage of failures. This is due to many reasons. From lack of team quality, to high cash burning rates, loss of traction in early stage etc... It is important to say that the survival rate of start-ups will vary across sectors and industry, according to their potential.

Following that, another common element that characterizes all start-ups is the multiple claims on equity. According to Da Rin and Hellmann (2020) "usually start-ups issue different kind of equity instruments, according to the stage and financing needs". The investors who invested in the first stages will try to protect their interests when the company issues a more favourable equity instrument in form of first claims on cash flows. Lastly, as we know, start-ups are not publicly traded, hence the investment in these companies will be very illiquid. This has many consequences, one of the most important is the higher risk that investors bear when they make such investments.

1.1.1 Financing

One of the main differences between start-ups and more mature companies is the way they finance their operations. This will depend, for instance, on whether the firm is publicly traded or not and which stage of the life cycle the company is currently experiencing. In fact, when a firm is private it has a restricted range of choices concerning its financing, which is usually far more expensive. According to Damodaran (2013) "to solve the scarceness sources of financing, the management team of a newly born venture usually has to involve a Venture Capitalist or get new financing from the owner in order to finance its operations". On the contrary, more mature companies, and specifically publicly traded ones, have a wide range of choices when they need to make financing decisions. Starting from Equity, Damodaran (2013) identified many ways that can be used to finance a venture rather than just common stocks:

1) Owner’s equity: these are funds provided from the founders to the company
2) Venture Capital and Private Equity: after developing what was initially a small business, the owners need to find additional funds to continue their operations. They usually find support in VCs or PE funds. These actors invest in highly risky companies by acquiring a share of the ownership. In exchange, given that the majority of their investments will be unsuccessful, they require a high return, given their high bearing risk. I will get to this topic in more detail during the literature review.
3) Common Stock: this is the most common way that publicly traded companies use to raise new equity. The price of the common stocks is just the price that the market is willing to pay to acquire one share. When a company is listed for the first time it is called Initial Public Offering (IPO).
4) Warrants: are frequently used by small companies. By issuing warrants the company commits to sell stocks in the future at an agreed fixed price
5) Contingent Value Rights: give the owner the right to sell the stock at an agreed fixed price (like a put option)

There are many ways to realize debt financing. As for equity, we have some differences and preferences between start-ups and more mature companies:

1) Bank Debt: this is the most used source of borrowing for private and public companies. Borrowing provides several advantages for a company: a) borrow low amount of money; b) allows the lender to get to know the company better and adjust the loan’s costs; c) does not need the assignment of any rating. Usually banks do not lend to start-up companies as they require assets as collateral.
2) Bonds: usually cheaper than bank debt, as the risk is usually shared by a plethora of investors. Moreover, bonds allow the firm to personalize the offering (e.g. convertible bonds).
3) Leases: usually known as financing leases, this way of financing is very common for its desirable features. Specifically, it allows to buy an asset and pay instalments and interests following a fixed schedule.

Other than Debt and Equity, we have Hybrid Securities, which have some common features with both of the abovementioned categories:

1) Convertible Debt: is a bond that can be converted in a predetermined number of common stocks. This is more attractive as the stock price increases.
2) Preferred Stock: holders of this kind of security give up their control rights to achieve higher economic rights. Specifically, their claim is satisfied after debtholders and before the other equity holders.
3) Option-Linked Bonds: this instrument is just a normal bond, combined with a call option on the stock.

Broadly speaking, there are two ways a company can finance its operations: a) Internal Financing: financing available thanks to the cash flows internally generated by the assets owned by the company ; b) External Financing: cash flows that come from outside the firm and are not generated by its assets, hence equity, debt and hybrid securities.

There are many reasons why a firm may prefer one source of financing rather than the other one. Internal financing, for instance, has many benefits but it is more difficult to raise for start-ups. Companies which are experiencing this lifecycle phase are not able to generate the level of internal cash-flows needed to sustain their operations. According to Damodaran (2013) this happens for many reasons as "usually start-ups are very innovative companies, which need to flow skyrocketing amount of cash flows to their R&D divisions. Moreover, they usually have small market share at the beginning of their operation". For this reason, such companies experience negative earnings even for very long periods of time before becoming profitable (e.g. Tesla). When a company is experiencing such stage of development, it needs to find external financing sources. Usually, in this stage, external financing sources are very difficult to raise and are not seen favourably by the founding team. The reason is simple: external financing (for example by involving a Venture Capitalist) implies a loss of control (as the VC will become a shareholder of the start-up). This discussion is different for more mature companies. Raising external capital for these organizations is much easier, even if still costly.

Due to these differences, the way companies choose to finance their operation will vary widely. Specifically, according to the phase of development which the company is experiencing, there will be a different source of financing. For instance, when a company matures, its cash flows become more stable and predictable, the company grows, and the high risk declines steadily. According to the following table provided by Damodaran, we can see the main sources of financing for each stage of the company's lifecycle:

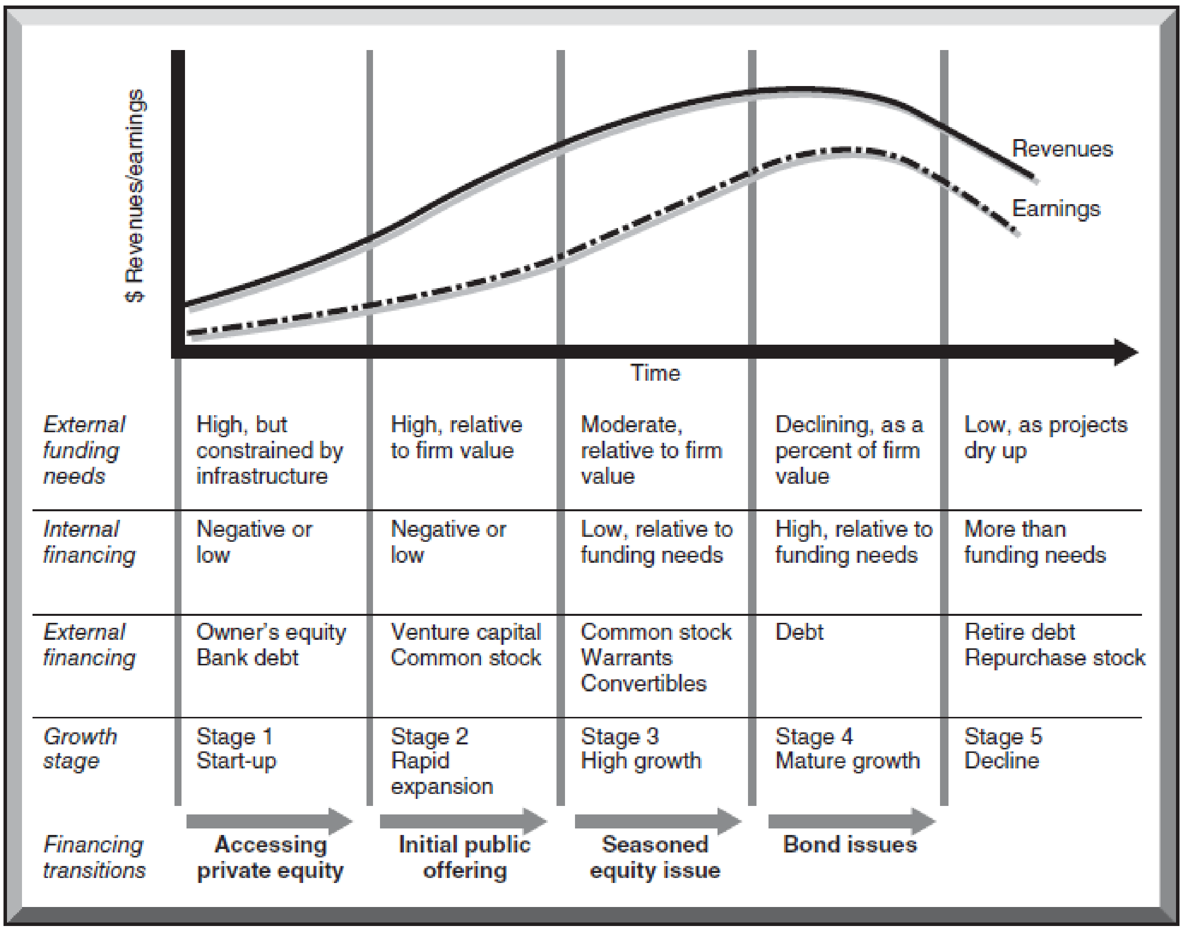

Figure II: Life Cycle Analysis of Financing. Damodaran (2013)

We can analyse these identified 5 stages of a company life cycle:

1) Start-up: is the initial phase of development of a company. Usually this kind of ventures are private and financed by means of owner's equity. Start-ups will rarely use debt as a financing source. Debt will be employed the most when a company's cashflows will become steadier and more predictable. This is due to many reasons. For instance, the tax

benefit from debt is non-existent in this phase, mainly due to the low or negative earnings. We have also studied the importance of debt as a disciplinary mean to reduce agency problems between shareholders and management. However, this instrument is not useful in this case, as the owners usually participate actively to the management of the company. Moreover, banks are reluctant to lend money to such unstable private initiatives.

2) Expansion: in this phase the company has grown and needs to expand. To achieve this goal the venture will finance its operation through external financing, as the internal generated cash flows will not be enough to sustain the cost needs. During this phase, the owners of the business will try to find financial support from either VC or PE. Alternatively, other firms will start their IPO process and get additional funding on public markets.
3) High growth: they are mostly publicly traded companies. These firms will have much broader financing choices with respect to the first two categories (e.g. common stock). During this phase, revenues will grow fast, while earnings will lag behind. The most used instruments to raise capital during these phases are common stocks, warrants and convertible debt.
4) Mature growth: as the company matures, both revenues and earnings increase, while the need to find new investments decreases. During this phase internal funding should be enough to cover the majority of the overall funding needs.
5) Decline: in the last stage of start-up life cycle the firm will experience a substantial decrease of both revenues and earnings. Moreover, the need to find additional investments will decline. According to this, the internal financing will exceed the investment needs. For this reason, companies in this phase will not issue new stocks or bonds but will rather start paying out dividends or buying back stocks.

According to Damodaran (2013) “not all companies will pass these 5 stages” for many reasons. Firstly, some of them will stop operating after the initial phase, due to the high failure rates. Secondly, other companies will never go public even if they continue to constantly grow strong and healthy. Thirdly, some companies will be able to produce a sufficient level of internal financing, such that no external funding needs will arise. In summary, there are many exceptions to the above illustrated framework. However, the designed company's lifecycle is still useful to better understand the needs and differences between the strategies they employ during their life.

1.1.2 Attract capital

From Figure II we understood the key role that VC and PE play for new-born ventures. The way start-ups attract new capital is very different from the way more mature companies do it. As we can see from Figure III, there are many stages of private equity financing, depending on the phase the company is currently in.

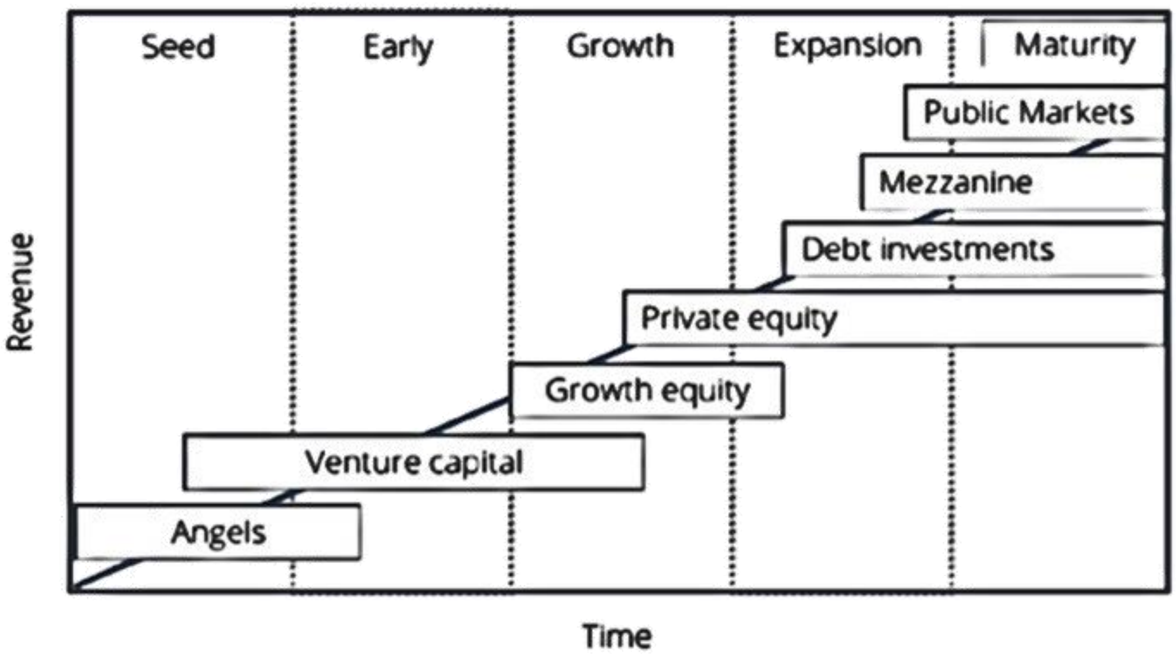

Figure III: Private equity investment stages. Damodaran (2013)

Raising new financing is a very different process for start-ups compared to more mature firms. First of all, "start-ups need to provoke equity investor interest" Berk, Green and Naik (2004). There are many new-born companies out there, for this reason it is crucial to differentiate their idea from others. There are two elements that will help the start-up during this phase. Firstly, the attractiveness of the industry, secondly the team quality. Then, the potential investor will evaluate the company and assess its potential return. This is a crucial and complex phase that will affect the future of the company. After that, the involved parties will structure the deal. Specifically, the VC and the company will have to agree on two things: a) the proportion of the company that the VC will demand for the requested investment; b) the VC will set some milestones that need to be achieved to get new financing. Next, we have the post-deal management. After the investment is made, the VC will be an active actor in the management of the company. It will put its knowledge and network on the table to help the start-up grow. Lastly, at some point in the future, the investor will exit the company. There are three ways VCs and PEs can profit from investing in a newly born firm: a) Achieving the public listing (IPO) and sell their shares on the public markets; b) Sell their holdings to another party; c) Liquidation.

1.1.3 Dividends

Another important difference between mature companies and start-up companies concerns the dividend policy. As for financing need, companies will adopt different dividend policies according to the life cycle stage they are currently in. For example, a company which is experiencing a high growth phase will benefit more from investing their funds in new investment opportunities, rather than pay them back to their investors. On the other hand, a more mature company which has few investment opportunities and is not able to undertake investment opportunities that yield a rate of return higher than the cost of financing will benefit more from paying back funds to its investors, as we can see from Figure IV.

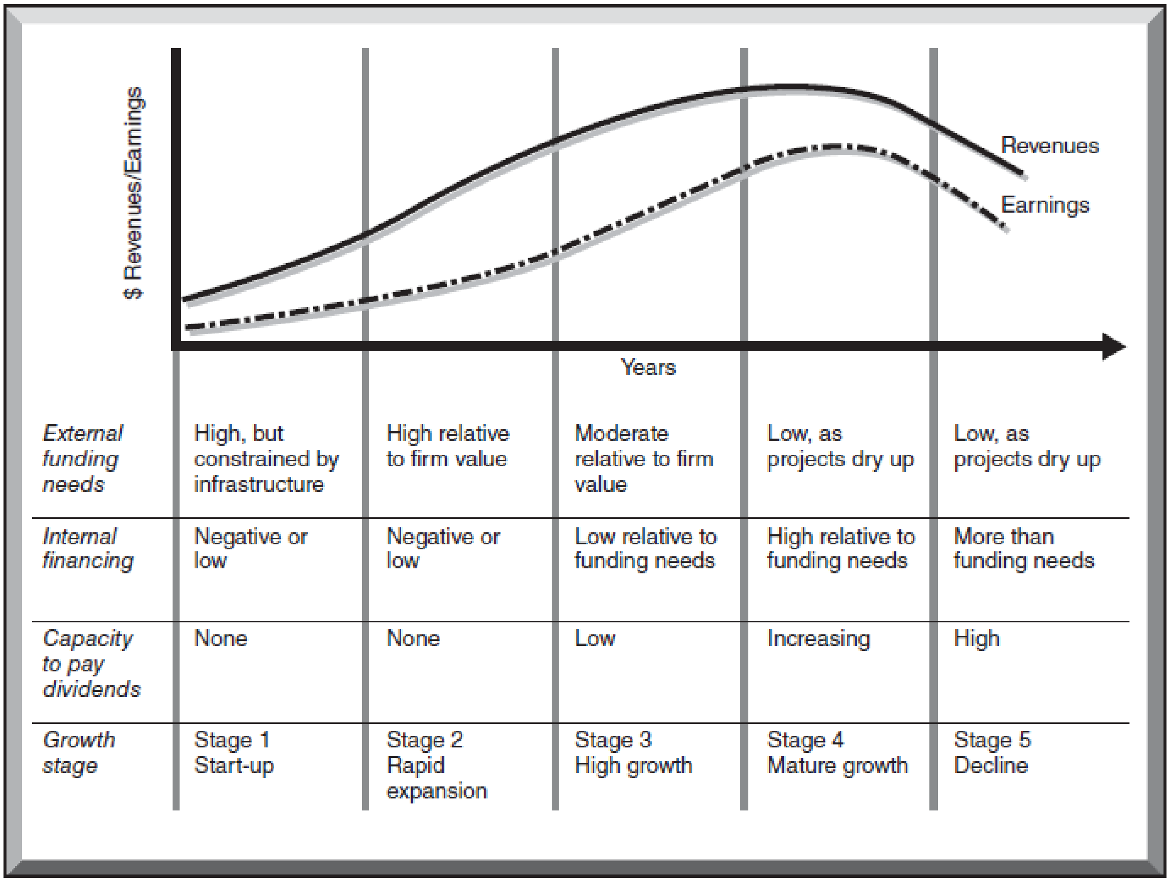

Figure IV: Life Cycle Analysis of Dividend Policy. Damodaran (2013)

1.2 Valuation challenges

Compared to more mature companies, it is much more difficult to value a start-up. This is mainly due to the critical factors that we analysed during this chapter. The valuation of a start-up at a certain moment in time is very important. However, their valuation is complex and the standard approaches we use to value a mature company (Income, Market, Cost approaches) are quite complex to apply. Specifically, the robustness of the valuation outcome is an issue, since there are many relevant parameters that can have an extreme impact on the value, leading to a wide range of potential valuation outcomes.

1.2.1 Income approach

Starting from the Discount Cash Flows (DCF) approach, there are many elements that we have to take into account to valuate a company. Each one of these elements has an additional degree of complexity if we are trying to evaluate a start-up. Starting from *cash flows from existing assets*, start-ups are characterized by very low levels of assets. In addition, firms in these stages provide little information about them, mainly due to a lack of historical data. Furthermore, also *cost levels* are not extremely informative in the first stages as they are usually needed to generate the current level of revenues. For this reason, we have to adjust the expenses such that we can distinguish between operating and non-operating ones. Then, we usually need to compute the *expected growth* of a company. This measure usually comes from the so called "growth assets" which are the core of a start-up's value. When we are evaluating a start-up, we cannot use past growth to estimate future revenues, as we lack past history data. Even if we would be able to forecast *revenues* in some ways, we would also have to understand how the *earnings* will evolve in the future. Usually, when we need to assess the growth of a mature firm, we analyse how much the firm has to reinvest to generate a certain growth level. A company is growing if the Return on Capital (ROC) is greater that its Cost of Capital (CoC). However, in start-ups the ROC is usually lower than zero. In summary, it is very difficult to estimate start-up growth. Following that, we need to compute the *discount rate*. In order to do so, we compute the beta, cost of equity, cost of debt and capital structure of a company. However, these data are not available when we talk about private companies. Additionally, as Damodaran points out "the equity in a young company is often held by investors who are either completely invested in the company (founders) or only partially diversified (venture capitalists). As a result, these investors are unlikely to accept the notion that the only risk that matters is the risk that cannot be diversified away and instead will demand compensation for at least some of the firm specific risk". Lastly, we need to compute the *Terminal Value (TV).* Terminal value calculation is extremely important when we value mature companies. However, it is even more crucial when computing the valuation of a young firm. In this case, the TV can even account for the 90% or 100% of the current value of the company. Consequently, the assumptions that we make about future growth will be crucial and will make a big difference on the final result.

As we have seen, we have many difficulties when applying DCF valuation with many risky elements not quantifiable. Practitioners usually solve this issue by increasing the Weighted Average Cost of Capital (WACC) to abnormally high levels in order to get reasonable cash flows. This is usually done by including a spread in both cost of equity and debt. However, this approach has many drawbacks. Firstly, valuation is extremely sensitive to: the WACC and the management assumptions coming from the business plan. Specifically, even a small change in one of those elements has a huge impact on the valuation of a start-up. Secondly, this approach systematically penalizes long-term projects. This is due to the fact that an abnormally high WACC will decrease exponentially the discount factor with time. Thirdly, it is very complex to include all the riskiness of the business in the WACC. This can lead to significant valuation errors.

1.2.2 Market approach

This may lead to the conclusion of employing a Relative Valuation approach (Market approach). However, this estimation method may be difficult to apply for many reasons. Firstly, we need to understand what do we scale value to. All multiple measures need to be scaled to some measure (e.g Earnings, Book Value, Revenue etc..). However, young companies usually have negative measures and common multiple measures cannot be computed (e.g. P/E, EV/EBITDA etc..). Book Value is usually very small, due to the fact that we are currently in the first stages of a company development. Also revenues can be useless because non-existent or too small to be relevant. Then, we need to understand which are the main peers. Usually, with more mature companies we use publicly traded firms in the same industry. For young firms, the best comparable companies are the ones in their same stage of maturity. However, they are usually private, so we have an information issue. After that, we need to assess which is the best proxy for risk. Specifically, for mature companies we use beta and standard deviation to assess the risk of a company. However, this is not possible for young companies. Lastly, we need to deal with differences in equity claims and illiquidity. As in the DCF approach we need to face the illiquidity issues as well as differences in the claims of different investors.

1.2.3 Cost approach

According to Titman (2016) “The cost approach uses the concept of *replacement cost* or *reproduction cost* as an indication of Fair Market Value”. Concerning the former, this approach is based on the assumption that an average market participant would pay no more for an asset than the amount for which the asset could be replaced with an asset with the same utility as the asset being appraised. Concerning the latter, the cost approach will assess how much does it cost to build the same asset/business from scratches. Between the 3 approaches discussed so far, this seems to be a good proxy of start-up valuation. However, the Cost Approach does not account for the potential that highly innovative companies have, leading to undervaluation on many occasions.

1.2.4 Current valuation approach and the success factors

Now we have a clearer view of the issues arising from start-up valuation compared to more mature companies. Like for well-established corporations, there are many ways to arrive to a final valuation concerning start-ups. For instance, the current valuation approach developed by Duff & Phelps consists in computing the start-up value coming from the Income approach and Cost approach and get a range of possible valuation outcomes, as shown in Figure V. Moreover, practitioners usually employ the market approach as a valuation check when data are available.

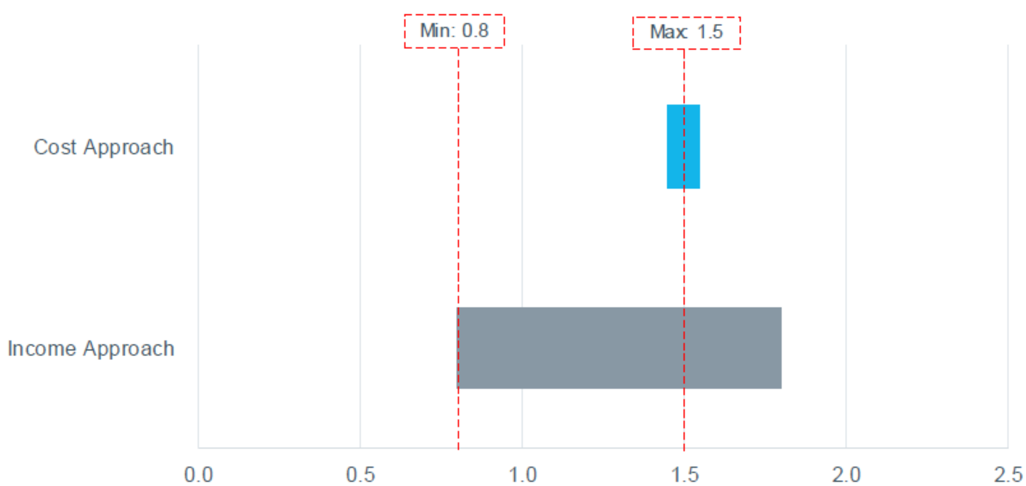

Figure V: Start-up valuation approach employed by Duff & Phelps. Numbers are exemplificative.

However, as we can see from Figure V, the valuation outcome is usually very wide. This is mainly due to the broad valuation range coming from the income approach when testing different scenarios. Specifically, the main issue of this approach is that all the risk associated to start-ups operation is embedded in the WACC. The main consequence of this methodology is that cashflows are discounted at high WACC levels (e.g. 40%-50%). For this reason, even a small change in the WACC will cause a huge increase or decrease of the valuation outcome. Contrary to Duff & Phelps, other actors may apply different approaches to start-up valuation. For this reason, Kohn (2018) said start-up valuation, "is more art than science. In view of this, it is particularly important to be aware of and understand the different underlying determinants that affect the valuation of startups". According to the author, many elements that have an impact on start-up valuation are linked to its *probability of success*. Consistently to Kohn (2018)'s view, many researchers tried to find some correlations between start-up characteristics (e.g. team composition, investor characteristics, external environment characteristics) and start-up success in order to develop a more accurate model to estimate the value of a start-up. According to Damodaran (2009), one way to improve this process is build a multifactor model to predict start-up success, apply it to the valuation process and get a more robust result, as demonstrated also by Cochrane (2005).

As I will show in the fourth and last chapter of this thesis, there are many ways to employ the probability of start-up success to improve its valuation. One possibility is to compute a valuation based on the weighted average between the income and cost approch; another way is to compute a weighted valuation between the going concern valuation coming from the income approach and the distress sale valuation, as suggested by Damodaran (2009); lastly, we can weight the cashflows coming from the income approach valuation by the probability of success and get a more reliable estimation. This methodology is based on the findings of many academics, like Titman et al. (2016) and Damodaran (2013), concerning risk incorporation during the valuation process. According to the authors, adjusting the cash flows is, academically speaking, a more correct approach.

In summary, start-up valuation must take into account a huge variety of factors compared to more mature companies. One way to increase the robustness of its valuation, is study the broad range of parameters that affect the probability of start-up success and consequently its valuation.

Chapter II - Literature review

The identification of relevant literature concerning start-up success factors was conducted in a systematic way through the Web of Science tool. This analysis is based on some of the most relevant papers on which I structured my work. Since there are many elements of interest concerning start-ups, I decided to structure the literature review in sub-paragraphs. Based on the literature review findings I formulated different hypothesis that I will test empirically in chapter 3.

2.1 Start-up valuation

In Kohn (2018), the author developed a review of the current state of the literature regarding start-up valuation. Particularly, with his work, he provided a conceptual framework that will guide researchers in their analysis of start-up valuation and success. He found that start-up valuation is determined by the interactions of the following determinants of a) Start-ups; b) Venture Capitalists; c) External Environment. For each of these determinants, he presented the key elements that influence start-up valuation. Concerning Start-ups elements, the author identified the start-up characteristics (e.g. industry and location), founder and team characteristics (e.g. team quality), intellectual property and alliances (e.g. number of patents filed) and financial information quality (e.g. accounting information). Of further relevance are the findings of Hsu (2007), who demonstated how entrepreneurs who achieved an IRR of at least 100% at an exit event in a previously founded start-up, achieved a higher valuation for their newly incorporated venture. Moreover, Wasserman (2016) found evidence that founders with previous incorporation experience achieved larger valuations compared to founders who didn’t. As I said earlier, Venture Capitalists elements play a crucial role in start-up valuation and success. According to Kohn (2018) study, VC Reputation is recognized, from the current state of the literature, as a key element in assessing start-up quality. Interestingly, Fitza et al. (2009) found out that VCs can also have a negative effect on start-up performance. These evidences highlight the importance and the impact, either positive or negative, that a Venture Capital can have on a new venture.

Next, the author identified external environment determinants to start-up valuation and success. Market factors, like demand and supply or public market valuation are viewed as a signal of a venture's potential success. Additionally, also institutional and cultural factors play an important role in start-up valuation and success, increasing the importance that external factors have with respect to contingent factors related to the start-up itself or the Venture Capital investor. Another interesting external element which has an impact on start-up valuation, as reported by Kohn (2018), is the fund inflow in the VC industry. This determinant was studied by Gompers and Lerner (1999) who showed the influence of fund inflows, as well as other elements, on venture capital's investment pricing. Specifically, they implemented an OLS regression where the dependent variable is start-up valuation and the independent variables are various start-up characteristics (e.g. age, stage of development, industry, inflows into venture capital funds). One of the most interesting regressor used in this study is the public market valuation variable. Specifically, the authors designed different industry indexes as a measure of industry investment opportunity. Firstly, they assigned, to each start-up in their sample, an industry SIC code. Secondly, they downloaded data about the companies that went public and had one of the SIC codes in their sample. Finally, they constructed two valuation measures based on this information. The first one was an equal and value weighted industry stock price index for each industry SIC code in their sample. The second one, was based on building price-earnings and market-to-book ratios to estimate market equity values. In their final paragraph, the authors concluded that the relation between market demand and start-up success is positive. According to their finding I decided to test weather market dynamics have an effect on start-up success:

> **H_1**: *Founding a start-up when there is more market demand, increases the probability of start-up success.*

In conclusion, Kohn's observations shape the gap researchers need to fill in future studies. He highlighted the need to expand the geographical scope of the research field, involving other countries apart from the US. Furthermore, he underlined that all studies so far rely too much on VC database, which disregards the valuation process itself. Then he pointed out how important would be to analyse the determinants of start-up valuation and success considering all the 3 classes identified above. In his conclusions, Kohn recognized that research so far "only scratched the surface" when we talk about determinants of start-up valuation and success.

As a matter of fact, the start-up valuation process is difficult to improve mainly because of information asymmetries. This issue gets even more complicated when evaluating a start-up in an emerging sector. The main consequences of this agency problem are adverse selection and moral hazard. Sanders and Boivie (2004) highlighted that in emerging economic sectors, where key metrics of venture quality are scarce, investors use observable secondary sources of information when investing in a start-up. One of the main indicators of firm quality in these new businesses is corporate governance. This is mainly due to the fact that correct corporate governance mechanisms are linked to efficient organizations. Furthermore, other researchers have suggested the efficiency and effectiveness in using secondary indicators of quality. Specifically, they highlighted the importance of having relations with prestigious parties in determining the perception of firm quality. There is evidence, also in previous literature (Stuart et al. 1999), of a positive relationship between make partnership with either strategic partners or high reputation venture capital and achieving a higher valuation at IPO. Concerning VC backing, the authors (Sanders and Boivie 2004) stressed how critical it is, among high-risk start-ups, to be supported by such investors. This is mainly due to resource access, especially in the first stages of the venture. With resource access they refer to, for instance, fundraising capabilities, a broad industry knowledge and access to a high-quality network of potential new investors and skilled workforce. Specifically, the researchers argued that being VC backed may be considered as a positive signal from other investors who are trying to fight agency problems in new and emerging industries. Another measure of venture capital belief of company's quality is represented and modelled by the researchers as the commitment of the VC after IPO. Accordingly, when venture capitalists sell relevant fractions of their investment in the company after it went public, this is considered to be a negative signal to external and potential investors. Moreover, also the Board of Directors structure is an important second-hand indicator of start-up quality. This is mainly due to the fact that an independent and active board plays a crucial role, especially in a small and new-born firm in an uncertain market. Additionally, higher quality firms should have an easier time to attract and retain talents in their board of directors. For this reason, the structure of the board is often used by investors as a second-hand indicator of firm quality in uncertain context. By performing the relevant analyses, the authors found empirical evidence of the important role that second-hand indicators of firm quality play for investors. This is relevant especially in emerging segments like internet-related industries, where investors are trying to evaluate a new venture. What is important to highlight, is that investors will rely more on second-hand indicators of firm quality when uncertainty is stronger. As a result, we should trust more sophisticated tools to assess a company value and potential performance as the industry/company matures.

Following that, Gornall and Strebulaev (2020) stressed both the importance of VC investments to realize growth and the complexity of the start-up valuation process. This is mainly due to the difficulty of evaluating a company in a new emerging sector, as well as taking into account the complex capital structure of the company itself. The latter is caused by the intrinsic characteristic of new ventures, which issue different class of equity every one/two years when they raise new financing. The valuation implications that this crucial difference has on newly born ventures and public companies is very hard to understand for outsiders as well as insiders. This is due to several reasons. Firstly, the shares issued by start-ups are very different from common stocks, debt and securities traded on the financial markets. Secondly, the issued shares are different not only from company to company but also between the financing rounds of the same company. A common measure of start-up valuation is the post-money valuation. According to the authors this measure is not correct as it assumes that all shares are worth the same, while in reality some classes may give the owner desirable rights which are valuable for him. The researchers studied 135 US unicorns (valuation above $1 billion) and developed a valuation model that accounts for the financial terms of the share subscription. According to their findings, on average, the analyzed unicorns are overvalued by 48%, while 14 out of 135 are 100% overvalued. After adjusting for the inflated valuation (as reported by the company), half of the sample lost its status. What the authors showed with their work is that start-up valuation is extremely sensitive to the contractual terms that investors negotiate. While just a small portion of these investors know these terms (because they are the ones who negotiated them) the remaing part experience problems to understand what effect these terms have on the final valuation. The concern of the authors, which is shared by the SEC, is that companies will try to use these terms to appear more valuable then what they are.

2.2 Success factors

As we have seen in Chapter 1, we can increase the robustness of start-up valuation by identifying and understanding the main factors that have a significant impact on its success according to the current state of the literature. A plethora of researchers studied the elements that cause success and failure of new ventures. For instance, Roure and Keeley (1990) found evidence of three main factors. The first one is the founding management. The founding team can be either an individual or a team. According to the authors, the founding team skills should influence performance as possessing a higher number of skills can lead to taking better decisions and avoid, on average, committing mistakes. Another key element in start-up performance related to the founding team concerns the number of components of the founding team. According to the authors it should be large enough to perform its task, but not too much. For this reason, I decided to test empirically the following hypothesis:

> **H2:** *Larger entrepreneurial teams have higher probability of start-up success.*

Other two elements distinguish successful and unsuccessful ventures concerning the founding team characteristics: 1) the degree of completeness. Hence whether the founders have complementary skills; 2) whether founders worked together before start-up foundation.
According to these findings I chose to test different team characteristics hypotheses and check whether they have an impact on start-up success. Firstly, I will test the skills of the founding team:

> **H3:** *Studying in a more prestigious University increases the probability of start-up success.*

> **H4:** *Achieving a higher education title increases the probability of start-up success.*

Secondly, how the team gets along together:

> **H5:** *Founding a previous start-up together with one or more members of the current founding team increases the probability of start-up success.*

> **H6:** *Attending University together with one or more members of the current founding team increases the probability of start-up success.*

H7: *Having a previous work experience together with one or more members of the current founding team increases the probability of start-up success.*

H8: *Achieving a previous venture success increases the probability of start-up success.*

Concerning how the team gets along together, Roure and Keeley (1990) found positive sides, like complicity and knowledge of the team, as well as negative sides, like common backgrounds, which may lead to decrease the level of diversity across the team. Moreover, a higher number of founders could mean, according to the authors, a higher quality network. This could influence the company's funding possibilities. The second key element of start-up success is the environment in which the new venture operates. In particular, the structure of the industry, as well as the competition level, are recognized as extremely relevant factor that contribute to start-up success or failure. Lastly, the strategic choices of the company, like product policy and technological advantage, are key determinants of a new venture success. In their conclusions, the authors suggest that success in new ventures can be explained using organizational, industrial and strategic theories. Morover, they advice that success can be predicted, with some limitations, using simple regressors and such predictions can be replicated across time and across samples, allowing to identify trends and shifts in the relative importance of variables.

Another relevant contribution to the literature concerning the determinants of start-up success is given by Song et al. (2008). The authors performed a meta-analysis of the current state of the literature regarding the successful factors of New Technology Ventures (NTVs). A meta-analysis is a statistical analysis from a number of independent studies which try to answer the same question. The main reason why they performed such a study is due to the extremely fragmented and controversial results that previous studies have found. From conducting the meta-analysis they found 24 factors related to NTVs' performance which can be divided in 3 main cathegories: 1) Market and Opportunity, 2) Entrepreneurial Team, 3) Resources. Of these 24, 5 have no significant effect on technology venture performance:1) R&D experience, 2) Prior start-up experience, 3) Enviromental dynamism (high pace environment), 4) Environmental heterogeneity (diversity and complexity of the environment), 5) Competition intensity. 11 out of 24 factors are important depending on the situation (i.e. not statistically significant). Only 8 out of 24 of these factors are considered significant and homogeneus across the different literature studies. Concerning the market and opportuny, only the market scope seems to be homogeneous and significant. Concerning the entrepreneurial team: a) Industry experience, b) Marketing experience. Lastly, concerning the resource cathegory, the researchers found 5 relevant and homogeneus factors predicting start-up success: a) Financial Resources, b) Firm Age, c) Patent Protection, d) Size of Founding team, e) Supply chain interegration. The authors suggested to take the developed framework into account for future research.

More insights were provided by Bernstein, Korteweg and Laws (2017) as they analysed the main start-up characteristics that drive early-stage investments. Specifically, the authors studied the criteria that early-stage investors take into account the most when they have to make investment decisions. Financing early-stage start-ups is a very difficult job for many reason. Uncertainty is king when we talk about start-ups as that they don’t have tangible assets that can be used as collateral and are characterized by high information asymmetries (adverse selection and moral hazard). All these elements do nothing but increase the riskness of early-stage investors compared to later stage ones. To begin with, the authors concentrate their studies on 3 main start-up characteristics: a) founding team; b) start-up’s traction; c) current investor characteristics. To understand which of these factors are the most important for early stage-investors the researchers employed a randomized field experiment. According to their findings, the most relevant element of early-stage investments is the founding team. This is due to many reasons, like the ability to raise capital, which is extremely important especially in the first stages, or the communication skills of the team, which are needed to differentiate the quality of their idea. What is interesting to point out is that investors not only care about team information for quality signal reason, but also because team composition and characteristics are relevant for operational reasons. Even more interestingly the authors have found evidence that the most successful investors reacted to team informations only. This suggests that team-based investing can be a viable and profitable strategy. Of course these results do not mean that other factors are not important to attract capital and achieve success for a newly born start-up. The findings of Bernstein, Korteweg and Laws (2017) also highlight the importance of investor characteristics as determinants of start-up success.

According to this, I decided to test empirically different hypotheses concerning investor characteristics in order to investigate their impact on start-up success:

> **H_9:** *Being backed by a Venture Capital firm increase the probability of start-up success.*
>
> **H_{10}:** *Being backed by a Venture Capital firm with a higher reputation/experience increases the probability of start-up success.*
>
> **H_{11}:** *Being financially supported multiple times by the Venture Capital with highest reputation/experience increases the probability of start-up success.*

One of the main elements of team quality is diversity. Concerning the latter, Aggarwal, Hsu and Wu (2020), despite recognizing the positive effect of individual-level knowledge diversity on firm's innovation, identified the need to investigate the impact of intra-firm diversity knowledge on knowledge recombination process. The authors based their study on US VC-backed biotech ventures. First of all, the researchers clarified the difference between within-team knowledge and across-team knowledge diversity. The former is a measure of the degree of different individual knowledge that an average team member has inside a venture. So this is a more individual measure of knowledge inside the firm. While the latter represents the degree of different team knowledge with respect to other teams in the firm. Hence, this is a more team-based measure of knowledge inside a company. With their study, the authors showed that knowledge diversity at the within-team level is associated with lower levels of producted innovation. On the other hand, an higher level of knowledge diversity at the across-team level has a positive and significant effect on the production of innovative output. This research has several implications. Firstly, the authors suggest that the more a team has within collaborative experience, the more likely they will draw upon knowledge developed by other teams in the firm. Secondly, in order to create knowledge related output, the sub-units inside a firm need to access information and knowledge to generate new one. This highlights the importance of human capital organization to increase the efficiency and effectiveness of new knowledge production. Thirdly despite recognizing the importance of individual knowledge, the authors stressed the key role that across-firm teams information sharing has on the final firm outcome. Finally, the authors showed the importance of human capital design as a source of competitive advantage. They stressed the importance that the team plays in a new venture, especially in our times where innovation can make a difference between success and failure. With their work, Aggarwal, Hsu and Wu (2020) contributed to highlight the importance that highly inventive human capital play in the innovation process.

2.3 Risk-return trade-off

In the context of VC investments and start-up valuation, it is crucial to discuss the risk-return trade-off for investors when evaluating a new venture. Specifically, in order to recognize an investment in a start-up as successful we need to better understand the risk and return dynamics that characterize start-ups as a whole. To begin with, Cochrane (2005) examined whether VC investments behave in the same way as publicly traded securities. As a result, the main objective of his research was to compute the return of VC investment and investigate whether there was any difference with trading securities. This can happen for many reasons. Firstly, due to the possible higher return that investors may require based on illiquidity and other characteristics of VC investments. Secondly, because VC, and more in general private equity, investment represent a big portion of an investor's wealth. Finally, because of the monitoring and control function that the VC performs in the venture. The author computed a return if the company got a new financing round, went public (IPO) or was acquired (hence achieved an exit opportunity for the VC). He then computed the mean, standard deviation, alpha and beta of VC investment before and after correcting for selection bias and found a significant difference. In his work, Cochrane used a maximum likelihood estimate that corrected for selection bias when computing the return. Overcoming this bias was crucial in order to estimate an unbiased measure or return for VC investments. He noticed that we can observe a return only when a firm achieves an exit opportunity, but this should not bias our estimated return measure. To achieve this result, he computed the probability of seeing the data he collected from VentureOne by means of a logistic function. He built this function as follows: Pr(new round at t| V_t) = 1/[1+e^(-a(ln(V_t)-b))] where Vt is the company value. He then modelled growth as a log normally distributed variable and simulated the probability of IPO, acquisition or getting a new financing round of 1$ investment according to the logistic and growth function he built. By doing so, he was able to create a probability structure of the data and compute the unbiased moments of VC investments. Finally, after applying this correction he concluded that VC investments are very similar to traded securities. However, he admitted the crudeness of his selection function, as it depends exclusively on firm's value. According to him, further research should take into account different determinants of start-up success, other than only the valuation of the company itself.

Next, Korteweg and Sorensen (2010), supporting the evidence of Cochrane (2005), built an asset pricing model that accounts for sample selection of observed returns. They argued that when an asset is scarcely traded we observe a sporadic valuation of that asset, hence measure a return only when that asset is traded. This sporadicness creates the so called "stale price" problem (the price of an asset does not reflect the latest available information), which biases the estimated price of the asset, its risk and return measures. Moreover, the authors identified a sample selection issue related to these assets. Their study is focused on Venture Capital investments in start-up companies and it is aimed at solving for sample selection. In this context the sample selection problem arises because we can observe a valuation for a new venture only when it experienced a liquidity event (new financing or exit). This is more frequent for companies which are performing well, hence have more probability of survive. The authors proposed a new methodology to account for this sample problem. The model they developed was able to compute the unobserved valuation (as well as the return) between two observable valuations. Correcting for this bias reduced the intercept and increases the risk exposure estimates of entrepreneurial investing. Moreover, they distinguished between investments depending on the stage of maturity in which the company was. By doing so, they found higher alphas for seed investments and lower alphas for more mature stage investments. According to the researchers, this is a starting point to understand the risk and return of entrepreneurial investing. However, as the authors noticed, their alpha estimates may not be a correct proxy of VC return. This is due to several reasons: a) investments are illiquid and are characterized by high systematic risk which is specific to VC investments; b) their returns are gross, and do not account for fees and other expenses; c) investments are not independent; d) investors prefer higher dollar-weighted returns.

Following these findings, Sorensen, Wang and Yang (2014) investigated the risk-return trade-off of private equity (PE) firms. While it is commonly recognized that, on average, PE firms earn an higher return compared to the market, the authors investigated whether the performance of PE investments was enough to compensate for both the risk that PE firms bear and its long term illiquidity. To answer their research question, the researchers developed a model which took into account different characteristics concerning private equity investments (illiquidity, riskiness, management fees and high alphas specifically). The developed model has several important implications. Firstly, shows the impact that both management and incentive fees have on PE performance. Secondly, allows to assess the illiquidity cost which is embedded in the nature of PE investments. Quantitatively speaking, they found that the illiquidity cost is significant. Specifically, the cost that an investor bears when investing in PE is 50% illiquidity, 25% management fees and 25% carried interest. Leverage contributes greatly to reduce the break-even alpha, as higher debt increases the amount of assets under management. Finally, the model was used to evaluate the performance of PE, compared to the most used metric of PE performance: IRR and PME.

Lastly, Korteweg and Nagel (2016) adjusted the VC return to account for the riskiness of its business. By doing so, they were able to compare the results without the risk-adjustment and make some considerations. Most of the VC literature concerning return calculations relies on the Public Market Equivalent (PME) measures. These measures were developed to overcome the IRR limitations in the VC context. The PME has several limitations and the authors tried to overcome them by means of a Generalized Public Market Equivalent (GPME). By applying they were able to build a performance benchmark for Venture Capital payoffs which adjusted for systematic risk. The results from PME to GPME were significantly different concerning VC performance. Specifically, the findings show how distorted the PME results are compared to GPME. The authors found negative abnormal returns of VC funds and positive ones for VC investment in start-ups. They also confirm the selection bias embedded in VC data and admitted that their research is not exempted to this issue.

Chapter III - Empirical Analysis

3.1 Research question

I developed my research questions based on the literature review in Chapter 2. Most of the literature studies conducted so far are US based, so it is also interesting to identify which factors contributed to start-up success also in Europe.

Venture capitalists, corporations etc. are entities that provide capital to small and new enterprises, characterized by high risk return trade-off. Given that 92% of start-ups fail, we can assume that the remaining 8% that survives needs to "hit it big'' for a VC to make a considerable profit. Nevertheless start-ups, as private economic initiatives, are becoming increasingly important, not only for venture capitalists. Considering the relevance dedicated to this matter by both Governments and investors, there is a need to expand the research field. The start-up valuation area of expertise is by far still unclear. Indeed, the analytical process of start-up valuation needs to take into account a huge variety of parameters, and usually the standard valuation approaches (as Income approach, Cost approach and Market approach) are mainly complex or ineffective in the first stage of this process. In fact, the reliability of the standard approaches grows progressively with the successful ageing of the start-up, when more historical data becomes available. Specifically, this thesis wants to sort out the broad range of parameters that affect the probability of Fintech start-up success in the European and American context in order to increase the robustness of its valuation. The main research question I am trying to answer is:

> **Research Question:** *"Which main actors and external conditions factors contributed to Fintech start-up success in Europe and United States from 2000 to 2018?"*

There are many ways to recognize start-up success. I decided to employ the definition of start-up success given by Cochrane (2005): "I recognize success when a start-up has experienced a liquidity event and so when is either: 1) acquired through an M&A deal; b) listed on the market through an IPO; c) achieved a target return.". In order to answer my research question, I decided to build different variables according to the sub-hypothesis developed in chapter 2 and check whether they have an impact on start-up success consistently to the literature review findings. These variables belong to 3 macro-categories of factors: a) Team characteristics; b) Investor characteristics; c) External environment characteristics. Concerning team characteristics, I build 5 variables to capture the skill level of the founding team and other 3 variables to capture how the founding team gets along together. Then, concerning investor characteristics, I chose to study the reputation and skills of the Venture Capitalist who invested in the start-up by constructing 3 variables. Lastly, concerning external environment characteristics, I investigated the impact of the market dynamics on start-up success.

3.2 Method

The objective of this study was to answer my main research questions and sub-hypothesis. To achieve this result, I firstly needed to perform a quantitative analysis. After a careful review of both theory and literature, I chose to perform my analysis using the Logistic regression. Applying this econometric model allowed me to overcome the drawbacks of the Linear Probability Model by restricting the dependent variable outcome, hence the probability of start-up success, between 0 and 1. This is possible by means of a logistic function, which is non-linear in parameters. In particular, 0 and 1 are the asymptotes of the logistic function, so the predicted probabilities will never be exactly 0 or 1 but can be very close. The model is built as follows

$$P(y = 1 \mid x_1, x_2, \dots, x_{13}) = G(\propto + \beta x_1 + \beta x_2 + \cdots + \beta x_{13}) = G(\propto + X\beta)$$

Where

$$G(\propto + X\beta) = \frac{exp(\propto + X\beta)}{1 + \exp(\propto + X\beta)} = \Lambda(\propto + X\beta)$$

is the logit function and $\Lambda(.)$ is the Cumulative Density Function (CDF) of a Logistic distribution. Due to the intrinsic non-linearity of the Logistic regression, the linearity assumption of OLS is violated. For this reason, the applied estimation method is the Maximum Likelihood which has desirable statistical properties. Maximum Likelihood Estimation finds the $\propto$ and β that maximize the function

$$f(y|X;\propto,\beta) = [\ G(\propto + X\beta)]^{y} \times [1 - G(\propto + X\beta)]^{1-y}$$

So, the intuition behind maximum likelihood, when fitting a logistic regression as in this case, is to find the coefficients ($\propto$ and β) so that the predicted probabilities of start-up success are as close as possible to the start-up's observed outcome.

As the logistic regression is a non-parametric technique, I do not need any assumption regarding normality and homoscedasticity, but I still need to check for missing data, independence of observations, perfect measurement and multicollinearity.

3.2.1 Data

This thesis topic required the researcher to construct a database. Due to the intrinsic nature of start-ups in their first stages, which are characterized by more failures than successes, I had to deal with data scarcity and incompleteness. Relevant data was hand-collected from multiple sources to create the final database used for the purpose of this study.

The focus of this thesis is on Fintech start-ups founded between 2000 to 2018 in Europe and United States. There are several reasons why I chose this industry. Firstly, Fintech companies have disrupted the financial market in the last 20 years, demonstrating a high level of success on different levels. Secondly, we are currently in the perfect stage of maturity to study which elements drove success in this industry.

I collected my data from multiple sources, the majority of which required data hand-collection. The main source of data is coming from the CB Insight database, that I accessed thanks to LUISS Guido Carli University. CB Insight has a huge amount of data regarding private and public companies, investors, venture capitalist, industry research and outlook. Moreover, complementary data sources were needed. LinkedIn, Crunchbase and AngelList websites were the main sources of founders' information. Round University Ranking (RUR) was the key university database used in this study. All RUR raw data, which span from 2010 to 2020, are provided by Thompson

Reuters. Thanks to this database I was able to retrieve relevant information about1100 universities around the globe. Other sources of data were S&P Capital IQ and Bloomberg, both provided by Duff & Phelps.

To begin with, I downloaded the name of all the Fintech start-ups founded between 2000 to 2018 in Europe and United States from the Fintech collection in CB Insight database. In total I identified 575 company names, either dead, acquired, private or public. Out of these 575 companies, I was able to retrieve relevant data for just 153 of them. Following that, I hand-collected data about each of the 338 founders regarding age, education, name, surname and university institution from which they graduated.

Next, data about 350 Venture capitalists who invested in the 153 companies in my sample were downloaded from CB Insight database or hand-collected, if not downloadable, from previously mentioned sources. Finally, data about sub-industry indexes were downloaded from S&P Capital IQ database for the abovementioned period of interest. Table I summarizes the main characteristics of my sample. The start-ups belong to six industries, according to CB Insight, and they present four possible outcomes: Acquired, Alive, Dead or IPO. The majority of the sample belongs to the Internet software & services industry and the most frequent outcome is Dead.

Table I

Sample Overview

The sample consists of acquired, alive, dead or public companies both in the US and Europe. The table below provides an overview of the main industries and startup status.

Industry	Acquired	Alive	Dead	IPO	Grand Total
Financial	2	1	4	1	8
Internet	4	5	9	4	22
Internet software & Services	7	25	40	10	82
Mobile & Telecommunication	0	4	0	0	4
Mobile Software & Services	2	9	18	2	31
Software	1	0	5	0	6
Total	16	44	76	17	153

Geographically speaking, 75% of my sample is US based. This reflects the higher number of fintech start-ups founded in the United States in the period. Among all fintech companies founded in Europe or America, 66.82% are founded in the US according to CB Insight database. This shows the ability of the American fintech ecosystem to produce more fintech start-ups with respect to Europe.

3.3 Variables

After a careful review of both theory and literature, I had the opportunity to interview some practitioners. The main objective of these conversations was to increase the robustness of my variable selection, hence model fit, and to discuss relevant measures used in this thesis.

3.3.1 Interviews

- *Interviewee I*

Profile: The first interviewee works in ING Labs, which is responsible to build new businesses for ING.
Discussion: the interviewee identified three main elements of start-up success: 1) Team quality; 2) Market conditions; 3) Product characteristics. We briefly discussed the definition of success according to this study and especially the target return to consider a start-up successful. According to the interviewee, a successful company can also be a company that has not yet achieved a big cash-on-cash multiplier but has the potential to do so in the future. The company needs to have potential, that's where investors consider them a success. ING is not looking explicitly to a percentage, but they are more into companies that are able to grow and pass certain stages. Concerning the cash-on-cash multiple as return proxy, the interviewee conveys that it is a good measure of return in this context. All selected and excluded variables were briefly discussed. An example is Competition, which was identified as complex: less competition could mean less potential in the market or an opportunity to do well. He suggested to implement market fragmentation if possible.

- *Interviewee II*

Profile: The first interviewee works in the investment team of LVenture, an Italian early stage venture capitalist

Discussion: identified success factors are 1) Team quality, 2) Market conditions; 3) Competition; 4) Product characteristics; 5) Traction (especially in early stage). The interviewee recognized that some of these elements cannot be easily modelled.

3.3.2 Variables definition and construction

To answer my research questions, I firstly needed to define my dependent variable as whether the start-up is successful or not. According to this research and to Cochrane (2005), "a start-up is successful when it has experienced a liquidity event and so when is either: 1) acquired through an M&A deal; b) listed on the market through an IPO; c) achieved a target return.".

The first step to construct my logistic regression is to define the variables I identified as most interesting according to the literature review. Starting from the dependent variable *Success*, the variable takes value of 1 if the venture is either acquired, publicly traded or achieved a target return. As return measure, I decided to implement the cash-on-cash multiple measure based on Da Rin, Hellmann and Puri (2013) as a proxy of return for an investor. Specifically, I computed *n* returns, where *n* is the number of financing round a venture has experienced and then computed the average:

$$Return = \frac{1}{N}\sum_{t=1}^{n}\frac{\Delta Valuation_t}{Investment_t}$$

$\Delta Valuation_t$ is the incremental value that the company gained (or loosed) compared to the previous financing round and $Investment$ is the investment that was needed to achieve that incremental valuation. According to this thesis I assumed that the cash-on-cash return threshold to consider a company successful is a 25% yearly return. I constructed this cap measure based on Industry Ventures research made by Yee and Swildens (2017). I want to stress that the return threshold to consider an investment successful depends on many factors. For instance, the risk profile, stage in which the start-up is currently in etc. Please refer to the limitations section for more details. According to this threshold, all the alive companies in my sample are considered as successful, with an average cash-on-cash multiple of 40% and a standard deviation of 0.29.

1. Number of founders variable consists of the number of founding team members at start-up foundation. I included this variable to capture two possible effects. The first one is the skill completeness of the founding team; the second one is team overfitting, which may lead to disorganization and inefficiencies.

2. University ranking is built using RUR database. RUR assigned a score from 1 to 100 to 1100 university around the world for the last 10 years, based on different elements. The most relevant ones include teaching, research, diversity, sustainability, reputation, academic ranking and citations per academic and research staff. As I was missing data for university rankings for most of the founders at the respective start-up foundation, I decided to normalize the university ranking over 10 years to get a reliable ranking at start-up incorporation. Specifically, I downloaded the university score for 1100 universities for the last 10 years and averaged it. Subsequently, I assigned one university ranking to each founder. Finally, I created one score for each start-up by averaging the normalized university ranking across the founding team.

I then created 3 dummy variables to capture founders' level of education. The 3. *Bachelor's degree*, 4. *Master's degree* and 5. *PhD* variables take value of 1 if the average level of education of the founding team at start-up foundation is : bachelor's degree, master's degree or PhD, respectively.

After that, I modelled 3 variables to capture how well the founding team gets along together. 6. *Founders previously founded a start-up together* is a dummy variable that takes value of 1 if at least two founders founded a start-up together previously to start-up foundation. 7. *Founders attended University together* is a dummy variable that takes value of 1 if at least two founders attended University together previously to start-up foundation. In order to construct this variable, I assumed that if at least two founders attended the same university in the same period, then they attended university together and met there. 8. *Founders worked together* is a dummy variable that takes value of 1 if at least two founders worked together previously to start-up foundation.

Start-up is VC-backed is a dummy variable that takes value of 1 if the venture has been supported by a VC firm during its life.

Consistently with the literature review, I decided to include a variable that captures VC reputation. Ideally, this variable should have been built based on the Asset Under Management of each Venture Capitalist. Unfortunately, due to data scarcity, I was not able to retrieve this data for all VCs. For this reason, I decided to measure Reputation/Skill as the percentage of IPO companies the VC achieved over total companies in which the VC invested. Accordingly, I called this variable 10. *VC IPO experience.* This measure was developed based on Bengtsson and Hsu (2015) using CB Insight data. Specifically, I decided to analyze the effect, if any, that having a VC with a higher IPO experience had on start-up success. 11. *Number of VC investment in the start-up* variable captures the number of investments that the VC with the highest IPO experience made in the company. This variable tries to measure the investment scope and commitment the highest reputation/skill venture capitalist made in the venture and was developed, as variable 10, by Bengtsson and Hsu (2015).

12. At least one founder achieved a previous success is a dummy variable that takes value of 1 if at least one of the founders achieved a success according to the definition used in this thesis.

The annualized 13. *log return of the market* variable tries to capture the demand and offer dynamics of the market in which the start-up operates. In order to build this variable, I followed the same reasoning of Gompers and Lerner (1999), who built industry indexes based on the companies who went public. However, I decided to look for some readily available industry index on S&P Capital IQ database. Based on the annualized price of the index I computed annual log returns for each year and each industry in my sample. Then I assigned to each company the 5-year average of the log return of their respective industry starting from the founding year. I chose to implement this 5-year average to try and model the market trend in the short-mid-term future. As I mentioned before, the start-ups included in my sample belong to 6 industries. For each one of them I found the most adequate index that matched the industry description of my companies. The selected Indexes are the following:

Table II

Market Index Statistics

The Market variable is build using 6 different Indexes, as retrieved from Capital IQ. The table below provides an overview of the indexes, as well as the respective CB Insight Industry classification. Concerning statistical figures, it provides number of observations, mean and standard deviation.

Index Name	CB Insight Industry Classification	Obs	Mean	Std. dev.
Software & Services Index	Internet Software & Services	19	4.56%	23.46%
Dow Jones - Internet Composite Index	Internet	19	2.40%	43.43%
Dow Jones U.S. Mobile Telecommunications Index	Mobile Software & Services	16	5.32%	36.21%
S&P 500 Diversified Financial Services	Financial	19	-7.49%	46.95%
S&P 500 Software	Software	19	4.49%	23.67%
Dow Jones U.S. Mobile Telecommunications Index	Mobile & Telecommunications	16	5.32%	36.21%

3.4 Findings

Having identified the relevant variables and having gathered the needed data, I performed the pertinent checks starting from data sparseness. Concerning the University Ranking variable, I was missing 15 observations. This because some Universities are private, hence no score was available. In order to avoid biases, I decided to assign the mean value of the distribution to these missing observations according to the winsorization technique[1]. Concerning VC IPO experience and number of VC investments in the company, I was missing information regarding start-ups which were never supported by a Venture Capitalist. In these occasions I assigned a value of 0. Then I performed data cleaning using the Box Plot tool:

[1] https://pdfs.semanticscholar.org/c34f/1b306d225bcf57bef83525da6e568f6381c1.pdf

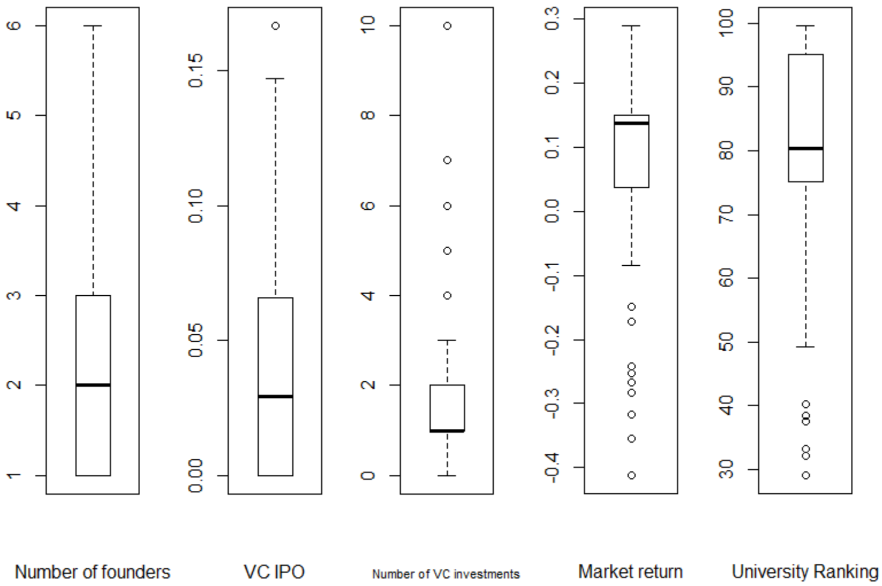

Figure VI. Box plot of numerical variables. I checked for outliers in the numerical variables trough the box plot tool. As we can see there are some outliers observations.

As we can see from the graph above, I found some outliers, especially in the market variable. As my observations are scarce, I decided to substitute the outliers with the lowest or highest quartile of the variable's distribution, according to the winsorization technique[1]. Here the results:

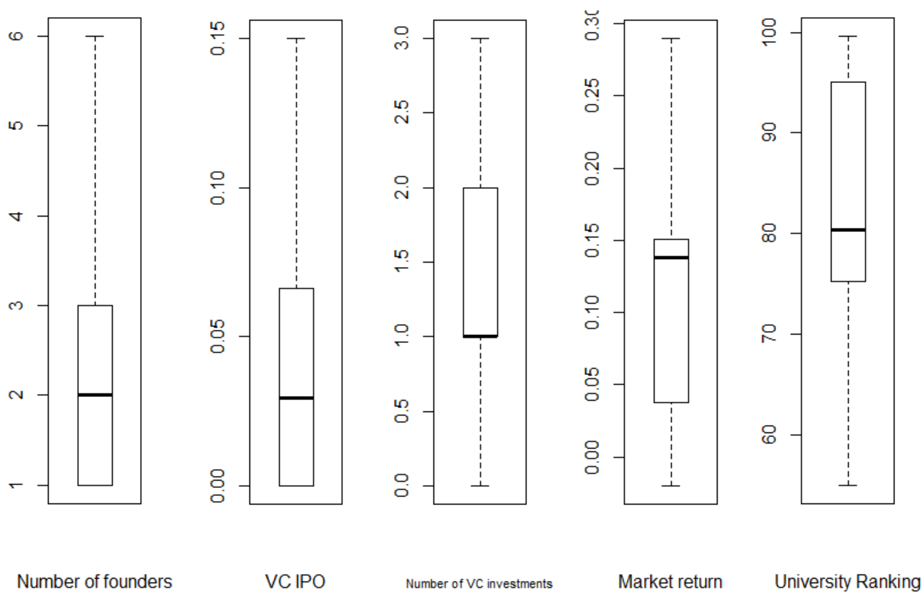

Figure VII. Box plot of numerical variables after winsorization. This figure shows how the variables look like after applying the winsorization technique to eliminate outliers.

Then I checked for influential observations using the Cook's distance. The rule of thumb is that if an observation has Cook's distance higher than 1, then that observation is considered as an outlier, while if it is higher than 0.5 than that observation should be investigated further. As we can see from the graphs below, none of my observations are classified as outliers or are particularly influent according to the Cook's distance.

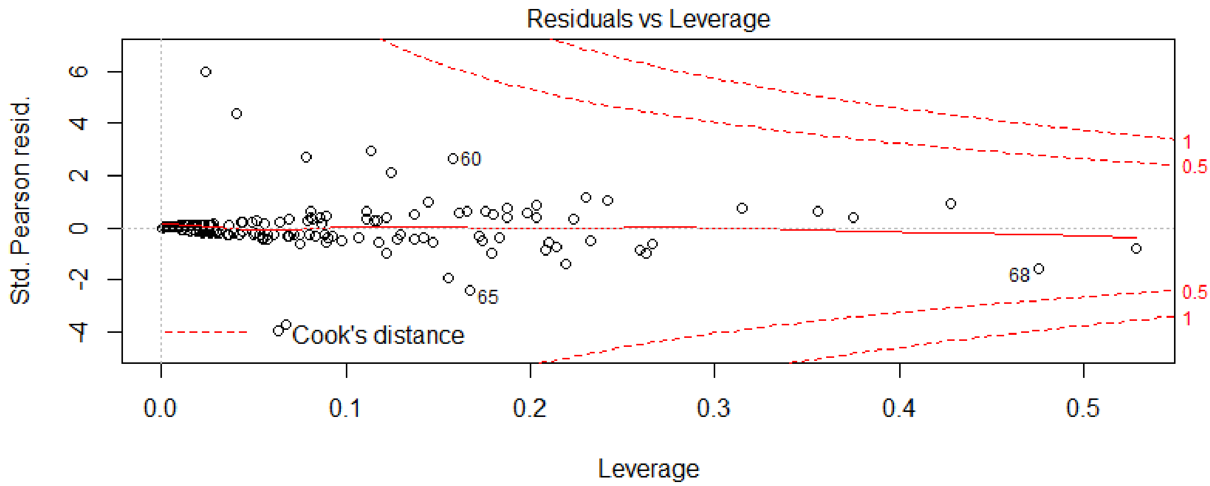

Figure VIII. Cook's Distance. I checked for influential observations by means of the cook's distance measure. A high influential observation has a Cook's Distance greater than 1.

After data checks, TABLE III summarizes the main features of the variables and helps us understand how the data looks like.

Table III

Summary Statistics

The sample consists of startups founded in either Europe or United States from 2000 to 2018. The table provides variable types, means and standard deviations for the 153 companies in the sample.

Variable Name	Variable type	MEAN	Std. dev.
Number of founders	Numeric	2.21	1.10
Bachelor's Degree	Dummy	0.44	0.50
Master's Degree	Dummy	0.35	0.48
PhD	Dummy	0.05	0.21
University Ranking	Numeric	81.42	13.11
At least one founder achieved a previous success	Dummy	0.40	0.49
Founders previously founded a startup together	Dummy	0.12	0.33
Founders attended University together	Dummy	0.12	0.33
Founders worked together	Dummy	0.26	0.44
Startup is VC-backed	Dummy	0.78	0.41
VC IPO experience	Numeric	0.04	0.04
Number of VC investments in the startup	Numeric	1.30	0.99
Log Return of the market	Numeric	0.11	0.08

After adjusting for data cleaning and data sparseness, I ran the model and checked for multicollinearity. Specifically, I computed the correlation between each pair of variables, as shown in Table VII.

Table VII

Matrix of correlations

This table summarizes the correlations between each of the variables in my model, as well as the respective significance level. To detect multicollinearity a correlation coefficient must be near to unity in absolute value and statistically significant.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Number of founders	1.000												
(2) Bachelor's Degree	0.108	1.000											
(3) Master's Degree	-0.051	-0.643***	1.000										
(4) PhD	0.101	-0.193*	-0.159*	1.000									
(5) University Ranking	0.158	-0.056	0.013	0.022	1.000								
(6) At least one founder achieved a previous success	0.221**	-0.073	0.052	0.013	0.118	1.000							
(7) Founders previously founded a startup together	0.361***	-0.053	0.142	0.107	-0.032	0.300***	1.000						
(8) Founders attended University together	0.271***	-0.013	0.142	0.012	0.164*	0.098	0.279***	1.000					
(9) Founders worked together	0.373***	-0.015	0.161*	0.083	0.071	0.305	0.588***	0.272***	1.000				
(10) Startup is VC-backed	0.071	-0.114	0.081	0.115	0.062	0.330	0.101	0.053	0.203*	1.000			
(11) VC IPO experience	0.126	-0.084	0.158	0.025	0.148	0.435***	0.232**	0.146	0.230**	0.499***	1.000		
(12) Number of VC investments in the startup	0.086	-0.108	0.126	0.091	-0.028	0.359**	0.146	0.086	0.255**	0.688***	0.424***	1.000	
(13) Log Return of the market	0.143	0.157	-0.074	-0.070	-0.002	-0.165	-0.003	0.082	0.041	-0.116	-0.150	-0.141	1.000

Significance level (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)

To detect multicollinearity a correlation coefficient must abnormally high (near to unity in absolute value) and statistically significant. By constructing the above-mentioned table, I verified that my variables are not multicollinear. Then I plotted the residuals to see how they looked like:

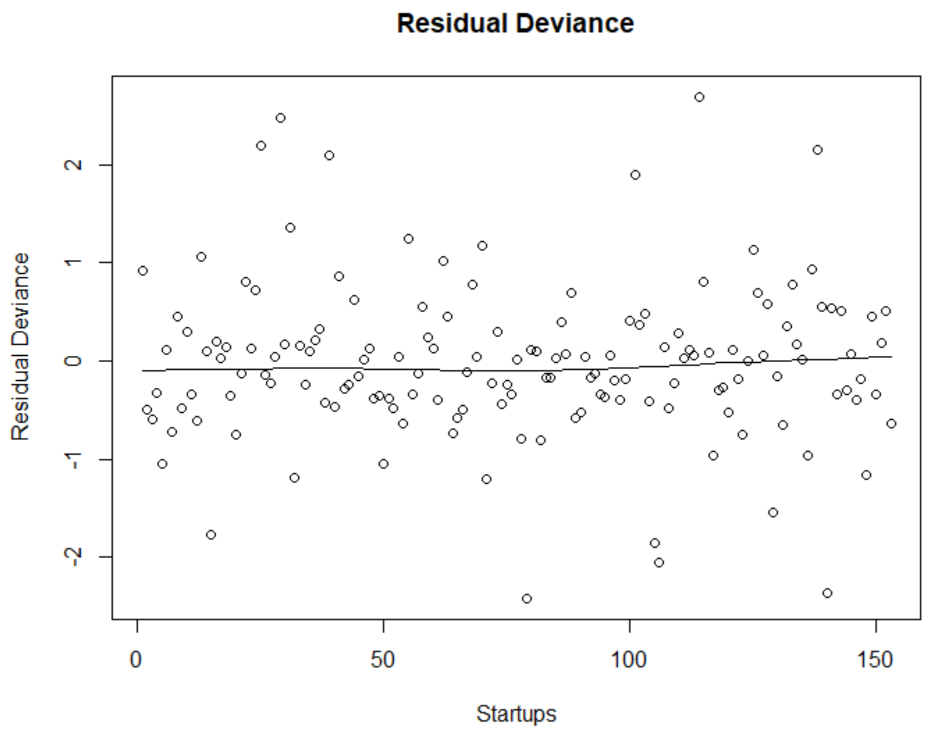

Figure IX. Deviance Residuals. As the standard residuals are not very informative when interpreting a logistic regression, I decided to plot the Deviance Residuals. As we can see the residuals are random and show no trends.

After a careful review of the theory, I decided to analyse the deviance residuals, because they are preferred above standard residual measures when analysing a logistic regression. In particular, deviance residuals are the difference between the observed outcome and the log likelihood function. Ideally, we would like to have all the observations as near as possible to 0 and no trends. By running the regression, I noticed that my deviance residuals are more or less symmetric with a median value of 0.01. This means that my model is not biased in one direction, as seen in the graph. In conclusion my final result is:

Table VIII

Identify Startup's Success Factors

This table reports different informations. Firstly, it summarizes the estimates obtained from the Logistic Regression of Success and Failure as dependent varialbe and the identified relevant independent variables. Secondly, It reports the standard errors in parentheses as well as the level at which variables are significant. Thirdly, it reporst the Average Marginal Effects (AME) of each variable, to allow meaningful interpretation. Lastly, it includes pseudo R-squared figures as a mesure of model fit.

VARIABLES	Estimate	Pr(>|z|)	AME
(Intercept)	-4.823*	0.042	
	(2.369)		
Number of founders	-0.281	0.486	-0.0222
	(0.403)		
Bachelor's Degree	-1.040	0.232	-0.082
	(0.870)		
Master's Degree	-0.291	0.719	-0.023
	(0.809)		
PhD	2.434*	0.093	0.192
	(1.449)		
University Ranking	0.018	0.461	0.001
	(0.025)		
At least one founder achieved a previous success	3.435***	0.000	0.272
	(0.799)		
Founders previously founded a startup together	3.675**	0.041	0.291
	(1.796)		
Founders attended University together	1.318	0.280	0.104
	(1.220)		
Founders worked together	-0.842	0.311	-0.067
	(0.831)		
Startup is VC-backed	-1.098	0.351	-0.0868
	(1.178)		
VC IPO experience	39.01***	0.000	3.084
	(9.916)		
Number of VC investments in the startup	1.17***	0.005	0.093
	(0.412)		
Log Return of the market	8.89*	0.052	0.703
	(4.569)		
Observations	153		
Pseudo R-squared	61.79%		

Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Interpreting results is the trickiest part of Logistic regression. It can be very tempting to read the coefficients and interpret them immediately, if they happen to make any sense whatsoever. To interpret the logistic regression, I needed to transform the coefficients I get from R. In order to find the effect of my x_s on $P(y = 1|X)$, hence the probability of success, I interpreted the coefficients through the Average Marginal Effect (AME). With the AMEs I can calculate the marginal effects at every observed value of X and average across the resulting effect estimates. Through the AME I transformed the coefficients such that they take into account the non-linear effect that a variable has on the probability of success according to the following formula:

$$\frac{\delta G(\alpha + X\beta)}{\partial x_i} = \frac{1}{N} \sum_{i=1}^{N} \lambda(\alpha + X_i\beta)\beta_i$$

Where $\lambda(\alpha + X_i\beta) = \Lambda(\propto + X\beta)(1 - \Lambda(\propto + X\beta))$

The interpretation is slightly different for dummy variables. In particular, I need to estimate the difference in the probability that y_i = 1 when x_k = 1 and x_k = 0:

$$\frac{\delta G(\alpha+X\beta)}{\partial x_k} = \frac{1}{N} \sum_{i=1}^{N}[\lambda(\alpha + \beta_1 x_{i1} + \cdots + \beta_{k-1}x_{k-1} + \beta_k) - \lambda(\alpha + \beta_1 x_{i1} + \cdots + \beta_{k-1}x_{k-1})]$$

For each i, this equation gives us the different effect that having a dummy variable with value 1 has on our dependent variable compared to when the same dummy takes value of 0. The margin command in R is able to distinguish between each variable type (numeric, factor, ordered and logical).

Statistically speaking, 6 coefficients out of 13 are strongly significant, as expressed by the low p-values. The constant is significant and negative. This makes sense as it is more likely to fail than to succeed when founding a start-up.

Economically speaking, starting from the PhD variable, I can say that the average predicted probability of start-up success for a founding team whose average level of education title seniority is PhD is 19.2 percentage points higher than those who don’t, holding other factors fixed. This relationship is understandable and consistent with the literature review findings in chapter 2.

Intuitively, a higher level of education is a good proxy of higher skills of the founding team, leading, on average, to a more desirable outcome.

The average predicted probability of start-up success for a founding team where at least one founder experienced a previous start-up success (as defined in this thesis) is 27.2 percentage points higher of those who didn't, holding other factors fixed. This relationship is understandable since having experienced a previous success could have helped the founders develop particular skills or knowledge on how to create and run a successful business.

The average predicted probability of start-up success for a founding team where at least two founders founded a previous start-up together is 29.1 percentage points higher of those who didn't, holding other factors fixed. This variable tries to capture the understanding and complicity of the founders before start-up foundation. Having had a previous venture experience together, is meant to be a proxy of team quality and solidity.

A 1% increase in the VC IPO experience, conditional on the company being VC backed, increases on average the predicted probability of start-up success by 3.08 percentage points, holding other factors fixed. This relationship is understandable. Receiving support by a VC who has a high reputation implies benefit from the experience, network and guidance that offers to the venture.

A 1 unit increase in the number of investments that the VC with highest IPO experience made in the company, conditional on the company being VC backed, increases on average the predicted probability of start-up success by 9.3 percentage points, holding other factors fixed. Again, this makes economic sense, since a higher commitment by a high reputation investor means a higher amount of resources (knowledge, money etc..) that flow into the new venture, increasing its probability of success. Lastly, a 1% increase in the 5-year average annual log return of the market increases on average the predicted probability of start-up success by 0.703 percentage points, holding other factors fixed. This makes sense, as the higher is the return of the market, the higher the demand and the offer of ventures in that industry will be.

The estimated model has a Residual deviance of 81.034, while the null deviance is 212.097.

There are two main measures of goodness of fit for the Logit model comparable to OLS. The first one is the Likelihood Ratio (LR) Test, which is similar to the F Test:

$$LR = 2(\mathcal{L}_{UR} - \mathcal{L}_R)$$

Where $\mathcal{L}_{UR}$ is the log-likelihood for the unrestricted model and $\mathcal{L}_R$ is the log-likelihood for the restricted model (null model). The difference is multiplied by 2 to approximate a χ^2 distribution under H_0. By performing this test, I found that my model represents a significant improvement with respect to the null model.

To understand the goodness of fit of the model I also computed the McFadden's R^2 also known as pseudo-R^2 which is given by

$$pseudo - R^2 = 1 - \frac{\mathcal{L}_{UR}}{\mathcal{L}_R}$$

The model has a pseudo R^2 of 61.79%.

3.5 Prediction

After performing inference analysis on my sample, I built a model to predict start-up success. In order to do so, I randomly divided my sample in two parts: a) train sample (composed by the 80% of the total sample i.e. 123 companies); b) test sample (composed by the 20% of the total sample i.e. 30 companies). Then I constructed a newmodel, composed only by the statistically significant variable in the inference analysis. Then I ran it using the train sample. By running the model, I obtained new coefficients that can be used to predict fintech start-up success according to my sample's characteristics.

Table IX

Training the model on the train sample

This table summarizes different informations for Model 1, the inference model, and Model 2, the train model using only statistically significant variables. Firstly, it summarizes the estimates obtained from the Logistic Regression of Success and Failure as dependent varialbe and the identified relevant independent variables. Secondly, It reports the standard errors in parentheses as well as the level at which variables are significant. Thirdly, it reports the Average Marginal Effects (AME) of each variable, to allow meaningful interpretations. Lastly, it includes pseudo R-squared figure, as a measure of model fit.

MODEL	(1)		(2)	
VARIABLES	Estimate	AME	Estimate	AME
(Intercept)	-4.823*		-4.527**	
	(2.369)			
Number of founders	-0.281	-0.02		
	(0.403)			
Bachelor's Degree	-1.040	-0.082		
	(0.870)			
Master's Degree	-0.291	-0.023		
	(0.809)			
PhD	2.434*	0.192	2.354*	0.210
	(1.449)			
University Ranking	0.018	0.001		
	(0.025)			
At least one founder achieved a previous success	3.435***	0.272	3.207***	0.287
	(0.799)			
Founders previously founded a startup together	3.675**	0.291	3.129**	0.280
	(1.796)			
Founders attended University together	1.318	0.104		
	(1.220)			
Founders worked together	-0.842	-0.067		
	(0.831)			
Startup is VC-backed	-1.098	-0.09		
	(1.178)			
VC IPO experience	39.01***	3.084	33.139***	2.962
	(9.916)			
Number of VC investments in the startup	1.17***	0.093	0.906***	0.081
	(0.412)			
Log Return of the market	8.89*	0.703	7.626*	0.682
	(4.569)			
Observations	153		123	
Pseudo R-squared	61.79%		57.90%	

Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Model 1 is just the inference model we already seen in Table V. Model 2 is the model based on the training sample, hence 80% of the overall dataset using the statistically significant variables as obtained by Model 1. Having done that, I predicted the companies outcome in the test sample using the predict command in R. By doing so I was able to assign to each company in my train set a probability of success between 0 and 1. To assess the accuracy of my model I had to build a confusion matrix. In order to do so, I assumed that if the model predicts a probability of success higher than 0.5 for a start-up, then the start-up is successful. The main results of the analysis are the following:

Table X

Confusion Matrix

The Table provides an overview of the prediction accuracy made by the model on the test sample.

	Predicted Failure	Predicted Success	Total
Real Failure	12	1	13
Real Success	3	14	17
Total	15	15	30

From the confusion matrix I can develop different measures of model precision and accuracy. The most important accuracy measure is the percentage of true success and true failures predicted over the total cases. The accuracy of my model is 86.67%. Then I can compute the Sensitivity (or true success rate) measured as the proportion of successes that were correctly predicted by the model, which in our case is equal to 93.33%. Lastly, I can compute the Specificity measures (or true failures rate), as the number of Actual Failures correctly classified, which is equal to 80.00 %.

So, theoretically, I can use the following model to predict the probability of success of a fintech start-up:

$$P(y = 1 \mid X) = 0.21x_{PhD} + 0.287x_{Previos\ Success} + 0.28x_{Previous\ Startup\ tog} + 2.962x_{VC\ IPO\ experience} + 0.081x_{N\ VC\ Investments} + 0.682x_{Market}$$

Chapter IV - How to increase the robustness of start-up valuation

The main objective of this thesis is to understand the start-up valuation process drawbacks, build a model to predict start-up success in the Fintech sector and suggest a way to use it in order to improve their valuation. How should practitioners benefit from applying this approach to start-up valuation? The current state of the literature highlights both the riskiness and uncertainty that characterize the start-up world and the complexity and sensitivity of their valuation approach to a wide range of parameters. That is why predicting the probability of success for a start-up can be a very powerful tool to increase the robustness of its valuation.

4.1 Income and cost approach

One way practitioners can use the predicted probability of success of a start-up in a valuation model is by computing a weighted valuation. As of today, the main methods that are used to perform start-up valuation are the Income and Cost approach. The latter is considered more reliable and robust. The former, is the one that really shows the potential upside of the company we are evaluating, but it is also the most sensitive to inputs and projections provided by the management plan. This is where the predicted probability of start-up success may improve start-up valuation.
A first suggestion to implement this measure would be to create a weighted valuation model where the probability of success p is the weight given to the Income Approach value, while $1\text{-}p$ is the weight assigned to the Cost Approach value:

$$NPV_t = NPV_{Income\ approach} \times p + (1-p) \times NPV_{Cost\ approach}$$

Estimated probability of success	0.9
Income approach NPV	25.9
Cost approach NPV	18.5
Estimated valuation	24.8

Figure X. Income and Cost approach weighted average. This figure shows a first suggestion of implementing the probability of success to increase the accuracy of start-up valuation. As of today, the main methods that are used to perform start-up valuation are the Income and Cost approach. The latter_is considered more reliable and less sensible. The former, is the one that really shows the potential upside of the company we are evaluating, but it is also the most sensitive to inputs and projections provided by the management plan. This is where the predicted probability of start-up success may support start-up valuation.

Following this approach, I can give more weight to the upside potential value (coming from the income approach) for a start-up that is more likely to succeed, according to the variables identified in the model, and more weight to a cost-based approach method for a start-up that is more likely to fail. In this way, I can get a more robust result and a lower range of possible valuation outcomes for the start-up I am evaluating.

4.2 Income approach and distress sale value

A second approach to implement the probability of success is suggested by Damodaran (2009). According to the author: “A DCF valuation values a firm as a going concern. If there is a significant likelihood of the firm failing before it reaches stable growth and if the assets will then be sold for a value less than the present value of the expected cashflows (a distress sale value), DCF valuations will overstate the value of the firm.”. So, once the probability of success or failure has been assessed, the valuation of the firm can be written as the expected value of the intrinsic value (coming from the DCF and based on the going concern assumption) and the firm’s distressed value:

$$E(startup) = Value\ of\ going\ concern\ \times p + (1-p) \times Distress\ sale\ Value$$

Where p is the probability of success. To apply this approach, first of all we need to compute the valuation of a start-up in a going concern perspective. This is done by estimating the expected cash flows needed to consider the company financially healty and the correct level of WACC, cost of equity and cost of debt. After that we need to compute the Distress sale Value, which for start-ups is usually very close to zero, since they have very small portion of assets.

Estimated probability of success	0.9
NPV (from income approach)	25.9
Distress sale Value	0.0
Estimated valuation	22.0

Figure XI. Going concern and distress sale value weighted average. This figure shows a second suggestion of implementing the probability of success to increase the accuracy of start-up valuation. Once the probability of success or failure has been assessed, the valuation of the firm can be written as the expected value of the intrinsic value (coming from the DCF and based on the going concern assumption) and the distress value under the failure scenario.

Why should we employ such approach to get a more robust valuation outcome? By weighting the valuation coming from the income approach by the probability of success and the distress sale valuation by the probability of failure I will assign both more weight to the upside potential valuation and less weight to the distress sale valuation of the companies that are more likely to succeed. Of course, it will be the other way around for companies that are more likely to fail. This will have the main implication of increasing the robustness of start-up valuation by restricting the possible range of values that I can give to a newly born start-up.

4.3 Adjusted cashflows

A third suggestion to implement this measure would be to weight the cash flows used to compute the start-up value through the Income approach. In this way I can incorporate the risk of failure already in the cashflows and then discount it at the appropriate discount rate, as shown in figure XII. When applying this methodology, I need to keep in mind that the riskiness of the business is already partially embedded in the cash flows. For this reason, I need to choose the correct discount rate, hence one that does not double count the risk.

WACC	9%						
Probability of success	90%						
	0	**1**	**2**	**3**	**4**	**5**	**TV**
Free Cash Flow	0.20	0.50	1.00	2.00	5.00	7.00	8.00
Free Cash Flow	0.20	0.50	1.00	2.00	5.00	123.57	
FCFO adj	**0.18**	**0.45**	**0.90**	**1.80**	**4.50**	**111.21**	
NPV	78.21						

Figure XII. Include the risk already in the cash flows. A third suggestion to implement this measure would be to weight the cash flows used to compute the start-up value through the Income approach. In this way we can incorporate the risk of failure or success already in the cashflows and then discount it at the appropriate discount rate, as shown in the figure above. When applying this method, we need to keep in mind that the riskiness of the business is already partially embedded in the cash flows. For this reason, we need to choose the correct discount rate, hence one that does not double count the risk.

Where $FCF\ adj_t = FCF_t \times p$. This approach is usually preferred by academics as incorporating all the risk related to start-up operations in the discount rate is very complex. Practitioners usually discount the cash flows for very high level of WACC (e.g. 40%-50%), systematically penalizing long-term projections. This can lead to mis-valuation and investment choices errors.

Limitations

My study has several limitations. Firstly, and most importantly, my sample is modest compared to studies published in high reputation journals. This is due to the fact that most of the data needed for this research was hand-collected. In order to obtain more robust results, it would be necessary to increase the number of companies in the sample. One way of doing so would be to get access to more sophisticated and complete start-up databases. Moreover, my sample is mainly US based, which can bias my results. The second most important limitation of my research is that the model I developed is not sensible and does not take into account the different stages start-ups experience. The main consequence of this is losing information and generalize conclusions that are, probably, more specific to different stages of the analysed venture. Further research should aim to create different models to predict start-up success, each one related to a specific stage (seed, serie A, serie B etc..) of start-up life. The results of this thesis are valid for the specific sample, industry, database and period that I chose to analyse.

Conclusions

The aim of this thesis is to understand the start-up valuation process drawbacks, build a model to predict start-up success in the Fintech sector and suggest a way to use it in order to improve their valuation. In order to build the multifactor model needed to improve start-up valuation I had to answer the following research question: "Which main actors and external conditions factors contributed to Fintech start-up success in Europe and United States from 2000 to 2018?". By conducting a Logistic regression, I was able to provide evidence that confirmed the existing literature concerning start-up success and how this metric can be employed to increase the robustness of start-up valuation. My results are based on CB Insight database, industry, years and geographic area I chose to analyse. According to my research, there is a positive and significant relationship between start-up success and whether the most frequent level of education seniority of a founding team is PhD. This confirms that a higher average level of education in the founding team has a positive effect on start-up success. The reason is that a higher level of education should imply a broader range of skills which could expose the founding team to make less mistakes. The evidence of my research highlights a positive relation between whether at least one founder experienced a previous start-up success (according to the definition provided in this thesis) and start-up success. I also found that if at least two founders founded a start-up together previously to start-up incorporation, the start-up is more likely to succeed. The aim of this variable is to capture the understanding and complicity of the founders before start-up foundation. This result is in line with the literature findings in chapter 1. My research further supports the importance of venture capital reputation (modelled as the percentage of IPO companies over total investments) as a key contributing factor to start-up success. Receiving support by a VC which has a high reputation allows the new venture to benefit from the experience, network and guidance that offers to the company. Interestingly, also the number of investments that the VC with highest reputation made in the company has a positive effect on start-up success. This variable tried to capture the scope and commitment that the VC with highest reputation made to the venture, hence it is supposed to be a measure of VC belief and support in the firm. The correlation of this variable with start-up success is positive as found also by Bengtsson and Hsu (2015) when studying the role of founders and VC partner co-ethnicity as influence factors in investing decisions. Finally, the 5-year average log return of the market in which the company operates has a positive relation with start-up success consistently with the literature review in chapter 1. This variable's aim is to capture whether demand and offer dynamics have a significant impact on start-up success or failure.

Based on the findings of my inference analysis, I then built a model to predict fintech start-up success. To begin with, I chose to design my model based on 6 variables, the ones that had a significant impact on fintech start-up success. Following that, I split my sample in two parts, training and test sample, then tried to predict the success or failure outcome of the test part. To conclude, I investigated the accuracy of my model in predicting start-up success or failure by means of a confusion matrix. This is the final model:

$$P(y = 1 \mid X) = 0.21x_{PhD} + 0.287x_{Previos\ Success} + 0.28x_{Previous\ Startup\ tog} + 2.962x_{VC\ IPO\ experience} + 0.081x_{N\ VC\ Investments} + 0.682x_{Market}$$

The results provide evidence that my model is able to correctly categorize 86.67% of the ventures in my test sample. The predicted probability of start-up success can be then used to increase the robustness of its valuation in many ways. In my research I suggest 3 ways to employ this metric according to both the literature review and the current approaches used in practice. Firstly, I can compute a weighted valuation based on the income and cost approach:

$$NPV_t = NPV_{Income\ approach} \times p + (1 - p) \times NPV_{Cost\ approach}$$

Secondly, I can employ a weighted valuation between the going concern valuation coming from the income approach and the distress sale valuation, as suggested by Damodaran (2009):

$$E(startup) = Value\ of\ going\ concern \times p + (1 - p) \times Distress\ sale\ Value$$

Lastly, we can weight the cashflows coming from the income approach valuation by the probability of success and get a more reliable estimation. This methodology is based on the findings of many academics, like Titman et al. (2016) and Damodaran (2013), concerning risk incorporation during the valuation process. According to the authors, adjusting the cash flows is, academically speaking, a more correct approach. By employing one of the above-described approaches, I can employ the constructed multifactor model to get a more reliable and robust start-up valuation outcome and reduce the probability of committing un-negligible valuation errors, as demonstrated also by Cochrane (2005).

References

Abetti, Pier A., and Robert Stuart. 1987. "Start-up Ventures: Towards the prediciton of initial success." *Journal of Business Venturing* 215-230.

Aggarwal, Vikas A., David H. Hsu, and Andy Wu. 2020. "Organizing Knowledge Production Teams Within Firms for Innovation." *Strategy Science, INFORMS* 1-37.

Bengtsson, Ola, and David H. Hsu. 2015. "Ethnic matching in the U.S. venture capital market." *Journal of Business Venturing* 338-354.

Berk, J., R. Green, and V. Naik. 2004. "Valuation and return dynamics of new ventures." *Review of Financial Studies* 1-35.

Brooks, Chris. 2002. *Introductory Econometrics for Finance.* imusti.

Cochrane, John. 2005. "The risk and return of venture capital." *Journal of Financial Economics* 3-52.

Cooper, Arnold C., Javier Gimeno-Gascon, and Carolyn Y. Woo. 1994. "Initial Human and Financial Capital as Predictors of New Venture Performance." *Jornal of Business Venturing* 371-395.

Da Rin, Marco, and Thomas Hellmann. 2020. *Fundamentals of Entrepreneurial Finance.* Amsterdam: Oxford University Press.

Da Rin, Marco, Thomas Hellmann, and Manju Puri. 2013. "A Survey of Venture Capital Research." *Handbook of the Economics of Finance* 574-608.

Damodaran, Aswath. 2013. *Applied Corporate Finance.* Wiley.

Damodaran, Aswath. 2009. "Valuing Young, Start-up and Growth Companies: Estimation Issues and Valuation Cahllenges." *Stern School of Business* 1-67.

Davila, Antonio, George Foster, and Mahendra Gupta. 2003. "Venture capital financing and the growth of startup firms." *Journal of Business Venturing* 689-708.

Dellermann, D, N. Lipsch, P. Ebel, K.M. Popp, and J.M. Leimeister. 2017. "Finding the Unicorn: Predicting early stage startup success through a hybrid intelligent method." *International Conference on Information Systems *ICIS* 1-15.

Duchesneau, Donald A., and William B. Gartner. 1990. "A profile of new venture success and failure in an emerging industry." *Journal of Business Venturing* 297-312.

Falik, Y, T Lahti, and H Keinonen. 2016. “Does startup experience matter? Venture capital selection criteria among Israeli entrepreneurs .” *Venture Capital Journal* 149-174.

Festel, Gunter, Martin Wuermsehr, and Giacomo Cattaneo. 2013. “Valuation of Early Stage High-tech Start-up Companies.” *International Journal of Business* 216-231.

Fitza et al. 2009. “Do VCs matter? the importance of owners on performance variance in start-up firms.” *Strategic Management Journal* 387-404.

Fried, V., and R. Hisrich. 1994. “Toward a Model of Venture Capital Investment Decision Making.” *Journal of Financial Management* 28-37.

Gartner, William B., Jennifer A. Starr, and Subodh Bhat. 1998. “Predicting New Venture Survival: an Analysis of "Anatomy of a Start-Up". Cases from Inc. Magazine.” *Journal of Business Venturing* (Journal) 215-232.

Gompers, Paul, and Josh Lerner. 1999. “Money chasing deals? The impact of fund inflows on private equity valuations.” *Journal of Financial Economics* 281-325.

Hastie, Trevor, Robert Tibshirani, and Gareth James. 2013. *An Introduction to Statistical Learning.* Springer.

Hellman, T., and M. Puri. 2002. “Venture capital and the professionalization of start-up firms: Empirical .” *The Journal of Finance* 169-197.

Hsu, DH. 2007. “Experienced entepreneurial founders, organizational capital, and venture capital founding.” *Res Policy* 722-741.

Khanin, D., J.R.: Mahto, R.V. Baum, and C Heller. 2008. “Venture capitalists’ investment criteria: 40 years of research.” *Small Business Institute* 187-192.

Knight, R. 1994. “Criteria Used by Venture Capitalists: A Cross Cultural Analysis.” *International Small Business Journal* 26-37.

Kohn, Andreas. 2018. "The determinants of startup valuation in the venture capital context: a systematic review and avenues for future research." *Management Review Quarterly* 3-36.

Kwak, Kyu Sang, and Hae Jong Kim. 2017. “Statistical data preparation: management of missing values and outliers.” *KJA* 1-5.

Lee, In, and Yong Jae Shin. 2018. “Fintech: Ecosystem, business models, investment decisions and challenges.” *Journal Business Management* 35-46.

Lumpkin, James R,. 1998. “Screening Practices of New Business Incubators: The Evaluation of Critical Success Factors.” *Americal Journal of Small Business* 59-81.

Macmillan, I', R. Siefel, and P. Narasimha. 1985. “Criteria used by venture capitalists to evaluate new venture proposals.” *Journal of Business Venturing* 119-128.

Mason, Colin, and Matthew Stark. 2004. “What do Investors Look for in a Business Plan?” *International Small Business Journal* 227-248.

Maxwell, Andrew L., Scott A. Jeffrey, and Moren Levesque. 2011. “Business angel early stage decision making.” *Journal of Business Venturing* 212-225.

Nahata, R., S. Hazarika, and K. Tandon. 2014. “Success in Global Venture Capital Investing: Do Institutional and Cultura Differences Matter?” *Journal of Financial and Quantitative Analysis* 1039-1070.

Roure, Juan B., and Robert H. Keeley. 1990. “Predictors of success in new techonology based ventures.” *Journal of Business Venturing* 201-220.

Sanders, Gerard, and Steven Boivie. 2004. “Sorting things out: valuation of new firms in uncertain markets.” *Strategic Management Journal* 167-186.

Song et al. 2008. “Success Factors in New Ventures: A Meta-analysis.” *Journal of Product Innovation Management* 7-27.

Stuart et al. 1999. “Interorganizational endorsements and the performance of entrepreneurial ventures.” *Administrative Science Quarterly* 315-349.

Titman, Sheridan. 2016. *The Art and Science of Corporate Investment Decisions.* Pearson.

Wasserman, N. 2016. “The throne vs. the kingdom: founder control and value creation in startups.” *Stategic Management Journal* 255-277.

Wooldridge, Jeffrey M. 2012. *Introductory Econometrics: A Modern Approach.* Cengage Learning.

Yee, Eric, and Hans Swildens. 2017. *Industry Ventures.* 7 February. https://www.industryventures.com/the-venture-capital-risk-and-return-matrix/.

Zider, B. 1998. “How venture capital works.” *Harvard Business Review* 131-139.

Page intentionally left blank

LUISS

Department of Impresa e Management

Course of Advanced Corporate Finance

A Multifactor Model to Improve Start-up Valuation (summary)

Prof. Raffaele Oriani

SUPERVISOR

Prof. Pierluigi Murro

CO-SUPERVISOR

Lorenzo Calanca

CANDIDATE

Academic Year 2019/2020

Table of Contents

Introduction

Venture capitalists are entities that provide capital to small and new enterprises, characterized by high risk-return trade-off. Given that 92% of start-ups fail, we can assume that the remaining 8% that survives need to ‘’hit it big” for an investor to make a considerable profit. Nevertheless start-ups, as private economic initiatives, are becoming increasingly important, not only for venture capitalists. Considering the relevance dedicated to this matter by both Governments and investors, there is a clear need to expand this research field. Specifically, the start-up valuation area of expertise is still unclear. The analytical process of start-up valuation needs to take into account a huge variety of parameters, and usually the standard valuation approaches (as Income approach, Cost approach and Market approach) are either complex or ineffective in the first stages of this process.

In this context, the main research questions that this thesis aims to answer is to identify the elements that drove Fintech start-up success between 2000 and 2018 in Europe and United States. Specifically, this research’s objective is to develop a multi-factor model to understand and predict the probability of success, which is essential for the robustness of the start-up valuation outcome.

This study will focus on which parameters define success for a start-up and to what extent these parameters predict success on a reliable basis. According to this thesis a start-up is *a company which started its operations with a skeletal business plan, product, or service and may, or may not, have reached more mature stages*. Moreover I recognize success “when a start-up has experienced a liquidity event and so when is either: a) acquired through an M&A deal; b) listed on the market through an IPO; c) achieved a target return.” Cochrane (2005). My sample consists of 153 start-ups either alive, dead, acquired or public founded in Europe or United States. However, this research topic required me to construct a database from different sources (e.g. LinkedIn, Crunchbase, Capital IQ, Bloomberg etc.). I chose to develop my model based on a logistic regression because of its desirable properties. Specifically, this econometric tool allowed me to restrict the probability outcome of start-up success between 0 and 1 by means of a non-linear transformation.

Chapter I - An overview on Start-ups and their valuation challenges

In this chapter I introduce the main differences between start-ups and mature companies concerning different elements: financing, capital raising and dividends. Lastly, I point out the main issues concerning start-up valuation and the importance that success factors may play in achieving a more robust valuation result.

1. Start-ups characteristics

Academics have studied organizations for decades. Unfortunately, not much attention has been given to start-ups, even if almost all mature and public corporations started their activity from a start-up phase. Usually a start-up begins with an idea from a founding team, which tries to fill an identified gap in the market. After that, this idea develops towards a more mature stage, where it is implemented in practice by realizing a new product or service. The latest stage is the one where the company is actually offering the product/service to the market and have the potential to achieve some profits in the future. One of the main characteristics of start-ups is that they represent, from a value perspective, just a small portion of the overall economy. However, the impact they have on the economy is huge for many reasons. Specifically, start-ups contribute greatly to employment, economic growth and to the realization of high returns for investors. Start-ups can be very different to each other and usually have a higher degree of complexity, compared to more mature companies. In particular, capital raising is more complex for these entities, as they have a restricted range of choices to finance their operations; also attracting capital is much more difficult and even more critical compared to mature companies. These elements highlight the importance of understanding and improve the complex start-up valuation process.

2. Valuation challenges

The valuation of a start-up at a certain moment in time is very important. However, their valuation is complex and the standard approaches we use to value a mature company (Income, Market, Cost approaches) are quite complex to apply. Specifically, the robustness of the valuation outcome is an issue, since there are many relevant parameters that can have an extreme impact on the value, leading to a wide range of potential valuation outcomes. The *income approach*, for instance, is very complex to apply as many risky elements are not quantifiable. Practitioners usually solve this issue by increasing the WACC to abnormally high levels in order to get reasonable cash flows.

However, this approach can lead to significant valuation errors. The *Market approach* is also complex to apply. This is mainly due to data lack, scale measurement issues, illiquidity and differences in equity claims. At a first glance, the *cost approach* seems to be a good proxy of start-up valuation, as it is more ground base. However, this valuation model does not account for the potential that highly innovative companies have, leading to undervaluation on many occasions.

Now we have a clearer view of the issues arising from start-up valuation compared to more mature companies. Like for well-established corporations, there are many ways to arrive to a final valuation concerning start-ups. For instance, the current valuation approach developed by Duff & Phelps consists in computing the start-up value coming from the Income approach and Cost approach and get a range of possible valuation outcomes. However, this approach leads to very wide valuation outcomes when testing different scenarios. Contrary to Duff & Phelps, other actors may apply different approaches to start-up valuation. For this reason, Kohn (2018) said start-up valuation, "is more art than science. In view of this, it is particularly important to be aware of and understand the different underlying determinants that affect the valuation of startups". According to the author, many elements that have an impact on start-up valuation are linked to its *probability of success*. Consistently to Kohn (2018)'s view, many researchers tried to find some correlations between start-up characteristics (e.g. team composition, investor characteristics, external environment characteristics) and start-up success in order to develop a more accurate model to estimate the value of a start-up. According to Damodaran (2009), one way to improve this process is build a multifactor model to predict start-up success, apply it to the valuation process and get a more robust result, as demonstrated also by Cochrane (2005). As I will show in the fourth and last chapter of this thesis, there are many ways to employ the probability of start-up success to improve its valuation. In summary, start-up valuation must take into account a huge variety of factors compared to more mature companies. One way to increase the robustness of its valuation, is study the broad range of parameters that affect the probability of start-up success and consequently its valuation.

Chapter II - Literature review

The identification of relevant literature concerning start-up success factors was conducted in a systematic way through the Web of Science tool. This analysis is based on some of the most relevant papers on which I structured my work. Since there are many elements of interest concerning start-ups, I decided to structure the literature review in sub-paragraphs. Based on the literature review findings I formulated different hypothesis that I will test empirically in chapter 3.

1. Start-up valuation

The first macro-theme of my literature review concerns start-up valuation. In Kohn (2018), the author developed a review of the current state of the literature regarding this topic. Particularly, with his work, he provided a conceptual framework that will guide researchers in their analysis of start-up valuation and success. He found that start-up valuation is determined by the interactions of the following determinants of a) Start-ups; b) Venture Capitalists; c) External Environment. For each of these determinants, he presented the key elements that influence start-up valuation. Concerning Start-ups elements, the author identified the start-up characteristics (e.g. industry and location), founder and team characteristics (e.g. team quality), intellectual property and alliances (e.g. number of patents filed) and financial information quality (e.g. accounting information). This determinant was studied by Gompers and Lerner (1999) who showed the influence of fund inflows, as well as other elements, on venture capital's investment pricing. One of the most interesting regressor used in this study is the public market valuation variable. Specifically, the authors designed different industry indexes as a measure of industry investment opportunity. According to their finding I decided to test weather market dynamics have an effect on start-up success:

> **H_1**: *Founding a start-up when there is more market demand, increases the probability of start-up success.*

As a matter of fact, the start-up valuation process is difficult to improve mainly because of information asymmetries. This issue gets even more complicated when evaluating a start-up in an emerging sector. The main consequences of this agency problem are adverse selection and moral hazard. Sanders and Boivie (2004) highlighted that in emerging economic sectors, where key metrics of venture quality are scarce, investors use observable secondary sources of information when investing in a start-up.

2. Success factors

As we mentioned in Chapter 1, we can increase the robustness of start-up valuation by identifying and understanding the main factors that have a significant impact on its success according to the current state of the literature. A plethora of researchers studied the elements that cause success and failure of new ventures. For instance, Roure and Keeley (1990) found evidence of the importance that founding team plays in start-up success. In particular the skill set of the founding team:

> **H_2**: *Larger entrepreneurial teams have higher probability of start-up success.*
>
> **H_3**: *Studying in a more prestigious University increases the probability of start-up success.*
>
> **H_4**: *Achieving a higher education title increases the probability of start-up success.*

And how the team gets along together:

> **H_5**: *Founding a previous start-up together with one or more members of the current founding team increases the probability of start-up success.*
>
> **H_6**: *Attending University together with one or more members of the current founding team increases the probability of start-up success.*
>
> **H_7**: *Having a previous work experience together with one or more members of the current founding team increases the probability of start-up success.*
>
> **H_8:** *Achieving a previous venture success increases the probability of start-up success.*

More insights were provided by Bernstein, Korteweg and Laws (2017) as they highlight the importance of investor characteristics as determinants of start-up success. According to this, I decided to test empirically different hypotheses concerning investor characteristics in order to investigate their impact on start-up success:

> **H_9:** *Being backed by a Venture Capital firm increase the probability of start-up success.*

H_{10}: *Being backed by a Venture Capital firm with a higher reputation/experience increases the probability of start-up success.*

H_{11}: *Being financially supported multiple times by the Venture Capital with highest reputation/experience increases the probability of start-up success.*

3. Risk-return trade-off

In the context of VC investments and start-up valuation, it is crucial to discuss the risk-return trade-off for investors when evaluating a new venture. Specifically, in order to recognize an investment in a start-up as successful we need to better understand the risk and return dynamics that characterize start-ups as a whole.

To begin with, Cochrane (2005) examined whether VC investments behave in the same way as publicly traded securities. As a result, the main objective of his research was to compute the return of VC investment and investigate whether there was any difference with trading securities. This can happen for many reasons like illiquidity or monitor function typical of VCs. After applying a selection bias correction, he concluded that VC investments are very similar to traded securities.

Next, Korteweg and Sorensen (2010), supporting the evidence of Cochrane (2005), built an asset pricing model that accounts for sample selection of observed returns. Specifically, they argued that when an asset is scarcely traded we observe a sporadic valuation of that asset. This sporadicness creates the so called "stale price" problem (the price of an asset does not reflect the latest available information), which biases the estimated price of the asset, its risk and return measures. The model they developed was able to compute the unobserved valuation (as well as the return) between two observable valuations. Correcting for this bias reduced the intercept and increases the risk exposure estimates of entrepreneurial investing.

Following these findings, Sorensen, Wang and Yang (2014) investigated the risk-return trade-off of private equity (PE) firms. While it is commonly recognized that, on average, PE firms earn an higher return compared to the market, the authors investigated whether the performance of PE investments was enough to compensate for both the risk that PE firms bear and its long term illiquidity. Quantitatively speaking, they found that the illiquidity cost is significant.

Chapter III - Empirical Analysis

1. Research question

I developed my research questions based on the literature review in Chapter 2. Most of the literature studies conducted so far are US based, so it is also interesting to identify which factors contributed to start-up success also in Europe.

> **Research Question:** *"Which main actors and external conditions factors contributed to Fintech start-up success in Europe and United States from 2000 to 2018?"*

There are many ways to recognize start-up success. I decided to employ the definition of start-up success given by Cochrane (2005): "I recognize success when a start-up has experienced a liquidity event and so when is either: a) acquired through an M&A deal; b) listed on the market through an IPO; c) achieved a target return.". In order to answer my research question, I decided to build different variables according to the sub-hypothesis developed in chapter 2 and check whether they have an impact on start-up success consistently to the literature review findings. These variables belong to 3 macro-categories of factors: 1) Team characteristics; 2) Investor characteristics; 3) External environment characteristics.

2. Methodology

After a careful review of both theory and literature, I chose to perform my analysis using the Logistic regression. Applying this econometric model allowed me to overcome the drawbacks of the Linear Probability Model by restricting the dependent variable outcome, hence the probability of start-up success, between 0 and 1. This is possible by means of a logistic function, which is non-linear in parameters:

$$P(y = 1 \mid x_1, x_2, \dots, x_{13}) = G(\propto + \beta x_1 + \beta x_2 + \cdots + \beta x_{13}) = G(\propto + X\beta)$$

where

$$G(\propto + X\beta) = \frac{exp(\propto + X\beta)}{1 + \exp(\propto + X\beta)} = \Lambda(\propto + X\beta)$$

Due to the intrinsic non-linearity of the Logistic regression, the linearity assumption of OLS is violated. For this reason, the applied estimation method is the Maximum Likelihood which has desirable statistical properties. As the logistic regression is a non-parametric technique, I do not need any assumption regarding normality and homoscedasticity, but I still need to check for missing data, independence of observations, perfect measurement and multicollinearity.

3. Data

This thesis topic required the researcher to construct a database. Due to the intrinsic nature of start-ups in their first stages, which are characterized by more failures than successes, I had to deal with data scarcity and incompleteness. Relevant data was hand-collected from multiple sources to create the final database used for the purpose of this study. The focus of this thesis is on Fintech start-ups founded between 2000 to 2018 in Europe and United States. There are several reasons why I chose this industry. Firstly, Fintech companies have disrupted the financial market in the last 20 years, demonstrating a high level of success on different levels. Secondly, we are currently in the perfect stage of maturity to study which elements drove success in this industry.

The main source of data is coming from the CB Insight database. Complementary sources where LinkedIn, Crunchbase, AngelList Round University Ranking (RUR), S&P Capital IQ and Bloomberg, both provided by Duff & Phelps. In total I identified 575 company names, either dead, acquired, private or public. Out of these 575 companies, I was able to retrieve relevant data for just 153 of them. Following that, I hand-collected data about each of the 338 founders regarding age, education, name, surname and university institution from which they graduated.

Next, data about 350 Venture capitalists who invested in the 153 companies in my sample were downloaded from CB Insight database or hand-collected, if not downloadable, from previously mentioned sources.

4. Variables

After a careful review of both theory and literature I build the variables needed to perform this study. Thanks to Duff & Phelps Amsterdam I had the opportunity to interview some practitioners as a variable-robustness check.

Success. This is the dependent variable of my model. It takes value of 1 if the venture is either acquired, publicly traded or achieved a target return. As return measure, I decided to implement the cash-on-cash multiple measure based on Da Rin, Hellmann and Puri (2013) as a proxy of return for an investor. Specifically, I computed n returns, where n is the number of financing round a venture has experienced and then computed the average:

$$Return = \frac{1}{N}\sum_{t=1}^{n}\frac{\Delta Valuation_t}{Investment_t}$$

$\Delta Valuation_t$ is the incremental value that the company gained (or loosed) compared to the previous financing round and Investment is the investment that was needed to achieve that incremental valuation. According to this thesis I assumed that the cash-on-cash return threshold to consider a company successful is a 25% yearly return.

Number of founders. Number of founding team members at start-up foundation. I included this variable to capture two possible effects. The first one is the skill completeness of the founding team; the second one is team overfitting, which may lead to disorganization and inefficiencies.

University ranking. Built using RUR database. RUR assigned a score from 1 to 100 to 1100 university around the world for the last 10 years, based on different elements. I created one score for each start-up by averaging the normalized university ranking across the founding team.

Bachelor's degree, *Master's degree* and *PhD*. Dummy variables that take value of 1 if the average level of education of the founding team at start-up foundation is: bachelor's degree, master's degree or PhD, respectively.

Founders previously founded a start-up together. Dummy variable that takes value of 1 if at least two founders founded a start-up together previously to start-up foundation.

Founders attended University together. Dummy variable that takes value of 1 if at least two founders attended University together previously to start-up foundation.

Founders worked together. Dummy variable that takes value of 1 if at least two founders worked together previously to start-up foundation.

Start-up is VC-backed. Dummy variable that takes value of 1 if the venture has been supported by a VC firm during its life.

VC IPO experience. Consistently with the literature review, I decided to include a variable that captures VC reputation. This measure was developed based on Bengtsson and Hsu (2015), and measures Reputation/Skill as the percentage of IPO companies the VC achieved over total companies in which the VC invested.

Number of VC investment in the start-up. Captures the number of investments that the VC with the highest IPO experience made in the company. This variable tries to measure the investment scope and commitment the highest reputation/skill venture capitalist made in the venture and was developed, as variable 10, by Bengtsson and Hsu (2015).

At least one founder achieved a previous success. Dummy variable that takes value of 1 if at least one of the founders achieved a success according to the definition used in this thesis.

Log return of the market variable. Captures the demand and offer dynamics of the market in which the start-up operates. In order to build this variable, I followed the same reasoning of Gompers and Lerner (1999), who built industry indexes based on the companies who went public. However, I decided to look for some readily available industry index on S&P Capital IQ database. Based on the annualized price of the index I computed annual log returns for each year and each industry in my sample. Then I assigned to each company the 5-year average of the log return of their respective industry starting from the founding year. I chose to implement this 5-year average to try and model the market trend in the short-mid-term future.

5. Findings

Having identified the relevant variables and having gathered the needed data, I performed the pertinent checks on the data like multicollinearity, data sparseness, influential observations and residual plot. Thanks to the boxplot tool, I was able to identify some outliers in my numerical variables. I decided to substitute the outliers with the lowest or highest quartile of the variable’s distribution, according to the winsorization technique. Moreover, no multicollinearity or other influential observation were observed. Lastly, residuals are more or less symmetric with a median value of 0.01. This means that my model is not biased in one direction. After data checks I ran the model and found the following inference results:

Identify Startup's Success Factors

This table reports different informations. Firstly, it summarizes the estimates obtained from the Logistic Regression of Success and Failure as dependent varialbe and the identified relevant independent variables. Secondly, It reports the standard errors in parentheses as well as the level at which variables are significant. Thirdly, it reporst the Average Marginal Effects (AME) of each variable, to allow meaningful interpretation. Lastly, it includes pseudo R-squared figures as a mesure of model fit.

VARIABLES	Estimate	Pr(>|z|)	AME
(Intercept)	-4.823*	0.042	
	(2.369)		
Number of founders	-0.281	0.486	-0.0222
	(0.403)		
Bachelor's Degree	-1.040	0.232	-0.082
	(0.870)		
Master's Degree	-0.291	0.719	-0.023
	(0.809)		
PhD	2.434*	0.093	0.192
	(1.449)		
University Ranking	0.018	0.461	0.001
	(0.025)		
At least one founder achieved a previous success	3.435***	0.000	0.272
	(0.799)		
Founders previously founded a startup together	3.675**	0.041	0.291
	(1.796)		
Founders attended University together	1.318	0.280	0.104
	(1.220)		
Founders worked together	-0.842	0.311	-0.067
	(0.831)		
Startup is VC-backed	-1.098	0.351	-0.0868
	(1.178)		
VC IPO experience	39.01***	0.000	3.084
	(9.916)		
Number of VC investments in the startup	1.17***	0.005	0.093
	(0.412)		
Log Return of the market	8.89*	0.052	0.703
	(4.569)		
Observations	153		
Pseudo R-squared	61.79%		

Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Statistically speaking, 6 coefficients out of 13 are strongly significant, as expressed by the low p-values. Results are interesting and consistent with previous literature findings. Interpreting results is the trickiest part of Logistic regression. It can be very tempting to read the coefficients and interpret them immediately, if they happen to make any sense whatsoever. To interpret the logistic regression, I needed to transform the coefficients I get from R. In order to find the effect of my x_s on $P(y = 1|X)$, hence the probability of success, I interpreted the coefficients through the Average Marginal Effect (AME). With the AMEs I can calculate the marginal effects at every observed value of X and average across the resulting effect estimates. I also computed two measures of goodness of fit for the Logit model: the Likelihood ratio (LR) and the McFadden's R^2 both demonstrating a good fit of the model.

6. Prediction

After performing inference analysis on my sample, I built a model to predict start-up success. In order to do so, I randomly divided my sample in two parts: a) train sample (composed by the 80% of the total sample i.e. 123 companies); b) test sample (composed by the 20% of the total sample i.e. 30 companies). Then I constructed a new model, composed only by the statistically significant variable in the inference analysis. Then I ran it using the train sample. By running the model, I obtained new coefficients that can be used to predict fintech start-up success according to my sample's characteristics.

Training the model on the train sample

This table summarizes different informations for Model 1, the inference model, and Model 2, the train model using only statistically significant variables. Firstly, it summarizes the estimates obtained from the Logistic Regression of Success and Failure as dependent varialbe and the identified relevant independent variables. Secondly, It reports the standard errors in parentheses as well as the level at which variables are significant. Thirdly, it reports the Average Marginal Effects (AME) of each variable, to allow meaningful interpretations. Lastly, it includes pseudo R-squared figure, as a measure of model fit.

MODEL	(1)		(2)	
VARIABLES	Estimate	AME	Estimate	AME
(Intercept)	-4.823*		-4.527**	
	(2.369)			
Number of founders	-0.281	-0.02		
	(0.403)			
Bachelor's Degree	-1.040	-0.082		
	(0.870)			
Master's Degree	-0.291	-0.023		
	(0.809)			
PhD	2.434*	0.192	2.354*	0.210
	(1.449)			
University Ranking	0.018	0.001		
	(0.025)			
At least one founder achieved a previous success	3.435***	0.272	3.207***	0.287
	(0.799)			
Founders previously founded a startup together	3.675**	0.291	3.129**	0.280
	(1.796)			
Founders attended University together	1.318	0.104		
	(1.220)			
Founders worked together	-0.842	-0.067		
	(0.831)			
Startup is VC-backed	-1.098	-0.09		
	(1.178)			
VC IPO experience	39.01***	3.084	33.139***	2.962
	(9.916)			
Number of VC investments in the startup	1.17***	0.093	0.906***	0.081
	(0.412)			
Log Return of the market	8.89*	0.703	7.626*	0.682
	(4.569)			
Observations	153		123	
Pseudo R-squared	61.79%		57.90%	

Standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)

To assess the accuracy of my model I had to build a confusion matrix. In order to do so, I assumed that if the model predicts a probability of success higher than 0.5 for a start-up, then the start-up is successful. The main results of the analysis are the following:

Confusion Matrix

The Table provides an overview of the prediction accuracy made by the model on the test sample.

	Predicted Failure	Predicted Success	Total
Real Failure	12	1	13
Real Success	3	14	17
Total	15	15	30

From the confusion matrix I can develop different measures of model precision and accuracy. The most important accuracy measure is the percentage of true success and true failures predicted over the total cases. The accuracy of my model is 86.67%. I can use the following model to predict the probability of success of a fintech start-up:

$$P(y=1\mid X) = 0.21x_{PhD} + 0.287x_{Previos\ Success} + 0.28x_{Previous\ Startup\ tog} + 2.962x_{VC\ IPO\ experience} + 0.081x_{N\ VC\ Investments} + 0.682x_{Market}$$

Chapter IV - How to increase the robustness of start-up valuation

The predicted probability of start-up success can be then used to increase the robustness of its valuation in many ways. In my research I suggest 3 ways to employ this metric according to both the literature review and the current approaches used in practice. Firstly, I can compute a weighted valuation based on the income and cost approach:

$$NPV_t = NPV_{Income\ approach} \times p + (1-p) \times NPV_{Cost\ approach}$$

Secondly, I can employ a weighted valuation between the going concern valuation coming from the income approach and the distress sale valuation, as suggested by Damodaran (2009):

$$E(startup) = Value\ of\ going\ concern \times p + (1-p) \times Distress\ sale\ Value$$

A last suggestion is to weight the cashflows coming from the income approach by the probability of success and discount at an appropriate discount rate, hence one that does not double count the risk. This methodology is based on the findings of many academics, like Titman et al. (2016) and Damodaran (2013), concerning risk incorporation during the valuation process. According to the authors, adjusting the cash flows is, academically speaking, a more correct approach. By applying one of the above-mentioned approaches, I can employ the constructed multifactor model to get a more reliable and robust start-up valuation outcome and reduce the probability of committing un-negligible valuation errors, as demonstrated also by Cochrane (2005).

Conclusions

The aim of this thesis is to understand the start-up valuation process drawbacks, build a multifactor model to predict start-up success in the Fintech sector and suggest a way to use it to improve their valuation. In order to build the multifactor model I had to answer the following research question:

"*Which main actors and external conditions factors contributed to Fintech start-up success in Europe and United States from 2000 to 2018?*".

By conducting a Logistic regression, I provided evidence that confirm the existing literature concerning start-up success. Based on my sample, the main elements that have an impact on Fintech venture success are: Team characteristics (*PhD*, *At least one founder achieved a previous success*, *Founders previously founded a start-up together*), Investor characteristics (*VC IPO experience*, *Number of VC investments in the company*) and Market characteristics (*log return of the market*). From the findings of my inference analysis, I then built a model to predict Fintech start-up success which correctly categorize 86.67% of the ventures in my test sample. Additionally, I suggested 3 ways practitioners and academics can employ the probability of success as a supporting tool to increase the accuracy of start-up valuation. My results are based on CB Insight database, industry, years and geographic area I chose to analyse and have several limitations, as discussed in the Findings section. My model does not substitute the judgement of experts concerning the assessment of successful or unsuccessful company; it is rather meant to be a supporting tool that can be useful, for both practitioner and academics, to increase the robustness of start-up valuation.