AN EMPIRICAL STUDY OF STARTUP VALUATION

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Abstract

This paper examines the challenge of valuing startups. The complexity of factors impacting the future success of a startup makes startup valuation a complicated and difficult task. Nevertheless, valuation is an important part of entrepreneurial finance, which prompts the question of how to do it. In this paper, the question of how to value a startup is examined through an analysis of existing valuation frameworks, a comparative study of five valuation frameworks, and an empirical analysis in a venture capital context.

Firstly, implications for various valuation frameworks are identified. Corporate financial valuation frameworks encounter difficulties because of high input requirements as well as inability to meet underlying model assumptions. Startup specific valuation frameworks solve some of the challenges of corporate financial valuation frameworks, but instead introduce a great deal of subjectivity while relying on average industry valuations or multiples. In the light of these implications, the paper argues that valuation frameworks should be considered accordingly to the available input and the corporate life cycle.

Additionally, a comparative study of five valuation methods rejects methodological independence in the context of startup valuation. Valuation frameworks produce large variability in both the level and concentration of valuations. Quantitative frameworks produce higher and more dispersed valuations compared to qualitative frameworks. Based on these findings, the paper proposes relying on multiple frameworks when valuing startups.

Lastly, analysis of 122 US investments reveals determinants of startup valuation in a venture capital context. Using univariate difference in means tests, multiple regression models, and Shapley value regression the paper finds several notable results. General startup characteristics as well as human capital attributes, such as relevant industry experience, previous founding experience, and academic capital, significantly and positively affect startup valuation. In reliance with these findings, the paper argues that entrepreneurs should signal certain qualities when seeking venture capital funding.

Viewed in its entirety, this paper underscores the difficulty of valuing startups and reinforce the notion that valuing a startup is part art and part science.

Keywords: entrepreneurial finance, startup valuation, valuation framework, venture capital, entrepreneurs, early stage investors, startup characteristics, human capital
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1 Introduction

“Valuing a business is part art and part science”

(Warren Buffett)

Startup valuation is one of the core mechanisms of entrepreneurial finance and a fundamental element to consider for both entrepreneurs and investors (Köhn, 2018). Entrepreneurs are trying to estimate the value of their company when seeking outside equity because the valuation determines how much equity is sold for a given capital infusion. Early stage investors focus on valuation since their internal rate of return is a product of the difference between entry and exit valuation. The mutual dependency on startup valuation as a tool makes it a connector between entrepreneurs and investors that both parties reflect upon when discussing the terms of obtaining financing and making investments.

According to traditional corporate financial theory, the value of a firm is the present value of expected future cash flows discounted back at a cost of capital that reflects both the sources and costs of financing (Damodaran, 1999). The idea of discounting future cash flows is one of the main principals of corporate valuation. However, early stage companies often lack the necessary data and information to undertake such a valuation, thereby complicating the applicability of traditional corporate valuation in a startup context. Adding the complexity of factors which impact the future success of startups, the process of accurately valuing a startup becomes extremely difficult, if not impossible.

Valuation should capture every element of a startup, its business model, its market, its competitive environment, its technology, its founding team, as well as all the risks associated with the startup. A legitimate valuation is therefore a strong bridge between these elements and final value estimation (Damodaran, 2017). Unfortunately, there is no universally accepted valuation framework for valuing startups. Instead, various perspectives and theories on how to value startups have emerged, all differing in their approaches to valuing startups. This leaves entrepreneurs and investors with the complicated task of not only valuing a startup, but also deciding on how to do it.
1. Introduction

1.1 Problem formulation

The purpose of this paper is to assess how to value startup companies and to examine the underlying drivers behind startup valuation. The emphasis of this particular paper is not on valuing a specific startup or proposing a new method for valuing startups. Instead, the paper is highly interested in understanding the underlying dynamics behind startup valuation through a critical assessment of existing theoretical valuation frameworks and empirical analyses. The objective of this paper can be summarised into the following simple research question:

*How to value startup companies?*

The answer to this question will be based on both theoretical as well as empirical analysis. To ensure a structured and logic approach to answering the research question, it is decomposed into several subquestions:

- What are the underlying implications of applying established valuation frameworks to startup valuation?

- How do different valuation frameworks distribute valuations, and based on this what can be inferred about the comparativeness of valuation frameworks?

- What are the determinants of startup valuation in a venture capital context?

Naturally, there are numerous ways to examine the questions above, both theoretically and empirically. This paper is restricted to a theoretical analysis of existing valuation frameworks, a comparative study across five valuation methods, and an empirical analysis of 122 early stage venture capital investments. The following part of the paper seeks to outline the delimitation of the paper.

1.2 Delimitation

In order to ensure a focused analysis in this paper, a natural selection of relevant aspects related to startup valuation has to be made. This also means not addressing the following aspects related to the subject of this paper:
1. Introduction

No case study: As already mentioned, the focus of this paper is not on valuing a specific startup, but it is instead on examining startup valuation from a more holistic perspective through theoretical and empirical analysis. Therefore, this thesis is delimited from a case study of a specific startup.

Term sheet: The term sheet is a document laying out proposed terms and conditions under which an investor makes an equity infusion in a startup. This document includes agreements on equity claims, pre-emption rights, tag-along rights, employee option plans, anti-dilutive provisions and good and bad leaver clauses. The implications of term sheet agreements on valuation will not be studied in the empirical analysis of this paper.

Sources of capital: This paper is restricted from studying the impact of sources of capital on valuation. Therefore, no attention will be given to the impact of smart money\(^1\) in the context of startup valuation.

Restricted focus on ten valuation frameworks: This paper is restricted to analysing ten valuation frameworks. Frameworks such as the asset-based valuation methods will not be analysed.

Restricted empirical focus: Most of the data used in the empirical analysis is data sourced from the American market. This limits the opportunity of exploring regional and national differences in valuation, and therefore, such differences will not be addressed in this paper.

1.3 Outline of thesis structure

Having narrowed the scope, the following section seeks to provide an overview of the progression of this paper. The paper proceeds as follows.

Chapter two presents the philosophical assumptions guiding the research, the research approach, and the empirical and theoretical foundation of this paper. In chapter three a literature review on existing research on the topic of startup valuation will be provided. Chapter four presents terminology related to startup valuation and the general context in which startup valuations are made. In chapter five and six existing corporate financial

\(^1\) Smart money is an investment term for investments carrying not only capital injections, but also strategic advice on how to grow the company
valuation frameworks as well as startup specific valuation frameworks will be analysed. Chapter seven follows with a comparative study of five different valuation methods. In chapter eight an empirical study of the underlying drivers behind startup valuation in a venture capital context will be conducted. Chapter nine discusses the results from the empirical analysis in the perspective of previous research, existing financial theory, and practical implications. The discussion will also include reflections about the limitations of this paper as well as suggested avenues for future research. Lastly, chapter ten concludes and sums up the main contributions of this paper. An overview of the structure of the paper is provided below:

Figure 1: Outline of thesis structure

All figures and tables of the paper, including the above, are produced by the author of this paper unless otherwise noted.
2 Research methodology

The purpose of this chapter is presenting the philosophical assumptions guiding the development of knowledge, the research approach, as well as the empirical and theoretical foundation of this paper.

2.1 Research philosophy

Before describing the research approach, it is crucial to have a clear understanding of the underlying beliefs and assumptions guiding the development of knowledge in this paper (Saunders, Lewis & Thornhill, 2016). Whether being consciously aware of them or not, all research is developed based on a set of ontological\textsuperscript{2} and epidemiological\textsuperscript{3} assumptions, which to a great extent influence the research process.

How to value startups is in this paper viewed through the lenses of postpositivism. The basic beliefs of postpositivism is that although a real world with real causes exists, it is impossible for humans to fully capture these causes due to imperfect sensory and intellective mechanisms (Guba, 1990). This inability to fully apprehend the reality leads to a critical realistic ontology. Postpositivism recognises the ability for a human inquirer to step outside the pale of humanness while conducting research (Guba, 1990). However, full objectivity cannot be achieved, but instead it can only be achieved reasonably closely (Guba, 1990). This inability to be fully objective leads to a modified objective epistemology. Methodologically, postpositivism responds to the critical realistic ontology and modified objective epistemology by putting a special emphasis on critical multiplism, often thought as an elaborated type of triangulation (Guba, 1990).

This paper acknowledges that startup valuation is driven by real causes but can only be incompletely understood. It is simply not possible to capture all the underlying dynamics behind startup valuation due to the complexity of the subject. Instead, startup valuation can only be partially understood. Finance professionals often say that \textit{price is what you pay and value is what you get}. This distinction between price and actual valuation confirms the notion that valuation in general is a subjective estimate based on incom-

\textsuperscript{2}Ontology is concerned with the nature of reality (Saunders et al., 2016).

\textsuperscript{3}Epistemology is concerned with what constitutes acceptable knowledge in the field of study (Saunders et al., 2016).
plete understandings. To best possibly obtain an understanding of how to value startups objectivity remains a regulatory ideal throughout this paper. This means coming clean about one’s own predispositions and constantly being critically and reflective towards the research (Guba, 1990). Also, the paper seeks to emphasise critical multiplism by relying on as many sources of data and theories as possible. This reliance on multiple sources will make it less likely that misleading interpretations will be made (Guba, 1990). The use of both empirical and theoretical sources will be discussed later in this chapter.

2.2 Research approach

The research approach of this thesis lies in the intersection between a deductive approach and an inductive approach (Saunders et al., 2016). Instead of proceeding from sensory perceptions to general concepts, a deductive approach, or proceeding from general ideas to particular instances, an inductive approach, this thesis will move back and forth between the two approaches (Landreth & Colander, 2002).

This paper specifically follows a research approach in which one or more hypotheses are stated in the beginning of chapters devoted to analysis. The idea of formulating of testable hypotheses, which may or may not contribute with new knowledge, is aligned with the abductive research approach. Known premises from existing valuation frameworks and previous research will be used to formulate these testable hypotheses.

This paper investigates startup valuation using three analyses all differing in their approach. Firstly, startup valuation is studied from a general perspective using theoretical valuation frameworks. Next, these frameworks are studied from an empirical point of view, while the last analysis is used to identify valuation patterns in venture capital context. The purpose of all these analyses, and the research approach in general, is not theory verification or new theory generation, but instead to explore the phenomenon of startup valuation from a diverse set of angles and perspectives (Saunders et al., 2016). The answer to the problem statement and the generalisation about how to value a startup will lie in the intersection between the different analyses (Saunders et al., 2016). The research approach as well as the answer to the problem statement acknowledge the implications of the critical realistic research philosophy.
2. Research methodology

2.3 Empirical and theoretical foundation

The research of this paper builds on both established theoretical perspectives as well as empirical data. This reliance on multiple sources is aligned with the principal of critical multiplism mentioned in the description of the research philosophy (Guba, 1990).

The theoretical foundation of this paper is based on established valuation frameworks. A total of ten valuation frameworks will be analysed. Firstly, five traditional corporate financial valuation frameworks will be analysed in a startup valuation perspective. Next, five startup specific valuation frameworks will be presented and their implications will be analysed. The theoretical foundation of this paper is used to understand how to value a startup from a theoretical point of view. The purpose is to critically assess the applicability of existing theoretical frameworks and analyse their various implications.

The empirical foundation of this paper is collected from two different sources. The first data source is data from Equidam, a European valuation consultancy. Equidam is the leading provider of online business valuation, used by 105,000 startups to compute the value of their companies. Based on answers to a number of qualitative and quantitative questions, Equidam performs valuations of startups across five different valuation methods using algorithms. The data collected from Equidam contains valuations of 2981 firms across five different valuation methods in the period 01-01-2017 to 25-01-2019. This data is used perform a comparative study across valuation methods in chapter 7.

Analysing and comparing results of algorithmic produced valuations have both advantages as well as disadvantages. One of the primary advantages is that valuations produced based on algorithms are not subject to the usual humane bias experienced during contractual negotiations between entrepreneurs and capital providers. A concern using this algorithmic data is that the underlying algorithms behind the five valuation methods are not fully disclosed. Instead, only the general notions of each method are disclosed as well as the fact that Equidam seeks to perform objective valuations using five established valuation methods. The lack of insights into the underlying algorithms makes it extremely difficult to determine the validity of valuations produced using these algorithms. This means that caution has to be taken with regards to the generalisability of the conclusions from the comparative analysis. Despite the limitations of the data, it represents an interesting opportunity of comparing valuation frameworks.
The second empirical data source is data collected from the Thomson Reuters Corporation, one of the world’s leading provider of information-based tools to professionals. This data is used in chapter 8 to empirically understand the drivers behind startup valuation in a venture capital context. From the Thomson Reuters database 242 US venture capital investments from 1/1/1998 to 10/28/2018 were collected. All of these investments were seed, series A, series B, or series C investments and had disclosed valuations. To make sure that the extracted data is relevant in relation to the research focus on valuation of early stage companies, the initial data extraction from Thomson Reuters is sub-segmented using the following two criteria: (i) the firm had to be less than five years old at the time of funding and (ii) general information about the startup and its founding team is publicly available. As multiple funding rounds and valuations are disclosed in the data, the earliest investment round and valuation is used due to the early stage research focus of this paper. All information related to the founding team is collected through excessive research, more than 100 hours of research, of all startups using company websites, LinkedIn, Crunchbase, and Bloomberg. Data from these sources gave educational and occupational histories of the founders. All information is cross checked across sources to ensure high validity of the collected data. After sub-segmenting the initial data extraction using the mentioned criteria, the final dataset includes a sample size of 122 startup valuations from venture capital investments.
3 Literature review

With the problem formulation and the methodological foundation of this paper in place, a brief review of the literature within startup valuation is necessary to demonstrate how the research on this topic has evolved through time. Many researchers and economists have tried to find ways of valuing startups, both from a theoretical as well as from an empirical perspective. As a result, various perspectives on the determinants of startup valuation have already emerged, which has led to a diverse research sphere on this topic.

3.1 Conceptual research framework

Given the diverse research sphere, it makes sense to develop an integrative research framework that conceptualises startup valuation in a broader context. This allows for a focused approach to reviewing existing literature on the topic of startup valuation. The following framework, inspired by Köhn (2018), conceptualises startup valuation as an interplay between four categories.

Figure 2: Conceptual research framework
This research on startup valuation can be divided into four categories: (i) internal factors of startups, (ii) valuation methodologies, (iii) determinants related to venture capitalists, and (iv) external environment factors. The focus of this literature review is on determinants related to internal factors of startups and valuation methodologies.

3.2 Focused empirical review

Having defined the scope of this literature review, the following section seeks to highlight selected academic papers, which touch upon the same focus as this paper. This enables for a later comparison between this paper’s findings and earlier research.

By researching startup characteristics impact on valuation, Draper et al (1998) find that startups having entered a profitable stage in the corporate life cycle have significantly higher valuations. Intuitively it does make sense that startups having proven some kind of financial feasibility will receive funding at higher valuations. However, financial information is not the sole determinant of startup valuation since Sievers et al (2013) find that financial statement information explains only 51 percent of pre-money valuation in terms of unadjusted $R^2$. They find that non-financial information is as powerful as financial statement information in explaining pre-money valuations (Sievers et al., 2013). In a study made by Davila, Foster, and Jia (2003) employee growth is found to be positively correlated with growth in pre-IPO valuation, while age is found to be a significant determinant in explaining pre-money valuation in a study by Miloud et al (2012). Overall, former empirical studies have found general startup characteristics as significant factors in explaining the valuation of startup companies (Köhn, 2018).

In general venture capitalists are very focused on founders and team characteristics when making investment decisions (Davila et al., 2003). Former empirical studies find that factors such as having multiple founders, a complete management team, prior startup experience, and prior relevant experience all have a positive impact on startup valuation (Miloud et al., 2012). Wasserman (2017) finds that previous founding experience significantly impacts the valuation of a startup. Entrepreneurs with prior founding experience should be in a better negotiation position when discussing the valuation of the startup due to previous learnings from former experience (Hsu, 2007). However, in another study by Gombers et al (2009) the authors find that venture capital firms are not eager to pay for
prior performance and therefore do not value startups with previous founding experience higher. David Hsu (2007) finds that academic capital positively impacts the pre-money valuation of startups. Generally, empirical studies suggest differences in the importance of founder and team attributes (Köhn, 2018).

Furthermore, specific industry factors and overall market conditions are often discussed when an entrepreneur and a venture capitalist negotiate the valuation of a firm. Miloud et al (2012) find the revenue growth rate as well as the level of differentiation in an industry have a significant impact on pre-money valuation. The overall market size and the return on investment of a specific market are both found to positively affect the valuation of a startup (Miloud et al., 2012). Studies by Gombers (2009) and Armstrong et al (2006) find public equity market indices as a significant variable in explaining startup valuation.

Valuation methodologies are often considered as the foundation for discussing the valuation of a company. In a study made by Baeyens, Vanacker, and Manigart (2006) they find that different opinions on valuation and what valuation methods to use, are the most common factors in failed negotiations between entrepreneurs and venture capital firms. Despite the different nature of startups, the fundamentals of valuation can be understood through the classical risk versus return perspective. Manigart et al (1997) show that venture capital investing is aligned with mainstream finance principals.

Table 1 provides an overview of selected articles focusing on valuation determinants related to internal factors of startups and valuation methodologies.
### Table 1: Reviewed articles

<table>
<thead>
<tr>
<th>Study</th>
<th>Data sources</th>
<th>Sample</th>
<th>Method</th>
<th>Research focus</th>
</tr>
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<tbody>
<tr>
<td>(Armstrong et al., 2006)</td>
<td>VentureOne and Venture Economics</td>
<td>502 startups</td>
<td>Rank regression</td>
<td>The impact of financial statement information for startup valuation</td>
</tr>
<tr>
<td>(Davila et al., 2003)</td>
<td>Dow Jones’ Venture Source, and Thomson ONE</td>
<td>494 startups</td>
<td>OLS regression</td>
<td>Past growth effects on startup valuation</td>
</tr>
<tr>
<td>(Draper et al., 1998)</td>
<td>VentureOne</td>
<td>479 startups</td>
<td>Multi-dimensional analysis</td>
<td>The stage of development, type of financing round, and industry type</td>
</tr>
<tr>
<td>(Gompers et al., 2009)</td>
<td>Dow Jones’ Venture Source</td>
<td>3,796 startups</td>
<td>OLS regression of log pre-money valuation</td>
<td>Performance persistence in entrepreneurship and its effect on valuation</td>
</tr>
<tr>
<td>(Hsu, 2007)</td>
<td>Survey</td>
<td>149 startups</td>
<td>OLS regression of log pre-money valuation</td>
<td>Prior startup founding experience, academic capital, and social capital</td>
</tr>
<tr>
<td>(Manigart et al., 1997)</td>
<td>Survey</td>
<td>136 startups</td>
<td>Descriptive analysis and mean difference test</td>
<td>Valuation methodologies and the valuation process used by venture capitalists</td>
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## Table 1: (Continued)

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<th>Data sources</th>
<th>Sample</th>
<th>Method</th>
<th>Research focus</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Miloud et al., 2012)</td>
<td>Thomson ONE</td>
<td>102 French startups</td>
<td>GLS-regression of log pre-money valuation</td>
<td>Industry structure, founder and team effects, and network effects</td>
</tr>
<tr>
<td>(Moghaddam et al., 2016)</td>
<td>Thomson ONE</td>
<td>151 French startups</td>
<td>OLS regression of log post-money valuation</td>
<td>Alliance formation on entrepreneurial firm market performance</td>
</tr>
<tr>
<td>(Sievers et al., 2013)</td>
<td>Hand-collected data set</td>
<td>127 German startups</td>
<td>OLS regression of log pre-money valuation</td>
<td>Relevance of financial versus non financial information</td>
</tr>
<tr>
<td>(Wasserman, 2017)</td>
<td>Survey</td>
<td>6,130 American startups</td>
<td>OLS regression of log pre-money valuation</td>
<td>Founders control</td>
</tr>
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4 The startup universe

Before proceeding to the analysis of existing valuation frameworks, this chapter will establish a basic framework for analysis of startup valuation. This represents an important stepping stone for the further analysis of this paper. Understanding the notions and concepts related to startup valuation as well as the general universe in which startup valuation occur is fundamental for the analysis of startup valuation. It is important to emphasise that because the terminology related to startup valuation is often ambiguous, the following should be interpreted as a guide to this paper rather than a universal understanding.

4.1 Startup characteristics

Due to this paper’s focus on startups, it is important to have a clear understanding of what a startup is. Startup companies are generally diverse, but they share some common characteristics, such as having limited history, little or no revenue, negative cash flows, being loss making, and being very dependent on equity financing. These characteristics are all information constraints that entrepreneurs and investors face when valuing startup companies (Damodaran, 2009).

Startup companies only have limited data available on operations and financing, which limits the ability to reveal a startups true operating performance and potential. Most startups have limited or even non-existent revenue while expenses often are associated with getting the business established rather than generating revenue (Damodaran, 2009). This combination of limited revenue and non-related operating expenses tend to lead to loss making and negative cash flows for most startups. As a result of early loss making and negative cash flows, startups are generally dependent on funding received from investors (Damodaran, 2009). This dependency on equity infusion from investors can be understood through the corporate life cycle illustrated in figure 3. This figure is inspired by Damodaran (2009).
The corporate life cycle is a general representation of the progression that companies go through from idea stage to mature stage. From the corporate life cycle, it is evident that revenue and earnings tend to increase as companies progress through the cycle (Damodaran, 2017). The scope of this paper is to understand the dynamics behind valuing companies in the beginning of the corporate life cycle where revenues are small, and earnings are often negative. The earliest stage of a startup is the idea stage in which the founders of the startup have an idea for a business that meets an unmet need in the market. After this stage, the founders start building a business model that converts the idea into an actual business experiencing small revenues and operating losses. As time progresses the startup will move to the profitability stage in which revenue increases and break-even is reached (Damodaran, 2009).

It is important to emphasise that not all startups survive through the corporate life cycle. Survival rates were found to range from 45 percent to 66 percent across different sectors in a study by Deutsch (2017). Sectors such as agriculture, services, retail trade, and manufacturing had the highest survival rates ranging between 55 percent and 66 percent, while mining, wholesale trade, and transportation all had survival rates below 50 percent (Deutsch, 2017). In a study of the top 20 reasons for startup failure, CB Insights (2018) finds that no market need was the primary reason for startup failure with this reason being noted in 42 percent of the studied cases. Lack of financing and team problems were noted in respectively 29 and 23 percent of the cases (Insights, 2018). Generally, most reasons of startup failure were related to the market conditions, operations around the business model, or financing inefficiencies (Insights, 2018).
Having understood the characteristics and progression of startups, the next section will highlight the different stages of financing along the life cycle of a startup company.

### 4.2 The financing stages

In the previous section it was established that one of the major challenges faced by an entrepreneur is the financing of a startup due to the financial needs in the beginning of the life cycle. This need for financing can mathematically be expressed (Tirole, 2001).

All startup investing starts with an entrepreneur who has an idea or project that need outside financing. The project involves some kind of initial cost, $I$, and the entrepreneur has initial equity $A < I$. For simplicity think of $A$ as the amount of cash the entrepreneur can contribute to cover the cost of the investment (Tirole, 2001). The investors’ outlay is $I - A$. Assuming binomial outcomes, the project will at the end yield some kind of discounted verifiable profit $R$ or be a failure yielding no profit. The probability of success is denoted by $p$. An agency problem arises when the probability of success is endogenous. Adopting the two-effort formulation in which the entrepreneur may "behave", acting in the interest of the shareholders, or "misbehave", acting in self-interest and not aligned with shareholders interest (Tirole, 2001). The probability of success is $p_H$ if the entrepreneur "behaves”, and $p_L$ if the entrepreneur "misbehaves”. Generally, the probability of success is greater if the entrepreneur behaves, therefore $p_H > p_L$. However, despite the lower probability of success, the entrepreneur might decide to misbehave because the entrepreneur enjoys a private benefit $B$ in case of misbehaving, while the entrepreneur enjoys none in the case of behaving (Tirole, 2001).

In the following, we will see that startups are only worth funding if they induce the entrepreneurs to behave. A general rule within financing is that projects will only be financed if the NPV of the project is positive (Tirole, 2001):

$$p_H R - I > 0 \quad (4.1)$$

As the probability of success is determined by the entrepreneur, the entrepreneur must be compensated more in case of success than in the case of failure. This means that the compensation $w$ in case of success must be greater than the private benefit that the
entrepreneur can enjoy by misbehaving. Based on this reasoning the following incentive constraint can be defined (Tirole, 2001):

\[(p_H - p_L)w \geq B\]  

(4.2)

The implication of the above incentive constraint is that the entrepreneur must be induced to forego the private benefit of misbehaving for a share of the profit in case of success. This essentially means that investors in startups cannot enjoy more than \(R - \frac{B}{(p_H - p_L)}\) without compromising entrepreneurs’ incentives. The necessary condition for startup financing is therefore that the pledgeable income exceeds investors outlay:

\[p_H(R - \frac{B}{p_H - p_L}) \geq I - A\]  

(4.3)

When equation 4.3 is satisfied, the project will be financed (Tirole, 2001). This equation applies to startup financing regardless of stage. The different financing stages along the corporate life cycle are illustrated in figure 4.

Figure 4: Financing stages along the corporate life cycle

Once again it is important to emphasise that not all companies go through the above cycle, and that it is a general representation of the different financing stages. In figure 4, seed capital and venture capital are often referred to as entrepreneurial financing rounds. These financing rounds are the scope of this paper and therefore relevant from a startup valuation perspective. Typically, seed capital is the first outside capital injection that a startup receives. The purpose of this capital is to help startups sustain themselves for a period of development. This capital is often provided by angle investors or family, friends, and "fools". The next financing stage is the venture capital financing stage, which
is divided into early and later stage venture capital financing. Early stage venture capital financing is provided to support startups in their first commercial phases while later stage venture capital financing is provided to expand startups beyond break-even point.

4.3 Investors’ decision making

Venture capital investing and the general principals of startup investing can be understood through the classical risk versus return perspective (Manigart et al., 1997). Essentially, valuation at its core comes down to a risk versus return relationship. Generally, the risk associated with holding a stock is understood through unsystematic and systematic risk, also referred to as firm-specific risk and market-specific risk (Berk & DeMarzo, 2007). Firm-specific risk is fluctuations in a stock’s return due to firm-specific news, while market-specific risk is fluctuations of a stock’s return due to market-wide news. This two-part risk distinction can be written as follows:

\[
\sigma^2_{ri} = \beta_i^2 \sigma^2_{rm} + \sigma^2_{\epsilon_i} \quad (4.4)
\]

, with beta of a company found as \( \beta_i = \frac{\text{Cov}(r_i, r_m)}{\sigma^2_{rm}} \). The beta of a company measures the sensitivity of a security’s return to the return of the market portfolio (Berk & DeMarzo, 2007). Building on the assumption that a risk-averse investor can diversify all firm-specific risk away by holding a portfolio of uncorrelated securities, the CAPM model can be written as follows (Berk & DeMarzo, 2007):

\[
E[R_i] = r_f + \beta_i (E[R_m] - r_f) 
\quad (4.5)
\]

, where \( E[R_i] \) is the expected return of the security, \( r_f \) is the risk-free rate, \( \beta_i \) is the beta of the company, and \( E[R_m] \) is the expected return of the market portfolio. The principal of rewarding higher risks with higher returns is aligned with the target rates of returns of venture capitalists. The typical target rate of return by venture capitalists is 60 percent for the seed financing stage, 40 percent for the second stage, and 30 for the third stage (Lütolf-Carroll & Pirnes, 2009). This decrease in required rate of return confirms that as companies progress through the life cycle, the perceived associated risk also decreases.
5 Analysis of corporate financial valuation frameworks

Having understood the general notions and concepts related to startup valuation and the context in which startup valuation occur, the following chapter now turn to the analysis of existing corporate financial valuation frameworks. Understanding whether startups can be valued using the same valuation frameworks as mature companies represents an important stepping stone for the overall analysis of this paper. This idea can be summarised into the following hypothesis:

**Hypothesis 1** Traditional corporate financial valuation frameworks can be applied to startup valuation in the same way as they are applied to mature companies.

To examine this hypothesis fundamental valuation methods, relative valuation methods, and real options analysis will be analysed. In this chapter the theoretical foundation of all of these valuation frameworks will be stated and their applicability to startup valuation will be analysed.

5.1 Fundamental valuation

In the following sections fundamental valuation will be analysed, specifically focusing on the discounted cash flow method as well as the discounted economic profit method.

5.1.1 Discounted cash flow method

The discounted cash flow method (DCF) is the favourite valuation framework among practitioners and academics because it relies solely on the flow of cash in and out of the company (Koller, Goedhart & Wessels, 2010). The DCF method discounts all free cash flow to all available investors at a weighted cost of capital. The value of a firm is obtained by discounting cash flows to the firm (i.e. the residual cash flows after meeting all operating expenses, reinvestment needs, and taxes, but prior to payment to either debt or equity holders) at a weighted cost of capital (WACC) (Damodaran, 2012). Mathematically, the discounted cash flow model can in its simplest form be written as follows:
5. Analysis of corporate financial valuation frameworks

\[
Value = \sum_{t=1}^{t=n} \frac{CF_t}{(1 + WACC)^t}
\]  

(5.1)

, where \( t \) is time, \( n \) is the expected life time, \( CF \) is the cash flow to the firm in period \( t \), and \( WACC \) is the weighted cost of capital. The \( WACC \) is defined as follows:

\[
WACC = \frac{E}{D + E} r_e + \frac{D}{D + E} r_d (1 - T)
\]  

(5.2)

, where \( D \) is the amount of debt held by the company, \( E \) is the amount of equity held by the company, \( r_e \) is the required rate of return by equity holders, \( r_d \) is the required rate of return by debt holders, and \( T \) is the marginal tax rate. It is important to note how the cost of debt is reduced by the marginal tax rate because of the tax shield on interest paid on debt. Generally, the \( WACC \) will be a function of the riskiness of the cash flows, with higher discount rates for riskier projects and lower discount rates for safer projects. The required rate of return by equity holders is usually found using the CAPM model. Having understood the \( WACC \), equation 5.1, the DCF model can be segmented into two parts. The first part is the present value of free cash flows during an explicit forecast period, while the second part is the present value of free cash flows after an explicit forecast period, also often referred to as the discounted terminal value (Koller et al., 2010). Mathematically, this two-part distinction can be defined as follows:

\[
Value = \sum_{t=1}^{t=n} \frac{CF_t}{(1 + WACC)^t} + \frac{TV}{(1 + WACC)^n}
\]  

(5.3)

, where the terminal value is found as \( TV = \frac{CF_{t+1}}{(WACC - g)} \). The terminal value is calculated as a growing perpetuity using a constant growth rate and constant weighted cost of capital. Alternatively, it can be found using a relative valuation multiple.

5.1.2 Discounted economic profit method

The discounted economic profit method\(^4\) is similar to the DCF method in the way that both of them use the \( WACC \) as a key determinant in the valuation process. However,

\(^4\)The discounted economic profit method is often referred to as the economic value added method.
Instead of discounting future cash flows, the economic profit method focuses on whether a company is earning its cost of capital and quantifies the amount of value created each year (Koller et al., 2010). Economic profit is measured as follows:

\[
Economic\ profit = Invested\ capital(ROIC - WACC) \tag{5.4}
\]

where ROIC is the return on invested capital. Generally, economic profit can be valued as follows:

\[
Value = Invested\ capital + \sum_{t=1}^{\infty} \frac{Economic\ profit}{(1 + WACC)^t} \tag{5.5}
\]

From equation 5.5 it is clear that the value of a company equals its book value of invested capital plus the present value of all future value created. Despite the different approach of the discounted economic profit method, this method can mathematically be derived directly from the DCF model\(^5\) (Koller et al., 2010).

5.1.3 The applicability of fundamental valuation in a startup valuation context

Having established the necessary theoretical foundation of the DCF method and discounted economic profit method, the focus will now be on the feasibility of these models in a startup valuation context. Given that these models are quite similar in their approach to valuation, it makes sense to discuss their applicability together.

From looking at both models, it is evident that both of them rely on either estimating future cash flows or future economic profit. In the DCF model, the cash flow is defined as earnings after taxes adjusted for depreciation and amortisation less changes in networking capital and capital expenditures. In the discounted economic profit method, the implied earnings figure is calculated as net operating profit less adjusted taxes divided by capital invested (Damodaran, 2009). Calculating the needed figures in both models requires detailed predictions of both the income statement as well as the balance sheet. This means carefully predicting aspects such as revenue, cost of goods sold, marketing expenses, general administrative costs, capital expenditures, taxes etc.

\(^5\)This proof is outside the scope of this paper.
A crucial component in making these predictions is examining current financial statements of the firm and its history to predict the future. However, as mentioned earlier when valuing startups there is going to be an absence of historical data, which makes it difficult to predict future growth rates as well as the general cost structure of the firm. In the first years of the corporate life cycle many startups are experiencing little or no income, which makes it difficult to forecast future revenue and top-line growth precisely. It is therefore difficult to establish a pattern for future revenues, why such a pattern is always going to be developed based on subjective judgements. Predicting the exact cost structure of the firm is also going to present a challenge, given that expenses in the beginning of the corporate life cycle are often associated with getting the business established. This makes it difficult to predict the future margin structure of the firm, which is a crucial component in both the DCF method and discounted economic profit method (Damodaran, 2009).

Similar for both models is the concept of discounting using an estimated discount rate. Central components in the WACC are the cost of capital and cost of debt. Usually, the beta for equity in the CAPM model is found by regressing returns of a stock against the returns of a market index while the cost of debt is found by looking at the current market prices of publicly traded bonds. Given that startup companies are not publicly traded and have no publicly traded bonds outstanding, it is not feasible to run a regression of past returns to get an equity beta or use a market interest rate on debt (Damodaran, 2009).

Also, the CAPM model builds on the assumption that the cost of equity focuses only on market risk, the risk that cannot be diversified away (Damodaran, 2009). However, the implicit assumption that the marginal investors in a company are fully diversified may not hold in practice in a startup investing context. Equity in startup companies is often held by either the founders, who are completely invested in the company, or venture capitalists, who are partially diversified. As result, these investors are unlikely to accept the implicit assumption that only market specific risk matters and will therefore instead demand compensation for some of the firm specific risk (Damodaran, 2009).

As mentioned earlier, equity in startup companies can come from multiple sources with different terms attached to it depending on the given financing round. These terms matter for the process of valuing a company since a startup company is usually illiquid, which means that cash flow and control rights have a direct influence on the risk associated with investing in the company. Term sheet agreements and equity claims will therefore lead
to a different cost of equity for different investors, which complicates the estimation of the cost of capital. Lastly, the capital structure of a startup will most likely differ along the different development stages of the firm. This will further complicate the process of estimating the weighted cost of capital (Damodaran, 2009).

Another implication of the models is their attempt to predict one scenario and value that particular scenario. Given the high failure rate of startups as well as the great uncertainty related to how a startup will progress through the corporate life cycle, there is simply too much uncertainty in a startup context to only consider one scenario. Instead, a proper valuation method should be more flexible in terms of incorporating multiple scenarios, thereby acknowledging the possibility of multiple outcomes.

In the DCF model an important parameter is the terminal value, which often accounts for a large proportion of the overall value of a typical firm. In a startup context it is not unusual that the terminal value can account for 90 to 100 percent of the estimated value (Damodaran, 2009). Therefore, the legitimacy of assumptions related to estimation of the terminal value is of great importance. However, a prerequisite for estimating the terminal value is answering questions such as whether the firm will reach stable growth, when the firm will make it to stable growth, and what the firm will look like when it reaches stable growth (Damodaran, 2009). Earlier in this paper the high failure rate of startups was highlighted, which could support the argument that a given startup may in fact never make it to stable growth. Assuming that a company will make it to stable growth presents the next challenge of estimating when the company will reach stable growth. Timing is crucial in both of the frameworks, which means that the judgement of when a startup will reach stable growth greatly affects the valuation of a company. Lastly, the growth rate used in the calculation of terminal growth is difficult to estimate given the lack of historical data on excess growth of young firms (Damodaran, 2009).

The analysis of the DCF method and the discounted economic profit method suggests that the frameworks are facing severe challenges limiting their application in a startup valuation context. Great uncertainty related to the inputs in the models as well as violence of critical model assumptions compromise the ability of the models to measure the value of startups accurately.
5. Analysis of corporate financial valuation frameworks

5.2 Relative valuation

In addition to the fundamental valuation frameworks corporate finance practitioners often use relative valuation approaches to determine the valuation of a company (Koller et al., 2010). The basic idea behind using multiples is that similar assets and companies should sell for similar prices. Relative valuation uses ratios to determine the value of a company. A relative valuation is achieved by multiplying the average of a given industry ratio with a specific accounting number of the firm. Some of the most commonly used relative valuation metrics are price to earnings, \( \frac{\text{Share price}}{\text{Earnings per share}} \), enterprise value (EV) to revenue, \( \frac{\text{EV}}{\text{Revenue}} \), enterprise value to EBITDA, \( \frac{\text{EV}}{\text{EBITDA}} \), and enterprise value to EBIT, \( \frac{\text{EV}}{\text{EBIT}} \). Common practice is to identify a peer group of 8 to 15 peers and take the average of the multiples of the peers. Identifying a legitimate peer group requires carefully considering the similarities between the corporation that you are trying to value and the companies in the peer group. This requires reflecting upon unique strategic advantages such as superior products, better access to customers, recurring revenues, and economies of scale (Koller et al., 2010). Relative valuation can be performed using either trading multiples, ratios of publicly traded companies, or transaction multiples, ratios from the past merger and acquisition transactions.

5.2.1 The applicability of relative valuation in a startup valuation context

Relative valuation in general faces difficulties in the attempt of valuing startups for numerous reasons. First of all, the measures used in relative valuation can lead to negative valuations. Startups who are early in the corporate life cycle often have negative EBITDA, EBIT, and net income, and it therefore does not make sense to multiply these measures with the average of a peer group. Also, startups very early in the life cycle often don’t have any revenue, which rules out the use of the enterprise value to revenue multiples.

In addition to the problems with what metric to use, relative valuation also faces implications in the process of identifying comparable companies. A logical comparison would be to form a peer group of 8 to 15 similar publicly listed startups. However, usually startups are not publicly listed meaning that such a comparison will have to be with companies within the same industry that are at a later stage in the corporate life cycle. These firms usually have different risk, cash flows, and growth characteristics than the young firm be-
ing valued, and therefore such a valuation does not make sense in practice (Damodaran, 2009). The same applies to the idea of identifying transaction multiples from the past merger and acquisition transactions. Usually the information from transactions at this stage in the corporate life cycle is not disclosed, which means that it would be very difficult if not impossible to identify a peer group based on previous transactions.

Problems related to the measurement of risk and control for survival also applies to relative valuation. Beta or standard deviation of equity returns are often used as measures of equity risk (Damodaran, 2009). However, these metrics cannot be used and compared in a peer group since most young firms are privately held. Also, relative valuation face difficulties when considering the high failure rate of young companies. This failure rate is not accounted for, which means relative valuation ignores the risk of failing.

In relative valuation an underlying assumption is that the given sector or the average transaction is correctly valued. If instead this is not the case, and a given industry or average transaction value is either over or undervalued, valuations based on this approach will be inaccurate (Damodaran, 1999). Therefore, caution has to be taken when volatility is high in the average valuation and when there is large variation in valuations within the peer group. Lastly, relative valuation ignores the impact of term sheet agreements.

There is no doubt that relative valuation methods solve the problem of estimating the future with great detail and precision. However, despite the simple approach, relative valuation also faces severe implications when valuing startups primarily due to the difficulties in identifying legitimate metrics as well as forming comparable peer groups.

5.3 Real options analysis

In 1997, Robert Merton and Myron Scholes won the Nobel prize in economics for developing an approach to value derivatives that avoids the need for estimating either cash flows or cost of capital (Koller et al., 2010). Their famous Black and Scholes model rely on the idea of creating a replicating portfolio, which perfectly mimics the cash flows of the security you are trying to value. They argue that if the cash flows of the replicating portfolio and the security are the same, they must have the same price. Many have tried translating this model’s power in valuing derivatives into corporate valuation. This is referred to as real options analysis or valuation (Koller et al., 2010).
5. Analysis of corporate financial valuation frameworks

5.3.1 The Cox-Ross-Rubinstein binomial option pricing model

A natural starting point for understanding real options valuation is the binomial option pricing model, which was originally proposed by Cox, Ross and Rubinstein (1979). An option generally gives its owner the right, but not obligation, to trade an underlying asset at a fixed price at any time on or before a given date (Cox, Ross & Rubinstein, 1979). The act of making this transaction is commonly referred to as exercising the option, while the fixed price is termed the strike price and the given date is referred to as the expiration date. Generally, options are divided into call and put options\(^6\) as well as American and European options\(^7\). To begin, assume that the price of the underlying asset follows as multiplicative binomial process over discrete periods (Cox et al., 1979). Assuming that the underlying asset is a stock, the rate of return of the underlying stock can either increase to \(uS\) or decrease to \(dS\) with \(u\) and \(d\) being multiplicative growth factors. The probability that the underlying asset increases is \(q\), while the probability that the underlying asset decreases is \(1 - q\). These potential movements can be represented as follows:

\[
\begin{align*}
S & \quad q \quad (1-q) \\
\downarrow & \quad \uparrow \quad \downarrow \quad \uparrow \\
S & \quad uS \quad dS \quad u^2S \\
\downarrow & \quad \downarrow \quad \downarrow \quad \uparrow \\
(1-q) & \quad (1-q)q \quad (1-q)^2 \\
\downarrow & \quad \downarrow \quad \downarrow \\
dS & \quad uS \\
\downarrow & \quad \uparrow \\
d^2S & \quad u^2S
\end{align*}
\]

Figure 5: Multi-period binomial option model

\(^6\)A call option gives the holder the right, but not obligation, to buy the underlying asset, while a put option gives the holder the right, but not obligation, to sell the underlying asset.

\(^7\)American options give the holder the right to exercise prior to the expiration date, whereas European options only can be exercised at the expiration date.
It is assumed that individuals can burrow or lend as much as possible at a constant interest rate, and that there are no taxes, transaction costs, or margin requirements (Cox et al., 1979). The riskless interest rate is denoted $r$, while it is required that $u > r > d$ to avoid the absence of arbitrage opportunities (Cox et al., 1979).

The value of a call option in the above multi-period binomial model can be found using the following reasoning. Let $C$ be the current value of the call. The value of the call is denoted $C_u$ if the value of the underlying is going to $S_u$, while the value of the call is $C_d$ if the value of the underlying asset is going to $S_d$. The value of the call is $C_{uu}$ if the underlying is increasing in both periods, and $C_{dd}$ if the underlying is decreasing in both periods. Lastly, the value of the call can increase in one period and decrease in the other and end up at $C_{ud}$. Based on these potential movements, the following rationale exercise policy imply (Cox et al., 1979):

$$C_{uu} = \max[0, u^2S - K]$$

$$C_{ud} = \max[0, udS - K]$$

$$C_{dd} = \max[0, d^2S - K]$$

Figure 6: Call value multi-period binomial option model

Given the value of this call option it is possible to create a replicating portfolio using a combination of risk-free borrowing/lending and the underlying asset to create the same cash flows as the option being valued (Damodaran, 2012). The principles of arbitrage apply here. Forming a portfolio containing $\Delta$ shares of stock and the dollar amount $B$ in riskless bonds, yielding a cost of $\Delta S + B$. It is possible to select $\Delta$ and $B$ in a way such that the values of the portfolio is equal to the value of the call at each possible outcome:
5. Analysis of corporate financial valuation frameworks

\[ \Delta uS + rB = C_u \] and \[ \Delta dS + rB = C_d. \] By solving the equations for \( \Delta \) and \( B \), the following expressions are found: \( \Delta = \frac{C_u - C_d}{(u - d)S} \) and \( B = \frac{uC_u - dC_d}{(u - d)r} \). By choosing \( \Delta \) and \( B \) this way, it is possible to create the replicating portfolio. To satisfy the no arbitrage condition the following must be true: \( C = \Delta S + B \). Using substitution and defining \( p \equiv \frac{r - d}{u - d} \) and \( 1 - p \equiv \frac{u - r}{u - d} \), the following expression for the value of a call can be defined:

\[
C = \left[ pC_u + (1 - p)C_d \right]/r \quad (5.6)
\]

Using similar analysis, the value of a call at either \( C_u \) or \( C_d \) can be defined as follows: \( C_u = \left[ pC_{uu} + (1 - p)C_{ud} \right]/r \) and \( C_d = \left[ pC_{du} + (1 - p)C_{dd} \right]/r \). From the defined equations, we see that generally the value of call options is the value of the discounted probability weighted outcome. Therefore, the value of call options is found by starting with the last period and moving backwards. Given the fact that the Cox-Ross-Rubinstein binomial option pricing model is a discrete model, this valuation approach has limited applicability when the number of periods increases. An approach solving this problem is the continuous approach developed by Black and Scholes (1973).

5.3.2 The Black and Scholes formula

The Black and Scholes formula\(^8\) builds on multiple assumptions such as known and constant interest rate, random walk in stock prices in continuous time, constant variance in the rate of return of the stock, no dividend distribution, no transaction costs, ability to burrow fractions of a security, and no penalties for short-selling (Black & Scholes, 1973). It is also important to emphasise that the Black and Scholes formula only applies to European options. The Black and Scholes formula can be written as follows:

\[
C = SN(d_1) - N(d_2)Ke^{-rt} \quad (5.7)
\]

\[
d_1 = \frac{ln(S/K) + (r + \sigma^2/2)t}{\sigma \sqrt{t}} \quad (5.8)
\]

\[
d_2 = d_1 - \sigma \sqrt{t} \quad (5.9)
\]

\(^8\)The mathematically derivation of The Black and Scholes formula is outside the scope of this paper.
In the above formulas $C$ is the call premium, $S$ is the current stock price, $t$ is time until option expiration, $r$ is the risk-free rate, $N$ is the cumulative normal distribution, and $\sigma$ is the volatility measured as standard deviation of the stock.

5.3.3 The applicability of real options analysis to startups

Real options analysis allows for capturing flexibility in outcomes, which is one of the weaknesses of fundamental valuation and relative valuation. This makes this valuation technique a powerful tool in cases where it is difficult to capture the expected expansion opportunities in fundamental valuation frameworks and where the startup has significant competitive advantages over the competition (Damodaran, 2009). Comparing the two option models, the Black and Scholes option pricing model is often fast to calculate, but not as flexible and transparent as the binomial model (Beaton, 2010).

Despite real options ability to capture flexibility, this valuation technique has various implications. First of all, real options analysis is a technical task, which requires careful estimation of given inputs and requires practitioners to make many simplifying assumptions. This suggests that strong and technical competencies are in fact needed for practitioners employing this method. As with the other methods, real option analysis does not take into account the impact of term sheet agreements.

Furthermore, the estimation of volatility presents a challenge in the context of a startup. In a study by Benninga and Tolkowsky (2002) it is found that the estimation of volatility greatly impacts the valuation. Financial options estimate the volatility from observed historical prices of the underlying assets (Van Putten & MacMillan, 2004). However, in the context of a startup there are no historical prices that practitioners can use. This severely complicates the process of accurately determining the volatility for a startup and coming up for arguments for a given volatility.

As mentioned earlier option pricing theory is built on the assumption that it is possible to create a replicating portfolio using the underlying asset and riskless lending or borrowing. This assumption may hold up in practice for frequently traded stocks, but for startups experiencing infrequent trading it will most likely will be violated. Additionally, option pricing models assume that the underlying inputs are known and constant. However, factors such as interest rate and volatility are not always constant. The Black and Scholes
model specifically assumes that the price of an asset follows a continuous process, which is not the case for startups due to infrequent funding rounds (Damodaran, 2005).

Generally, real options are found to overestimate the value of uncertain projects and companies (Van Putten & MacMillan, 2004). Combined with the input uncertainty and lack of respect for model assumptions, startup valuations produced by real option analysis must be considered as questionable.

5.4 Interim conclusion

This chapter sought out to examine the hypothesis that traditional corporate financial valuation frameworks can be applied to startups in the same way as they are applied to mature companies. After having analysed fundamental valuation frameworks, relative valuation approaches and real options analysis, this hypothesis must be rejected. Uncertainty of inputs, failure to meet model assumptions, and problems related to finding comparable firms all contribute to limiting the application of corporate financial valuation frameworks in a startup context. Table 2 provides an overview of identified implications.

Table 2: Implications of corporate financial valuation frameworks

<table>
<thead>
<tr>
<th>Valuation framework</th>
<th>Implications in a startup context</th>
</tr>
</thead>
</table>
| Fundamental valuation | - Absence of historical data to predict future financials  
- Difficulties in estimating beta  
- Violence of CAPM assumptions  
- Lack of emphasis on term sheet agreements  
- Emphasis on predicting one scenario  
- Great dependency on estimation of terminal value  
- Lack of respect for terminal value assumptions |
| Relative valuation | - Metric problems due to negative financials  
- Difficulties in identifying comparable companies  
- Difficulties in identifying comparable transaction multiples  
- Lack of respect for firm specific risk and high failure rate  
- Implicit assumption of correct market valuations  
- Lack of emphasis on term sheet agreements |
| Real options analysis | - Technical nature of method requiring careful estimation  
- Lack of emphasis on term sheet agreements  
- Great dependency on accurate estimation of volatility  
- Inability to create replicating portfolio  
- Violence of the constant and known input assumption  
- Tendency to overvalue uncertain companies |
6 Analysis of startup specific valuation frameworks

Having analysed the difficulties that corporate financial valuation frameworks face when valuing startups, the scope of this paper now turns to startup specific valuation frameworks and their applicability. An initial hypothesis for analysing specific startup valuation frameworks is:

**Hypothesis 2** *Startup specific valuation frameworks solve the difficulties of corporate financial frameworks and are able to produce accurate and unbiased valuations.*

When examining this hypothesis startup specific valuation frameworks are divided into qualitative and quantitative valuation frameworks.

6.1 Qualitative frameworks

The following sections seek to analyse qualitative valuation frameworks\(^9\) and how they approach valuation differently. The Berkus method, the scorecard method, and the risk factor summation method will be analysed in the following.

6.1.1 The Berkus method

The Berkus method\(^10\) was invented by Dave Berkus (2009) with the purpose of valuing pre-revenue startups. Berkus came up with a method of assessing the value of critical elements of a startup without relying on projected financials. The table below summarises what factors are considered in the Berkus method (2009):

<table>
<thead>
<tr>
<th>If Exists:</th>
<th>Add to value up to:</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Sound idea (basic value and product risk)</td>
<td>USD 0.5 million</td>
</tr>
<tr>
<td>2. Prototype (technology risk)</td>
<td>USD 0.5 million</td>
</tr>
<tr>
<td>3. Quality management team (execution risk)</td>
<td>USD 0.5 million</td>
</tr>
<tr>
<td>4. Strategic relationships (market risk and competitive risk)</td>
<td>USD 0.5 million</td>
</tr>
<tr>
<td>5. Product rollout or sales (financial or production risk)</td>
<td>USD 0.5 million</td>
</tr>
</tbody>
</table>

---

\(^9\)Qualitative valuation frameworks are often referred to as rule of thumb methods.

\(^{10}\)The Berkus method is often referred to as the checklist method.
The numbers are the maximum that can be added to the valuation of a startup, thereby allowing for post-product rollout valuation of up to USD 2.5 million in the Berkus method. Investors can also attach lower values to each element if they prefer to. The maximum valuation of USD 2.5 million has been subject to critique, and therefore the maximum cap is often adjusted allowing for a higher maximum valuation. The general idea of this method is to decompose valuation into the five attributes.

6.1.2 The scorecard method

The scorecard method can be seen as a further developed version of the Berkus valuation method. The rationale behind this method is to compare a given target company to typical angel-funded startups and adjusting the average valuation of these startups (Payne, 2011a). The first step in the scorecard methodology is to determine the average pre-money valuation of pre-revenue companies in the region and business sector of the target company. The next step is to compare the target company to the average of these companies considering the following factors (Payne, 2011a):

Table 4: The scorecard method

<table>
<thead>
<tr>
<th>Comparison factor</th>
<th>Range</th>
<th>Adjustment</th>
<th>Multiplicative factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strength of entrepreneur and team</td>
<td>30% max</td>
<td>125%</td>
<td>0.3750</td>
</tr>
<tr>
<td>Size of the opportunity</td>
<td>25% max</td>
<td>150%</td>
<td>0.3750</td>
</tr>
<tr>
<td>Product/technology</td>
<td>15% max</td>
<td>100%</td>
<td>0.1500</td>
</tr>
<tr>
<td>Competitive environment</td>
<td>10% max</td>
<td>75%</td>
<td>0.0750</td>
</tr>
<tr>
<td>Marketing/sales/partnerships</td>
<td>10% max</td>
<td>80%</td>
<td>0.0800</td>
</tr>
<tr>
<td>Need for additional investment</td>
<td>5% max</td>
<td>100%</td>
<td>0.0500</td>
</tr>
<tr>
<td>Other factors</td>
<td>5% max</td>
<td>100%</td>
<td>0.0500</td>
</tr>
<tr>
<td>Sum</td>
<td></td>
<td></td>
<td>1.0750</td>
</tr>
</tbody>
</table>

The adjustments\(^{11}\) are based on subjective opinions of whether the given startup is superior or inferior compared to the average of the identified similar startups. Percentages above 100 percent suggest that the given startup is superior, while percentages below suggest that the given startup is inferior. Finally, the valuation of the examined startup

\(^{11}\)The numerical adjustments in table 4 are for illustrative purposes.
can be found by multiplying the sum of factors with the average pre-money valuation of the region and business sector (Payne, 2011a).

6.1.3 The risk factor summation method

The most thorough of the qualitative valuation frameworks is the risk factor summation method. This method considers a broader set of variables compared to the previous qualitative methods in determining the valuation of a startup (Payne, 2011b). Like the scorecard valuation method, this method starts with an average industry pre-money valuation. Based on the following list of risks associated with the startup and its industry, this average industry pre-money valuation is adjusted:

Table 5: The risk factor summation method

<table>
<thead>
<tr>
<th>Risk factors</th>
<th>Risk rationale</th>
<th>Ratings</th>
<th>Additions/subtractions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Management</td>
<td>Very positive</td>
<td>+2</td>
<td>Add USD 500,000</td>
</tr>
<tr>
<td>Stage of the business</td>
<td>Positive</td>
<td>+1</td>
<td>Add USD 250,000</td>
</tr>
<tr>
<td>Legislation/political risk</td>
<td>Positive</td>
<td>+1</td>
<td>Add USD 250,000</td>
</tr>
<tr>
<td>Manufacturing risk</td>
<td>Neutral</td>
<td>0</td>
<td>No adjustment</td>
</tr>
<tr>
<td>Sales and marketing risk</td>
<td>Negative</td>
<td>-1</td>
<td>Deduct USD 250,000</td>
</tr>
<tr>
<td>Funding/capital raising risk</td>
<td>Positive</td>
<td>1</td>
<td>Add USD 250,000</td>
</tr>
<tr>
<td>Competition risk</td>
<td>Very negative</td>
<td>-2</td>
<td>Deduct USD 500,000</td>
</tr>
<tr>
<td>Technology risk</td>
<td>Positive</td>
<td>1</td>
<td>Add USD 250,000</td>
</tr>
<tr>
<td>Litigation risk</td>
<td>Neutral</td>
<td>0</td>
<td>No adjustment</td>
</tr>
<tr>
<td>International risk</td>
<td>Neutral</td>
<td>0</td>
<td>No adjustment</td>
</tr>
<tr>
<td>Reputation risk</td>
<td>Neutral</td>
<td>1</td>
<td>Add USD 250,000</td>
</tr>
<tr>
<td>Potential lucrative exit</td>
<td>Positive</td>
<td>0</td>
<td>No adjustment</td>
</tr>
</tbody>
</table>

The risk factors\(^{12}\) are based on the various types of risks which a particular venture must manage in order to achieve a lucrative exit (Payne, 2011b). An adjustment for a given risk factor can be between adding and deducting USD 500,000 depending on the degree of the risk rationale. The advantage of this model lies in its ability to foster reflection about various types of risks associated with a startup. This will ensure a focus on not only positive factors, but instead a consideration of negative factors.

\(^{12}\)The numerical risk adjustments in table 5 are for illustrative purposes.
6. Analysis of startup specific valuation frameworks

6.1.4 Limitations of qualitative startup valuation frameworks

There is no doubt that the simplicity of qualitative startup valuation frameworks solves some of the problems encountered when using corporate financial valuation frameworks. Instead of projecting future financial statements in great detail, these methods are decomposing and adjusting valuation based on various non-financial factors related to a startup. Despite their simpler approaches, qualitative valuation frameworks will also encounter challenges in a startup context.

First of all, all of the three methods examined have some kind of a cap. The Berkus method is capped off at a maximum valuation while the scorecard and risk factor summation method are both limited in their adjustments from the average industry pre-money valuation. This essentially means that these methods in practice will never be able to estimate unique valuations to unique companies. Uniqueness will simply not be captured in these valuation frameworks, which means they are limited in their application of valuing unique investment cases. Instead, they are more suited to ”average” startups exhibiting small deviations from the general.

The next implication of these frameworks is related to determination of the maximum allowed valuation or the average industry pre-money valuation. As mentioned in the analysis of relative valuation, identifying comparable companies is often a great challenge in a startup context due to the lacking disclosure of startup valuations. This could mean that a crucial component of these valuation frameworks is severely challenged by the availability of data.

Generally, the qualitative startup specific frameworks complement relative valuation quite well due to their incorporation of adjustable factors. However, incorporating adjustable factors to relative valuation also introduces a great deal of subjectivity to the valuation. Many of the factors included in the analysed frameworks are mostly a matter of opinion rather than a question of true objectivity. Take for instance the management team of a startup, a common adjustable factor across all three frameworks. Having to adjust a valuation based on this factor raises the question of what actually constitutes a strong management team and vice versa what makes up a bad management team. The key takeaway from this is that despite their immediate simple approaches to valuation, these frameworks prompts complex questions, which are indeed very difficult to answer.
6.2 Quantitative frameworks

The focus now turns to quantitative startup specific valuation frameworks\(^{13}\) with the venture capital method and the First Chicago method being subject for analysis.

### 6.2.1 The venture capital method

The venture capital method (VC method) is a simple net present value method that takes the perspective of the investor instead of the firm (Hellman, 2001). The venture capital method developed by Sahlman and Scherlis (1989) starts by determining the post-money valuation as follows:

\[
POST = \frac{\text{Anticipated exit value}}{(\text{Target ROI})^t} \tag{6.1}
\]

The anticipated exit value is found using relative valuation multiples in the year of exit while the target ROI of the investor is used as a discount factor. The venture capital method therefore requires an estimate of either revenue or earnings in the year of exit, but not necessarily in the years between. Once the post-money valuation is estimated, the pre-money valuation can be found by deducting the initial investment as follows:

\[
PRE = POST - \text{Investment} \tag{6.2}
\]

Equation 6.2 assumes no subsequent investment and no dilution. Often new equity is issued in later rounds to either new key employees or other early round investors, which means that an investor can expect to suffer dilution (Sahlman, 2009). A commonly used way of adjusting for this expected dilution in the venture capital method is simply reducing the pre-money valuation, equation 6.2, by the estimated level of dilution.

### 6.2.2 The First Chicago method

The First Chicago method was developed in the 1970s by the equity group of the First Chicago National Bank and is today widely used by venture capitalists (Venionaire, 2015).\(^{13}\)

\(^{13}\)Quantitative startup specific valuation frameworks are often referred to as comprehensive methods.
This method can be seen as an extension of the discounted cash flow method allowing for valuing several scenarios. Usually, three different scenarios are considered: success, survival, and failure. In all scenarios cash flows are projected until the anticipated exit while the final year’s cash flow is used to estimate the terminal value. The investor will then discount each year’s cash flows and the terminal value based on the investors required return on investment. After establishing the three scenarios the present value of each scenario is weighted according to the probability of each scenario. Mathematically, this can be expressed as follows (Venionaire, 2015):

\[
Valuation = \sum_{i=1}^{3} p_i Valuation_i
\]

The First Chicago method solves the problem of estimating one particular scenario by using a weighted average valuation to account for various possibilities in outcomes.

### 6.2.3 Limitations of quantitative startup valuation frameworks

The venture capital method and the First Chicago method are commonly used by early stage investors (Venionaire, 2015). Both of these methods use investors required return on investment as a proxy for the discount rate. This represents the first limitation of these frameworks. The required rate of return of an investor is often a result of subjective opinions rather than objective risk assessment. This essentially means that these methods can produce varying results between investors based on differences in risk perception.

Furthermore, both frameworks rely on accurate estimation of the exit horizon. In general, there is great uncertainty in estimating the exit horizon in a startup context since equity held in startup companies is often not fully liquid due to infrequent trading of company equity. Therefore, accurate estimation of the time horizon is a challenge that may implicate an underlying assumption in these frameworks.

At the point of exit both models make use of relative valuation to estimate the terminal value. This means that all of the implications addressed in the section about relative valuation applies to these frameworks as well. However, these frameworks are actually further implicated by the fact that the relative valuation in these frameworks is a product of a future estimated financial metric and the average of a future industry or transaction
multiple. Predicting the general level of trading and transaction multiples at the time of exit is without doubt a great challenge.

Both frameworks are quite similar in their approach with the primary difference being that the First Chicago method includes yearly cash flows up until exit and allows for multiple scenarios. The venture capital method simply ignores all cash flows between the initial investment and the exit of the investor. This means that an underlying assumption in this model is lack of dividend payments. The First Chicago method on the other hand assumes that it is possible to estimate the probabilities of each scenario. Estimating the probabilities of the success, survival, failure scenarios require thorough analysis of the underlying risk-drivers for a startup.

### 6.3 Interim conclusion

Returning to the hypothesis posed at the beginning of this chapter, it is now possible to state that startup specific valuation frameworks solve some of the difficulties of corporate financial frameworks but are also encountering severe practical implications. Based on analysis of three qualitative and two quantitative startup specific valuation frameworks, hypothesis 2 must be rejected. Despite more simplistic approaches, startup specific valuation frameworks introduce a great deal of subjectivity while relying on average industry valuations or multiples. The subjective nature of input estimation in these frameworks means that the accuracy of these frameworks will most likely be questioned. Table 6 provides an overview of the identified implications.

Table 6: Implications of startup specific valuation frameworks

<table>
<thead>
<tr>
<th>Valuation framework</th>
<th>Implications in a startup context</th>
</tr>
</thead>
<tbody>
<tr>
<td>Qualitative frameworks</td>
<td>- All frameworks have a cap limiting their adjustments&lt;br&gt;- Difficulties in determining average industry valuation&lt;br&gt;- Adjustable factors introduce a great deal of subjectivity&lt;br&gt;- Tough questions need to be answered</td>
</tr>
<tr>
<td>Quantitative frameworks</td>
<td>- Use of inventors required rate of return as discount rate&lt;br&gt;- Rely on accurate estimation of exit horizon&lt;br&gt;- Rely on relative valuation to estimate terminal value&lt;br&gt;- VC method neglects potential cash flows up until exit&lt;br&gt;- FC method introduces subjective probability estimations</td>
</tr>
</tbody>
</table>
7 Comparative analysis of valuation frameworks

This chapter builds on the analyses done in chapter 5 and 6, and seeks to conduct a comparative analysis of five of the valuation frameworks discussed. The purpose of this chapter is to understand how the valuation frameworks empirically are connected to the valuation of startups. The previous chapters revealed significant differences between the various methods in both approach as well as needed inputs. Naturally, this raises the question of whether or not the methods are actually comparable. In an ideal world use of different valuation frameworks should estimate identical valuations since the methodology used should not affect the outcome of a valuation. Data from Equidam enables for a comparative analysis of five valuation methods and a test of the following hypothesis:

Hypothesis 3 Different valuation frameworks will yield identical valuations meaning valuations are independent of the valuation framework applied.

This hypothesis will be tested by comparing valuations produced by the scorecard method, the checklist method, the venture capital method, the DCF with long term growth as well as the DCF with exit multiple. These five methods are analysed because these are the five methods used by Equidam.

7.1 Conceptual framework of valuation frameworks

Before diving into the statistical analysis of five valuation frameworks, the analysed frameworks are depicted along the corporate life cycle. This is done in figure 7.

![Figure 7: Valuation frameworks along the corporate life cycle](image-url)
The analyses of the previous chapters revealed that the qualitative startup specific frameworks have less technical approaches to valuation and fewer input requirements, which benefits their applicability in the beginning of the corporate life cycle. As startups progress through the life cycle and start earning revenues, quantitative startup specific frameworks become more applicable. The input requirements and the model assumptions of relative valuation and real options fit the stage where revenue is increasing and firms are turning profitable. Lastly, fundamental valuation frameworks are ideal when companies have reached the more mature stages of the corporate life cycle. Obviously, the above conceptualisation should not be perceived strictly in that sense that a given valuation framework is only applicable at the specified stage in the corporate life cycle. Instead, it is merely a representation of how the input requirements and the underlying assumptions of the different valuation frameworks generally fit along the corporate life cycle.

7.2 Comparative statistics

Before analysing comparative statistics across valuation methods, the data received from Equidam has been cleaned. First of all, only valuations of firms having fully completed both the qualitative and quantitative questionnaire provided by Equidam were included. This was done to improve the validity of the raw data and ensure that only valuations where all inputs were available were included. Also, the data was examined for extreme outliers, and outliers produced by unusual combinations of all variables were excluded from the data. This led to an exclusion of negative valuations. It is important to emphasise that outliers were detected using log-transformed valuations given the skewed nature of the data. This log transformation is in line with many of the studies reviewed in the literature review.

Having cleaned the data, the data will now be assessed using arithmetic means, medians, standard deviations, percentiles, minimum and maximum observations, as well as coefficients of variance. This allows for an initial comparative analysis of the valuations produced across the five valuation methods.
An initial look at table 7 reveals that the five valuation methods generally produce highly dispersed valuations, with the more qualitative methods producing lower valuations compared to the quantitative methods when looking at median, mean and percentiles. Given the nature of the scorecard method and the checklist method, it makes sense that these methods produce lower valuations due to the fact that they are capped off at a certain maximum valuation.

Comparing the scorecard method and the checklist method reveals that these two qualitative startup specific frameworks produce relatively similar valuations compared to the other methods. The scorecard method has a median and mean of 1,901.41 and 2,597.13 respectively, while the checklist method has a median of 1,692.94 and mean of 2,265.15. This indicates that the scorecard method is producing slightly higher valuations compared to the checklist method. This is also confirmed when examining the 25 and 75 percent percentiles. The two frameworks have almost identical coefficients of variation indicating similar variability of valuations in relation to the mean.

The venture capital method is the only startup specific quantitative framework examined. This method produces a median of 3,857.94 and a mean of 24,461.71 indicating a significant difference between the two statistics. This difference suggests that the data is in fact skewed. A coefficient of variation of 3.22 is indicating a greater level of dispersion around the mean compared to the qualitative startup specific frameworks. Generally, the
venture capital method produces summary statistics falling in between the qualitative startup specific frameworks and the DCF methods.

Looking at the DCF with long term growth as well as the DCF with exit multiple, these methods are by far producing the highest valuations when looking at median, mean and percentiles. Comparing the two ways of calculating the terminal value, the DCF with exit multiple is producing nearly a twice as high median, mean, and percentiles compared to the DCF with long term growth. This suggests that the way of calculating the terminal value in the DCF methods is of great importance for the overall valuation when using the DCF in a startup context. The coefficient of variation for the DCF with long term growth and the DCF with exit multiple is 3.67 and 3.46 respectively, indicating great dispersion around the mean.

Having analysed and understood comparative statistics for the five valuation methods, the following section seeks to further understand their various valuation distributions using density plots.

### 7.3 Distribution of valuations

An initial look at the density plot for each of the valuation methods reveals extremely skewed valuations for each valuation method. Therefore, the valuation data is log-transformed in line with many of the studies reviewed in the empirical literature review. Figure 8 shows density plots of log valuations produced by each of the five valuation methods.
By looking at the area under the black curves in figure 8 it is possible to gain insights into the proportion of valuations that fall in a given range of valuations noted on the x axis. From the density plots it is clear that the scorecard and checklist method generally have more concentrated distributions compared to the venture capital method and the
7. Comparative analysis of valuation frameworks

discounted cash flow methods. Both qualitative valuation frameworks seem to produce quite similar distributions when studying their respective density plots. This is also confirmed by linearity in the valuations produced by the two methods looking at appendix 1a. The density curves of the scorecard method and the checklist method seem to exhibit log double gaussian distribution patterns. This means that two peaks of data exist, which indicates the existence of two different valuation groups. This essentially means that these methods divide startup valuations into two groups, one group with high valuation startups and one with lower valuation startups. These log double gaussian distribution patterns can be explained by the fact that both qualitative methods are adjusted based on some kind of industry reference point. It is conceivable that these reference points are divided into two different valuation groups thereby explaining the log double gaussian distribution patterns. However, this paper does now have any evidence supporting this hypothesis and therefore it is merely a reflection.

The density plots for the venture capital method and the DCF methods show a greater level of dispersion compared to the qualitative methods. Especially the DCF methods produce very dispersed valuations. All the quantitative methods produce log gaussian distribution patterns. Generally, the density plots confirm many of the results from the analysis of comparative statistics.

7.4 Interim conclusion

The purpose of this chapter was to examine the hypothesis that different valuations frameworks yield identical valuations, thereby suggesting methodological independence in the context of startup valuation. Based on comparative statistics and examination of distribution patterns this hypothesis must be rejected. The comparative analysis reveals significant differences across valuation methods when examining key statistics such as median, mean and percentiles. Furthermore, the distribution patterns of each framework are different, with quantitative methods producing more dispersed valuations when looking at density plots and coefficients of variation. Qualitative methods such as the scorecard and the checklist method exhibit log double gaussian distribution patterns while quantitative methods exhibit log gaussian distribution patterns. Overall, the results support the notion that valuations are not independent of the valuation framework applied.
8 Empirical analysis of valuation in a venture capital context

Having conducted a comparative study of five valuation frameworks and rejected methodological independence, the paper now turns to an empirical analysis of 122 US startups. The purpose of this chapter is to understand empirically what factors influence startup valuation in a venture capital context. The following chapter is organised a little differently compared to the previous chapters. Instead of examining one hypothesis, multiple hypotheses will be formulated and examined. The hypotheses are formulated in the following section.

8.1 Hypothesis formulation

All hypotheses formulated in this section are inspired by previous research reviewed in chapter 3, the description of the startup universe from chapter 4, and the examined inputs of theoretical valuation models analysed in chapter 5 and 6. The hypothesis formulation is divided into general startup characteristics and human capital of founders.

8.1.1 General startup characteristics

In chapter 4 the corporate life cycle was presented, revealing a general positive relationship between time and size of revenue and profits. All else being equal, later stages of the corporate life cycle is generally associated with less risk given their more stable revenue and profits. From the analysis of both corporate financial valuation frameworks as well as startup specific valuation frameworks, it is clear that most valuation frameworks penalise risk in form of lower valuation. The risk factor summation method specifically adjusts valuations based on the stage of the business, with startups in later stages receiving higher valuations. Obviously, the stage of the business depends on many factors, including what industry the startup is operating in. However, a common factor across industries is age, with older companies generally having progressed further through the corporate life cycle. The idea that older companies receive higher valuations can be summarised into the following hypothesis:

**Hypothesis 4** The age of a startup is positively related to valuation.
In figure 4, the financing stages were depicted along the corporate life cycle. Looking at the figure, earlier financing rounds are typically associated with investments in companies having lower revenue and profits, sometimes even negative, while later rounds are usually associated with more positive financials. A natural hypothesis to build from this is:

**Hypothesis 5** *The number of prior financing rounds is positively related to valuation.*

In a given financing round either one or multiple investors invest in the startup. The number of investors in a funding round reveals how many different investors are infusing capital to a startup at a given valuation. Multiple investors may suggest two things: (i) no investor is willing to infuse the total needed equity alone, or (ii) multiple offers is a proxy of competition over startup equity (Hsu, 2007). Given that the majority of the investors in the sample of this research are large US venture capital firms founded on the premise of engaging in risky early stage investments, lack of willingness to supply the full capital amount does not seem as a plausible explanation. Instead, the interpretation of the number of investors may be tied to the perceived quality of the startup. In the risk factor summation method valuation is positively adjusted based on the potential for a lucrative exit. All else being equal, a higher number of investors in a given round reveals a higher number of independent investors eyeing a potential lucrative exit. Based on this reasoning, the following hypothesis can be formulated:

**Hypothesis 6** *The number of investors in a financing round is positively related to valuation.*

The equity infusion in a given round is often subject to a great amount of discussion when entrepreneurs meet with investors. On the one hand, entrepreneurs seek a large equity infusion to being able to invest in future growth opportunities, while on the other hand they do not want to give up too much equity and control. Therefore, it is extremely interesting to study if the relative relationship between equity infusion and pre-money valuation impacts the pre-money valuation of the company:

**Hypothesis 7** *The relative size of the equity infusion impacts the valuation.*
8.1.2 Human capital of founders

With the increasing complexity of new technologies and global competition it is extremely difficult to found a company alone, simply because it is not possible to have all the necessary skills (Miloud et al., 2012). One of primary intangible assets in startups is the human capital of the founders. The total human capital of the founders is a product of the number of founders times the human capital of each founder. All of the qualitative startup specific valuation frameworks positively adjust valuations based on the strength and quality of the management team. A natural hypothesis focusing on the impact of multiple founders is therefore:

**Hypothesis 8** Founding teams with more founders will receive higher valuations.

Having formulated a hypothesis capturing the quantitative part of the human capital equation, a natural next step is trying to define what actually constitutes human capital in a valuation context. To examine this, four types of experiences related to the human capital of the founders are considered: (i) relevant industry experience, (ii) top management experience, (iii) previous founder experience, and (iv) educational experience.

Creating a successful startup is a big challenge. Creating a successful startup with no prior industry experience is an even bigger challenge. In order to build a successful startup, it is essential to have knowledge about the customers, products, competitors, manufacturing, distribution, as well as key market trends. Such industry knowledge may to a great extent foster the ability to make good strategic choices resulting in a unique competitive position. Founders with no previous industry experience will usually have limited knowledge about the industry as a whole and will therefore have to learn everything by trial and error. This potential trial and error is costly in the eyes of an investor, and therefore the following hypothesis seems natural:

**Hypothesis 9** Founders with previous relevant industry experience will receive higher valuations.

Creating a successful startup is very dependent on the founders’ ability to scale and grow
the venture through the corporate life cycle. To do this, the management of a startup, often its founders, must succeed in monitoring key trends and pivot accordingly while also aligning the vision and goals of the startup internally. Many of the core skills needed to become a successful startup CEO are often associated with people having some kind of top management experience. A natural hypothesis to build from the importance of managerial competencies in a startup context, is the following:

**Hypothesis 10** *Founders with previous management experience will receive higher valuations.*

Anecdotal evidence suggests that founders having some kind of prior start-up experience should have an advantage when discussing the valuation of a given startup (Hsu, 2007). Consider the case of Jim Clark, a serial entrepreneur founding five companies between 1981 and 1999. With each startup Jim was able to raise money faster and at higher valuations, most likely for two reasons (Hsu, 2007). First of all, founders having previously founded a company actually know what is required when founding a startup, and have acquired some kind of relevant entrepreneurial knowledge, regardless of the outcome of previous ventures. Secondly, founders with prior founding experience might have engaged in funding negotiations for previous ventures improving their ability to negotiate valuations (Hsu, 2007). A natural hypothesis to build from this is the following:

**Hypothesis 11** *Founders with previous founding experience will receive higher valuations.*

Lastly, educational experience cannot be neglected in the human capital formation of the founders. Despite the fact that educational experiences often cannot directly be applied in the operating of a new startup, the educational level of the founders may impact their ability and approach to problem solving, and most likely also investors’ perception of the founders (Hsu, 2007). A natural hypothesis is therefore:

**Hypothesis 12** *Founders with strong academic capital will receive higher valuations.*
8.2 Model measurements and summary statistics

This section contains a description of variables analysed in the empirical study as well as summary statistics for all variables. Before elaborating on this matter, it is important to emphasise that the purpose of this empirical analysis is to analyse the hypotheses stated in the previous section, not to maximise the R-squared value of the model. Therefore, the explaining power of the model should not be considered a success criteria in itself. Naturally, there are numerous ways of measuring the variables in the model. In this research all variables are measured to best possibly examine the hypotheses stated in the previous section while acknowledging constraints in data availability.

8.2.1 Dependent variable

The focus of this analysis is on further understanding valuation from an empirical point of view. To do this, the pre-money valuation of the companies in the sample is chosen as the dependent variable. This variable is found by deducting the equity infusion in the examined round from the post-money valuation. An initial look at pre-money valuations in the sample reveals significant skewness in the data. To overcome this skewness, the pre-money valuations are log transformed in line with similar studies reviewed in the literature review.

8.2.2 Independent variables

The independent variables are divided into three areas: startup characteristics, human capital of founders, and control variables related to the category and the market.

Start up characteristics

The first startup characteristic measured is the age of the startup. This variable is measured as the difference between the founding data and financing date in months. The idea of using age in the model is to use it as a rough proxy for the matureness of the startup. Prior funding rounds is measured as the number of disclosed funding rounds prior to the examined funding round. It is important to emphasise that this variable is collected based on disclosed funding rounds in data from Thomson Reuters Corporation. There might be
pre seed funding not disclosed in this data. *Number of investors* is measured as the total number of investors in a funding round while *equity infusion* is measured as the relative relationship between equity infusion and pre-money valuation. All independent variables related to startup characteristics are collected from the Thomson Reuters Corporation database.

**Human capital of founders**

The first variable related to the human capital of founders is the *number of founders*, which is measured as the total number of founders in the startup. Instead of measuring this variable as a numeric variable, this variable could have been measured as a dummy variable with one outcome for multiple founders and one for solo founders. However, this paper is highly interested in examining the marginal effect of an extra founder, and therefore numerical measurement is chosen.

Next, *industry experience* is measured as a dummy variable, with ”1” indicating one of the founders having previously worked in the industry of the startup. Similarly, to industry experience, *management experience* is measured as a dummy variable, with ”1” indicating one of the founders having previously worked in a top management position (VP or above). *Founder experience* is measured as a dummy variable, with ”1” indicating one of the founders having previous founder experience. Obviously, any experience can be measured both as numeric variables and dummy variables. The use of dummy variables is mostly a consequence of constraints in the available data. It was simply not possible to quantify many of the variables related to former experiences of the founders as numeric variables. Therefore, dummy variables are instead used as proxies.

Academic capital is measured through three different variables: (i) *MBA degree*, (ii) *PhD degree*, and (iii) *Top school*. The first variable is a dummy variable for *MBA degree*, with ”1” indicating one of the founders having a master in business administration at the time of funding. The second variable is a dummy variable for *PhD degree*, with ”1” indicating one of the founders having a doctoral degree at the time of funding. Lastly, the third variable is a dummy variable for *Top school*, with ”1” indicating one of the founders having attended a top school. Top schools are defined as the top 20 schools in the 2019 edition of the QS World University Rankings, one of the most widely read university rankings in the world (Appendix 2). It would be more optimal to define whether the founders have
attended a top school based on published rankings in the year of the examined funding round. This would to a greater extent measure the perceived quality of the school the founders have attended at the time of funding. However, due to lacking identical top school rankings over the time span of the data set, the 2019 edition is used as a rough proxy in this research.

Control variables
The diverse set of approaches to valuing startups examined in chapter 5 and 6 revealed that valuing a startup is in fact a very complicated task. Because of the complexity associated with valuing startups, control variables are an important part of the research. These control variables are contributing factors that are included in the hope of clearly identifying relationships between the examined variables and the dependent variable. In this research category segment dummies, a financial market proxy, and a market risk proxy are included as control variables.

The first set of control variables included is category segment dummies, with the purpose catching differences in valuations across different categories. These variables are defined using the North American Industry Classification System (NAICS) and descriptive keywords for a startup noted on Crunchbase. Included category dummies are internet, software, communication, and pharmaceuticals and medical. The excluded category is other, meaning startups not fitting any of the included category segment dummies.

The second control variable is the state of the financial market. A natural relationship would be that venture capital financing is closely related to the overall financial markets. The S&P500 is chosen as a proxy for the state of the financial markets. This control variable is measured as the adjusted close points of the S&P500 at the date of funding. A natural argument here would be that the valuation of a startup is not a product of one day of analysis, but is instead a product of continuous analysis up until the date of funding. Therefore, one could argue that instead of looking at the S&P500 at the date of funding, it would make sense to use the average adjusted close points in a certain period up until the date of funding. However, this is not done for three reasons: (i) lack of knowledge about the average time to value a startup, (ii) potential differences in time to value a startup, and (iii) the fact that the day of funding represents the actual commitment to the valuation.
Lastly, a *market risk* proxy is included as a control variable. Earlier in the paper it was stated that risk and perceived risk play a role in the determination of valuation. The CBOE Volatility Index, also referred to as the VIX Index, is chosen as a proxy for *market risk*. This is a popular measure of the stock market’s expectation of volatility implied by S&P 500 index options and often referred to as the fear index. The VIX Index value quotes the expected annualised change in the S&P 500 index over the following 30 days. This control variable is measured as the VIX Index value at the date of funding. For similar reasons as with the control variable for state of the financial markets, the VIX Index value at the date of funding is used.

All of the included variables as well as their respective variable definitions are summarised in table 8 providing an overall overview.
Table 8: Variable definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable:</strong></td>
<td></td>
</tr>
<tr>
<td>(1) Pre-money valuation</td>
<td>Valuation of a company at a given funding round minus equity infusion, in USD millions</td>
</tr>
<tr>
<td><strong>Startup characteristics:</strong></td>
<td></td>
</tr>
<tr>
<td>(2) Age of startup</td>
<td>The difference between the founding data and financing date in months</td>
</tr>
<tr>
<td>(3) Prior funding rounds</td>
<td>Number of disclosed funding rounds prior to examined funding round</td>
</tr>
<tr>
<td>(4) Number of investors</td>
<td>Total number of investors in funding round</td>
</tr>
<tr>
<td>(5) Equity infusion</td>
<td>Equity infusion measured as the relative relationship between equity infusion and pre-money valuation</td>
</tr>
<tr>
<td><strong>Human capital of founders:</strong></td>
<td></td>
</tr>
<tr>
<td>(6) Number of founders</td>
<td>Total number of founders</td>
</tr>
<tr>
<td>(7) Industry experience</td>
<td>Dummy variable, with &quot;1&quot; indicating one of the founders having worked in the industry</td>
</tr>
<tr>
<td>(8) Management experience</td>
<td>Dummy variable, with &quot;1&quot; indicating one of the founders having previous management experience</td>
</tr>
<tr>
<td>(9) Founder experience</td>
<td>Dummy variable, with &quot;1&quot; indicating one of the founders having previous founder experience</td>
</tr>
<tr>
<td>(10) MBA degree</td>
<td>Dummy variable, with &quot;1&quot; indicating one of the founders having a master in business administration</td>
</tr>
<tr>
<td>(11) PhD degree</td>
<td>Dummy variable, with &quot;1&quot; indicating one of the founders having a doctoral degree</td>
</tr>
<tr>
<td>(12) Top school</td>
<td>Dummy variable, with &quot;1&quot; indicating one of the founders having attended a top school</td>
</tr>
<tr>
<td><strong>Control variables:</strong></td>
<td></td>
</tr>
<tr>
<td>(13 - 16) Categories</td>
<td>Category dummies for internet, software, communication and pharmaceuticals and medical. Excluded category is other.</td>
</tr>
<tr>
<td>(17) Financial market</td>
<td>The adjusted close points of the SP500 at the date of funding</td>
</tr>
<tr>
<td>(18) Market risk</td>
<td>The VIX Index value at the date of funding</td>
</tr>
</tbody>
</table>

Note: log transformed variables will be denoted \( \log X \).

To further understand the representativeness of the sample the mean, standard deviation, as well as minimum and maximum for all variables are provided in table 9.
From the above table it is evident that the average pre-money valuation in the sample is USD 36.85 million with the lowest valuation being USD 1.20 million and the highest being USD 356.00 million. On average, the 122 examined startups are 27.36 months old at the examined capital round, with the youngest startup being 1 month and the oldest being 59 months. The number of prior funding rounds are between 0 and 5 with an average of 4.08 investors present in the examined round. The average relative relationship between equity infusion and pre-money valuation is 48 percent.

Since the experience related variables are measured as dummy variables, the mean of these variables can be interpreted as percentages. In the sample, 87 percent of the founders have industry experience, 56 percent have management experience, and 51 percent have previous founder experience. The sample is sourced from different categories, with startups from pharmaceuticals and medical industry being the most frequent. The average adjusted close points of the SP500 at the date of funding is 1,244, with the minimum and maximum being 751 and 2,080 respectively. Lastly, the average VIX Index value at the date of funding is found to be 20.6.
8.3 Checking model assumptions

Before reporting the empirical results, various assumptions of OLS regression need to be tested. Because the $i$th residual $\hat{\epsilon}_i$ estimates the noise $\epsilon_i$, the residuals are effective in determining whether the assumptions behind the model hold (Ruppert, 2011). Multiple regression has five key assumptions: (i) the independent residuals assumption, (ii) the assumption of correct functional form, (iii) the assumption of normality, (iv) the constant variance assumption, and (v) the no multicollinearity assumption.

The assumption of independent residuals is basically the same as saying that we need independent observations. Given that all valuations in the data set are completely independent from one another, and that no repeated measures have been taken at several time points, this assumption is considered to be fulfilled. The assumption of correct functional form, linearity of the conditional expectation, is tested by plotting the residuals against all independent variables (Appendix 3). These plots do not suggest any systematic non-linear trends between log pre-money valuation and the independent variables, and therefore the assumption of linearity is said to be fulfilled (Ruppert, 2011).

The assumption of normally distributed residuals, $\epsilon_i$ is normally distributed for all $i$, can be tested using a histogram of the residuals, a Q-Q plot of the residuals, and a Shapiro-Wilk test. If a histogram and density plot of residuals display a reasonable bell-shape and reasonable symmetry, it may indicate that the normality assumption holds. Also, linearity of the points in a Q-Q plot may suggests that the residuals are in fact normally distributed.

![Density plot](a) Density plot  
![Q-Q plot](b) Q-Q plot

Figure 9: Normality of residuals L pre-money valuation
Looking at the histogram and density plot in figure 9 the residuals seem to exhibit a reasonable bell-shaped pattern and follow the blue normal distributed band quite well. When examining the Q-Q plot, there is a straight-line appearance indicating that the normality assumption holds. Lastly, a Shapiro-Wilk test is performed to test the hypothesis that the sample is in fact normally distributed. The null-hypothesis of the Shapiro-Wilk test is normally distributed data.

\[
\text{Shapiro-Wilk normality test}
\]

\[
data: \ Premoney.res
W = 0.9895, \ p-value = 0.4785
\]

Figure 10: Shapiro-Wilk test

The p-value of 0.4785 is greater than the 5 percent significance level, and therefore the test fails to reject that the data is normally distributed. Overall, the histogram of the residuals, the Q-Q plot of the residuals, and the Shapiro-Wilk test suggest acceptance of the assumption of normality.

The validity of the constant variance, \( \text{Var}(\epsilon_i) = \sigma^2 \) for all \( i \), is tested by plotting the residuals against values of the independent variables as well as the fitted values. When looking at these plots the pattern of residual fluctuations around 0 is used to determine whether the assumption is fulfilled. Looking at appendix 3, all residual plots versus the independent variables have a horizontal band appearance showing no systematic trends. The residuals versus fitted values seen in appendix 4 has a similar horizontal band appearance indicating no heteroskedasticity. Therefore, the constant variance assumption is said to hold. Note that despite indication of homoskedasticity, heteroskedasticity consistent standard errors are used as this is best practice in empirical studies.

The last assumption of no multicollinearity can be tested using a correlation matrix as well as variance influence factors (VIF). A correlation matrix of all variables can be seen in appendix 5. Multicollinearity is often regarded as being severe if at least one simple correlation coefficient between the independent variables is 0.9 (Bowerman, O’Connell & Koehler, 2005). Appendix 5 reveals that none of the independent variables have correlation coefficients close to this threshold, and that the highest observed correlation coefficient is 0.5 between age and number of prior funding rounds. Correlation coefficients give a preliminary understanding of the data but cannot fully be relied upon in the exam-
8. Empirical analysis of valuation in a venture capital context

8. Empirical analysis of valuation in a venture capital context

Empirical analysis of valuation in a venture capital context. Therefore, the variance inflation factors for all independent variables, $X_j$, are calculated as follows (Ruppert, 2011):

$$VIF_j = \frac{1}{1 - R^2_j} \quad (8.1)$$

where $R^2_j$ is the multiple coefficient of determination for the regression model that relates $X_j$ to all other independent variables in the set. Generally, multicollinearity between independent variables is considered severe if (i) the largest inflation factor is greater than 10, or (ii) the mean of all variance inflation factors is substantially greater than 1 (Bowerman et al., 2005). In appendix 6, all variance inflation factors are calculated. The largest inflation factor is not greater than 10, and the average of the inflation factors is 1.916, which is not considered as substantially greater than 1 (Bowerman et al., 2005). Therefore, the multicollinearity among the independent variables is not considered to be severe. This means that the use of t-statistics and related p-values to access the importance of independent variables is not hindered by multicollinearity. The above analysis suggests that all necessary assumptions of the multiple regression model is fulfilled.

8.4 Empirical results

The empirical assignment is to test the hypotheses stated earlier. A starting point for the analysis is to conduct univariate difference in means tests. Such tests are conducted for all founder and team related variables in table 10.

Table 10: Univariate difference in means tests

<table>
<thead>
<tr>
<th></th>
<th>Dummy = (1)</th>
<th>Dummy = (0)</th>
<th>t-stat: Equal means</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry experience</td>
<td>3.036</td>
<td>2.126</td>
<td>-2.973***</td>
</tr>
<tr>
<td>Management experience</td>
<td>3.068</td>
<td>2.727</td>
<td>-1.563</td>
</tr>
<tr>
<td>Founder experience</td>
<td>3.250</td>
<td>2.572</td>
<td>-3.356***</td>
</tr>
<tr>
<td>MBA degree</td>
<td>3.245</td>
<td>2.805</td>
<td>-2.068**</td>
</tr>
<tr>
<td>PhD degree</td>
<td>3.168</td>
<td>2.770</td>
<td>-2.016**</td>
</tr>
<tr>
<td>Top school</td>
<td>3.170</td>
<td>2.664</td>
<td>-2.457***</td>
</tr>
</tbody>
</table>

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$, indicating significance at 1%, 5% or 10% level, respectively.

Note: all means reported are means of log pre-money valuations.

Note that the Welch’s t-test is used instead of Student’s t-test since Welch’s t-test performs better than Student’s t-test whenever sample sizes and variances are unequal.
between groups (Delacre, Lakens & Leys, 2017). The null-hypothesis for the above tests is that the means are equal while the alternative hypothesis is that the means are not equal. Examining the results reported in table 10 measures for industry experience, management experience, founder experience, MBA degree, PHD degree, and top school all have low p-values suggesting a rejection of the null-hypothesis in favour of the alternative. The difference in means between having management experience and not having management experience, is not statistically significant at any of the noted significance levels.

Despite being suggestive of various relationships, univariate difference in means tests do not control for various firm and market effects. To control for these effects, a multiple linear regression model is introduced. The multiple linear regression model can be written as follows (Ruppert, 2011):

\[ Y_i = \beta_0 + \beta_1 X_{i,1} + \ldots + \beta_p X_{i,p} + \epsilon_i \]  

(8.2)

, where \( Y_i \) is the log pre-money valuation and the least square estimates are the values \( \hat{\beta}_0 + \hat{\beta}_1 + \ldots + \hat{\beta}_p \) of the independent variables that minimise:

\[ \sum_{i=1}^{n} \{ Y_i - (\hat{\beta}_0 + \hat{\beta}_1 X_{i,1} + \ldots + \hat{\beta}_p X_{i,p}) \}^2 \]  

(8.3)

Table 11 reports the estimates of the OLS estimation on pre-money valuation. Model 1.1 is the baseline model only including control variables related to the category and the market. In model 1.2 all general startup characteristics are added. All independent variables are included in model 1.3, while model 1.4 includes all independent variables as well as interactive variables. The estimation of multiple models is done as a robustness check to see how certain regression coefficient estimates behave when the regression specification is modified in some way (Lu & White, 2014).
8. Empirical analysis of valuation in a venture capital context

Table 11: Multiple regression models, dependent variable: L pre-money valuation

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Model 1.1</th>
<th>Model 1.2</th>
<th>Model 1.3</th>
<th>Model 1.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age of startup</td>
<td>−0.002</td>
<td>0.003</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>Prior funding rounds</td>
<td>0.213**</td>
<td>0.103</td>
<td>0.205*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.104)</td>
<td>(0.111)</td>
<td></td>
</tr>
<tr>
<td>Number of investors</td>
<td>0.131***</td>
<td>0.101***</td>
<td>0.098***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.032)</td>
<td>(0.031)</td>
<td></td>
</tr>
<tr>
<td>L equity infusion</td>
<td>−0.676***</td>
<td>−0.689***</td>
<td>−0.644***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.130)</td>
<td>(0.117)</td>
<td>(0.120)</td>
<td></td>
</tr>
<tr>
<td>L number of founders</td>
<td>−0.053</td>
<td>−0.072</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.174)</td>
<td>(0.167)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry experience</td>
<td>0.609***</td>
<td>0.630***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.222)</td>
<td>(0.06)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Management experience</td>
<td>0.035</td>
<td>0.042</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.170)</td>
<td>(0.171)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Founder experience</td>
<td>0.351**</td>
<td>0.356**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.165)</td>
<td>(0.176)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MBA degree</td>
<td>0.273</td>
<td>0.509*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.198)</td>
<td>(0.307)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PhD degree</td>
<td>0.368**</td>
<td>0.389**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.165)</td>
<td>(0.166)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top school</td>
<td>0.009</td>
<td>0.367*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.181)</td>
<td>(0.222)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Internet</td>
<td>0.552*</td>
<td>0.108</td>
<td>0.195</td>
<td>0.222</td>
</tr>
<tr>
<td></td>
<td>(0.316)</td>
<td>(0.295)</td>
<td>(0.278)</td>
<td>(0.285)</td>
</tr>
<tr>
<td>Software</td>
<td>0.170</td>
<td>0.038</td>
<td>−0.074</td>
<td>−0.098</td>
</tr>
<tr>
<td></td>
<td>(0.228)</td>
<td>(0.243)</td>
<td>(0.241)</td>
<td>(0.244)</td>
</tr>
<tr>
<td>Communication</td>
<td>0.672*</td>
<td>0.538</td>
<td>0.755***</td>
<td>0.716*</td>
</tr>
<tr>
<td></td>
<td>(0.363)</td>
<td>(0.348)</td>
<td>(0.366)</td>
<td>(0.373)</td>
</tr>
<tr>
<td>Pharmaceuticals and medical</td>
<td>0.084</td>
<td>−0.064</td>
<td>−0.255</td>
<td>−0.235</td>
</tr>
<tr>
<td></td>
<td>(0.206)</td>
<td>(0.252)</td>
<td>(0.224)</td>
<td>(0.230)</td>
</tr>
<tr>
<td>L financial market</td>
<td>1.273*</td>
<td>1.273***</td>
<td>1.233***</td>
<td>1.293***</td>
</tr>
<tr>
<td></td>
<td>(0.703)</td>
<td>(0.550)</td>
<td>(0.492)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>L market risk</td>
<td>−0.424</td>
<td>−0.337</td>
<td>−0.261</td>
<td>−0.258</td>
</tr>
<tr>
<td></td>
<td>(0.275)</td>
<td>(0.225)</td>
<td>(0.206)</td>
<td>(0.203)</td>
</tr>
<tr>
<td>Pfunding rounds x Top school</td>
<td></td>
<td></td>
<td></td>
<td>−0.281**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.122)</td>
</tr>
<tr>
<td>MBA x Founder experience</td>
<td></td>
<td></td>
<td></td>
<td>−0.271</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.369)</td>
</tr>
<tr>
<td>Constant</td>
<td>−5.112</td>
<td>−6.585</td>
<td>−7.219*</td>
<td>−7.830**</td>
</tr>
<tr>
<td></td>
<td>(5.417)</td>
<td>(4.308)</td>
<td>(3.899)</td>
<td>(3.839)</td>
</tr>
<tr>
<td>N</td>
<td>122</td>
<td>122</td>
<td>122</td>
<td>196</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.130</td>
<td>0.457</td>
<td>0.563</td>
<td>0.582</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.084</td>
<td>0.408</td>
<td>0.491</td>
<td>0.504</td>
</tr>
</tbody>
</table>

*** p < 0.01; ** p < 0.05; * p < 0.1, indicating significance at 1%, 5% or 10% level, respectively.

(Standard errors in parentheses)
Comparing all models in table 11, the estimates are quite consistent throughout except for small variability. This is also confirmed by the average coefficients for different model sizes seen in appendix 7. The estimates for MBA degree and top school change from being insignificant to being significant once two interactive dummies are added. Looking across all models, there is generally an increase in both $R^2$ and the adjusted $R^2$ as independent variables are added. Model 1.4 has $R^2$ and adjusted $R^2$ values of 0.582 and 0.504 respectively, indicating that roughly half of the variation in valuations of the 122 startups is explained by the full multiple regression model. The adjusted $R^2$ is included since $R^2$ is biased in favour of larger models because $R^2$ always will increase when more predictors are added, even if they are independent of the response (Ruppert, 2011). The reported $R^2$ and adjusted $R^2$ are reasonable given the complexity of valuing startups. In the following, the empirical findings will be used to provide answers to the stated hypotheses.

8.4.1 Findings related to general startup characteristics

From table 11 it is evident that startup age is estimated not to have a statistically significant relationship with pre-money valuation, thereby failing to support hypothesis 4. The estimated coefficient for prior funding rounds is positive and significant at a 10 percent significance level. The coefficient of 0.205 suggests that one additional prior funding round is associated with a 20.5 percent increase in pre-money valuation, a result that supports hypothesis 5. Number of investors is positive and significant at a 1 percent significance level supporting hypothesis 6. Lastly, the variable equity infusion is negative and significant at a 1 percent significance level. This suggests a negative relationship between the relative relationship between equity infusion and pre-money valuation, and the valuation of a startup. It is important to note that the interpretation of this coefficient is a little different due to the measurement of this variable. This variable is originally measured in percentage terms as noted in table 8, and the log-log relationship in the regression models means that the interpretation is as follows: a one percent change in the relative relationship between equity infusion and pre-money valuation is associated with a negative 0.64 percent change in pre-money valuation.
8.4.2 Findings related to human capital of founders

The first regression coefficient related to the human capital of the founders is the number of founders. This variable is not significant at any of the significance levels, thereby failing to support hypothesis 8. It is quite interesting that the quantitative element of the human capital equation does not seem to have a significant effect on pre-money valuation in the sample. The estimated effect of prior industry experience is positive at a 1 percent significance level, indicating a positive relationship between specific industry knowledge and pre-money valuation. This positive relationship supports hypothesis 9. The results do not show a significant relationship between pre-money valuation and management experience, meaning that the empirical analysis fail to support hypothesis 10. Previous founding experience is found to be associated with 35.6 percent higher valuations in model 1.4 when looking at the coefficient founder experience. This coefficient is significant at a 5 percent significance level, a result that supports hypothesis 11. Lastly, academic capital is measured through three variables. Having a PhD degree is estimated to have a positive and significant effect at a 5 percent significance level. In the sample, startups with a founder having a PhD degree are associated with 38.9 percent higher valuations. A MBA degree and educational enrolment at a top school are not found to be significant in model 1.3, but were both found to be significant at a 10 percent significance level in model 1.4. Overall, the results indicate a positive relationship between the academic capital of the founders and startup valuation, thereby supporting hypothesis 12.

8.4.3 Findings related to control variables

Because studying valuation cannot be done in a vacuum, category as well as market effects are included as control variables. From table 11 it is evident that startups within the communication category seem to receive higher valuations in the sample. The coefficient of 0.716 is significant at a 10 percent significance level, suggesting that startups within the communication sector receive 71.6 percent higher valuations. Significant category dummies suggest differences in valuation across categories. The coefficient for financial market, measured using the S&P500, has a positive coefficient of 1.293 significant at a 1 percent significance level. This coefficient suggests that a 1 percent change in the S&P500 index is associated with a 1.29 percent change in pre-money valuation. The fact that this
coefficient is above 1 is quite interesting since it suggests that startup valuation is more volatile compared to the market. The market risk proxy is not found to be significant in any of the models. Lastly, two interaction terms are included in model 1.4, with only one of them found significant at a 5 percent significance level.

8.5 Shapley value regression

Having revealed significant relationships between included regressors and pre-money valuation, a natural progression of this empirical analysis is to study the relative importance of the included regressors. Relative importance refers to the quantification of an individual regressor’s contribution to a multiple regression model (Grömping et al., 2006). Anova provides the sequential sums of squares. Sequential means that the regressors are added to the model in the exact order they are listed. However, evidence shows that the exact order in which the regressors are added can impact the relative importance assessment (Grömping et al., 2006). Given that there is no natural ordering of the variables in this study, an approach based on the sequential R squared of one fixed order of regressors is not appropriate for studying relative importance (Grömping et al., 2006).

The metric $LMG$, also known as Shapley value regression, is based on sequential $R^2$s, but solves the dependence on orderings by averaging over orderings using unweighted averages (Grömping et al., 2006). For describing the metric, it is useful to briefly describe some notions. The $R^2$ for a model with regressors in a set $S$ is given as:

$$R^2(S) = \frac{\text{Model } SS(\text{model with regressors in } S)}{\text{Total } SS} \quad (8.4)$$

The incremental $R^2$s when including additional regressors in a set $M$ to a model with the regressors in set $S$ is given as (Grömping et al., 2006):

$$\text{seq}R^2(M\mid S) = R^2(M \cup S) - R^2(S) \quad (8.5)$$

The order of the available regressors $x_1, ..., x_p$ can be denoted by the tuple of indices $r = (r_1, ..., r_p)$. Defining the set of regressors in a model before regressors $x_k$ in the order $r$ as $S_k(r)$, the portion of $R^2$ allocated to regressor $x_k$ in order $r$ can be written:
\[ seqR^2(x_k|S_k(r)) = R^2(x_k \cup S_k(r)) - R^2(S_k(r)) \] (8.6)

Using equation 8.6 and summarising orders \( S_k(r) = S \) into one summand, the metric \( LMG \) can be written as follows (Grömping et al., 2006):

\[
LMG(x_k) = \frac{1}{p!} \sum_{S \subseteq \{x_1, \ldots, x_p\} \backslash \{x_k\}} n(S)! (p - n(S) - 1)! seqR^2(x_k|S) \] (8.7)

This formula shows \( LMG \) as the average over average contributions in models of different sizes, an interesting metric decomposing \( R^2 \) (Grömping et al., 2006). The R package relaimpo allows for computation of \( LMG \) metrics\(^{14}\). Table 12 shows the relative importance of all regressors included in model 1.3.

Table 12: Relative importance of regressors

| Multiple regression model 1.3 allocated \( R^2 \) (Total 56.3%) |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| LMG | 1.47 | 4.84 | 4.86 | 19.2 | 0.19 | 4.16 | 0.68 | 3.63 | 1.26 | 2.08 | 1.65 | 1.03 | 0.19 | 2.60 | 1.01 | 4.88 | 2.58 |

Note: numbering corresponds to variable numbering in table 8. Metrics are not normalised. All values are noted in percentage terms summing to a total allocated \( R^2 \) of 56.3%.

The reported LMG metrics in table 12 are the \( R^2 \) contributions averaged over orderings among regressors. From the results it is evident that especially the relative relationship between equity infusion and pre-money valuation, variable (5), accounts for a big part of the \( R^2 \) contribution with a LMG metric of 19.2%. Intuitively, it does make sense that this relationship has a large \( R^2 \) contribution since the relative size of an equity infusion is often subject to a great amount of discussion when entrepreneurs meet with investors. The first three independent variables, (2) age, (3) prior funding rounds, and (4) number of investors, have \( R^2 \) contributions of 1.47%, 4.84%, and 4.86% respectively.

It is interesting that the number of founders, variable (6), only has a \( R^2 \) contribution of 0.19%, indicating a low contribution to the multiple regression model. Experience related variables, variable (7) - (9), have dispersed \( R^2 \) contributions with previous industry and founder experience having higher contributions than top management experience. The measurements for academic capital, variable (10) - (12), have \( R^2 \) contributions of 2.08%,

\(^{14}\)LMG requires a lot of computation in case of many regressors. Due to the computer intensive nature of this metric, interactive dummies were not included in the relative importance assessment.
1.65%, and 1.03% respectively. Lastly, control variables show different $R^2$ contributions with especially the S&P500, variable (17), having a large contribution of 4.88%.

### 8.6 Interim conclusion

The objective of this chapter was to empirically understand what factors influence startup valuation in a venture capital context. Nine hypotheses were formulated based on previous chapters. The analysis finds significant relationships between startup valuation and the number of prior funding rounds, the number of investors in a financing round, and the relative size of the equity infusion. Additionally, human capital attributes such as having relevant industry experience, founding experience, and strong academic capital all are found to be positively related to startup valuation. Lastly, the analysis decomposed $R^2$ of the multiple regression model to examine the relative importance of the included regressors. A summary of the findings from the empirical analysis can be seen in table 13, while all the findings will be discussed in a broader perspective in chapter 9.

Table 13: Summary of findings from the empirical analysis

<table>
<thead>
<tr>
<th>General startup characteristics:</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>H4:</strong> The age of a startup is positively related to valuation</td>
<td>Unsupported</td>
</tr>
<tr>
<td><strong>H5:</strong> The number of prior financing rounds is positively related to valuation</td>
<td>Supported</td>
</tr>
<tr>
<td><strong>H6:</strong> The number of investors in a financing round is positively related to valuation</td>
<td>Supported</td>
</tr>
<tr>
<td><strong>H7:</strong> The relative size of the equity infusion impacts the valuation</td>
<td>Supported</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Human capital of founders:</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>H8:</strong> Founding teams with more founders will receive higher valuations</td>
<td>Unsupported</td>
</tr>
<tr>
<td><strong>H9:</strong> Founders with previous relevant industry experience will receive higher valuations</td>
<td>Supported</td>
</tr>
<tr>
<td><strong>H10:</strong> Founders with previous management experience will receive higher valuations</td>
<td>Unsupported</td>
</tr>
<tr>
<td><strong>H11:</strong> Founders with previous founding experience will receive higher valuations</td>
<td>Supported</td>
</tr>
<tr>
<td><strong>H12:</strong> Founders with strong academic capital will receive higher valuations</td>
<td>Supported</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Control variables:</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>C1:</strong> Category dummies</td>
<td>Significant</td>
</tr>
<tr>
<td><strong>C2:</strong> Financial market (S&amp;P500 index)</td>
<td>Significant</td>
</tr>
<tr>
<td><strong>C3:</strong> Market risk (VIX Index)</td>
<td>Insignificant</td>
</tr>
</tbody>
</table>
9 Discussion

In the following chapter, the results from the empirical analyses will be discussed in the perspective of previous research, existing valuation frameworks, and practical implications for entrepreneurs and investors. Furthermore, this chapter aims at discussing potential limitations and pitfalls in the analyses of this paper. Lastly, potential avenues for further research will be suggested.

9.1 Linking empirical findings to previous research

This part of the discussion seeks to relate the empirical findings to the results found in previous research. This represents an important part of the discussion since comparing and contrasting the empirical findings of this paper to findings of other studies helps support the overall importance of the results. Results related to general startup characteristics, human capital for the founders, and control variables will be discussed.

The first startup characteristic examined in this paper is age. The empirical analysis of this paper does not find statistical evidence of a significant relationship between the age of a startup and its valuation. This finding is aligned with studies by Moghamddam et al (2016), Sievers et al (2013), and Armstrong et al (2006). However, Hsu (2007), Miloud et al (2012), and Wasserman (2017) all find positive and significant relationships between age and the valuation of a startup. This suggests that the relationship between age and valuation is ambiguous and highly dependent on the given sample. Furthermore, the number of prior funding rounds is found to be positively related to the valuation of a startup, a result which corresponds to the findings in a similar study by Sievers et al (2013). This supports the argument that later funding rounds carry higher valuations.

Another startup characteristic studied in the paper is the number of investors in a given funding round. Given the complexity of measuring the quality of a startup, the number of investors in a financing round is used as a rough proxy in the empirical analysis. The idea of using the number of investors as a rough proxy for the quality of a startup is inspired by Hsu (2007). Both this paper and the study by Hsu (2007) find a positive relationship between the number of investors in a round and valuation. This may indicate that competition over startup equity will drive up valuation. Additionally, the relative size of
the equity infusion compared to the pre-money valuation is found to negatively impact valuation. Previous studies all focus on the impact of equity dilution rather than the relative relationship between equity infusion and pre-money valuation. Therefore, no direct connections can be drawn between this part of the analysis and previous studies.

In addition to studying general startup characteristics, the research of this paper extends existing work on the importance of the human capital of the founders when determining pre-money valuations. The analysis reveals a non-significant relationship between the number of founders and pre-money valuation, a result which corresponds to the findings of Sievers et al (2013) and Hsu (2007). Wasserman (2017) on the other hand find a positive relationship between the number of founders and pre-money valuation, significant at a 1 percent significance level. This suggests an ambiguous relationship between the number of founders and pre-money valuation.

The human capital attribute relevant industry experience is found to positively impact pre-money valuation. This finding is aligned with the findings of Miloud et al (2012). On the contrary, no significant relationship is established between having top management experience and receiving higher valuations. This result is inconsistent with the findings of Miloud et al (2012). The difference in results can be caused by the fact that Miloud et al (2012) use a French sample, while this study is based on an American sample.

The positive and significant relationship between previous founding experience and valuation is consistent with numerous papers. Wasserman (2017), Sievers et al (2013), Moghamdam et al (2016), and Miloud et al (2012) all find positive relationships between founder dummies and valuation. Gombers et al (2009) is the only study not finding a positive relationship between founder experience and valuation. Hsu (2007) specifically examines the impact of founding experience using a numerical variable of the number of startups founded previously, and find a positive relationship between both the number of startups founded as well as high prior startup returns. Lastly, this paper finds positive relationships between academic capital attributes and valuation, a result which corresponds to both the study of Hsu (2007) as well as the study of Sievers et al (2013).

In addition to studying general startup characteristics as well as founder attributes, control variables are included in this study. Despite the fact that these variables are not included to test specific hypotheses, it is interesting to compare the results of them with previous
9. Discussion

Studies by Gombers (2009), Armstrong et al (2006), and Miloud et al (2012) all find market indices as a significant variable in explaining startup valuation, while this paper finds a significant relationship between valuation and the adjusted close points of the S&P500 at the date of funding. No studies have previously included market risk proxies, and therefore no connections can be made to this part of the research.

Generally, several results from the empirical analysis accord with existing literature. The findings corresponding to previous research results support the overall relevance of the results. On the contrary, certain relationships seem to be ambiguous and very dependent on the nature of the sample.

9.2 Linking empirical findings to existing valuation frameworks

In general, there is little research connecting empirical research on startup valuation with existing valuation frameworks. This section seeks to make this connection. The purpose is not to confirm nor deny any of the frameworks, but instead to establish some kind of connection between the empirical findings of this paper and theory.

The risk factor summation method positively adjusts valuations if a startup is at the later stages in the corporate life cycle. In the empirical analysis of this paper, the age of a startup as well as the number of previous funding rounds are used as proxies for the stage in the corporate life cycle. Only the number of prior funding rounds is found to have significant impact on pre-money valuation. This positive adjustment based on later funding rounds accords with the adjustment in the risk factor summation method. Furthermore, funding and capital raising risk is addressed in the risk factor summation method. All else being equal, later funding rounds will carry less funding and capital raising risk due to a lower expected dilution. Overall, the idea of adjusting valuations based on the stage of the business seems to be aligned with the empirical findings.

In all of the qualitative valuation frameworks, the strength of the management team is an adjustable factor for determining the valuation of a startup. However, none of the frameworks actually answer the question of what constitutes a strong management team. The empirical analysis of this paper specifically analyses the founding team based on the number of founders, industry experience, management experience, founding experience, and academic capital. Positive and significant relationships between valuation and industry
experience, founding experience, and academic capital are established. These significant relationships can potentially explain some of the elements that investors associate with a strong management team. In general, the principal of adjusting valuations based on the qualities of the management team seems reasonable given the empirical findings.

The risk factor summation method positively adjusts valuation based on the potential for a lucrative exit, while the empirical analysis of this paper uses the number of investors in a funding round as a rough proxy for the potential for a lucrative exit. A positive relationship between the number of investors in a funding round and valuation is established, a result which supports the idea of adjusting valuation based on the potential for a lucrative exit. However, more precise proxies for the potential for a lucrative exit will have to be found and tested.

Relative valuation is a crucial component in all of the startup specific valuation frameworks. This suggests that valuation should be adjusted based on the average industry valuation or a peer group as the level of valuations varies across industries and categories. The empirical analysis finds significant category dummies supporting this argument. This essentially means that the theoretical idea of adjusting valuations based on industries or categories is supported by the results from the empirical analysis.

Making connections between the empirical analysis and existing valuation frameworks is difficult because many of the frameworks are not specified in great detail. Instead, they guide how to value a startup from a more universal perspective through equations or based on broad adjustable factors. This essentially requires entrepreneurs and investors to answer difficult questions on how to connect stories with numbers or on how to decompose adjustable factors. Drawing on empirical findings, it would be possible to help connect stories with numbers or further decompose the adjustable factors in the theoretical valuation frameworks. This can potentially help entrepreneurs and investors answering these difficult questions, and eventually on how to value startups.

9.3 Implications for entrepreneurs and investors

What are the implications of the results for entrepreneurs when seeking outside financing from early stage investors? And on the other side of the table, what are the implications for investors when valuing prospective targets? The purpose of this section is to discuss the
results from a practical perspective through the eyes of entrepreneurs and investors.

The findings in chapter 5 and 6 implicate both entrepreneurs and early stage investors. Analysis of ten valuation frameworks suggests severe differences in their approach to valuation as well as required inputs. To cope with these differences, both entrepreneurs as well as early stage investors must consider the stage of the startup when deciding on what valuation methods to use. This means carefully considering how the available input fits the input requirements of the valuation framework while also acknowledging the assumptions of the framework. It is important to rely on financial and non-financial information as both are important inputs in valuation frameworks. Most entrepreneurs and investors will most likely experience that no single valuation framework will perfectly fit with the available input. Instead, they will therefore consider multiple valuation methods. The consideration and reliance on multiple valuation frameworks is legitimate considered the findings of the comparative study in chapter 7.

The comparative study reveals great dispersion of valuations across valuation frameworks. Taking an entrepreneur’s point of view, it will make the most sense to value a startup using quantitative methods given their higher valuation distributions. This will decrease the cost of capital for the entrepreneurs, and thereby minimise their experienced equity dilution for a given equity infusion. On the other side of the table, investors should prefer the use of more qualitative methods such as the scorecard method and the checklist method given their lower valuation distributions. Investing in a startup at a lower entry valuation will increase the proportion of the equity they receive for a given equity infusion, and thereby improve their internal rate of return. Overall, the large variability in valuations produced by valuation frameworks suggests that a natural starting point is to agree on what methods to use. This will most likely facilitate a more productive negotiation in which the starting point for a value discussion is more equal.

The empirical analysis conducted in chapter 8 reveals significant relationships between startup valuation and startup characteristics as well as founder attributes in a venture capital context. Obviously, these significant relationships do not necessarily imply causation and may be subject to omitted variable bias. Nonetheless, significant relationships are established and they are to a great extent also found to be aligned with both theory and previous empirical research. Therefore, it will be natural to advise entrepreneurs to
9. Discussion

Entrepreneurs can use the empirical results to better understand what venture capital investors look for and to identify factors that can justify higher pre-money valuations. Specifically, entrepreneurs should for example make sure to signal the human capital of the founders by including information regarding their previous industry experience, founder experience, and academic experience in investment memorandums. A natural way to do this is including team-oriented information in investment memorandums thereby adapting this material to the preferences of the investors. If a team of founders is missing key resources in form of human capital, founders will have a better chance at raising money at higher valuations by attracting new co-founders or hires having skills within the areas they are lacking. Obviously, attraction of these new human capital resources come at a cost, which introduce a trade-off between foregoing ownership and human resource attraction. The results of the study also suggest that entrepreneurs should make sure to highlight the number of previous funding rounds and the number of interested investors, as these variables are found to positively impact valuation.

The implications of this paper for both entrepreneurs and investors is conceptualised in figure 11 showing different suggestions along the valuation assessment process.

<table>
<thead>
<tr>
<th>Valuation assessment</th>
<th>Negotiation and final valuation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consider available input</td>
<td>Negotiate valuations</td>
</tr>
<tr>
<td>Decide on what valuation frameworks to use</td>
<td>Agree on final valuation</td>
</tr>
<tr>
<td>Carefully consider the implications identified in chapter 5 and 6 and how the frameworks fit the stage of the startup.</td>
<td>Make sure to signal significant startup characteristics and human capital attributes found in chapter 8.</td>
</tr>
<tr>
<td>Conduct valuation using multiple frameworks as frameworks produce varying valuations based on findings in chapter 7.</td>
<td>Be transparent and ask intelligent questions about the use of valuation frameworks, rather than focusing purely on exact valuation.</td>
</tr>
</tbody>
</table>

_Rely both on financial and non-financial input as both are important in valuation frameworks._

---

Figure 11: Implications for entrepreneurs and investors

Negotiations about startup valuations are sometimes perceived as zero-sum games, situations in which the gains of one party is equivalent to the losses of the other party (Villalobos, 2007). Such perception can lead to each player withholding information and intense negotiations about the exact valuation of a startup. However, valuation discussions are not zero-sum games. Instead, they present an opportunity for both parties to achieve total net gains by working together towards the common goal of building successful companies. This means that, ideally entrepreneurs and investors ought to work collaboratively.
in the valuation process, instead of seeing one another as conflicting parties. Valuation should be used as an opportunity to understand underlying value drivers rather than a single-point valuation discussion (Goedhart, Koller & Wessels, 2016).

The analysis of this paper confirms that valuing a startup is an extremely difficult task, and that startup valuation will most likely always be as much of an educated guess as true estimation. No one can predict the future with certainty and the process of valuing a startup must therefore be considered part art and part science. Despite the subjective nature of startup valuations, entrepreneurs and early stage investors need to make decisions on what valuations to assign given capital injections. The analysis of this paper does not come up with the perfect formula for how to do this, and intended neither to do so. Instead, it reveals severe implications of existing valuation frameworks, and finds interesting empirical patterns in the world of startup valuation. These results should be used to foster critical reflection as well as ability to ask intelligent questions in the process of valuing a startup. By being critically reflective and asking intelligent questions, both entrepreneurs and investors can ensure a more qualified and transparent dialogue about the valuation of a startup. This will help them in the process of negotiating valuations and eventually lead to better decision making.

9.4 Limitations and avenues for future research

Before discussing the limitations of this paper and potential avenues for future research, it makes sense to summarise the main contributions of this paper. Figure 12 provides a concise summary of the focus of this paper’s analyses and their main contributions.

| Analysis 3 (chapter 8): Empirical analysis of valuation in a venture capital context. | Examination of 122 venture capital valuations focusing on general startup characteristics and the human capital of the founders. | Understanding of the determinants of startup valuation in a venture capital context. |

Figure 12: Summary of this paper’s analyses and main contributions
There is no doubt that most studies on the topic of startup valuation will encounter the challenge of data availability. This study is no exemption and acknowledges lack of accessible data as a challenge in the context of startup valuation.

While relevant variables may be included in this study, several additional variables could have been interesting to include. This includes variables such as financial statement information, intangible information about the founders, team completeness, previous successful exit, employee count, network effects, firm investments, and market growth rates and sizes. Lack of inclusion of these variables may have caused omitted variable bias if included variables are correlated with the omitted variables, and if the omitted variables are in fact determinants of startup valuation.

In addition to including additional variables related to the startup and its founders, it could have been interesting to study the effect of term sheet agreements. Agreements on equity claims, pre-emption rights, tag-along rights, employee option plans, anti-dilutive provisions, and good and bad leaver clauses may all affect the agreed valuation between entrepreneurs and investors. The impact of these agreements is not studied in this paper due to the private nature of such information.

Another limitation of this study is that the empirical study is solely based on 122 US based startups in a limited time period. This limits the generalisability of the results. To improve the generalisability of the study it could have been interesting to examine a global sample of startups over an extended observation period. Such a sample could provide insights into national and time related differences in both the level of valuations as well as the underlying drivers behind valuations.

As mentioned earlier, the comparative study is restricted to algorithmic data, which means that caution also has to be taken with regards to the generalisability of the conclusions drawn from this part of the paper. It could be interesting to further examine the legitimacy of these conclusions. Finding similar data not developed by algorithms is most likely not possible. Instead, qualitative data in form of interviews with both entrepreneurs and investors could provide with valuable insights into the experienced comparativeness of the different frameworks.

This paper is restricted from studying how valuations differ across different types of early
stage investors as mentioned in the delimitation. Anecdotal evidence suggests that entrepreneurs are highly interested in the possibility of receiving smart money from previous successful investors or venture capital firms. It is called smart money because a startup receives both investors’ wisdom as well as capital. An interesting avenue for further research is accounting for the investors previous experiences and ability to provide strategic advice. This could potentially deepen the understanding of the value-added role of an investor in the process of valuing a startup.

Given the mentioned limitations and restrictions, multiple avenues for future research exist: (i) include additional independent variables related to the startup and its founders, (ii) study the effect of term sheet agreements, (iii) extend the study to a global sample of startups over an extended period of time, (iv) test the validity of the comparative study using qualitative data, and (v) explore the value-added role of an investor in a startup valuation context.
10 Conclusion

This paper sought out to answer the research question of how to value a startup and contribute with valuable and applicable knowledge on the topic of startup valuation. To answer the research question, three analyses were conducted exploring startup valuation from a diverse set of angles and perspectives. Firstly, the implications of existing valuation frameworks in a startup context were analysed. Secondly, the comparativeness of different valuation frameworks was studied. Lastly, drivers behind startup valuation in a venture capital context were identified through empirical analysis.

The analysis of traditional corporate financial valuation frameworks addresses how uncertainty of inputs, failure to meet model assumptions, as well as problems related to finding comparable firms, all contribute to limiting the application of such valuation frameworks in a startup context. Startup specific valuation frameworks solve some of these implications due to their simplistic approaches to valuation, but do at the same time introduce a great deal of subjectivity as well as reliance on average industry valuations or multiples. No valuation method is found to be perfect for all stages of the corporate life cycle. Instead, the use of different valuation frameworks should be considered accordingly to how the input requirements and model assumptions of the frameworks fit along the corporate life cycle. This requires careful consideration and analysis done by both investors and entrepreneurs when deciding on what valuation method to use.

The comparative study of five different valuation frameworks reveals how different valuation methods produce valuations with large variability in both the level and concentration of valuations. Quantitative methods produce higher and more dispersed valuations compared to qualitative methods, which generally produce lower and more concentrated valuations. Furthermore, distribution patterns differ across frameworks, with qualitative methods exhibiting log double gaussian distribution patterns and quantitative methods exhibiting log gaussian distribution patterns. Overall, methodological independence in the context of startup valuation must be rejected. Given that the valuation of a startup is to some extent methodologically bound, a natural starting point in the negotiations between entrepreneurs and investors is to rely and agree on multiple valuation frameworks. This will most likely facilitate more productive discussions as well as reflection upon what is actually driving value beyond the pure mechanics of valuing a startup.
The empirical analysis of this paper establishes interesting significant relationships in a sample of 122 US venture capital investments. Using univariate difference in means tests as well as multiple regression models, the analysis finds no significant relationship between the age of a startup and valuation. The same applies to the number of founders and previous management experience. On the contrary, the number of prior funding rounds as well as the number of investors in a funding round are both found to be positively related to startup valuation. Additionally, factors such as relevant industry experience, previous founding experience, and the academic capital of the founders are all found to be significant. Lastly, a relative importance assessment of the multiple regression model reveals that especially the relative relationship between equity infusion and pre-money valuation explains a large part of the variation in valuations. Generally, the results of the empirical analysis of startup valuation in a venture capital context may be suggestive of factors that can justify higher pre-money valuations. These results are especially useful for entrepreneurs when raising venture capital financing.

Overall, this paper acknowledges that valuing a startup is an extremely complicated task. Regardless of how thoroughly each input is considered and how carefully a valuation framework is selected, the valuation of a startup will always be an estimate. This reinforces the notion that the process of valuing a startup is as much art as it is science. However, a qualified suggestion on how to value a startup company involves critical reflection about the nature of valuation frameworks, reliance on multiple valuation frameworks, and thorough assessment of underlying value drivers. These takeaways may all help demystify the art of valuing startups. Despite this paper’s contributions, the paper only constitutes a small step toward a thorough understanding of how to value startup companies. Given the mentioned limitations and restrictions of this paper, further research is in fact needed to fully understand the nature of startup valuation.
References


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### Abbreviations and Acronyms

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<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Angle investors</strong></td>
<td>Wealthy individuals providing seed capital for startups.</td>
</tr>
<tr>
<td><strong>Beta</strong></td>
<td>The sensitivity of a security’s return to the return of the market portfolio.</td>
</tr>
<tr>
<td><strong>CAPM</strong></td>
<td>Capital asset pricing model.</td>
</tr>
<tr>
<td><strong>Corporate life cycle</strong></td>
<td>General representation of the progression that companies go through from idea stage to mature stage.</td>
</tr>
<tr>
<td><strong>DCF</strong></td>
<td>Discounted cash flow.</td>
</tr>
<tr>
<td><strong>Dilution</strong></td>
<td>Decrease in ownership as result of later equity issuance.</td>
</tr>
<tr>
<td><strong>FFF</strong></td>
<td>Family, friends, and fools. The term fools is included due to the great risk associated with investing at seed level.</td>
</tr>
<tr>
<td><strong>LMG</strong></td>
<td>A metric used to assess the relative importance of regressors.</td>
</tr>
<tr>
<td><strong>NPV</strong></td>
<td>Net present value.</td>
</tr>
<tr>
<td><strong>Peer group</strong></td>
<td>Group of companies that have similar characteristics.</td>
</tr>
<tr>
<td><strong>OLS</strong></td>
<td>Ordinary least squares.</td>
</tr>
<tr>
<td><strong>Post-money valuation</strong></td>
<td>The valuation of a company after an equity insurance has been made.</td>
</tr>
<tr>
<td><strong>Pre-money valuation</strong></td>
<td>The valuation of a company before an equity insurance has been made.</td>
</tr>
<tr>
<td><strong>Seed capital</strong></td>
<td>The first round of funding received from outside investors.</td>
</tr>
<tr>
<td><strong>Series A, B, C</strong></td>
<td>Early stage venture capital funding rounds.</td>
</tr>
<tr>
<td><strong>TV</strong></td>
<td>Terminal value.</td>
</tr>
<tr>
<td><strong>Venture capital</strong></td>
<td>A type of private equity focusing on early stage investments usually involving a substantial element of risk.</td>
</tr>
<tr>
<td><strong>WACC</strong></td>
<td>Weighted average cost of capital.</td>
</tr>
</tbody>
</table>
Appendices

Appendix 1: Comparative scatter plots of valuations across valuation methods
Appendix 1: (Continued)
### Appendix 2: Top school ranking

<table>
<thead>
<tr>
<th>Rank</th>
<th>University</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Massachusetts Institute of Technology (MIT)</td>
<td>United States</td>
</tr>
<tr>
<td>2</td>
<td>Stanford University</td>
<td>United States</td>
</tr>
<tr>
<td>3</td>
<td>Harvard University</td>
<td>United States</td>
</tr>
<tr>
<td>4</td>
<td>California Institute of Technology (Caltech)</td>
<td>United States</td>
</tr>
<tr>
<td>5</td>
<td>University of Oxford</td>
<td>United Kingdom</td>
</tr>
<tr>
<td>6</td>
<td>University of Cambridge</td>
<td>United Kingdom</td>
</tr>
<tr>
<td>7</td>
<td>ETH Zurich - Swiss Federal Institute of Technology</td>
<td>Switzerland</td>
</tr>
<tr>
<td>8</td>
<td>Imperial College London</td>
<td>United Kingdom</td>
</tr>
<tr>
<td>9</td>
<td>University of Chicago</td>
<td>United States</td>
</tr>
<tr>
<td>10</td>
<td>UCL (University College London)</td>
<td>United Kingdom</td>
</tr>
<tr>
<td>11</td>
<td>National University of Singapore (NUS)</td>
<td>Singapore</td>
</tr>
<tr>
<td>12</td>
<td>Nanyang Technological University, Singapore (NTU)</td>
<td>Singapore</td>
</tr>
<tr>
<td>13</td>
<td>Princeton University</td>
<td>United States</td>
</tr>
<tr>
<td>14</td>
<td>Cornell University</td>
<td>United States</td>
</tr>
<tr>
<td>15</td>
<td>Yale University</td>
<td>United States</td>
</tr>
<tr>
<td>16</td>
<td>Columbia University</td>
<td>United States</td>
</tr>
<tr>
<td>17</td>
<td>Tsinghua University</td>
<td>China</td>
</tr>
<tr>
<td>18</td>
<td>University of Edinburgh</td>
<td>United Kingdom</td>
</tr>
<tr>
<td>19</td>
<td>University of Pennsylvania</td>
<td>United States</td>
</tr>
<tr>
<td>20</td>
<td>University of Michigan</td>
<td>United States</td>
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</tbody>
</table>

Source: The 2019 edition of the QS World University Rankings
Appendix 3: Residuals against values of independent variables
Appendix 3: (Continued)
(q) L market risk

Appendix 3: (Continued)
Appendix 4: Residuals versus fitted values
Appendix 5: Correlation matrix of independent variables

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<tbody>
<tr>
<td>(1) L Pre-money valuation</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
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## Appendix 7: Average coefficients for different model sizes

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Appendix 8: R-code comparative study

#### Packages ####
library(tidyverse)
library(AER)
library(stargazer)

#### Data import ####
Valuationdata <- read.table("ONLYUSD.csv",
sep = ";", header = TRUE, skip = 0,
stringsAsFactors = FALSE)
stargazer(Valuationdata, type = "text", summary.stat =
c("n", "median", "mean", "sd", "p25", "p75", "min", "max"))

#### Removing negative values ####
Valuationdata <- Valuationdata[Valuationdata$valuation_method1 >= 0, ]
Valuationdata <- Valuationdata[Valuationdata$valuation_method2 >= 0, ]
Valuationdata <- Valuationdata[Valuationdata$valuation_method3 >= 0, ]
Valuationdata <- Valuationdata[Valuationdata$valuation_method4 >= 0, ]
Valuationdata <- Valuationdata[Valuationdata$valuation_method5 >= 0, ]

#### Log-transforming data ####
Valuationdata$valuation_method1 <- log(Valuationdata$valuation_method1)
Valuationdata$valuation_method2 <- log(Valuationdata$valuation_method2)
Valuationdata$valuation_method3 <- log(Valuationdata$valuation_method3)
Valuationdata$valuation_method4 <- log(Valuationdata$valuation_method4)
Valuationdata$valuation_method5 <- log(Valuationdata$valuation_method5)
stargazer(Valuationdata, type = "text", summary.stat = c("n", "median", "mean", "sd", "p25", "p75", "min", "max"))

#### Removing outliers ####
boxplot(Valuationdata$valuation_method1)$out
outliers <- boxplot(Valuationdata$valuation_method1, plot=FALSE)$out
print(outliers)
Valuationdata[which(Valuationdata$valuation_method1 %in% outliers),]
Valuationdata <- Valuationdata[-which(Valuationdata$valuation_method1 %in% outliers),]
boxplot(Valuationdata$valuation_method1)

boxplot(Valuationdata$valuation_method2)$out
outliers <- boxplot(Valuationdata$valuation_method2, plot=FALSE)$out
print(outliers)
Valuationdata[which(Valuationdata$valuation_method2 %in% outliers),]
Valuationdata <- Valuationdata[-which(Valuationdata$valuation_method2 %in% outliers),]
boxplot(Valuationdata$valuation_method2)

boxplot(Valuationdata$valuation_method3)$out
outliers <- boxplot(Valuationdata$valuation_method3, plot=FALSE)$out
print(outliers)
Valuationdata[which(Valuationdata$valuation_method3 %in% outliers),]
Valuationdata <- Valuationdata[-which(Valuationdata$valuation_method3 %in% outliers),]
boxplot(Valuationdata$valuation_method3)
```r
boxplot(Valuationdata$valuation_method4)
outliers <- boxplot(Valuationdata$valuation_method4, plot=FALSE)$out
print(outliers)
Valuationdata[which(Valuationdata$valuation_method4 %in% outliers),]
Valuationdata <- Valuationdata[-which(Valuationdata$valuation_method4 %in% outliers),]
boxplot(Valuationdata$valuation_method4)

boxplot(Valuationdata$valuation_method5)
outliers <- boxplot(Valuationdata$valuation_method5, plot=FALSE)$out
print(outliers)
Valuationdata[which(Valuationdata$valuation_method5 %in% outliers),]
Valuationdata <- Valuationdata[-which(Valuationdata$valuation_method5 %in% outliers),]
boxplot(Valuationdata$valuation_method5)

### Comparative statistics ###
stargazer(Valuationdata, type = "text",
    summary.stat = c("n", "median", "mean", "sd", "p25", "p75", "min", "max"))

### Distribution plots ###
hist(Valuationdata$valuation_method1, prob=TRUE, ylim=c(0,0.8),
    breaks=40, main="", xlab="Log valuation")
lines(density(Valuationdata$valuation_method1), col='black')
rug(Valuationdata$valuation_method1)
curve(dnorm(x, mean(Valuationdata$valuation_method1),
    sd(Valuationdata$valuation_method1)),
    add=TRUE, col="darkblue", lwd=2)

hist(Valuationdata$valuation_method2, prob=TRUE, ylim=c(0,0.8),
    breaks=40, main="", xlab="Log valuation")
lines(density(Valuationdata$valuation_method2), col='black')
rug(Valuationdata$valuation_method2)
curve(dnorm(x, mean(Valuationdata$valuation_method2),
    sd(Valuationdata$valuation_method2)),
    add=TRUE, col="darkblue", lwd=2)

hist(Valuationdata$valuation_method3, prob=TRUE, ylim=c(0,0.8),
    breaks=40, main="", xlab="Log valuation")
lines(density(Valuationdata$valuation_method3), col='black')
rug(Valuationdata$valuation_method3)
curve(dnorm(x, mean(Valuationdata$valuation_method3),
    sd(Valuationdata$valuation_method3)),
    add=TRUE, col="darkblue", lwd=3)

hist(Valuationdata$valuation_method4, prob=TRUE, ylim=c(0,0.8),
    breaks=40, main="", xlab="Log valuation")
lines(density(Valuationdata$valuation_method4), col='black')
rug(Valuationdata$valuation_method4)
curve(dnorm(x, mean(Valuationdata$valuation_method4),
    sd(Valuationdata$valuation_method4)),
    add=TRUE, col="darkblue", lwd=3)

hist(Valuationdata$valuation_method5, prob=TRUE, ylim=c(0,0.8),
    breaks=40, main="", xlab="Log valuation")
lines(density(Valuationdata$valuation_method5), col='black')
```

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rug(Valuationdata$valuation_method5)
curve(dnorm(x, mean(Valuationdata$valuation_method5),
        sd(Valuationdata$valuation_method5)),
       add=TRUE, col="darkblue", lwd=3)

##### Relative plots ##### - EXP all data before
p <- ggplot(Valuationdata, aes(x = valuation_method1,
                                y = valuation_method2)) +
    geom_point() + stat_smooth(method = lm) +
    geom_rug(col="steelblue", alpha=0.1, size=1.5) +
    labs(x = "DCF (Long-term)", y = "DCF (Exit)")
print(p)
Appendix 9: R-code empirical study

#### Packages ####
library(tidyverse)
library(AER)
library(stargazer)

#### Data import ####
Thompsondata <- read.table("Book1.csv",
  sep = ";", header = TRUE, skip = 0,
  stringsAsFactors = FALSE)

stargazer(Thompsondata, type = "text",
  summary.stat = c("n", "median", "mean", "sd", "p25",
  "p75", "min", "max"))

#### Log-transforming variables ####
Thompsondata$logPremoney <- log(Thompsondata$Premoney)
Thompsondata$SP500 <- log(Thompsondata$SP500)
Thompsondata$VIX <- log(Thompsondata$VIX)
Thompsondata$Equityout <- log(Thompsondata$Equityout)
Thompsondata$Nfounders <- log(Thompsondata$Nfounders)

#### Removing outliers ####
boxplot(Thompsondata$logPremoney)$out
outliers <- boxplot(Thompsondata$logPremoney, plot=FALSE)$out
print(outliers)
Thompsondata[which(Thompsondata$logPremoney %in% outliers),]
Thompsondata <- Thompsondata[-which(Thompsondata$logPremoney %in% outliers),]
boxplot(Thompsondata$logPremoney)

#### Summary statistics import ####
stargazer(Thompsondata, type = "text",
  summary.stat = c("n", "median", "mean", "sd", "p25",
  "p75", "min", "max"))

#### Data-check, box-plots and T-tests ####
Datacheck <- subset(Thompsondata, Topschool == "0") #done for all variables
shapiro.test(Datacheck$logPremoney)

qqnorm(Datacheck$logPremoney, pch = 1, frame = FALSE, main="")
qqline(Datacheck$logPremoney, col = "darkblue", lwd = 2)

boxplot(logPremoney ~ Iduexperience, data = Thompsondata)
t.test(logPremoney ~ Iduexperience, alternative="two.sided", data = Thompsondata)

boxplot(logPremoney ~ Mexperience, data = Thompsondata)
t.test(logPremoney ~ Mexperience, alternative="two.sided", data = Thompsondata)

boxplot(logPremoney ~ Sexperience, data = Thompsondata)
t.test(logPremoney ~ Sexperience, alternative="two.sided", data = Thompsondata)

boxplot(logPremoney ~ MBA, data = Thompsondata)
```r
t.test(logPremoney ~ MBA, alternative="two.sided", data = Thompsondata)
boxplot(logPremoney ~ PHD, data = Thompsondata)
t.test(logPremoney ~ PHD, alternative="two.sided", data = Thompsondata)
boxplot(logPremoney ~ Topschool, data = Thompsondata)
t.test(logPremoney ~ Topschool, alternative="two.sided", data = Thompsondata)

# #### Multiple regression models ####
model <- lm(logPremoney ~ Age + Pfunding + Investors + Equityout + Nfounders + Iduexperience + Mexperience + Sexperience + MBA + PHD + Topschool + Internet + Soft + Com + MedicalandPharma + SP500 + VIX + Topschool*Pfunding + MBA*Sexperience, Thompsondata)
summary(model)
coeftest(model, vcov = sandwich)

formulas <- list(logPremoney ~ Age + Pfunding + Investors + Equityout + Nfounders + Iduexperience + Mexperience + Sexperience + MBA + PHD + Topschool + Internet + Soft + Com + MedicalandPharma + SP500 + VIX + Topschool*Pfunding,
logPremoney ~ Age + Pfunding + Investors + Equityout + Nfounders + Iduexperience + Mexperience + Sexperience + MBA + PHD + Topschool + Internet + Soft + Com + MedicalandPharma + SP500 + VIX + Topschool*Pfunding + MBA*Sexperience,
logPremoney ~ Internet + Soft + Com + MedicalandPharma + SP500 + VIX,
logPremoney ~ Age + Pfunding + Investors + Equityout + Internet + Soft + Com + MedicalandPharma + SP500 + VIX,
logPremoney ~ Age + Pfunding + Investors + Equityout + Nfounders + Iduexperience + Mexperience + Sexperience + MBA + PHD + Topschool + Internet + Soft + Com + MedicalandPharma + SP500 + VIX)
models <- lapply(formulas, function(f) lm(f, data = Thompsondata))
coeftests <- lapply(models, coeftest, vcov = sandwich)
stargazer(models, type = "text", se = lapply(coeftests, function(x) x[, 2]), keep.stat = c("n", "rsq", "adj.rsq"))

# #### Checking assumption 2 and 3: linearity and constant variance ####
residuals(model) #Find residuals
Fitted <- fitted(model) #Define fitted values as a variable
Lpremoney.res = resid(model) #Define residuals as a variable
plot(Thompsondata$Age, Lpremoney.res, ylab="Residual", xlab="Age") #Residuals against all independent variables
abline(0, 0, col="darkblue")
plot(Fitted, Lpremoney.res, ylab="Residual", xlab="Fitted Value")
abline(0, 0)
```

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residualPlots(model)  # Automated residual plots
plot(model)  # Automated residual plots

# BP test #
bptest(model)  # Breusch-Pagan test

++++++ Checking assumption 4: Normally distributed residuals++++++
hist(Lpremoney.res, prob=TRUE, ylim=c(0,0.8), breaks=10,
    main="", xlab="L␣pre-money␣valuation")
lines(density(Lpremoney.res),col='black')
rug(Lpremoney.res)
curve(dnorm(x, mean(Lpremoney.res),
    sd(Lpremoney.res)), add=TRUE, col="darkblue", lwd=2)

# QQ plots #
qqnorm(Lpremoney.res, pch = 1, frame = FALSE, main="")
qqline(Lpremoney.res, col = "darkblue", lwd = 2)

# Normality test #
shapiro.test(Lpremoney.res)

++++++ Checking assumption 5: No multicollinearity++++++
cor(Thompsondata[,2:19])

library(Hmisc)
Matrix <- rcorr(as.matrix(Thompsondata[,2:19]))
Matrix

++++++ Relative importance of predictors++++++
library(relaimpo)
LMGmetric = calc.relimp(model, type = "lmg", rela=FALSE)
LMGmetric # Shapley value regression
plot(LMGmetric, names.abbrev = 1)