BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Thesis Master of Science
Final master thesis – Counts 80% of total grade

Factors that influence Tech IPO underpricing and their applicability in pricing decision

Navn: Gediminas Meskauskas, Joshua Lundula Mukanya

Start: 02.03.2018 09.00

Finish: 03.09.2018 12.00

Master Thesis

Norwegian Business School BI

Factors that influence Tech IPO underpricing and their applicability in pricing decision.

MSc programme:
Master of Science in Business – with major in Finance

Hand-Out date:
01.01.2018

Acknowledgement

The past two years have been a great expedition. We have had the opportunity to meet new people, gain knowledge and become wiser. In this regard, we would like to send our gratitude's to the department of finance at the Norwegian Business School BI, for the support and knowledge gained in and outside lectures. We also give our special gratitude to our supervisor, Leon Bogdan Stacescu; For challenging us to think, act and behave on next level, and providing us with extraordinary guidance towards making this thesis possible. We also give our earnest thanks to our families and friends, for the moral support and guidance. Your support and care has been of great comfort in the last two years of our lives.

Gediminas Meskauskas

Joshua L. Mukanya

Abstract

The aim of this thesis was to identify the main factors impacting underpricing in the Tech industry and analyse their applicability in IPO pricing decisions. The main factors that were examined: Number of Underwriters, Issue Size, Price per Share, Underwriter Reputation, Hot & Cold market ratio, Fear & Greed ratio, Fed rates, Treasury Bills and Investor Sentiment. In earlier studies, all of the factors exhibited substantial explanatory power on IPO underpricing, and were established as significant by various researchers. Our findings showed that, Fear & Greed ratio, Fed rates, Treasury Bills and Investor Sentiment did not exhibit any explanatory power for Tech IPOs, while being very significant for non-Tech IPOs. On the other hand - Number of Underwriters, Issue Size, Price per Share, Underwriters Reputation and Hot & Cold market ratio provided high significance for Tech IPOs. It was determined that an increase in Number of Underwriters and/or Issue Size decreases the expected underpricing. In contrast, an increase in Price per Share, Underwriters Reputation and Hot & Cold market ration – increases the underpricing. Therefore, we concluded that by controlling these factors, companies and their management can anticipate and, to higher or lower extent, control the underpricing of the IPOs. Lastly, as the Tech industry is becoming more mature, we observed a decaying effect in the explanatory power of each of the factors. Before the financial crisis of 2007-2008, the factors were able to explain nearly 30% of the underpricing variation, however after crisis it dropped down to a mere 13%. Therefore, due to the decaying explanatory power, some of the factors might no longer be applicable in the IPO pricing decisions to the same extent.

Table of Contents

Table of Figures

1 Motivation

Throughout different courses during our bachelors and master program, and more especially in valuation and investment analysis classes. We have learned that tech companies are more underpriced on average as opposed to other industries. Since then, our desire has always been to investigate further on what are the potential causes of such significant first day returns, leading to significant levels of underpricing. When we started our masters' program, we then decided that a potential topic for our master's thesis will be to investigate Tech Initial Public Offering underpricing; with the vision of creating a model that can take into account different factors, which can assist issuers and underwriters gauge potential signals that will determine a further increase or decrease in the offer price.

The research is also important and interesting with regards to the increase in the usage of technological advancements in different spheres of our lives. The way we thought of technology a decade ago, is certainly not the same definition technology has now, nor will have in the decades to come. Therefore, an investigation of tech company valuation by looking at different factors, is not just a matter concerning this thesis, rather something that is actual in our different fields and aspects. Some of us are already consulting companies in the application and usage of different technological solutions in various industries, such as logistics and the health sector among others. Our main task is evaluating the potential benefits of applying new technologies in daily business routines and thereby increase productivity and efficiency. However, while in our work we see the value that various companies bring to the world, the Initial Public Offering analysts seem to rarely agree with the market. This causes great mismatch between the offer price during the Initial Public Offering, and the price investors are willing to pay. This particular matter got us interested to analyse the reasons behind the dissonance and why it exists in Tech industry to such a high extent.

Given the value technology and technological companies will add to the future, it is worthwhile investigating the factors that play an important role in such valuation processes, their impact and application in pricing decisions.

2 Introduction

During the last two decades, technology has taken an enormous portion of our daily lives. Leading scholars and practitioners characterise such time-period as the 4th industrial revolution, trending by the name “technological revolution”. There is no doubt that technology has and will continue to play an important part in our lives. Thus, with such great anticipation concerning the opportunities these advancements promise to bring about. Technology is already entering sectors or industries, which previously have been less affected by it. The Agriculture, Retailing and Education sector are just a few among many others, that are becoming more and more dependent on such advancements. Virtual reality, bio-technology, machine-learning and artificial intelligence are affecting the way we live, learn and do business. Companies that employ these new technologies become more effective, competitive and thereby gain more value. Eventually, most of these companies will go public and will face the same issue – how to correctly price their Initial Public Offering (hereafter, IPO). Therefore, in this paper we are going to analyse various factors that affect the IPO mispricing, and how they can be used for pre-IPO price discovery.

It is evident that the process of Initial Public Offering is amongst the landmarks for most privately-owned companies. The public listing of a private company stems infinite amount of opportunities, such as raising public capital, the opportunity to obtain funding’s at a lower-cost of capital and attracting external investors. Nonetheless, the IPO process has risen great questions amongst researchers, such as: Are investors periodically optimistic about the earnings potential of young growth companies? Do firms take advantage of periods known as “window of opportunity”?

Due to their increasing importance in the world, technological companies have been endorsed with ever growing valuations. However, these high valuations can be difficult to reconcile with the true fundamental value of the company in the long run. Some of the arguments for this long-term misalignment are that, most companies suffer stock price decline after their initial offering. In contrast, there are also examples of companies whose stock price has substantially increased since their IPO. Examples of companies whose stock price has increased substantially are; Apple, Facebook and Amazon. The three worse IPOs that managed to raise enough funds to later cease operations are, eToys, pets.com and Groupon. Additionally, high initial underpricing of companies are often followed by long-term underperformance (Saunders, 1990). Numerous scholars in academia have often viewed this wonder as a market anomaly, and have performed numerous analyses in hope of finding an explanation to this phenomenon (Ritter, 1991). In this thesis, we use findings from decades of research worldwide. By analysing various studies, we will attempt to identify various factors influencing IPO underpricing and suggest how they can be used in pricing decisions.

For the purpose of this study, the companies were defined as "Tech" if the fundamental activities of the company were based on high involvement of new technologies. This means that the company does not have to be specifically registered as one, but provide sufficient evidence that its main undertakings are based on technological advancements. Therefore, all of the companies that met this requirement were considered Tech, and were included in the analysis.

2.1 Descriptive Analysis

A closer investigation on the history of tech IPOs provides a precedent for the analysis. Exhibit 1 (*Appendix*) provides a comparison between Tech and Overall IPOs. It is observed that, while the average annual number of IPOs per year does not display any trends, number of Tech IPOs grows gradually. This is even more evident from Exhibit 2, where the number of Tech IPOs are expressed as percentage of Total IPOs, and a positive trend is very clear. Additionally, Exhibit 4 presents comparison of a 3-year moving average number of Tech IPOs. A clear pattern emerges from the findings, showing an improvement in the segment - from less than 6 IPOs per year just after the dot.com bubble, to more than 25 IPO per year in 2017. These findings support our previous extrapolations about increasing number of Tech companies and their importance in the world, however this is only one side of the pie. Further on we will also identify factors that explain this marvel.

Business cycles or economic shocks in the last decades have significantly attributed to increased uncertainties, thereby increasing the level of valuation mispricing, which further amplifies investor’s uncertainty. For this thesis, such periods include the internet bubble - also known as the dot.com bubble of the late nineties, and the recent financial crisis of 2007-2008. The described periods are characterized as periods of increased uncertainty and high volatility due to economic downturns. During these periods, we observe great variation in public offerings and mispricing. Pre-crisis period[1] (2000-2008) had an average Tech IPO underpricing of 32,06%. However, this was greatly influenced by the dot.com bubble. Taking the outlier out of the calculations, we estimate an average underpricing of only 18,35%. Post-crisis exhibits much larger average underpricing of 26,17%. Number of IPOs during these two periods also varies significantly, 141 against 204 IPOs for pre- and post-crisis periods respectively, once again supporting the prompt about increasing number of Tech companies.

The above observations can be supported by the market timing theory. Frank and Goyal discuss three major capital structure theories, these theories amongst other are amid the determining factors leading to why companies choose to go IPO; through the issuance of new shares to the public to raise funding's by either issuing equity or taking on debt. This theory argues that; companies choose to issue equity when the company is anticipating a stock price run-up. The basic idea in this theory is that, managers tend to look for favourable conditions in both debt and equity markets before making decisions that effects capital structure. However, if managers are unable to identify any favourable conditions, they tend to omit equity issuance, till the markets are in their favour. Market timing theory has been argued to be the theory justifying, why there are more IPOs in certain periods and less in others period. However, the theory is still not fully established, as there are still ongoing disputes amongst scholars regarding the validity of this hypothesis.

Lastly, we discern that underpricing of IPOs in Tech segments is an increasing problem. Therefore, in this paper we analyse numerous factors that were proven to influence overall IPO underpricing, and test them on the Tech industry. Investor Sentiment, Underwriters reputation, Hot and Cold markets are just a few among many, that are covered in the research. Our goal is to identify and prove the significance of these factors and therefore stipulate a model, that could

[1] Financial Crisis of 2007-2008

credibly anticipate first day price change of an IPO. Success in this undertaking should allow the managers to foresee and anticipate a certain degree of underpricing, thereby controlling for its effects.

2.2 A controversial approach

This study will take a rather controversial approach in analysing different factors and their hypothesised impact on the underpricing. All the elements will be analysed in two ways - separately and as a group. This type of analysis (*separate*) was chosen due to several reasons, which are: (i) We anticipate the variables to have different impact when conducted alone, as opposed to group analysis. Moreover, we hypothesised that the significances of various factors might change in the presence of other variables; (ii) Since all the factors are chosen from previous studies, to begin with we want to replicate these studies with regards to Tech industry, and compare our findings to these of other researchers; (iii) Some of the factors have missing or incomplete/inconsistent data, preventing the simulation of all the variables together. While this type of approach might seem to be somewhat unorthodox, we anticipate that the findings from such type of examination should provide reasonable insights and noteworthy findings.

The analysis will be split into two parts. First part will cover theory and literature (*Section 3*), methodology used for analysis (*Section 4*), factor and their relevance discussion (*Section 5*) and hypotheses for final model (*Section 6*). Second part will cover the empirical analysis and the findings of the paper, providing individual factor analysis (*Section 7*), final model generation and testing (*Section 8),* robustness test (*Section 9)* and discussion of the results (*Section 10*). The predictive power of the model will be tested in Section 11. Lastly, we will conclude upon the findings.

3 Literature Review

Practitioners and researchers have throughout the years developed methods and techniques, but also theories trying to explicate different reasons why companies go public. Theories such as life cycle theories, market timing theory and many others attempt to shade more light on why companies go public. Further research has been extended with regards to; why initial offerings are often underpriced but also IPO long-term performance. In this aspect, several theoretical models have been constructed and tested, all with the intention of proving and providing evidence as to why the existence of IPO underpricing and IPO long-term underperformance; Thus far, the discussion is still on going.

In this section, we provide with an overview of the theoretical framework; exhibiting most of the notable theories, factors, different models and the prerequisites needed for conducting the analysis and tests needed for the topic of this thesis.

3.1 Why companies choose to go public

There are many different theories explaining and justifying why companies go public. Primarily speaking, we first define what an IPO is. I.P.O are three letters abbreviating, *Initial Public Offering*. The initial public offering, is the first time a privately-owned company issues its shares to the public. The main objective with an IPO is for the company to raise external capital, but also give an opportunity for initial investors to cash out their initial investments. It is also argued that an IPO increase the liquidity of company shares.

The IPO process is quite a long procedure, once the company has decided to go public. The company normally employs an investment bank, whom are also identified as underwriters. Underwriters consist of a lead underwriter, who form a syndicate of underwriters that assist with necessary financial advice and planning. Their aid is to ensure that the IPO process is successful. By conducting market research and identifying potential investors. Thus, coming up with the number of new shares to be issued, and at which offer price range. This price range is derived through either a bookbuilding or fixed price process to determine the final offer price. The book building is the mostly practiced in the United State of America, and it is therefore anticipated that it is the methods used by all IPOs analysed in this thesis.

3.2 Underpricing

Underpricing of IPOs is a topic that has received considerable attention in the finance literature and is certainly relevant for this paper. The above-mentioned price discovery methods such as bookbuilding, are mechanisms often used in the price discovery of an IPO; as a means of reducing underpricing. Underpricing is measured from a theoretical point of view as, the calculated difference between first day closing price and offer price divided by the offer price, which is sometimes referred to as initial returns. The formula used in this thesis is explained in *equation 1* below. In other terms, underpricing is explained as when the offer price of a stock is below the true market value and as the result of this, the stock yields positive initial returns after the price run up on its first trading day.

Given the above argument, the derivation and calculation of underpricing are calculated by the formula outlined below. This is the formula used to calculate underprcing in this thesis.

$$\text{Underpricing} = \frac{P_{\text{closing}} - P_{\text{offer}}}{P_{\text{offer}}}$$

Equation 1, Formula for underpricing calculation

The academic literature has come up with theories or suggestions attempting to enlighten the phenomenon known as “money left on the table”, which implies that the issuing companies could have raised more money from an IPO by pricing their equity at a slightly higher offer price.

The literature suggests a handful of theories; these are discussed below in the section. The first explanation suggested by financial economists, is also related to information asymmetry. High quality companies tend to underprice their stocks such that they can signal their company`s potential, this is because high quality companies signal their ability to bear costs of underpricing, with the aim of attracting more investors in the future, such as during seasonal equity offerings (Georgieva, 2011).

A second argument in relation to IPO underpricing is that, companies do intentionally underprice their stocks simply because, they want to avoid lawsuits

from displeased investors. This is mainly because, in case of underpricing, such litigations are very unlikely (Yong & Isa, 2003).
A third explanation which has been postulated in regards to IPO underpricing, has its roots from the underwriter's side. It is obvious that underwriters financially benefit from underwriting IPOs, but also gain a goodwill from their clients if an IPO is underpriced. It is arguable to observe that; underwriters are therefore faced with a question of whether to entertain the issuing company or investors. Underwriters should therefore find a fine balance favourable for clients on both sides, when they are considering underpricing an IPO (Georgieva, 2011).

Considering the above mentioned, as shown in the descriptive analysis with regards to IPO performance over the years. IPO underpricing tends to differ across the time-series, this does not only apply for the tech-industry, but also across countries, industries, even sectors.

3.3 Underwriter reputation

Asymmetric information has been used as a rationalisation leading to underpricing or overpricing in the IPO literature. Ritter and Beatty (1986) have postulated in their paper that asymmetry information theory, is examined by two determinants. Namely, investors uncertainty and underwriter's reputation.
However, when we investigate IPO history; It is certainly not obvious to say that all IPOs have been successful, as in our sample we have one incident of overpricing, while the rest of the times it is observed that there has been sharp increase in first day returns/prices.
Ritter and Beatty use an empirical model, for IPOs during a 22 years' period starting from 1960 – 1982. This is used to justify the hypothesis that, larger amount of ex ante uncertainty for the issue value, is accompanied by significant anticipated underpricing. Since the issue assessment is uncertain, well-informed investors are able to take advantage of the information in their possession. The paper further investigates the degree to which underpricing favour underwriters. This is observed with regards to how underpricing preserves underwriter's reputation. Therefore, if the issue is highly mispriced. This should denote a potential risk for the underwriter, as this would imply loss of market share, which diminishes their returns and consequently reputation. Hence, if the issuance is

excessively underpriced, there will be considerable amount of "*money left on the table*" for the issuing company. However, if the underpricing is not good enough, investors are less likely to participate as their anticipated returns are not high enough (Ritter & Beatty,1986).

In the same paper, the authors have also recognised a negative relationship between reputation of the underwriters and underpricing. This notion has also been reinforced by more recent research, such as the one conducted by Booth & Chua, (1996). Consequently, companies considering going IPO hires prominent underwriters as a means of decreasing underpricing. Carter and Manaster (1990) have considered the relationship between underpricing and underwriter reputation. Their findings provide that, though underpricing is observed to favour underwriters, it can be quite costly. Hence, companies characterised under moderate risk class are able to differentiate themselves by assigning more prestigious underwriters, and this in return sends a positive signal to investors as a form of reduced risk and information asymmetry. The results obtained demonstrated that higher underwriter's reputation is associated with lower risk, for issuing stocks. In the research the authors were able to account for deal size, as a another measure of underpricing.

However, further research conducted by Loughran and Ritter (2002), has concluded on slightly different findings than the ones presented in previous research. In this paper, evidence proves a positive relationship between the level of underpricing and reputation. The authors argument is that, underwriters with higher reputation are very likely to underprice with a significant amount due to increased analyst coverage on the IPO. All in all, an observation from the literature proves that. There is not yet established wisdom concerning the impact of underwriter's reputation in the finance literature, the results might differ depending on the sample period or even type of companies been analysed.

3.4 Signalling Theory

The signalling hypothesis was initially accredited to (Ibbotson, 1975), the intuition behind this theory is that; underwriters underprice in order to "leave a good taste in the investors mouth". It is further proposed that, there exist two kinds of issuers, *High-quality* and *Low-quality* issuers. These raise equity in two stages, namely the IPO and on a later stage. Moreover it is explained that, the issuers are more informed as opposed to investors regarding the present value of the company and other associated risks. On this account it was emphasised that, companies that are eager to trade their shares at the average price, are characterised as *low-quality* issuers. In this regard, for *high-quality* companies to differentiate themselves from the low-quality issuers. They signal the true value of their company, by selling their shares at prices that are below what the market believes as the fair price. This deliberate depression in price, restricts low quality companies from doing the same Welch & Ritter, (2002). The up-front sacrifice from the issuers at IPO is anticipated to be regained at a later stage, normally during the seasonal equity offering Welch, (1989).

Yet, if signaling is used as an indication for high quality company, it is still quite hard reconciling why underpricing is the most effective method for signaling high quality. Welch & Ritter, (2002), argued that. It is more reconcilable and efficient to spend money on a charitable cause or donation, than through underpricing. Other researchers and scholars such as Lungjqvist al et. (2006) favour this notion. The authors reason that, by hiring a reputable underwriter or an auditor, this should be a good enough signal for high quality which is obtained at a much lower cost.

Scholars have undertaken and tested the signaling theory Welch, (1989). The author documents extensive amout of post IPO market activity. It is however, stressed that, there exist no vivid proof that any underpricing gives a guarantee that a company would return in the market, for a season equity offering (SEO) Welch & Ritter, (2002). However, Jegadeesh, Weinstein and Welch (1993) finds evidence that, post-IPO performance might give particular indication as to why companies return for a season equity offering, rather than the level of underpricing.

On one hand, Michaely & Shaw (1994) argues that, judgments on whether to underprice, the level of underpricing and season equity offering are independent of one another. Hence, they model this as a simultanious equation model. Given this, there findings indicate that, underpricing and season equity offering at a latter stage are statistically insignificant of one another. These findings firmly opposes and rejects the signaling model. Further findings also indicate that, companies that underprice have higher likelihood of not paying out dividends.

3.5 Behavioural Finance

In recent years, the assumption of rationality and their implication for market efficient has been challenged by numerous scholars within the academic field. There has been a shift in the academic world, the shift has been de-trending away from the traditional economic time series analysis. This detour has led researchers into developing models that are mainly based on human psychology (Shiller, 2003). Financial researchers alongside psychologist, have discovered evidence that; there is a violation in the efficient market hypothesis which is explained by some sort of behavioural biases (Lo, 2005).

Professor Robert Shiller has argued that, the practice of the rationality assumption in reality, cannot be described by anything other than an absurd assumption. The reason behind his argument is that, in order for the models to work, the condition which must be satisfied is that the rational investors must be able to offset the biasness of the irrational investors. In this regard, we have that the efficient markets proposition states that; when an irrational investor purchase stocks, smart money sells and the other way around. This gives way for the counter effect which irrational investors create in the market prices (Shiller, 2003).
The behavioural finance approach is necessary, as we attempt to enlighten the effect of investor sentiment or the hot and cold markets on underpricing.

3.6 Hot and Cold Markets fluctuations

Alongside other market features, several factors that have been proven to explain and determine the level of underpricing are market cycles. In this regard the description of Hot and Cold market is often used to characterise such market conditions. Hot markets have been depicted as the bullish markets in which there are substantially high IPO activity volumes, greater amount of underpricing and oversubscription. As opposed to Hot markets, Cold markets are typified as bearish markets. This is a period where issuing volumes are significantly less and the amount of underpricing or oversubscriptions volumes are infrequent.
Evidence documented by Ibbotson and Jaffe (1975) proves that underpricing behaviour is cyclical, with an observed difference on monthly basis in underpricing levels Ibbotson & Jaffe, (1975).

Another theory, which should be considered in the light of hot and cold markets is. The window of opportunity hypothesis, which advocates that. Most companies are prone to experience overvaluation if the company goes IPO in the period of high IPO volumes (Ritter, 1991). Such periods with high volumes are characterised by investors who hold very optimistic views about future growth prospects. Thus, issuers seek to take advantage of this investor optimism and therefore tend to successfully time their equity issuance and sell their shares in such market conditions. However, companies that choose to offer their equity in markets with high volumes, are prone to suffer long-term underperformance due to the stock price overvaluations during the time of their IPO. It is therefore argued that, periods with high volumes have the lowest performance in the long-run. Hot and Cold markets is one of the factors analysed in the factors analysis.

3.7 Investor sentiment

In recent years' scholars within the field of corporate finance, have extended the scoop and assumptions made early in the literature, such as the Modigliani and Miller approach which assumes rational investors. The Nouveau approach is envisioned to explain, to what degree are investors rational and to what extent can managers and investors be irrational. This effect of irrational or investor sentiment was first brought to our attention by Ljungqvist, Nanda, & Singh, (2006).

The authors in this paper attempts to investigate underpricing by observing the level and degree of investor sentiment; they argue that, investors are not fully rational when making assessments regarding the fundamental value of an investment, as the result of this, investors flee to their own sentiment when considering purchasing or trading their assets.

Thus, issuers attend to exploit this market behaviour by issuing equity in periods with high investors optimism, and are therefore able to sell their stocks when they are "overvalued" by the market. Hence, maximise the fundamental value of their company and stocks. This is observed in the light of IPO long-term underperformance as suggested by Ritter, (1991), as this overvaluation is corrected for in the long-run. However, the question regarding why underpricing is persistent in the IPO literature, is still resloved.

In the interest of this thesis, Investor sentiment is an interesting factor, which shall be considered. This is because, we believe investor sentiment can gauge certain factors that influence IPO pricing. In their paper Baker & Wurgler, (2007), they analysed the behavioural impact of rational and irrational investors to the stock returns. While we stress that this paper does not analyse nor try to predict stock returns, it is merely the concept and rationing behind the theory outlined in the research which is highly relevant for this paper.

The research conducted, has analysed how investors' psychology; such as overconfidence or conservatism impacts their investment decisions. The research found among others that, young, high volatile and growth companies are the most sensitive to investor sentiment. Additionally, the authors add that the higher the uncertainty about a stock, the higher the magnitude of sentiment impact. Seen in the light of tech companies, these points are particularly anticipated to be applicable for Tech IPOs.

Another point outlined is that, all stock prices should move upwards when sentiment increases, and downwards if it decreases. Based on these premise, we apply investor sentiment to our analysis.

Furthermore, it is worth noting that current investor sentiment has lagged outcomes, and therefore a high current sentiment would imply poorer future performance and vice versa.

The investor sentiment is amongst the factors to be analysed as one of the factors influencing underpricing.

3.8 Fear & Greed Index

Fear & Greed index was created by CNN, in order to assess the current market overview from somewhat behavioural perspective of traders. The index is comprised of 7 different variables, each carrying equal weight. The variables are: (i) Stock Price Momentum, measured by the difference between spot price of S&P 500 and its 125-days moving average; (ii) Stock Price Strength, measured in the relative number of stocks hitting 52-week highs and lows (on NYSE); (iii) Stock Price Breadth, measured in the difference between the volume of shares trading on the rise, versus the declining ones; (iv) Put-Call Options or the put-call ratio, measured in trading volume of bullish call to trading volume of bearish put options; (v) Junk Bond Demand, measured in the spread between yields on investment grade bonds and junk bonds; (vi) Market Volatility, measured by the VIX index; and (vii) Safe Haven Demand, measured in the difference in returns of stocks versus treasuries. The index is measured on the scare 0 – 100, where 50 indicates indifference, above 50 indicates Greed and below 50 indicates Fear. As David L. Blain indicated in one of his lectures, the index provides a spectacularly accurate representation of the current market behaviour, and therefore every investor should pay attention to it when making investment decisions. One of the several explanations of the index for investors is rather counter-intuitive, stating that when market is "Hot" – above 50 on Fear & Greed index, the investors should short. This is because there might be overconfidence and overpricing in the market. Alternatively, when the market is "Cold" – below 50 on Fear & Greed Index, the investors should long, because it implies an indication of over-pessimism and underpricing in the market (money.cnn.com, 2018).

Since the Index is rather new, and have only been in the market for barely several years (as compared to century for stock market), there have not been many research performed of its actual effectiveness or ability to provide valuable insights have proven its effectiveness in behavioural finance areas (Rachev, Fabozzi, & Racheva-Iotova, 2017). This measure will be applied as one of the factors in addition to investor sentiment, trying to examine market conditions, but also as a description on the level of underpricing.

3.9 The Fed Rates

Financial institutions, more especially banks after the recent financial crisis are required to maintain a balance, which is reserved at the central bank. Just like most individuals have bank deposits. Banks in the same way are obligated to maintain their reserves at the Federal Reserve bank (the FED). There is a minimum amount set by the Fed, to be placed in a reserve account. This amount is often determined by the number of clients' a given bank has. This requirement has led to appearance of the term fed rate, which is defined as. The interest rate financial institutions or credit unions lend to other depository banks overnight, on an uncollateralized basis. Today the market has evolved in a certain way that, the fed rates are used for different quotations in the money market. In the US it is used as a benchmark for interest rates setting in the credit market (Bodie, Kane, & Marcus, 2014).

In valuation, the discount rate is used as a discounting factor to derive the valuation of a company or equity value. One of the main factors determining a company's cost of capital, which is also used in the derivation of the *weight average cost of capital* (WACC). In US, this kind of interest rate is often called fed rates. Following the standard Capital Asset Pricing Model, we have:

$$R_e = r_f + \beta(r_m - r_f)$$

Equation 2 Capital Asset Pricing Model (CAPM)

Where $R_e$stands for cost of equity, r_f- risk free rate, β- systematic risk of asset in relation to the market, and r_m- market returns. In this theoretical model, US treasury bills are often used as risk-free interest rates, therefore clearly affecting the overall pricing of the assets. The treasury bills are somehow related and affected by the fed rates as such.

The risk-free interest rate has a significant inference on the company`s cost of capital and should there be able to give us some tangible evidence with regards to Tech IPO underpricing. This is because, when interest rates are low; companies should trade-off by taking on more debt as opposed to offering equity or the rates should be perceived as an indication for economic downturns, which might imply IPO activity due to decreased investors optimism.

This is thesis will investigate the impact of fed rates on IPO underpricing, because we believe that; the tech sector is more sensitive to change in interest rate, which might influence their decision of issuing equity by going public.

3.10 Size of the IPO

Many scholars and practitioners have argued saying that, the issue size does give some indications concerning the degree of IPO underpricing. Research conducted by Yong (2009) has proven that, the issue size might impact the level of underpricing, especially in the aftermarket performance. The author argues that; small issues significantly outperform big issues. The findings indicate that, there is negative relationship between issue size and underpricing. Hence, the size of the issue should affect the relative pricing of a company. Therefore, it is worthwhile to control for issue size as one attempts to explain factors that might influence underpricing.

The findings exhibited in Yong`s paper were based on the Malaysian market and are therefore to be taken with a grain of salt, given that this thesis is focusing on American tech IPOs, which are completely two different markets.

Nonetheless, the notion of offer size was further amplified by Ritter and Kim (1999), in their paper the authors state that. The mispricing inaccuracy was larger for younger companies, mainly because younger companies used peer valuations. They further elucidate the notion that, size and age are closely related, and therefore a control variable on the issue size should be applied and examine its impact on underpricing.

It has also been disputed that, most institutional investors are met with restrictions regarding which companies they can invest in. This is because most private equity companies are more prone to invest in more matured growth companies, as opposed to younger companies with very limited financial record.

The ceteris paribus effect as the result of this is that, investors whom are assigned shares in large companies are on average characterised as high quality investors, compared to investors who are allocated shares in smaller companies. The paper finds that. Observed from IPO history, large shares of quality investors are often associated with better aftermarket performance in contrast to IPO that are of low quality investors. With respect to this, issue size should be an indicating factor determining after market performance.

The study conducted by Benveniste & Spindt, (1989) demonstrates some rather interesting insights, the authors studies two resistances, influencing underpricing. The two arguments presented in the paper states that, issuing companies might pretend to be high quality companies when they actually are low quality companies, in order to attract quality investors to subscribe to their stocks. Regardless of these findings, research by Michaely and Shaw finds opposing results. They find that, there is no evidence showing that certain companies pretend to be high quality companies, such that they can attract more investors (Michaely & Shaw, 1995).

To determine the issue size, we have conducted some adjustments to derive this factor. How we calculated it is discussed in section 7.3, internal IPO factors. Further in the analysis we consider the impact of issue size on tech IPO underpricing.

4 Methodology

This section describes the approach adopted when finding and defining the factors that should be used when determining the valuation model. The section will cover data selection, variables and summary of the data, as well as various definitions of ambiguous terminologies.

4.1 Definition of Tech

For the purpose of the topic this thesis is analysing, the companies were defined as "Tech" if the fundamental activities of the company were based on high involvement of new technologies. Such cases include, but are not limited to: (i) agricultural companies, that bases their activities on technologically advanced means of performance – such as *BySpire*; (ii) retailer, that employed AI as main means of communicating with customers – such as *Alibaba*; (iii) financial advisory companies, whose whole business model was based on new scripts for market analysis and representation – such as *Commerzbank*; etc. The extended definition of Tech allowed us to segment the companies based on their business models and services, thereby allowing us to analyse the actual Tech market, as opposed to generic industry grouping, which no longer provides valuable information.

4.2 General Data

The main focus of this thesis is Tech IPOs listed on the US stock market during the period from January 2000 to December 2017. The data used in the analysis was gathered from Professor Jay Ritter's website[2]. It was found that, since 2000 there has been around total of 3048 IPOs of which 346 were tech IPOs.

To make our sample and data more comprehensive, certain adjustments were considered such as, the chosen time frame. The reason why the period between 2000 to 2017 was preferred is because of the availability of data on different tech IPOs and other comparable factors which have been used in this thesis.

In addition, various online and offline data centres and modules were used for obtainment of miscellaneous data. Such sources include, but are not limited to: Yahoo! Finance; Nasdaq; NYSE; Wharton research data services (*WRDS*); etc.

[2] https://site.warrington.ufl.edu/ritter/ipo-data/

Fed rates were extracted from Federal Reserve Bank of United States of America official website.

4.3 Investor Sentiment data

In order to check the applicability of Investor Sentiment on IPO underpricing, we have used the data provided by (Baker & Wurgler, 2007). In the dataset, Sentiment index is based on first principal component of six (standardized) sentiment proxies over 1962-2005 data, where each of the proxies has first been orthogonalised with respect to a set of macroeconomic conditions[3].

4.4 Regression Analysis

To test for the postulated hypothesis this thesis is testing for, the Ordinary Least Squares (OLS) regressions has been used. It must be said that, the OLS is subjected to the assumptions of the Classical Linear Regression Model (CRLM).
The application of a multivariate analysis permits us to detach a variable's influence from the other variables affecting our regression results. Hence the OLS enables us to investigate and determine the degree to which different independent variables impact the dependent variable (Wooldridge, 2013).

$$Y_i = \alpha + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_n X_{n,i} + \varepsilon_i$$

Equation 3, Estimation Model

4.5 Testing for multicollinearity

Multicollinearity is another issue of concern our data and regression output might suffer. Multicollinearity implies that, there is high degree of correlation between numerous independent variables (Brooks, 2014). However, it should be stressed that, the existence of multicollinearity is not a violation of the OLS assumption, that is with the exemption of perfect multicollinearity. If near multicollinearity is present in the model, it is still possible to estimate the coefficients in the model. The OLS will still *be Best Linear Unbiased Estimator* (BLUE), though the interpretation is not reliable (Brooks, 2014). Tests have been conducted to detect the presence of multicollinearity in the model for this thesis.

3 https://www.federalreserve.gov

4.6 Potential issues

In econometrics, we have that H_0 is usually rejected if the t-test is statistically significant at a chosen significance level. The two most common errors that can be encountered or made in this respect are.

1. Rejection of the H_0 when it is true; this is known as *type I error*.
2. Not rejecting the H_a when it is false; this is known as *type II error*.

Brooks, 2014 argues that the likelihood of a type I error is the probability of inaccurately rejecting a correct null hypothesis, in this case it is also the size of the test. Alternative description to this is called the *power of the test*. Hence, the power of the test is defined as the probability of (appropriately) rejecting an incorrect null hypothesis. The power of the test can also be expressed as, one minus the probability of a type II error.

4.7 Endogeneity problems

Given that, this paper will apply the OLS model to test for different variables explaining Tech IPO underpricing. Specification issues are more likely to occur and thereby cause endogeneity problems. This is mainly because, there might be correlation between one or more of the independent variables or the error term (Wooldridge, 2013). Thereby, leading to a violation of the one of the OLS model assumption which are addressed in the Appendix (*Exhibit 6*). Endogeneity can appear because of, (i) measurement error, (ii) omitted variable; which is a functional form of misspecification and (iii) simultaneity or reverse causality. Endogeneity might be a problem in the final model estimation and robustness testing. For this thesis, we have used the Wald test, to test for endogeneity using an instrumental variable.

4.8 Classical Linear Regression Model Assumptions (CLRM)

In order for the OLS-model to yield unbiased estimates, a listed number of assumptions have to be satisfied. (Brooks, 2014), provides us with six assumptions which are to be satisfied in order for us to accurately conduct the hypothesis test with regards to the coefficients of the models. The violation of these assumptions can cause issues relating to the interpretations of the results and therefore disregarding them can led to incorrect estimation of the coefficients. Now, assuming that all the classical linear regression model (CLRM) assumptions holds, it is said that the OLS estimators are the best linear unbiased estimators (BLUE).

It is further argued that, the first four assumptions form the base for the unbiasedness of the OLS. However, the fifth assumption is rather an auxiliary used to stem the standard variance formulas and therefore conclude that the OLS is the *best linear unbiased estimate* (BLUE) (Brooks, 2014). There is also an implicit assumption that there is no multicollinearity, given that all the necessary assumptions hold and that all estimated parameters are BLUE.

4.9 Unit Root Testing

Non-stationarity is an issue we might encounter when working with time-series data. However, we have that stationarity is an indispensable condition necessary for generating statistical inference. Testing for non-stationarity is not directly tested for our data sample, given that we are working with Tech IPO underpricing. Which is a one-time thing. On the other hand, since this thesis will also investigate the impact of Fed-rates and investor sentiment on Tech IPO underpricing. Conducting an hypothesis test and raising the hypothesis requires that the time-series been tested is stationary.

The academic literature has given many reasons as to why it is vital that variables that are non-stationary should be treated differently from those that are stationary. In our literature stationarity is characterised or defined as, a time series with constant mean, constant variance and constant autocovariances for each given lag. However, we are working with some data that can be non-stationary. With non-stationary it is generally implied that, non-stationarity is reflected by the fact that the data been used is characterised by non-constant mean and variances over time, which do not revert to its mean over the long-time horizon (Brooks, 2014).

This thesis will conduct stationarising of Fed-rate and investor sentiment, using the first difference.

To be able to detect non-stationarity in the data this thesis is working with, the Augmented Dicky-Fuller (ADF) has been used.

The time-series data that was found to be non-stationary, and has been de-trended by taking the first differences. Conducting this might lead to data loss. Thus, the same data using the trended and non-detrended will be regressed and finally compare the results between the two. With the intention of explaining potential reasons leading to the differences.

4.10 The Goodness of Fit: R^2 and Adjusted R^2

Traditionally speaking, the R^2 is used as a scaled of the goodness of fit statistic. This goodness of fit statistics is expressed by the ratio of the explained sum of squares to the total sum of squares as presented by (Brooks, 2014). (*Exhibit B*)

5 Factor Discussion

5.1 Fed Rates & 3 Months Treasury Bills

As covered in the literature review, Fed rates & 3 months treasury bills might have significant impact on the valuation of the company. In order to calculate the financial value of a company, most of the models are using the perceived risk-free rate, which more often than not, is assumed to be the 3 months treasury bills. While this works great in theory, most of the models barely calculate the assumed value – value that, based on various financials and market positioning, should reflect the true value. This is almost never true. The real value of the company only becomes apparent, once the company goes public. In other words, the market, not the financial forecasts, determines the real value of business. Once the company goes public, the market no longer cares about the prevailing risk-free rate, thereby creating misalignment between the true and assumed value of the company. Higher risk-free rate might lead to lower underpricing, while lower risk-free rate might lead to higher one. However, this does not mean that smaller or larger risk-free rate would impact all of the companies the same. On the contrary, companies with different systematic risk would experience this phenomenon oppositely. Based on the simplistic cost of capital model (Equation 4) and valuation formula (Equation 5), companies with Beta smaller than that of market[4] would experience a theoretically higher cost of capital (R_e) and thereby higher underpricing, with higher prevailing risk-free rate and vice versa. On the other hand, companies with Beta larger than that of market would experience higher underpricing under higher risk-free rate, and lower underpricing under low risk-free rate.

$$R_e = r_f + \beta(R_m - r_f) \quad => \quad R_e = r_f - \beta r_f + \beta R_m$$

Equation 4, Capital Asset Pricing Model

[4] Beta of market is assumed to be 1

$$Value = \sum_{n=1}^{t} \frac{CF_n}{(1+i)^n} + \frac{TV_t}{(1+i)^t}$$

Equation 5, Simplistic company valuation formula, where CF(n) is cash-flow at time n, i is cost of capital and TV is terminal value at time t

Theoretical example:

After an IPO, the company was valued at $10'000. Under various fictional risk-free rate scenarios, the underpricing would vary significantly. Based on different prevailing risk-free rates, the calculated value would vary between $5'000 to $9'000. However, the real value determined by the market would be the same - $10'000. Due to this, each of the scenarios would present us with different level of underpricing, from 50% in Risk-free (I) to 10% in Risk-free (III).

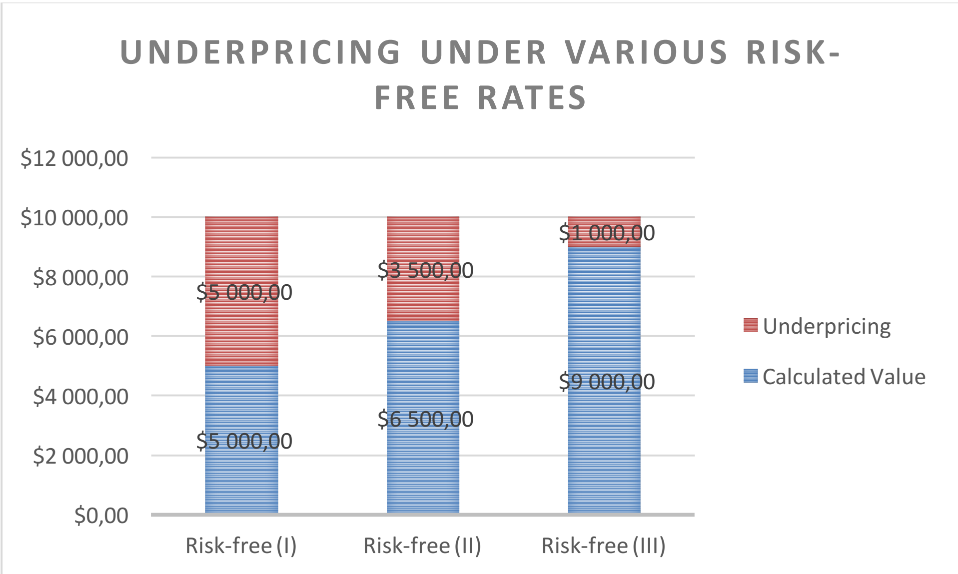


Figure 1, Fictional Underpricing under various risk-free interest rates

There could be many explanations to this theoretical behaviour, and in Sections 7.1 and 7.2 we are going to analyse whether changes in risk-free rates have any effect on Tech IPO underpricing. If it does, we'll try to determine what kind of effect, and how significant it is.

5.2 Internal IPO Factors

In addition to theoretical calculations, we were interested in how the internal factors of an IPO influences its under-/overpricing. The factors that we have considered are: (i) number of the underwriters per the IPO; (ii) total monetary value raised during the IPO; (iii) Initially offered price per share. There are several articles arguing that, such factors explain the degree of underpricing. Yong

(2009) conducted a study which looks at the effect of issue size (YONG, 2009). His argument is that, small issues outperform big issues. In his paper, he finds that, there is a negative relation between issue size and underpricing. In our paper, we will replicate this study, but only considering the Tech sector and compare the findings with the overall market.

In addition to issue size, number of underwriters participating in an IPO has been discussed in the corporate finance literature to influence the level of underpricing. Corwin and Schultz (2005) has addressed the effects that, number of underwriters has on price discovery by; observing the number of underwriters. In the paper, they present that each additional underwriter in a syndicate results in one additional market marker. The authors also identified that, every additional co-underwriter results in 0.8 additional analysts issue reports in the three months after an IPO. The implications being, every additional manager`s report and analyst coverage significantly contributes to the price discovery, which bring the valuation close to the “true” or “fair” market value of the company (Corwin & Schultz, 2005). Given these findings, we believe that the number of underwriters participating in an IPO should be able to come up with an offer price which is close to the market value and therefore reduce the amount of underpricing.

Furthermore, we look at the initial offer price. There are several papers in the literature addressing this issue, especially with respect to the relationship between offer price and underpricing. Some scholars suggest a negative relation between the two variables. Ibbotson (1975) but also Ritter & co (1994) reported a divergent relationship between offer price and underpricing. Their findings indicated that, companies which offered IPOs at a lower price, are more underpriced. The higher underpricing can be explained by the fact that, such companies are more riskier and therefore, lowering their prices should attract more investors. Thus, resulting into more underpricing. As we also discussed in the signalling theory, price per share plays an important part in determining the level of underpricing. This is because quality companies tend to lower their offer price to send a positive signal in the market about the fundamental value of the company (Welch and Ritter, 2002). As this factor is believed to be impacting underpricing, we consider including it in our regression analysis.

To check whether these findings are applicable for the Tech segment, we analyse the relationship between the offer price and the level of underpricing for tech companies.

5.3 Underwriters Reputation

Ibbotson in his 1975 paper conducted an analysis, which looked at the reputation of underwriters and the degree of underpricing. The paper ranked the underwriters as *high* and *low* quality. The argument presented in the paper is mainly based on the notion that, high quality underwriters have both the incentives and means to underprice an IPO such that, they can "leave a good taste in the mouth of investors" for later stage equity raising, such as seasonal equity offering (SEO). Given this perception, we include underwriter's reputation and examine its impact on tech IPO underpricing (Ibbotson, 1975). We also note that, Carter and Manaster identified different results as opposed to Ibbotson, (1975), they identified an inverse relationship between underwriter's reputation and underpricing. They suggest that, reputation of the underwriter is signalling the risk-level of a company. Therefore, the higher the reputable an underwriter is – the less underpricing. In addition, the authors argue that, underwriter's reputation reveals the expected level of "informed" activity, thereby increasing or reducing the uncertainty. The argument is based on this notion; the less uncertainty there is about an IPO, the less underpricing.

Given the above, we further analyse the impact of underwriter's reputation on Tech IPO underpricing, and compare it with the overall market.

5.4 Hot & Cold Markets

In recent years, several scholars have characterized IPO markets to be quite cyclical. The cyclicality in IPO market has led to periods of substantial high returns, but also periods of lower initial returns. On this basis, researchers and practitioners identify and observed certain periods to be what they typify as "hot" and "cold" markets. Hot markets are described as periods of high IPO activity, which are followed by higher abnormal returns. Additionally, hot markets experience increased number of companies going public; but also, higher oversubscription rates (Helwege & Liang, 2004). Cold markets are periods of less IPO activity, with less oversubscription and reduced underpricing. To further explore, whether this phenomenon has impact on tech underpricing, we analyse the Hot & Cold market as hypothesised in section 7.5.

5.5 Fear & Greed Index

Furthermore, we have decided to expand the analysis by including stock market fluctuations. In addition to Hot & Cold markets, we considered adding the Fear & Greed index. Both factors are somewhat similar in the sense that, they all are trying to explain the bearish and bullish behaviour of traders, however, Hot & Cold ratio provides more insights into the IPO market, while Fear & Greed expands this understanding into the overall market, but also into day-trader's behaviour. One of main reasons for this, is that once the company goes public, it's shares are being transacted by the day-traders, who will in fact determine whether the price of the stock will go up or down. As research by (Lo & Repin, 2002) and its expansion by (Lo, Repin, & Steenbarger, 2005) found, day-traders exhibit significant emotional patterns in decision making. Both studies confirmed a strong relationship between emotional reactivity and trading performance, thereby concluding that fear or greed have a significant impact not only upon the personal results of distinct traders, but also on the overall market. Based on the above-mentioned premises, we anticipate that Fear & Greed index could provide additional explanatory power, in better understanding tech IPO underpricing. This factor is analysed in section 7.6

5.6 Investor Sentiment

In the paper "*Investor Sentiment in the Stock Market*" (Baker & Wurgler, 2007) , Baker and Wurgler argue and states that, among other things, younger, non-dividend paying, high-volatility growth companies are likely to be particularly sensitive to investor sentiment. They hypothesised that high sentiment causes initial overvaluation and lower future returns. The findings confirmed the initial intuition, proving that high sentiment in the market leads to lower subsequent market returns and vice versa. Over-optimism of traders raises the prevailing stock prices, which eventually leads to underperformance, while over-pessimism lowers the prices and leads to over-performance. We therefore anticipate, investor sentiment to have a similar effect on the IPO pricing and returns, and we are going to analyse this factor in section 7.7.

6 Hypotheses

Grounded on the previous studies which are covered in factor discussion and literature review, we have raised the following hypotheses:

Based on fundamental capital asset pricing model and the common usage of Fed rates and 3 months treasury bills as a proxy for the risk-free rate (*Section 5.1)*, we hypothesise that:

> ***H(1):*** Fed Rates or 3 Months Treasury bills have a significant explanatory power on Tech IPO underpricing

A number of studies have been performed in order to find whether internal factors from a company and IPO plays a role in stock price movement. (YONG, 2009), (Corwin & Schultz, 2005), (Welch & Ritter , 2002), (Welch, 1989) and others have identified that Price Per Share, Offer Size and Number of Underwriters have a significant explanatory power on IPO over-/underpricing (*Section 5.2*). Due to this, we hypothesise that:

> ***H(2):*** Internal IPO factors have a significant explanatory power on Tech IPO underpricing

Many researchers have analysed Underwriters Reputation and its impact on IPO underpricing. (Carter & Manaster, 1990), (Ibbotson, Sindelar, & Ritter, 1988) and many others found that reputation has a significant impact on underpricing (*Section 5.3*). Based on these premises, we are going to analyse whether:

> ***H(3):*** Underwriters Reputation has a significant explanatory power on Tech IPO underpricing

In their paper, (Helwege & Liang, 2004), the authors speculated that Hot & Cold market periods have very strong patterns and significant impact on underpricing (*Section 5.4*). Based on their anticipation, we hypothesise that:

> ***H(4):*** Hot & Cold markets have a significant explanatory power on Tech IPO underpricing

Research by (Lo & Repin, 2002) and its expansion by (Lo, Repin, & Steenbarger, 2005) found that day-traders exhibit significant emotional patterns in decision making (*Section 5.5*). They concluded that Fear & Greed had substantial impact on their performance, and therefore we expect that:

> ***H(5):*** Fear & Greed of investors has a significant explanatory power on Tech IPO underpricing

In the paper "*Investor Sentiment in the Stock Market*" (Baker & Wurgler, 2007) the authors have concluded that Investor Sentiment has a significant explanatory power on market returns (*Section 5.6*). We anticipate similar results for IPO price fluctuations, and therefore hypothesise that:

> ***H(6):*** Investor Sentiment has a significant explanatory power on Tech IPO underpricing

7 Factor Analysis & Empirical Findings

This section outlines the descriptive statistics, empirical analysis and interpretations of the results for each of the factors covered in Section 5 of the paper.

7.1 Fed Rates and Underpricing

Based on the arguments raised in the Factor Discussion part, here we analyse whether Fed Rates have a significant impact on Tech IPO underpricing. Moreover, we also check for any lagged effects Fed rates might have. For comparison purposes, the same analyses will be performed for the Overall Market IPO underpricing.

7.1.1 Sub-Hypotheses

Sub-Hypothesis 1:

H(0): Fed rates do not explain any variation in Tech IPO underpricing

H(a): Fed rates explains variation in Tech IPO underpricing

Sub-Hypothesis 2:

H(0): None of the Fed rates lagged variables explain variation in Tech IPO underpricing

H(a): Fed rates lagged by 6, 9, 12, 15 or 18 months explain variation in Tech IPO underpricing

7.1.2 Analysis

In order to test for sub-hypotheses, the following regression was used:

$$\mathrm{IPO}_{\mathrm{Underpricing}} = \alpha + \beta_{\mathrm{Fed}}\mathrm{Fed} + \varepsilon$$

Equation 6, Regression for IPO Underpricing based on Fed rates

One of the requirements for running a regression test is that, all the variables must be stationary. After running an ADF test for stationarity on the three time-series, overall market IPO underpricing and Tech IPO underpricing did not exhibit any unit roots or non-stationarity (Table 1). The p-values for the two were 0,00108 and 0,00286 for Overall and Tech respectively, and since both are lower than the threshold of 0,05, the test concludes that both are stationary. Fed rates, however, did not fully comply with the 95-percentile requirement, providing the p-value of 0,05178, and had to be concluded non-stationary. This was solved by taking the first difference, which is presented as Fed rates (-1) in the *Table 1*. This approach has solved the issue, presenting the p-value of 0,00014, which complies with the ADF test's stationarity requirements.

	IPO Underpricing (Overall)	IPO Underpricing (Tech)	Fed rates	Fed rates (-1)
Alpha	0,05000	0,05000	0,05000	0,05000
p-value	0,00108	0,00286	0,05178	0,00014

Table 1. Stationarity

7.1.2.1 Part I – Fed Rates

The following results were observed after running the regressions:

	IPO Underpricing (Overall)		IPO Underpricing (TECH)	
	Regression 1	Regression 2	Regression 3	Regression 4
Intercept	0,098212***	0,113683***	0,233005***	0,23463***
(Std. Error)	(0,008095)	(0,006261)	(0,026844)	(0,020516)
Fed rates (Level)	0,888261***		0,434613	
(Std. Error)	(0,309059)		(0,981793)	
Fed rates (-1)		-0,004682		0,062028**
(Std. Error)		(0,009107)		(0,02439)
F-Value	8,2603	0,2643	0,1960	6,46762304
Significance F	0,0045	0,6077	0,6587	0,01213942
Observations	203	203	134	134
R Square	0,039474	0,001313	0,001482	0,21612163
Adjusted R Square	0,034695	-0,003655	-0,006082	0,03948665

Significance: * (10%); ** (5%); *** (1%)

Table 2, Fed-Rates (-1) and IPO Underpricing Regression Results

From the *Table 2,* it can be observed that Fed rates at level have a significant explanatory power over the overall market IPO underpricing (significant at 99% confidence interval). However, it somewhat fails to explain the variation in the tech companies underpricing. The significances are 0,0045 and 0,6587 for Regression 1 and Regression 3 respectively. The significance of Regression 1 is lower than 0,01, therefore it is concluded to be significant. The significance of Regression 3 is higher than 0,01; 0,05 and 0,1, therefore we concluded that it is insignificant at any conventional confidence interval. These regressions, however, do not provide any appropriate interpretations due to the non-stationary nature of the independent variable. Even though Regression 1 was proven to be significant, it might lead to spurious findings and therefore has to be disregarded.

Regressions 2 and 4 exhibits the significances of 0,6077 and 0,0121 respectively. On the basis of these findings, regression 4 presents a positive relationship which is significant at 5%. However, regression 2 is insignificant at all conventional levels. Taking this into consideration, we find evidence supporting that fed-rates have a statistically significant explanatory power on Tech IPO underpricing. The findings imply that a 1% change in the Fed rates would lead to 0,06% change in Tech underpricing, in the same direction. Nonetheless, we fail to find evidence explaining the variation in regression 2. These findings are somewhat surprising, because Fed Rates seem to explain Tech industry, which is a sub-set of the Overall Market, however it fails to explain the Overall Market itself. An argument in favour of this can be that, maybe it's the specific nature of tech companies which lead to this conclusion.

7.1.2.2 Part II – Lagged Fed Rates

	Underpricing (Overall)				
	Regression 1	**Regression 2**	**Regression 3**	**Regression 4**	**Regression 5**
Intercept	0,100003***	0,09669***	0,096333***	0,096147***	0,095637***
(Std. Error)	(0,007923)	(0,00779)	(0,007922)	(0,008)	(0,008074)
Fed rates (Lag 6m)	0,02039				
(Std. Error)	(0,027916)				
Fed rates (Lag 9m)		0,007748			
(Std. Error)		(0,027239)			
Fed rates (Lag 12m)			-0,009409		
(Std. Error)			(0,028033)		
Fed rates (Lag 15m)				-0,007914	
(Std. Error)				(0,028109)	
Fed rates (Lag 18m)					0,029981
(Std. Error)					(0,028152)
F-Value	0,5335	0,0809	0,1127	0,0793	1,1341
Significance F	0,4660	0,7764	0,7375	0,7786	0,2883
Observations	196	193	190	187	184
R Square	0,002742	0,000423	0,000599	0,000428	0,006193
Adjusted R Square	-0,002398	-0,004810	-0,004717	-0,004975	0,000732

Significance: * (10%); ** (5%); *** (1%)

Table 3 Lagged Fed Rates & Overall Underpricing

To check whether there is a relationship between IPO underpricing and lagged interest rates, we ran regressions on lagged Fed rates of 3, 6, 9, 12 and 15 months. The analysis was conducted for both, the Overall Market and Tech IPOs. However, the results did not present any reasonable findings and concluded that current interest rates do not have any statistically significant explanatory power on future IPO underpricing. The outcomes of the regressions can be observed in *Tables 3 and 4*.

	Underpricing (TECH)				
	Regression 1	**Regression 2**	**Regression 3**	**Regression 4**	**Regression 5**
Intercept	0,231552***	0,227655***	0,228013***	0,228235***	0,228792***
(Std. Error)	(0,020663)	(0,020921)	(0,020845)	(0,021202)	(0,021437)
Fed rates (Lag 6m)	-0,009316				
(Std. Error)	(0,129677)				
Fed rates (Lag 9m)		0,010707			
(Std. Error)		(0,024234)			
Fed rates (Lag 12m)			-0,025403		
(Std. Error)			(0,024071)		
Fed rates (Lag 15m)				0,006913	
(Std. Error)				(0,02434)	
Fed rates (Lag 18m)					-0,012427
(Std. Error)					(0,024324)
F-Value	0,0052	0,1952	1,1137	0,0807	0,2610
Significance F	0,9428	0,6594	0,2933	0,7769	0,6104
Observations	132	128	127	125	123
R Square	0,000040	0,001547	0,008831	0,000655	0,002152
Adjusted R Square	-0,007652	-0,006377	0,000902	-0,007469	-0,006094

Significance: * (10%); ** (5%); *** (1%)

Table 4 Lagged Fed Rates & Tech Underpricing

7.1.3 Summary

In Part I, we found evidence that Fed rates do influence the level of Tech underpricing. The findings can be explained by the nature and the differences in the types of Tech companies. Changing interest rates would provide a different fundamental value for the company[5], while the market would still maintain their perceived value of it. In other words, increasing interest rates raises the cost of capital for the company, thereby lowering its valuation and creating a larger spread between the market value[6] and the financial value[7]. This in fact increases underpricing of the company.

[5] Calculated using financial models
[6] Perceived by investors
[7] Calculated using financial models

In Part II, we could not identify any statistically significant results, which would suggest that lagged Fed rates does not influence future IPO underpricing. Therefore, we conclude that there is no relationship between lagged Fed rates and spot pricing of the IPO.

Based on the findings, we reject H(null) of sub-hypothesis 1, concluding that Fed rates do explain variation in Tech IPO underpricing. However, we cannot reject H(null) of sub-hypothesis 2, therefore conclude that lagged version of Fed rates do not have any explanatory power of Tech IPO udnerpricing.

7.2 Risk-free interests (Treasury Bills 3M) and Underpricing

7.2.1 Analysis

7.2.1.1 Part I

After the analysis of Fed rates, we wanted to double check whether Treasury Bills with 3 months maturity would provide different results. The same hypotheses and regression models as in 6.1 were applied in the analysis, only substituting fed rates with 3 months Treasury bills. To begin with, we analysed the spot rates of 3 months Treasury Bills against the overall market, followed by Tech IPO underpricing. Thereafter, we have conducted an analysis on the lagged versions of 3 months Treasury Bills, with lags of 3, 6, 9, 12 ,15, 18 and 21 months. The 18 and 21 months lags are not represented in the *Table 5*, as they were completely insignificant.

	IPO Underpricing (Overall)	IPO Underpricing (TECH)
Intercept	0,112804***	0,242179***
(Std. Error)	(0,006289)	(0,021142)
TB3m (-1)	0,010068	-0,018806
(Std. Error)	(0,012932)	(0,038075)
F-Value	0,6061	0,2440
Significance F	0,4372	0,6222
Observations	203	134
R Square	0,003006	0,001845
Adjusted R Square	-0,001954	-0,005717

Significance: * (10%); ** (5%); *** (1%)

Table 5, Relationship between 3 Months Treasury Bills and IPO underpricing

Table 5 exhibits regression outprint performed on the overall market and Tech IPOs. TB3m (-1) is a representation of stationarized 3 months Treasury Bills.

Based on the results, we are unable to find any statistically signicant relationship between the 3 month Treasury Bills and underpricing for both the overall market and Tech IPOs. The significance of the regressions are 0,4372 and 0,6222 for Overall market and Tech respectively. Neither of them complies with the conventional significance levels for hypothesis testing acceptance.

7.2.1.2 Part II

Below is the summary of the findings from regressions between underpricing and 3 months Treasury Bill, with various lags:

	Underpricing (Overall)				
	Regression 1	**Regression 2**	**Regression 3**	**Regression 4**	**Regression 5**
Intercept	0,112952***	0,107749***	0,105918***	0,105424***	0,103908***
(Std. Error)	(0,006296)	(0,005437)	(0,00533)	(0,005333)	(0,00537)
TB3m (lag 3)	-0,004953				
(Std. Error)	(0,018313)				
TB3m (lag 6)		-0,005333			
(Std. Error)		(0,010004)			
TB3m (lag 9)			-0,002814		
(Std. Error)			(0,009565)		
TB3m (lag 12)				-0,008975	
(Std. Error)				(0,009513)	
TB3m (lag 15)					0,005997
(Std. Error)					(0,00951)
F-Value	0,0732	0,2842	0,0866	0,8900	0,3976
Significance F	0,7871	0,5946	0,7689	0,3467	0,5291
Observations	200	197	194	191	188
R Square	0,000369	0,001455	0,000451	0,004687	0,002133
Adjusted R Square	-0,004679	-0,003666	-0,004755	-0,000579	-0,003232

Significance: * (10%); ** (5%); *** (1%)

Table 6 Underpricing and the 3-months Treasury for the Overall Market

From the regressions' out-print in *Tables 6 and 7*, we could not identify any statistically significant results. Therefore, we conclude that there is no relationship between lagged 3 months Treasury Bills and underpricing of Tech IPOs.

	Underpricing (Tech)				
	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
Intercept	0,238815***	0,227975***	0,230092***	0,231053***	0,228769***
(Std. Error)	(0,02125)	(0,020773)	(0,020917)	(0,021077)	(0,021544)
TB3m (lag 3)	-0,028956				
(Std. Error)	(0,043302)				
TB3m (lag 6)		0,010139			
(Std. Error)		(0,037992)			
TB3m (lag 9)			-0,068108		
(Std. Error)			(0,050356)		
TB3m (lag 12)				-0,045103	
(Std. Error)				(0,039095)	
TB3m (lag 15)					-0,014396
(Std. Error)					(0,045356)
F-Value	0,4472	0,0712	1,8294	1,3310	0,1007
Significance F	0,5049	0,7900	0,1786	0,2509	0,7515
Observations	132	129	127	125	123
R Square	0,003428	0,000560	0,014424	0,010705	0,000832
Adjusted R Square	-0,004238	-0,007309	0,006539	0,002662	-0,007426

Significance: * (10%); ** (5%); *** (1%)

Table 7 Underpricing and the 3-Months Treasury for the Tech Industry

7.2.2 Summary

In part I, it was proven that the 3 months Treasury Bills do not explain any variations in IPO underpricing. In Part II, the analysis also indicated that there is no significant relationship between any of the lagged variables and IPO underpricing. Neither 3 months Treasury Bills, nor its lagged variables could provide any valuable insights. Based on the findings, we conclude that 3M Treasury Bills to be insignificant in the light of Tech IPO underpricing.

7.3 Internal IPO Factors and Underpricing

In this part, we analyse various factors related to the actual IPO, and their influence on underpricing. The factors that we have considered are: (i) number of the underwriters per the IPO; (ii) total monetary value raised during the IPO; (iii) Initially offered price per share. The number of underwriters (*NoU*) was gathered from the documentation of IPOs provided by the issuing company; Monetary value (*Val*) was calculated as natural logarithm of the value raised[8] and the initial offer price per share (*P*) was taken from the IPO documents.

[8] in billions

7.3.1 Sub-Hypotheses

We have raised the following hypothesis:

Sub-Hypothesis 1:

H(0): Number of underwriters do not explain any variation in Tech IPO underpricing

H(a): Number of underwriters explain variation in Tech IPO underpricing

Sub-Hypothesis 2:

H(0): Number of underwriters together with Value raised, does not explain any variation in Tech IPO underpricing

H(a): Number of underwriters together with Value raised, explains variation in Tech IPO underpricing

Sub-Hypothesis 3:

H(0): Number of underwriters together with Value raised and Price per share, do not explain any variation in Tech IPO underpricing

H(a): Number of underwriters together with Value raised and Price per share, explains variation in Tech IPO underpricing

Sub-Hypothesis 4:

H(0): Number of underwriters together with Price per share, do not explain any variation in Tech IPO underpricing

H(a): Number of underwriters together with Price per share, explains variation in Tech IPO underpricing

7.3.2 Analysis

To check for the relationship between underpricing and various factors, we conducted a multivariate regression analysis. The following regressions were used in hypothesis testing:

$$\mathrm{IPO}_{\mathrm{Underpricing\ (Tech)}} = \alpha + \beta_{\mathrm{NoU}}\mathrm{NoU} + \varepsilon$$

Equation 7, Regression for IPO Underpricing based on Number of Underwriters

$$IPO_{\text{Underpricing (Tech)}} = \alpha + \beta_{NoU} NoU + \beta_{Val} Val + \varepsilon$$

Equation 8, Regression for IPO Underpricing based on Number of Underwriters and Issue Value

$$IPO_{\text{Underpricing (Tech)}} = \alpha + \beta_{NoU} NoU + \beta_{Val} Val + \beta_{P} P + \varepsilon$$

Equation 9, Regression for IPO Underpricing based on Number of Underwriters, Issue Value and Price Per Share

$$IPO_{\text{Underpricing (Tech)}} = \alpha + \beta_{NoU} NoU + \beta_{P} P + \varepsilon$$

Equation 10, Regression for IPO Underpricing based on Number of Underwriters and Price Per Share

*Where "NoU" is the Number of Underwriters per IPO, "Val" is the logarithm of total issue value in billions (Price per share * number of shares issued) and "P" is the logarithm of price per share.*

The summary of outcomes from the regressions are presented in the *Table 8.*

	Underpricing (Tech)			
	Regression 1	**Regression 2**	**Regression 3**	**Regression 4**
Intercept	0,369371***	0,637294***	-0,743839***	-0,663463***
(Std. Error)	(0,04264)	(0,083876)	(0,225353)	(0,14177)
Nr. Underwriters	-0,037785**	-0,072936***	-0,063634***	-0,067392***
(Std. Error)	(0,016565)	(0,018847)	(0,017866)	(0,015863)
LN Issue Value		0,089599***	-0,012815	
(Std. Error)		(0,024458)	(0,027907)	
LN Price Per Share			0,436923***	0,419746***
(Std. Error)			(0,066736)	(0,055204)
F-Value	5,2032	9,4743	21,3618	32,0097
Significance F	0,0231	0,0001	0,0000	0,0000
Observations	353	352	352	352
R Square	0,014607	0,051498	0,155515	0,155003
Adjusted R Square	0,011800	0,046063	0,148235	0,150161

Significance: * (10%); ** (5%); *** (1%)

Table 8, Regressions summary for Tech IPO Underpricing based on Number of Underwriters, Issue Value and Price Per Share

All of the regressions in *Table 8* seems to provide high significance levels, however, some anomalies were observed between Issue Value and Price Per

Share. As the result of this, we thought of checking for correlation between the independent variables. To check for correlation, we performed a correlation analysis, followed by VIF[9] analysis (Calculated using Equation 11).

$$VIF_j = \frac{S_{x,j}^2 (n - 1) SE_{b,j}^2}{S^2}$$

Equation 11, Formula for calculation of Variance Inflation Factor

While the Correlation matrix (Table 9) did not present any extremely unusual results, Price Per Share seemed to have somewhat high correlation with Issue Value. VIF analysis in *Table 10* presented very significant results. Price Per Share exhibited a score of nearly 80, when the standard acceptance threshold is 10. After removal of Price Per Share, the rest of the variables behaved ordinarily (Adjusted Regression, Table 10). Due to this, Regressions 3 and 4 in Table 10 will be held invalid, and we will proceed only with Number of Underwriters and Issue Value for further analysis.

Correlation Matrix

	Underpricing	*Nr of Underwriters*	*LN Issue Value*	*LN Price Per Share*
Underpricing	1			
Nr of Underwriters	-0,122576**	1		
LN Issue Value	0,103902*	0,500871***	1	
LN Price Per Share	0,333624***	0,240743***	0,591457***	1

Significance: * (10%); ** (5%); *** (1%)

Table 9, Correlation matrix between Underpricing, Number of Underwriters, Issue Value and Price Per Share

	Original Regression	Adjusted Regression
Variable	**VIF**	**VIF**
Nr of Underwriters	5.388910	5.354822
LN Issue Value	10.72287	7.355030
LN Price Per Share	79.23451	

Table 10, Summary of Variance Inflation Factors

Disregarding regressions 3 and 4, we have observed other significant results. From regression 2, Number of underwriters seem to negatively affect the underpricing. For every additional underwriter of an IPO, underpricing is expected to be reduced by approximately 7,29%. Additionally, 1 point increase in

[9] Variance Inflation Factor

Log of Issue Value[10] is expected to increase the underpricing by approximately 8,96%

7.3.3 Summary

Based on the findings, we reject H(0) of Sub-Hypothesis 1 and 2, concluding that Number of Underwriters and Total Issue Value has a significant explanatory power on Tech IPO underpricing. While Price Per Share also exhibited highly significant results, collinearity issue did not permit us to reject H(null) of sub-hypothesis 3 and 4, thereby preserving it.

7.4 Underwriter's Reputation and Tech Underpricing

As identified by several researchers, reputation of the underwriters plays an important role in an IPO. Carter and Manaster (1990) identified a significant inverse relationship between underpricing and underwriters' reputation: the higher the reputation of the underwriter – the less underpricing in IPO was observed. Taking that into consideration, we are analyse how the reputation of the underwriters affect underpricing in one specific segment – Tech. In addition, we analyse whether the reputation has a higher or lower explanatory power in existence of previously identified significant factors – number of underwriters and total IPO value raised.

In the analysis, we use three different measurements of reputation:

i. Reputation calculated based on the number of IPOs led by the underwriter over total number of IPOs – UR(I)
ii. Average monetary value raised by the underwriter per IPO – UR(II)
iii. Positioning of the underwriter in IPO announcement – UR (III)

Due to three different measurements for the reputation, the analysis will be split into three different parts, part 1 covering UR(I), part 2 – UR (II) and part 3 – UR(III). For the Underwriters Reputation, we have raised following sub-hypothesis:

[10] An increase of total value raised by approximately $368 Millions

7.4.1 Sub-Hypotheses

Sub-Hypothesis 1:

H(0): Reputation of the underwriter based on UR(I) does not explain any variation in Tech IPOs' underpricing

H(a): Reputation of the underwriter based on UR(I) explains variation in Tech IPOs' underpricing

Sub-Hypothesis 2:

H(0): Reputation of the underwriter based on UR(I) together with Issue Value and Number of Underwriters does not explain any variation in Tech IPOs' underpricing

H(a): Reputation of the underwriter based on UR(I) together with Issue Value and Number of Underwriters explains variation in Tech IPOs' underpricing

Sub-Hypothesis 3:

H(0): Reputation of the underwriter based on UR(II) does not explain any variation in Tech IPOs' underpricing

H(a): Reputation of the underwriter based on UR(II) explains variation in Tech IPOs' underpricing

Sub-Hypothesis 4:

H(0): Reputation of the underwriter based on UR(II) together with Value Raised and Number of Underwriters does not explain any variation in Tech IPOs' underpricing

H(a): Reputation of the underwriter based on UR(II) together with Value Raised and Number of Underwriters explains variation in Tech IPOs' underpricing

Sub-Hypothesis 5:

H(0): Reputation of the underwriter based on UR(III) together with Value Raised and Number of Underwriters does not explain any variation in Tech IPOs' underpricing

H(a): Reputation of the underwriter based on UR(III) together with Value Raised and Number of Underwriters explains variation in Tech IPOs' underpricing

7.4.2 Analysis, UR (I)

To test for hypothesis 1 and 2, we have used the following regressions:

$$\mathrm{IPO}_{\mathrm{Underpricing\,(Tech)}} = \alpha + \beta_{\mathrm{UR(I)}}\mathrm{UR(I)} + \varepsilon$$

Equation 12, Regression for IPO Underpricing based on Underwriters Rating (I)

$$\mathrm{IPO}_{\mathrm{Underpricing\,(Tech)}} = \alpha + \beta_{\mathrm{UR(I)}}\mathrm{UR(I)} + \beta_{\mathrm{Val}}\mathrm{Val} + \varepsilon$$

Equation 13, Regression for IPO Underpricing based on Underwriters Rating (I) and Issue Value

$$\mathrm{IPO}_{\mathrm{Underpricing\,(Tech)}} = \alpha + \beta_{\mathrm{UR(I)}}\mathrm{UR(I)} + \beta_{\mathrm{Val}}\mathrm{Val} + \beta_{\mathrm{NoU}}\mathrm{NoU} + \varepsilon$$

Equation 14, Regression for IPO Underpricing based on Underwriters Rating (I), Issue Value and Number of Underwriters

*Where **UR(I)** is the underwriters rating 1, **NoU** is the Number of Underwriters per IPO and **Val** is the logarithm of total issue value in billions (Price per share * number of shares issued).*

The UR(I) was calculated from the total number of IPOs led by the underwriter over the overall number of IPOs (Equation 15). The formula was applied to each underwriter to calculate its reputation to be used in regressions.

$$\mathrm{UR(I)} = \frac{\mathrm{IPO_L}}{\mathrm{IPO_T}} * 100$$

Equation 15, Underwriters Reputation (I). IPO(L) indicates nr. of IPOs led by the underwriter & IPO(T) is total number of IPOs

The *Table 11* presents the out-print from the regressions' summaries. The results from Regression 1 indicates a significant positive relationship between underwriter's reputation and underpricing of an IPO. A 1 point increase in the rating of an underwriter would lead to 0,6% increase in the underpricing of a particular IPO. Regression 2 presents a slightly better model, explaining 0,32% more variation in the underpricing, however the Issue Value seems to be insignificant. Once included the Number of Underwriters, Regression 3 exhibited the best explanatory power, with an R-square of 6,92%. All the explanatory variables in Regression 3 were significant at least 95% confidence interval and provided the following insights:

i. 1 point increase in Underwriters Rating (I) would increase the underpricing with 0,606%
ii. 1 point increase in Issue Value would increase the underpricing with 7,19%
iii. An additional underwriter would decrease the underpricing with 7,76%

	Underpricing (Tech)		
	Regression 1	Regression 2	Regression 3
Intercept	0,201067***	0,265783***	0,525413***
(Std. Error)	(0,037914)	(0,071284)	(0,093855)
Rating of Underwriter	0,006043***	0,005128**	0,006061**
(Std. Error)	(0,002238)	(0,002395)	(0,002352)
LN Total Issue Value		0,024643	0,071879***
(Std. Error)		(0,022988)	(0,025219)
Nr. Underwriters			-0,077584***
(Std. Error)			(0,018783)
F-Value	7,2922	4,2222	8,6313
Significance F	0,0073	0,0154	0,0000
Observations	352	352	352
R Square	0,020410	0,023625	0,069255
Adjusted R Square	0,017611	0,018029	0,061231

Significance: * (10%); ** (5%); *** (1%)

Table 11, Tech Underpricing with Underwriters Rating etc

7.4.3 Summary, UR(I)

Based on the findings, we cannot reject H(0) of sub-hypotheses 1 and 2. Furthermore, we conclude that Regression 3 has the best explanatory power, describing underpricing in Tech IPOs, with an R-squared of 6,93%. Additionally, including Issue Value and Number of Underwriters in the regression significantly improves models explanatory power.

7.4.4 Analysis, UR (II)

To test for hypothesis 3 and 4, we have used the following regressions:

$$IPO_{Underpricing\,(Tech)} = \alpha + \beta_{UR(II)} UR(II) + \varepsilon$$

Equation 16, Regression for IPO Underpricing based on Underwriters Rating (II)

$$IPO_{Underpricing\,(Tech)} = \alpha + \beta_{UR(II)} UR(II) + \beta_{Val} Val + \varepsilon$$

Equation 17, Regression for IPO Underpricing based on Underwriters Rating (II) and Issue Value

$$IPO_{Underpricing\,(Tech)} = \alpha + \beta_{UR(II)} UR(II) + \beta_{Val} Val + \beta_{NoU} NoU + \varepsilon$$

Equation 18, Regression for IPO Underpricing based on Underwriters Rating (II), Issue Value and Number of Underwriters

The UR(II) was calculated based on the average value of IPO per underwriter. The average value of an IPO per underwriter was estimated to be $ 148 199 395,92, with a standard deviation of $ 75 188 035,92. Based on this premise, underwriters were assigned ratings of: (IV) - for underwriter with an average value higher than [Mean + one standard deviation]; (III) - for underwriter with an average value between [Mean & Mean + one standard deviation]; (II) - for underwriter with an average value between [Mean & Mean - one standard deviation]; (I) - for underwriter with an average value lower than [Mean - one standard deviation]; (note that, an underwriter with ranking of IV implied best rating, etc).

In total, 43 different lead underwriters managed 352 Tech IPOs in a period between 2000-2017. As observed from Table 12, 7 underwriters were assigned a rating of (IV), 11 – a rating of (III), 20 – a rating of (II) and 5 – a rating of (I). Underwriters with rating of (IV) led 226 IPOs, with rating of (III) – 63 IPOs, rating of (II) – 58 IPOs and rating of 5 – 5 IPOs. An interesting finding from the statistics, is that 7 top underwriters led more than 64% of the IPOs in a test period. This might create some biases, therefore had to be checked carefully.

	Underwriter Ratings				
	(I)	**(II)**	**(III)**	**(IV)**	**Total:**
Total Underwriters / Rating	5	20	11	7	43
Total IPOs / Underwriter Group	5	58	63	226	352

Table 12 Group of Underwriters and IPOs

Once the ratings were assigned, we conducted the analysis which is presented in *Table 13.* All the regressions proved to be significant at 99% confidence interval. Regression 1 confirmed the initial hypothesised intuition in Hypothesis 3, rejecting H(0) and accepting that UR(II) explains the variation in underpricing. Same as with UR(I), Regression 3 provided the best explanatory power, explaining 7,56% of the variation in underpricing. Additionally, all the variables in Regression 3 were significant at least at 95% confidence interval. Based on the findings, we rejected H(0) of Hypothesis 4 and accepted the alternative, that UR(II) together with Issue Value and Number of Underwriters have a significant explanatory power, in describing the variations in IPO underpricing.

	Underpricing (Tech)		
	Regression 1	**Regression 2**	**Regression 3**
Intercept	-0,012528	0,058314	0,312337**
(Std. Error)	(0,092284)	(0,123157)	(0,136123)
UR (II)	0,086489***	0,078053***	0,081983***
(Std. Error)	(0,026043)	(0,027802)	(0,027234)
LN Total Issue Value		0,019826	0,067417***
(Std. Error)		(0,022814)	(0,025278)
Nr. Underwriters			-0,074951***
(Std. Error)			(0,018645)
F-Value	11,0295	5,8885	9,4827
Significance F	0,0010	0,0031	0,0000
Observations	352	352	352
R Square	0,030550	0,032643	0,075570
Adjusted R Square	0,027780	0,027100	0,067601

Significance: * (10%); ** (5%); *** (1%)

Table 13, Tech Underpricing with second Underwriter Reputation – UR(II)

In addition to the above analysis, we have checked for the differences in average underpricing between the different underwriters' reputation groups. The results are summarised in *Table 14*. One interesting finding was that lead underwriters with higher ratings, were observed to have higher levels of IPO underpricing. IPOs with underwriters from the lowest reputation group experienced on average only 15,39% underpricing, while IPOs with the best reputational underwriters on average experienced an underpricing of 34,08%. In addition, *Table 14* presents a summary of the differences between the means of various groups. Mean underpricing of group (I) seems to be statistically different only from group (II), however due to very small number of variables no conclusions can be drawn from these findings. Group (II) and (III) had an average underpricing of 17,24% and 20,16% respectively. These averages do not appear to be statistically different from each other, thereby we could conclude that having underwriters from either group would not have significant difference in underpricing. However, means from both groups are statistically different from group (IV), which pooled the best underwriters. Based on these findings we can state that underwriters with best reputation has a greater impact on underpricing, as opposed to groups (II) or (III).

(Rating) Mean Underpricing	**(I) 0,1539**	**(II) 0,1724**	**(III) 0,2016**	**(IV) 0,3408**
NR. IPOs	6	58	63	226
(I)				
(II)	**XXX**			
(III)	**O**	**O**		
(IV)	**O**	**XXX**	**XX**	

Significance: X - 10%; XX - 5%; XXX - 1%; O - insignificant

Table 14, Differences in Mean Underpricing between different UR(II) groups

7.4.5 Summary, UR (II)

Based on the findings from the analysis above, we rejected H(0) of the sub-hypotheses 3 and 4, and accepted H(a) in both of them. Regression 3 in *Table 13* exhibited the best explanatory power of the variations in Tech IPO underpricing, explaining 7,56%. Additionally, we found that 16,3% of the underwriters led more than 63% of the Tech IPOs, which might create some biasedness issues. Lastly, the differences regarding average underpricing in various underwriter groups presented that underwriters with best reputation have significantly different mean from all other groups. The differences between the means of other groups were concluded to be insignificant.

7.4.6 Analysis, UR (III)

The following regression has been used, to test for hypothesis 5:

$$\mathrm{IPO}_{\mathrm{Underpricing\,(Tech)}} = \alpha + \beta_{\mathrm{UR(III)}}\mathrm{UR(III)} + \beta_{\mathrm{NoU}}\mathrm{NoU} + \beta_{\mathrm{Val}}\mathrm{Val} + \varepsilon$$

Equation 19, Regression for IPO Underpricing based on Underwriters Rating (III), Number of Underwriters and Issue Value

For the UR(III), underwriters were segmented based on the system introduced by R. Carter and S. Manaster in their paper "*Initial Public Offerings and Underwriter*

Reputation" (Carter & Manaster, 1990). In the research, the authors assigned different values between 1 - 9, based on the seniority of underwriters, in the IPO publication, i.e. if a bank was the lead underwriter, it would assume a value of 9, second tier underwriter would assume a value of 8, tertiary would assume a value of 7, and so forth.

Once all the underwriters were evaluated, regression 1 (*Table 15*) was performed. However, it did not indicate any statistically significance between the underpricing of Tech companies and underwriter's reputation *UR (III).* To adjust for possible outliers, we have removed all of underwriters who participated in less than 4 IPOs, and ran the regression again (regression 2, in Table 15). The removal of the outlier underwriters did not improve the results. Underwriters rating still did not present any statistical impact on the underpricing of Tech IPOs. Additionally, removal of several underwriters worsened the model, as observed by lower significance of other variables, smaller goodness of fit and adjusted R square.

	Underpricing (Tech)	
	Regression 1	**Regression 2**
Intercept	0,801785*	0,522679
(Std. Error)	(0,442457)	(0,47425)
UR (III)	-0,01945	0,010774
(Std. Error)	(0,051367)	(0,054829)
Nr. Underwriters	0,089676***	-0,071879***
(Std. Error)	(0,024489)	(0,019393)
LN Total Issue Value	-0,073518***	0,075686***
(Std. Error)	(0,018932)	(0,026134)
F-Value	6,3485	5,1717
Significance F	0,0003	0,0017
Observations	352	332
R Square	0,051889	0,045166
Adjusted R Square	0,043715	0,036433

Significance: * (10%); ** (5%); *** (1%)

Table 15 Tech Underpricing with Third Underwriter Reputation

7.4.7 Summary, UR (III)

The underwriters' reputation represented in the model by Carter & Manaster, (1990) did not yield signficant results for our sample. The intercept and UR(III) were both oberved to be insignificant at all conventional statistical levels. Since this model was examing the statistical significance of UR(III), we do not find evidence in favour of sub-hypothesis 5 and therefore conclude that underwriters reputation based on seniority does not explain underpricing in Tech IPOs.

7.4.8 Summary, Underwriters Reputation

Issue Value and Number of Underwriters were significant in all the final regressions for each of the UR models, which outlines their importance in explaining underpricing of the Tech IPOs. Moreover, UR(II) exhibited the best goodness of fit of 7,56% over 6,94% and 4,52% for UR(I) and UR(III) respectively. In addition, it was identified that the reputation of the underwriters also plays a role, and IPOs led by underwriters with best reputation experienced the most underpricing, while IPOs with poor reputation experienced the least underpricing. We also observed differences between mean underpricing, this difference was statistically different. Given these findings, UR(II), Issue Value and Number of Underwriters will be used for further analysis and in the final model generation.

7.5 Hot & Cold Markets and Underpricing

There are quite a few papers analysing different behavioural patterns of investors under various market circumstances, such patterns cannot be explained by pure technical analysis. Behavioural impact is especially apparent among inexperienced and emotional investors, where the investment decisions seems to be contradicting empirical knowledge. Therefore, in this part, we are going to analyse a particular branch of "Hot & Cold" markets, and its impact on the Overall market and Tech IPO underpricing. We start the analysis with two different models. First model is based on the NASDAQ stock index[11] movements against its 125-day moving average. This specific index was chosen due to higher concentration of stocks that are of particular interest for this research, and representing the stock market. Second model was based on the paper by Helwege & Liang (Helwege & Liang, 2004), where the Hot & Cold markets are clustered

[11] NASDAQ stock index - ^IXIC

by the number of IPOs per period. Periods with high number of IPOs are classified as Hot, and those with low number of IPOs as Cold. This type of segmentation provides us with valuable insights into the Hot & Cold IPO markets, as opposed to overall stock market.

7.5.1 Sub-Hypotheses

Sub-Hypothesis 1:

H(0): Hot & Cold (I) market indicator or it's lagged version does not explain any variation in Tech IPO underpricing

H(a): Hot & Cold (I) market indicator or it's lagged version explains variation in Tech IPO underpricing

Sub-Hypothesis 2:

H(0): Hot & Cold (II) market indicator or it's lagged version does not explain any variation in Tech IPO underpricing

H(a): Hot & Cold (II) market indicator or it's lagged version explains variation in Tech IPO underpricing

7.5.2 Analysis

To test for sub-hypotheses 1 and 2, following regression model was used:

$$\mathrm{IPO}_{\mathrm{Underpricing(Tech)}} = \alpha + \beta_{\mathrm{H\&C}}\mathrm{H\&C} + \varepsilon$$

Equation 20, Tech underpricing regression for H&C

7.5.2.1 Part I, H&C (I) market indicator

To run the regressions, Hot & Cold (I) market indicator was estimated. The spot price of IXIC[12] was differenced with its 125-day average, providing either positive or negative value. Positive values indicate "Hot" market, and are characterised by the investors' optimism, resulting in the spot stock price above 125-days moving average. Negative values indicate "Cold" market, and reflect investor's pessimism, resulting in spot price which is below its 125-days moving average. The values are calculated by using *Equation 21*, where the H&C value indicates the percentage value of stock price position with regards to the moving average.

[12] NASDAQ stock index

$$H\&C = \frac{IXIC_S - IXIC_{S-125}}{IXIC_{S-125}}$$

Equation 21, Formula for calculation of H&C (I) indicator. IXIC(S) represents the spot price of the index and IXIC(S-125) represents its 125-day moving average

Table 16 presents the summary of findings from the regressions. Regressions 1 and 2 were performed on the Overall Market IPO underpricing, and regressions 3 and 4 on Tech IPO underpricing.

	Underpricing (Overall)		Underpricing (Tech)	
	Regression 1	**Regression 2**	**Regression 3**	**Regression 4**
Intercept	0,111805***	0,109014***	0,235635***	0,232337***
(Std. Error)	(0,006364)	(0,005507)	(0,021995)	(0,021489)
H&C	0,116877		0,211799	
(Std. Error)	(0,076785)		(0,306997)	
H&C, Lag 3M		-0,05309		0,001074
(Std. Error)		(0,064313)		(0,27785)
F-Value	2,3169	0,6814	0,4760	0,0000
Significance F	0,1296	0,4101	0,4915	0,9969
Observations	201	198	134	131
R Square	0,011509	0,003465	0,003593	0,000000
Adjusted R Square	0,006541	-0,001620	-0,003956	-0,007752

Significance: * (10%); ** (5%); *** (1%)

Table 16, Underpricing with respect to NASDAQ Stock Index's Hot & Cold market indicator

As observed from the table, neither of the regressions provide any statistically significant values. Neither Overall Market, nor Tech IPO underpricing can be explained with the H&C (I) market indicator. Thus, we cannot reject H(0) of sub-hypotheses 1, and conclude that H&C market indicator or its 3 months lagged variable does not provide any explanatory power on underpricing variation.

7.5.2.2 Part II, H&C (II)

Hot & Cold market indicator (II) was based on two different standardisations of variables. For the first method, we have used the number of monthly IPOs, compared to the monthly average. Thereafter, each period was assigned a value of 1- 4, depending on the activity level. Qualifications of each rating are represented in *Table 17*.

Rating	(I)	(II)	(III)	(IV)
Qualification (X)	X < Mean - Std. Dev	Mean - Std. Dev < X < Mean	Mean < X < Mean + Std. Dev	Mean + Std. Dev < X

Table 17, Rating qualification for Hot & Cold (II) market indicator

After the calculations, we have estimated that on average there were 14 IPOs per month, with a standard deviation of 9 IPOs. Based on these premises and the qualification requirements, periods with more than 23 IPOs were classified as Hot, between 14 and 23 as semi-Hot, between 5 and 14 as semi-Cold and below 5 IPOs per period - as Cold.

Second standardisation method was based on actual number of IPOs per month. All the periods were standardised using logarithms and regressed on underpricing – represented as *LN Nr. IPO* in *Table 18*. Once all the ratings were assigned, regressions were performed on the level ratings, as well as their respective one-period lagged variables. The results are summarized in *Tables 18 and 19*, for Overall Market and Tech industry respectively.

	Underpricing (Overall)			
	Regression 1	**Regression 2**	**Regression 3**	**Regression 4**
Intercept	0,046714***	0,042121**	0,053194***	0,051954**
(Std. Error)	(0,017553)	(0,019968)	(0,017625)	(0,020044)
H&C (II), Level	0,027327***			
(Std. Error)	(0,006704)			
LN Nr. IPOs, Level		0,02929***		
(Std. Error)		(0,007763)		
H&C (II), Lag			0,024342***	
(Std. Error)			(0,007763)	
LN Nr. IPOs, Lag				0,024951***
(Std. Error)				(0,007791)
F-Value	16,6166	14,2361	13,1049	10,2558
Significance F	0,0001	0,0002	0,0004	0,0016
Observations	201	201	200	200
R Square	0,077066	0,066762	0,062078	0,049246
Adjusted R Square	0,072428	0,062073	0,057341	0,044444

Significance: * (10%); ** (5%); *** (1%)

Table 18, Regression for Overall Market IPO Underpricing based on H&C (II), LN of IPO quantity and their respective lagged variables

	Underpricing (Tech)			
	Regression 1	Regression 2	Regression 3	Regression 4
Intercept	0,164757**	0,078855	0,127929*	0,12838
(Std. Error)	(0,072218)	(0,094083)	(0,065583)	(0,078368)
H&C (II), Level	0,027277			
(Std. Error)	(0,072218)			
LN Nr. IPOs, Level		0,059094*		
(Std. Error)		(0,033561)		
H&C (II), Lag			0,04157*	
(Std. Error)			(0,023176)	
LN Nr. IPOs, Lag				0,042284
(Std. Error)				(0,028744)
F-Value	1,1988	3,1004	3,2171	2,1640
Significance F	0,2756	0,0806	0,0752	0,1437
Observations	134	134	133	133
R Square	0,009000	0,022949	0,023969	0,016251
Adjusted R Square	0,001492	0,015547	0,016519	0,008741

Significance: * (10%); ** (5%); *** (1%)

Table 19, Regression for Tech IPO Underpricing based on H&C (II), LN of IPO quantity and their respective lagged variables

The Overall Market seems to be very significantly responsive to both methods, however, H&C (II) level model provides the best explanatory power, with R-squared of 7,7%. This implies that the current month activity has best explanatory power, yet previous month falls short by only 1,5%, with R-squared of 6,2%. Since all the variables are significant at 99% confidence interval, we conclude that previous month activity still explains a portion of future IPO underpricing variation in Overall Market. The tech industry did not seem to follow the same path, as the prevailing month's activity did not provide any significant explanation on underpricing variation. However, one-period lagged version of H&C (II) was significant at 90% confidence interval, thereby providing some insights and concluding on their statistical significance, with only the exemption of log number of IPOs.

7.5.3 Summary

In part I, we were unable to detect any significant findings that would support the Hot & Cold (I) markets influence on the underpricing of both, the Overall Market and Tech IPOs. In part II, we identified evidence supporting H&C (II) market indicators' significance. Hot & Cold markets categorised by the IPO activity at the prevailing month, explained more than 7,7% of the variation in Overall Market IPO underpricing. One-period lagged version of it seemed to be slightly deteriorated, explaining 6,2% of the variation. Both were significant at 99% confidence interval. Tech market behaved slightly different, where the activity of the prevailing month did not have any statistical significance. Nevertheless, one-period lagged version of H&C (II) were significant at 90% confidence interval, explaining 2,4% of the variation in Tech IPO underpricing. Based on the findings, we cannot reject H(0) of sub-hypothesis 1, and conclude that H&C (I) or it's lagged version do not explain any variation in IPO underpricing. The opposite findings were detected for sub-hypothesis 2, where we rejected H(0), and concluded that H&C (II) or it's lagged version provides significant explanatory power, describing the variation in IPO underpricing.

7.6 Fear & Greed ratio and Underpricing

In this part, we are going to analyse the Fear & Greed index and its hypothesised impact on underpricing. The index was created by the *Cable News Network* (CNN), which is used as an indicator for the underlying sentiment in the market at any given point in time.

7.6.1 Sub-Hypothesis:

H(0): Fear & Greed index does not explain any variation in Tech IPO underpricing
H(a): Fear & Greed index explains variation in Tech IPOs' underpricing

7.6.2 Analysis:

To test for the sub-hypothesis, we have used the following regression:

$$IPO_{\text{Underpricing(Tech)}} = \alpha + \beta_{\text{F-G(ratio)}} \text{F - G}_{\text{ratio}} + \varepsilon$$

Equation 22, Tech underpricing regression for F-G ratio

Our compiled F-G ratio (Fear & Greed) is somewhat similar to the one created by CNN Finance, however, instead of 7 variables we used only 3 which we believe are most important for tech companies. The 3 variables contributing to the ratio are: VIX index, measuring the volatility in the market; (*H&C*) bearish vs. bullish markets, represented by the difference between S&P 500 spot price and it's 125 days moving average; (*LN(Vol)*) Log of trading volume in the US stock market. Each of the variables are weighted equally in the calculations of the F-G ratio (Equation 23).

$$F\text{ - }G_{ratio} = \frac{VIX + H\&C + LN\,(Vol)}{3}$$

Equation 23, Fear & Greed Ratio formula

The summary of the findings from regressions are outlined in the *Table 20.*

	Underpricing (Overall) Regression 5	Underpricing (Tech) Regression 6
Intercept	0,095234***	0,202465***
(Std. Error)	(0,008976)	(0,038173)
F-G ratio	0,000815***	0,001462
(Std. Error)	(0,000289)	(0,001232)
F-Value	7,9310	1,4089
Significance F	0,0053	0,2374
Observations	201	134
R Square	0,038327	0,010561
Adjusted R Square	0,033494	0,003065

Significance: * (10%); ** (5%); *** (1%)

Table 20 Underpricing with respect to the Fear & Greed ratio

As observed from the *Table 20*, the underpricing of Overall Market IPOs are marginally but significantly influenced by the F-G ratio. All the variables of Regression 5 are significant at 99% confidence interval, thereby signalling that F-G ratio has a significant explanatory power on Overall Market. However, as it can be observed from Regression 6 in *Table 20*, F-G ratio does not have the same effect on the Tech IPO underpricing. The variables are statistically insignificant, therefore we cannot reject H(0) of the sub-hypothesis, and conclude that Fear & Greed ratio does not have a significant explanatory power on Tech IPO underpricing.

7.6.3 Summary

The analysis above has identified that; the Fear & Greed ratio has a significant explanatory power on IPO underpricing of the Overall Market. However, Tech IPO underpricing could not be explained by this ratio due to insignificance in the findings.

7.7 Investor Sentiment and Underpricing

7.7.1 Sub-Hypotheses

Based on the theory about the Investor Sentiment, we have raised the following hypothesis:

H(0)*: Investor Sentiment does not explain any variation in Tech IPO underpricing*
H(a)*: Investor Sentiment explains variation in Tech IPO underpricing*

7.7.2 Analysis

As observable from *Table 21*, at level, the *Investor Sentiment* (IS) exhibits non-stationarity and thus, unit root. This could be explained by the nature contained in investor sentiment data set, and because it is created from a combination of trending variables. Once differentiated, the changes in investor sentiment appears to be stationary, de-trended and ready for predictive analysis, represented by IS (-1).

	IS (Level)	IS (-1)
Alpha	0,05	0,05
p-value	0,524	0,001

Table 21 ADF Test for Investor Sentiment at Level and 1st Difference

Once the data was stationarized, we ran the regression (Equation 24) and observed following findings:

$$\text{IPO}_{\text{Underpricing}} = \alpha + \beta_{\text{IS}(-1)}\text{IS}(-1) + \varepsilon$$

Equation 24, Regression for IPO underpricing based on Investor Sentiment, IS(-1)

	IPO Underpricing (Overall) Regression 1	Regression 2	IPO Underpricing (TECH) Regression 3	Regression 4
Intercept	0,102934***	0,111016***	0,201324***	0,218218***
(Std. Error)	(0,008874)	(0,008845)	(0,02801)	(0,02717)
IS (Level)	0,035571***		0,063364	
(Std. Error)	(0,012585)		(0,040878)	
IS (-1)		0,000611		0,003599
(Std. Error)		(0,000514)		(0,005049)
F-Value	7,9886	1,4160	2,4028	0,5080
Significance F	0,0055	0,2365	0,1258	0,4785
Observations	119	119	70	70
R Square	0,063915	0,011958	0,034129	0,007415
Adjusted R Square	0,055914	0,003513	0,019925	-0,007182

Significance: * (10%); ** (5%); *** (1%)

Table 22 Regression Results Between Investor Sentiment and IPO Underpricing

As it can be observed from *Table 22*, the overall market and Tech sector does not exhibit any significant relationship with the Investor Sentiment [*IS (-1)*]. Regression 2 is only significant at 75% confidence (Significance F of 0,2365), while Regression 4 at only 50% (Significance F of 0,4785). Neither of them fits 95% confidence interval, which is the requirement for most statistical acceptance. On the other hand, the overall market seems to be strongly correlated with Investor Sentiment level data (Regression 1). This can lead to false conclusions and exhibit spurious relationship, because the level data of Investor Sentiment is non-stationary. This is because, we have checked for stationarity in the independent variable, and are able avoid committing a type I error (False positive) and conclude that there is no relationship between the underpricing of IPO's and Investor Sentiment.

7.7.3 Summary

Given the results of the analysis, we cannot reject H(0) of the sub-hypothesis. Therefore, we conclude that changes in Investor Sentiment does not explain any variation in Tech IPO underpricing. These findings can be partially explained by the findings in the research paper "Investor Sentiment in the Stock Market" (Baker & Wurgler, 2007). The authors have outlined that the sentiment is strongly driven by irrational traders and amateur, short term speculators. However, most brokerage firms have strict requirements for the investors who wishes to participate in IPOs, thereby filtering out the average & small ones, or as Baker &

Wurgler defines - irrational investors. Eventually, this leads to mostly preserving rational, long term value investors, and prevents IPOs from been influenced by the prevailing sentiment in the market.

8 Final Model

The final model considers a multivariate regression analysis, consisting of all the factors analysed in the factor section. This is because we believe that other factors, though been insignificant, might still be able to act as control variables or help better explain underpricing once conducted together with other significant factors. Model 1 denoted by *Equation 25* will contain all the factors, while model 2 denoted by *Equation 26* contains only significant factors from model 1, as identified in Part 7 of the paper.

$$\text{Underpricing} = \alpha + \beta_{\text{Fed}}\text{Fed} + \beta_{NrU}\text{NrU} + \beta_{Issue}Issue + \beta_{\text{PPS}}\text{PPS} + \beta_{\text{UR}}\text{UR} + \beta_{\text{H\&C}}\text{H\&C} + \beta_{\text{F\&G}}\text{F\&G} + \beta_{\text{IS}}\text{IS} + \varepsilon$$

Equation 25, Final regression model with all factors

$$\text{Underpricing} = \alpha + \beta_{\text{Fed}}\text{Fed} + \beta_{NrU}\text{NrU} + \beta_{\text{Issue}}Issue + \beta_{\text{UR}}\text{UR} + \beta_{\text{H\&C}}\text{H\&C} + \varepsilon$$

Equation 26, Final model with only significant factors

Index

Fed: Fed rates and/or 3 months Treasury bill as defined in *sections 7.1 and 7.2*

NrU: Number of underwriter as defined in *section 7.3*

Issue: Issue size, calculated by natural log of offer size in billions as in *section 7.3*

PPS: calculated by the log of price per share as defined in *section 7.3*

UR: Underwriter reputation calculated as UR (II) as defined in *section 7.4*

H&C: Hot and cold markets estimator based on H&C (II) as in *section 7.5*

F&G: Fear and Greed ratio as defined in *section 7.6*

IS: Investor sentiment as defined in *section 7.7*

	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
Intercept	-1,178148***	0,057721	0,07015	0,065387	-1,197736***
(Std. Error)	(0,252804)	(0,252804)	(0,1633)	(0,16364)	(0,251598)
NrU	-0,063957***	-0,07407***	-0,071958***	-0,07165***	-0,062549***
(Std. Error)	(0,017974)	(0,018855)	(0,018484)	(0,018525)	(0,017607)
Issue	-0,020223	0,074149***	0,074886***	0,07005***	-0,024852
(Std. Error)	(0,028372)	(0,02526)	(0,025204)	(0,025078)	(0,028038)
PPS	0,411944***				0,419391***
(Std. Error)	(0,066176)				(0,065795)
UR	0,07434***	0,086365***	0,086459***	0,089766***	0,07641***
(Std. Error)	(0,025895)	(0,027199)	(0,027173)	(0,027155)	(0,025811)
H&C	0,068148***	0,071328***	0,07369***	0,069471***	0,066368***
(Std. Error)	(0,025121)	(0,026454)	(0,026116)	(0,026041)	(0,024675)
F&G	0,000409	0,000834			
(Std. Error)	(0,001363)	(0,001434)			
Fed	0,043612	0,063935	0,063499		
(Std. Error)	(0,037851)	(0,03972)	(0,039675)		
F-Value	11,7253	6,5089	7,7579	9,0163	16,1629
Significance F	0,0000	0,0000	0,0000	0,0000	0,0000
Observations	352	352	352	352	352
R Square	0,192635	0,101687	0,100806	0,094149	0,189343
Adjusted R Square	0,176206	0,086064	0,087812	0,083707	0,177629

Significance: * (10%); ** (5%); *** (1%)

Figure 2 Summary from the regression of final models

Figure 2 represents the findings from different regressions, where regression 1 and 2 were based on Equation 25 and regressions 3 and 4 on Equation 26. Regression 1 presented the highest goodness of fit, with R-squared of 19,26%. However, as in Section 7.3, share price presented high collinearity and correlation with Issue Value (VIF[13] – 72). Therefore, Regression 2 was performed, excluding the price per share. With the exclusion of price corrected for collinearity, however, the predictive power of the model was reduced drastically, from 19,26% to 10,17%. This implied that price per share has a significant predictive power, therefore cannot be removed from the model.

When compared, factors in Regression 1 yielded similar results as in previous analyses conducted in Part 7 of the paper. The significances of variables remained the same, whether regressed alone or in combination. The exemption was Fed rates, which was found to be significant on tech IPOs in section 7.1. However, once examined with other factors, we concluded that Fed rates are not statistically significant, which can be observed from Regressions 1, 2 and 3. Regressions 3

[13] Variance Inflation Factor

and 4 compares the impact of this particular factor on the explanatory power of the model. As observed from Regression 4, removal of Fed rates reduced the goodness of fit with 0,66%, while F-value increased. Other variables or their standard errors didn't seem to be affected by the removal of Fed rates, therefore we concluded that the factor does not have any significant explanatory power on underpricing, nor does it act as a control variable.

Fear & Greed ratio was another factor (Regression 1), which, compared to section 7.6, preserved the same sign, same insignificance, and did not present any controls over other variables. Therefore, Fear & Greed was also concluded insignificant for Tech IPO.

As it can be observed from Regression 5, Removal of Fed rates and Fear & Greed ratio didn't affect the goodness of fit, while improving the adjusted R-squared and F-value. Due to the fact, we reject hypothesis 1 and 5 from Part 6, and conclude that Fed rates and Fear & Greed ratio does not provide any additional explanatory power to the model. All other variables have higher or lower explanatory power with regards to Tech IPO underpricing, and although Issue Value did not convey any significance on its own, it acted as a control variable for Price Per Share, therefore had to be preserved.

Investor Sentiment data was only available up to the year 2010 and because of this, we have performed a separate analysis with a full model to check for its explanatory power, thereby testing for hypothesis 6[14]. Additionally, to check for the strength of the model during different time periods, we have performed an analysis on pre-crisis[15] period and post-crisis period. The summary of the findings are presented in *Table 23.* Regression 1 and 2 presents findings of pre-crisis period, while Regression 3, post-crisis. Moreover, Regression 1 was performed with Investor Sentiment factor, while Regression 2 without. As it can be observed, removal of IS factor did not have any significant impact on the model. R-squared dropped with 0,1%, while adjusted R-squared and F-value slightly improved. Removal of the IS did not change signs of any of the variables, nor did it affect any significances. The only exception was number of underwriters, which became weakly significant. We therefore conclude that inclusion of IS worsens the model, hence rejecting hypothesis 6 from part 5.

[14] From Part 6 of the paper
[15] Financial crisis of 2007-2008

	Pre-Criss		Post-Crisis
	Regression 1	Regression 2	Regression 3
Intercept	-1,865653***	-1,839651***	-0,743849**
(Std. Error)	(0,526857)	(0,519458)	(0,287824)
NrU	-0,112598	-0,115756*	-0,02769
(Std. Error)	(0,06911)	(0,068247)	(0,018)
PPS	0,60417***	0,60565***	0,07052***
(Std. Error)	(0,129059)	(0,128571)	(0,07052)
Issue	-0,007203	-0,00716	-0,025209
(Std. Error)	(0,057589)	(0,057405)	(0,029745)
UR	0,087345**	0,086456**	0,055258
(Std. Error)	(0,041288)	(0,041071)	(0,033681)
H&C	0,17623***	0,168546***	-0,006642
(Std. Error)	(0,067422)	(0,063209)	(0,027453)
F&G	-0,0035	-0,0033	0,003036*
(Std. Error)	(0,003282)	(0,003217)	(0,001617)
Fed	-0,410825	-0,40141	0,049743
(Std. Error)	(0,663829)	(0,661115)	(0,031694)
IS	-0,003121		
(Std. Error)	(0,009305)		
F-Value	7,5127	8,6249	4,2978
Significance F	0,0000	0,0000	0,0002
Observations	147	147	200
R Square	0,303387	0,302819	0,135465
Adjusted R Square	0,263004	0,267709	0,103945

Significance: * (10%); ** (5%); *** (1%)

Table 23, Summary of the findings of the model on pre- and post- financial crisis periods

The comparison of pre- and post-crisis period is presented in Regressions 2 and 3. First and foremost, pre-crisis period exhibits substantially higher goodness of fit, with R-squared of 30,28% versus 13,55% for post-crisis period. F-value and Adjusted R-squared is also significantly higher in pre-crisis period. Moreover, NrU, UR and H&C had lost their significances, while Fear & Greed ratio became weakly significant during the post-crisis period. Based on these findings, we concluded that the model had much higher explanatory power before the crisis, as opposed to after. Some of the plausible explanations for this could be: (i) false findings due to small sample sizes; (ii) change in investors perspective; (iii) market efficiency theorem and many more. The most plausible explanations will be covered in discussion part.

9 The Robustness Test of the Final Model

In the context of our model, we used the Hot & Cold markets as an exogenous variable. However, it has been argued in the literature, and often observed in reality, that the decision to go public is not random. Companies carefully plan the timing for best results, and often even withdraw their planned IPO if the market isn't "Hot" enough. This creates endogeneity biases, due to the fact that companies are actually controlling the possible effects of underpricing, and our results from OLS regression might be spurious.

To control for endogeneity, we run Two-Stage least squares regression (2SLS). First, we regress H&C using trading volume as an instrumental variable. Thereafter, we regress the original model substituting the H&C with the estimated values (Regression 3, Table 24). Summary of results are presented in *Table 24*.

Regression 2 (Table 24) was performed using H&C as the dependent variable and including trading volume (*Tvol*) as instrumental variable. 2SLS requires the instrument to meet two requirements: (i) the relevance and (ii) exclusion condition. In order for relevance condition to be fulfilled, partial correlation between the instrument (*Tvol*) and endogenous variable (*H&C*) must not be zero, while the exclusion condition requires the that covariance between the instrument and error term is 0, cov(z, u)=0. Based on the suggestions by (Roberts & Whited, 2013) we conclude that exclusion condition cannot be checked, since the error term u of regression is unobservable. However, we performed an empirical check for the relevance condition using Walds test for significance, where H(null) implied *Tvol*=0 and H(alternative) – *Tvol*≠0. The test provided a t-value of 8,48 with p-value of 0,0000 (Figure 3). Since p-value is smaller than 0,05, we reject H(null) and accept that variable *Tvol* is statistically significant from 0. This finding meets the relevance condition for 2SLS. Based on the findings, we concluded that both conditions are met, and therefore the instrument is compliant.

	Original Regression	Regression 2 H&C	Regression 3 2SLS
Intercept	-1,178148***	3,692021***	-1,733259***
(Std. Error)	(0,252804)	(0,29176)	(0,325712)
NrU	-0,063957***	0,015055	-0,050138***
(Std. Error)	(0,017974)	(0,033634)	(0,018544)
Issue	-0,020223		-0,028175
(Std. Error)	(0,028372)		(0,028151)
PPS	0,411944***	0,021264	0,426184***
(Std. Error)	(0,066176)	(0,109408)	(0,065797)
UR	0,07434***	-0,058421	0,092124***
(Std. Error)	(0,025895)	(0,049637)	(0,026576)
H&C	0,068148***		0,208148***
(Std. Error)	(0,025121)		(0,06001)
F&G	0,000409	0,01352***	-0,000742
(Std. Error)	(0,001363)	(0,002703)	(0,001427)
Fed	0,043612	-0,06019	0,061058
(Std. Error)	(0,037851)	(0,073367)	(0,038253)
Tval		-0,271877***	
(Std. Error)		(0,29176)	
F-Value	11,7253	11,4627	12,5346
Significance F	0,0000	0,0000	0,0000
Observations	352	352	352
R Square	0,192635	0,142107	0,203228
Adjusted R Square	0,176206	0,129709	0,187015

Significance: * (10%); ** (5%); *** (1%)

Table 24, Two-stage least squares regression for robustness check

Wald Test
H(Null): *Tvol* = 0

Test Statistic	Value	df	Probability
t-statistic	8,481053	345	0,000000
F-statistic	71,92825	1,345	0,000000
Chi-square	71,92825	1	0,000000

Figure 3, Wald test for Tvol significance in the regression

A comparison between the Original Regression and 2SLS (Table 24) does not present substantially different results. All the variables preserve the initial signs and significances, while the changes in the estimated values and error terms and minuscule. Based on the above findings, we conclude that our original OLS estimators are robust.

10 Discussion of the Findings

In the theoretical framework, we have outlined different theories that has been hypothesised by several scholars in the IPO literature. These theories laid foundation for the conventional knowledge explaining; (i) why companies choose to go public, (ii) how companies time their IPO, (iii) why underpricing is persistent in the IPO literature and (iv) other behavioural factors such as the signalling hypothesis, fear and greed and investor sentiment. The analysis conducted in the paper did to a large extent use the above-mentioned theories as the base. We therefore also base the rest of the discussion in this section upon these theories.

We constructed a model that considered all the factors which we analysed in the factors analysis and checked for the impact these factors have in explaining underpricing. In addition, we also performed a further analysis by observing, whether these factors would present different results once conducted in different time periods. The periods were divided into the pre-crisis and the post-crisis period. Pre-crisis is defined to be the period from *2000 – 2007* and post-crisis from *2008 – 2017*. The final model consisted of five different regressions, presented in *Figure 2,* and the finding of each factor were as follows:

Number of Underwriters

The model in *Figure 2* exhibited that number of underwriters is statistically significant at 1% level, which is significant in all the five regressions. The coefficient is carrying a negative sign, implying that an increase in the number of underwriters by one, would reduce underpricing by approximately 6,3%. This is consistent with the findings by Corwin and Schultz, (2005), who argued that, the offer price is more likely to be revised in response to information disclosure. This is due to synergies from several underwriters working together, who presents different offer price range given different valuation methods. The different valuation methods provide more transparency and leads towards a more accurate offer price, thereby reducing the level of underpricing.

Issue Size

The results presented in *Figure 2* shows that, issue size is statistically insignificant in regression 1 and 5. However, significant in regression 2, 3 and 4 once controlled for price per share, fear and greed ratio and fed rates. The fact that issue size is insignificant in regression 1 and 5 is inconsistent with the findings by both (Yong, 2009) and Habib and Ljungqvist, (2001). On the other hand, the results in regression 2, 3 and 4 are also consistent with (YONG, 2009) whom had found that, underpricing is increasing with the issue size. This implies that, the larger the issue size the more likely are we to expect higher levels of underpricing in the tech industry. However, once we disregard the significance level in regression 1 and 5, the coefficient signs are consistent with Habib and Ljungqvist 2001 who also concluded that; underpricing is decreasing as the issue size increase.

Price Per Share

From *Figure 2,* we observe that; the price per share is statistically significant at 1% level, in regressions 1 and 5. This factor was removed from regressions 2, 3 and 4 as it was observed to raise possible collinearity issues with Issue Size. However, it was added back to regression 5 as it carries significant explanatory power over underpricing. Price per share is positively correlated with underpricing, which is inconsistent with the findings of Ibbotson and Ritter (1994). In their research, authors identify that underpricing decreases as the price per share increases, while our analysis presents opposite findings – underpricing increases in-line with offer price. This is somewhat curious, and might be specific for Tech industry, where higher price might imply better quality of the company, thereby playing on the behavioural and psychological aspect of the traders and investors. On the other hand, there might be some potential biases, therefore a more detailed analysis should be performed on this particular factor.

Underwriter Reputation

In *Figure 2*, all the five regressions exhibit significant results on all conventional levels. The coefficient is carrying a positive sign, implying that the more reputable an underwriter is; the more likely are we to observe an increase in the level of underpricing. These findings are in accord with the results presented by Beatty and Ritter (1986) and Binay et. Al (2007), who find that, the more reputable underwriters are, the more they have the incentives to underprice. This is because underwriters want to maintain their relationship with investors, and underpricing is one way to favour this relationship. This effect is reasonable with regards to tech companies, as most tech companies are highly uncertain about their future performance, which is hard to determine. Leaving some money on the table for investors, is also one way that underwriters can maintain and attract more investors next time they underwriter an IPO. This is consistent with the argument presented by Binay and Co that, it is mainly less liquid companies which experience more underpricing when employing reputable underwriters. However, Carter & Manaster, (1990) and Booth & Smith II, (1986) find opposing results. Suggesting that, hiring of prestigious underwriters is one way of eliminating the information asymmetry between the company and investors. They argue that certified underwriters with more experience in valuating such companies, are better qualified to assess the potential risks associated, and therefore eliminate the adverse inside information problem, which reduces the degree of underpricing. However, based on the results exhibited in *Figure 2*, this paper presents the same conclusions as Binay, Gatchev, & Pirinsk, (2007), that underpricing in Tech industry increases with underwriters reputation.

Hot and Cold markets

The H&C ratio in *Figure 2* present very signficant results on all convetional levels. The coefficients are carrying positive signs on all five regressions, denoting that Tech IPOs are more underpriced when markets are hot and less underpriced in cold markets. These findings are also consistent with results presented by Helwege & Liang, (2004). Their results suggest that, hot markets leads to oversubuscription of shares and therefore more underpricing. They also argue that, hot markets are periods when quality companies tend to go public. This can also be observed in our sample, as we have periods of more IPO activity; more especially after the 2008 financial crisis. We also see that 8 out of the 10 biggest tech IPOs in history, went public between 2010 and 2017, this is a period which has been characterzed by many analyst as an hot market periods. Therefore, the findings by Helwege and Liang are consistent with our results.

Fear and Greed

Our final model exhibits that fear and greed is insignificant in both regression 1 and 2. As observed from the final model, the fear and greed ratio was found to add little explanatory power, and was thus removed from the model. The insignificant results are inconsistent with the findings by (Lo & Repin, 2002) and (Lo, 2005), who find fear and greed to be very signinficant in the day traders environment. Their findings are associated with high stock tradings activities. Such environments are characterized by high price fluactuations, which cause day-traders to exhibit strong emotional patterns in their decision making choices, given that they have little time to make the decision. Thus, they are more prone to take actions based on their emotions. As opposed to day-traders, tech companies do take their time, in both valuing their offer price and timing of their equity offering period. As dicussed in previous sections, there are more people involved in determining the offer price, which in turn increase the likelihood of discovering a fair offering price. On this basis, it is reasonble to argue that fear and greed should not exhibit a significant impact on underpricing, which is also consistent with our findings.

General Discussion

Based on the overall assesment, we finalize the research by concluding that, the majority of the findings in the Tech industry are consistent with previous research and analysis of overall market. Majority of the factors that were identified as significant in our study, were found significant in other studies. On the other hand, we have identified several factors that behaves inversly in the Tech industry, compared to previous findings on the Overall Market. Most notable one is the Offer Price, which was identified to be inversly related in the Overall Market by previous studies, however in our analysis, the results presented a direct relationship between the two. Additionally, the biggest surprise was the insignificance of Investor Sentiment, which was previously identified to be extremely significant by a number of papers. However, we stipulate that this might have been caused by several factors, such as small sample size or particularity of the industry, thereby affecting the results and misrepresenting the findings. Further analysis of this particular factor is suggested.

Difference between the grouped and individual factor analysis

As introduced in Part 2 of the paper, we have conducted two different analysis of the factors – separate and combined. The findings indeed presented some noteworthy findings. (i) Separate factor analysis presented that Fed rates had significant impact on Tech IPO underpricing, however, in combination with other factors this significance was eliminated. (ii) In separate factor analysis, Underwriters Reputation based on Carter & Manaster (1990) ranking system did not provide any explanatory power of underpricing in Tech industry. In contrast, Final Model exhibited significant impact of the reputation when using ranking system by Binay, Gatchev & Pirinsk (2007). (iii) Psychological influence was indicated as a very significant factor by (Lo & Repin, 2002) and (Lo, 2005), however neither individual, nor grouped factor analysis indicated any significant impact of Fear & Greed ratio on Tech IPOs.

Tech Industry versus Overall Market

We have identified several important differences between the Tech industry and Overall Market. As introduced above, Fed rates have shown significance for Tech IPOs when regressed individually, however this factor fail to present any explanatory power on the overall market. We extrapolate that this might be due to distinctiveness of the analysis and Tech market's particular sensitivity to interest rate changes. The overall market, however, does not get affected because it is highly diversified, thereby removing this unsystematic variability. Fear & Greed ratio, on the other hand, presents the opposite findings to Fed rates. The particular ratio is significant at 99,9% confidence interval for the Overall Market, however completely insignificant for Tech IPOs. As this is somewhat a new measure, and sightly different from the definition of bearish and bullish markets, further analysis of this factor is suggested.

11 Testing of the Final Model & Factor Applicability

Once the model was finalized, we performed an examination of the model's ability to predict the underpricing. Summary of the results is presented in *Figure 4*, where (I) indicates the summary of actual underpricing during the period, (II) indicates summary of predicted underpricing and (III) the dispersion between the actual and predicted results. One of the most disturbing results identified is that, on average the model over-/underestimated the underpricing by approximately 26,46%. There were several instances where the estimation error was a mere 0,3%, however at times the model was off by more than 150%. Additionally, (II) presents much higher median underpricing, suggesting that the model often overestimates underpricing. Standard deviation of underpricing of (II) is also much smaller than (I), outlining that the predictive model is constrained within a narrower interval than (I). Differences in Skewness between (I) and (II) also indicates that the predictive model often over-estimates underpricing, thereby providing misleading valuations.

	Mean	Median	Kurtosis	Skewness	Std. Deviation	Low	Max
(I) Actual	0,28576	0,18833	5,93434	2,05512	0,40323	-0,34880	2,34259
(II) Estimated	0,28576	0,29039	0,99239	-0,14853	0,17546	-0,50565	0,86268
(III) Estimation Error	0,26463	0,20601	9,32959	2,52881	0,24815	0,00320	1,67519

Figure 4, Summary of statistics, Final Model's predictive power with regards to Underpricing

Due to serious issues with the predictive power of the model, we conclude that it is not advisable to use this model on and in itself, and one should not take the estimations for granted either. However, separate elements of the model can provide justifiable guidance in a valuation process. Factors such as Number of Underwriters, Underwriter's Reputation, Hot & Cold market indicator and others, can provide great benefits when attempting to set expectations of possible valuation. While these factors present the anticipated underpricing, as opposed to expected share price itself, managers can use this as a lead for IPO price adjustments. The applicability of the factors with regards to expected underpricing are as follows:

i. The higher the underwriter's reputation – the more underpricing should be expected. An increase in the reputation by one rank is expected to increase the underpricing by approximately 7,64%.

ii. The more underwriters are employed – the lower underpricing should be expected. An addition of one underwriter is expected to decrease the underpricing by 6,25%.

iii. The "*Hotter*" the market, the more irrational are the investors and higher underpricing can be anticipated. One level change in the Hot & Cold market indicator is expected to affect the underpricing by 6,64% in the same direction.

iv. The higher the offer price per share, the better quality of the firm it signals, thereby increasing underpricing. One point change in the logarithm of the price is expected to affect the underpricing by 41,94% in the same direction.

v. The larger the overall offer size – the less underpricing should be expected. One point change in the logarithm of issue volume is expected to inversely affect the underpricing by 2,49%.

	Factor	**Underpricing**
(i)	High Reputation Underwriters	Increases
	Low Reputation Underwriters	**Decreases**
(ii)	**Number of Underwriters increase**	**Decreases**
	Number of Underwriters decrease	Increases
(iii)	Hot Market	Increases
	Cold Market	**Decreases**
(iv)	Higher Price Per Share	Increases
	Lower Price Per Share	**Decreases**
(v)	**Higher Offer Size**	**Decreases**
	Lower Offer Size	Increases

Table 25, Factors and their impact on IPO Underpricing

12 Contribution to the literature

Given the analysis conducted in this thesis on Tech companies' IPOs, the most important contribution is the distinction between Tech industry and the Overall Market. For Tech industry specifically, we've found that by increasing the number of underwriters, companies reduce the expected underpricing for Tech IPOs. The overall offer size of an IPO has a negative influence on Tech underpricing – which is inconsistent with the findings of Yong (2009) & Habib and Ljungqvist (2001). However, mentioned researchers analysed Overall Market, as opposed a specific industry. In addition, we found inconsistencies between the IPOs of Tech industry and the Overall Market with regards to Price Per Share. Our analysis indicates positive significant relationship between the offer price and the underpricing of Tech IPOs, contradicting findings by Ibbsotson and Ritter (1994), who found the particular factor to be significantly inversely related. Furthermore, Hot markets have a positive influence on tech underpricing, providing evidence that the signalling hypothesis holds for tech IPO during this sample period. In conclusion, the main contribution to the literature is the distinction between the behaviour of various factors in Tech industry as opposed to Overall Market. The findings that most of the factors behave differently in Tech environment, compared to Overall Market, suggests that analysis of Overall Market as one entity could lead to wrong interpretations of discoveries. This in fact could lead to misleading proposals for companies operating in different industries.

13 Conclusion

As presented in the introduction, our main goal in this thesis was to analyse and present factors, which could be used in Tech IPO pricing decisions. Furthermore, with the help of these factors we were anticipating of creating a model, capable of predicting the underpricing of Tech IPOs. In order to construct such a model, we gathered numerous factors that were previously identified to have an effect on underpricing. The factors that were chosen for an application and analysis on Tech IPOs were: (i) Fed rates; (ii) Risk-free rates; (iii) Number of Underwriters per IPO; (iv) Underwriters Reputation; (v) Offer Price; (vi) Fear & Greed ratio; (vii) Hot & Cold Market ratio; (viii) Investor Sentiment; (ix) issue Size. After an in-depth analysis and comparison with previous studies, Fed rates, Risk-free rates, Fear & Greed ratio and Investor Sentiment were discarded, concluding that these factors are insignificant in the Tech industry. The remaining factors were concluded to have significant explanatory power with regards to Tech IPO underpricing, and thereby used for creation of the predictive model. Worth noting, it was also discovered that some of the factors are significant for the Tech industry, while insignificant for non-Tech, and vice versa. Separate analysis of each factor presented that Fed rates have statistically significant influence on Tech IPOs, while insignificant for non-Tech. On the other hand, F&G ratio was only significant for non-Tech, and had no significance upon Tech IPOs. Such differences outline the distinctiveness between the Tech industry and the Overall Market.

The predictive model as such did not present any significant findings. The predicted underpricing was rarely accurate, and most of the time substantially overestimated. Due to inconsistency of the model, we concluded that the predictive power of it is very limited. On the other hand, separate factors from the model can and do provide justifiable guidance in a valuation process. Factors such as Number of Underwriters, Underwriter's Reputation, Hot & Cold market indicator and others, can provide great benefits when attempting to set expectations of possible valuation. By analysing separate factors the issuers can anticipate the price change direction and magnitude, thereby controlling for this effect. It was determined that an increase in Number of Underwriters and/or Issue Size DECREASES the expected underpricing. In contrast, an increase in Price per Share, Underwriters Reputation and Hot & Cold market ratio – INCREASES the underpricing. By knowing the extent of each factor's impact and the anticipated underpricing level, managers can improve their IPO pricing.

Given the distinctiveness of our analysed industry, and the misalignment of several findings with previous researches, we can still state that suggestions drawn from our study are applicable in Tech industry.

14 Bibliography

Lawrence , B. M., & Walid , B. Y. (1997, December 04). Bookbuilding vs. Fixed Price: An Analysis of Competing Strategies for Marketing IPO. *32*.

Baker, M., & Wurgler, J. (2007). *Investor Sentiment In The Stock Market.* Cambridge: National Bureau Of Economic Research.

Benveniste, L. M., & Spindt, P. A. (1989). How investment bankers determine the offer price and allocation of new issues. *Journal of Finanicial Economics, 24*(2), 343-361.

Binay, M. M., Gatchev, V. A., & Pirinsk, C. A. (2007, September). The Role of Underwriter-Investor Relationships in the IPO Process. *Journal of Financial and Quantitative Analysis , 43*(2), 785-810.

Bodie, Z., Kane, A., & Marcus, A. (2014). *Investments.* (10th, Ed.) Published by McGraw-Hill Education.

Booth, J. R., & Chua, L. (1996). Ownership dispersion, costly information, and IPO underpricing. *Journal of Financial Economics, 41*(2).

Booth, J. R., & Smith II, R. L. (1986). Capital raising, underwriting and the certification hypothesis. *Journal of Financial Economics, 15*(1-2), 261-281.

Booth, J., & Chua, L. (1996). Ownership Dispersion, Costly Information, and IPO Underpricing. *Journal of Financial Economics*, 291-210.

Brooks, C. (2014). *Introductory Econometrics for Finance* (3rd ed.). Cambridge University Press.

Brown, G. W. (1999, April). Volatility, Sentiment, and Noise Traders. *Financial Analyst Journal, 55*(2).

Brown, S. J., & Warner, J. B. (1980, September). Measuring security price performance. *Journal of Financial Economics, 8*(3), 205-258.

Busaba, W. Y., & Chang , C. (2010, June). Bookbuilding vs. fixed price revisited: The effect of aftermarket trading. *Journal of Corporate Finance, 16*(3), 370-381.

Carter, R., & Manaster, S. (1990, September). Initial Public Offerings and Underwriter Reputation. *XLV*(4).

Corwin, S. A., & Schultz, P. H. (2005, July 20). The Role of IPO Underwriting Syndicates: Pricing, Information Production, and Underwriter Competition. *Journal of Finance*, 443-486.

DERRIEN, F. (2005). IPO Pricing in "Hot" Market Conditions: Who Leaves Money on the Table? *Journal of Finance, 60*(1), 487-521.

Emilsen, N. H., Pedersen, K., & Sættem, F. (1997). Børsintroduksjon. *BETA: Tidsskrift for Bedriftsøkonomi, 11*(3), 1 -13.

Georgieva, K. (2011). The issue of underpricing in Initial Public Offerings. *University of Essex, Department of Economics* .

Habib, M. A., & Ljungqvist, A. P. (2001, April). Underpricing and Entrepreneurial Wealth Losses in IPOs: Theory and Evidence. *The Review of Financial Studies, 14*(2), 433–458.

Helwege, J., & Liang, N. (2004, Sep). Initial Public Offerings in Hot and Cold Markets. *The Journal of Financial and Quantitative Analysis, 39*(3), pp. 541-569.

Ibbotson, R. G. (1975, September). Price performance of common stock new issues. *Journal of Financial Economics, 2*(3), 235-272.

Ibbotson, R. G., & Jaffe, J. F. (1975, September). "Hot Issue" Markets. *Journal of Finance, 30*(4), 1027-1042.

Ibbotson, R. G., Sindelar, J. L., & Ritter, J. R. (1988). INITIAL PUBLIC OFFERINGS. *Journal of Applied Finance, 1*(2), 37-45.

Jegadeesh, N., Weinstein, M., & Welch, I. (1993, October). An empirical investigation of IPO returns and subsequent equity offerings. *Journal of Financial Economic, 34*(2), 153-175.

Kim, M., & Ritter, J. R. (1999, June). Valuing IPOs. *Journal of Financial Economics, 53*, 409 - 437.

Ljungqvist, A., Nanda, V., & Singh, R. (2006, July). Hot Markets, Investor Sentiment, and IPO Pricing. *The Journal of Business, 79*(4), 1667-1702.

Lo, A. W. (2005). Reconciling Efficient Markets with Behavioral Finance: The Adaptive Markets Hypothesis. *Journal of Investment Consulting, 7*(2), 21-44.

Lo, A. W., & Repin, D. V. (2002). The Psychophysiology of Real-Time Financial Risk Processing. *Journal of Cognitive Neuroscience, 14*(3), pp. 323–329.

Lo, A. W., Repin, D. V., & Steenbarger, B. N. (2005, 5). Fear and Greed in Financial Markets: A Clinical Study of Day-Traders. *COGNITIVE NEUROSCIENTIFIC FOUNDATIONS OF ECONOMIC BEHAVIOR, 95*(2), pp. 352-259.

Loughran, T., & Ritter, J. R. (2002). Why don't issuers get upset about leaving money on the table in IPOs? *The Review of Financial Studies, 15*(2), 413-443.

Michaely, R., & Shaw, W. H. (1995). The pricing of initial public offerings: Tests of adverse selection and signaling theories. *The Review of Financial Studies, 7*(2), 279-319.

money.cnn.com. (2018, May 31). *What is the Fear & Greed Index?* Retrieved from http://money.cnn.com/investing/about-fear-greed-tool/index.html

Murray , F. Z., & Vidhan , G. K. (2009, April 28). Capital Structure Decisions: Which Factors Are Reliably Important? *Financial Management Association International., 38*(1).

MYERS, S. C. (1984). The Capital Structure Puzzle. *39*(3), 574-592. Retrieved from Journal of Finance .

Rachev, S., Fabozzi, F. J., & Racheva-Iotova, B. (2017, September). Option Pricing with Greed and Fear Factor: The Rational Finance Approach. *ResearchGate*.

Ritter, J. R. (1984). Signalling and the valuation of unseasoned new issues: A comment. *Journal of Finance, 39*, 1231-1237.

Ritter, J. R. (1987, January). The Costs of Going Public. *Journal of Finance* , 269 - 281.

Ritter, J. R. (1991, March). The Long-Run Performance of initial Public Offerings. *46*(1), pp. 3-27.

Ritter, J. R. (2003, October 20). Differences between European and American IPO Markets. *9*(4), pp. 421 - 434.

Ritter, J. R., & Beatty, R. P. (1986). Investment Banking, Reputation, and the Underpricing of Initial Public Offerings. *Journal of Financial Economics , 15*(1-2), 213-232.

Roberts, M. R., & Whited, T. M. (2013). Endogeneity in Empirical Corporate Finance∗ Michael R. Roberts. *Handbook of the Economics of Finance, 2*, 493-572.

Saunders, A. (1990, March). Why are so many new stock issues underpriced? *Business Review* , 3-12.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *JOURNAL OF ECONOMIC PERSPECTIVES, 17*(1), 83-104.

Welch, I. (1989, June). Seasoned Offerings, Imitation Costs, and the Underpricing of Initial Public Offerings. *The Journal of Finance, 44*(2), 421-449.

Welch, I., & Ritter , J. R. (2002). A Review of IPO Activity, Pricing, and Allocations. *The Journal of Finance, 57*(4), 1795-1828.

Wilhelm, W. J., & Ljungqvist, A. (2003, April). IPO pricing in the dot-com bubble. *Journal of Finance, 58*(2), 723-752.

Wooldridge, J. (2013). *Introductory Econometrics: A Modern Approach.* (5th, Ed.) South-Western Cengage Learning .

YONG, O. (2009). SIGNIFICANCE OF INVESTOR DEMAND, FIRM SIZE, OFFER TYPE AND OFFER SIZE ON THE INITIAL PREMIUM, FIRST-DAY PRICE SPREAD AND FLIPPING ACTIVITY OF MALAYSIAN IPOS. *University Kebangsaan Malaysia*, 395-412.

Yong, O., & Isa, Z. (2003). Initial performance of new issues of shares in Malaysia. *Applied Economic , 35*(8), 919 - 930.

Zingales, L. (1995). Insider ownership and the decision to go public. *The Review of Economic Studies Limited* .

15 Appendix A

Exhibit 1, Annual comparison between number of Tech IPOs and Overall number of IPOs

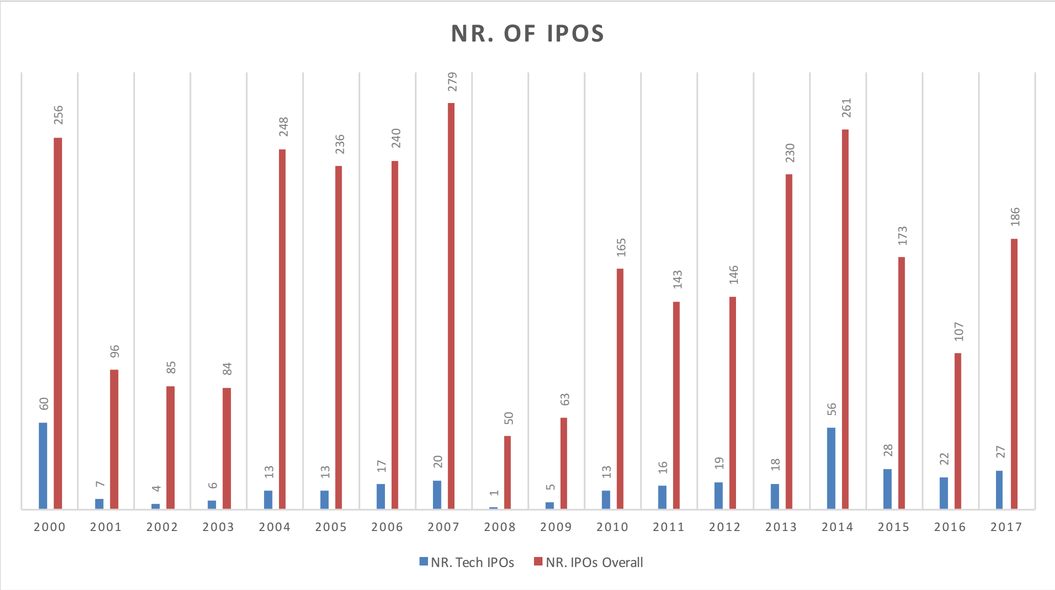


Exhibit 2, Tech IPOs as % of Overall IPOs

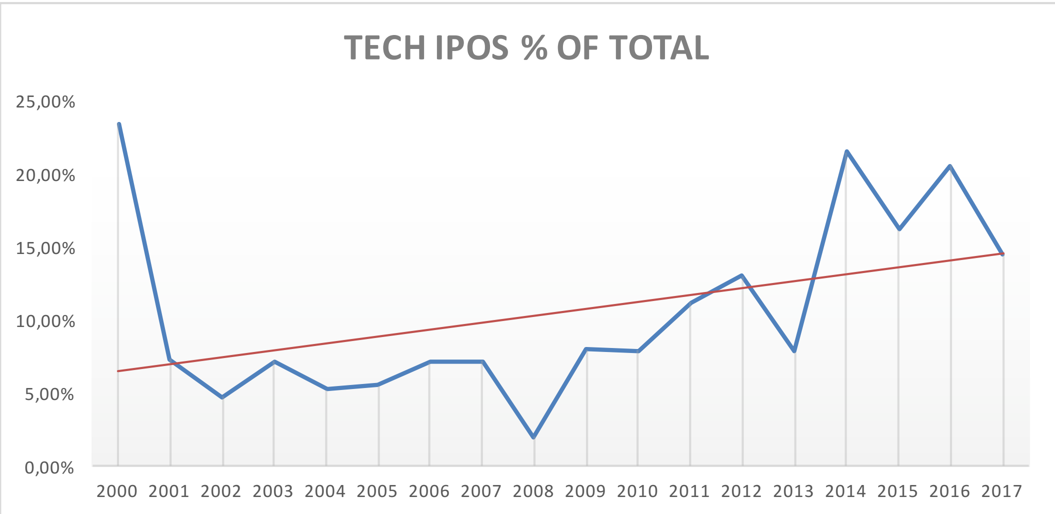


Exhibit 3, Comparison between Tech IPO and Overall IPO underpricing

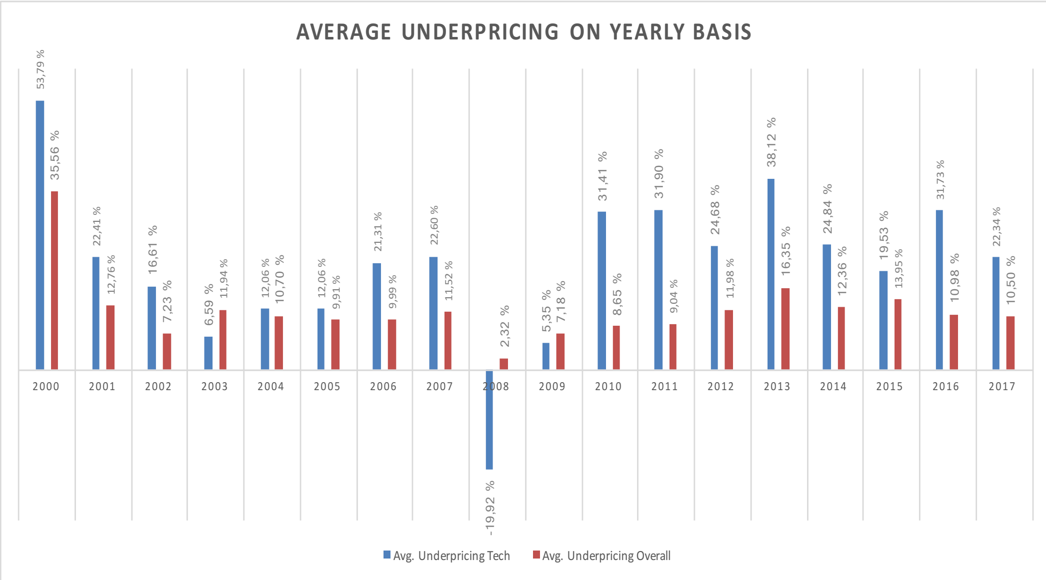


Exhibit 4, Comparison of 3-year moving average number of IPOs

Year	Nr. IPOs
2003	5,67
2004	7,67
2005	10,67
2006	14,33
2007	16,67
2008	12,67
2009	8,67
2010	6,33
2011	11,33
2012	16,00
2013	17,67
2014	31,00
2015	34,00
2016	35,33
2017	25,67

Exhibit 5, IPO Underpricing Cheat-Sheet for issuers

	Factor	Underpricing
(i)	High Reputation Underwriters	Increases
	Low Reputation Underwriters	**Decreases**
(ii)	**Number of Underwriters increase**	**Decreases**
	Number of Underwriters decrease	Increases
(iii)	Hot Market	Increases
	Cold Market	**Decreases**
(iv)	Higher Price Per Share	Increases
	Lower Price Per Share	**Decreases**
(v)	**Higher Offer Size**	**Decreases**
	Lower Offer Size	Increases

16 Appendix B

16.1.1 Assumption 1: $E(u_t) = 0$

This assumption postulates that, the error terms have zero mean. It is stated that, the assumption will never be violated so long as a constant term is added to the regression equation. Given this, a constant term should be added to our regressions.

16.1.2 Assumption 2: $var(u_t) = \sigma^2 < \infty$

The second assumption states that, the variance of the errors is constant finite over all values. This implies that a sample with random observations, and that each individual element in the sample has the same probability, which is often an assumption in cross-section data-sets. A violation of the second assumption will cause the OLS estimators to be inconsistent, this implies that. The coefficients have no minimum variance along the class of the linear unbiased estimators. An omission of this will potentially lead to misleading conclusions and therefore the standard errors will be incorrect.

16.1.3 Assumption 3: $cov(u_i, u_j) =0$

Assumption three postulates that, the errors are linearly independent from one another. This assumption is related to issues of autocorrelation; this can be the case if the errors are correlated with each another. Since, we might encounter cross-sectional data in this paper.

16.1.4 Assumption 4: $Cov(u_t;= X_t) = 0$

The fourth assumption states that, error terms and corresponding X_t are uncorrelated. The violation of this assumption will imply that, the OLS estimators will be inconsistent and biased. This is because the estimators dispense explanatory power to the independent variables. The outcome of this is because, there exits correlation between the dependent variable and the error term.

16.1.5 Assumption 5: $u_t \sim N(0; \sigma^2)$

The normality assumption postulates that, the sample population errors are independent of the explanatory variables, and are normally distributed with zero mean and variance σ^2. The abuse of this assumption is a critical factor for the sample size, especially if the sample size is relatively small. It is therefore advisable to stick to a sample size which is relatively large enough, in order for avoid this.

16.1.6 Assumption 6. No perfect multicollinearity

This is the assumption of no perfect multicollinearity stating that, none of the independent variables are constant and that, there is no exact linear relationship among the independent variables.

16.1.7 The R^2

$$R^2 = \frac{ESS}{TSS} = \frac{\Sigma(\hat{y} - \bar{y})^2}{\Sigma(y - \bar{y})^2}$$

Equation 27, Goodness of Fit

ESS stands for the Estimated Sum of Squares and TSS stands for Total Sum of Squares. The R^2 explains the variation or the part of the dependent variable which is specified by the model, this measure is labelled between 0 and 1, with 1 giving the perfect model explanation. It has been disputed in financial econometrics that, this measure has quite some significant drawbacks. The argument behand this disagreement is that; the measure does not drop if one is to add new explanatory variables. This is because additional information would not decrease the sum of squares. Hence, a further suggestion has been proposed and this is the adjusted R^2.

16.1.8 Adjusted R^2

$$\bar{R}^2 = 1 - \left[\frac{T - 1}{T - k}(1 - R^2)\right]$$

Equation 28, Adjusted R-Squared

Where the letters in the model present, T is the total number of observations and the total number of variables is presented by k. It is suggested in the literature that, the adjusted R^2 will only increase when the value of the newly added information by the new variable is higher than the offsetting amount of degrees of freedom, such that the Adjusted R^2 actually drops. Therefore, the application of the Adjusted R^2 helps as a decision-making tool for the determination of whether a given variable should be included or discarded. The ruling behind this assumption is that, the inclusion of the variable should be able to increase or decrease the Adjusted R^2.

17 Appendix C, Preliminary Thesis Report

BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Forprosjekt, Thesis MSc

Pricing of tech IPOs with irregular CF: Identifying the main deterministic factors of correct pricing. Are they applicable for future IPO valuations?

Navn: Gediminas Meskauskas, Joshua Lundula Mukanya

Start: 01.01.2018 09.00

Finish: 15.01.2018 12.00

Table of Contents

Study Program:
MSc in Business, Major in Finance

Topic: *Pricing of tech IPOs with irregular CF: Identifying the main deterministic factors of correct pricing. Are they applicable for future IPO valuations?*

Supervisor:
Leon Bogdan Stacescu

General

Introduction

The aim in this preliminary thesis is to give an introduction of what we envisage and plan of achieving in the final version of the master thesis. We therefore note that, the final version might deviate a little from the initial proposal.

With the above mentioned, this thesis intends to develop a valuation model that is anticipated to give better predictive power. This is expected to be achieved by applying different factors that might influence the valuation of a company. Hence, the purpose of the thesis is presumably creating an adjusted version of the Discounted Cash Flow (DCF) which we have chosen to call the "Adjusted Discounted Cash Flow (ADCF)" model.

Topic

Nowadays, there is a lot of attention with regards to IPO valuations. Consequently, most of the discussions are centered on the arguments stating that most of these companies are overvalued. Mostly, the type of companies that often come in the spotlight preceding this kind of news are the so called "unicorns" or tech companies which are claimed to have high market value compared to what is argued to be their "true" value. However, there is little in-depth discussion regarding how these valuations are conducted. This is the reason why this thesis has taken upon the challenge in conducting a thorough analysis of such companies by applying an adjusted approach of estimating cash flows with possible relevant external and internal factors and therefore deriving at the "real" company value.

Another reason attributing to why this topic has been chosen, is the growing need and the integration of technological equipment's, appliances, applications and use in different aspects of our daily lives and most certainly in the nearest future.

Given the need for such technologies, this thesis attempts to find possible factors that can be identified, such that they can be included in the valuations and therefore, if possible help in justifying today's high valuations of tech companies or prove the opposite.

In essence, our decision on conducting a valuation of such companies caught our attention since the first semester of our master's degree. Our motivation and interest as soon graduates with major in finance is that, writing about this topic broadens our understanding, by putting into practice the knowledge acquired so far during our studies and working experience.

Topic: ***Pricing of tech IPOs with irregular CF: Identifying the main deterministic factors of correct pricing. Are they applicable for future IPO valuations?***

Valuation Methods

From previous corporate finance courses, we know that the value of a company is a sum of company's equity and debt, less cash. However, there are a handful number of debt and equity types. Common examples of debt and equity are bank loans, common equity and preferred stocks, respectively. Miller and Modigliani further argues that, the total value of a company (Vm) is a component of, the value of the unlevered firm (Vu) plus the present value of the tax shields:

$$V_m = V_u + V_x$$

The emphasis in such kind of valuations is that, as one attempts to value a company is it important that a company's capital structure is carefully estimated and adjusted correctly. Consistency is a word which is often stressed, implying that when selecting debt estimates we should use the market value of debt and not accounting values.

There are different methods for valuing companies. Below we classify different methods of valuation. The main valuation methods are: Balance Sheet, Income Statement, Mixed (Goodwill), Discounted Cash Flow (DCF), Value Creation and Options valuations.

Balance Sheet Approach

This method aims at calculating shareholder's equity value, which is done by estimating the value of the company's assets. The argument in favor for this approach is that, the underlying value of the company lies in a company's assets. This is because value creation is derived from the utilization of assets and liabilities. However, we argue that. This approach is less applicable for this thesis, given the of kind of tech companies this thesis is going to analysis. We have that the balance sheet method gives static values of a company`s current assets not to be mention that balance sheet figures are backward looking, this might make calculation challenging and inconsistency. This is because the valuations to be conducted in this paper predominantly focuses on possible future evolutions, market penetrations, growth etc, which are non-static variables. This is something the asset based or balance sheet approach does not account for in a reliable way. Another disadvantage is that, using this method it is very demanding gaining a reasonable value of assets such as intangible assets. Assets such as Intellectual property (IP) and Human Capital (HC) are hard to value today, and are therefore subjected to mispricing when applying the above methodology (Fernandez , 2007).

Income Statement-Based methods

This approach takes into account a company's income statement, the method attempts to capture value creation by determining the size of a company's earning, sales and other relevant indicators. Hence, this approach consists of performing an asset pricing valuation and therefore comparing them with proxies. This method can also involve another subcategory called PER. In response, this approach attempts at bring equity value by multiplying price-earnings ratio (PER) with earnings (Fernandez , 2007). However, in the interest of this paper we are not going to use this approach. Given that, most of the tech companies have negative cash flows and because of differences in the revenue structure in the companies this thesis will analysis and value (Fernandez , 2007).

The Goodwill-Based methods

With goodwill method, the valuation involves valuing intangible assets. The assumption behind this method is that, the company value is above the book or adjusted book value. Hence, the method attempts at bring about the “true” value of the intangible assets such as brand name or certain strategic alliances. These are assets which often are less captured in the balance sheets. Nonetheless, challenges often arise when determining their value, as of today there is no full consensus concerning the correct pricing methodology regulating the value of such assets. Hence, this thesis given the selected companies to be analyzed, goodwill is irrelevant for most of these “unicorn” companies (Fernandez , 2007).

The Discounted Cash Flow Methods (DCF)

The aim using this method is, determining the value of the company by projecting the future cash flows that the company will generate and therefore discounting for the appropriate discount factor that matches the riskiness of the cash flows. Hence, obtain the present value of the company. The discount cash flow based approach is widely used in today's corporate world, the arguments in favor of this method are mainly that the methodology is conceptually more correct compared to other methods such as the ones mentioned above in this paper. This is because, in the DCF analysis, the company is perceived as a cash flow generator, and the value of the company is derived by discounting these cash flows. The suitable discount rates are determined by the types of future cash flows, the discount rate should therefore account for the risk, historic volatility and other relevant risk factors that might possibly influence the discount rate (Koller, Goedhart, & Wessels, 2015).

With this said, for valuations purposes. This paper will apply the Discounted Cash Flow analysis with a more adjusted approach. The purpose is calculating the present value between the future cash inflows and future outflows. These future cash flows as mentioned are discounted at a discount rate which accounts for the monetary time value of the cash flows. The time period can be five or ten years. In this thesis will consider a five-year period, given that the technology industry is subjected to rapid changes.

The formula for the DCF is given as:

$$\sum_{i=1}^{n} \frac{CF_i}{(1+r)^i} + PV(TV)$$

Discounting the Cash Flows

To understand the cash flows considered in a DCF valuation, the cash flows are de-componented into three types. We have the Free Cash Flows (FCF, CFi in the formula), which are discounted at the appropriate discount rate, the Weighted Average Cost of Capital (WACC). Equity Cash Flows(ECF), these cash flows are discounted at the shareholders required return to equity also known as the cost of equity, often denoted as (Ke). The third type of cash flows are the Debt Cash Flows (CFd), the debt cash flows are discounted for the debt holders required return on debt adjusted for default and financial distress risk.

The Adjusted Discount Cash Flow (ADCF)

Formula:

$$\sum_{i=1}^{n} \frac{CF_i[(1+MC_i)(1+Ma_{i-1})(1+IP_i)(1+RD_{i-1})(1+Age_i)(1+MS_i)]}{(1+Discount\ Rate)^{\frac{i}{4}}} + PV(TV)$$

Discount rates

Cost of equity

In order for calculate the cost of equity we use the capital asset pricing model (CAPM). The CAPM determines the required return on equity by the shareholders by applying the following terms.

$$CAPM = k_e = r_f + \beta\,(R_m - r_f)$$

We have the risk premium defined as, (Rm-rf). Rm is the expected market return, rf is the market risk-free rate and finally B_e, the equity beta representing systematic risk of the company in the market/industry. In our case, we will consider either levering and unlevering the beta when possible.

Assuming that we are able to identify and calculate the above measures, we should therefore be able to estimate the company's cost of equity.

Cost of debt

The cost of debt will be calculated using the yield on the government bond and other markets related rates associated with bond issuing adjusted for the risk and other factors that might influence the beta of debt. Hence, the cost of debt will also be calculated using the CAPM, only substituting with debt beta (B_{d}).

The Weighted Cost of capital (WACC)

WACC is the discount rate that incorporates the total cost of capital for the entire company, given shareholders required return on equity adjusted for the ratio between the ratio of equity to total market value of debt and equity. The WACC will be adjusted for the appropriate tax rate for the given company. The same applies for the debt value, the mathematical expression of the formula is shown below:

$$WACC = \tfrac{E}{V}R_e + \tfrac{D}{V}R_d\,(1 - T_c)$$

Terminal or continuing value and growth rates, in connection with the calculation of the terminal valuation will be calculated with the growth rates and cash flows for the rest of the company’s life span, will consider a terminal value or continuing value capturing cash flows in perpetuity as a going concern.

Perception of Technological companies

As mentioned in the introduction, this paper will consider the valuation of tech companies. We have noted that, the definition of technology and tech companies is perceived quite differently as opposed to the way this paper will do. In this regard, we have also taken a step further in defining more specifically what this paper will considers as tech companies. We define tech companies as companies that are producing or offer products that can be used and applied by both consumers and companies. With this definition, we intend to incorporate companies that are creating or intend of selling technological products for health care improvements, business purpose, social network, applications and many more. Products produced by these companies are often less valued in today's markets, simply because the technology might not yet be ready for the end user. However, the future value of these technologies can be very valuable. Certainly, as it can be observed today, the technological revolution is disrupting in almost all the different business sectors been financial, facility management or health sector to mention a few. All these industries are working and preparing to put in use different technological products that will increase the efficiency of their day to day activities. Hence, the demand for such technologies offering these services will attain a higher demand in the near future.

Another reason for this classification is that, this definition enables us to include companies that might not be listed as tech companies. We have companies like Snapchat Inc. which are listed as hardware companies or a company like Uber listed as a transport company but using a certain technology for their business model. In essence, these companies can be perceived as tech companies regardless of their listed industry in this thesis.

Limitations

Considering that this is a master thesis with the aim of providing insights concerning a possible better valuation method for tech companies with irregular cash flows. Certain limitations are going be considered, such as.

- Valuation period (Age)
- Availability of quarterly projections given that certain companies do not publically publish their financial statements before they go public.
- Distribution of the different factors might not be standard, thus might imply standard errors.

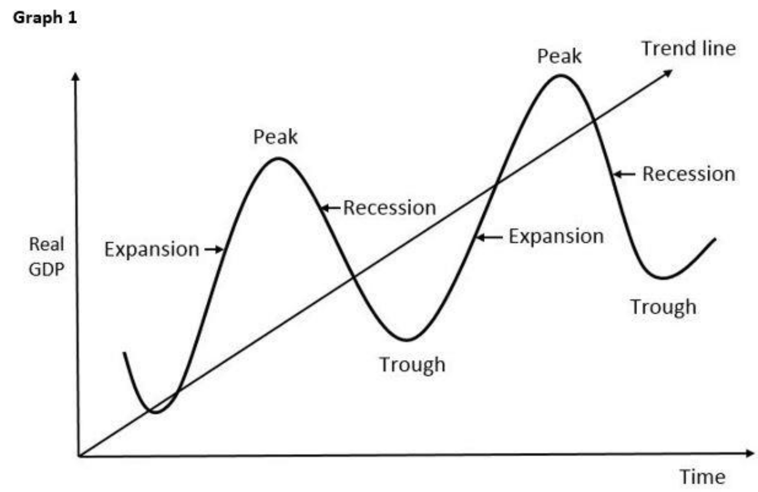
- Market structure might be hard to quantify, due to the nature of different companies as opposed to their listed industry.
- Some companies might have intellectual capital, which is often excluded from the valuation.
- Accessibility of pre-IPO financial documents
- Personal and company secrets, which were available only to an exclusive group of people/investors prior to IPO.
- More limitation will arise during the analysis process.

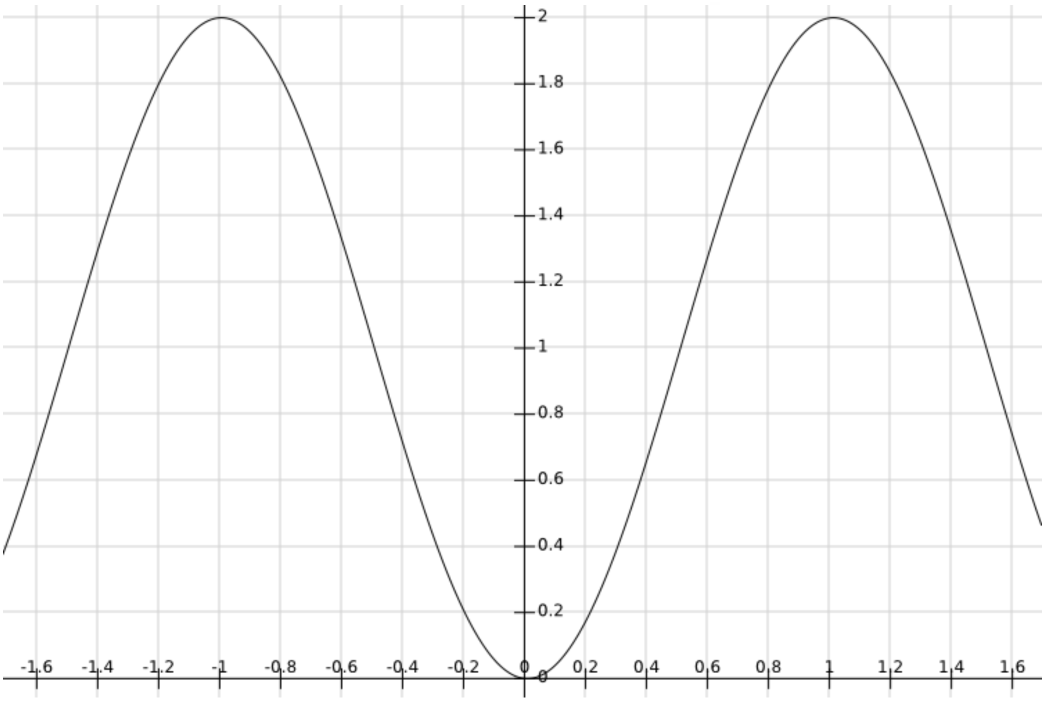
Factor Description

Market Cycle (MC)

Incorporation of Market Cycle (hereinafter MC) might have a substantial influence on the valuation. This comes as the result of the current position of the business cycle, which does not only provide the present information, but indirectly implies the future expectation. If the market is currently in the recession or trough, expansion and peak will be anticipated, therefore improving the probability of higher or faster returns. On the other hand, if the company is currently in the peak or just after it, the recession might be awaiting, where the market will have much lower expectations. Accordingly, by positioning the company in the market cycle, we will try to anticipate how the earnings could be affected based on the future market expectations.

As researchers suggest, an average business cycle lasts between 4-6 years (Canova, 1998) (Graph 1). Based on this observation, the company will be positioned on the currently prevailing position of the business cycle (Graph 2), which is based on the peak-to-peak arrangement, ranging from values (-1) to 1 on the x-axis and from 0 to 2 on the y-axit.

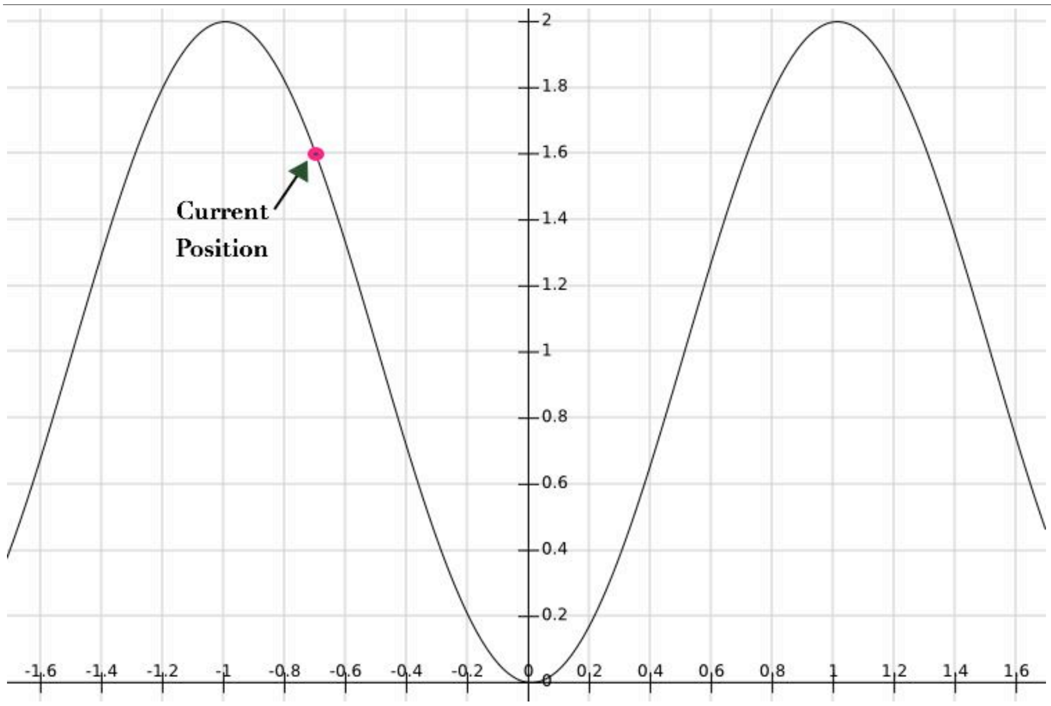




(Graph 2)

In order to quantify the implied value of the position, several calculations will be needed. Firstly, based on the position on the curve, the x-value and the y-value will be multiplied. Thereby, the number received (the MC-value) will be compared in a factor table, thereby assigning a proper factor value for the MC-faktor.

Example:



Current position in the cycle is early-recession, approximately -0.7 x-value and 1.6 y-value. By multiplying these two we get -1,12 as MC-value, thereby from the table 1 we can use the factor 0,97001 for the first quarter cash flow valuation.

Table 1. Factor Values

MC-value	Factor
-1,282	0,96819
-1,278	0,96829
-1,273	0,96839
-1,269	0,96848
-1,265	0,96858
-1,261	0,96867
-1,256	0,96877
-1,252	0,96886
-1,248	0,96896
-1,244	0,96906
-1,239	0,96915
-1,235	0,96925
-1,231	0,96934
-1,227	0,96944
-1,222	0,96954
-1,218	0,96963
-1,214	0,96973
-1,21	0,96982
-1,205	0,96992
-1,201	0,97001
-1,197	0,97011
-1,193	0,97021
-1,188	0,97030
-1,184	0,97040
-1,18	0,97049
-1,176	0,97059
-1,171	0,97069

Moreover, since the cycle is assumed to last 6 years, it implies 24 quarters, and thereby will be divided into 24 equal stages. Thereby, for the 2nd quarter valuation, the market will be assumed to have taken 1/24 leap along the curve to the right on the x-axis. By this, when calculating 2nd quarter, the prevailing x-value will be assumed to be -0,6167 and the y-value 1,3789. The product of these two numbers is -0,8503, which postulates factor value of 0,9778. The same process is to be assumed for the remaining 18 quarters.

The intention behind employing this factor in the cash flow valuation, is to adjust the cash-flows for the appropriate place in the market cycle, which might imply the customer's willingness to spend money under the circumstances. Due to an expected reduction in consumer's welfare.

Note: the graph and the table values provided are purely for demonstrational purposes and do not bear any real value. Actual shape of the curve and the values of the factors will be derived and regressed from the historical entries of the market.

Base for the analysis:

IPO Market Cycles: Bubbles or Sequential Learning? (Lowry & Schwert, 2002)

Marketing activities (Ma)

While many companies use marketing to boost their brand awareness or introduce new products, the actual impact is not directly taken into DCF valuation. By including this factor in the DCF adjustment, it is anticipated to identify different trends that might result out of the lagged effect regarding the percentage budget spending of the marketing. This might indirectly have an impact on the projected cash-flow, however the significance of it will have to be statistically proven.

The initial idea regarding quantifying marketing activities is to compare percentage budget spending and the corresponding lagged effect on the realized earnings. Afterwards, a specific factor could be created representing the potential lagged impact on the future cash-flows. Worth noting, this particular factor should not be regarded as a marketing impact on sales, but rather a more general, market expansion factor, which leads to unforeseen revenue changes.

A potential model for this analysis, as described by the authors, is known as "Multiplicative Competitive Interaction (MCI) Model", which follows:

$$
\begin{aligned}
s_i &= \frac{\mathcal{A}_i}{\sum_{j=1}^{m} \mathcal{A}_j} \\
\mathcal{A}_i &= \prod_{k=1}^{K} f_k(X_{ki})^{\beta_k}
\end{aligned}
$$

Where:

s_i = the market share of brand i

$\mathcal{A}_i$ = the attraction of brand i

m = the number of brands

X_{ki} = the value of the k^{th} explanatory variable X_k for brand i (e.g., prices, product attributes, expenditures for advertising, distribution, sales force)

K = the number of explanatory variables

f_k = a monotone transformation on X_k, $(f_k(\cdot) > 0)$

β_k = a parameter to be estimated.

Base for the analysis:

Market-Share Analysis. Evaluating Competitive Marketing Effectiveness (Understanding Market Shares, 1988)

Intellectual Property (IP)

Majority of the valuations take this particular point as given - especially if the company have received seed, A or B level of funding's already. In our case, it will be considered by looking at the additional impact this particular variable might have on:

- Cash-flow. Most likely this will not have a direct impact on the already projected cash-flows, however we will have to verify this for statistical proof for confirmation.
- Company Valuation. Will try to check whether IP might have been part of the error term regarding the initial miss-pricing, and if so, will try to regress the effect of this particular factor, as well as how it could be used for future valuations.

Base for the analysis:

The Handbook of Business Valuation and Intellectual Property Analysis, Part IV - Intellectual Property Valuation Issues. (Reilly & Schweihs, 2004)

Research & Development (RD)

Research and development costs are in most of the cases included in the cash flow as the operating costs, and does not have an explicit impact on the increase or the decrease in the future projected cash flows. Nonetheless, this might often result in omission or negligence of its impact when doing the valuation. In order to check for the importance of this factor, a regression against several different factors, such as IP, growth and Adjustment Factor, will be conducted. If concluded significant, this will become part of the valuation method - ADCF (Adjusted DCF).

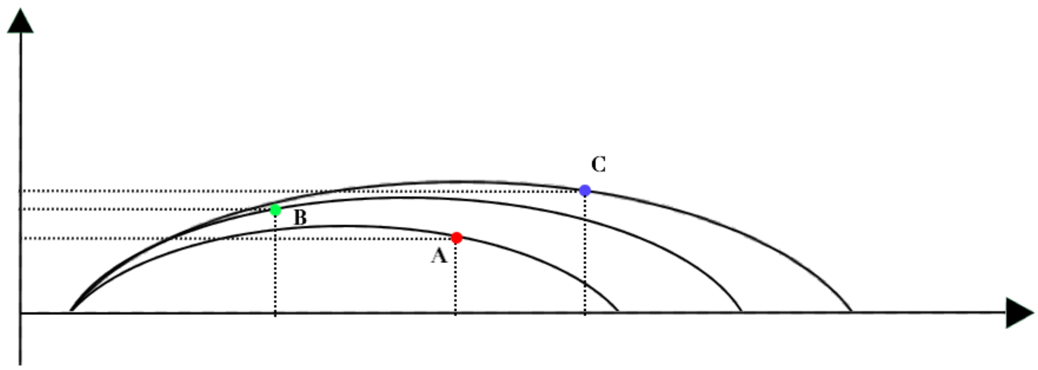
Base for the analysis:

Explaining the Short- and Long-Term IPO Anomalies in the US by R&D (Guo, Baruch, & Shi)

Age

Age of the company can carry many different aspects, not only the calendar definition of time. By quantifying the age, we anticipate to include many various factors such as technology employed, maturity, market structure and occupied share, future prospects and more. Each of the different factors would either prolong or shorten the implied "age" of the company, thereby providing and implication of this particular feature on the projected cash-flows. The "young" company would carry a stronger factor, improving the projected cash-flow, because it is either competitive, early bird, has strong fundamentals, etc. On the other hand, the "old" company might not be as competitive, it might not be able to follow-up with the trends, the market share might be shrinking due to competition, and more.

Example:



Here are depicted several different "ages" of one company. Point A identifies current position of an established company. The downwards slope of the point implies the maturity of the company, as well as possibly shrinking market share. If the company was to introduce a new technology or product, it could be moved to point B, where the upwards sloping point indicates increased competitiveness. Point C depicts a big corporation, with little-to-none significant new offerings, and slightly decreasing market power.

In the factor analysis, once again, these points will be standardized and given an appropriate value, which will reflect a respective factor to be used in the cash-flow valuation.

Base for the analysis:

While there aren’t many researches performed in such a manner, several papers covered the significance of separate factors such as age and potential new technology, which hopefully will be an inspiration.

- Pre-IPO Financial Performance and Aftermarket Survival (Hong & Peristiani, 2004)
- Takeover Defenses of IPO Firms (Field & Karpoff, 2002)

Market Structure (MS)

The prevailing market structure might have some degree of influence regarding valuation. Whether the market is fragmented or monopolistic might imply the probability and viability of the company’s further success. Additionally, it might imply the upcoming threats or opportunities, which are not allocated during the traditional DCF valuation. This is an addition to the age of the company, and will depend on currently prevailing share that the company currently captures.

Analysis & Application

As detailed above, many factors will be analyzed in order to determine the significant ones. The process will cover not only the quantitative part, but will also try to apply the qualitative part, such as significant media and market events at the time of the IPO. Moreover, with the help of already performed researches, we will try to extract the most important aspects of each factor, that could have an influence on the final valuation of the company for the IPO.

For the quantitative part, a total of 720 different combinations of factors is expected to be analyzed, in order to distinguish the best predictive elements. If such factors, or combinations of the factors are identified as significant, several tests will be performed in order to determine their usefulness. One of the main tests, which we anticipate of running is as follows:

- Comparing an originally announced IPO share price versus the adjusted share price estimated by using ADCF model. The investigation will try to determine if the share price predicted by ADCF would be closer to the highest 1st day trading price, the average and median 1st day trading price, or the lowest 1st day trading price.

While we initially try to improve the general DCF model by applying some adjustments, it is possible that some of the adjustment factors are not going to directly affect the cash-flow itself, and therefore might be checked for significance in another shape or position during the valuation. This would include factors such as the IP, which might not have a direct influence on the already predicted quarterly or annual cash-flows, but rather affect the overall valuation towards the positive or negative side, depending on the IP's outstanding. Due to this, all of the factors will be examined in different circumstances as well as different positioning.

Another issue which is worth considering during the analysis process, is the endogeneity of the regressed factors. This will be one of the priorities, as we are trying to estimate the predictive power of the different factors, the presence of endogeneity in these factors might imply that the results obtained from the regression does not give us any predictive power, hence worthless.

Lastly, it is worth mentioning the potential problem of negative CF and ADCF. The framework only assumes positive cash-flows, and accounts positive news with an increase in factor, which in-fact increases the expected cash flow. In order to counter for this, the framework will have to take into consideration the prevailing cash-flow, and have a function: If(CF<0; T=(-1); T=(1)). By performing this check, the framework will be able to identify the negative cash flows and use the inverse function on them, thereby improving the negative cash flows.

Expectations

At the end of the analysis, we hope to have identified one or more factors, that has not previously been accounted for during the valuation process, which has a predictive power. If such factors exist, we expect the ADCF valuation to provide more accurate valuation of a company preparing for the IPO.

$$\sum_{i=1}^{n} \frac{CF_i\left[\,(1+MC_i)\,(1+Ma_{i-1})\,(1+IP_i)\,(1+RD_{i-1})\,(1+Age_i)\,(1+MS_i)\,\right]}{(1+Discount\ Rate)^{\frac{1}{i}}} + PV(TV)$$

Preliminary Hypothesis:

- H(0): None of the additional factors separately improves the valuation, compared to standard DCF. H(A): at least one of the factors improves the DCF valuation.
- H(0): None of the additional 2-factor combinations improves the valuation, compared to standard DCF. H(A): at least one pair of the factors improves the DCF valuation.
- H(0): None of the additional 3-factor combinations improves the valuation, compared to standard DCF. H(A): at least one 3-factor combination improves the DCF valuation.
- H(0): None of the additional 4-factor combinations improves the valuation, compared to standard DCF. H(A): at least one 4-factor combination improves the DCF valuation.
- H(0): None of the additional 5-factor combinations improves the valuation, compared to standard DCF. H(A): at least one 5-factor combination improves the DCF valuation.
- H(0): ADCF does not improve the valuation, compared to standard DCF. H(A): ADCF improves the DCF valuation.

Data

The planned data collection for this thesis, we are mainly going to use the data provided by stern university for industry betas, standard deviations, market risk premiums and the available cash flows if application. Other sources will also be considered, during the final version of the thesis (Stern University, 2017).

Bibliography

Canova, F. (1998). Detrending and business cycle facts. *Journal of Monetary Economics*(41), 475-512.

Fernandez , P. (2007, February). Company Valuation Methods. The most Common Errors in Valuations. *University of Navarra - IESE Business School*.

Field, L. C., & Karpoff, J. M. (2002). Takeover Defenses of IPO Firms. *The Journal of Finance, 57*(5), 1857-1889.

Guo, R.-J., Baruch, L., & Shi, C. (n.d.). Explaining the Short- and Long-Term IPO Anomalies in the US by R&D.

Hong, G., & Peristiani, S. (2004). Pre-IPO Financial Performance and Aftermarket Survival. *FEDERAL RESERVE BANK OF NEW YORK, 10*(2).

Koller, T., Goedhart, M., & Wessels, D. (2015). Valuation: Measuring and Managing the Value of Companies (Wiley Finance). (6th, Ed.)

Lowry, M., & Schwert, G. W. (2002). IPO Market Cycles: Bubbles or Sequential Learning? *The Journal of Finance, 57*(3), 1171-1200.

Reilly, R. F., & Schweihs, R. P. (2004). *The Handbook of Business Valuation and Intellectual Property Analysis.* McGraw-Hill.

Stern University. (2017, January). *Damodaran Online*. Retrieved from Data: http://pages.stern.nyu.edu/~adamodar/New_Home_Page/data.html

Understanding Market Shares. (1988). In L. G. Cooper, M. Nakanishi, & J. Eliashberg (Ed.), *Market-Share Analysis, Evaluating Competitive Marketing Effectiveness* (pp. 17-55). London: Kluwer Academic Publishers.