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IPO underpricing in the US technology market during and after the dotcom bubble – A transformation after the bubble burst?

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IPO underpricing in the US technology market during and after the dotcom bubble – A transformation after the bubble burst?

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Abstract

Given the enormous amount of money left on the table in the US IPO market especially during the dotcom bubble, an increased academic interest arose for explaining those extreme numbers. This thesis contributes to the existing literature on IPO underpricing by investigating the first-day excess returns of the US technology market with a unique and current data set including 1,276 IPOs from 1995 to 2017. The analysis indicates that the US technology IPO market environment changed after the burst of the dotcom bubble in 2000. This is supported by the finding that underpricing in the form of excess returns dropped from 54% in the bubble period (1995-2000) to 18% in the post-bubble period (2001-2017). We further found evidence that the excess returns in the bubble period can be partly explained by asymmetric information theories and behavioural theories, whereas in the post-bubble period none of the tested proxies of the winner's curse - a sub-theory of asymmetric information - and none of the tested proxies of behavioural theories showed significance. On the contrary, we did not find evidence for an impact of ownership & control theories in the bubble period. In the post-bubble period, however, the ownership and control theory proxy exhibited a highly significant influence. Thus, this thesis yields new insights about explaining the excess returns in the US technology IPO market as well as about changing patterns after the bubble burst.

Key Words: IPO, IPO Underpricing, US Technology Industry, dotcom Bubble

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1. Introduction

When examining some of the most prominent initial public offerings (IPO) of the US technology (tech) sector over the last years more carefully, a highly positive first day development of shares can be observed. With an offer price of $17.00 per share and a closing price on the first trading day of $24.48 per share, Snap going public in 2017 exhibited an initial return of approximately 44%, adding up to a total of $1.1bn left on the table. Others like Fitbit in 2015 showed a first-day return[1] of ca. 48%, while Twitter in 2013 a first-day return of ca. 73% and Yelp in 2012 a first-day return of ca. 64%. Those numbers obviously raise the question about the rationale behind those extreme return rates just for buying those shares for the offer price and selling them again after one day in the aftermarket. From an efficient market perspective, a specific share price is determined based on a company's fair value and therefore it should not be possible to obtain such high first-day returns in IPO markets. At a first glance it is not comprehensible why these issuers granted to sell their shares at a too low price and thereby leave millions of dollars on the table.

It should be noted, however, that this abnormality of initial IPO returns is neither limited to the IPOs just mentioned, nor to the US tech IPO market. Scientists proved that this so-called IPO underpricing phenomenon is prevalent in many IPO markets all over the world. The first researchers who discovered this anomaly were Reilly and Hatfield (1969), Logue (1973a) and Ibbotson (1975). They confirmed that when companies perform an IPO, shares are underpriced on average and consequently experience a substantial increase on the first days of trading. Since that time, comprehensive research has been conducted trying to find explanations why shares are underpriced on average. Over the time four superordinate underpricing theories evolved, namely: asymmetric information theories, behavioural theories, institutional theories and ownership and control theories.

Building on these findings, in this thesis, we want to find out if chosen underpricing theories can explain the levels of underpricing observed in the US tech market during and after the dotcom bubble. When examining the first-day returns in the total US market more precisely, fluctuations across industries and over time can be observed. In particular, the dotcom bubble appears the most conspicuous period, where researcher documented average first-day returns of 65% between 1999 and 2000, adding up to an average amount of money left on the table of approximately $ 85 million per IPO (Loughran & Ritter, 2004). Large parts of this severe underpricing of the total US IPO market during the bubble were driven by tech company IPOs, as they accounted for approximately 72% of

[1] Throughout this thesis the terms first-day return, initial return on the first trading day and underpricing are used interchangeably.

all US IPOs at that time (Ritter & Welch, 2002). Taking all these factors into consideration it is highly interesting to perform an in-depth analysis of the short-term after IPO performance of US tech companies.

1.1 Problem statement & research approach

This thesis deals with the broad topic of the IPO underpricing phenomenon. It is known from existing research that underpricing is prevalent in many markets all over the world and that the level of underpricing fluctuates across industries and over time. During and after the dotcom bubble many individual classical underpricing theories failed to explain the extreme fluctuations of underpricing in the US on a standalone basis. Therefore, the goal of this thesis is to investigate to what extent chosen underpricing theories together are able to explain the levels of excess returns[2] of US tech IPOs during and after the dotcom bubble. In addition, the focus of this research is to detect potential paradigm shifts over time, e.g. if issuers are nowadays putting higher pressure on underwriters to change the way IPOs are priced given the vast amount of money left on the table during the dotcom bubble. The primary goal of this thesis is to answer the following research question.

How can excess returns of US tech IPOs during and after the dotcom bubble be explained by chosen underpricing theories and how far is it possible to detect changing patterns over time?

Table 1: Main research questions of this thesis

(Source: own contribution)

As the topic of underpricing is researched extensively in the literature and hence a large number of underpricing theories emerged over time, we will specify this research question further into research sub-questions to understand the ultimate scope of this thesis.

[2] For a detailed explanation of excess returns see section 4.1 "Preliminary hypothesis: Excess returns". It should be noted, throughout this thesis excess return (ER) constitutes a measure of underpricing and is defined as follows: $Excess\ Return = First\ day\ return\ IPO - Market\ Return\ (NASDAQ100)$.

1. Sub-Question	*Is underpricing in form of excess returns prevalent in the US tech IPO market during and after the dotcom bubble and how far is it possible to detect changing patterns over time?*
2. Sub-Question	*How can excess returns of US tech IPOs during and after the dotcom bubble be explained by chosen* ***asymmetric information theories*** *and how far is it possible to detect changing patterns of over time?*
3. Sub-Question	*How can excess returns of US tech IPOs during and after the dotcom bubble be explained by chosen* ***behavioural theories*** *and how far is it possible to detect changing patterns over time?*
4. Sub-Question	*How can excess returns of US tech IPOs during and after the dotcom bubble be explained by chosen* ***ownership & control theories*** *and how far is it possible to detect changing patterns over time?*

Table 2: Research sub-questions of this thesis

(Source: own contribution)

To be able to answer these research questions (see Table 1 and Table 2), we elaborated the following research approach for this thesis. In general, we are primarily using a quantitative research method as we want to test specific hypothesis via a compiled set of data. These quantitative results are then combined with a qualitative discussion. More precisely, we are taking already existing underpricing theories into account and test them via proxies on a new dataset. Thereby, we are using a joint approach by combining selected theories of underpricing in our model so that we can explain the observed levels of excess returns over time. In addition, we are primarily following a deductive approach (see Figure 1) with the goal to prove the impact of the individual theories on underpricing in our dataset at hand (Cooper, Schindler, & Sun, 2006). This deductive, top-down approach is also mirrored in our paper structure as we start with looking at the general theories, then based on this formulate specific hypotheses, observe the results of the testing of these hypotheses and finally conclude in a discussion whether we can confirm our consulted theories (Greener, 2008).

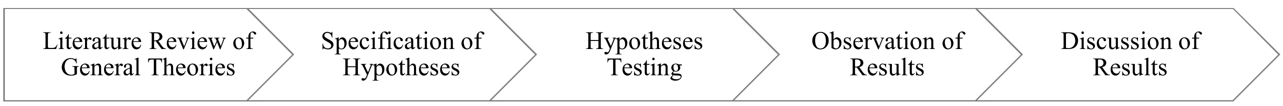

Figure 1: Deductive research approach

(Source: Greener, 2008)

More practically, the first part of the paper helps to obtain an overview about the scope of this thesis. After presenting what has been found earlier about IPOs in general, particularly the ones from tech companies, and about the IPO underpricing phenomenon, section 3.1 “Methodology” presents our strategy for the analysis and how we plan to tackle our research question more detailed.

1.2 Motivation & academic contribution

In the second semester of our master's program (Finance & Strategic Management), we did a business project about a strategic and financial valuation of Snap Inc. which performed one of the largest US based IPOs of the last years.[3] During this analysis we observed that the valuation of the fair price for a Snap share varied greatly among equity analysts of different banks, which was essentially because the firm had an unproven business model and still showed negative profits. This opaqueness of determining the fair price for a tech company, in combination with the fact that the IPO yielded enormous first-day returns of approximately 44%, raised our attention about the general topic of IPO underpricing within the tech industry. In addition to its academic as well as practical relevance, this topic also allows to combine traditional financial theories with more modern theories like behavioural finance and to apply statistical testing tools. Thus, this field of studies qualifies to perform a thorough academic research.

Generally, this thesis contributes to the vast literature on IPO underpricing by examining the short-term initial returns of US tech IPOs.

First, while many of the existing studies are based on older data, we are investigating a unique and extremely current data set. In total, we have collected a customized data set with a final sample of 1,276 observations between 01.01.1995 and 31.12.2017, of which 859 belong to the bubble period and 417 to the post-bubble period. Following the recommendation from Ritter & Welch (2002) that literature should put more emphasis on explaining the time variations of this phenomenon, we are explicitly analysing a longer time range and divide it into the three different periods: total period, bubble period, and the post-bubble period. This approach may help to generate new findings and to check if the results from earlier studies are still valid in today's business environment.

Second, to our best knowledge such an in-depth analysis of US tech IPOs has not been conducted so far. Whereas most of the existing studies are based on one single theory with the objective to prove this new theory, we are performing a joint analysis combining the existing theories in order to be able to explain the degree of underpricing in form of excess returns for tech IPOs. In addition, our proxies for testing the impact of individual underpricing theories were tailored to variables that are especially interesting regarding tech firms.

We deliberately decided not to investigate the total US IPO market, but rather focus on the US tech market for several reasons. This scope is particularly interesting when considering that most of the IPOs in the US during the dotcom bubble were conducted by tech companies. Whereas in the 1980s

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[3] For further reading about the strategic and financial valuation of Snap Inc. see: Leidecker, Tacke, & Walz (2017).

only ca. 25% of all US IPOs were based on tech companies, during the dotcom bubble this number raised to ca. 72%. After the burst of the bubble, this number immediately declined in 2001 to only 29% of all US IPOs (Ritter & Welch, 2002). With that in mind, it seems that tech IPOs are the main driver for the severe level of underpricing of the total US IPO market during the bubble period. Therefore, it is of special interest to investigate separately the development and causes for the underpricing of tech companies during and after the dotcom bubble. By only incorporating tech IPOs in our analysis we are inherently eliminating cross-industry effects which could otherwise distort the clarity of the results.

Moreover, IPOs of technology-based companies are especially interesting when looking at their company characteristics. They often go public without a proven business model nor having positive profits. Therefore, the determination of the fair value of a tech company at IPO is particularly challenging as traditional valuation techniques like the discounted cash flow model may not be applicable. Instead, they are often valued based on their future growth potential. According to Ritter & Welch (2002) until the 1980s it was inconvincible for prestigious underwriter to bring a company public that at least exhibited four quarters of positive earnings. But things changed, in the 1990s and especially with the beginning of the dotcom bubble even companies with no immediate outlook for positive earnings in the upcoming quarters were brought to public exchanges. Based on these arguments, it is especially interesting to investigate the underpricing phenomenon during and after the dotcom bubble with a tech IPO dataset.

1.3 Delimitation

As mentioned above, this thesis analyses the short-term performance of IPOs of the US tech market during and after the dotcom bubble. Due to the extensive existing literature about IPO underpricing it is necessary to provide some delimitations with regard to the scope of this paper.

First, the goal is to investigate if the existing underpricing theories are able to explain the levels of excess returns observed in our data set. We do not intent to refute the principle of any of the existing theories. Moreover, it should be noted, that we are by no means aiming to derive new theories within the scope of this paper.

Second, we do not pursue a holistic approach, meaning that we do not attempt to take into account every underpricing theory researched, but rather the ones most relevant for our analysis. In our case, most relevant means theories that obtained substantial academic support in the relevant literature and - at the same time - seem highly interesting with regards to our tech IPO dataset. We further restrict our analysis because of data availability and the difficulty to test specific theories in practise. For instance, underpricing theories based on confidential private data are beyond the scope of this thesis. Also, the introductory sections of this paper about IPOs in general and the US technology industry do not intend to be all-encompassing, but rather build the foundation for a better understanding of our analysis part.

Third, as we are focussing only on the US tech IPO market, our findings are not necessarily applicable for other countries or industries. On the one hand, we cannot apply them directly in other regional markets because each market has individual characteristics and is subject to different regional circumstances (e.g. regulations, tax systems, accounting systems, investors, etc). Further, the chosen US market is one of the largest and most mature IPO markets of the world. On the other hand, our results are also not directly applicable to other industries mainly due to the fact that companies in tech industry are often accompanied with specific company characteristics. Moreover, we take the dotcom bubble period into consideration and US tech companies were the ones most strongly affected by the bubble effects. Thus, our results are not directly indicative for other industries.

Fourth, although there is also vast literature trying to explain the long-term performance of IPOs, this thesis specifies on the analysis of short-term performance of US tech IPOs to ensure a narrow focus and an in-depth analysis.

Fifth, it should be noted, we limit our data collection on IPOs and do not take secondary equity offerings (SEO) into account for our quantitative analysis. This was chosen because in our opinion IPOs and SEOs are not directly comparable and accordingly would distort the results of our regression analysis.

Sixth, we are using a multiple regression analysis that has proven useful by prior researchers (e.g. Logue, 1973a; Ljungqvist & Wilhelm, 2003; Loughran & Ritter, 2004) and do not discuss in-depth the statistical model because this study should be seen as a financial rather than statistical study.

As a concluding remark, our focus is to test prior academic results concerning the underpricing phenomenon on our dataset at hand in an academic way. We therefore focus on the academic contribution rather than giving practical investment strategies in this field of research.

1.4 Structure

To assure a maximum level of understanding and thoroughness of our analysis, this paper is principally structured in 7 chapters.

After this introduction chapter, the second section builds the foundation of our thesis by giving an overview about IPOs in general, the US tech industry and the existing literature on short-term IPO underpricing, including a presentation of the four main underpricing theories: asymmetric information theories, behavioural theories, institutional theories, ownership and control theories. Categorizing the existing literature into these four superordinate theories enables to us to determine which of these theories are relevant with regard to our analysis.

Before we derive our hypotheses in chapter 4, we shortly explain our methodology and how we gathered our data in chapter 3. The hypothesis development consists of 10 hypotheses whereas the first one is a presupposing hypothesis which tests whether the initial IPO returns are abnormal compared to a market index. Building on that, the remaining 9 hypotheses aim to explain the levels of excess returns detected in our dataset. These are structurally organized towards the existing underpricing theories. In chapter 5, we are then testing these hypotheses via a multiple regression analysis, showing the results and determining the econometric accuracy of our models. Subsequently, chapter 6, gives an interpretation of our findings and discusses the individual results of our analysis in a broader context. This section is divided in two sub-parts. We are first providing an individual discussion and interpretation of each individual tested theory and then follow up with a discussion of the overall issuer/underwriter incentives. The latter also includes not tested theories to present a more complete picture why underpricing is prevalent in IPO markets. The thesis ends with a conclusion of our findings, a reflection on limitations and recommendations for future research.

2. IPO, US Technology Industry and Underpricing Review

In order to understand the underpricing phenomenon, in this chapter we first introduce the process of an IPO. In a second step we will then show why the technology industry and its characteristics are of special interest before analysing the existing literature on the topic of the underpricing. Four superordinate theories are illustrated in order to explain why issuers leave considerable amounts of money on the table when going public. It should be noted that this literature review does not aim to be all-inclusive, but rather sets the scene for the analysis part of this paper.

2.1 The initial public offering process

Why do companies go public? In order to e.g. finance growth or for investments, companies often face the need for additional capital. To raise capital companies can fundamentally choose between

two basic options. The first one is to issue equity while the second one is to borrow money from e.g. financial institutions (like a bank loan) or to publicly issue debt (e.g. bonds). In this paper, we will focus on the process of issuing equity for the first time, the so called initial public offering (IPO).
In an IPO new shareholders trade in cash for a part of a company. In this process, a company shifts from being privately held to become publicly held due to the public offering of shares on a stock exchange. The key players in this process are the issuing firm, the underwriter(s) and the investors (as the new shareholders) (Eckbo, 2007), while the Securities and exchange commission (SEC) supervises the legal environment during the process.

2.1.1 The stages of an IPO

Following Ernst & Young (2013) there are three main stages in the process of going public. In the planning and preparation phase the company does a readiness check of the business model, the market, the financials and commits to the IPO. The execution and implementation phase is then introduced to meet the legal requirements and establish a communication strategy to future investors. During the realization phase, the shares are finally priced for the opening of the stock and the IPO transaction is closed. These stages can be divided into the following sub-steps (see Figure 2):

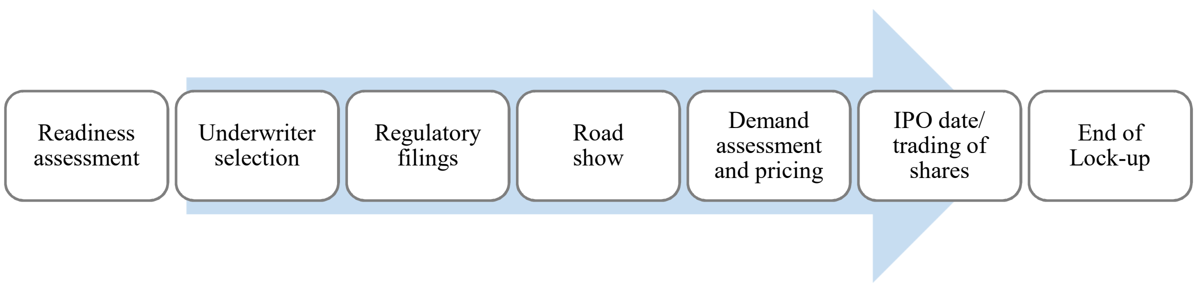

Figure 2: Sub-steps during the IPO

(Source: Ramsinghani, 2014)

The preparatory stage usually starts about one to two years before the IPO date. After this readiness assessment the execution phase will be divided into several sub-steps. During this, the issuing company will select an underwriter which will provide the prospectus for the IPO. In this prospectus all relevant information (including a preliminary pricing and price range) about the issuer concerning the IPO will be presented. The regulatory filings need to be approved by the SEC in order to be released to the public. When the preliminary prospectus is filed to the SEC, the quiet period starts. During this period the company is prohibited from sharing any information that is not part of the

prospectus with the public. During the road show, the underwriter will create interest for the issuing stock and try to arrange deals with the (institutional) investors to sell the stock, which will be used for final pricing. At the IPO date, the stock will be firstly listed on a stock exchange and can be traded to any interested investor.
Right after the equity was issued and the shares are traded to the public, the lockup-period starts. This is a contractual restriction to prevent insiders that were holding shares prior to the IPO to sell them during the beginning of going public. This period typically lasts for the first 90-180 days after the IPO date (Field & Hanka, 2001). The SEC does not require the companies going public to have this lockup-period, but issuers rather decide themselves and/or with the underwriter to lockup their shares.

2.1.2 The key players in the IPO

The key players in the IPO process are the issuing firm, the underwriter, the SEC and the investors.

The issuing firm

The issuing firm is the firm that wants to initially place their shares on a public stock exchange and therefore change their company characteristic from privately held to publicly held.

The underwriter

The underwriter is the intermediary between the issuing firm and the outside investors as well as the SEC. Primarily, the underwriter is responsible for the bookbuilding, the pricing of the stock and the preparation of regulatory filings.
Due to an information asymmetry about the true value of a prior privately held firm between the insiders of the firm and the prospective investors, it is important to have a trusted intermediary which helps to exchange information between the parties involved (Wilhelm, 1999, 2005). Therefore, a (typically investment) bank is often involved as an intermediary (called the underwriter) between the company issuing equity and the public. In the case of using multiple underwriters, e.g. due to a large issuing volume, these underwriters will work together in a syndicate to share the risk.
Generally, two IPO methods can be identified that will be used for most of the issuings. The first is called the bookbuilding method that includes a (non-legally binding) collection of the interest in buying shares of potential institutional investors at a preliminary offer price. Instead, the second type uses a uniform price auction to find the offering price and is therefore called auction method (Sherman, 2005).

The bookbuilding method can be can be further subdivided in two types of underwriting. The first bookbuilding type, is the firm commitment underwriting where the issuing company sells all the shares to the underwriter who will then bear the risk of not reselling all of the shares to the open market for the offer price. The second type, the best efforts underwriting, differs from the first one, that the underwriter is just legally bound to use its best effort to sell as many shares (in the best case all) of the issuing company but does not have to bear the risk of unsold shares. This technique therefore does not guarantee a fixed amount of raised capital to the issuer up front.

In the auction method, the underwriter does not set a fixed price but rather collects offers from the investors for which price they are willing to buy how many shares. The underwriter will then choose the price for which it can sell all of the provided shares and distributes them amongst the interested institutional investors.

There is evidence, that the auction method has a lower (cost-)spread than the bookbuilding method for the issuer (Papaukthuanthong, Varaiya, & Walker, 2007) and both explained methods are used in practise. However, bookbuilding methods are most commonly used for equity offerings (Loughran & Ritter, 2004) whereas auction methods are mainly used in bond markets by e.g. governments (Hillier, Clacher, Ross, Westerfield, & Jordan, 2017).

The Securities and Exchange Commission (SEC)

In order to get publicly traded and listed on an American stock exchange, the underwriter has to publish a prospectus of the issuing firm. This is to make sure to follow the rules on how the issuing firm and the underwriters communicate with potential investors. The prospectus can be seen as a business plan of the issuer where every information needed to price the stock can be found. There is no regulation on how the price of the stock is set and the prospectus is rather seen as an information material also concerning the indicative price range and the number of shares that are sold to the public. When signing the registration statement with the SEC, the so called quiet period starts and lasts at least for the first 40 days after the IPO was set and the stock is available for trade. During the quiet period, the management and other insiders are restricted to talk to the public about any business-related decisions because the whole communication will be limited to ordinary announcements. This is to make sure that all prospect inventors have access to the same information (Hillier et al., 2017).

The investors

Investors can be typically separated into two groups (Eckbo, 2007). On the one hand, there are the institutional investors (non-bank persons or organization) that trade a large amount of dollars. Often, they are organizations that invest on behalf of their members. On the other hand, retail investors are typically managing a rather low amount of dollars. These are individual investors that buy and sell for their personal account.

2.1.3 The cost of an IPO

The overall costs for an IPO can be divided into direct and indirect costs. The direct costs consist of the gross spread which is the fee paid to the underwriter by the issuer by selling them the shares below the offering price (in the US market this is about 7% of the issuing volume (Loughran & Ritter, 2004). Other direct costs are fees and taxes that are directly linked to the IPO and therefore stated in the prospectus. The indirect costs cannot all be completely monitored and expressed in numbers. On the one hand, there is the time that the management and employees spend time on working on the new issue. On the other hand, there is the underpricing that is also called money left on the table from selling the equity below the real value if the stock price increases dramatically during the first day of an IPO. Additionally, the Green Shoe Option/Overallotment Option (OAO) gives the underwriter the right to buy additional 15% of the issuing shares at the offering price (Hillier et al., 2017). Generally, this option will be only executed when the market price rose above the offering price. An OAO is not legally required and is only based on the agreement between the issuing company and its underwriter. If executed, the gross spread will occur on the additionally sold shares which will therefore increase the paid fee of a successful IPO.

2.1.4 The IPO motivation

In order to understand the IPO patterns, we want to focus on the motivation of companies going public and their timing. Ritter & Welch (2002) argue that in many cases, the reason why a company issues equity via an IPO is to raise capital and the possibility for the founders and other shareholders to be able to convert their (on book) shares into cash. Additionally, they conclude that non-financial reasons like e.g. the increase of brand and product awareness due to the focus of the media is of secondary importance.

One of the first theories about the decision to go public was published by Zingales (1995). The Life cycle theory states that the decision to go public can be based on the aim to sell a company. A public company is therefore easier to take-over because it is easier to spot. He further argues that floating shares make it harder to put pricing pressure on the possible acquisition target. Following this, Maksimovic & Pichler (2001) find evidence that a publicly traded company can add value to itself as the characteristic of being listed on a public exchange can increase the outside view of the firm from e.g. other stakeholders like investors, customers and suppliers. Black & Gilson (1998), on the other hand, point-out that the entrepreneurs can regain control of their companies with an IPO if the company was backed with venture capital in the past. They argue that IPOs are less an exit for the management and founder rather than for the venture capital giver.

Another theory is called the market timing theory. Lucas & McDonald (1990) argue that companies will postpone an equity issue if – due to e.g. asymmetric information – the market will temporarily undervalue the company until a more bullish market offers the possibility to attract more favourable prices. Choe, Masulis & Nanda (1993) further argue that firms are more reluctant to issue new shares in times when there are only a few other (high quality) issuings. Following this, Subrahmanyam & Titman (1999) suggest that markets can provide information spill-overs to IPO firms by signalling high prices based on growth opportunities.

Despite the advantages of going public, there are also (non-)financial legal regulations that a company issuing equity on a public stock market must face. First, there is the loss of privacy especially regarding the operational strategy and markets. This information will now be publicly displayed and discussed in order to price the company. Ramsinghani (2014) also mentions the periodic reporting to obey to the legal regulations as additional and reoccurring costs. Following the principal-agent conflict, a free-float of shares and therefore decreased concentration of ownership reduces the ability to control the management which can lead to inefficiencies (Berk & DeMarzo, 2014).

2.2 US technology industry

In order to understand the focus of our work, in the following we want to highlight some facts about the US technology industry and its characteristics.

2.2.1 US technology industry and IPO market

The US technology industry shows patterns of highly cyclical IPO trends compared to other (traditional) industries starting in the 1980s (Lowry, 2003). During the two-year timeframe from the beginning of 1998 until the beginning of 2000, publicly traded tech/internet companies showed a stock return of 1000% (Ofek & Richardson, 2003). Bartov, Mohanram, & Seethamraju (2002) demonstrated that right before the crash in 2000, the internet industry had become the number two in wealth creation with a market value above the level of $1 trillion.

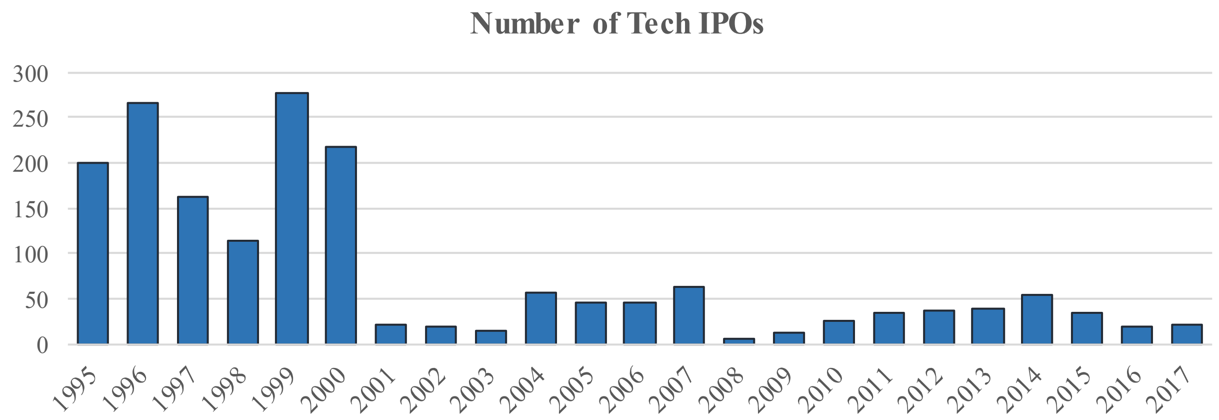

Figure 3: Number of technology IPOs in the US (1995-2017)

(Source: Thomson One New Issue Database)

The US tech IPO market in the end of the 20th and beginning of the 21st century shows a large number of IPOs (see Figure 3). The peak of this time period, that will be later defined as the internet bubble, is in 1999 with a total of 278 IPOs of tech companies in the United States of America. After the burst of the bubble in 2000, the number of tech IPOs strongly declined to only 21 in 2001. Between 2001 and 2017 in the US technology sector, there was no single year coming close even to 100 IPOs.

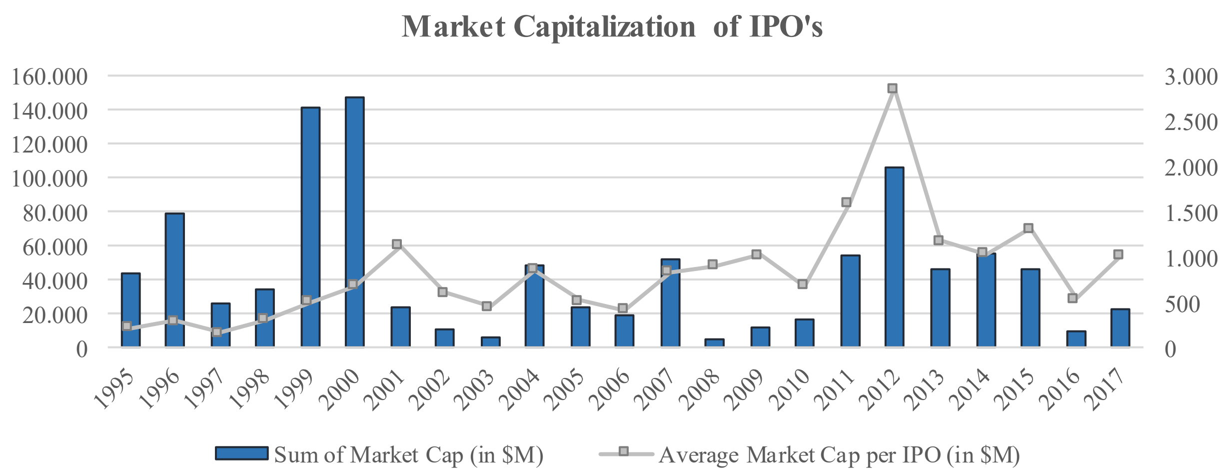

Figure 4: Market capitalization of US tech IPOs in $M (1995-2017)

(Source: Thomson One New Issue Database)

Even though there is a huge decline in the number of tech IPOs in the USA after the bubble, the total average market capitalization per IPO was slowly increasing (see Figure 4). When looking at the average dollars that were raised over the years, there was a peak of around $3 billion in 2012 per IPO. This is mainly influenced by the Facebook IPO that was solely raising around $81 billion. Facebook is by far the largest tech IPO in the USA between 1995-2017 (followed by $23 billion of Google in 2004).

2.2.2 US technology company characteristics

After reviewing the US technology IPOs, we want to have a closer look at the industry and company characteristics.

First, when looking at the business models, there is a difference between traditional industries (like e.g. manufacturing industry with a high share of physical assets) and the technology industry (with a large share of intellectual property/intangible assets). Intangible investments like e.g. Research & Development (R&D) increase the information asymmetry to external investors due to accounting restrictions compared to investments into tangible assets (Aboody & Lev, 2000; Guo, Lev, & Shi, 2006). Furthermore, Bartov et al. (2002) indicate that large R&D proportions are negatively viewed by investors due to the lack of history of tech companies. Additionally, large assets of intellectual property increase the cost of financing (e.g. debt) because this is directly linked to great operational risks due to little to no collateral value outside the company (Uzzi, 1999).

Second, there is a large number of different business models inside the tech sectors. Even when comparing the IPOs of two closely related business models like Facebook (IPO in 2012) and Twitter (IPO in 2013), there are two completely different endings for their whole IPO and the returns of the first trading day. While Facebook closed on the first day with a return of about +1%, Twitter's stock price achieved a first-day return of about +73% compared to the offering price.

Third, internet firms that are persuading an IPO can be typically classified as rather young companies (few years or months of history) compared to other industries (Kim, Pukthuanthong-Le, & Walker, 2008). The age at the time a company goes public will affect the outcome of the IPO so that younger firms typically yield higher first-day returns (Loughran & Ritter, 2004). Further Aldrich & Fiol (2007) find evidence that the uncertainty about the outlook on profits is extraordinarily high for young companies in the high-tech industry. Additionally, there is evidence that the expected volatility increases due to the lack of publicly available historical financial and operational data (Bartov et al., 2002).

Fourth, the investor characteristics of publicly traded tech companies differ to other industries. There are indications that the relative number of institutional shareholders compared to other shareholders is significantly lower in the tech sector (median of 26% of institutional investors) than in other industries (median of 40%) (Ofek & Richardson, 2003). Research shows indications that these institutional traders are different to retail investors when comparing the rationality of their beliefs (Barber & Odean, 2000, 2001; Shiller & Pound, 1989). Following this argumentation, the increased number of retail investors could therefore lead to a market that is more prone to biases connected to behavioural finance. This is in line with Chen, Hong, & Stein (2002) who argue that the lack of institutional investors can be a sign of an overvaluation of a company.

Fifth, there is an increased fraction of companies that went public with negative earnings (Kim et al., 2008; Ritter & Welch, 2002). One explanation is that many tech companies are expected to show large increases in sales while not making any profits (Bartov et al., 2002; Loughran & Ritter, 2004). In order to finance these growth opportunities and to grab market shares, these companies tend to go public (Schultz, 1993). This is further analysed by Schultz & Zaman (2001) who argue that going public can be also seen as a pre-emptive strategy to pursue an aggressive growth/acquisition strategy. This argumentation goes hand in hand with the valuation in the IPO prospectus of internet and non-internet firms. Several researchers show that traditional measures, like e.g. negative earnings, were not influencing the valuation of internet companies and alternative value drivers were used to price internet stocks (Demers & Lev, 2001; Hand, 2003; Trueman, Wong, & Zhang, 2000).

Sixth, venture capitalists are typically looking for small and young firms that are operating in fast changing environments and therefore connected with a higher level of uncertainty (Gompers & Lerner, 2001). Particularly tech companies with high growth potential are often subject to VC funding. Nowadays venture capitalists play a relevant role as a financial intermediary in capital markets because they provide funds to these companies in the early stages of their company's life cycle. In exchange, they receive a certain equity share of the firm which is usually still held privately (Gompers & Lerner, 2001). After a certain timeframe of usually 10 years, VC firms are then trying to liquidate their investments as they are interested to generate returns for their investors. This is often done by conducting an IPO or arranging an acquisition of the firm. According to Gompers & Lerner (2001), an IPO is the exit strategy that yields the highest proportion of profits for venture capitalists.

2.2.3 The dotcom bubble

New valuation models for technology companies, that are based on growth opportunities rather than direct operational excellence and the presence of a large number of investors that are very optimistic, can lead to a bubble. A pessimistic investor could take the counter-position and short-sell these overpriced stocks to bring the market back to the equilibrium, but in the case of IPOs there are often restrictions to short-selling shortly after going public (especially during the lock-up period). During the end of the 20th century these pessimistic traders were being overrun by the optimistic ones that defined the prices of stocks due to sales constraints and oversubscribed shares (Miller, 1977; Ofek & Richardson, 2003). This market circumstance of overoptimistic investors leads firms to issue more equity in the so called window of opportunity (Baker & Wurgler, 2000). Earlier Shiller (1990) proposed the viewpoint of the underwriter that there is the hot IPO market phenomenon when underwriters see that there is an industry that is ripe and therefore strive to perform in the IPO market. He also finds evidence that in order to attract additional investors, offer prices of new issues tend to be below their true value. Lowry (2003) argues that growth perspectives as one of the most relevant variables for pricing an tech IPO are positively correlated with the IPO volume that supports the findings of Shiller (1990).

Although the presented positive outlooks for IPOs in the technology industry, the end of the lockup period that restricted the short-selling had a significant impact on the stock prices of internet companies (Ofek & Richardson, 2003). As presented, the largest number of IPOs in the tech sector happened in 1999 and their lockup period ended latest in 2000 so that the inside-inventors (including venture capitalists) were able to sell their shares if their opinion about the stock price was not as optimistic as the market. When the selling of these (inside) shares increased, the stock prices began to decrease (Ofek & Richardson, 2003). Additionally, following Brav & Gompers (2000) former venture capitalists that supported the issuing company before the IPO tend to pass/sell their shares once the selling restrictions are over to avoid reporting obligation. This behaviour can therefore increase the negative impact of the end of the lockup period.

2.3 IPO underpricing phenomenon

According to Fama (1970) and the semi-strong efficient market hypothesis, a specific share price in competitive markets already reflects all public available information. Consequently, there should be no possibility of earning persistently positive excess returns in IPO markets by buying shares for the offer price and selling them subsequently in the aftermarket if underwriters incorporate all public available information during the price setting (Lowry & Schwert, 2004).

However, market history shows that there are abnormalities in IPO markets. One of the most researched anomalies is the so-called IPO underpricing phenomenon, which at least represents a puzzle for efficient market hypothesis supporters (Adams, Thornton, & Hall, 2008).

Generally, IPO underpricing is characterized by extreme investor interest in shares of firms going public the first time (Reilly & Hatfield, 1969). More precisely, it is defined by the percentage difference between the offer price in the primary market and the price of the same stock subsequently traded in the aftermarket (Ljungqvist, 2007). For calculating these initial underpricing returns, most of the relevant literature use the closing price of the first trading day as reference variable (Ljungqvist, 2007; Ritter & Welch, 2002). Apart from that, Ljungqvist (2007) pointed out that using other short-term reference variables, like the price of the first trading week, typically does not change the occurrence of IPO underpricing in a given data set.[4]

By assuming that shares are sold at a too low price - here the offer price instead of the aftermarket trading price - each IPO issuing company leaves a considerable amount of money on the table. Based on this, the extent of underpricing can also be measured by the total amount of money left on the table which is determined by the spread between aftermarket trading price and offer price, multiplied by the total number of shares issued at the IPO (Ljungqvist, 2007). For instance, the underwriter of the Twitter IPO in 2013 determined the offer price at $26. After the first day the stock traded at $45, resulting in a tremendous underpricing of 73%. By taking into account that Twitter issued 70 million shares, this adds up to $1.33 billion left on the table.

In general, there is vast empirical evidence supporting this short-term anomaly in IPO markets. Reilly & Hatfield (1969) were the first who documented the underpricing phenomenon on small a dataset compiled of 53 IPOs between 1963-1966. Subsequently, Logue (1973a) and Ibbotson (1975) confirmed that when firms issue new equity, shares tend to be underpriced initially and therefore undergo a significant price jump on the first trading day. Since then comprehensive research has been conducted about this topic.

It should be noted that IPO underpricing is not limited to the US market. The vast literature also demonstrated empirical evidence for most of the European, Asia-Pacific and Latin American countries (Pazarzi, 2014). However, the extent of underpricing clearly fluctuates across countries,

[4] It should be noted that the long-term performance of IPOs is discussed controversially in the existing literature. For further readings about long-term IPO underperformance see: Ritter (1991); Ritter & Welch (2002).

industries and over time (Loughran & Ritter, 2004; Ritter, 1984). Due to the scope of this paper, the following focusses on the US market.

One of the most influential researcher on after IPO performance in the US market is Jay Ritter. He conducted several empirical studies on IPO underperformance ranging from 1960 until today and revealed that the amount of money left on the table varies substantially over time. The percentage of average IPO underpricing in the US added up to 21.2 % between 1960 and 1969. Then it strongly decreased to 7.1% between 1970-1979 and stayed on a low level of 6.9% between 1980-1989. Subsequently, initial returns increased strongly to 21.0% between 1990-1999 (Ritter, 2018). Investigating the time frame between 1999-2000 more precisely, US IPOs were underpriced on average by 71% and 57% (as shown in Figure 5), respectively which is mainly due to the irrational behaviour of investors during the dotcom bubble (Ritter, 2018). An earlier study by Ljungqvist & Wilhelm (2003) recorded similar first-day return figures during the dotcom bubble with 73% in 1999 and 58% in 2000. Such extreme numbers were also found by Loughran & Ritter (2004) who documented an average first-day return of 65% between 1999 and 2000, leading to an average amount of money left on the table per IPO of ca. $85 million. After the burst of the dotcom bubble, the overall number of IPOs declined, and the average underpricing decreased to 14 % between 2001 and 2016.

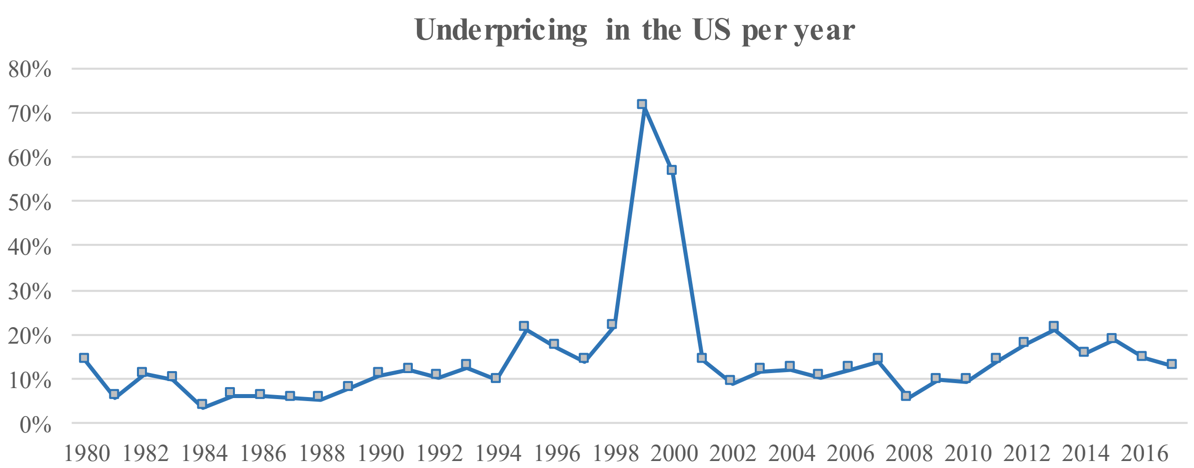

Figure 5: Underpricing in the US per year (1980-2017)

(Source: Ritter, 2018)

By examining individual industries in more detail, Loughran & Ritter (2004) identified that between 1999 and 2000 especially companies in the tech sector with 80.6% average first-day returns were subject to more severe levels of underpricing compared to non-tech companies with only 23.1% during the dotcom bubble. Even from a historical viewpoint, first-day returns of tech IPOs

outperformed non-tech IPOs significantly with 10.2% versus 6.2% between 1980 and 1989, and 22.2% versus 11.3 % between 1990 and 1998 (Loughran & Ritter, 2004).
In a more recent study, Kennedy, Sivakumar & Vetzal (2006) suggest that tech companies are subject to greater uncertainty and therefore experience a higher level of underpricing. Furthermore, Lowry & Shu (2002) documented that high-tech IPOs are subject to a great level of underpricing which is mainly due to the high uncertainty of their future growth opportunities. This is in line with the reasoning of Chemmanur (1993) who argues, that obscure firms with projects which are difficult and therefore costlier to evaluate, face greater underpricing.

In summary, there is empirical evidence that IPOs are on average underpriced and that the extent varies over time and industry. Considering that large parts of historical underpricing are driven by the severe underpricing of technology companies, an in-depth analysis of this sector appears to be interesting. Based on the vast empirical appearance of IPO underpricing and the money left on the table, researchers tried to find explanations for this new issue anomaly. In general, there are four superordinate theories explaining the levels of underpricing: Asymmetric information theories, behavioural theories, institutional theories and ownership and control theories. It should be noted that we do not intend to present a conclusive review of all in the literature existing sub-theories, but rather an introduction to the ones that are most important for understanding the scope of this thesis and its analysis section.

2.3.1 Asymmetric information theories

Broadly speaking, asymmetric information theories imply superior information for one of the participating parties at the IPO. According to Ljungqvist (2007) asymmetric information is one of the primary reasons for short-term abnormal IPO returns. Generally, scholars worked out four asymmetric information explanation models: The winner's curse, information revelation theories, principal-agent models and signalling.

Winner's curse:

One of the most accepted asymmetric information theories is the so-called winner's curse, which is in line with Akerlof's (1978) well-known lemons problem. Conforming to Rock (1986), there is asymmetric information about the fair value of issuing shares between two groups of investors, the informed and the uninformed. The informed investors have superior information and therefore only invest into attractive new issues, while the uninformed invest randomly. This leads to the winner's curse for uninformed investors since they receive all shares in unattractive new offerings whereas in attractive new offerings they are ruled out by informed investors. Thus, uninformed investors earn negative returns on average and consequently leave the market. Following Rock (1986), the primary market, however, is heavily dependent on the uniformed investors because otherwise there is not enough demand for new issuing shares. To encounter this adverse selection problem, issuing firms and underwriters have to deliberately underprice IPOs, so that uniformed investors at least break even and stay in the market.

Testable implications and evidence:

The empirical evidence for the winner's curse theory is widespread. A main empirical implication which has been tested extensively is that greater ex-ante uncertainty, leads to higher expected initial IPO returns. This positive relationship between initial returns and ex-ante uncertainty was documented and tested by Ritter (1984) and Beatty & Ritter (1986).

Following this, scholars used several proxies for testing this hypothesis which can be categorized into four groups: company characteristics, offering characteristics, prospectus disclosure, and aftermarket characteristics (Ljungqvist, 2007). Conforming to Jenkinson & Ljungqvist (2001), an influence on the degree of underpricing was especially detected for company variables such as age at IPO, log sales at IPO as well as offering variables such as offer price and underwriting fee. Moreover, Chambers & Dimson (2009) found a negative relationship between underpricing and company age as well as market capitalization at IPO as proxies for firm risk.

Another important empirical implication to the winner's curse is to reduce the information asymmetry between the uninformed and informed investor so that underpricing can be diminished (Ljungqvist, 2007). Some scholars argue that this can be achieved for example by appointing a renowned underwriter (Beatty & Welch, 1996; Booth & Smith, 1986; Carter & Manaster, 1990). More precisely, Carter & Manaster (1990) and Carter, Dark, & Singh (1998) reason that a prestigious underwriter fulfilled a superior certification role during the 1980s and thus investors did not require as large of a discount in form of underpricing on these IPOs. However, empirical results to these characteristics are still discussed controversial in the literature. On the one hand, studies documented a negative relationship between underwriting bank reputation and level of underpricing (Ljungqvist, 2007). On the other hand, Beatty & Welch (1996) found a reversing relationship in the 1990s stating that appointing an underwriting bank with a high reputation leads to higher initial returns for

investors. Furthermore, Loughran & Ritter (2004) documented that IPOs executed during the dotcom bubble by a highly prestigious underwriter showed 22.1% higher underpricing compared to IPOs with a less prestigious underwriter.
A further implication, which is especially interesting with regard to tech IPOs, is the link between venture capital (VC) backing and underpricing. Again, it bases on the fundamental winner's curse consideration that greater ex-ante uncertainty leads to higher expected underpricing and vice versa (Beatty & Ritter, 1986). Following this line of argumentation, Megginson & Weiss (1991) claim that venture capitalists can certify the quality of a company as a reliable disclosure of the true value of a firm and thereby reduce information asymmetry between investors and the issuing firm at the IPO. As a result of this third-party certification role of venture capitalists, underpricing for VC backed IPOs is reported to be significantly lower compared to non-VC backed IPOs. Barry, Muscarella, Peavy Iii, & Vetsuypens (1990) agree with the principal proposition that VC backing decreases underpricing. However, they argue that this is, because VCs reduce uncertainty by intensively monitoring the company and controlling its investment decisions.
Despite this, the empirical significance of the relationship between VC backing and initial IPO returns is discussed controversial in the relevant literature. Whereas Megginson & Weiss (1991) and Lin & Smith (1998) found empirical evidence that VC backing leads to lower underpricing, Francis & Hasan (2001) and Lee & Wahal (2004) documented the opposite.

Information revelation theories:

Together with the transition trend from pro-rata allocation to bookbuilding methods in IPO processes, information revelation theories received more and more attention in the literature. Again, in reference to Rock (1986), there are informed investors possessing superior knowledge compared to other investors or the issuing company. How those informed investors reveal their information is the focal point in information revelation theories.
Bookbuilding methods stress the role of investment banks in eliciting this superior information for setting an appropriate offer price and distributing allocations of new issues. However, there was no inducement for the informed investors to reveal their superior knowledge to the bank, since they anticipate an increasing offer price as response to their disclosure. Inversely, by anticipating the underwriter's behaviour, informed investors were even incentivized to give wrong information to the bank in order to put downward pressure on the offer price and hence gain higher profits. This undesirable behaviour can only be redirected if the underwriter incentivizes the informed investors

with a kind of reward mechanism for revealing true information (Ljungqvist, 2007). According to, Benveniste & Spindt (1989), Benveniste & Wilhelm (1990) and Spatt & Srivastava (1991), bookbuilding as a specific method of underwriting can function as such a mechanism as long as certain conditions are fulfilled.

By measuring the initial investors' appetite for new issues during bookbuilding, the underwriter can reward the investors who are bidding aggressively, and thereby revealing relevant information, with a large fraction of the shares whereas the ones who are bidding conservatively are penalised with no or only a small fraction. As a result, when the IPO is initially underpriced by the bank, informed investors are incentivized to bid aggressively and thereby reveal their superior knowledge as they strive to appropriate a large fraction of the initially underpriced shares (Ljungqvist, 2007).

Hanley (1993) argues for a partial adjustment phenomenon induced by bookbuilding. When investors are revealing relevant information during bookbuilding, the offer price will be increased by the bank, but only partially benchmarked against the information value. Thus, the other part is left on the table in order to compensate the investors for the truthful revelation. The more favourable the information, the greater the amount of money which has to be left on the table. Concluding this line of argumentation, there is evidence for a positive relationship between price revisions during the bookbuilding process and initial returns in the aftermarket.

Testable implications and evidence:

In general, there are several studies discussing the empirical evidence of information revelation theories by testing bookbuilding of IPO underpricing directly. However, many of them rely on confidential investment bank data and therefore not accessible with respect to our analysis.[5]

The hypotheses by Benveniste & Spindt (1989) can be tested without private allocation- or bidding-data. They argue that the number of shares offered and the fact that the offer price is above, within or below the original price file range, mirror the investors' appetite and thereby the information value revealed by informed investors. Correspondingly, positive information leads to a pricing towards the higher end of the pricing range, whereas low investor appetite leads to a pricing in the lower range. In line with the partial adjustment theory stated by Hanley (1993), the offer price is then only adjusted partially, thus rewarding the investors for the revelation of positive information with money left on the table. In his study, Hanley (1993) examined a dataset compiled of 1,430 IPOs from 1983-1987

[5] For further readings about direct testing of bookbuilding theories see: Cornelli & Goldreich (2001, 2003); Jenkinson & Jones (2004).

and documented a positive correlation between investor appetite during bookbuilding and money left on the table. Although there are several subsequent papers which confirmed the empirical evidence of the partial adjustment theory, Loughran & Ritter (2002) criticized Hanley's (1993) study by questioning if underwriting banks fully incorporate all public information in form of market returns prior to the IPO when determining the offer price. This also opposes the argumentation of Benveniste & Spindt (1989) who state that every investor has free access to public information and therefore no compensation in form of money left on the table is needed.

Principal agent models:

Conforming to Loughran & Ritter (2004), there is a potential for agency conflicts in IPO markets between the issuing company and the underwriter when determining the offer price.

One of the first who documented a relationship between agency problems and IPO underpricing were Baron & Holmström (1980). They argue that the underwriter (agent) can use their superior information regarding investor appetite to minimize effort in marketing and distributing the new issue of the company (principal), when the used effort is not observable and not verifiable (moral hazard). In extreme cases, the underwriting bank may even be incentivized to betray the issuer by accepting side payments offered from investors who heavily want to participate in an underpriced new issue. For instance, the Credit Suisse First Boston was fined $100 million for accepting such side payments in 2002. Such regulatory investigations of banks especially during and after the dotcom bubble, raised the attention of the academia for principal agent theories explaining underpricing (Ljungqvist, 2007). However, the question if principal agent theory is able to explain the varying levels of IPO underpricing is still discussed controversial in the existing literature. On the one hand, there are studies explaining the level of underpricing based on agency theory, but on the other hand, these are showing contradicting results (see e.g. Muscarella & Vetsuypens, 1989).

Despite the fact that agency theories for explaining underpricing gained relevance with the detection of the dotcom bubble, they are not possible to test empirically.[6] Therefore we will have a closer look at these theories in the discussion part of this paper.

Signalling theory:

In the underlying assumption of signalling theory, contradicting to Rock (1986), the issuing company has superior information about its fair value compared to investors. Thus, the issuer is consciously

[6] For further readings about agency theories see: Ljungqvist & Wilhelm (2003); Muscarella & Vetsuypens (1989).

underpricing the new issue in order to signal firm quality by triggering a stock price increase after the IPO. This is in line with Ibbotson (1975) who suggests that underpricing is used to "leave a good taste in investors' mouths'" (Ibbotson, 1975, p. 264). Despite the fact that issuers leave money on the table in an initial offering, Ljungqvist (2007) argues that this is compensated by better conditions in a secondary offering. Since this paper is focusing on initial public offerings not secondary offerings, a further investigation of secondary offerings is not made within our analysis.[7]

Nevertheless, the signalling effect of underwriters and venture capitalists will be tested as described in the winner's curse with regard to the information asymmetry between the two investor groups. Moreover, it plays an important role for the discussion of issuer and underwriter incentives in section 6.4.

Summing up, empirical evidence shows that asymmetric information theories contribute to a specific extent to IPO underpricing. However, the tremendous fluctuation of underpricing over time and especially the enormous amount of money left on the table during the dotcom bubble, raised the question if asymmetric information-based argumentations can explain these extreme amounts of money left on the table. Following this, some scholars argue that non-rational explanations are one of the main determinants for IPO underpricing.

2.3.2 Behavioural theories

Behavioural theories for explaining the underpricing puzzle are relatively new, but recently raised more and more attention in the literature after the dotcom bubble since rational theories failed to explain the extreme fluctuations of underpricing that were observed. Thus, behavioural literature and its empirical testing on underpricing is still in its early stages Ljungqvist (2007). In general, behavioural theories are based on the assumptions that one of the key parties of an IPO is not acting rational and therefore causing underpricing. There are either irrational investors who bid up the share price beyond its fair value after the IPO or irrational issuers who are not able to put enough pressure on the underwriting banks to diminish underpricing. Categorically, the relevant literature for this thesis can be condensed in three sub-theories: investor sentiment theory, hot/cold issue markets, as well as prospect theory and mental accounting.

[7] For further readings about signaling theories see: Allen & Faulhaber (1989); Welch (1989, 1996).

Investor sentiment theory:

Generally, investor sentiment theory assumes that there are non-rational investors in the market bidding up the share price. Referring to Black (1986), and Baker & Wurgler (2007), sentiment investors make investment decisions based on beliefs about future cashflows that are not backed by any facts. This theory is particularly relevant for IPO markets since new issuing companies have no historical (publicly available) data which makes it even more difficult for the investors to evaluate the fair value for a share. Moreover, Baker & Wurgler (2007) stated that especially young, fast growing, no-dividend paying and loss making firms – like technology companies – are hence difficult to value and therefore highly affected by investor sentiment.

According to Ljungqvist, Nanda, & Singh's (2006), non-rational retail investors value new issues too optimistic. As a first measure, issuers would like to exploit this situation by flooding the market with shares, but they anticipate the resulting downward pressure on prices. Hence, the best approach would be to retain shares initially in order to uphold prices which is, however, not allowed due to legal restrictions (Ljungqvist, 2007). As a consequence, issuers deploy an indirect approach meaning that issuing firms first sell their shares to institutional investors who then resell them to the retail investors. Initially, the institutional investors do not market all shares immediately to the sentiment retail investor in order to keep the share price up. However, by retaining some of the shares over time, the institutional investors face the risk of a market downturn. To be rewarded for this inventory risk, they demand initially underpriced shares from the issuer. Accordingly, Ljungqvist, Nanda, & Singh (2006) propose that during periods with high sentiment underpricing is more severe.

Testable implications and evidence:

Lowry & Schwert (2002) documented that greater underpricing leads to a higher number of companies going public in the following six months. These underlying considerations are in line with the sentiment investor theory of Ljungqvist, Nanda, & Singh (2006) since investors are too optimistic about the future during hot market periods and issuers are exploiting this irrationality by performing the IPO during those periods. Moreover, they propose that during periods with higher sentiment, underpricing is more severe. Despite offering a plausible explanation, Ljungqvist, Nanda, & Singh (2006) did not back their theory quantitatively.

In a European study consisting of 486 IPOs between 1995 and 2002, Cornelli, Goldreich, & Ljungqvist (2006) argue for a positive relationship between firm-level sentiment and post-issue prices by using pre-issue (grey) market prices as a proxy. Nonetheless, they did not find a robust evidence between market-wide sentiment and after IPO prices when using index market returns as a proxy for sentiment.

In a more recent US study, Hrnjic & Sankaraguruswamy (2010) examined the influence of market-wide investor sentiment on the US IPO market by analysing 5,198 IPOs between 1981 and 2009. They observed statistically significant results for the positive relationship between market-wide sentiment of investors and IPO underpricing.

Hot/Cold issue markets:

As preliminary type of investor sentiment theory, already earlier Ibbotson & Jaffe (1975) developed the so called hot/cold issue markets theory. Generally, they argue that initial IPO returns do not follow a random walk. Instead, they can be identified by a relationship between the timing of an IPO and short-term aftermarket returns. More specifically, they hypothesized that during hot markets, which are periods with high market returns and high number of IPOs, the level of underpricing is significantly higher compared to cold markets. This is because sentiment investors are too bullish during those time periods and issuers/underwriters exploit such situations. In their study, Ibbotson & Jaffe (1975) investigated a US dataset between 1960 and 1970. However, it should be noted that they could not record empirically significant results for their hypothesis due to limited data availability and statistical difficulties obscuring the results.

Prospect theory and mental accounting:

Loughran & Ritter (2002) analyse the underpricing phenomenon from another perspective. They argue that irrational managers of the issuing firm instead of investors are the decisive factor. Broadly speaking, prospect theory suggests that under risk humans are more sensitive to losses compared to gains (Kahneman & Tversky, 1979). Building on that, Ljungqvist & Wilhelm (2005) documented that prospect theory can help to explain IPO market developments. According to mental accounting, managers of the issuing firm only take into account total wealth losses or gains (Thaler, 1980). Therefore, managers balance their wealth losses incurred by underpricing, with their wealth gains incurred by increasing aftermarket prices of retained shares. As long as these managers perceive an overall wealth gain in consequence of the IPO, they are satisfied, which, in turn, leaves space for the underwriting bank to underprice the IPO.[8]

[8] For further reading about prospect theory in IPOs see: Ljungqvist & Wilhelm (2005).

As explained above, the prospect theory and mental accounting provide interesting approaches in order to explain IPO underpricing from a behavioural perspective. Due to their limited practicability for empirical testing it is not included in our model. However, prospect theory and mental accounting are part of our discussion of underwriter/issuer incentives in section 6.4. Nevertheless, we will include behavioural theories in our quantitative model by testing investor sentiment and hot/cold issue markets.

2.3.3 Institutional theories

Institutional theories for underpricing in the relevant literature are mainly backed by three explanations: Litigation, price stabilization and taxes.

According to litigation considerations, IPOs are consciously underpriced due to legal reasons, more detailed, to avoid lawsuits from investors.[9]

Price stabilization theory states that underpricing is not intentional, but rather a consequence of price stabilizing activities of underwriting banks once trading starts. In particular, underwriters are pushing up the aftermarket price by bidding on the shares as soon as it falls below its offer price.[10]

Tax related theory argues, that underpricing an IPO stock can be beneficial due to tax advantages.[11]

In short, empirical evidence for institutional theories is controversial, since underpricing is also perceived in countries where litigation, price stabilization and taxes are less relevant for IPO markets (Ljungqvist, 2007). Based on this and due to their limited practicability for quantitative testing, institutional theories are not included in our regression models. Moreover, we assume that institutional theories are not able to explain the extreme fluctuations of underpricing over time since we are focussing on one specific market, e.g. we do not have to compare totally different tax systems of various countries.

2.3.4 Ownership and control theories

The ownership and control theories are fundamentally based on the eventual separation of ownership and control induced by an IPO. As owners possess the task to monitor the management, ownership characteristics shape management activities with regard to optimal operating and investment choices. The main sub-theories are retained control theory and reducing agency costs theory (Ljungqvist, 2007).

[9] For further readings about litigation considerations see: Ibbotson (1975); Logue (1973b).
[10] For further reading about price stabilization theory see: Ruud (1993).
[11] For further reading about tax related theory see: Rydqvist (1997).

Retained control theory:

According to retained control theory, underpricing an IPO helps to compile the shareholder base and therefore helps to regulate the intervention from outside shareholders as soon as the firms goes public. Thus, underpricing is used strategically to maintain company control after the IPO. Brennan & Franks (1997) suggests that by underpricing an IPO and thereby generating excess demand, managers can trigger a scattered ownership structure. This is, because the additional demand leads to more freedom when allocating the shares initially. In relation to governance theory, a diverse ownership structure causes low incentives for the individual shareholder to monitor management activities which in turn entrenches managerial control. More precisely, it makes it easier for the management to derive private benefits at the expense of the minority shareholders (expropriation) (La Porta, Lopez-de-Silanes, Shleifer, & Vishny, 2000; Shleifer & Vishny, 1986; Thomsen & Conyon, 2012).

There is the general assumption, that managers favour a scattered ownership instead of a few large shareholders (Booth & Chua, 1996; Brennan & Franks, 1997). However, different reasoning is used why the dispersed ownership is favourable. Booth & Chua (1996) argue that managers prefer scattered ownership structure since it enhances the liquidity of shares traded in the aftermarket. Brennan & Franks' (1997) study is based on general considerations from Grossman & Hart (1980), who propose that underpricing fosters a dispersed ownership structure, which, in turn, reduces the risks from hostile takeovers. In contrast, Zingales (1995) believes that an IPO is often the first stage of a multi-period exit strategy formulated by the founders. Based on this assumption, dispersed ownership makes it easier for insider owners to sell a controlling part of the shares for a higher price later in the aftermarket due to limited price pressure from the buyer’s side.

Reduced agency costs theory:

The diametrical opposing argumentation to retained control theory is the reduced agency costs theory stated by Stoughton & Zechner (1998). They, however, argue that issuers should strive to distribute most of the shares to large outside investors because large shareholders have strong incentives to monitor the management. Hence, agency costs between managers and owners are reduced. As long as the reduced agency costs outweigh the private benefits of the management with dispersed ownership, an allocation of shares towards large shareholder is supposed to be a superior strategy. Nonetheless, the shareholders demand to be compensated for making large investments in an IPO which is fulfilled by underpricing the IPO initially (Stoughton & Zechner, 1998). In other words, underpricing is performed consciously in order to reduce agency costs. So far, this theory has received only little attention in the literature and little empirical significant evidence supporting it.

Testable implications and evidence:

Brennan & Franks (1997) and Stoughton & Zechner (1998) argue that post-issue ownership has an influence on underpricing. Whereas the former claim that diffused ownership is preferred, the latter assert that block holding ownership is superior. Brennan & Franks (1997) test the hypothesis that underpricing leads to greater ownership dispersion by using detailed bid- and allocation data in a sample of 69 U.K. IPOs between 1986 and 1989. They concluded that the more an IPO is underpriced, the allocation of shares is more favourable for small bids compared to big ones.

Booth & Chua (1996) back their fundamental theory that dispersed ownership induced by underpricing helps to increase aftermarket liquidity with testing their sample compiled of 2,151 IPOs in the US market between 1977 and 1984. They suggest that underpricing is a positive function of scattered ownership.

Nonetheless, the impact of post-issue ownership on underpricing is also discussed controversially in the literature. Hill (2006) shows evidence on a UK dataset that the level of underpricing is not a significant determinant of post-issue ownership structure. Hill (2006) tested the hypothesis based on a dataset including 502 unseasoned listings from 1991 until 1998. These findings support a previous study conducted by Field & Sheehan (2004) who recorded that the relationship between initial IPO returns and ownership structure is very weak when analysing a final sample of 953 IPOs between 1988 and 1992.

Summing up the complete underpricing phenomenon section 2.3, there is no all-encompassing theory explaining the fluctuations of first-day IPO returns over time. There is evidence that the level of underpricing fluctuates over time and across industries (Loughran & Ritter, 2004). Consequently, it is interesting to investigate if one can see changing patterns after the burst of the dotcom bubble as most of the studies were performed before or around the turn of the millennial. Moreover, in this section we showed that a large part of historical underpricing is driven by the severe underpricing of tech companies. Because of this, we are testing underpricing theories on a current dataset of US tech IPOs which takes the dotcom bubble period as well as the post dotcom bubble period into account.

3. Methodology & Data

The prior review of how other scientists approached the topic of IPO underpricing, builds the fundament for our methodology. In order to be able to provide an answer to our research question formulated in section 1.1: “How can excess returns of US tech IPOs during and after the dotcom bubble be explained by chosen underpricing theories and how far is it possible to detect changing patterns over time?” as well as the derived sub-questions, we will present our used methodology and data in the following.

3.1 Methodology

In contrast to many of the studies conducted on IPO underpricing which test the validity of individual proxies and their underlying theories, we are consulting a joint approach in this thesis. This means, we are combining multiple already existing underpricing theories in our model and thereby try to explain the observed levels of excess returns of US tech IPOs over time. The literature review helps to synthesize the underpricing theories that are testable with regards to the data availability and their relevance for the tech IPO industry. Thus, we set the focus of our quantitative analysis on the following three underpricing theories and their respective sub-theories:

1. Asymmetric information theories
    a. Winner’s curse
    b. Information revelation
2. Behavioural theories
    a. Investor sentiment
    b. Hot/cold issue markets
3. Ownership and control theory
    a. Retained control theory

Before we can investigate the just mentioned theories, as an initial prerequisite we first have to test if the underpricing phenomenon is prevalent in our dataset. This is done by using a Student’s t-test and a Wilcoxon signed-rank test, which examine if the first-day IPO returns are indeed in excess compared to a market index. If this condition does not prove to be true, the thesis would end at this point.

If this condition proves to be true, we will use a deductive approach to test whether chosen underpricing theories can explain the excess returns in our dataset (Saunders, Lewis, & Thornhill, 2008). For our hypothesis testing on which proxies significantly influence excess returns, we will use a multiple regression analysis estimated via the OLS method that is also used by other researchers (e.g. Logue, 1973a; Ljungqvist & Wilhelm, 2003; Loughran & Ritter, 2004; Chambers & Dimson, 2009). In general, a multiple regression analysis is characterized by one dependent variable and two or more independent variables. The inclusion of any of our independent variables into our model is exclusively driven on theoretical grounds. This approach is in line with Studenmund & Cassidy (2014) who emphasize, that theory should be the primary reason for including an explanatory variable in a statistical regression model and not its statistical fit.

In order to find evidence if there are changing patterns in the explanatory power of different proxies and therefore their underlying theories over time, this multiple regression testing is performed for three predetermined time periods: the total period (01.01.1995-31.12.2017), the bubble period (01.01.1995-31.12.2000) and the post-bubble period (01.01.2001-31.12.2017). Subsequently, we compare and discuss our results of each period with the initial hypothesis to shed further light on the reasons for excess returns of US tech IPOs during and after the dotcom bubble. Due to the statistical testing of our dataset, we conduct a quantitative research of our chosen hypotheses. The composition of this dataset is presented in the following section.

3.2 Dataset composition

This section of the paper first gives an overview about the data collection process, then it shows how we prepared the data with regards to our empirical testing to give the opportunity to reproduce our analysis. In the last subsection we assess the quality of our data at hand.

3.2.1 Tech IPO dataset collection

The primary source for collecting our data is the Thomson Financial SDC Platinum New Issues database, from where we gathered an initial sample of 1,783 tech IPOs executed between 01.01.1995 and 31.12.2017 (retrieved on the 8th of March 2018).

To find a relevant sample of IPOs, we performed a thorough search strategy. We defined our search criteria by first selecting only IPOs with United States of America as primary exchange nation of issuers stock. As second criteria, we focussed on IPOs with issue dates between 01.01.1995 and 31.12.2017 and excluded all IPOs with offer price smaller than $5.00 per share. The offer price criteria is implemented to specify on IPOs that are big enough to be interesting for institutional investors (Loughran & Ritter, 2004) .Third, we use an industry filter for tech companies via specific Standard Industrial Classification (SIC) codes. For this classification we followed Loughran & Ritter

(2004). They define technology related IPOs as those with SIC codes: 3571, 3572, 3575, 3577, 3578 (computer hardware); 3661, 3663, 3669 (communications equipment); 3671, 3672, 3674, 3675, 3677, 3678, 3679 (electronics); 3812 (navigation equipment); 3823, 3825, 3826, 3827, 3829 (measuring and controlling devices); 3841, 3845 (medical instruments); 4812, 4813 (telephone equipment); 4899 (communications services); and 7371, 7372, 7373, 7374, 7375, 7378, 7379 (software).

In our search criteria we excluded the security types American Depositary Receipts, American Depositary Shares, American Depositary Debentures, American Depositary Notes, American Depositary Preference Shares as well as deals defined as Real Estate Investment Trust, because we want to target common IPOs in our analysis. This approach is in line with relevant scholars (e.g. Loughran & Ritter, 2004; Ritter & Welch, 2002).

3.2.2 Data preparation

As described above, the entered search criteria lead us to an initial sample size of 1,781 IPOs. Subsequently, we made several adjustments to this initial database and collected further missing data as information was lacking with regard to our hypothesis testing proxies which will be explained in detail below. If relevant data points for our hypothesis testing were still missing after taking into consideration additional data sources (e.g. from the Ritter Website), we excluded those observations from our analysis. This preparation leads us to our final unique dataset comprising a sample of 1,276 US tech IPOs.

As it will be explained in section 4.1 “Preliminary hypothesis: Excess returns”, we calculate our dependent variable excess returns by subtracting the market return of the NASDAQ100 from the initial return of the IPO. Whereas the initial return is obtained by gathering offering price and the closing price of the first trading day from the Thomson Financial SDC Platinum New Issues database, the data of the NASDAQ100 index was downloaded from Thomson Reuters Datastream.

The raw data for computing our explanatory variables age at IPO, market capitalization at IPO, VC backing, offer price revisions, IPO activity and floating rate were retrieved from the Thomson Financial SDC Platinum New Issues database. The variable company age at IPO is calculated by subtracting the foundation date from the issuing date and is displayed in full years. However, as the Thomson Financial SDC Platinum New Issues database is lacking some data about the foundation date of the issuer, we filled the gaps with Ritter's IPO founding dates database provided on his homepage (Ritter, 2018) by matching it via the issuer’s 9-digit CUSIP. We determined the variable market capitalization at IPO by multiplying the shares outstanding after the IPO with the offering price, both accessed via Thomson Financial SDC Platinum New Issues database. For the variable IPO activity, we additionally gathered IPO data from 1994 to be able to calculate the number of IPOs conducted in the previous 180 days for the issues from 1995.

For testing the variable top/prestigious underwriter, we integrated Ritter's IPO underwriter reputation rankings into our databank that are disclosed on Ritter's website (Ritter, 2018) and manually matched them with the bookrunner(s) of each IPO obtained from Thomson Financial SDC Platinum New Issues database. A list of the top underwriters can be found in Appendix 1. The list provided by Ritter only covers data until 2015, so we assumed that the underwriter reputation for 2016 and 2017 is according to the year 2015.

The index data of our explanatory variables CBOE VIX and NASDAQ100 were downloaded from Thomson Reuters Datastream and the index data of the University of Michigan Consumer Sentiment Index (CSI) was obtained from the University of Michigan surveys of consumers website (University of Michigan, 2018). Table 3 gives a detailed overview of the different sources from where the specific data for the tested variables was gathered.

Variable	**Source**
Excess returns	Thomson Financial SDC Platinum New Issues database, Datastream
Age at IPO	Thomson Financial SDC Platinum New Issues database, Ritter website
Market Cap at IPO	Thomson Financial SDC Platinum New Issues database
Top/prestigious Underwriter	Thomson Financial SDC Platinum New Issues database, Ritter website
Venture Capital backing	Thomson Financial SDC Platinum New Issues database
Upward revision	Thomson Financial SDC Platinum New Issues database
Downward revision	Thomson Financial SDC Platinum New Issues database
Consumer Sentiment Index	University of Michigan surveys of consumers website
CBOE VIX	Datastream
IPO activity	Thomson Financial SDC Platinum New Issues database
Floating rate	Thomson Financial SDC Platinum New Issues database

Table 3: Overview of variables and their source of origin for the initial model

(Source: own contribution)

In addition, in the “Interpretation & Discussion” part of this paper, we used the overallotment option and number of bookrunners both gathered from Thomson Financial SDC Platinum New Issues database.

3.2.3 Data quality

The quality of a research and its findings are heavily dependent on the quality of the data input to perform the analysis. Therefore, we briefly want to evaluate the reliability and validity of our data at hand. As explained above, our initial dataset is retrieved from the Thomson Financial SDC Platinum New Issues database which is a very well-known financial database provided by Thomson Reuters and is also used by several relevant scholars for obtaining equity data. Since we are investigating a large dataset with a sample size with more than 1,200 observations, the weighting of each individual observation for the outcome is reduced and hence the accuracy of our dataset is enhanced. We are limiting our sample on tech IPOs executed in the US. On the one hand, this limits the accuracy for the interpretation for non-tech, or non-US IPOs, but on the other hand helps to ensure a homogeneous set of data. Moreover, we extended and cross-checked our dataset with data provided by J. R. Ritter who is one of the most influential researcher on IPO underpricing. His IPO data is published on his website and was already used and cited by several other relevant researchers. For collecting the Index data of the NASDAQ100 and CBOE VIX we used the Datastream database provided by Thomson Reuters. With more than ten million time series, Datastream is one of the world's largest financial markets time-series database (Thomson Reuters, 2018).

It should be noted, as this thesis is focussing on short-term underpricing the setup is not affected by a survivorship bias. Hence, this often-neglected bias does not distort the results and interpretation of this analysis. Against these backgrounds, we classify our data as reliable and valid.

4. Hypothesis Development

In this section we are illustrating the development of our hypotheses which we want to test later on in the analysis part. As explained in the previous chapter 3. “Methodology & Data”, we are particularly interested in comparing the three different time periods: Total period (01.01.1995-31.12.2017), bubble period (01.01.1995-31.12.2000) and post-bubble period (01.01.2001-31.12.2017). Hence, each derived hypothesis is tested on the three different time periods in order to explain excess returns over time and to detect changing patterns.

Generally, the hypothesis development consists of 10 hypotheses whereas the first one is a preliminary hypothesis which tests whether the initial IPO returns are excess to a market index. The remaining 9 hypotheses contribute to explain the levels of excess returns detected in our dataset.

4.1 Preliminary hypothesis: Excess returns

Before we can test the influence of the in the methodology mentioned theories on excess returns (see Formula 3), we first have to analyse if underpricing is even present in our data set at hand. Therefore, we define underpricing as the first-day return of a stock after the IPO was set and the shares are publicly traded.

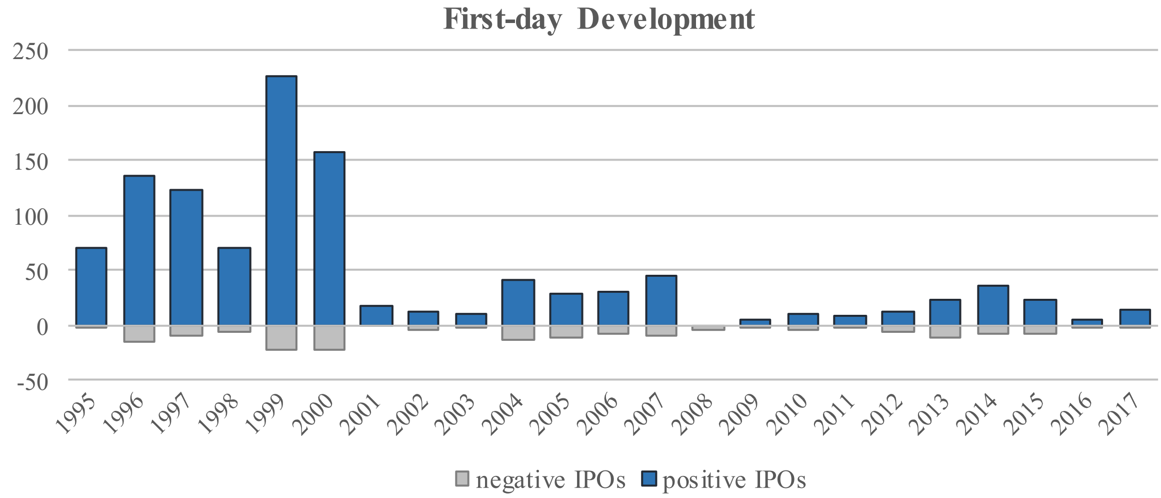

Figure 6: First-day returns of US tech IPOs per year (1995-2017)

(Source: Thomson One New Issue Database)

When looking at our data set, we can see that the absolute number of IPOs with positive first day development clearly outweighs the number of IPOs with negative first day development over our timeframe from 1995-2017, except for the year 2008 when the financial crisis started (as shown in Figure 6). Thus, there is the tendency observable that on average an IPO stock will have a first-day closing price that is above the offering price.

Besides simply looking at the qualitative outcome of an IPO at the first day (rising or falling stock price), it is even more interesting to look at the extent of underpricing by analysing the percentage difference between offering price and the closing price of the same stock subsequently traded in the aftermarket. For calculating first-day returns in our paper, we use the offering price and the closing price of the first trading day in the aftermarket. We therefore define the first-day return as:

$$First - day\ return = \frac{price_{closing\ day\ 1} - price_{offering}}{price_{offering}}$$

Formula 1: Calculation first-day return

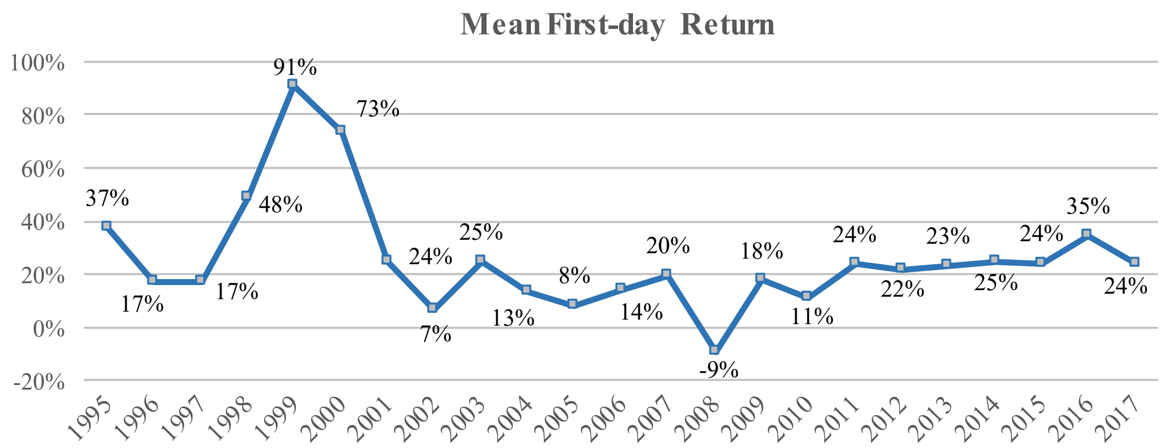

Figure 7: Average first-day returns of US tech IPOs per year (1995-2017)

(Source: Thomson One New Issue Database)

In Figure 7 we can also see, that the average of the first-day returns fluctuates over time and are especially high in 1999 with on average +91% and in 2000 with +73% right before the internet bubble busted and the first-day returns again strongly declined. This is in line with the analysis of Ljungqvist & Wilhelm (2003) who had a look at the whole IPO market during the internet bubble. Since we even find a premium on top of the underpricing in their all industry analysis, we conclude that the technology industry had a substantial impact when looking at the underpricing phenomenon at that time.

As we are comparing different time horizons, we want to neutralize the market influences that can have an impact on the first day development of the stock prices. Especially during the years of 1995-2000 the development of the general technology market can have a severe influence on the IPO first-day returns. Ideally, the used index should be selected based on the same industry and therefore same level of risk, so that it constitutes as an alternative investment to our tech IPO dataset. To do so, we use the NASDAQ100 as a proxy for the general technology market movement.

The NASDAQ exchange has gained the reputation of a technology exchange where a lot of the IPOs in the US technology sector take place. The NASDAQ 100 index is represented by the 100 company stocks with the highest market capitalization on this exchange (while excluding financial companies) and is highly focussed on technology companies (included among others: Amazon, Apple, Google/Alphabet, Intel, Microsoft, etc.) (NASDAQ, 2018).

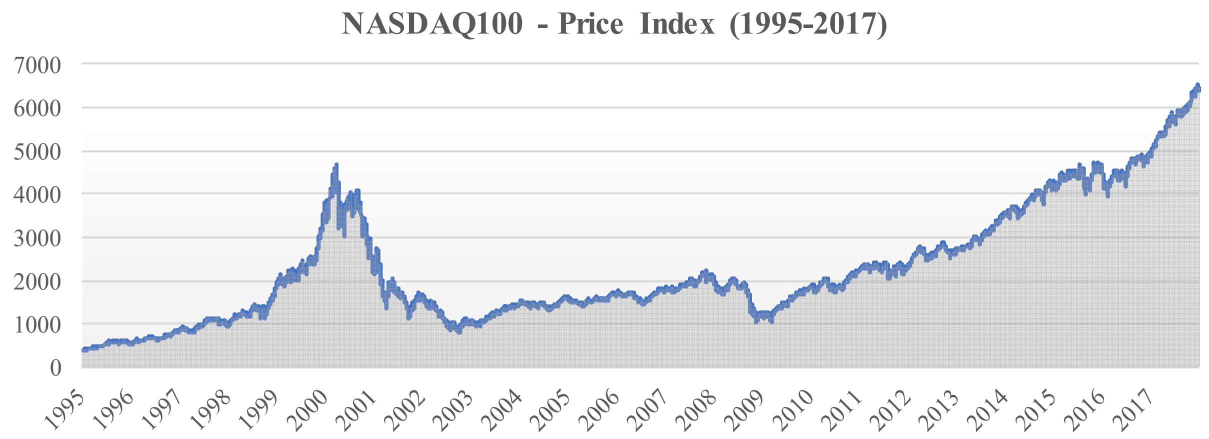

Figure 8: Price index of NASDAQ100 (1995-2017)

(Source: Datastream)

As shown in Figure 8, there is a substantial increase of the price index in the NASDAQ 100 during the internet bubble to around 10 times compared to the beginning of 1995. The time period after is defined with a slow and rather steady increase from about 1,000 points in the year 2003 to about 2,000 points at the end of 2008. After the financial crisis of 2008 and the and the decline of the price index to again about 1,000 points, the NASDAQ100 rose to its maximum of around 6,500 points at the end of 2017.

$$Market\ Return\ at\ IPO = \frac{NASDAQ100_{closing\ day\ 1} - NASDAQ100_{offering}}{NASDAQ100_{offering}}$$

Formula 2: Calculation market return

With this background, it is interesting to test if there are positive excess returns on average for the IPOs when adjusting for market development (NASDAQ 100 price index at the same time). In order to compare the first-day returns with the general tech market movement, we will adjust them with the return of the NASDAQ 100 index at the same time.

$$Excess\ Return = ER = First\ day\ return\ IPO - Market\ Return\ at\ IPO$$

Formula 3: Definition excess returns

$$ER = \frac{price_{closing\ day\ 1} - price_{offering}}{price_{offering}} - \frac{NASDAQ100_{closing\ day\ 1} - NASDAQ100_{offering}}{NASDAQ100_{offering}}$$

Formula 4: Calculation excess returns

We therefore test the preliminary hypothesis:

Preliminary Hypothesis: The mean first-day IPO returns are significantly larger than the mean tech market index returns (NASDAQ100) of the first trading day.

4.2 Asymmetric information theory hypotheses

One of the theories that is discussed among researchers concerning the pricing and first-day return of newly issued stock is asymmetric information. This follows the reasoning of Beatty & Ritter (1986), that uncertainty leads to underpricing since the true value of a firm cannot be distinguished. We therefore want to analyse the information asymmetry among investors, the role of the underwriter, the certification function of venture capital backing and the information asymmetry between underwriters and investors. Following Jenkinson & Ljungqvist's (2001) classification, we therefore analyse issuer company characteristics as well as offering characteristics to test for asymmetric information.

4.2.1 Winner's curse

Our first hypothesis will be based on the information asymmetry among investors. When Rock (1986) proposed his theory about the winner's curse, he was analysing the investors and separated them into two groups – the informed ones and the uninformed ones. In order to analyse the differences concerning the information about the fair value of a firm, we use the company age (at the IPO), the market capitalization of the issuer (also at the IPO), the underwriter reputation and venture capital backing as proxies.

Age of the issuer at IPO

Depending on how long a company was doing business prior to the IPO, the information that is (publicly and privately) available increases with the duration of the commercial activities (Ritter, 1991). Ritter (1991) then follows, that this information will have a negative influence on the level of underpricing because it reduces uncertainty. In line with this study, Loughran & Ritter (2004) also find evidence that the company age is negatively correlated with first-day returns. This was further analysed by Mezhoud & Boubaker (2011) who find evidence that that younger companies are confronted with higher uncertainty from the investors viewpoint, which will therefore result in higher underpricing of their stock.

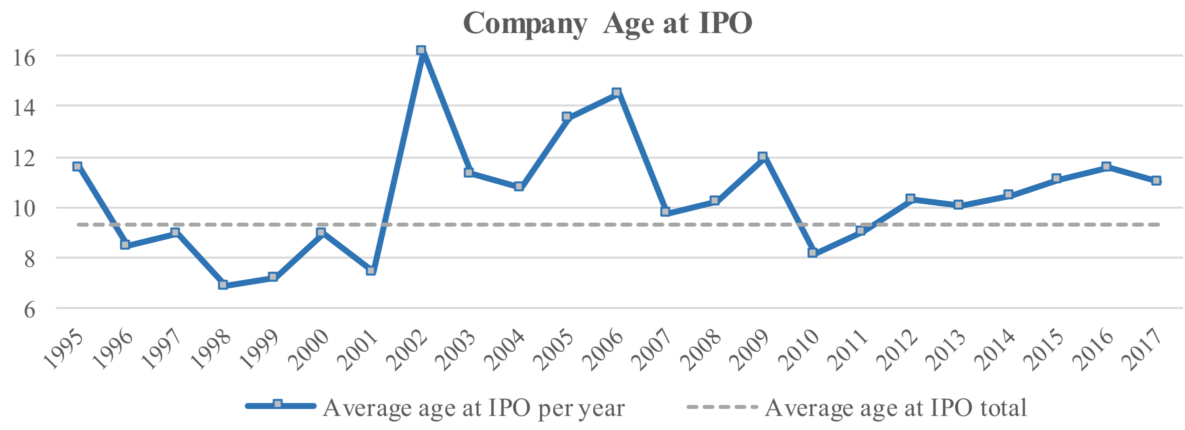

Figure 9: Average age of the issuer company at IPO (1995-2017)
(Source: Thomson One New Issue Database; Loughran & Ritter, 2004)

When looking at our data (see Figure 9), we can see that the average company age at the IPO is around 9 years. Especially during the second half of the 1990's and the years 2000 and 2001, the firms age when going public was below the average. After the bubble burst, in 2002 the average maturity of a technology company issuing shares in an IPO doubled to about 16 years compared to the year before. The IPOs during the years 2002 until 2017 are shaped by rather above average mature companies (except for 2010).

In this hypothesis, we are testing the relationship between the company age at IPO as a proxy for firm risk and underpricing. This is interesting because according to Loughran & Ritter (2004) not only the average age of the IPO issuers dropped during the bubble period, but also, the underpricing increased. Aldrich & Fiol (2007) therefore concluded that this uncertainty is of special relevance for young tech companies. Additional researches also find evidence that issuer age has a negative relationship to information asymmetry and therefore a negative relationship to underpricing (e.g. Megginson & Weiss, 1991; Muscarella & Vetsuypens, 1989). Furthermore, this hypothesis is particularly interesting to investigate with regards to our tech IPO data set at hand as tech companies tend to go public very early in their business life cycle and often do not have positive profits nor a proven business model at that time.

We therefore follow up with the following hypothesis:

Hypothesis 1: There is a negative relationship between company age at IPO and first-day excess IPO returns.[12]

[12] Throughout this paper, the wording in our hypotheses "negative relationship to excess IPO returns" indicates that if the independent variable increases the dependent variable decreases and vice versa.

Market Capitalization of the issuer at IPO

Following Bartov et al. (2002) the valuation of internet companies is based on growth opportunities (rather than profitability at the time of the IPO), that are therefore reflected in the market capitalization of the issues (Demers & Lev, 2001; Hand, 2003; Trueman et al., 2000). This valuation technique was introduced specifically for companies in the technology sector during the internet bubble and can therefore be identified as the future outlook for the issuing company which is – by nature – subject to risk. Baker & Wurgler (2007) support this viewpoint by finding evidence that, the lower the market capitalization of the issue, the lower the underpricing will be.

In this hypothesis we want to test the impact of the market capitalization on excess returns. For defining the market capitalization of an IPO, we follow Loughran & Ritter (2004). Accordingly, we use the number of shares outstanding after the issue multiplied with the offer price.

$$Market\ capitalization = total\ outstanding\ shares_{offering} * price_{offering}$$

Formula 5: Calculation proxy market capitalization

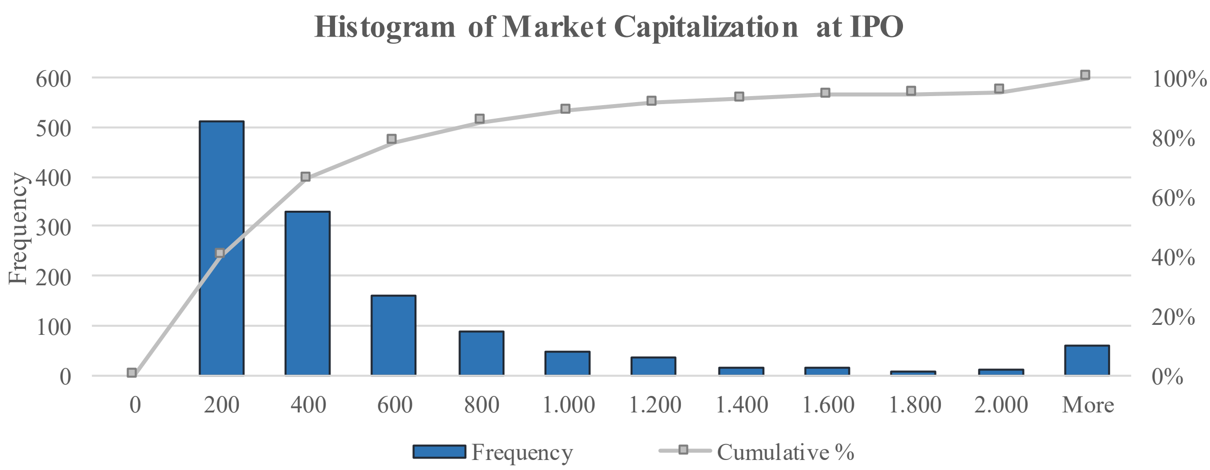

Figure 10: Histogram of market capitalization at IPO (1995-2017)

(Source: Thomson One New Issue Database)

Our data set shows (Figure 10), that two thirds of the tech companies (66%) have market capitalization at IPO below $ 400 million at the IPO. It is also interesting that there is a spike for (extreme) IPO issues with a market capitalization of $ 2 billion and above (about 5% of our dataset, among others, Facebook, Google, Twitter and Snap). Following the argumentation that growth opportunities are not certainly predictable, we want to test if the market capitalization has an impact on excess returns.

We therefore follow up with the following hypothesis:

Hypothesis 2: There is a positive relationship between market capitalization at IPO and first-day excess IPO returns.[13]

Underwriter reputation

By including the underwriter reputation into our model, we examine the information asymmetry inside the pool of possible underwriters that are available for an IPO as well as their ability to provide the investors with the same information. Correspondingly, this hypothesis tests whether hiring a good/prestigious underwriter helps to reduce information asymmetry and thus reduces IPO underpricing.

As mentioned before, the underwriter is responsible for the preparation of the prospectus, which is the only way an issuing company or its underwriter is allowed to promote company information to the public during the quiet period.

For our underwriter reputation ranking, we use the database of Loughran & Ritter (2004) where they rank the underwriting firms on a scale of –9.00 (lowest) to 9.00 (highest) according to their activity during specific timeframes. We then use this ranking in order to see if one of the underwriters can be considered as good/prestigious and therefore assume that the IPO/IPO syndicate will be better in minimizing information asymmetry among investors due to their high quality of underwriting. Additionally, since the underwriter bears the risk of distributing the IPO shares, we assume that good/prestigious underwriters use signalling when they are taking part in an IPO (Loughran & Ritter, 2004).

Carter & Manaster (1990) earlier showed evidence that the signal of a prestigious underwriter gives the investors less incentive to acquire information that therefore reduces the information asymmetry among the pool of investors. Following their analysis, they connect high underwriter reputation with lower IPO (first-day) returns.

As we can see in Figure 11, the percentage of top underwriter covering US technology IPOs increased during our observed time period. This follows the argumentation of Loughran & Ritter (2004) that the issuers started putting more importance on the underwriter reputation and therefore the expected analyst coverage.

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[13] Throughout this paper, the wording in our hypotheses "positive relationship to excess IPO returns" indicates that if the independent variable increases the dependent variable also increases and vice versa.

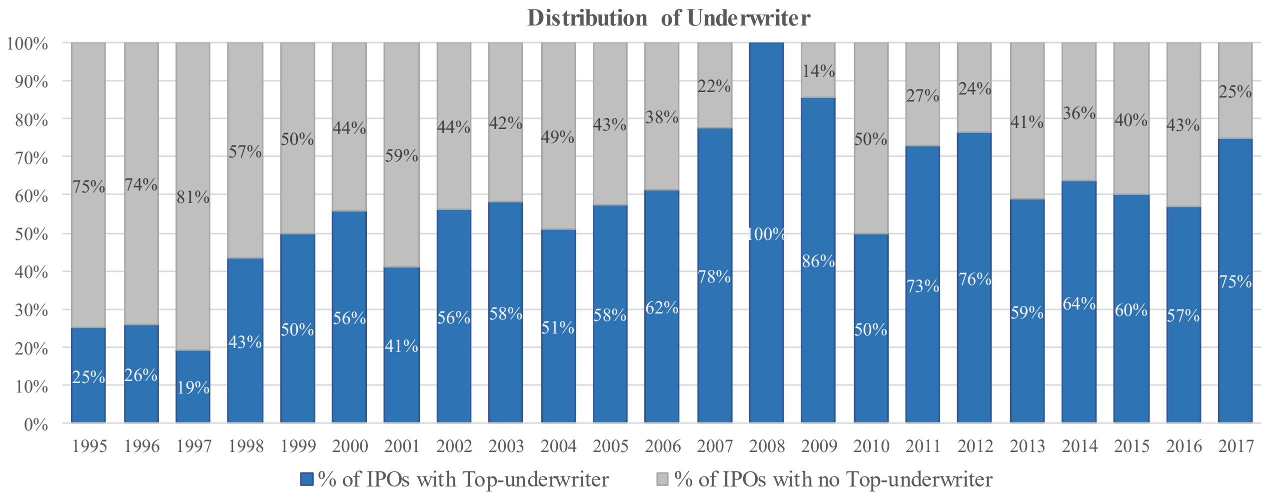


Figure 11: Distribution of Top-underwriter per year (1995-2017)
(Source: Thomson One New Issue Database; Loughran & Ritter, 2004)

In the research universe, there are opposing perspectives about the influence of a good/prestigious underwriter on the level of underpricing. Following the information asymmetry theory, we want to analyse if the technology environment gives room for the underwriter to influence this uncertainty. We therefore use a dummy variable that has the value of 1 if one of the in the prospectus mentioned underwriter is listed under the top underwriters that are characterized with a top score of 9.0 following the list of Loughran & Ritter (2004) (see Appendix 1). If, however, none of the underwriters is in the list of top underwriters, we allocate a value of 0. Following our argumentation, we assume that a good/prestigious underwriter/underwriter syndicate will reduce the information asymmetry concerning Rock's Winner's curse (1986).
We therefore follow up with the following hypothesis:

Hypothesis 3: There is a negative relationship between underwriter reputation and first-day excess IPO returns.

Venture Capital backing

In this hypothesis we want to investigate the link between venture capital (VC) backing and underpricing of an IPO more precisely. The results are especially interesting for us with regard to our tech IPO data set at hand since VC backed companies are frequently based on innovative business models and therefore often operate within the tech industry. This is confirmed by Carleton (1986) who recorded that VC is particularly invested into young and small firms which are built upon technological innovations. Furthermore, over the last decade, venture capitalists manifested their role as a financial intermediary for financing young tech companies.

Generally, this hypothesis is based on the fundamental winner's curse theory stating that greater ex-ante uncertainty (information asymmetry) leads to higher expected underpricing and vice versa (Beatty & Ritter, 1986). Following this line of argumentation, Megginson & Weiss (1991) suggested that venture capitalists fulfil a certification role by confirming the real quality of a company and therefore reduce information asymmetry between investors and the issuing company at the IPO. This role is assigned to venture capitalists as they are performing detailed company analyses (e.g. due diligence) before making the decision to invest funds into a specific company (Kaplan & Strömberg, 2004). Fundamentally, we are following this reasoning and propose that in our dataset at hand, VC backed IPOs are subject to lower underpricing compared to non-VC backed IPOs. For the testing, we are implementing a dummy-variable which indicates 1 if the IPO is backed by VC and 0 if the IPO is not backed by VC.

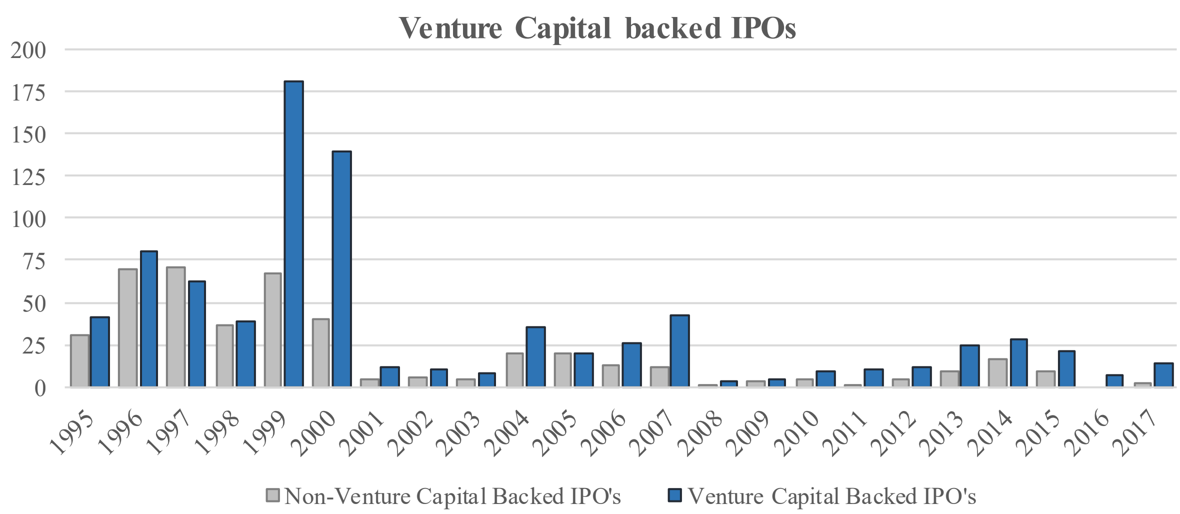


Figure 12: Number of VC / Non-VC backed IPOs per year (1995-2017)

(Source: Thomson One New Issue Database)

This testing is highly relevant when looking into our data set at hand as we can see in Figure 12 an extreme increase of VC backed IPOs compared to Non-VC backed IPOs during the dotcom bubble. Whereas in 1996, 1997 and 1998 VC and Non-VC backed IPOs approximately equally distributed, in 1999, 2000, and 2001 VC backed IPOs already account for ca. 75% of all IPOs.

In line with the argumentation above that venture capital backing fulfils a certification role, we are testing the following hypothesis:

Hypothesis 4: There is a negative relationship between venture capital backing and first-day excess IPO returns.

4.2.2 Information revelation

The second theory concerning information asymmetry is about the relationship between the underwriter and the investors that arises during the bookbuilding process prior to the IPO. In this phase, the investors reveal how many shares they are (potentially) willing to purchase for a stated price. This price is only preliminary and will be set later within the real prospectus. As mentioned in the literature review, there are incentives for investors to not reveal their true intent about how many shares they really want to buy due to a possible moral hazard problem.

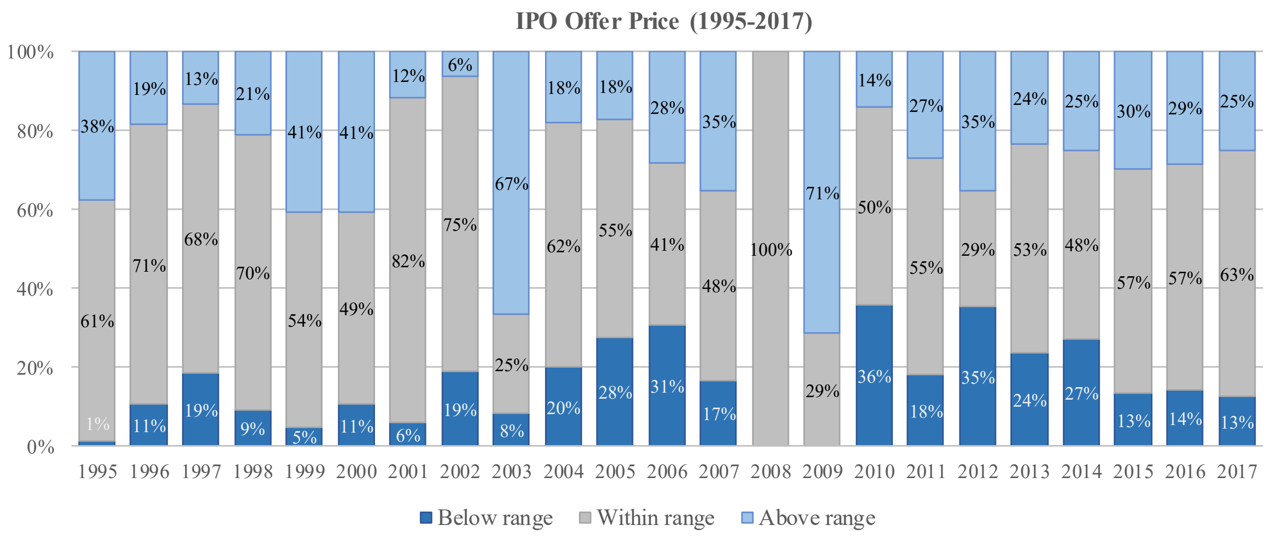


Figure 13: IPO offer price revisions per year (1995-2017)

(Source: Thomson One New Issue Database)

Our data shows (Figure 13) that except for the years 2003 and 2009 (where most offering prices where above the initial range), most final offering prices are within the preliminary price range that is stated in the prospectus. Additionally, we observe that the price is more likely to be set above than below the range. One would assume, that if the demand of the shares is exceeding the supply for a specific price during bookbuilding, the final offer price will be positively adjusted until the demand

matches the supply. In order to test the information revelation theory, we use two seperate dummy variables that will be 1 if the final offering price is outside of the initial range stated in the preliminary prospectus. In other words, the first dummy indicates 1 for price revisions above the range and respectively the second dummy indicates 1 for price revisions below the range.
We therefore follow up with the following hypotheses:

Hypothesis 5a: There is a positive relationship between price revisions above the initial range and first-day excess IPO returns.
Hypothesis 5b: There is a negative relationship between price revisions below the initial range and first-day excess IPO returns.

4.3 Behavioural theory hypotheses

As explained in the literature review, behavioural theories for explaining the underpricing are relatively young, but gained relevance during and after the dotcom bubble as rational theories failed to explain the extreme fluctuations during that time. In the following, we are explicitly testing the influence of behavioural theory on excess returns via investor sentiment and hot/cold issue markets.

4.3.1 Investor sentiment

In this hypothesis we want to investigate the relationship between investor sentiment and the level of IPO underpricing for tech companies. Specifically, we are testing if higher investor sentiment leads to a higher level of excess returns in our dataset at hand.

Consumer Sentiment Index (CSI) and CBOE Volatility Index (VIX)

In general, we base our hypothesis on the investor sentiment theory stated by Ljungqvist et al.'s (2006). They suggest that issuing firms have to sell their new issued shares to institutional investors at a discount in order to compensate them for the risk of a market downturn before reselling the shares gradually to sentiment investors. Accordingly, they propose that during periods with high sentiment, underpricing is more severe. Hrnjic & Sankaraguruswamy (2010) tested the influence of market-wide investor sentiment on IPO underpricing by using the Index of Consumer Sentiment and the Index of Consumer Confidence as proxies, which were both conducted by the University of Michigan and Confidence Board. For the testing of the sentiment theory in our paper, we are basically building upon the framework of Hrnjic & Sankaraguruswamy (2010). As explained in section 2.3.2, behavioural theories that try to explain underpricing are still in its early stages and therefore no universally accepted testing method is set.

For measuring market-wide investor sentiment we are using two proxies: The University of Michigan Consumer Sentiment Index (CSI) as a direct measure of sentiment, and the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) as an indirect measure of sentiment.

The CSI is reported on a monthly basis and defined as direct measure of sentiment since it is based on direct investor surveys about the outlook of the US economy. Survey proxies are classified as a precise indicator of investor sentiment since they are directly linked to the market expectations of investors (University of Michigan, 2018).

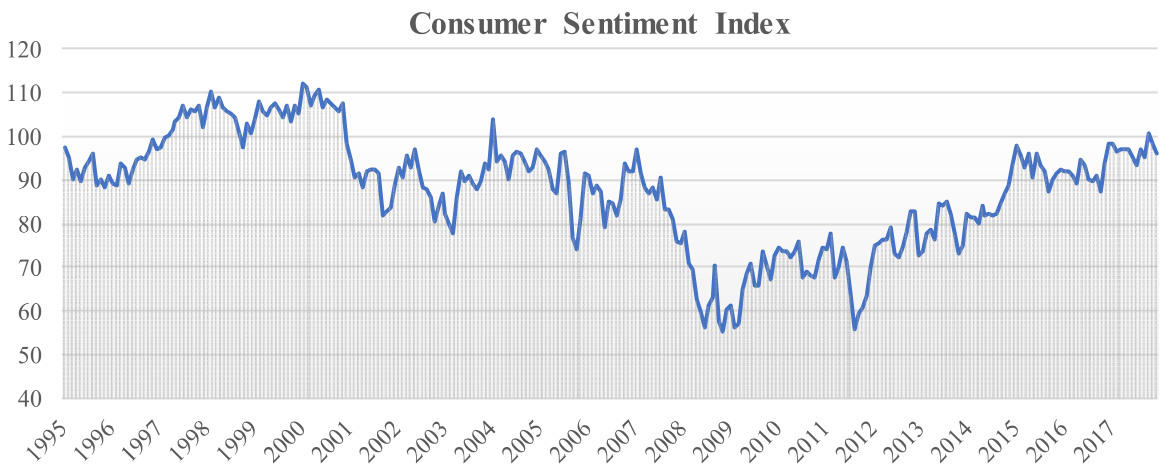


Figure 14: University of Michigan Consumer Sentiment Index (1995-2017)

(Source: University of Michigan, 2018)

As could be seen from Figure 14, the highest level of the CSI in the last 20 years can be detected during the dotcom bubble period, followed by a downturn after the bubble burst. Further severe downturns can be identified in the post-bubble period, more specifically after the financial crisis in 2007-2008 and in 2011-2012. Nevertheless, since then it raised again and reached a pre-crisis level in 2015.

In addition to the direct measure, we also test an indirect measure of sentiment, the CBOE VIX. An indirect measure is derived from existing market movements and therefore frequently reported on an ongoing basis. The VIX is often referred to as “fear gauge" by practitioners and measures the implied volatility of S&P 500 index option prices (CBOE, 2018). Using the VIX as a proxy for measuring investor sentiment is appropriate corresponding to Baker & Wurgler (2007).

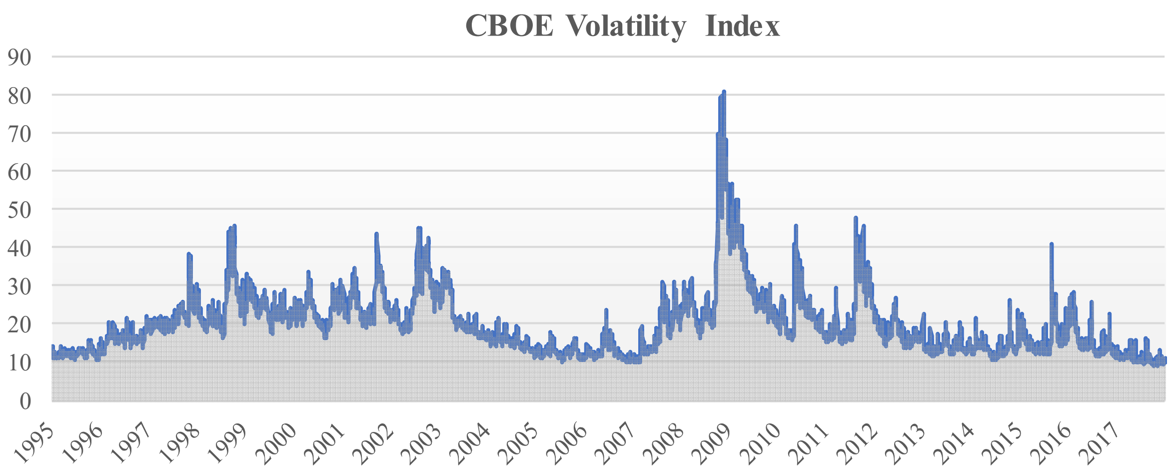


Figure 15: CBOE Volatility Index (1995-2017)

(Source: Datastream)

As depicted in Figure 15, the VIX strongly fluctuates over time and is characterized by an extreme peak in 2009 after the financial crisis. It is worth noting, that this peak exhibits almost twice as high numbers of the VIX in comparison to the dotcom bubble period.
Based on the considerations above, we propose the following hypotheses:

Hypothesis 6: There is a positive relationship between the CSI and first-day excess IPO returns.

Hypothesis 7: There is a positive relationship between the VIX and first-day excess IPO returns.

4.3.2 Hot/Cold issue markets

Another behavioural explanation for IPO underpricing is the theory about hot/cold issue markets. In general, the underlying considerations are in line with the investor sentiment theory stated by Ljungqvist et al. (2006). According to Ibbotson & Jaffe (1975), hot issue market theory is based on irrational investors. Issuers therefore are exploiting the too optimistic beliefs from these investors by executing IPOs during periods with high sentiment. Thus, this results in a higher level of underpricing during hot markets.

IPO activity

Referring to this, our paper tests if IPOs issued in hot markets (periods with high IPO activity) are subject to more severe levels of excess returns compared to cold markets (periods with low IPO

activity). Our data set at hand includes the dotcom bubble period which is often labelled as one of the most irrational periods in the US market. Therefore, the findings of this hypothesis are of special interest with regards to the comparison of dotcom bubble and after dotcom bubble period results.
A crucial factor for the testing of this hypothesis is how to define an appropriate proxy for the level of heat in a specific market. We define the level of heat in the market based upon the number of IPOs previously conducted during the last 180 days in our dataset at hand.

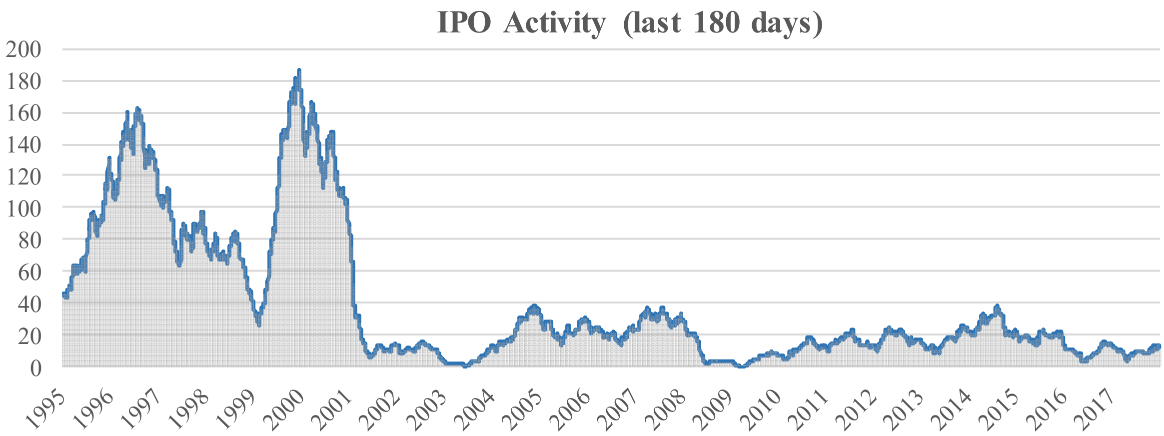


Figure 16: IPO activity last 180 days (1995-2017)

(Source: Thomson One New Issue Database)

As can be seen from Figure 16, the overall IPO activity of the last 180 days is extremely high in the bubble compared to the post-bubble period. On the one hand, we can detect two extreme spikes during the bubble period in 1996-1997 and in 2000-2001 with peaks of more than 160 IPOs conducted in the recent 180 days. On the other hand, the post-bubble period is characterized by a continuing low level of IPO activity which is at no time higher than 45 IPOs. The only thing striking is a downturn after the financial crisis of 2007-2008.
Based on the considerations above, we propose the following hypothesis:

Hypothesis 8: There is a positive relationship between number of IPOs previously executed in the market and first-day excess IPO returns.

4.4 Ownership and control theory hypothesis

As explained in section 2.3.4, the ownership and control theory is based on the assumption that the allocation of shares has an impact on first-day returns. Whereas Stoughton & Zechner (1998) assert that concentrated ownership is preferred after the issue, Brennan & Franks (1997) argue that a diffused ownership reduces the influence of large blockholders which thereby reduces the risk of hostile takeovers.

4.4.1 Retained control theory

In line with retained control theory and reduced agency cost theory, we want to test in this hypothesis if the ownership structure has an influence on excess IPO returns. Therefore, we are using the ratio of the shares offered in the market via IPO relative to the total number of shares outstanding (defined as the floating rate) as a proxy for testing ownership and control theory:

$$Floating\ Rate = \frac{Number\ of\ Shares\ offered}{Total\ Number\ of\ Shares\ Outstanding\ after\ the\ Offering}$$

Formula 6: Calculation proxy floating rate

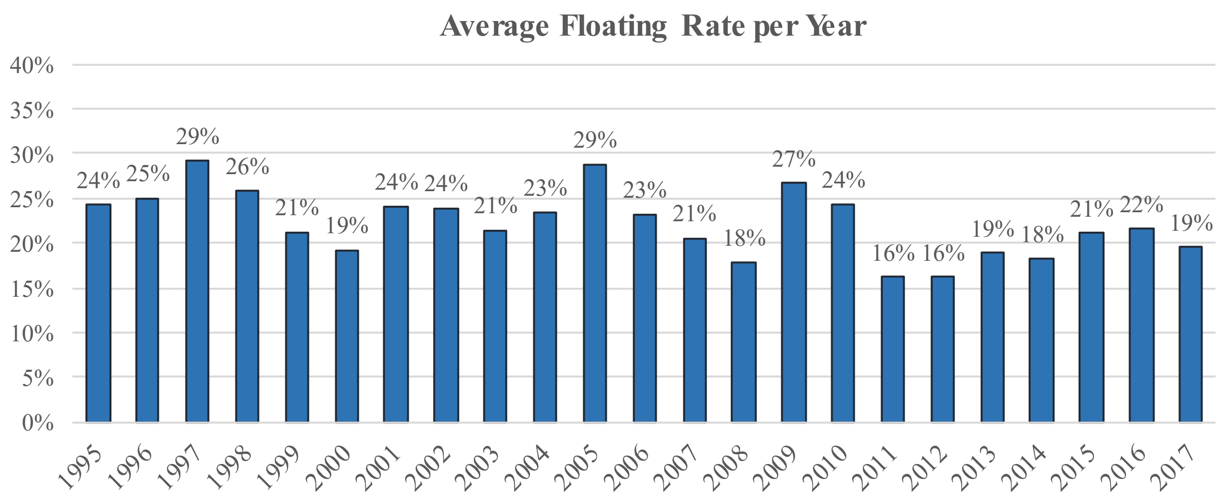


Figure 17: Average floating rate per year (1995-2017)

(Source: Thomson One New Issue Database)

More specifically, we want to analyse whether there is a positive relationship between the percentage of shares floated in the market and the level of excess returns in our dataset at hand. By testing this, we indirectly contribute to the studies of Brennan & Franks (1997) as we use their theory as a starting point. They argue that initial owners use underpricing to induce a widespread share ownership which, in turn prevents hostile takeovers. We assume, that if a firm floats a larger proportion in the market, initial shareholders have to force underpricing even stronger in order to induce a dispersed ownership structure and thereby reduce the risk of a hostile takeover. Inversely, if an issuing firm only floats a small proportion of its outstanding shares in the market it is exposed to a lower risk of hostile takeovers since potential acquirer are not able not to purchase a large enough stake in the market for controlling the firm. Following this line of argumentation, we propose, that a low floating rate requires a lower level of underpricing.

Our dataset shows (Figure 17), the average floating rate per year fluctuates over time. It seems that the ups and downs follow a kind of regular cycle. Further, a tendency for a lower floating rate can be observed in the post-bubble period after the year 2010.

Accordingly, we propose:

Hypothesis 9: There is a positive relationship of the floating rate and first-day excess IPO returns.

4.5 Overview of hypotheses

Based on our hypothesis development, we will test the following relationships on first-day excess IPO returns:

Nr.	Theory	Sub-Theory	Proxy used	Expected relationship
1	Asymmetric Information	Winner's Curse	Company Age	Negative
2	Asymmetric Information	Winner's Curse	Market Capitalization	Positive
3	Asymmetric Information	Winner's Curse	Underwriter Reputation	Negative
4	Asymmetric Information	Winner's Curse	Venture Capital backing	Negative
5a	Asymmetric Information	Partial Adjustment	Upward price revision	Positive
5b	Asymmetric Information	Partial Adjustment	Downward price revision	Negative
6	Behavioural Theory	Investor Sentiment	Investor sentiment index	Positive
7	Behavioural Theory	Investor Sentiment	CBOE Volatility index	Positive
8	Behavioural Theory	Hot/Cold Issue Markets	IPO activity	Positive
9	Ownership & Control Theory	Retained Control	Floating rate	Positive

Table 4: Hypotheses overview

(Source: own contribution)

5. Analysis & Results

While the previous section outlined the development of our 10 hypotheses, this chapter presents the results of testing these. First, we are showing the results of our testing for the preliminary hypothesis of excess returns. Second, the outputs of our three multiple regression analyses (total period, bubble period, post-bubble period) are illustrated. Subsequently, we are shortly determining the overall goodness-of-fit of these models and summarize the results for our individual β-coefficient estimates. Third, we test the overall assessment of the econometric accuracy of our models before checking the robustness of our model estimates.

5.1 Testing of the preliminary hypothesis of excess returns

Following the first-day return (Formula 1), the return of the NASDAQ100 during the first trading days of the observed IPOs (Formula 2) and excess returns (Formula 3), we get the following descriptive statistics:

Time period	Variable	Obs.	Mean	Std. Dev.	Min	Max
Total	First-day return	1,276	0,4272	0,7200	-0,4615	6,2667
	NASDAQ100 return (at IPO date)	1,276	0,0009	0,0185	-0,0739	0,0695
	Excess return	1,276	0,4262	0,7190	-0,4771	6,2656
Bubble	First-day return	859	0,5461	0,8316	-0,4615	6,2667
	NASDAQ100 return (at IPO date)	859	0,0014	0,0209	-0,0739	0,0695
	Excess return	859	0,5447	0,8306	-0,4771	6,2656
Post-bubble	First-day return	417	0,1821	0,2703	-0,3010	2,1700
	NASDAQ100 return (at IPO date)	417	0,0000	0,0123	-0,0670	0,0653
	Excess return	417	0,1821	0,2693	-0,2969	2,1658

Table 5: Descriptive statistics of first-day return, NASDAQ100 return and excess returns

(Source: own contribution)

Table 5 shows that all of our three observed time periods have positive means of first-day returns, NASDAQ100 returns (at the IPO offering date), and excess returns. Following our previous argumentation for excess returns, the means of IPO first-day and excess returns are higher in the bubble period than in the post-bubble period (mean first-day return of 55% in bubble vs. 18% in the post-bubble, excess returns of 54% in bubble vs. 18% in post-bubble). Looking at the index returns, we can see a tremendously lower level compared to the first-day IPO returns. In all of the three periods average NASDAQ100 returns (at IPO date) are less than 0.2%.

To test the relationship of our chosen proxies on excess returns, we first need to prove that excess returns are present in our chosen dataset. We will therefore use the Student's t-test and the Wilcoxon signed-rank test in the following section.

5.1.1 Student's t-test

In order to test our preliminary hypothesis, we are comparing our sample means of the first-day returns with the returns of the NASDAQ100 index for the same time. This is done with a Student's t-test, which assumes normal distribution of returns and equal variances for the unknown population. Using the Student's t-statistic in STATA we get the following results for our three time periods:

Time period	**H0: mean FDR - mean NASDAQ = 0**	**HA: diff != 0**	**HA: diff > 0**
	t-value	**Pr(|T| > |t|)**	**Pr(T > t)**
Total	21.1394	0.0000	0.0000
Bubble	19.1918	0.0000	0.0000
Post-bubble	13.7460	0.0000	0.0000

Table 6: Results of two-sample t-test with equal variances

(Source: own contribution)

As we can see in the Table 6 (full results in Appendix 2), the calculated t-statistics in the total period with 21.1394, in the bubble period with 19.1918, and in the post-bubble period with 13.7460 are higher than the respective critical t-values with a significance level of 1% and more than 100 degrees of freedom (critical value 2.326). Hence, for all observed time periods the t-statistics suggest rejecting the null hypothesis that the means are the same for the first-day return and the index at the 1% significance level. Moreover, the test shows us that there is a significant difference between first-day returns and the index returns that suggests that the mean first-day return is greater than the mean index movements at the IPO date (at any level greater than 0.00%). This leads us to accept the alternative hypothesis that the difference between the means of the first-day returns and the mean of the returns of the NASDAQ100 is positive.

5.1.2 Wilcoxon signed-rank test

As an alternative, we use the Wilcoxon signed-rank test (Wilcoxon, 1945) to test the equality of the matched pairs of observations to the null hypothesis that both distributions (First-day return and NASDAQ 100) are the same.

Time Period	H0: First-day return = NASDAQ 100 return	
	z-value	Probability to accept H0:
Total	25.986	0.0000
Bubble	24.445	0.0000
Post-bubble	12.855	0.0000

Table 7: Results of Wilcoxon signed-rank test

(Source: own contribution)

Following our results (see Table 7, full results in Appendix 3) the probabilities to accept the null hypothesis are for all three tested time periods is 0.00%. This alternative test therefore confirmed our finding that the first-day returns are significant different from the market index returns (here the NASDAQ100 at IPO offering date).

The testing has demonstrated that the level of excess returns clearly fluctuates within the three different time periods. Whereas the sample mean of the bubble period shows severe levels of 54.47%, the sample mean of post-bubble period exhibits relatively lower returns of 18.21%. These findings indicate a shift of the US tech IPO market after the burst of the dotcom bubble in 2000. Further, the finding of significant excess returns will serve as the basis for testing our following hypotheses for explaining the reasons underlying the excess returns of IPO stocks in the technology sector.

5.2 Testing of our hypotheses via multiple regression analysis

As explained in chapter 3. "Methodology & Data", we are conducting a multiple regression analysis for the statistical testing of our hypotheses. Generally, a multiple regression analysis is identified by one dependent variable and two or more independent variables. We just confirmed the existence of excess returns, that will represent our dependent variable. In our model we analyse the influence of our 10 independent variables on excess returns: (1) ln(1+age), (2) ln(Market Cap), (3) top underwriter dummy variable, (4) VC backing dummy variable, (5) Upward revision dummy variable, (6) Downward revision dummy variable, (7) University of Michigan CSI, (8) CBOE VIX, (9) IPO activity (number of IPOs previously conducted in the last 180 days), (10) Floating rate.

Technically, the testing of our hypotheses for each variable is based on a two-sided hypothesis testing. This means, the null hypothesis states that the individual coefficients are equal to zero. If we can reject a null hypothesis and thereby accept the alternative hypothesis, we can infer that the respective coefficient is statistically different from zero. Table 8 below summarizes the testing of our hypotheses.

Nr.	Theory	Proxy	Null hypothesis H_0	Alternative hypothesis H_1	Expectation
1	Winner's Curse	Ln (1+Age)	H_0: $\beta_1 = 0$	H_1: $\beta_1 \neq 0$	$\beta_1 < 0$
2	Winner's Curse	Ln (Market Cap)	H_0: $\beta_2 = 0$	H_1: $\beta_2 \neq 0$	$\beta_2 > 0$
3	Winner's Curse	Underwriter Reputation	H_0: $\beta_3 = 0$	H_1: $\beta_3 \neq 0$	$\beta_3 < 0$
4	Winner's Curse	Venture Capital backing	H_0: $\beta_4 = 0$	H_1: $\beta_4 \neq 0$	$\beta_4 < 0$
5a	Partial Adjustment	Upward price revision	H_0: $\beta_5 = 0$	H_1: $\beta_5 \neq 0$	$\beta_5 > 0$
5b	Partial Adjustment	Downward price revision	H_0: $\beta_6 = 0$	H_1: $\beta_6 \neq 0$	$\beta_6 < 0$
6	Investor Sentiment	Investor sentiment index	H_0: $\beta_7 = 0$	H_1: $\beta_7 \neq 0$	$\beta_7 > 0$
7	Investor Sentiment	Volatility index	H_0: $\beta_8 = 0$	H_1: $\beta_8 \neq 0$	$\beta_8 > 0$
8	Hot/Cold Issue Markets	Number of IPOs (last 180 days)	H_0: $\beta_9 = 0$	H_1: $\beta_9 \neq 0$	$\beta_9 > 0$
9	Retained Control	Floating rate	H_0: $\beta_{10} = 0$	H_1: $\beta_{10} \neq 0$	$\beta_{10} > 0$

Table 8: Technical testing of hypotheses

(Source: own contribution)

5.2.1 OLS

Before being able to test our hypotheses, we first have to estimate our regression coefficients. For this estimation of the coefficients of our multiple regression model, we are using the so-called Ordinary Least Squares (OLS) method. More precisely, it is estimating the regression coefficients by minimizing the sum of the squared residuals from our data at hand. The OLS has become one of the most accepted methods for estimating a regression equation (Studenmund & Cassidy, 2014).

This results in the following OLS model:

$$Excess\ Returns = \beta_0 + \beta_1 * \ln(1 + Age) + \beta_2 * \ln(Market\ Cap) + \beta_3 * Top\ Underwriter + \beta_4 * VC + \beta_5 * UpRev + + \beta_6 * DownRev + + \beta_7 * CSI + + \beta_8 * VIX + + \beta_9 * IPOactivity + \beta_{10} * Floating + u_i$$

Formula 7: OLS of our tested model

However, it should be noted that for an accurate testing and interpretation of these β coefficients estimates, a number of underlying assumptions have to be fulfilled which will be examined in detail in section 5.3 “Econometric issues”.

5.2.2 Regression results

Performing the multiple regression analysis for our dataset at hand via the statistical software STATA yields the following output table for the three different periods:

Time period	Total	Bubble	Post-Bubble
Model	**Initial**	**Initial**	**Initial**
Ln(1+Age)	-0.0582**	-0.0642*	0.0058
	(0.0242)	(0.0330)	(0.0183)
Ln(MarketCap)	0.0639***	0.0911***	-0.0069
	(0.0206)	(0.0336)	(0.0130)
TopUnderwriter	0.1275***	0.1769***	0.0323
	(0.0398)	(0.0564)	(0.0274)
VC	0.1165***	0.1457***	0.0270
	(0.0373)	(0.0527)	(0.0263)
UpRev	0.4325***	0.5088***	0.2231***
	(0.0414)	(0.0584)	(0.0289)
DownRev	-0.1608***	-0.2866***	-0.0953***
	(0.0536)	(0.0880)	(0.0302)
CSI	0.0098***	0.0138**	-0.0008
	(0.0022)	(0.0056)	(0.0015)
VIX	0.0104***	0.0077	-0.0025
	(0.0037)	(0.0076)	(0.0026)
IPOactivity180	0.0019***	0.0017**	-0.0006
	(0.0004)	(0.0007)	(0.0014)
Floating	-0.0556	0.1279	-0.4140***
	(0.1536)	(0.2193)	(0.1120)
Constant	-2.2362***	-3.1674***	0.4415
	(0.4649)	(0.7309)	(0.3112)
Observations	1,276	859	417
R-squared	0.2734	0.2640	0.2683
Standard errors in parentheses			
***** p<0.01, ** p<0.05, * p<0.1**			

Table 9: Regression results of our initial model

(Source: own contribution)

Before analysing the individual β coefficients of our outputs in detail (see Table 9, full regression results in Appendix 4-6), we first want to assess the overall goodness-of-fit of our three regression models estimated of the OLS method (the R^2).

In the total period, the R^2 of the regression equals 0.2734 and the adjusted R^2 0.2677. Generally speaking, the R^2 is a very common measure to evaluate the goodness of fit of a model and indicates to which extent observed outcomes are reproduced by our model (Studenmund & Cassidy, 2014). In addition, we are consulting the adjusted R^2 which is modifying the R^2 measure by the number of independent variables integrated into the model (degrees of freedom). Looking into the R^2 of our total period, this means that 27.34% of the variance of the excess returns can be explained by the variance of our model, whereas 72.66% remain unexplained by our model. The R^2 (0.2640) and adjusted R^2 (0.2553) in the bubble period as well as the R^2 (0.2683) and adjusted R^2 (0.2503) in the post-bubble period are both similar to the level of fit in the total period. Despite the fact that our R^2-values might seem rather low in all three periods, it should be noted that there is no universal hurdle to determine whether a model can be regarded as good or bad. Assessing the goodness of fit heavily depends on the subject that is examined. Moreover, it is important to understand that the R^2 is only one of many existing measures of fit and does not imply anything about the significance of the individual coefficients of our model and whether they are in line with the existing theory (Studenmund & Cassidy, 2014).

In the following, we present the estimation results of our multiple regression analyses for each of the three periods. To ensure the highest level of consistency and understanding, the determination of statistical significance of a coefficient is based on the p-value. In general, the p-value measure is easy to understand as it shows the lowest significance level at which the individual null hypothesis can be rejected (Studenmund & Cassidy, 2014).

Before examining the results of the regression analysis, it should be noted that as we are testing via multiple regression analysis, the interpretation of the individual coefficients happens partially. In other words, a partial regression coefficient indicates the relationship between a certain independent variable and the dependent variable under the condition that all other independent variables of our model are held constant (Studenmund & Cassidy, 2014; Wooldridge, 2015).

β_0: Intercept

The constant term of a linear regression β_0 (intercept) constitutes the expected value of the dependent variable when all of the independent variables are equal to zero (Studenmund & Cassidy, 2014). However, in our model such kind of interpretation of the β_0 coefficient is not appropriate because for some of our variables a value of zero is inapplicable. Particularly, for the variables floating rate and ln (market cap)/market capitalization a value of zero makes no sense. As a consequence, the value of the intercept as well as its statistical significance is of no special interest for our analysis and the interpretation part.

β_1: Age of the issuer at IPO (Ln(1+Age))

As expected in our hypothesis development, over the total period and the bubble period the variable ln (1+age) has a negative β_1 coefficient with values of -0.0582 and -0.0642, respectively. While the β_1 coefficient in the total period with a p-value of 0.016 is statistically significant on the 5% level, the one of the bubble period with a p-value of 0.052 is statistically significant on the 10% level. However, when examining the post-bubble period, we can see that the sign of the coefficient (0.0058) is now positive and moreover lost its statistical significance due to a high p-value of 0.753.

β_2: Market Capitalization of the issuer at IPO (Ln(Market Cap))

Whereas the variable ln (Market Cap) has a positive coefficient in the total period (0.0639) and the bubble period (0.0911), in the post-bubble period (-0.0069) the sign of the coefficient changed. We can detect a strong statistical significance (1%) of these β_2 estimates in the total period with a p-value of 0.002 and in the bubble period with a p-value of 0.007. However, a p-value of 0.593 of the coefficient in the post-bubble period indicates statistical insignificance. Therefore, we cannot reject the null hypothesis that the coefficient is statistically different from zero in the post-bubble period.

β_3: Underwriter reputation (TopUnderwriter)

Contradicting our theoretical based expectation of a negative sign, the underwriter reputation parameter estimates show positive β_3 coefficients in all three periods (Total period: 0.1275, bubble period: 0.1769, post-bubble period 0.0323). However, only the ones in the total period and bubble period exhibit statistical significance on a 1% level. In the post-bubble period, the parameter is statistically insignificant due to a p-value of 0.240. Therefore, we cannot infer that the parameter is statistically different from zero in the post-bubble period.

β_4: Venture Capital backing (VC)

As for the variable underwriter reputation, the VC backing parameter estimates have positive values in all three periods, although the theory argues for a negative sign. While the parameter estimates in the total period (0.1165) and bubble period (0.1457) are quite sizeable and significant on a 1% level with p-values of 0.002 in the total period and 0.006 in the bubble period, the β_4 of the post-bubble period is statistically insignificant because of a p-value of 0.305.

β_5: Upward price revision (UpRev)

As expected, the Upward revision β_5 coefficients are constantly positive over all three periods and exhibit a relatively strong influence on excess returns with values of 0.4325 in the total period, 0.5088 in bubble period and 0.2231 post-bubble period. Moreover, the estimated coefficients are one of two variables tested that are highly significant on a 1% level in all three periods due to p-values of 0.000. This means, we can reject the null hypotheses, accept the alternative hypotheses and thereby conclude that Upward revision has a positive relationship with excess returns.

β_6: Downward price revision (DownRev)

Downward revision is the second variable that shows a robust significance on a 1% level in all three periods. Thus, we can reject the null hypothesis and accept the alternative hypothesis that there is a negative relationship between downward revisions below the initial range and excess returns. As expected the three estimated β_6 parameters show a negative sign. Despite the impact on excess returns in absolute numbers is lower compared to upward revision, the absolute magnitude of the β_6 coefficients of downward revision with –0.1608 in the total period, -0.2866 in the bubble period and -0.0953 in the post-bubble period are still on a very high level.

β_7: Consumer Sentiment Index (CSI)

The β_7 estimates of the CSI exhibit rather low impact in the total period (0.0098) and in the bubble period (0.0138). Whereas the coefficient estimate of the total period is significant on a 1% level, the estimate of the bubble period is significant on the 5% level. However, due to the rather low magnitude of both β_7 coefficients, the economic importance of this variable remains subject to further discussion. Moreover, when looking at the post-bubble period, the p-value of 0.599 indicates statistically insignificant results of β_7.

β_8: Volatility Index (VIX)

In the total period, the β_8 coefficient of the VIX (0.0104) shows a rather small, but significant impact with a p-value of 0.005. Investigating the bubble period and post-bubble period separately, the coefficients show statistically insignificant results with p-values of 0.312 and 0.343, respectively.

This means, that the null hypothesis cannot be rejected and accordingly we cannot conclude that the regression coefficients of these two periods are statistically different from zero.

β_9: IPO activity (IPOactivity180)

The β_9 coefficients of IPO activity over all three periods (Total period: 0.0019; bubble period: 0.0017; post-bubble period: -0.0006) are quite small in terms of magnitude and therefore question its economic importance. Despite being statistically significant on a 1% level in the total period (p-value: 0.000) and on a 5% level in the bubble period (p-value: 0.013), the β_9 coefficient of IPO activity is statistically insignificant when looking at the post-bubble period with a p-value of 0.661.

β_{10}: Floating rate (Floating)

The floating rate coefficients β_{10} in the total period (-0.0556) and the bubble period (0.1279) exhibit high statistical insignificance due to p-values of 0.718 and 0.560, respectively. Thus, we fail to reject the null hypothesis. While being insignificant in the total and bubble period, it is very interesting to see that the floating rate coefficient is highly statistical significant on a 1% level in the post-bubble period. Apart from that, the estimated β_{10} coefficient is quite sizable with a value of –0.4140. This means if the floating rate increases (decreases) by 1%, the excess returns decrease (increases) by 0.4140% holding all other variables constant.

The following Table 10 summarizes the results from our multiple regression analysis for our three periods and compares it with our expected influence from the hypotheses development to give a quick recap of our assumptions and results:

	Proxy	Fore-cast	β Total	P-value	Signifi-cance	β Bubble	P-value	Signifi-cance	β Post-Bubble	P-value	Signifi-cance
1	Ln(1+Age)	-	-0.5082	0.016	5%	-0.0642	0.052	10%	0.0058	0.753	No
2	Ln(Market Cap)	+	0.0639	0.002	1%	0.0911	0.007	1%	-0.0069	0.593	No
3	TopUnderwriter	-	0.1275	0.001	1%	0.1769	0.002	1%	0.0323	0.240	No
4	VC	-	0.1165	0.002	1%	0.1457	0.006	1%	0.0270	0.305	No
5a	UpRev	+	0.4325	0.000	1%	0.5088	0.000	1%	0.2231	0.000	1%
5b	DownRev	-	-0.1608	0.003	1%	-0.2866	0.001	1%	-0.0953	0.002	1%
6	CSI	+	0.0098	0.000	1%	0.0138	0.014	5%	-0.0008	0.599	No
7	VIX	+	0.0104	0.005	1%	0.0077	0.312	No	-0.0025	0.343	No
8	IPOactivity (180 days)	+	0.0019	0.000	1%	0.0017	0.013	5%	-0.0006	0.661	No
9	Floating	+	-0.0556	0.718	No	0.1279	0.560	No	-0.4140	0.000	1%

Table 10: Summary hypotheses and results of the multiple regression analysis

(Source: own contribution)

5.3 Econometric issues

The reliability of our results from the OLS regression depends highly on its unbiasedness. In order to test if the chosen OLS estimation is the best for our parameters in the dataset, we will test for the classical assumptions I to VII of Studenmund & Cassidy (2014). The first six assumptions are needed to identify our estimators as "BLUE" while the seventh assumption is included for the reliability of the hypothesis testing.

For an estimator to be interpret as BLUE the following can be understand (Gujarati & Porter, 2003):

- **B**est = The estimator has minimum variance in the field of all other linear unbiased estimators
- **L**inear = The estimator has a linear relationship to the dependent variable in the regression model
- **U**nbiased = The estimators expected value is equal to the true value so that: $(E(\beta_2) = \beta_2)$, holds
- **E**stimator

The seven Classical Assumptions (Studenmund & Cassidy, 2014) that we will have a closer look are the following (see Table 11):

Nr.	Classical Assumption
I.	The regression model is linear, correctly specified and has an error term
II.	The error term has a zero population mean
III.	All explanatory variables are uncorrelated with the error term
IV.	Observations of the error term are uncorrelated with each other (no serial correlation)
V.	The error term has a constant variance
VI.	No explanatory variable is a perfect linear function of any other (no perfect multicollinearity)
VII.	The error term is normally distributed

Table 11: Seven classical assumptions

(Source: Studenmund & Cassidy (2014))

It should be noted, that this paper is categorized as a financial thesis. Therefore, econometric assumptions are tested to see if our results are exposed to any violations. Accordingly, we will not explain or discuss these tests in detail.

I. The regression model is linear, correctly specified and has an error term

First, the tested model must be specified with a linear function of the independent variables $(x_1, x_2, x_3, \dots, x_k)$, an unobservable error term (u) and their influence on the dependent variable (y) in the form of:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k + u$$

Formula 8: Example of a model equation

For the model, a transformation like the logarithm transformation of the independent variables Market Capitalization or Company Age is no problem since it can still be described in the model with a linear β. Second, the model should be correctly specified, this assumes that there are no omitted variables or incorrect forms of the variables. Third, the model must also include an unobserved error term (u) that cannot be replaced by any of the other variables in the equation.

Following our model that is shown in Formula 7, we match the condition of specifying a linear model with an added error term. According to our hypothesis development in chapter 4, we use proxies for our test on the influence on excess returns and grouped them together to test for appropriate theories in the IPO underpricing universe. It may, however, when looking at the R^2 of our tested models (as mentioned in 5.2.2), raise the question for omitted variables since we cannot explain all variance of our sample with the chosen model. We will have a look at the omitted variable issue more closely in the third assumption (III: all explanatory variables are uncorrelated with the error term).

II. The error term has a zero population mean

The added error term (u) that accounts for the variation of the dependent variable (y) that is not explained by any of the independent variables $(x_1, x_2, x_3, \dots, x_k)$ needs to be distributed with a mean of zero throughout the population.

Since we are using a sample of the population, the error term might not be (exactly) equal to zero but with an increasing number of observations, the mean of the error term will come closer to zero (Studenmund & Cassidy, 2014).

To avoid this possible problem, we added a constant term (β_0) to our model which will therefore specify the error term (u) with a mean of zero as long as the other assumptions are met (Studenmund & Cassidy, 2014).

III. All explanatory variables are uncorrelated with the error term

This assumption tells us, that the explanatory variables $(x_1, x_2, x_3, \dots, x_k)$ need to be independent from the error term (u).

If there would be a correlation between the explanatory variables $(x_1, x_2, x_3, \dots, x_k)$ and the error term (u) the OLS program could mistakenly attribute some of the explanatory power of the proxy to the error term which would therefore interfere with the real value of the proxy and the parameter would be tampered. This assumption can be violated if the omitted variables problem is present in the model since the error term (u) will then inherit the influence of the omitted variables on the dependent variable (y). Further, the omitted variable could be correlated with a variable in the model and therefore the error term would be correlated with this explanatory variable in the model, following up in a violation of this assumption.

Due to the scope of this thesis and the model specifications based on the hypothesis development in in chapter 4, we do not test for every possible theory and variable that could affect the excess returns at day one of an IPO. Due to this fact the omitted variable problem can arise and turn the error term into an endogenous variable with explanatory power. Although the stated concerns due to the limitation of our model, when looking at the component-plus-residual plots of all the independent variables $(x_1, x_2, x_3, \dots, x_k)$ there is no observable correlation with the error term (u) present during any of the tested time periods (see Appendix 7-9).

IV. Observations of the error term are uncorrelated with each other

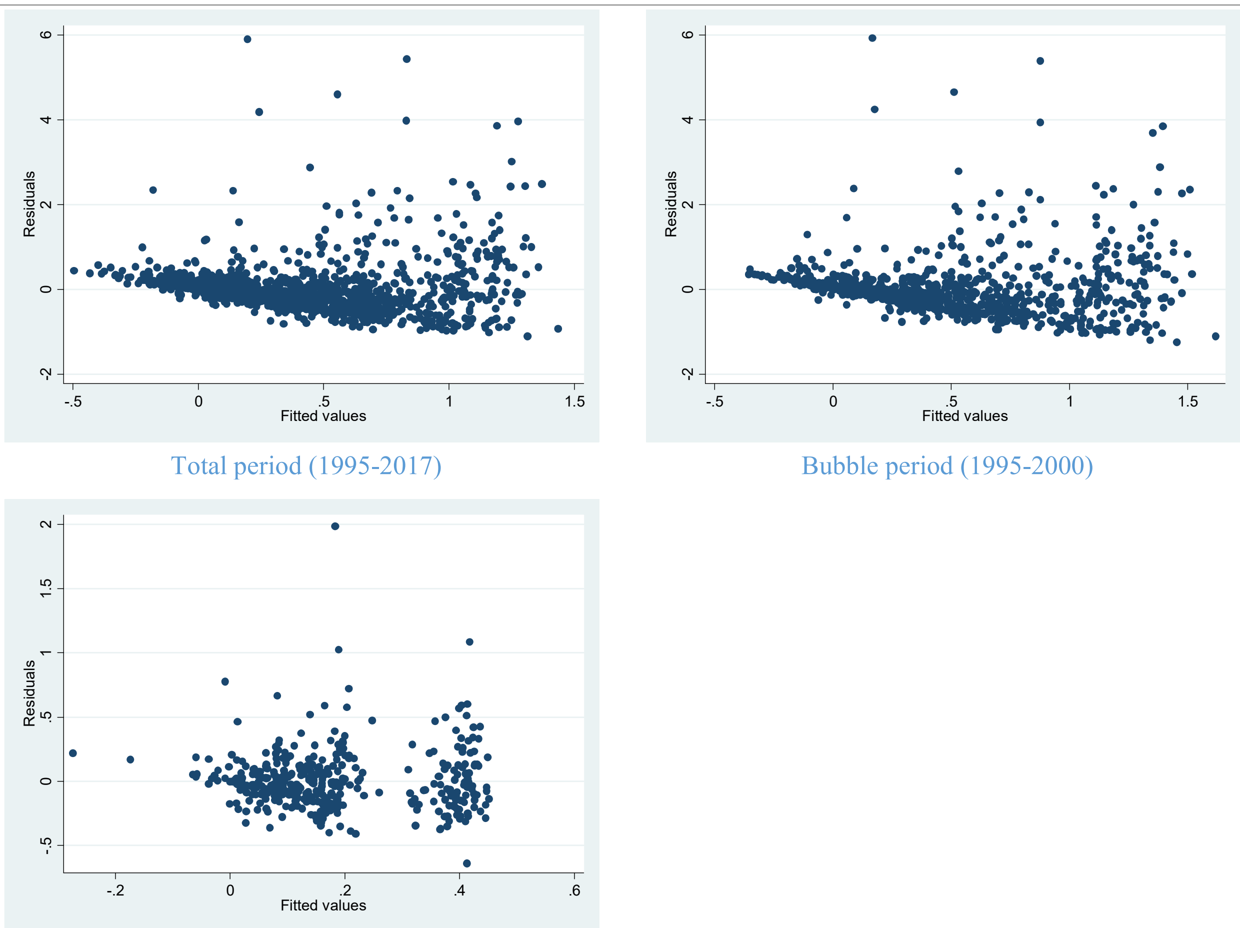
This assumption is especially important when testing time series models since the error term of one observations should not affect the error term of another period. Especially when looking at data with a random shock, multiple observations can show a same effect of the error term since this kind of shock can last for multiple periods.

Since we are using a cross sectional dataset for our specific IPO issues, this assumption is fulfilled.

V. The error term has a constant variance

This assumption means that the variance of the error term (u) is constant across all observations of the dependent variable (y).

We will test this assumption with the postestimation plot of the residual-versus-fitted values for all our tested time periods.



Total period (1995-2017)

Bubble period (1995-2000)

Post-Bubble period (2001-2017)

Figure 18: Residual-versus-fitted plots for the different time periods

(Source: own contribution)

When looking at our results (Figure 18) the plot for the total time-period we can see a negative trend that seems to be expanding with increased values of the fitted variable. That can be interpret as a violation of the homoskedasticity assumption. The same kind of violation is observable in the bubble period whereas the post-bubble period seems to show homoscedastic error terms.
The violation of the homoscedasticity in error terms can lead to inaccurate estimates of the standard errors of the coefficients. To correct for this, we will redo the regression analysis in the robustness test with the assumption of heteroscedasticity in the standard error to calculate unbiased t-values (see section 5.4).

VI. No explanatory variable is a perfect linear function of any other

A perfect (multi-)collinearity between independent variables implies that they are multiples or a simple parallel shift of each other. OLS estimation would therefore not be able to differentiate between the effects of the affected variables. Even though perfect (multi-)collinearity is rather unusual in practice, even imperfect (multi-)collinearity can cause problems within the OLS estimation. To test this assumption, we check the correlation factors and the Variance Inflation Factors.

Correlation factors

Perfect correlation is prevailed if two or more of the independent variables share a factor of 1 or -1. According to Gujarati & Porter (2003) coefficients higher than 0.8 or lower than -0.8 can be an indication for multicollinearity.
According to our model, none of the pairs of variables shares a (absolute) correlation factor of 0.8 or higher (see Appendix 10). The highest correlation factor between the VIX and the CSI during the bubble period shows a correlation of 0.7. This test therefore does not assume any multicollinearity in our tested models.

Variance Inflation Factor (VIF)

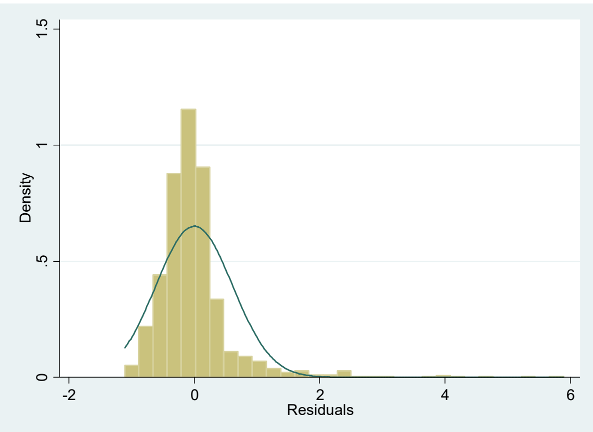
The VIF measures the degree on how the variance of a specific explanatory variable is inflated by other explanatory variables of the model. The lower border of the VIF is 1, whereas there is no upper border. Among researchers, there is no universal VIF that is considered high. Depending on the source the rule of thumb concerning the VIF varies mostly between 5 and 10 (e.g. Hair et al., 1998; Kennedy, 2003; Menard, 1995; Neter, Kutner, Nachtsheim, & Wasserman, 1996).

The VIF in all three of our tested time periods do not exceed a value of 2.37 (Ln(MarketCap) in the bubble period, followed by CSI and VIX which also show the largest correlation factor, see Appendix 11). Additionally, the mean VIF is always close to 1, thus according to the STATA manual (StataCorp, 2013) there is no sign of multicollinearity present in our tested model.

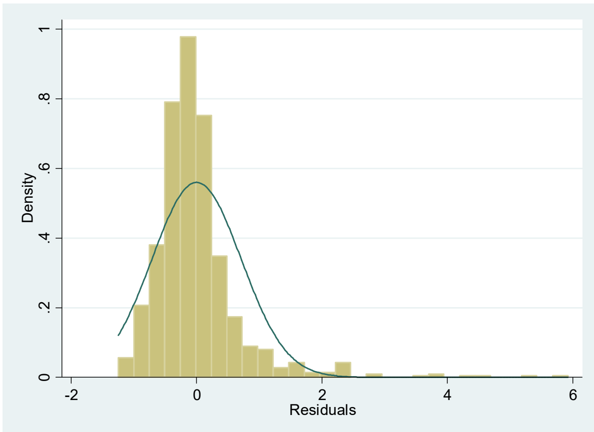
Following both of our tests we can fulfil the assumption that there is no multicollinearity present in our model.

VII. The error term is normally distributed

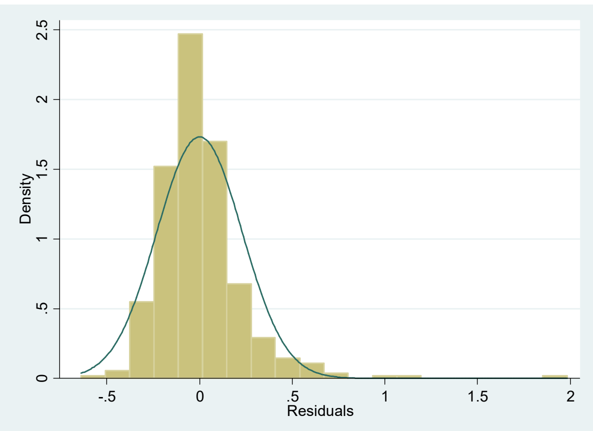
To complete the previous tested assumptions about the error term (II: error term has a mean of zero, IV: error term has nor serial correlation and V: error term has a constant variance) the shape of the residuals is also important. This assumption is included because of its importance for hypothesis testing which we will use for our analysis and discussion.



Total period (1995-2017)



Bubble period (1995-2000)



Post-Bubble period (2001-2017)

Figure 19: Histogram of the residuals for the different period and normal distribution

(Source: own contribution)

To test this assumption, we have a look at the residuals during every of our three observed time periods. Following the first qualitative analysis of the graphical histogram (see Figure 19), the predicted residuals are not completely normally distributed.
In order to use a quantitative analysis, we continue to use the Shapiro-Wilk W test for normality.

Variable	Obs	W	V	z	Prob>z
Residuals All	1,276	0.7422	203.058	13.288	0.00000
Residuals Bubble	859	0.7690	126.847	11.918	0.00000
Residuals Post-bubble	417	0.8550	41.437	8.879	0.00000

Table 12: Results of Shapiro-Wilk W test for normality

(Source: own contribution)

Following the results of the Shapiro-Wilk W test for normality (Table 12), we need to reject the hypothesis, that our error term is normally distributed. Thus, this leads to a violation of the tested assumption (VII). However, as our tests are based on a large data set with significantly more than 100 observations across all time periods (Total period: 1,276; bubble period: 859; post-bubble: 417), the central limit theorem permits to neglect this violation (Gujarati & Porter, 2003; Newbold, Carlson, & Thorne, 2013). This theorem implies, that in sufficiently large samples an estimator is approximately normally distributed (Wooldridge, 2015).

Conclusion of the econometric issue testing

Following the testing of the econometric accuracy of our models, we can conclude that most of the seven classical assumptions are fulfilled. Still, we potentially violate the assumption of homoscedasticity which we will take care of with the correction of heteroscedastic standard errors. The normal distribution of our error term is additionally violated, but of minor importance due to the large number of observations. We will keep these infringements in mind for the discussion of our parameters and hypotheses.

5.4. Robustness test

Following the signs of the violation of the homoscedastic distributed error term assumption (5), we first want to see if our model is incorrectly estimating our parameters. To correct for these biased t-statistics and therefore significance levels, we use a correction for the robust variance calculation, that - following Davidson & MacKinnon (1993) - results in confidence intervals that are more conservative and therefore better when the model faces heteroscedasticity (see Appendix 12 for the results compared to our initial model). As we can see from the estimation results, proxies that showed a significant influence on excess returns are still significant, while non-significant proxies are still considered insignificant. Following this, we will keep the standard model estimation for our analysis. An additional way of checking the robustness of our proxies is the division of the total time period (1995-2017) into our bubble (1995-2000) and post-bubble (2001-2017) period. With this separation, we can find that the proxies that are significant for the total period are also significant for the bubble period (except for the VIX).

The post-bubble period, however, shows non-robust results concerning all variables (except for the price revision proxies) to be insignificant to the 10% significance level. At the same time, the floating rate shows a highly significant (on the 1% significance level) negative influence on excess returns while being not significant in the other time periods.

These results raise the question about some fundamental changes in the IPO environment after the bubble burst in 2000, which we will discuss in more detail in the following chapter.

6. Interpretation & Discussion

In this chapter, we will discuss the results from our analysis in a broader context. In principle, this section is conceptually divided in two parts. The first, discusses the impact of the tested theories based on the proxies selected in our model on excess returns over time. This part is structured along the three superordinate underpricing theories: asymmetric information theories (6.1), behavioural theories (6.2) and ownership and control theories (6.3). The second part, then follows up with a broader discussion about the underlying incentives of the issuer and the underwriter for underpricing an IPO (section 6.4). Here we are also using the not tested theories to present possible explanations of our observations. Thereby, we want to deliver a more conclusive picture by showing how excess returns during and after the dotcom bubble can be explained by tested as well as not tested underpricing theories.

6.1 Interpretation of results of asymmetric information theories testing

This interpretation and discussion section of our results concerning the asymmetric information theories are further divided into the subsections concerning the winner’s curse and the information revelation.

6.1.1 Winner's curse

For testing the influence of the winner's curse theory to explain underpricing, we consulted four different variables: (i) the age of the issuer at IPO, (ii) the market capitalization of the issuer at IPO, (iii) underwriter reputation and (iv) VC backing. We will first discuss our results for each individual variable before finding a concluding remark about the winner's curse (Rock, 1986).

Age of issuer at IPO

Our initial hypothesis of this proxy is that the longer a company is actively doing business, the less uncertainty about the company will be prevalent at the IPO (from an investors view, Ritter, 1991), due to the availability of information (from e.g. prior annual statements, press releases, etc.).

Following our model, the proxy for company age at IPO (ln(1+age)) has a significant negative influence on the excess returns in the total period (to the 5% significance level) and the bubble period (10% significance level). That means that during these periods, the older a company was at the IPO, the less excess return was realized on the first trading day after the IPO following a more appropriate pricing for the offering. Contrary to these periods, during the post-bubble period the age parameter is highly insignificant with a t-statistic of 0.32 and a p-value of 0.753.

One explanation could be the differences in average and median age parameters especially during the bubble and post-bubble period. The age at IPO was increasing after the burst of the internet bubble in 2000 so that our data concerning company age in the post-bubble period is higher (see Figure 9). This gives room to an interpretation that there can be a critical value for this proxy. This means that if a company is older than this critical value, the additional information that is accessible possibly will not reduce the information asymmetry and therefore uncertainty about a company going public, because it is too far related to the past.

Another factor could be that the founding date of a company is too simple to interpret just by their single number. Not only age, but also the (close) relationship to other companies like for instance a more mature parent company can influence the uncertainty that is projected on an IPO issuing company.

In our dataset at hand, we can e.g. find the parent company Thermo Electron Corporation that was founded in 1956 and has four daughter technology companies that went public during our observed time period (see Table 13):

Year of IPO	Issuer	Age at IPO	Price offer	Price closing	First-day return	NASDAQ Index Return at IPO	Excess Return
1998	ONIX Systems Inc	4	14,50	14,50	0,00%	1,42%	-1,42%
1997	Thermo Vision	2	7,50	7,75	3,33%	-1,66%	5,00%
1996	Thermo BioAnalysis	1	14,00	14,00	0,00%	0,71%	-0,71%
1996	Thermo Optek Corp	1	13,50	13,75	1,85%	0,65%	1,20%

Table 13: Key details of daughter companies of Thermo Electron Corporation

(Source: Thomson One New Issue Database)

None of those daughters were founded more than four years prior to their IPO and the excess returns only varied between -1.4% and +5% (first-day returns between 0% and +3,33%). These example IPOs took place during the bubble period that would additionally suggest that there was a high underpricing following the literature (section 2.3.1) and our previous results from testing (section 5.2.2). This seems to support our additional hypothesis that the age of the parent company can also influence the uncertainty and therefore excess returns on the first day of trading, especially when going public via spin-offs and carve-outs.

When looking at an example from the sociodemographic field of research, e.g. age and salary of a person, age shows an inverted u-curve in relation to salary. This would follow to the conclusion that there is a negative effect concerning age and salary above a turning point. Applying the same thinking to company age and excess return at IPO, we tested the influence of an updated proxy (the squared company age proxy, to see if this will lead to different results of our model.

Time Period	**Total**	**Total**	**Bubble**	**Bubble**	**Post-bubble**	**Post-bubble**
Model	**Initial**	**squared age**	**Initial**	**squared age**	**Initial**	**squared age**
Ln(1+Age)	-0.0582**		-0.0642*		0.0058	
	(0.0242)		(0.0330)		(0.0183)	
Ln(1+Age)sq		-0.0163***		-0.0202**		-0.0001
		(0.0057)		(0.0080)		(0.0040)
Note: This table only shows the output of the discussed variables. For the complete table please see Appendix 13.						
Observations	1,276	1,276	859	859	417	417
R-squared	0.2734	0.2748	0.2640	0.2662	0.2683	0.2682
Standard errors in parentheses						
***** p<0.01, ** p<0.05, * p<0.1**						

Table 14: Excerpt comparison initial model and model with squared age proxy

(Source: own contribution)

The overall R^2 of our model increased to a little fraction of about 0.2%-points during the total and bubble period, whereas the explanatory power of the model during the post-bubble period is untouched. The coefficient of the squared age proxy is robust to the original model with a negative influence on excess returns while the significance level increased from 5% to 1% in the total period and from 10% to 5% in the bubble period. The coefficient in the post-bubble period, however, is still insignificant. There is no significant change of the other variables in the model depending on which proxy for company age is used.

Following our discussion, it seems that after the internet bubble company age is no perfect proxy for representing the uncertainty about a company or its business model. In the disruptive environment especially in the technology industry, new players may still get a lot of attention from the media so that it will be possible to gather a lot of relevant information about these companies. More mature companies that decide to go public may also face the fact, that only the very recent past will be reflected for considerations about pricing the IPO so that not every additional business year will lead to less uncertainty. Further, spin-offs and carve-outs from established parent companies can obtain reputational spill-overs which can influence the valuation and therefore reduce the excess returns at the IPO. Last but not least, against the background of a fast-changing environment based on disruptive innovations (digitalization, big data, block chain, artificial intelligence, etc.) new players in the technology sector can emerge and capture a market within short time no matter how long they are already doing business. This can be observed as some important players in the tech market, like for example Facebook, are still pretty young compared to the fact that they are listed within the top 120 of the world's biggest public companies (Forbes, 2018). This leads us to the assumption that the explanatory power of company age is becoming less important for the technology sector in the post-bubble period.

Market Capitalization of the issuer at IPO

For our testing of underpricing theory, we use the proxy market capitalization as a measurement for the size of the IPO issuer. Our initial hypothesis about market capitalization is that due to the special valuation methods for technology companies (as described in section 2.2), the higher the value of this proxy, the larger the uncertainty and therefore the excess return at IPO.

In our analysis, we defined the market capitalization of the issuer with ln(Market Capitalization) in order to get closer to a normal distribution of this variable. In the total as well as in the bubble period, this parameter is considered highly significant with a positive influence on the excess return, whereas the post-bubble period shows no significant effect on the excess return with a t-statistic of -0.53 and a p-value of 0.593.

There are two opposing views among researchers concerning the valuation and therefore market capitalization of IPOs and their relationship to excess returns. Besides our assumption of a positive influence on excess returns (see hypothesis development in section 4.2.1), which our dataset supports for 2 out of 3 tested periods, researchers argue that the larger a company gets valued (in this case in terms of market capitalization) the lower is the possibility of it to fail. Therefore, a large market capitalization will reduce uncertainty which will have a negative influence on excess returns the IPO (Chambers & Dimson, 2009).

Due to our focus on the US technology industry and the valuation dependency of companies in this industry on growth opportunities rather than actual profitability performance (Demers & Lev, 2001; Hand, 2003; Trueman et al., 2000), we find evidence that a large market capitalization leads to increased uncertainty and therefore excess returns.

Additionally, when looking at the Wall Street Journal and Dow Jones VentureSource "Billion Dollar Startup Club" we can find that 115 out of the total 171 venture-capital backed private companies that are valued at $ 1 billion or more can be attributed to the technology industry.[14] This could additionally support the special valuation techniques of technology companies based on future growth opportunities that could therefore be subject to increased risk.

Other researchers test for the size of a company with e.g. sales or profits at the IPO. We decided to stick to the market capitalization as a measure of business activity due to the fact that sales do not allow any conclusion about e.g. profitability. Profits, on the other hand, are heavily dependent on the company life cycle. When looking at the profitability of e.g. Facebook or Amazon at the time of their IPO they did not make any respectable earnings since they focused on growth opportunities (which were transferred into their valuation and therefore market capitalization) and we cannot control for these life cycle characteristics. Furthermore, the mentioned alternatives for size are static financials from a prior time period to the IPO which has therefore low explanatory power about the after-IPO company.

The relationship of company size that we proxied with the market capitalization on excess returns for the IPO is hard to distinguish especially in our post-bubble period. We find evidence that the larger

[14] https://www.wsj.com/graphics/billion-dollar-club/ (accessed 06.04.2018), Industries that were accounted to "technology" are the following: Hardware, Consumer Internet, Software, E-Commerce and Entertainment and Games.

the market capitalization, the higher the risk due to the valuation techniques of the underwriter and therefore excess returns in the past. Following the opposing viewpoint that larger companies (measured by market capitalization) are less likely to get bankrupt, this later found evidence (e.g. Chambers & Dimson, 2009) may offset the explanatory power for our post-bubble period. All this might be an indicator for a changing environment in the post-bubble.

Underwriter Reputation

In our previous analysis, we use the underwriter reputation as a signal to show outside investors that the issuer has a certain quality. Following our line of thoughts, an underwriter with an excellent market reputation would only work for an issuer if they assume that the IPO will be successful. Therefore, we came up with the hypothesis that a high underwriter reputation will reduce information asymmetry of the issuer and the underwriter towards the investors and thus reduce excess returns.

Looking into the results of our model, we can find statistically significant influence on excess returns on the 1% significance level in the total and bubble period. The model, however, shows that a high underwriter reputation has a positive influence on excess returns. The post-bubble period shows no statistical significant parameters for the discussed proxy.

First, we want to discuss the insignificance of this parameter in the post-bubble period. From our dataset, we can conclude that in the post-bubble period, the percentage share of IPOs with one of the top underwriters increased, while the number of IPOs decreased. During the years of the post-bubble period between 60-100% of the IPOs were using the services from top ranked underwriters, whereas in the bubble period only 20-60% were consulting top-underwriters (see Figure 11). Accordingly, we seem to confirm the findings of Loughran & Ritter (2004) that issuers put more importance to underwriter reputation and therefore IPO coverage by e.g. the media after the burst of the dotcom bubble.

Additionally to the increased fraction of issues with a high underwriter reputation, we also see that during the bubble period an issue had on average 1,03 bookrunners (max of 5), while in the post-bubble period an IPO issue had on average 2,08 bookrunners (max of 10) (see Appendix 14). Due to our definition of the dummy proxy top underwriter that will get the value of 1 if one of the underwriters is listed as a top underwriter (according to the Loughran & Ritter (2004) score), the increased number of underwriters per IPO can therefore directly influence our chosen proxy.

To check, if the number of underwriters has an influence on excess returns we exchange the proxy top underwriter with the proxy number of underwriters and see if we can find an additional influence (see regression results in Appendix 15).

Interchanging the number of bookrunners with the top underwriter dummy does not increase the explained variance of the model (R^2), nor does it show significance for any of the tested time periods. Including both variables in the model will lead to a minor increase of R^2 but still, the parameter for number of bookrunners is not significant. All other variables do not significantly change for any of the described model adaptions. Following the slight increase in the average market capitalization per IPO during our observed time frame (see Figure 4), the increase in the number of bookrunners may not decrease the risk per bookrunner. We therefore conclude that the increase in the average number of bookrunners does not have an influence on excess returns.

Second, we want to discuss the positive influence of underwriter reputation on the excess returns. Contrary to our hypothesis that underwriters will reduce the uncertainty about an issue, there seems to be higher excess returns when one of the top underwriter takes part in the issue. This raises the question if top investment banks do exploit their superior knowledge and therefore the existing information asymmetry to reward the institutional investors during the bookbuilding process (we will discuss this repeated game more detailed in section 6.4.2). Additionally, the theory about legal liability that the underwriter can face lawsuits when (over-)pricing an IPO, may prevent especially the well-known investment banks to rather underprice an IPO to increase the chance of positive first-day and excess returns (Ibbotson, 1975; Logue, 1973b).

A more recent study concerning short term IPO returns and the underwriter's centrality and industry expertise shows evidence, that underwriters with higher centrality and large industry knowledge tend to underprice IPOs more (Chuluun, 2015). Following Chuluun's (2015) definition of centrality (e.g. number of interactions with other underwriters, importance of the connected underwriters, etc.), he finds high rankings for the same underwriters that Loughran & Ritter (2004) defined as top underwriter (their definition implies that a high underwriter reputation is based on the underwriting activity). Following the argumentation of the underwriting activity, Boeh & Dunbar (2016) argue that the bookrunner's pipeline of IPOs will give the underwriter market power and therefore has a significant positive influence on first-day returns. This would be also in line with the underwriter reputation ranking calculation based on Loughran & Ritter (2004) that we used. The study of Chua (2014) concludes that top-tier underwriters increase first-day returns in order to decrease the possible long-term underperformance during IPOs (in order to keep a high reputation), while low tier underwriter issues maximize cash flows and therefore try to minimize underpricing.

Following our results, we see higher excess returns when top-tier underwriters are involved in the IPO process especially during the bubble period. Several researchers argue that network properties of top-tier underwriters lead to these increased excess returns rather than our initial hypothesis of reduced uncertainty of signalling when using a prestigious underwriter. There is no clear evidence that a top underwriter has a significant influence on excess returns in the post-bubble period of US technology IPOs.

Venture Capital Backing

Testing the Winner's Curse theory via a VC backing proxy appeared especially interesting to us with regards to our tech data set at hand, since in today's business environment, venture capitalists capture an important role for financing young tech companies. Based on the existing theory (Beatty & Ritter, 1986; Megginson & Weiss, 1991), we expected that VC backing has a negative influence on excess returns. This is because theoretically a venture capitalist who is investing into a specific company fulfils a certification role and thus reduces the information asymmetry between the issuing company and investors about the real quality of a company. However, in our models we detected a positive relationship with excess returns. Whereas the coefficient estimates in the total period and bubble period were statistically significant on the 1% level, the coefficient in the post-bubble period was not statistically significant.

These results raise the question about the rationale behind this inconsistency of the statistical significance between the periods. To answer this question, first we want to look at the number of IPOs that were subject to VC backing. As for all tested variables, the post-bubble period contains only 447 observations which can be a first indicator why we see statistical insignificance of this parameter in the post-bubble period. Moreover, only 131 IPOs of these 447 IPOs in the post-bubble period are non-VC backed which increases the risk that outliers can distort the statistical significance. With a view to the relative distribution between VC and non-VC IPOs over the time, we can see no major differences. In all years, except 1997, the percentage share of VC backed IPOs is bigger than the share of non-VC backed IPOs (see Figure 12). Thus, this gives no indication for the inconsistency between the periods in our model.

From a theoretical perspective, the researchers Gompers & Lerner (1997) already questioned the certification role of venture capitalists. In a perfect experiment setting, we would rather want to know if a specific company exhibits higher excess returns when it is VC backed compared to if the same company would not be VC backed. However, by nature, this impossible to test and therefore we ended up examining the level of excess returns between VC and non-VC backed company IPOs. Thus, we cannot make inferences about the causality of the effect of VC backing on underpricing (Lee & Wahal, 2004). Still, when comparing VC and non-VC backed IPOs, it should be noted that VC backing is not randomly distributed, as venture capitalists actively choose which company they want to support with venture funds. Therefore, a selectivity bias might be prevalent (Gompers & Lerner, 1997). Carleton (1986) stated that venture capitalists rather invest into young, small and therefore more risky firms which are built upon technological innovations compared to their non-VC backed counterparts. This is confirmed by Megginson & Weiss (1991) who argue that VC backed companies perform an IPO at a considerable earlier stage of their business life cycle. When looking at our data set at hand, we can agree to these statements as the age of VC backed IPOs with an average age of 8.1 years is considerable lower than the average age of non-VC backed IPOs with 11.5 years (see Appendix 16). Thus, our dataset supports the assumption that a selectivity bias might be prevalent which can have an influence on the significance of our coefficient estimates.

The results of our regression analysis also raise a second question, namely why we observe a positive relationship between VC backing and excess returns instead of an expected negative one. Usually venture capitalists hold relatively large proportions of a company not only before the IPO, but even after the firm went public which reinforces the question why they tolerate to leave considerable amounts of money on the table. Before analysing this from a theoretical perspective, we want to examine the correlations between VC backing and the other variables more precisely as scholars (e.g. Lee & Wahal, 2004) argue that high correlations may be apparent. Bradley & Jordan (2002) go one step further and claim that when controlling the influence of correlated variables such as age, underwriter reputation and industry effects, there is no significant difference in level of underpricing between VC and non-VC backed IPOs.

	Ln (1+Age)	Ln (Market cap)	Top Under-writer	UpRev	DowRev	VIX	CSI	IPO activity	Floating
VC (Total)	-0.0928	0.0918	0.1520	0.1627	-0.1076	0.0542	-0.0045	0.0208	-0.0993
VC (Bubble)	-0.1211	0.1434	0.1534	0.1506	-0.0712	0.1039	0.1179	0.1366	-0.0897
VC (Post-Bubble)	-0.0729	-0.0552	0.1245	0.1996	-0.1944	0.0444	-0.0586	-0.0069	-0.1172

Table 15: Comparison of correlations between VC and other variables

(Source: own contribution)

Table 15 suggests that there is no major correlation prevalent between VC backing and the other variables of our model. With rather low correlations it seems that ln (1+age) and ln (Market Cap) have no major relation with VC backing. The only slightly striking correlation is the one with Top Underwriter which is between 0.12-0.15 over the three periods. Looking into our data set, we see that while on average 53% of all VC backed IPOs are performed via a top underwriter, non-VC backed IPOs exhibit only 37% (see Appendix 16). Even though this indicates that VC backed companies tend to hire prestigious underwriter for their IPO, it is not sufficient for explaining the rather high positive coefficient estimates of VC backing in the total period and bubble period.

In the following, we discuss two possible theories for explaining our observations of a positive relationship between VC backing and excess returns.

First, as already mentioned, venture capitalists acquire relatively large proportions of a company. According to Megginson & Weiss (1991), they hold on average a 36.6% share before an IPO and still a 26.3 % share after the IPO. Similar numbers are confirmed by Barry et al. (1990) who stated numbers of 34.3% before an IPO and 24.6% after the IPO. Based on these numbers, one possible explanation of the higher level of underpricing for VC backed IPOs can be made by means of linking the VC ownership with retained control theory. As VC funds are mostly formed as limited partnerships, they are obligated to retract their investments within a specific time period of usually 10 years and distribute the returns to the investors. This together with the argumentation from Zingales (1995) indicates that an IPO may be the beginning of a multi period exit strategy, where venture capitalists favour a dispersed ownership, because it makes it easier to sell a controlling part of the shares for a higher price later on in the aftermarket. To facilitate this dispersed ownership and regulate the intervention from outside shareholders after the IPO, in turn, a higher underpricing may be required (Brennan & Franks, 1997). Our proposition that VC firms strive for an exit via an IPO is supported by the findings of Sahlman (1990) who recorded that most of the proceeds of venture

capitalists that are distributed to investors are actually gained by putting the companies on a publicly traded stock market.
Second, another possible explanation for the positive relation between VC backing and IPO underpricing is based on the grandstanding theory. Within the existing body of literature, Gompers (1996) already found that VC backing leads to a higher level of underpricing. Based on these findings, he criticised the certification role of VC backing and introduced the grandstanding theory. More precisely, Gompers (1996) argues that venture capitalists deliberately allow underpricing in order to establish a positive reputation as a high-quality venture capitalist in the market, who is able to successfully guide a company through an IPO. This positive reputation in turn facilitates attracting new investors and thereby raising new capital for the venture capital fund in the future, which is extremely important to continue business as their funds are mainly raised via limited partnerships with predetermined expiration dates. In other words, due to the predetermined expiration dates, raising new capital is essential for the VC firms to recapitalize themselves and thus being able to proceed with their business. Building this line of argumentation one step further, Gompers (1996) infers that non-experienced venture capitalists have to deliberately allow even higher levels of underpricing to signal quality compared to experienced venture capitalists who already have a specific extent of reputation and therefore incur relatively lower levels of underpricing.

In summary, despite our initial expectation we found a positive relationship between VC backing and excess returns in our dataset at hand. Nonetheless, we have to be careful with our interpretation that VC backing per-se leads to higher initial returns as a selectivity bias might be prevalent. Even though, we presented two theoretical explanations why VC backing might indeed lead to higher excess returns, we cannot observe any relationship with excess returns in the post-bubble period.

The analysis on winner's curse theory showed that especially for tech companies age is no perfect proxy for representing uncertainty about a company after the bubble period. The same holds for the proxy of the market capitalisation, underwriter reputation and VC backing since after the bubble, there is no significant explanatory influence on excess returns. This raises the question about some serious changes in the IPO environment after the burst of the dotcom bubble and if the winner's curse theory for explaining underpricing is still pivotal in today's IPO environment.

6.1.2 Information revelation theory

The second theory we used for testing the asymmetric information issue, is information revelation. During the bookbuilding process, the underwriter collects orders from investors on the initial price range which was defined for the issue. Still, it is possible for the responsible underwriter to adjust the final offer price above or below this stated price range of the initial prospectus. We want to discuss our model results with regards to the informational content of price adjustments beyond this initial price range.

Price Revision (upward and downward)

The underwriters set the initial price range for an IPO to collect preliminary orders from investors during the bookbuilding process. While we assumed that there is a positive influence of upward price revisions (due to a possible oversubscription) on excess returns, vice versa we assumed a negative relationship on excess returns in combination with a downward price revision (since the demand may be lower than the supply of IPO shares).

In our model we find an on the 1% significance level robust (across all three time periods) positive influence on excess returns for upward pricing revisions and an on the 1% significance level robust negative influence on excess returns for downward pricing revisions. These two dummy variables are the only proxies that are statistically significant for all three tested time periods while also showing a large effect on excess returns.

We can see from our results (see Table 9), that an upward price revision can have a magnitude of 0.2331 to 0.5088 on the excess returns of an IPO. This means, that in the bubble period, an upward price revision during the bookbuilding will increase first-day returns minus the NASDAQ returns of about 50.88%, holding all other variables constant. On the other hand, a downward price revision can have a magnitude of -0.0953 to -0.2866 on the excess returns at IPO.

The possibility of price revisions is dependent on the issuing process via the bookbuilding approach. This in mind raises the question if the bookbuilding approach is value maximizing for the issuer or if the bookbuilding intermediary - in our case often an investment bank, or a syndicate of multiple of them that is responsible for the underwriting process - is exploiting the superior information he gets from setting the initial price range and receiving orders from investors. We find evidence, that top tier underwriters tend to set the prices rather close to the lower price border due to reputational concerns about participating in a successful IPO (Chua, 2014). This supports the study of Roosenboom (2012) who argues that underwriters put a discount on the fair value estimate of the issuer when setting the stage for the initial offer price. He argues further, that price revisions will only recover parts of the prior discount even when controlling for investor demands.

Additional to our dummy testing of upward and downward price revisions, the study made by Loughran & McDonald (2013) analyses the level of uncertainty and therefore higher first-day returns and their relationship to (absolute) price revisions. They find evidence that positive absolute price adjustments have a positive influence on the underpricing and vice versa. To test the robustness of our results we got with our dummy variables, we want to perform a testing of the absolute difference between the final offer price and the mid filing price. We therefore use the following equation:

$$Absolute\ Revision = pice_{offering} - price_{mid-filing}$$

Formula 9: Calculation of absolute price revision proxy

Exchanging the dummy variables (UpRev and DownRev) for the absolute price revision variable we get the following results:

Period	Total	Total	Bubble	Bubble	Post-Bubble	Post-Bubble
Model	**Initial**	**Abs. rev.**	**Initial**	**Abs. rev.**	**Initial**	**Abs. rev.**
UpRev	0.4325***		0.5088***		0.2231***	
	(0.0414)		(0.0584)		(0.0289)	
DownRev	-0.1608***		-0.2866***		-0.0953***	
	(0.0536)		(0.0880)		(0.0302)	
absoluteRev		0.1244***		0.1638***		0.0556***
		(0.0098)		(0.0147)		(0.0064)
Note: This table only shows the output of the discussed variables. For the complete table please see Appendix 17.						
Observations	1,276	1,276	859	859	417	417
R-squared	0.2734	0.2863	0.2640	0.2839	0.2683	0.2485
Standard errors in parentheses						
***** p<0.01, ** p<0.05, * p<0.1**						

Table 16: Excerpt comparison initial model and model with absolute price revision

(Source: own contribution)

Our model results (as seen in Table 16) support the findings of Loughran & McDonald (2013) that every dollar difference of the final offering price from the initial mid filing price will influence the excess returns of the IPO. As the dummy variables were significant across all time periods, we find that the absolute price revision is also statistically significant to the 1% significance level across all observed time periods. This leads to the conclusion that every deviation from the mid filing price will influence the excess returns in the same direction.

Besides looking at the price revisions, it is also interesting to discuss the reasons why a price adjustment is made. The study of Deng & Zhou (2015) of ChiNext index IPOs (a Chinese counterpart for the American NASDAQ 100) shows evidence, that oversubscription is one of the major drivers of initial underpricing. From a theoretical point of view concerning a market equilibrium, price revisions only seem logical if there is a mismatch between demand and supply. Following this, discounting the fair value of an issuer enterprise in an IPO process by the underwriter would therefore automatically lead to an oversubscription of the allocated shares (in perfect markets). Since the underwriter in the firm commitment underwriting bears the full risk of allocating all shares to investors, the underwriter will try to get an oversubscription to minimize this risk from the non-binding orders of investors. Assuming that, a price increase may reduce investor demand (and vice versa) and some level of oversubscription may be desired by the underwriter and price revisions could help achieving this equilibrium.

In sum, price revisions are highly correlated with the bookbuilding method where the underwriter is the intermediary who determines the fair value of a firm and collects orders of shares from potential investors. This creates an informational vacuum because there is no direct interaction or exchange of information between the issuer and the investors directly. This fact gives room to hypothesize that the underwriter uses his power over the pricing mechanism of an IPO issue to reduce his risk of not being able to get all shares sold in the offering. In order to manage the shares and orders, the underwriter may use price adjustments that show a significant influence on excess returns in our model. While upward price revisions assume an oversubscription and therefore a positive influence on excess returns, downward price adjustments are correlated negatively with excess returns. These findings are statistically significant across all our observed timeframes.

When looking at e.g. the Google IPO in 2004, they used a Dutch auction method and therefore matched the information about demand and supply of their shares without using the bookbuilding method that could lead to additional information asymmetry. Still Google showed an excess return of about 16% compared to the 13% on average for the year 2004.

The second tested theory, the partial adjustment theory, builds on information asymmetry about investors' appetite during the bookbuilding process. The variables upward- and downward price revision are the only ones that were highly statistically significant on the 1% level for all three periods and therefore exhibit a considerable impact on initial IPO returns. Based on these findings, it remains questionable whether the bookbuilding method is value maximizing for the issuing company or rather enabling underwriting banks to exploit their superior knowledge.

6.2 Interpretation of results of behavioural theories testing

For analysing the impact of behavioural theory on initial IPO returns, we were testing two theories. First, investor sentiment theory based on Ljungqvist et al.'s (2006) which we tested via the proxies CSI and VIX. Second, the hot/cold issue markets theory stated by Ibbotson & Jaffe (1975) that we tested via the IPO activity during the previous 180 days.

6.2.1 Investor sentiment

For investigating the impact of investor sentiment on excess returns, we were testing two hypotheses with different variables. First, we tested the CSI as a direct proxy for investor sentiment and second, the VIX as an indirect proxy. In accordance with the theory stated by Ljungqvist et al.'s (2006), we postulated a positive relationship between investor sentiment and excess returns.

CSI

For the CSI in the total period (0.0098) und bubble period (0.0138) we received positive β coefficient estimates that are in line with our expectations and statistically significant. However, in the post-bubble period we obtained no significance for our β coefficient estimate due to a p-value of 0.599.
Before going into the discussion, it should be noted that there is no one perfect proxy for investor sentiment. Each proxy has advantages and disadvantages and can therefore be discussed controversially (Baker & Wurgler, 2006). One advantage of the CSI is that it is based on a direct survey. In general, the survey proxies are classified as a precise indicator of investor sentiment since they are directly linked to the market expectations of investors. However, as one of the disadvantages of direct measures, most of them are not reported on a daily basis. The CSI is reported on a monthly basis, therefore does not account for daily sentiment changes which can be a potential reason for the inconsistency of our results in the post-bubble period. As another drawback of the CSI, the survey to predict the level of consumer sentiment is only carried out with US investors. Thus, a US bias may be prevalent in this index. On the other side, the US IPO market is not only open for trading for investors from the US, but rather accessible for investors from all over the world. Especially due to

the increased public access to the internet in the late 1990s in combination with the possibility of online stock trading, the US equity market got more and more global. In this sense an index whose surveys are based on investors from all over the world might be more accurate in todays rather global IPO market.

Moreover, when we then investigate the historical development of the CSI (see Figure 14), we can identify that the overall development in the post-bubble period is mainly driven by three extremes. First, the downturn after the dotcom bubble (around the year 2000). Second, the downturn after the financial crisis (around the year 2008). Third, the overall increase over the last decade which yields us now similar levels of consumer sentiment as during the dotcom bubble. Therefore, these extreme changes of the CSI might be also a possible explanation for the insignificance of our β-coefficient estimate in the post-bubble period.

VIX

Our second proxy for testing investor sentiment, the VIX, also yields inconstant results. Whereas the variable exhibits a positive and significant β estimate in the total period, the bubble period and post-bubble period show statistically insignificant results of the coefficients.

On the one hand, as an advantage of the VIX – contrary to the other chosen index the CSI – it is based on market movements and therefore reported on an ongoing basis. On the other hand, it is not based on a direct survey of investors but rather on the overall market volatility.

When looking into the historical development of the VIX over time (see Figure 15), we can detect some extreme spikes, especially after the financial crisis in 2008 and 2009. Such extreme numbers may be one reason for the statistical insignificance in the post-bubble period.

Concluding our analysis, the VIX as a proxy for investor sentiment is statistically significant in the total period. However, for the bubble period as well as the post-bubble period we found no prove that underwriting banks are exploiting periods of higher sentiment by an increased offer price.

In general, it seems that we can agree with the consumer sentiment theory stated by Ljungqvist et al. (2006) that underwriters exploit periods of higher consumer sentiment. However, in our models we cannot entirely conclude that investor sentiment has an impact on excess returns in the post-bubble period. One potential explanation for the insignificance of all tested investor sentiment proxies in the post-bubble period can be due to the fact that behavioural theories are no coherent theory like efficient markets, but rather based upon observations made in the markets. This is in line with some supporters of the efficient market hypothesis who argue that behavioural anomalies are often short-term and straightened out over time. Hence, our findings raise the question if IPO markets in the post-bubble period became more efficient compared to the bubble period.

6.2.2 Hot/Cold issue markets

By testing hot/cold issue markets, we are contributing to the concept of behavioural theory for explaining IPO underpricing. According to Ibbotson & Jaffe (1975), issuers exploit too optimistic beliefs of investors by going public in periods with high sentiment. Consequently, they found a higher level of underpricing in hot issue markets and a lower level of underpricing in cold issue markets. Based on this, we hypothesized a positive relationship between the number of IPOs previously conducted in the market and the level of excess returns for our data set at hand. However, only the estimates in the total and bubble period exhibit statistical significance at the 1%, 5% level, respectively. This questions the economic importance of the hot/cold issue markets theory in our model.

For our analysis we used the number of IPOs during the previous 180 days as a proxy for the heat of the market. Nonetheless, using a time period of 180 days can be discussed controversially. Therefore, we perform an additional testing of IPO activity during the time periods of the previous 90 days as well as during the previous 360 days.

Time Period	**Total**	**Total**	**Total**	**Bubble**	**Bubble**	**Bubble**	**Post-Bubble**	**Post-Bubble**	**Post-Bubble**
Model	**Initial**	**90 days**	**360 days**	**Initial**	**90 days**	**360 days**	**Initial**	**90 days**	**360 days**
IPOactivity180	0.0019***			0.0017**			-0.0006		
	(0.0004)			(0.0007)			(0.0014)		
IPOactivity90		0.0029***			0.0020			-0.0024	
		(0.0008)			(0.0012)			(0.0024)	
IPOactivity360			0.0005**			-0.0002			0.0005
			(0.0002)			(0.0004)			(0.0006)
Note: This table only shows the output of the discussed variables. For the complete table please see Appendix 18.									
Observations	1,276	1,276	1,276	859	859	859	417	417	417
R-squared	0.2734	0.2693	0.2635	0.2640	0.2609	0.2588	0.2683	0.2698	0.2692
Standard errors in parentheses									
***** p<0.01, ** p<0.05, * p<0.1**									

Table 17: Excerpt comparison initial model and model with IPO activity 90, 360 days

(Source: own contribution)

As can be seen from Table 17, running the analysis with a 90 days and 360 days time period provides similar results as our original model. The only major change that the β coefficients for the 90 days period as well as the 360 days period show no statistical significance in the bubble period.
But still, we want to test the robustness of our results by performing a further testing with a dummy variable for hot/cold markets. More precisely, we define this dummy variable so that it states the value of 1 (hot market) if the number of IPOs conducted during the previous 180 days of the individual IPO is higher than the average of the respective period (overview of averages can be found in Appendix 19). If, however, the number of previous IPOs is below the average, we allocate a value of 0 (cold market).

Time Period	**Total**	**Total**	**Bubble**	**Bubble**	**Post- Bubble**	**Post- Bubble**
Model	**Initial**	**Dummy**	**Initial**	**Dummy**	**Initial**	**Dummy**
IPOactivity180	0.0019***		0.0017**		-0.0006	
	(0.0004)		(0.0007)		(0.0014)	
Hot/Cold Dummy		0.1576***		0.0980*		-0.0377
		(0.0540)		(0.0530)		(0.0251)
Note: This table only shows the output of the discussed variables. For the complete table please see to Appendix 20.						
Observations	1,276	1,276	859	859	417	417
R-squared	0.2734	0.2658	0.2640	0.2616	0.2683	0.2720
Standard errors in parentheses						
***** p<0.01, ** p<0.05, * p<0.1**						

Table 18: Excerpt comparison initial model and model with hot/cold issue market dummy
(Source: own contribution)

As can be seen from Table 18, the statistical significance for the new β coefficients estimated via the dummy variable are similar to the ones from our original models with statistical significance in the total period (p-value: 0.004) and in the bubble period (p-value: 0.065), but statistical insignificance in the post-bubble period (p-value: 0.134).
In conclusion, by performing additional testing of hot/cold issue markets with several other proxies, we can confirm the robustness of our original results. On the one hand, the variable showed statistical significance for all of our tests in the total period. On the other hand, also in all of our testings the variable was insignificant in the post-bubble period. Thus, it seems that sub-dividing the rather cold post-bubble period additionally into hot and cold markets does not help to explain excess IPO returns.

Based on the analysis above, we suggest that behavioural theory partly accounts for the variations of underpricing over time periods including hot and cold markets periods (e.g. our total period). When looking separately into the specific type of market, we saw that during an extremely hot market (bubble period) behavioural theory can partly explain the level of excess returns, whereas during a cold market (post-bubble period) we cannot record any statistical significant relationship.

6.3 Interpretation of results of ownership & control theory testing

For analysing the impact of ownership & control theory on excess returns, we were using a practical modification of retained control theory stated by Brennan & Franks (1997).

6.3.1 Retained control theory

In our previous analysis, we used the floating rate as a proxy for testing ownership & control theory. Based on findings of Brennan & Franks (1997), we followed a reasoning that underpricing is used as a precautionary measure for hostile takeovers by inducing a dispersed ownership when a large share of the company is issued. Vice versa, when only a smaller percentage of shares is floated, we expected a lower level of excess returns. With regards to our tech data set, this testing might lead to interesting implications as a non-negligible proportion of tech start-ups are managed by a founder CEO who is interested in retaining control of a company after the public offering.

It should be noted that our analysis was showing different results than expected. The coefficient estimates in the total period and post-bubble period are highly insignificant due to p-values of 0.718 and 0.560, respectively. However, in the post-bubble period things change. We exhibit a very sizeable β coefficient of -0.4140 that is highly statistical significant on the 1% level. This considerable shift calls for further inquiry if there is any potential rationale behind these observations. Further, we will analyse the sign of the coefficient estimate in the post-bubble period more detailed since we expected an opposing relationship.

Before examining the shift over time, we first want to evaluate the fit of our proxy floating rate for testing ownership and control theory. Most of the previous relevant studies of ownership and control theory for explaining IPO underpricing, are based on detailed bid- and allocation data. However, due to the private character of detailed bid- and allocation data we were unable to use these in our analysis. As an alternative we consulted the floating rate as a proxy mainly due to its data availability. Indeed, this is a rather vague proxy for overall ownership structure. Nonetheless, it gives an indication about which percentage of the company is actually traded in the market and which percentage is retained by the initial owners. A limitation of using the floating rate as a proxy is that we do not take into consideration the different types of issued shares. For example, if a company floats a large proportion of only non-voting shares, the risk of a hostile takeover is still limited. This reasoning is in line with Smart & Zutter (2003) who documented that firms which are issuing non-voting shares exhibit less underpricing and a higher level of institutional ownership after the offering compared to the issue of voting shares. Moreover, in the US shares are differentiated not only between common stock and preferred stock, but also between different classes of stocks with a specific amount of voting rights. Hence, this complicates the meaningfulness of the floating rate when comparing between different companies. All the arguments stated are possible explanations for our insignificant results of ownership and control theory in the total und bubble periods.

In the following, we present a potential explanation for the considerable shift of the floating rate variable for explaining excess returns in the post-bubble period based on a principal-agent perspective. Generally, in line with principal-agent theory, the issuer has superior information compared to the investors about the real quality of the company. During the dotcom bubble, issuers may have exploited this superior information about the real value of the company together with the irrational behaviour of investors by performing an IPO no matter how god or bad the future outlook for the company was. With the burst of the dotcom bubble many shareholders lost tremendous amounts of money which could have induced a paradigm shift in the mind of the investors. After the dotcom bubble investors could be deterred and anticipated, that a higher floating rate is signalling bad firm quality due to the superior information of the issuer. More detailed, since the issuer has superior information about the real quality of the issuing company, the investors may perceive a high floating rate as a signal for a worse than expected future outlook of the company. In other words, if the issuer expects a bad future of his own company, he rather tries to cash-in immediately by floating an as large as possible amount of shares. As a result, investors may be anticipating this behaviour and avoid participating in those IPOs. Thus, the relationship between floating rate and excess returns is negative. Inversely, if the issuer – with superior information about the future outlook – expects a flourishing future, he rather tends to issue a lower amount now and cash-in at a later point of time, for example via an SEO. Consequently, as investors are keen on IPOs with lower floating rates, the demand for such IPOs increases which in turn leads to a higher level of underpricing.

In summary, the floating rate is a rather vague proxy for testing the retained control theory. Despite the fact, that there are some drawbacks of this variable, the results provide interesting implications about a potential paradigm shift in the mind of investors after the dotcom bubble.

6.4 Discussion of issuer and underwriter incentives

As can be seen from our regression results, we cannot explain all of the variance of initial IPO returns with the three tested theories (asymmetric information theory, behavioural theory and ownership & control theory) in our model. To complement the interpretation of our results, we now want to discuss the incentives of the issuer and the underwriter to give possible additional explanations about the underpricing phenomenon.

This discussion builds upon principal agent theory. The principal-agent conflict is based in a different interest and asymmetric information universe where an agent makes decisions that have an impact on the principal (Hendrikse, 2003). In a typical IPO the issuer (principal) hires an underwriter(s) (agent) to bring the company public as the underwriter has a comparative advantage in executing this task. All players are assumed to be profit maximizing and self-interested which can lead to a conflict of interest. In order to understand this conflict, we will have a closer look on the incentive trade-off of our principal and the agent. The aim of this section is to additionally discuss an incentive-based picture by showing how excess returns can be explained by tested as well as not tested underpricing theories.

6.4.1 Issuer (principal) incentives

Complementing the motivation of a firm going public (see section 2.1.4) the incentives of the issuer in the IPO process seem to circle around the image of having a “successful” IPO. This includes the costs, media coverage and first-day returns (or from the viewpoint of the issuer money left on the table) as specified by e.g. Habib & Ljungqvist (2001) or Loughran & Ritter (2002).

On the one hand, there are the direct costs of the equity issue such as fees paid to the underwriter. In principle, the underwriter fee is a variable reward system based on the amount of capital raised by means of the IPO and should therefore align the interests of the issuer with the one of the underwriter. According to Statista (2018), in 2016 the average underwriter fee in the US amounted between 5% and 7% of the gross proceeds of the offering. A study focussing on US underwriting fees shows evidence, that by demanding a lower underwriting fee, banks can gain additional market shares of the underwriting market (Dunbar, 2000). Controversially, it is also argued that top banks can keep

charging high fees and still increase their market share, which could indicate, that the issuers expect some kind of compensation for the higher fees paid. Additionally, Habib & Ljungqvist (2001) show that issuers are willing to pay higher cost, when they plan a larger IPO (in terms of shares offered).
One reason that can offset the higher fees charged by the top underwriters is identified as the media coverage to promote the issuer during its process of becoming a public company (Habib & Ljungqvist, 2001). The same study argues, that every dollar spend on promotional activities will reduce the wealth loss at about the same level. This is supported by Loughran & Ritter (2004) who argue that media attention is more important to the issuer than underpricing. Additionally, the study of Ritter (2011) concludes, that issuers put the focus of finding the right underwriter with respect to a bundling of services rather than maximizing the offer price. These studies show an indication, that issuers are maybe willing to accept a certain underpricing, when therefore the attention caught by the media is appropriate.
Loughran & Ritter (2002) additionally argue that even though there is money left on the table, most of the issuers will find themselves wealthier than expected. This finding is also in line with signalling theory. In general, the signalling theory is based on asymmetric information between the issuer and the investors about the real quality of a firm. Therefore, the issuer is deliberately underpricing the IPO to send a positive signal to investors about the firm quality. Despite the fact that the issuing company leaves considerable amounts of money on the table, this initial underpricing, in exchange, may provide positive publicity due to the image of having a successful IPO.
Following mental accounting (Thaler, 1980), the gains for the issuer (e.g. media attention and wealth of the shareholders) tend to offset the costs for the IPO because otherwise their interest would not be going public in the first place. Prior studies show a positive relationship of first-day underpricing and incomes from subsequent secondary equity offerings (SEO) (Allen & Faulhaber, 1989; Welch, 1989). Additionally, there is evidence, that issuers stick to their IPO underwriter (even though there was a large underpricing) in a following SEO, which can indicate, that the issuer was satisfied with the IPO. Ljungqvist & Wilhelm (2005) measured the decision makers satisfaction with the IPO by comparing the (perceived) wealth loss of underpricing with the wealth gains of price revisions. They found, that this behavioural explanation of satisfaction even leads to higher fees of the underwriter in following SEOs. Following this, (short-term) losses of going public in form of money left on the table, that are directly correlated to the first-day excess returns, seem to be counted against possible (long-term) future SEO gains, due to high publicity and the success of the IPO. Therefore, every retained share which is not offered in the IPO will increase its value with the stock price increase that can be

collected in later stage SEOs (Loughran & Ritter, 2002). This argumentation is therefore in line with the discussion of our results concerning the floating rate.

Summing up, the discussion above showed, there are many arguments mitigating the fact that money is actually left on the table by the issuers. Underpricing an IPO seems to be correlated with higher media coverage and positive publicity due to positive first-day returns and higher success rates of possible SEOs.

Thus, all these (long term) incentives of the issuer could be potential theory why IPOs are deliberately underpriced. Still, there is no clear evidence if e.g. the importance of media attention or the intention for a SEO changed over time for the issuers. Although it is interesting, that the studies concerning the publicity along an IPO arose at the end or after the burst of the internet bubble.

6.4.2 Underwriter (agent) incentives

Before going into the discussion of underwriter incentives, it should be noted that underwriter not only have a principal-agent relationship with the issuer, but also with the investors.

In order to see, if the underpricing is based on the incentive system of the underwriter, we want to discuss more deeply the underwriting method, the fees charged by the underwriter, the role of institutional investors, the Green Shoe/overallotment option and the legal environment covering the IPO process.

The auction underwriting method was firstly used in an US IPO in 1999, but only a handful of auctions were used after during our observed timeframe and industry. One of the most well-known (Dutch) auction IPOs was Google performed in the post-bubble period. Research suggests that the auction method reduces the first-day returns (and therefore underpricing) while at the same time having lower underwriter spreads (Papaukthuanthong et al., 2007). This would, on the one hand, increase the incentive of underwriters to use the auction method (due to the lower underpricing that leads to a larger issuing volume and therefore absolute spread), but at the same time reduce the relative (percentage) spread. Depending on the real change in underpricing and underwriter spread, no universal decision if the auction method would be maximizing underwriter incentive can be made. As discussed in the issuer incentives section, lower spreads while facing less underpricing should be both in line with maximizing the issuers wealth. But still, the issuer (who has the decisive power over the IPO method) tends to use accept the bookbuilding method in most of the times.

Following the studies of Sherman (2000, 2005) the bookbuilding approach reduces the risk for the issuer as well as the investors, because the underwriter has the exclusive control on the allocation of the issued shares. As mentioned earlier, the bookbuilding method is based on the (mostly institutional) investors revealing their (true) intentions about participating in the IPO, based on a preliminary offer price and price range. This indicates, that the distribution of shares within the bookbuilding method reveals the characteristics of a repeated game between the underwriter and the institutional investors. An equilibrium that may be identified in this underwriter-investor game is, that the investor shows his intention about buying shares in the IPO, while the underwriter will reward the institutional investor with a discount to the fair value of the firm (therefore underpricing). This can therefore be translated in a reduction of risk, since all shares can be placed in the market by giving the underwriter the power to set the price and distribute the shares. Because there is no end of this repeated game, the underwriter and institutional investors should collaborate in other future IPOs, because none of the players (underwriter and institutional investors) have the intention to cheat on their behaviour to maximize his own profits (Hendrikse, 2003).

Additional to the spread that is given to the underwriter, we find that in 1,266 IPOs of our dataset (99% of our total dataset of IPOs) the underwriter is given the Green Shoe/Overallotment option (OAO). This OAO allows the underwriter to exercise a call option to buy up to 15% additional shares for the issuing price. Including the overallotment (dummy) proxy into our model that becomes 1, when the OAO is granted and 0 if there is no such option, we get the following results:

Time Period	**Total**	**Total**	**Bubble**	**Bubble**	**Post-Bubble**	**Post-Bubble**
Model	**Initial**	**Incl. OAO**	**Initial**	**Incl. OAO**	**Initial**	**Incl. OAO**
Overallotment		-0.5383***		-0.4790		-0.3484***
		(0.1964)		(0.4249)		(0.0902)
Note: This table only shows the output of the discussed variables. For the complete table please see Appendix 21.						
Observations	1,276	1,276	859	859	417	417
R-squared	0.2734	0.2777	0.2640	0.2651	0.2683	0.2943
Standard errors in parentheses						
***** p<0.01, ** p<0.05, * p<0.1**						

Table 19: Excerpt comparison initial model and model with OAO

(Source: own contribution)

Our results in Table 19 show, that the overallotment proxy is highly significant in the total and post-bubble period (respectively at the 1% significance level) with a negative relationship to the excess returns. However, it is puzzling, that the extension of the OAO in the bubble period does not show a significance on the explanation of our independent variable excess returns. It should be noted that in the bubble period only three IPOs do not exhibit an OAO. Thus, the small number of observations may be a reason for the distorted statistical significance of this variable in the bubble period. Nevertheless, the relationships and significance levels of all of the other dependent variables in the model is not changed.

On the one hand, since the OAO is only exercised when there is an increase in the share price compared to the offering price, one would suggest that the influence of the OAO is positive to excess returns because this exercise will increase the total underwriter fee (Carter & Dark, 1990). On the other hand – supporting our model estimates – there is evidence that the OAO can be used to adjust the issuing volume and price the IPO shares closer to the fair value, which will therefore also benefit the issuer (Jiao, Kutsuna, & Smith, 2017). Additionally, there is evidence that the OAO works as a price stabilizer and therefore reduces aftermarket price uncertainty (and therefore volatility). This is due to the nature of the call option that counterbalances a possible short position of the underwriter itself (Franzke & Schlag, 2003). These explanations are therefore in line with our estimation results especially during the latest post-bubble period.

Another reason why an underwriter could underprice an IPO is to avoid legal problems. This argumentation is in line with the institutional underpricing theory following the litigation subsector (Ibbotson, 1975; Logue, 1973a). If an IPO shows a negative development especially during the first-day, investors are more likely to use the prospectus and its valuation as a sign of fraud and therefore feel obliged to take legal measures, which can lead to compensatory payments by the underwriter. In addition to the compensatory payments, litigations can also damage the overall reputation of an underwriter and thereby reduce the probability of getting assigned for future mandates.

In conclusion, despite the fact of a lower absolute underwriter fee, the underwriters are incentivized by several theories to underprice an IPO. First, via underpricing the underwriters can reward the institutional investors for revealing their true appetite during bookbuilding. This, in turn, results in a reduced risk for the underwriters of not being able to place all shares in the market. Second, the OAO allows the underwriter to execute an option to buy up to 15% additional shares for the offer price within 30 days after the offering. Thus, the underwriter can make additional income, when the stock in the aftermarket trades higher than the offer price. Third, by underpricing a stock initially also the risk of litigations by investors can be reduced. All in all, we assess those underwriter incentives as a main driver for the presence of underpricing in IPO markets. Additionally, even after the first auction

IPO in the late 1990's there is no indication that the IPO bookbuilding method has lost its popularity. Thus, it seems that the overall underwriter incentives remained equally important over time.

7. Conclusion & Outlook

In this final chapter, we summarize the findings of our tested models and the discussion & interpretation of our results in order to come up with a final conclusion before stating the limitations of our findings. In the last sub-section, we reflect on our results with the focus on recent changes in the IPO technology environment, to put the thesis in perspective and to provide recommendations for further research.

7.1 Conclusion

Researchers have found vast empirical evidence for the IPO underpricing phenomenon across several markets, industries and time periods. Our thesis supports this by showing indications that the US technology IPO environment and the explanatory power of tested underlying proxies are changing.

Firstly, our tech IPO dataset was analysed with a Student's t-test and a Wilcoxon signed-rank test. We found that underpricing in form of excess returns is indeed prevalent in all of our three predetermined time periods (total 1995-2017, bubble 1995-2000 and post-bubble 2001-2017). More precisely, our analysis yielded average excess returns of 43% for US tech IPOs in the total period. The sample mean in the bubble period showed extreme excess returns of 54%, while the sample mean in the post-bubble period dropped to 18%, which indicate some severe changes of the US tech IPO market after the bubble burst in 2000.

Secondly, we performed a multiple regression analysis in order to explain the excess returns by testing the explanatory power of certain IPO characteristics (i.e. company, market and underwriting characteristics) that refer to the three superordinate underpricing theories (information asymmetry, behaviour, and control & ownership). We identified significant explanatory power of eight from our proxies in the total period: company age, market capitalization, underwriter reputation, venture-capital backing, price revisions, investor sentiment index, volatility index and IPO activity. The bubble period exhibited similar results, except for a statistical insignificance of the volatility index. The post-bubble period, however, showed a shift in the explanatory power for most of our variables as only the proxies of price revision and the floating rate are statistically significant. Our results therefore confirm that the US tech IPO market exhibits changing patterns after the bubble burst.

In order to explain the effect of asymmetric information theories on excess returns during and after the dotcom bubble, we first tested the winner's curse. The discussion of the variable company age showed that it is no perfect proxy for uncertainty, since for instance company relationships (e.g. to parental companies) may decrease information asymmetry and a long history of business may not be relevant due to a critical value. Further, when considering the fast-changing environment of the technology industry, especially for tech firms, age seems to be no adequate measure for uncertainty. For the variable market capitalization, we found two opposing views concerning the company size at IPO. The "too big to fail" reduction of uncertainty may be offset from the "growth opportunities and future outlook" uncertainty, which can therefore lead to a non-significant influence of this proxy in the post-bubble period. Since our model suggested that a top underwriter will increase excess returns, we conclude that the assumed signalling function of a high underwriter reputation may be used to attract attention from media rather than reducing the underpricing at IPO. Despite our initial expectation of a negative relationship between the variable venture capital backing and excess returns due to a certification role. Surprisingly, our testing showed the opposite to be true. We presented the grandstanding theory as one possible explanation for this. All in all, the winner's curse as sub-theory of asymmetric information theory seems of less importance in the post-bubble period compared to the time periods including the internet bubble, which calls for further research within this area.

The second theory used for testing the asymmetric information theory was information revelation. The proxies upward- and downward price revision showed a considerable impact on excess returns and are the only proxies, that exhibited highly significant influence over all three periods. With these findings, we questioned if bookbuilding is value maximizing for the issuers, or rather enabling underwriters to exploit their superior knowledge. Generally, price adjustments are in the authority of the bookrunner and while these adjustments seem to be used to align subscription rates, the prices seem not to fully match the supply and demand of the IPO shares. In addition, we confirmed the robustness of these findings by showing that the absolute difference between the offer price and the mid filing price - as an alternative proxy - yields similar results as our original model.

For analysing the impact of behavioural theories on excess returns over time, we tested investor sentiment theory as well as hot/cold issue markets theory. While our results supported investor sentiment theory in periods including the bubble, the ones in the post-bubble period do not. This insignificance of investor sentiment theory in the post-bubble period pose the question if IPO markets became more efficient after the bubble burst in 2000. The investor sentiment indices seem to confirm the findings of the hot/cold issue markets that underwriters exploit periods of higher IPO activity. We therefore question the usefulness of sub-dividing a rather cold market like the post-bubble period further into hot and cold phases, since we could not find a significant influence on excess returns during this period.

By testing the effect of ownership & control theories on excess returns via the retained control theory, we also detected a potential changing pattern over time. While showing insignificant results in the total and bubble period, our analysis yielded a highly significant coefficient in the post-bubble period. Consequently, we presented a possible explanation that this changing pattern may be due to a potential paradigm shift in the mind of investors after the dotcom bubble. More precisely, our results suggested that after the bubble, a high floating rate may signal bad firm quality and vice versa, since the issuer has superior knowledge about the real quality of the firm. Based on this, issuers anticipate that it is more profitable for good quality firms to issue additional shares in a later SEO than directly in the IPO. Our findings indicate the need for further research and empirical testing with regards to this severe paradigm shift.

To sum up, based on our analysis on selected underpricing theories, we can partly explain the levels of excess returns observed in the US tech IPO market. Moreover, we recorded not only changing patterns in the absolute amount of average excess returns over time, but also in the explanatory power of tested variables. Even though the average excess returns declined from the bubble period to the post-bubble period, it appears that issuers still accept to leave money on the table in an IPO. We therefore had a closer look at the issuer and underwriter incentives towards a fair pricing of an IPO. As a possible conclusion, we find that inducing a successful IPO may require a certain positive first-day development due to e.g. higher media coverage, wealth gains of retained shares, the possibility to exercise the overallotment option, the repeated game during the bookbuilding process with institutional investors and a reduced risk of litigations by investors. We therefore conclude, that – in common with the signalling function – issuers seem to show quality with underpricing their IPO.

7.2 Limitations

Our research results show, that many prior scientifically tested theories and proxies about IPO underpricing are not explaining the excess returns of US technology IPOs when excluding the time period of the internet bubble (1995-2000). Therefore, we want to critically reflect on the limitations this paper presents due to our chosen focus and methodology.

First, it is important, that our results and conclusions are not meant to be projected universally across the whole IPO universe, since we limited our IPO analysis on data of the US technology sector during the time period of 1995 until 2017. When sub-dividing our total period into the bubble and post-bubble period, we find a discrepancy of the number of observations. Even though the bubble period is shorter when looking at the simple time frame, we find more than twice the number of IPO observations that fall into the bubble period (859) than the post-bubble period (417). Further, we excluded those IPOs, where we were unable to gather all variables needed for the testing of our hypothesis. This - in combination with the tendency that larger IPOs may publish more complete data to databanks compared to smaller IPOs – could lead to an availability bias in our dataset at hand. Moreover, the breakdown of our total period into two sub-periods (bubble, post-bubble) is based on our own methodology. Therefore, our results are conditional on the applied methodology. Dividing the total period into other sub-periods might possibly lead to different outcomes.

Second, the specific proxies included in our model are a potential source to limit our results. On the one hand, the chosen type of proxies might affect our findings for the individual underpricing theories. As already explained in the individual discussion parts of each variable, there are indications that our chosen variables are no perfect proxies especially in the post-bubble period. We use e.g. the floating rate as a proxy for testing ownership & control theory, despite the likelihood that it would be more appropriate to select detailed bid- and allocation data. However, due to the private character of detailed bid- and allocation tables, this data is not publicly available for our analysis. Additionally, the Consumer Sentiment Index is based on a qualitative survey that can be exposed to an individual state of mind. Our results are therefore strongly dependent on the proxies selected that were available to us. Nevertheless, we would like to point out, that each of our used variables is based on theoretical grounds and therefore deemed as accurate. The initial studies concerning our superordinate theories (information asymmetry, behavioural, ownership & control) are mostly based on US IPOs without any industry restriction, which can therefore lead to inaccuracies within our chosen focus.

Third, in accordance with our methodology we use the standard hypothesis testing approach of our proxies to test for a significant explanation of IPO excess returns. Here, it should be noted, that a failure to reject the null hypothesis does not automatically lead to the conclusion that the null hypothesis must be right. This outcome needs to be rather seen as that there is not enough power, that this hypothesis is definitely wrong (Linton, 2017). On the other hand, a p-value, that is derived from a t-statistic, to show statistical significance does not imply any information about the size of a proxy nor the importance concerning the overall analysis. A small significant departure from a null hypothesis in a large sample can be less of an importance than a large insignificant difference.

Fourth, our model can inherit econometric issues. As prior tested in section 5.3, we find violations of the assumption concerning the homoskedasticity and normal distribution of the error term. Even though we tested for heteroscedasticity corrected standard errors in our robustness test (section 5.4) and the implication of the central limit theorem, that in large samples the distribution of most estimators is approximately normal, our estimators can be biased. Additionally, even though we test for omitted variables, we do not apply every possible proxy for company, market and IPO characteristics due to our chosen focus of our model.

Lastly, we used the excess return as the independent variable in our model. Therefore, we adjusted the first-day return of an IPO with the NASDAQ100 return that we defined as the appropriate technology market index return. Due to a possibly fast changing environment especially in the technology sector, this market index may only adapt to new business models with a lagged reaction which may in turn lead to inaccuracies.

7.3 The thesis in perspective & further research

Throughout this thesis we already addressed the question if the bookbuilding method is value maximizing from an issuers perspective. Our results from the partial adjustment theory indicate that the success of an IPO for the issuer is substantially influenced by the actions of the underwriting bank(s). In our dataset, we can identify Google with its (Dutch) auction IPO in 2004 as one of the exotics, since most IPOs were still based on a bookbuilding process. Just recently, the IPO of Spotify on the 03.04.2018 (not part of our analysed dataset due to time restriction of IPOs between 1995-2017) used an alternative approach in form of a direct listing to issue their shares and therefore using the disintermediation to e.g. avoid information asymmetry.

The question about the function of the underwriter as an intermediary as well as if bookbuilding continues to be the preferred IPO method will be even more interesting when considering recent technologies like the blockchain technology or other peer-to-peer network technologies. Because blockchain technology allows to eliminate intermediaries in a specific process, IPOs on the blockchain recently attracts more and more attention. In other words, the blockchain technology is based on a decentralized publicly available ledger which facilitates to raise capital on a global peer-to-peer level (Tapscott & Tapscott, 2017).

On the one hand, as one of the possible advantages of the blockchain technology, underwriter fees could be avoided, and any form of side payments and/or economic crime could be reduced. Moreover, it may function as an enabler to reduce the transaction cost for the investors and issuers. On the other hand, the decentralization via the blockchain technology does not come along without any cost. The fact that there is no regulatory oversight currently, may hinder an issuer from choosing this option in the IPO.

During the last years, especially for start-up companies a so-called initial coin offering (ICO) already represented an alternative funding mechanism to conventional IPOs. Generally speaking, ICOs are based on blockchain technology. The issuing company collects funds and, in exchange, issues token - a cryptocurrency - with specific rights on the company (e.g. to participate with a specific share on future profits, voting rights, etc.) (PWC, 2018). In 2017, already a total of $5.5 billion were funded via ICO's (Financial Times, 2018). In order to understand the importance of these technologies on the more traditional theories of underpricing, we would suggest conducting a study with regard to the disintermediation and therefore existence of underpricing in this IPO environment. The technology industry could therefore be one of the first adopters that may present observations in this area.

As a concluding remark, it remains an intriguing future topic if new technologies like the blockchain technology or coin issuings are able to disrupt traditional IPO processes and therefore lead to a considerable shift of IPO markets. Thus, further theoretical considerations and empirical testing of this topic is necessary.

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II. Appendices

List of appendices:

Underwriter	1992-2000	2001-2004	2005-2007	2008-2009	2010-2011	2012-2017
Citigroup		Top	Top	Top	Top	
Credit Suisse First Boston	Top	Top	Top	Top		
Deutsche Banc Alex Brown	Top	Top	Top	Top		
Deutsche Bank AG	Top	Top				
Donaldson Lufkin & Jenrette	Top					
First Boston Corp	Top					
Goldman Sachs & Co	Top	Top	Top	Top	Top	Top
HSBC Securities Inc		Top	Top	Top		
JP Morgan (JPM)	Top	Top	Top	Top	Top	Top
Lazard	Top	Top	Top			
Lehman Brothers	Top					
Merrill Lynch & Co Inc	Top	Top	Top	Top		
Morgan Stanley & Co	Top	Top	Top	Top	Top	Top
Nomura International Limited	Top					
Salomon Brothers	Top					
Salomon Smith Barney	Top	Top				
Santander Investment Bank				Top		
Schroder Salomon Smith Barney	Top					

Appendix 1: List of Top-underwriters

(Source: own contribution, Data: Loughran & Ritter (2004)

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Firstd~n	1276	.4271646	.0201561	.7199979	.3876219	.4667073
NASDAQ~n	1276	.000936	.0005187	.0185296	-.0000817	.0019536
combined	2552	.2140503	.0109269	.552	.1926237	.2354769
diff		.4262286	.0201627		.3866916	.4657656

```
    diff = mean(Firstdayreturn) - mean(NASDAQ100Return)              t =  21.1394
Ho: diff = 0                                        degrees of freedom =     2550

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Total period (1995-2017)

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Firstd~n	859	.5461181	.0283741	.8316094	.4904273	.601809
NASDAQ~n	859	.0013942	.000713	.0208964	-5.16e-06	.0027936
combined	1718	.2737562	.0156361	.6480958	.2430884	.3044239
diff		.5447239	.0283831		.4890548	.6003931

```
    diff = mean(Firstdayreturn) - mean(NASDAQ100Return)              t =  19.1918
Ho: diff = 0                                        degrees of freedom =     1716

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Bubble period (1995-2000)

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Firstd~n	417	.1821259	.0132363	.2702936	.1561075	.2081443
NASDAQ~n	417	-8.02e-06	.0006005	.0122635	-.0011885	.0011725
combined	834	.0910589	.0073344	.2118106	.0766629	.105455
diff		.1821339	.01325		.1561267	.2081412

```
    diff = mean(Firstdayreturn) - mean(NASDAQ100Return)              t =  13.7460
Ho: diff = 0                                        degrees of freedom =      832

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Post-Bubble period (2001-2017)

Appendix 2: Full results of the two-sample t-test with equal variances

(Source: own contribution)

Wilcoxon signed-rank test

sign	obs	sum ranks	expected
positive	1045	749488	407363
negative	231	65238	407363
zero	0	0	0
all	1276	814726	814726

```
unadjusted variance   1.733e+08
adjustment for ties       -.125
adjustment for zeros          0
                     ----------
adjusted variance     1.733e+08

Ho: Firstdayreturn = NASDAQ100Return
             z =  25.986
    Prob > |z| =   0.0000
```

Total period (1995-2017)

Wilcoxon signed-rank test

sign	obs	sum ranks	expected
positive	735	347954	184685
negative	124	21416	184685
zero	0	0	0
all	859	369370	369370

```
unadjusted variance    52912253
adjustment for ties           0
adjustment for zeros          0
                     ----------
adjusted variance      52912253

Ho: Firstdayreturn = NASDAQ100Return
             z =  22.445
    Prob > |z| =   0.0000
```

Bubble period (1995-2000)

Wilcoxon signed-rank test

sign	obs	sum ranks	expected
positive	310	75233	43576.5
negative	107	11920	43576.5
zero	0	0	0
all	417	87153	87153

```
unadjusted variance   6064396.25
adjustment for ties        -0.13
adjustment for zeros        0.00
                      ----------
adjusted variance     6064396.13

Ho: Firstdayreturn = NASDAQ100Return
             z =  12.855
    Prob > |z| =   0.0000
```

Post-Bubble period (2001-2017)

Appendix 3: Full results of Wilcoxon signed rank test

(Source: own contribution)

Source	SS	df	MS
Model	180.192167	10	18.0192167
Residual	478.865216	1265	.378549578
Total	659.057383	1275	.516907751

Number of obs	1276
F(10, 1265)	47.60
Prob > F	0.0000
R-squared	0.2734
Adj R-squared	0.2677
Root MSE	.61526

Excessreturn	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnAge	-.0581728	.0242097	-2.40	0.016	-.1056684	-.0106773
lnMarketCap	.0639206	.0205875	3.10	0.002	.0235311	.10431
TopUnderwriter	.1274667	.0398389	3.20	0.001	.0493091	.2056243
VCDummy	.1164592	.0372612	3.13	0.002	.0433587	.1895598
UpRev	.4325061	.0414318	10.44	0.000	.3512235	.5137888
DownRev	-.1608369	.0535952	-3.00	0.003	-.2659821	-.0556916
CSI	.0097882	.0022246	4.40	0.000	.005424	.0141524
VIX	.0103908	.0037349	2.78	0.005	.0030635	.0177181
IPOactivity180days	.0018931	.0004044	4.68	0.000	.0010998	.0026864
Floating	-.055554	.1536274	-0.36	0.718	-.3569465	.2458384
_cons	-2.236206	.4649262	-4.81	0.000	-3.148318	-1.324095

Appendix 4: Full regression results initial model (Total period)

(Source: own contribution)

Source	SS	df	MS
Model	156.277445	10	15.6277445
Residual	435.695113	848	.513791407
Total	591.972558	858	.689944707

Number of obs	859
F(10, 848)	30.42
Prob > F	0.0000
R-squared	0.2640
Adj R-squared	0.2553
Root MSE	.71679

Excessreturn	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnAge	-.0641653	.033023	-1.94	0.052	-.1289816	.0006511
lnMarketCap	.0911204	.0336125	2.71	0.007	.0251469	.157094
TopUnderwriter	.1769095	.0563642	3.14	0.002	.0662797	.2875392
VCDummy	.1457223	.0526888	2.77	0.006	.0423065	.2491382
UpRev	.5087985	.0583906	8.71	0.000	.3941915	.6234056
DownRev	-.2865761	.0880429	-3.25	0.001	-.4593837	-.1137686
CSI	.0137526	.0055983	2.46	0.014	.0027645	.0247407
VIX	.0077285	.0076326	1.01	0.312	-.0072526	.0227096
IPOactivity180days	.0016869	.0006801	2.48	0.013	.000352	.0030219
Floating	.1278744	.2193262	0.58	0.560	-.3026115	.5583603
_cons	-3.167418	.7308515	-4.33	0.000	-4.601908	-1.732928

Appendix 5: Full regression results initial model (Bubble period)

(Source: own contribution)

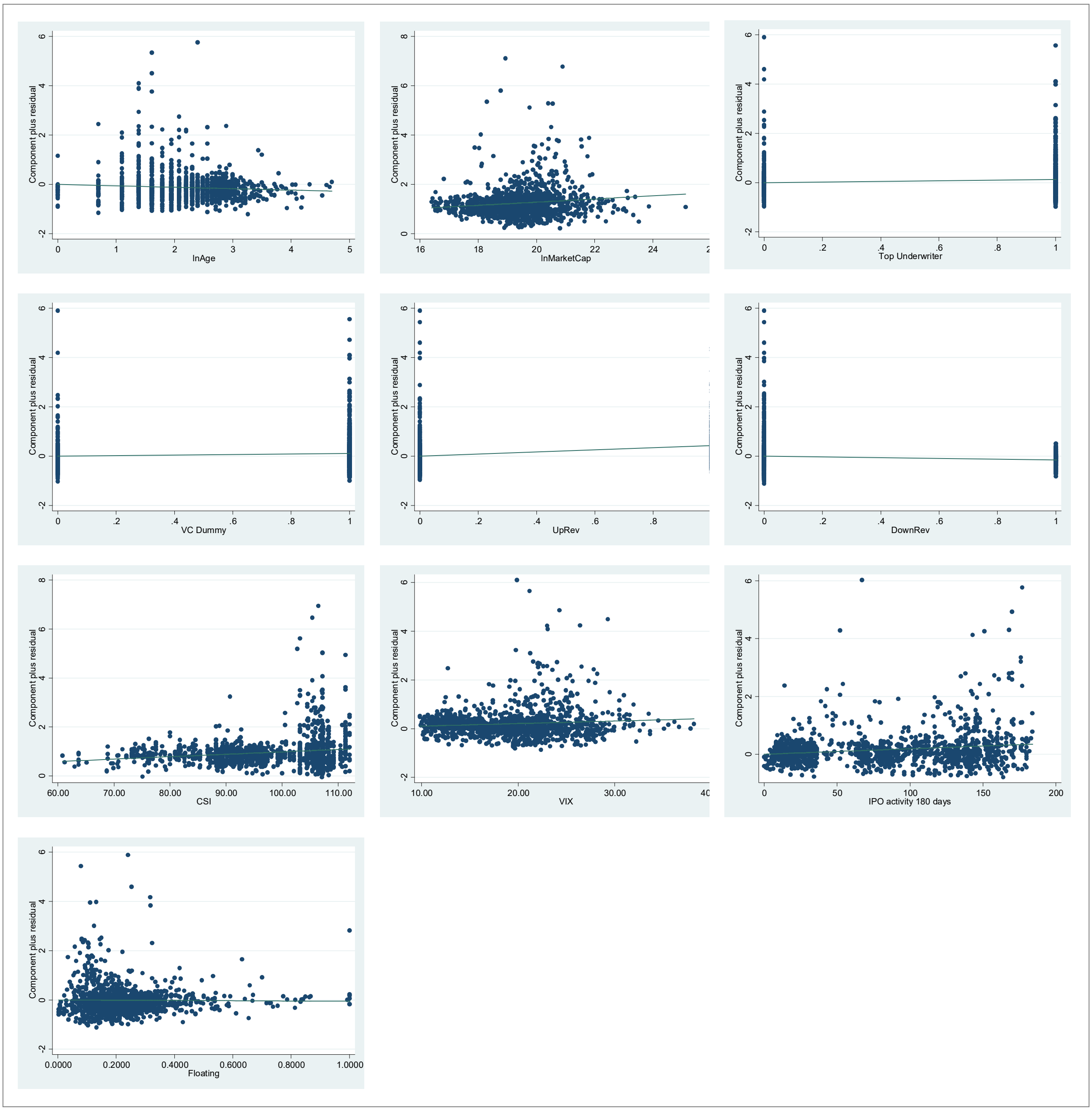
Source	SS	df	MS
Model	8.09762713	10	.809762713
Residual	22.0800743	406	.054384419
Total	30.1777014	416	.072542551

Number of obs	= 417
F(10, 406)	= 14.89
Prob > F	= 0.0000
R-squared	= 0.2683
Adj R-squared	= 0.2503
Root MSE	= .2332

Excessreturn	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnAge	.0057811	.018323	0.32	0.753	-.0302387	.0418009
lnMarketCap	-.0069378	.0129684	-0.53	0.593	-.0324315	.0185558
TopUnderwriter	.0323092	.0274376	1.18	0.240	-.0216283	.0862466
VCDummy	.0269705	.0262771	1.03	0.305	-.0246857	.0786268
UpRev	.2231132	.0288866	7.72	0.000	.1663272	.2798993
DownRev	-.0953167	.0302223	-3.15	0.002	-.1547285	-.0359049
CSI	-.0007847	.0014911	-0.53	0.599	-.0037159	.0021466
VIX	-.0024894	.0026213	-0.95	0.343	-.0076423	.0026636
IPOactivity180days	-.0006116	.0013939	-0.44	0.661	-.0033517	.0021285
Floating	-.41403	.1119781	-3.70	0.000	-.6341592	-.1939008
_cons	.4414532	.3111987	1.42	0.157	-.1703087	1.053215

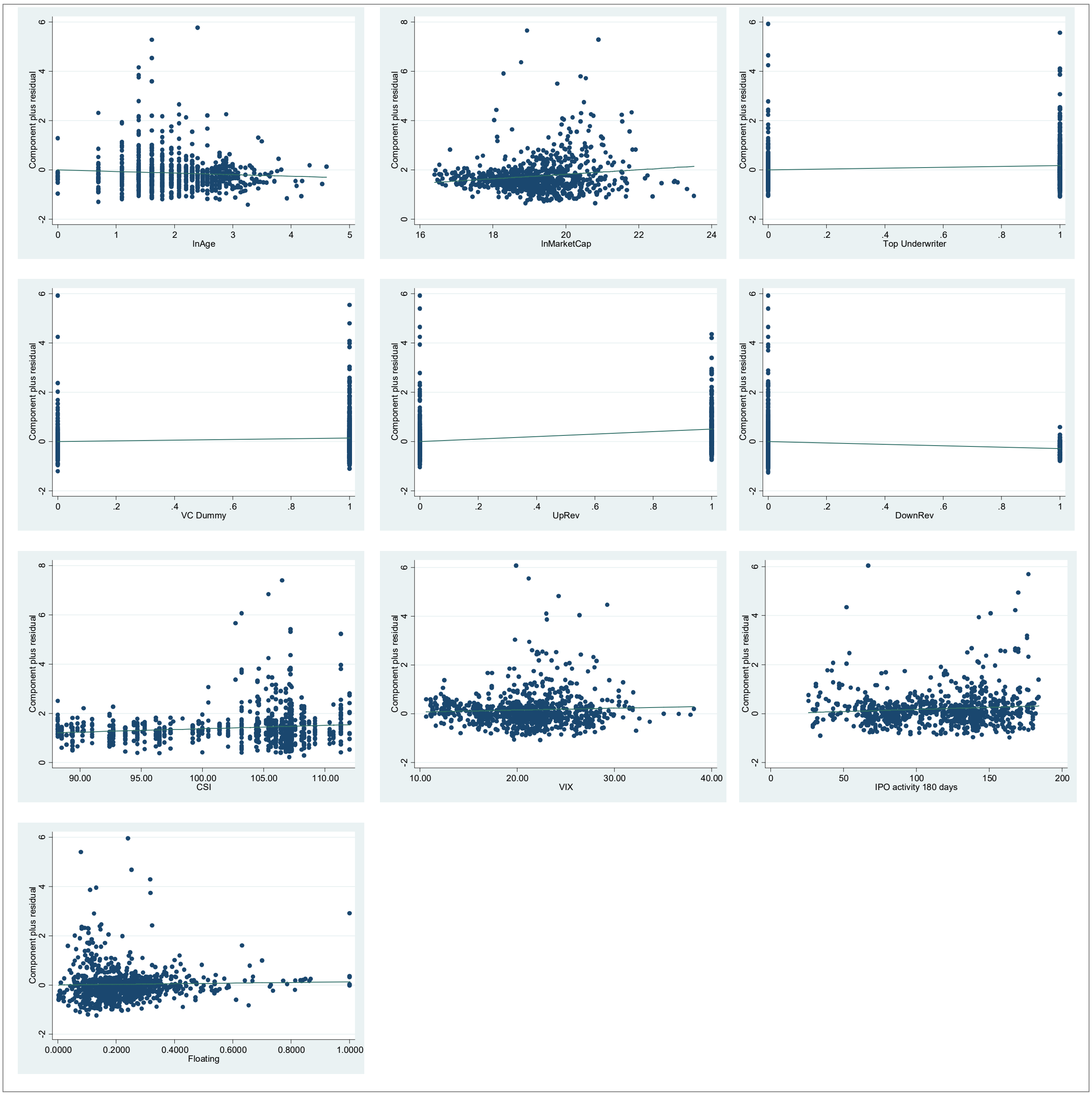
Appendix 6: Full regression results initial model (Post-Bubble period)

(Source: own contribution)



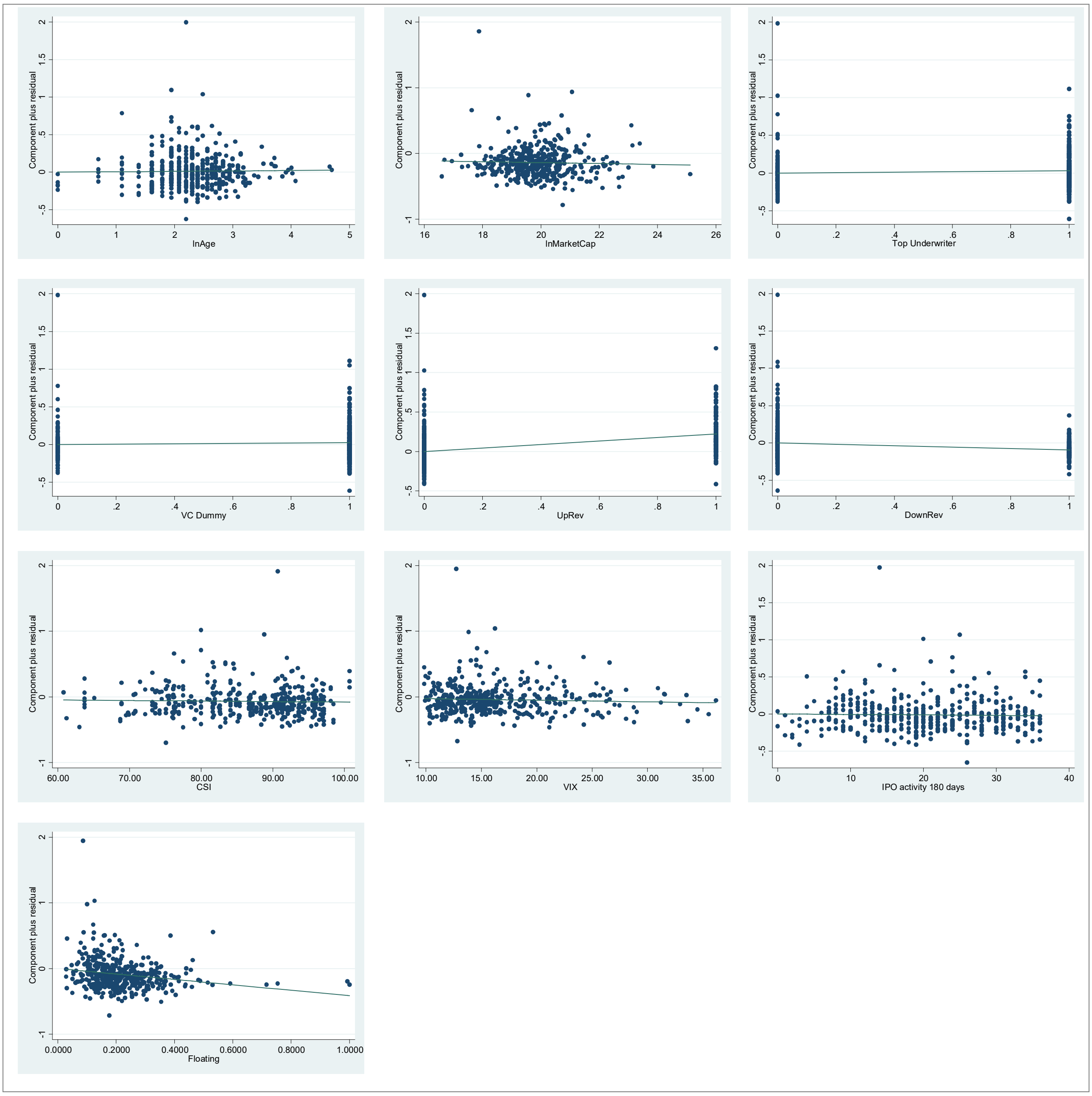
Appendix 7: Test correlation of dependent variables and error term (Total period)

(Source: own contribution)



Appendix 8: Test correlation of dependent variables and error term (Bubble period)

(Source: own contribution)



Appendix 9: Test correlation of dependent variables and error term (Post-Bubble period)

(Source: own contribution)

	lnAge	lnMark~p	TopUnd~r	VCDummy	UpRev	DownRev	CSI	VIX	I~80days	Floating
lnAge	1.0000									
lnMarketCap	0.0306	1.0000								
TopUnderwr~r	0.0171	0.4794	1.0000							
VCDummy	-0.0928	0.0918	0.1520	1.0000						
UpRev	-0.0775	0.2948	0.1748	0.1627	1.0000					
DownRev	0.1163	-0.0814	0.0000	-0.1076	-0.2493	1.0000				
CSI	-0.1725	-0.1185	-0.0960	-0.0045	0.0717	-0.1373	1.0000			
VIX	-0.1767	0.0214	0.0041	0.0542	0.0340	-0.0281	0.4527	1.0000		
IPOac~80days	-0.1856	-0.1434	-0.1281	0.0208	0.0667	-0.1231	0.5978	0.2889	1.0000	
Floating	0.0138	-0.5665	-0.2492	-0.0993	-0.1731	0.0248	0.0269	-0.0364	-0.0091	1.0000

Total period (1995-2017)

	lnAge	lnMark~p	TopUnd~r	VCDummy	UpRev	DownRev	CSI	VIX	I~80days	Floating
lnAge	1.0000									
lnMarketCap	-0.0669	1.0000								
TopUnderwr~r	-0.0747	0.4423	1.0000							
VCDummy	-0.1211	0.1434	0.1534	1.0000						
UpRev	-0.0793	0.3659	0.1699	0.1506	1.0000					
DownRev	0.1278	-0.1305	-0.0464	-0.0712	-0.2129	1.0000				
CSI	-0.0581	0.2908	0.2151	0.1179	0.1068	-0.0007	1.0000			
VIX	-0.0967	0.1948	0.1414	0.1039	0.0467	0.0704	0.7095	1.0000		
IPOac~80days	-0.0033	0.1985	0.0998	0.1366	0.0622	0.0171	-0.0011	-0.0906	1.0000	
Floating	0.0256	-0.6345	-0.2619	-0.0897	-0.1797	0.0054	-0.0918	-0.0584	-0.1091	1.0000

Bubble period (1995-2000)

	lnAge	lnMark~p	TopUnd~r	VCDummy	UpRev	DownRev	CSI	VIX	I~80days	Floating
lnAge	1.0000									
lnMarketCap	0.0448	1.0000								
TopUnderwr~r	0.0740	0.4568	1.0000							
VCDummy	-0.0729	-0.0552	0.1245	1.0000						
UpRev	-0.0407	0.2273	0.2334	0.1996	1.0000					
DownRev	0.0121	-0.1462	-0.0227	-0.1944	-0.3058	1.0000				
CSI	0.0592	-0.1085	-0.1051	-0.0586	-0.0329	-0.0562	1.0000			
VIX	-0.0945	0.0912	0.0342	0.0444	-0.0474	0.0099	-0.4206	1.0000		
IPOac~80days	-0.0533	-0.0118	0.0287	-0.0069	-0.0504	0.0621	0.0689	-0.2642	1.0000	
Floating	0.0293	-0.4329	-0.2000	-0.1172	-0.1689	0.0915	0.1256	-0.0823	0.0235	1.0000

Post-Bubble period (2001-2017)

Appendix 10: Correlation factors of our independent variables

(Source: own contribution)

Variable	VIF	1/VIF
lnMarketCap	1.95	0.513496
CSI	1.83	0.546279
IPOac~80days	1.62	0.618936
Floating	1.50	0.666115
TopUnderwr~r	1.33	0.750345
VIX	1.29	0.773284
UpRev	1.19	0.838075
DownRev	1.11	0.903385
lnAge	1.07	0.931240
VCDummy	1.07	0.938853
Mean VIF	1.40	

Total period (1995-2017)

Variable	VIF	1/VIF
lnMarketCap	2.37	0.421661
CSI	2.16	0.463356
VIX	2.10	0.477175
Floating	1.73	0.578126
TopUnderwr~r	1.27	0.787276
UpRev	1.21	0.825833
DownRev	1.09	0.913617
IPOac~80days	1.09	0.921223
VCDummy	1.08	0.926523
lnAge	1.04	0.958183
Mean VIF	1.51	

Bubble period (1995-2000)

Variable	VIF	1/VIF
lnMarketCap	1.61	0.620140
TopUnderwr~r	1.36	0.737983
VIX	1.34	0.748519
Floating	1.28	0.783759
CSI	1.25	0.800795
UpRev	1.23	0.814393
DownRev	1.17	0.857583
VCDummy	1.14	0.876632
IPOac~80days	1.10	0.911661
lnAge	1.03	0.966242
Mean VIF	1.25	

Post-Bubble period (2001-2017)

Appendix 11: Variance Inflation factors of our independent variables

(Source: own contribution)

Time Period	Total	Total	Bubble	Bubble	Post-Bubble	Post-Bubble
Model	**Initial**	**Hetero**	**Initial**	**Hetero**	**Initial**	**Hetero**
Ln(1+Age)	-0.0582**	-0.0582***	-0.0642*	-0.0642**	0.0058	0.0058
	(0.0242)	(0.0198)	(0.0330)	(0.0261)	(0.0183)	(0.0143)
Ln(MarketCap)	0.0639***	0.0639***	0.0911***	0.0911***	-0.0069	-0.0069
	(0.0206)	(0.0195)	(0.0336)	(0.0308)	(0.0130)	(0.0177)
TopUnderwriter	0.1275***	0.1275***	0.1769***	0.1769***	0.0323	0.0323
	(0.0398)	(0.0368)	(0.0564)	(0.0519)	(0.0274)	(0.0236)
VC	0.1165***	0.1165***	0.1457***	0.1457***	0.0270	0.0270
	(0.0373)	(0.0337)	(0.0527)	(0.0443)	(0.0263)	(0.0317)
UpRev	0.4325***	0.4325***	0.5088***	0.5088***	0.2231***	0.2231***
	(0.0414)	(0.0452)	(0.0584)	(0.0629)	(0.0289)	(0.0308)
DownRev	-0.1608***	-0.1608***	-0.2866***	-0.2866***	-0.0953***	-0.0953***
	(0.0536)	(0.0297)	(0.0880)	(0.0460)	(0.0302)	(0.0254)
CSI	0.0098***	0.0098***	0.0138**	0.0138***	-0.0008	-0.0008
	(0.0022)	(0.0017)	(0.0056)	(0.0051)	(0.0015)	(0.0014)
VIX	0.0104***	0.0104***	0.0077	0.0077	-0.0025	-0.0025
	(0.0037)	(0.0030)	(0.0076)	(0.0079)	(0.0026)	(0.0025)
IPOactivity180	0.0019***	0.0019***	0.0017**	0.0017**	-0.0006	-0.0006
	(0.0004)	(0.0005)	(0.0007)	(0.0008)	(0.0014)	(0.0014)
Floating	-0.0556	-0.0556	0.1279	0.1279	-0.4140***	-0.4140***
	(0.1536)	(0.1702)	(0.2193)	(0.2263)	(0.1120)	(0.1533)
Constant	-2.2362***	-2.2362***	-3.1674***	-3.1674***	0.4415	0.4415
	(0.4649)	(0.4411)	(0.7309)	(0.7428)	(0.3112)	(0.4464)
Observations	1,276	1,276	859	859	417	417
R-squared	0.2734	0.2734	0.2640	0.2640	0.2683	0.2683
Standard errors in parentheses						
***** p<0.01, ** p<0.05, * p<0.1**						

Appendix 12: Comparison initial model and for heteroscedasticity corrected model

(Source: own contribution)

Time Period	Total	Total	Bubble	Bubble	Post-bubble	Post-bubble
Model	**Initial**	**squared age**	**Initial**	**squared age**	**Initial**	**squared age**
Ln(1+Age)	-0.0582**		-0.0642*		0.0058	
	(0.0242)		(0.0330)		(0.0183)	
Ln(1+Age)sq		-0.0163***		-0.0202**		-0.0001
		(0.0057)		(0.0080)		(0.0040)
Ln(MarketCap)	0.0639***	0.0660***	0.0911***	0.0943***	-0.0069	-0.0068
	(0.0206)	(0.0206)	(0.0336)	(0.0336)	(0.0130)	(0.0130)
TopUnderwriter	0.1275***	0.1262***	0.1769***	0.1748***	0.0323	0.0331
	(0.0398)	(0.0398)	(0.0564)	(0.0563)	(0.0274)	(0.0274)
VC	0.1165***	0.1089***	0.1457***	0.1366***	0.0270	0.0264
	(0.0373)	(0.0375)	(0.0527)	(0.0529)	(0.0263)	(0.0265)
UpRev	0.4325***	0.4315***	0.5088***	0.5077***	0.2231***	0.2225***
	(0.0414)	(0.0414)	(0.0584)	(0.0583)	(0.0289)	(0.0289)
DownRev	-0.1608***	-0.1563***	-0.2866***	-0.2750***	-0.0953***	-0.0954***
	(0.0536)	(0.0536)	(0.0880)	(0.0882)	(0.0302)	(0.0302)
CSI	0.0098***	0.0098***	0.0138**	0.0137**	-0.0008	-0.0008
	(0.0022)	(0.0022)	(0.0056)	(0.0056)	(0.0015)	(0.0015)
VIX	0.0104***	0.0101***	0.0077	0.0070	-0.0025	-0.0026
	(0.0037)	(0.0037)	(0.0076)	(0.0076)	(0.0026)	(0.0026)
IPOactivity180	0.0019***	0.0019***	0.0017**	0.0017**	-0.0006	-0.0007
	(0.0004)	(0.0004)	(0.0007)	(0.0007)	(0.0014)	(0.0014)
Floating	-0.0556	-0.0433	0.1279	0.1396	-0.4140***	-0.4127***
	(0.1536)	(0.1536)	(0.2193)	(0.2190)	(0.1120)	(0.1123)
Constant	-2.2362***	-2.3101***	-3.1674***	-3.2461***	0.4415	0.4534
	(0.4649)	(0.4620)	(0.7309)	(0.7275)	(0.3112)	(0.3093)
Observations	1,276	1,276	859	859	417	417
R-squared	0.2734	0.2748	0.2640	0.2662	0.2683	0.2682
Standard errors in parentheses						
***** p<0.01, ** p<0.05, * p<0.1**						

Appendix 13: Full results comparison initial model and adaption with squared age proxy

(Source: own contribution)

Time Period	Average nr. of bookrunner	Max nr. of bookrunner
Bubble	1,03	5
Post-bubble	2,08	10

Appendix 14: Number of bookrunner in the bubble and post-bubble time period

(Source: own contribution)

Time Period	Total	Total	Total	Bubble	Bubble	Bubble	Post-Bubble	Post-Bubble	Post-Bubble
Model	**Initial**	**Nr.**	**Init+Nr.**	**Initial**	**Nr.**	**Init+Nr.**	**Initial**	**Nr.**	**Init+Nr.**
Ln(1+Age)	-0.0582**	-0.0582**	-0.0582**	-0.0642*	-0.0666**	-0.0618*	0.0058	0.0088	0.0071
	(0.0242)	(0.0243)	(0.0242)	(0.0330)	(0.0332)	(0.0330)	(0.0183)	(0.0183)	(0.0184)
Ln(MarketCap)	0.0639***	0.0984***	0.0728***	0.0911***	0.1278***	0.0953***	-0.0069	-0.0075	-0.0147
	(0.0206)	(0.0212)	(0.0226)	(0.0336)	(0.0324)	(0.0337)	(0.0130)	(0.0146)	(0.0157)
TopUnderwriter	0.1275***		0.1277***	0.1769***		0.1844***	0.0323		0.0336
	(0.0398)		(0.0398)	(0.0564)		(0.0566)	(0.0274)		(0.0275)
NrBook		-0.0219	-0.0225		-0.1251	-0.1573		0.0088	0.0095
		(0.0235)	(0.0234)		(0.1083)	(0.1081)		(0.0108)	(0.0108)
VC	0.1165***	0.1305***	0.1155***	0.1457***	0.1591***	0.1434***	0.0270	0.0325	0.0273
	(0.0373)	(0.0371)	(0.0373)	(0.0527)	(0.0528)	(0.0527)	(0.0263)	(0.0260)	(0.0263)
UpRev	0.4325***	0.4339***	0.4281***	0.5088***	0.5073***	0.5069***	0.2231***	0.2319***	0.2270***
	(0.0414)	(0.0418)	(0.0417)	(0.0584)	(0.0587)	(0.0584)	(0.0289)	(0.0290)	(0.0292)
DownRev	-0.1608***	-0.1490***	-0.1588***	-0.2866***	-0.2835***	-0.2905***	-0.0953***	-0.0925***	-0.0969***
	(0.0536)	(0.0537)	(0.0536)	(0.0880)	(0.0885)	(0.0880)	(0.0302)	(0.0301)	(0.0303)
CSI	0.0098***	0.0093***	0.0093***	0.0138**	0.0152***	0.0138**	-0.0008	-0.0006	-0.0005
	(0.0022)	(0.0023)	(0.0023)	(0.0056)	(0.0056)	(0.0056)	(0.0015)	(0.0015)	(0.0015)
VIX	0.0104***	0.0102***	0.0101***	0.0077	0.0070	0.0073	-0.0025	-0.0020	-0.0019
	(0.0037)	(0.0038)	(0.0038)	(0.0076)	(0.0077)	(0.0076)	(0.0026)	(0.0027)	(0.0027)
IPOactivity180	0.0019***	0.0018***	0.0018***	0.0017**	0.0017**	0.0017**	-0.0006	-0.0003	-0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0007)	(0.0007)	(0.0007)	(0.0014)	(0.0014)	(0.0014)
Floating	-0.0556	-0.0165	-0.0322	0.1279	0.1573	0.1498	-0.4140***	-0.4158***	-0.4206***
	(0.1536)	(0.1560)	(0.1556)	(0.2193)	(0.2209)	(0.2197)	(0.1120)	(0.1123)	(0.1123)
Constant	-2.2362***	-2.7730***	-2.3256***	-3.1674***	-3.8182***	-3.0973***	0.4415	0.4150	0.5359
	(0.4649)	(0.4549)	(0.4742)	(0.7309)	(0.7017)	(0.7320)	(0.3112)	(0.3145)	(0.3295)
Observations	1,276	1,276	1,276	859	859	859	417	417	417
R-squared	0.2734	0.2680	0.2739	0.2640	0.2566	0.2658	0.2683	0.2670	0.2697
Standard errors in parentheses									
***** p<0.01, ** p<0.05, * p<0.1**									

Appendix 15: Comparison initial model and adaption with number of bookrunners

(Source: own contribution)

	Average Age at IPO (in years)	IPO's with Top Underwriter (in %)
VC-backed	8,1	53%
Non VC-backed	11,5	37%

Appendix 16: Company age and top underwriter concerning VC-backing

(Source: own contribution)

Period	Total	Total	Bubble	Bubble	Post-Bubble	Post-Bubble
Model	**Initial**	**Abs. rev.**	**Initial**	**Abs. rev.**	**Initial**	**Abs. rev.**
Ln(1+Age)	-0.0582**	-0.0513**	-0.0642*	-0.0520	0.0058	-0.0020
	(0.0242)	(0.0240)	(0.0330)	(0.0325)	(0.0183)	(0.0185)
Ln(MarketCap)	0.0639***	0.0579***	0.0911***	0.0637*	-0.0069	-0.0050
	(0.0206)	(0.0204)	(0.0336)	(0.0336)	(0.0130)	(0.0131)
TopUnderwriter	0.1275***	0.1274***	0.1769***	0.1596***	0.0323	0.0427
	(0.0398)	(0.0394)	(0.0564)	(0.0556)	(0.0274)	(0.0274)
VC	0.1165***	0.1170***	0.1457***	0.1360***	0.0270	0.0382
	(0.0373)	(0.0368)	(0.0527)	(0.0520)	(0.0263)	(0.0263)
UpRev	0.4325***		0.5088***		0.2231***	
	(0.0414)		(0.0584)		(0.0289)	
DownRev	-0.1608***		-0.2866***		-0.0953***	
	(0.0536)		(0.0880)		(0.0302)	
absoluteRev		0.1244***		0.1638***		0.0556***
		(0.0098)		(0.0147)		(0.0064)
CSI	0.0098***	0.0085***	0.0138**	0.0131**	-0.0008	-0.0014
	(0.0022)	(0.0022)	(0.0056)	(0.0055)	(0.0015)	(0.0015)
VIX	0.0104***	0.0103***	0.0077	0.0105	-0.0025	-0.0040
	(0.0037)	(0.0037)	(0.0076)	(0.0075)	(0.0026)	(0.0026)
IPOactivity180	0.0019***	0.0017***	0.0017**	0.0019***	-0.0006	-0.0007
	(0.0004)	(0.0004)	(0.0007)	(0.0007)	(0.0014)	(0.0014)
Floating	-0.0556	-0.0956	0.1279	-0.0034	-0.4140***	-0.4006***
	(0.1536)	(0.1522)	(0.2193)	(0.2169)	(0.1120)	(0.1134)
Constant	-2.2362***	-1.9423***	-3.1674***	-2.6314***	0.4415	0.5172*
	(0.4649)	(0.4635)	(0.7309)	(0.7284)	(0.3112)	(0.3132)
Observations	1,276	1,276	859	859	417	417
R-squared	0.2734	0.2863	0.2640	0.2839	0.2683	0.2485
Standard errors in parentheses						
***** p<0.01, ** p<0.05, * p<0.1**						

Appendix 17: Full results comparison initial model and adaption with absolute revision

(Source: own contribution)

Time Period	Total	Total	Total	Bubble	Bubble	Bubble	Post-Bubble	Post-Bubble	Post-Bubble
Model	**Initial**	**90 days**	**360 days**	**Initial**	**90 days**	**360 days**	**Initial**	**90 days**	**360 days**
Ln(1+Age)	-0.0582**	-0.0587**	-0.0648***	-0.0642*	-0.0630*	-0.0635*	0.0058	0.0045	0.0079
	(0.0242)	(0.0243)	(0.0243)	(0.0330)	(0.0331)	(0.0332)	(0.0183)	(0.0183)	(0.0183)
Ln(MarketCap)	0.0639***	0.0612***	0.0585***	0.0911***	0.0962***	0.1072***	-0.0069	-0.0066	-0.0079
	(0.0206)	(0.0206)	(0.0207)	(0.0336)	(0.0337)	(0.0336)	(0.0130)	(0.0130)	(0.0130)
TopUnderwriter	0.1275***	0.1267***	0.1227***	0.1769***	0.1787***	0.1774***	0.0323	0.0337	0.0308
	(0.0398)	(0.0400)	(0.0401)	(0.0564)	(0.0565)	(0.0566)	(0.0274)	(0.0274)	(0.0274)
VC	0.1165***	0.1169***	0.1207***	0.1457***	0.1517***	0.1639***	0.0270	0.0266	0.0258
	(0.0373)	(0.0374)	(0.0375)	(0.0527)	(0.0528)	(0.0526)	(0.0263)	(0.0262)	(0.0263)
UpRev	0.4325***	0.4378***	0.4389***	0.5088***	0.5108***	0.5047***	0.2231***	0.2219***	0.2274***
	(0.0414)	(0.0415)	(0.0417)	(0.0584)	(0.0586)	(0.0586)	(0.0289)	(0.0289)	(0.0291)
DownRev	-0.1608***	-0.1589***	-0.1695***	-0.2866***	-0.2741***	-0.2665***	-0.0953***	-0.0943***	-0.0963***
	(0.0536)	(0.0538)	(0.0539)	(0.0880)	(0.0880)	(0.0890)	(0.0302)	(0.0302)	(0.0302)
CSI	0.0098***	0.0110***	0.0124***	0.0138**	0.0147***	0.0148**	-0.0008	-0.0007	-0.0009
	(0.0022)	(0.0022)	(0.0023)	(0.0056)	(0.0056)	(0.0057)	(0.0015)	(0.0015)	(0.0015)
VIX	0.0104***	0.0102***	0.0106***	0.0077	0.0056	0.0042	-0.0025	-0.0029	-0.0022
	(0.0037)	(0.0037)	(0.0038)	(0.0076)	(0.0076)	(0.0079)	(0.0026)	(0.0026)	(0.0025)
IPOactivity180	0.0019***			0.0017**			-0.0006		
	(0.0004)			(0.0007)			(0.0014)		
IPOactivity90		0.0029***			0.0020			-0.0024	
		(0.0008)			(0.0012)			(0.0024)	
IPOactivity360			0.0005**			-0.0002			0.0005
			(0.0002)			(0.0004)			(0.0006)
Floating	-0.0556	-0.0587	-0.0988	0.1279	0.1475	0.1556	-0.4140***	-0.4156***	-0.4189***
	(0.1536)	(0.1543)	(0.1544)	(0.2193)	(0.2196)	(0.2203)	(0.1120)	(0.1119)	(0.1120)
Constant	-2.2362***	-2.2660***	-2.2898***	-3.1674***	-3.2479***	-3.2977***	0.4415	0.4485	0.4316
	(0.4649)	(0.4661)	(0.4686)	(0.7309)	(0.7315)	(0.7377)	(0.3112)	(0.3090)	(0.3083)
Observations	1,276	1,276	1,276	859	859	859	417	417	417
R-squared	0.2734	0.2693	0.2635	0.2640	0.2609	0.2588	0.2683	0.2698	0.2692
Standard errors in parentheses									
***** p<0.01, ** p<0.05, * p<0.1**									

Appendix 18: Full results comparison initial model and adaption with IPO activity 90, 360 days

(Source: own contribution)

Time Period	Total	Bubble	Post-Bubble
Average number of IPOs last 180 days	39	102	16

Appendix 19: Average of number of IPOs conducted last 180 days

(Source: own contribution)

Time Period	Total	Total	Bubble	Bubble	Post- Bubble	Post- Bubble
Model	Initial	Dummy	Initial	Dummy	Initial	Dummy
Ln(1+Age)	-0.0582**	-0.0599**	-0.0642*	-0.0646*	0.0058	0.0044
	(0.0242)	(0.0244)	(0.0330)	(0.0331)	(0.0183)	(0.0183)
Ln(MarketCap)	0.0639***	0.0693***	0.0911***	0.0945***	-0.0069	-0.0058
	(0.0206)	(0.0213)	(0.0336)	(0.0337)	(0.0130)	(0.0130)
TopUnderwriter	0.1275***	0.1262***	0.1769***	0.1757***	0.0323	0.0331
	(0.0398)	(0.0401)	(0.0564)	(0.0565)	(0.0274)	(0.0274)
VC	0.1165***	0.1268***	0.1457***	0.1506***	0.0270	0.0279
	(0.0373)	(0.0375)	(0.0527)	(0.0527)	(0.0263)	(0.0262)
UpRev	0.4325***	0.4359***	0.5088***	0.5099***	0.2231***	0.2212***
	(0.0414)	(0.0416)	(0.0584)	(0.0585)	(0.0289)	(0.0288)
DownRev	-0.1608***	-0.1549***	-0.2866***	-0.2837***	-0.0953***	-0.0943***
	(0.0536)	(0.0541)	(0.0880)	(0.0882)	(0.0302)	(0.0301)
CSI	0.0098***	0.0109***	0.0138**	0.0146***	-0.0008	-0.0010
	(0.0022)	(0.0024)	(0.0056)	(0.0056)	(0.0015)	(0.0015)
VIX	0.0104***	0.0099***	0.0077	0.0071	-0.0025	-0.0035
	(0.0037)	(0.0038)	(0.0076)	(0.0076)	(0.0026)	(0.0027)
IPOactivity180	0.0019***		0.0017**		-0.0006	
	(0.0004)		(0.0007)		(0.0014)	
Hot/Cold Dummy		0.1576***		0.0980*		-0.0377
		(0.0540)		(0.0530)		(0.0251)
Floating	-0.0556	-0.0643	0.1279	0.1378	-0.4140***	-0.4143***
	(0.1536)	(0.1551)	(0.2193)	(0.2196)	(0.1120)	(0.1117)
Constant	-2.2362***	-2.3874***	-3.1674***	-3.1734***	0.4415	0.4723
	(0.4649)	(0.4666)	(0.7309)	(0.7326)	(0.3112)	(0.3092)
Observations	1,276	1,276	859	859	417	417
R-squared	0.2734	0.2658	0.2640	0.2616	0.2683	0.2720
Standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Appendix 20: Full results comparison initial model with hot/cold issue market dummy

(Source: own contribution)

Time Period	Total	Total	Bubble	Bubble	Post-Bubble	Post-Bubble
Model	**Initial**	**Incl. OAO**	**Initial**	**Incl. OAO**	**Initial**	**Incl. OAO**
Ln(1+Age)	-0.0582**	-0.0568**	-0.0642*	-0.0647*	0.0058	0.0104
	(0.0242)	(0.0242)	(0.0330)	(0.0330)	(0.0183)	(0.0181)
Ln(MarketCap)	0.0639***	0.0611***	0.0911***	0.0843**	-0.0069	-0.0017
	(0.0206)	(0.0206)	(0.0336)	(0.0341)	(0.0130)	(0.0128)
TopUnderwriter	0.1275***	0.1282***	0.1769***	0.1767***	0.0323	0.0317
	(0.0398)	(0.0397)	(0.0564)	(0.0564)	(0.0274)	(0.0270)
VC	0.1165***	0.1204***	0.1457***	0.1470***	0.0270	0.0380
	(0.0373)	(0.0372)	(0.0527)	(0.0527)	(0.0263)	(0.0260)
UpRev	0.4325***	0.4322***	0.5088***	0.5069***	0.2231***	0.2278***
	(0.0414)	(0.0413)	(0.0584)	(0.0584)	(0.0289)	(0.0284)
DownRev	-0.1608***	-0.1642***	-0.2866***	-0.2885***	-0.0953***	-0.0935***
	(0.0536)	(0.0535)	(0.0880)	(0.0880)	(0.0302)	(0.0297)
CSI	0.0098***	0.0094***	0.0138**	0.0138**	-0.0008	-0.0012
	(0.0022)	(0.0022)	(0.0056)	(0.0056)	(0.0015)	(0.0015)
VIX	0.0104***	0.0113***	0.0077	0.0078	-0.0025	-0.0016
	(0.0037)	(0.0037)	(0.0076)	(0.0076)	(0.0026)	(0.0026)
IPOactivity180	0.0019***	0.0019***	0.0017**	0.0017**	-0.0006	-0.0001
	(0.0004)	(0.0004)	(0.0007)	(0.0007)	(0.0014)	(0.0014)
Floating	-0.0556	-0.0718	0.1279	0.0935	-0.4140***	-0.4026***
	(0.1536)	(0.1533)	(0.2193)	(0.2214)	(0.1120)	(0.1101)
Overallotment		-0.5383***		-0.4790		-0.3484***
		(0.1964)		(0.4249)		(0.0902)
Constant	-2.2362***	-1.6308***	-3.1674***	-2.5578***	0.4415	0.6679**
	(0.4649)	(0.5136)	(0.7309)	(0.9091)	(0.3112)	(0.3116)
Observations	1,276	1,276	859	859	417	417
R-squared	0.2734	0.2777	0.2640	0.2651	0.2683	0.2943
Standard errors in parentheses						
***** p<0.01, ** p<0.05, * p<0.1**						

Appendix 21: Full results comparison initial model and adaption with OAO

(Source: own contribution)