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Master Thesis

The Next Tech Bubble?

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A B S T R A C T

In this paper, the current situation on the US equity market is studied to investigate if there is a stock bubble forming in the tech sector. Two econometric techniques, difference-in-differences (DID) and propensity score matching (PSM), are applied for estimations. The matching solves for differences in observable characteristics after which several regressions are run with the matched sample. Underpricing, trading volume and volatility are investigated as indicators of stock bubbles. Where underpricing is a recurring IPO symptom current underpricing tends to be above long term average while IPO numbers have been down. Comparing tech versus non-tech IPOs I find that for tech stocks the accounting standards have decreased with many of the companies performing an IPO having negative earnings. Looking at the ratios of trading volume and volatility between the NASDAQ and the S&P500 both ratios have relatively increased for stocks on the NASDAQ. The regression coefficients of the 2016 tech interaction variable with the independent variables trading volume and volatility indicate the exact opposite relation with the PE ratio compared to long term average. This is the case for both the regressions with the full and matched sample and indicates markets to behave irrationally. The current rally of prices for tech stocks seems hard to justify where underlying earnings do not grow in line with this increase. Low interest rates result in increased corporate lending's which are mainly used for share repurchases and dividend payments.

Keywords: stock bubble, underpricing, high-tech, propensity score matching, Dotcom, PE Ratio, trading volume, volatility, difference-in-differences

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NON-PLAGIARISM STATEMENT

By submitting this thesis, the author declares to have written this thesis completely by himself/herself, and not to have used sources or resources other than the ones mentioned. All sources used, quotes and citations that were literally taken from publications, or that were in close accordance with the meaning of those publications, are indicated as such.

Table of Contents

1. Introduction

In the history of our modern economy markets have experienced several bubbles. Bubbles are formed because of the way investors do business and are a good demonstration of the weaknesses of human emotion in economics. A bubble is part of an economic cycle of rapid expansion followed by a contraction (Brenner, 2002). Financial bubbles refer to situations where there is high trading volume on a particular equity or asset class at price levels that are higher than their intrinsic values. In other words; *a bubble occurs when certain investments are bid up to prices that are far too high to be sustainable in the long-run* (Gallant, 2016).

One of the first bubbles can be traced back all the way to the 16th century. The Dutch Tulip Mania resulted in tulip prices to rise to more than 10 times the annual income of a skilled worker (Garber, 1990). Over a century later the second and third bubble occurred. The so-called South Sea and Mississippi bubble were the first ´speculative stock bubbles´ (Garber, 1990). Executives speculated which led to an increase in stock prices. After some time, the market realized that the speculations by the executives were nothing but a hoax with the consequence of investors hitting the panic button. This resulted in a dramatic drop of stock prices. More modern and recent examples of financial bubbles are the Florida real estate bubble, Black Monday, and the Dotcom bubble. The latter occurred from the mid to the late 1990s where stock prices of technology (tech) companies reached enormous heights. In 2000 there was the burst of the bubble which resulted in enormous losses on the NASDAQ and other stock exchanges. The NASDAQ composite lost over 78% of its value during the burst after which a lot of companies and investors went bankrupt.

Over the past years, there has been an interesting development in Silicon Valley, California. Since Apple planted its roots in this area of the United States, Silicon Valley has always been at the heart of technological development. High-tech companies have a lot of potential and growth opportunities but are active in a very volatile industry. The growth potentials attract all different kind of venture capitalist and other investors which are looking for value-creating investment opportunities (Mansharamani, 2015). Over the years there has been a hype by tech firms to move to Silicon Valley and ride the technology wave. Consequently, renting cost for houses around the San Francisco area reached astronomic levels even being the highest in the entire United States. With this craze continuing funds are investing heavily in tech startups and other tech businesses in Silicon Valley. These investors do possess the funds to invest but it is doubted if they also possess the quality and skill set to improve, or make more efficient the specific tech industry they are investing in. Most of the funds are not specialized in the development and growth of these high-tech companies. The high amount of invested capital created enormous value of which some is presumed to be questionable (Srivastava & Theodore, 2015).

Economists believe that this rush in the high-tech sector is just another bubble that is exploding as we speak. Over the past year, there were some interesting developments which could point towards a bursting bubble. The initial public offering (IPO) market has been slowing down since 2015. This is having a big impact on the economy. In July 2014 chair of the Federal Reserve, Janet Yellen, warned investors for high stock valuation in the tech sector and mentioned the potential danger of a bubble. A strong measurement in forecasting long-term future stock return is the Robert Shiller's Cyclically Adjusted PE ratio (CAPE Ratio). The ratio compares stock prices to earnings over the course of 10 years. The ratio is adjusted for business cycles and inflationary pressure on earnings. Looking at historical CAPE ratios we find that high ratio trends highly correlate with boom periods. From 1881 till 2015 the average CAPE ratio for the US was around 17 while the current CAPE ratio is much higher. Professor Shiller found that previous crashes in 1929, 2000 and 2007 returned higher CAPE ratios before the burst. These years were all periods where the economy boomed at peaks followed by periods of recession and downward markets

In the private markets, there are a lot of companies valued into the millions and sometimes even the billions. There is a growing number of Unicorns (over $1 billion), Pentacorns (over $5 billion) and Decacorns (over $10 billion). The valuation of these companies continuous to increase with new investment rounds by different funds. Plenty of the companies never generated any profit. Around the world, economist have been questioning this development wondering what the real underlying value of these companies is. At least 145 private companies exceed this $1 billion valuation and numbers are increasing. Making money might not be the priority of startups but valuations like this could be questionable. Where venture investments were sky high in recent years, executives of the companies receiving these investments had to spend wildly, to outgrow rivals, increase recruiting or for other reasons. Now, the question rises if these companies can survive on their own when funding dries up.

In this paper, I will further elaborate on previous bubbles in the history of our modern economy and I will try to detect signals that indicate that the economy is experiencing a bubble as we speak. Most important and relevant for this research is the tech bubble also known as the Dotcom bubble that occurred at the end of the 90s. A wide range of empirical research has been conducted on this bubble which showed some remarkable signals which could be indicators of a bubble. Because the economic environment and regulations have changed it is important to notice the difference between the current situation and that of 16 years ago. There has been a change in the standards for going public. Since the enactment of the SOX-act stricter regulations makes it more difficult to raise money through an IPO. Stricter regulations on the amount of debt a company can have on its books are implemented.

The rest of the paper is organized as follows. Chapter 2 presents a review of the literature on past economic bubbles and the current situation. In chapter 3 bubbles are investigated and the related hypotheses are constructed. Chapter 4 discusses the data and applied methodology. In chapter 5 the empirical findings are reported. In chapter 6 the findings are discussed and the results are linked to previous findings in other research. Chapter 7 concludes. Last chapter 8 provides concluding remarks as well as shortcomings and propose recommendations for future research.

2. Theoretical Framework

The first part of the theoretical framework focusses on the concept of bubbles. Secondly there is an overview of historical bubbles and further elaboration on the different symptoms during these bubbles. The third part elaborates on the scope of literature available on ways of identifying a bubble.

2.1 The Concept of a Bubble

The scope of literature available covering the topic of bubbles is very broad and academics around the world cannot agree on whether certain events can be identified as a bubble or not. The book written by Kindleberger and Aliber define a bubble as *"an upward price movement over an extended range that then implodes"* (Kindleberger & Aliber, 1978). Another paper states: *"When looking at the basic terminology of an economic bubble most sources refer to it as a financial bubble which is characterized by rapid acceleration of asset prices and overheated economic activity which often goes hand in hand with uncontrolled supply of money and credit expansion"* (Ljungqvist & Wilhelm, 2003).

A very intuitive definition of a bubble was opted by Stiglitz. According to him the reason that the price is high today is only because investors believe that the selling price tomorrow will be higher. When fundamental factors like net profit do not justify the high prices, a bubble exist (Stiglitz, 1990). In academic papers the fact that bubbles in stock markets exist is often traced to John Keynes description of an equity market. He describes an equity market as an area in which speculators anticipate "what average opinion expects average opinion to be," rather than focusing on the market fundamentals. Most inefficiencies in market prices are small and often even so small that they are only statistically and not economically significant. Bubbles are often of such a big magnitude that this might be the reason this phenomenon has been covered so extensively.

A speculative bubble is usually caused by exaggerated expectations of growth, price appreciation, or other events that cause an increase in asset values. This results in higher trading volumes because more investors rally around the high expectations (Stiglitz, 1990). Buyers start outnumbering sellers pushing prices beyond a point to which the valuation exceeds the analysis of intrinsic value. The bubble is completed after prices fall back to normalized values which often involved steep decline in share prices in which investors start to panic and sell their investments. Stiglitz insists that if an infinite deadline for investments is impossible, the sole market power cannot guarantee economic growth in a path without a burst or boom, because investors can always exit their investments before asset prices fall back to their intrinsic value which makes it still possible to earn a positive return (Stiglitz, 1990). When looking at from a rational perspective, speculative bubbles can always survive when a limit of investment horizon is given because of the continued entry of speculators. This explains why the investing in assets suspected to be in a bubble is not per se irrational behavior. "*Under certain circumstances, there are rational components of the bubbles"* (Stiglitz, 1990).

Economist Hyman Minsky provided an early characterization of bubbles and the following burst. This characterization distinguishes between five phases (Kindleberger & Aliber, 1978). The first phase is that of an initial displacement like for example a new technology or innovation. This leads to increased expectations on growth and profits.

The first phase is followed by a boom phase which is characterized by low volatility, credit expansion, and increasing amount of capital invested. Asset prices start to rise, initially a low pace but with growing momentum. During this boom phase, the increased prices may start exceeding the actual fundamental increases from the new technology or innovation.

The boom is followed by a phase of euphoria in which investors trade overvalued assets in high volumes resulting in price to increase explosively. This is the point that some investors might be aware of the possible bubble, but they are confident that they can sell the asset in the future. High trading volumes and observed price volatility are characteristic of this phase. This is what we saw during the Dotcom bubble at the end of the 90s. At some point, informed investors will start reducing their position and cashing in on their investments. This profit taking face can hold for a while due to high demand of stocks by less sophisticated investors who still want to participate in the specific market.

The last phase is the panic phase in which prices start to fall rapidly when investors dump the assets. Prices spiral down which is often accelerated by margin calls. If the initial increase was financed with credit, spillover effects kick in, which can lead to severe overshooting. This concept was confirmed by Barber and Odean (2001) cited by Bhattacharya et al. (2010).

Much of the theoretical literature covering bubbles is an attempt to formalize the above-mentioned phases. Later in the literature review I will focus on the previous written research and the different symptoms to detect a bubble (Kindleberger & Aliber, 1978). The phases described give the opportunity to look at different variables at different stages to see if a bubble can be detected.

2.2 Historical Bubbles

When looking at the history of our modern economy there have been different bubbles on which different researches have been conducted. The goal of this part of the theoretical framework is to get an overview of bubbles that occurred in history and get an overview of common grounds. Between economists, it has always been a discussion when an event is referred to as a bubble so therefore the selection of bubbles reviewed in this theoretical framework is reduced to four. When researching the available literature these four bubbles experience the broadest recognition around the world.

2.2.1 Tulipmania

According to Mackay (1852), the tulipmania can best be described as a speculative bubble. In the current 21st century Holland is known as the tulip country in the world. Holland acquired this status around the 16th century somewhere in the Netherlands. During this century Holland became the

European center for the development and growing of new tulip varieties. Tulips found their way into Europe from the Ottoman Empire, present-day Turkey in the mid-1500s. When Carolus Clusios wrote a bestseller about the tulips in his garden in 1592 the flower became immensely popular around the world. The flower even became so popular that Mr. Clusios tulip bulbs got stolen from his garden on a daily basis. With the growing Dutch Golden age, so did the colorful tulip (Garber, 1990). Prices started to get out of hand in the 17th century. In 1625 a tulip bulb sold for an amount of gold worth $16,000 at $400 per ounce while other regular flower bulbs sold for significantly lower prices. The increase in prices attracted different kind of speculators which stewed prices to even higher levels. In February 1637, the moment was there that prices suddenly collapsed and tulip bulbs became worth only 10 percent of the highest values reached just months earlier. A century later, in 1739, prices of the bulbs had fallen to even lower levels often not being worth more than 0.005 percent of the value it had a peak price (Garber, 1989). This is the first even recorded bubble and shows what speculation can do.

2.2.2 South Sea Bubble

The South Sea bubble is one of the firs bubbles with a real stock market crash. In the 17th century, the financing of the United Kingdom was a completely unorganized and chaotic mess. Different government departments were responsible for their loans and there was a lack of a clear oversight on financial expenses and income. This all changed when a chancellor proposed to straighten out these inefficiencies. The first steps in straightening out the mess was the reconsideration of the monopoly right of the Bank of England. The Bank of England had the right to manage all the country's loans on a monopoly basis. By granting other private enterprises to participate in these loans more companies started to participate in loans on behalf of the government.

In 1711 the South Sea Company was founded as one of these competitors of the Bank of England. The company was promised a monopoly on all trade to the Spanish colonies in South America in exchange for taking over part of the national debt from the War of Spanish Succession earlier that century. The value of taking on all this debt strongly depended on the outcome of the war. In 1713 the war ended with the treaty of Utrecht. This made an end to the Spanish Succession war and Queen Anne´s war. This treaty negatively influenced the trade opportunities for the South Sea Company because of the confirmation of Spain's sovereignty over its new world colonies. The South Sea Company was left with limited options in the slave trade, interest to be paid by the government on the loan from the South Sea Company, and low trade opportunities in the colonies of Spain in South America due to this sovereignty of Spain. Although the low levels in the South Sea trade, the company did persuade the British government to approve the conversion of successive portions of the national debt into South Sea Company shares. Building on the war debt conversion of 1711 the government authorized the South Sea Company in 1719 to assume an additional portion of the national debt.

In January of 1720, South Sea Company stock was trading at a price of £128. In an effort to increase interest in the company's stock, the directors committed fraud with false claims of success. As a result, the share price increased to £175 in February that year. Over the next month's interest in the company increased. At a certain point, the British government approved a proposal from the company to assume even more of the national debt in exchange for South Sea Company shares. Remarkably this proposal was chosen over that of the Bank of England. With this new approval investor confidence increased and the share price climbed to around £330 just one month later by the end of March.

The South Sea Bubble was not a single isolated bubble event. As the South Sea Bubble was developing, a general interest in joint-stock investment opportunities was growing in popularity. By the mid of 1720, also known as the year that the bubble burst, the market was flooded with new ventures, each creating smaller speculative bubbles. The South Sea Company stock benefited from this rush by investors resulting in stock prices to rising to £550 by May. The Bubble Act was passed in June, requiring all joint-stock companies to receive an approval via a royal charter. This regulation had been introduced by the South Sea Company, as a means of controlling competition. The South Sea Company received its approval, perceived as a vote of confidence in the company, and by the end of June, its share price reached the peak of £1050 per share. After this investor confidence began to decrease. The sell-off began by early July with the collapse of share prices as a consequence. By the end of August, the stock price had decreased to £800 and by September the share price had plummeted to values below £175 per share. In 1721 investigations by the government exposed corruption and bribery that led to the prosecution of major players in the crisis, including both company and government officials.

2.2.3 Dotcom Bubble

A more recent burst occurred around the year 2000. America was on a winning streak in the pre-9/11 rise and the 'Dotcom' economy was growing rapidly with new internet based companies popping up daily. During the Dotcom era, the structural change was the relatively new invention of the internet. Immensely high valuations and unprofitable business models were justified by the new market created because of the internet. "*In the two-year period from early 1998 through February 2000, the Internet sector earned over 1000 percent returns on its public equity. In fact, by this date, the Internet sector equaled 6 percent of the market capitalization of all U.S. public companies and 20 percent of all publicly traded equity volume"* (Ofek & Richardson, 2003). Between 1998 and 1999 in total 147 small firms changed or adjusted their names so it contained "Dotcom". This "Dotcom" name change produced 74% cumulative abnormal returns (CAR) for the 10 days surrounding the announcement day (Cooper, et al., 2001). In March 2000, the rise abruptly came to an end with the burst of the Dotcom bubble. Stock prices plummeted and enormous amounts of invested money vaporized.

During the 1990s investors, venture capitalist and other big funds started to invest heavily in internet based companies. This resulted in a rise in equity markets fueled by the investments from over the world. Internet was a relatively young and new invention which took an increasingly important part in people´s life. The American consumer culture started to shift from store retailers to an increase in online retailing. With the increased popularity of the internet and a growing amount of investments, stock values started to grow rapidly. The value of the NASDAQ, the second biggest US index on technology companies, grew from around 1,000 points in 1995 to more than 5,000 points at the end of 2000. IPOs were creating ridicules returns for companies and shareholders. Stock prices sometimes doubling in value on the first trading day (Green & Goodnight, 2010). Because of this “hot” IPO market many firms, of which some not even active in the technology sector, raised capital through an IPO. This attracted both private and in institutional investors which raised stock prices even more. March 11 2000, all of this ended with stocks and the NASDAQ crashing. March 30 the NASDAQ was valued at 4,500 points compared to around 5,000 points on March 10. This meaning a loss of around $960 billion in just 15 trading days. Around the end of May, the NASDAQ was down to around 3.500 points indicating a loss of over the trillion dollars (Anon., 2015). With these enormous losses technology companies started to suffer and fall over. Investors limited their portfolio exposure to the industry and sold most of their shares.

Interesting about this specific collapse is the role of Chief Executive Officers (CEOs) and institutional investors. When a company performances an IPO the CEO of the company often holds a percentage of the stocks. During the Dotcom time, CEOs were not allowed to sell their shares after an IPO until the lock-up period ended. With markets being hot and CEOs having a good understanding about the company’s real value they started to sell their stocks as soon as this lock-up period ended. Institutional investors noticed this and started selling their shares as well. Private investors were not as good informed and therefore kept buying. With the market being flooded with shares prices plumbed. Private investors were hit hardest during this bubble. In their research Ljungqvist and Wilhelm found that during the run-up period the average offer price increased where the average age of firms performing an IPO decreased. Accounting standards decreased. They also found that the deal value significantly increased over the years until the burst (Ljungqvist & Wilhelm, 2003). During the Dotcom bubble, a lot of companies that went public did not generate any profit.

2.3 Identifying bubbles

When looking at our modern economy it becomes evident that almost all recognized bubble cases gathered speed through expansion of money and credit (Kindleberger & Aliber, 2005). This does not imply that every money and credit expansion leads to a mania but every mania can be associated with the expansion of credit. The tulip bubble developed with the credit of sellers of the bulbs. During the South Sea bubble the UK relied on the Sword Blade Bank as a credit source. In this research the first focus will therefore be on an increase on the amount of available capital by institutional and professional investors in a favorable market.

With this increase in available capital comes a second phenomenon detected in previous bubbles which is that of the existence of high prices and high trading volume. In addition, there is often high price volatility observed with this increase in capital (José & Wei, 2003). In the model by José and Wei they mention the fact that the ownership of a stock provides an opportunity to profit from the overvaluation of other investors. In their research, Alpert and Raiffa suggest that people overestimate the precision of their knowledge in some circumstances (Alper & Raiffa, 1982). High prices are often association with high PE ratios. During the Dotcom bubble companies had high PE ratios compared to long-term average. The PE ratio is an interesting metric to further examine because it gives an idea about the fundamental value of companies.

During the Dotcom bubble period in the late 90s, many authors studied and wrote whether the internet stock prices could be explained by the companies' fundamentals or by non-financial measures. An interesting phenomenon that was found regarding this period is that of underpricing. In research done by Ljungqvist and Wilhelm on the Dotcom bubble, they looked at underpricing during bubble periods. By looking at the difference between the offer price and the share price at the end of the first trading day they determined the initial return. What they found is that during the Dotcom bubble in 1999 and 2000 underpricing reached astronomical levels. Where the average initial first-day returns on an IPOs was around 17 percent in 1996 this increased to an average first-day return of 73% in 1999 (Ljungqvist & Wilhelm, 2003). These returns completely outperformed any historical numbers and are a clear sign of a bubble. There are many studies that cover this underpricing during the Dotcom and earlier bubbles but research on more recent bubbles is still rare or nonexistent.

2.3.1 Venture Capital

These days' tech firms largely avoid IPOs because there is a lot of private funding available. Firms that have gone public did not perform so well, offering little incentive for other to do so. According to some investors, investments are scaled back signaling a cooling down of the markets. The years 2015 and 2016 show significant fewer IPOs than previous years (Bryan, 2016). After the enactment of the Sarbanes-Oxley Act, in 2002, companies are required to comply with different regulations like financials reporting and internal controls. The risk today is almost completely evolved by private companies backed with private money.

Strange to see is the fact that 2016 was a year with a relative low number of tech IPOs while the amount of private companies valued over $1 billion has more than doubled over the past two years as figure 2 on the next page illustrates (Insight, 2016). The problem with these private deals is the fact that they are too big for the VCs to handle on their own. They therefore seek for public money in the form of investment funds, PE and hedge funds to carry the weight. From figure 2 it can be seen that it is not the amount of new investments that increased, but the actual deal values.

Figure 1: Development Total Number of Unicorns

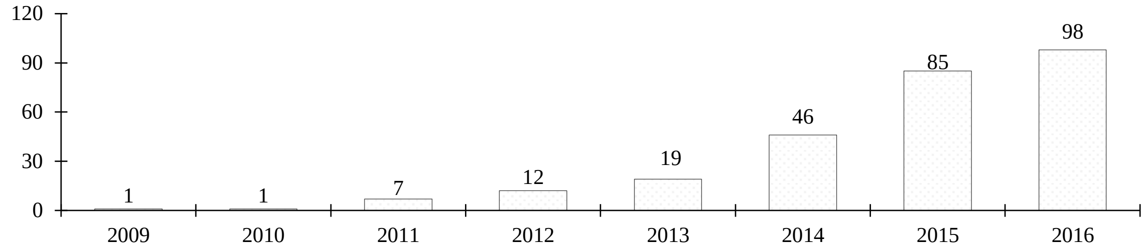
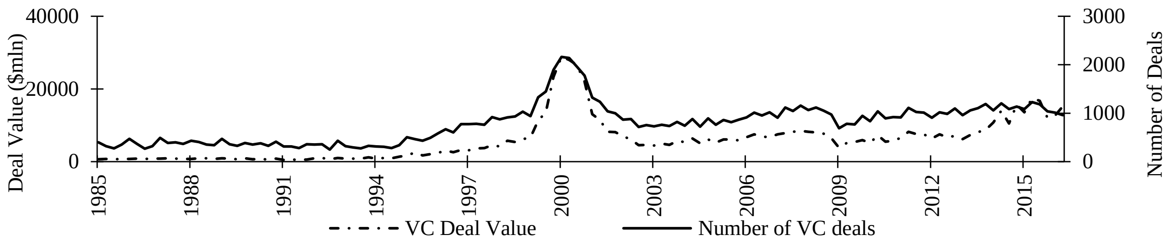


Figure 2: VC Investment by Deal Value and Number of Deals.



VC focuses on capital for start-ups or young high-growth companies[1]. The capital is provided by private investors or specialized financial institutions and for this funding, they demand an equity stake in the startup. Compared to private equity this form of investing is riskier due to the high uncertainty. It is found in academic research that venture capital backed IPOs experience larger first-day returns than comparable non-venture backed IPOs (Lee & Wahal, 2003). As mentioned before Silicon Valley is an area where a lot of high-tech companies are headquartered. This attracts a lot of VC which are seeking for good investment opportunities. Over the years there has been a development of increasing amounts of available capital resulting in a rush by VC firms to find good investments (Peggy M. Lee, 2004). When looking at the current amount of VC invested in companies in the US this amount is almost as high as seen during the Dotcom bubble and this amount is still increasing (Insight, 2016). What also becomes evident is that the type of company's VC invests in is differentiating. Where at the end of the 90s their focus was on tech startups they currently invest in a wider range of sectors. Appendix 8 gives a further elaboration on the amount of invested capital per sector and shows that investments are close to levels just before the Dotcom bubble burst. Years before the Dotcom bubble at a time that venture capital was becoming more popular two researchers wrote an article examining the relation between the backing of companies by venture capital and underpricing. They argued that firms backed by venture capital have better capabilities in attracting higher quality underwriters. Due to this, there is lower information asymmetry which again leads to less underpricing (Carter & Manaster, 1990). Contrary to this research is that of Mogilevky and Murgulov in 2012. They compared IPO underpricing of firms backed by venture capital, private equity, and non-sponsored IPOs. They found that private equity backed IPOs experience significant lower underpricing compared to venture capital and non-backed

[1] The first venture-backed startup dates to 1957 with the startup company Fairchild Semiconductors.

IPOs since private equity-backed IPOs tend to be larger and more profitable (Mogilevsky & Murgulov, 2012). This research again proved the relative power of participants in IPO deals. Company value consists of current earnings but a large part is also captured in the growth option value of a specific company.

2.3.2 Underpricing

The main goal of companies participating in a stock market launch is that of raising new capital. With this newly raised capital companies can repay investors, reinvest and continue business. In general, a firm performs an IPO when the cost of going public are lower than the cost of staying private (Pagano, et al., 1998). Participating in an IPO has both costs and benefits. When assuming perfect capital markets the hypothesis states that when a firm goes public, its IPO price should equal the expected market price. Not having perfect capital markets this is the biggest pitfall of an IPO. The highest costs come from adverse selection[2] because of information asymmetry and the fact that the value of the firm going public is unknown. And as known to all economist liquidity increases price[3].

Looking at historical numbers it becomes evident that IPOs come in waves. IPO waves can be predicted with high market returns, followed by low market returns, and accompanied by high stock prices just as during the Dotcom bubble in 2000 (Pastor & Veronesi, 2003). An interesting phenomenon noticed by Logue (1973) and Ibbotson (1975) is the fact of underpricing. What they noticed was that share prices increased exceptionally on the first trading day after an IPO. This indicated the IPO to be priced below its real market value which again would indicate firms tending to leave significant amounts of IPO proceeds on the table. Currently, IPOs still tend to be underpriced on average (Lowry, et al., 2010). Since the finding of Logue and Ibbotson there have been many economists trying to understand and explain this phenomenon.

IPO activity is cyclical, periods with many offerings are followed by periods with very few offerings, typically after a stock market crash (Ritter, 1996, and Ibbotson, Sindelar and Ritter, 1994). During a period of high returns, for example from 1977 to 1996, the high returns were followed by increasing IPO volume also referred to as “hot issue” markets. Interesting to see is that firm which issued during the years of high volume performed significantly worse than the companies that went public at the start of such an IPO cycle (Ibbotson, et al., 1994). According to Ritter returns are large for IPOs (Ritter, 1998). In the research done by Ljungqvist and Wilhelm on the Dotcom bubble, they looked at underpricing by looking at the difference between the offer price and the share price at the end of the

[2] Adverse selection refers to a situation where the seller has more information than the buyer or vice versa and is most famously explained through *Akerlof's market for lemons*

[3] Illiquidity puts downward pressure on the price of securities as of the fact that investors need to wait before they can divest their shares. Shareholders selling their shares during an IPO benefit from because they can reinvest their capital and more importantly diversify their portfolio.

first trading day. What they noticed was that in the run-up to the bubble underpricing increased exponentially.

IPO underpricing is a well-known phenomenon, calculated as first-day returns of issued shares. After the first trading day, it is possible to observe how the market values the stock. As mentioned above an often-mentioned reason for underpricing is that of *information asymmetry*. When the true value of a firm is unknown and one of the two parties, either the manager or investors, has more and better information about the true value of the firm this is called information asymmetry. The first thing a firm, intending to perform an IPO, does is hire an investment bank. This investment bank takes the role as underwriter[4]. This underwriters task is to measure the willingness of the market and start the book building. In this process, it discovers what the market is willing to pay for a share of the firm intending to perform an IPO. The underwriter mainly relies on the bids of well-informed investors. When the minimum required number of investors is reached, the underwriter can price the shares according to what the well-informed investors are willing to pay. Not always an underwriter is able to fill the books with well-informed investors. In this case, less informed investors come into play to fill the books. These uninformed investors lack costly information and therefore demand lower prices resulting in the underwriter deliberately underpricing the stock. If an underwriter can fill the books with more informed investors this results in lower underpricing. Research showed that prominent underwriter, who have access to more informed investors, are better able to attract enough investors (Carter, et al., 1998). Loughren and Ritter (2004) found a positive correlation between the reputation of the underwriter and underpricing. There is a wide range of literature covering different ways of measuring underwriter prestige. Another asymmetric model is that of the Winner's Curse. This model was first introduced by Rock (1986) and assumes that some investors are more informed than other investors (Rock, 1986).

Another explanation of underpricing is based on the *principal-agent problem.* This concept argues that underwriters might have other incentives than the optimization of the IPO proceeds for the issuer. When underwriters, for example, search for potential investors they often incur the cost of this search. Therefore, it could be more cost-effective to limit this search resulting in a higher eventual profit for the underwriter. Where the underwriter, in this case, would earn more this would have negative consequences for the issuer of the securities. In other words, the search for investors by the underwriter could be a trade-off for the highest profit (Carter, et al., 1998). A second trade-off an underwriter might have are the clients the company maintains on the investors side. Where the underwriting of an IPO is a one-time event the investors buying in on this are often long-term and well-known clients of the investment bank. If the investment bank wants to maintain its reputation and satisfy the investors this might lead to underpricing (Fang, 2005).

[4] Underwriting is stated as the process of raising money in either the form of debt or equity but in the case of an IPO focusses on in the form of raising equity.

Thirdly there is the control theory which reflects the agency problem. The agency problem is a conflict of interest in a relationship where a party is expected to act in the other's best interest. In finance, this would be the interest between company's management and the company's stockholders. When a company performs an IPO, there is a separation between control and ownership because shareholders are the new owners while management remains unchanged (Brennan & Franks, 1997). More recently there have been alternative theories on underpricing focusing on the valuation of a company and the behavioral economics side of an IPO. There are many ways to value a company and there is an ongoing never ending discussion regarding the best way of valuing a company. Underpricing is an efficient response to the complex art of valuing a company because of uncertainty (Lowry, et al., 2010). A research done by Loughran and Ritter (2004) found a positive correlation between the riskiness of an IPO and underpricing. The fact that the phenomenon of underpricing keeps on existing shows that firms accept the fact that this is a normal occurrence.

2.3.3 Capital Markets

The behavior of market prices and trading volumes of assets during historical price bubbles presents a challenge to asset pricing theories. The significant correlation between high turnover rates and high prices as a key characteristic of the 1929 boom and crash and of the Internet bubble in 90s is emphasized in research by Cochrane. *"I verify that the elements of a trading-related convenience yield are there in each case, in particular that high prices are associated with high volume and low share supply"* (Cochrane, 2002). In his research, Cochrane commented on the broadly discussed topic of the Palm case which occurred during the Dotcom bubble. On march 2, 200, 3Com sold a percentage of shares of Palm through an IPO. The Palm stock was enormous volatile during this period, with 7.2% standard deviation of daily returns and 15.4% standard deviation over weekly returns. This is comparable to the same volatility of the S&P500 over an entire year. Research by Ofek and Richardson (2003) pointed out that between 1998 and 2000, internet firms represented as much as 20 percent of the dollar volume in the public equity market, even though their market capitalization never exceeded 6 percent. "*Using the eigenvalues and eigenvectors of correlations matrices of some of the main financial market indices in the world, we show that high volatility of markets is directly linked with strong correlations between them. This means that markets tend to behave as one during great crashes"* (Leonidas & De Paula France, 2011).

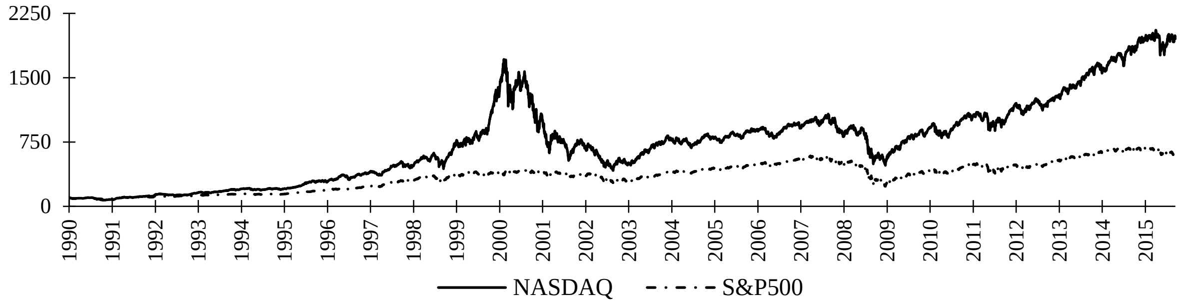
These articles all show a general finding of increased volatility during the run up to major crashes. Secondly, they found that the trading volume increases after the burst. Figure 3 illustrates the indexed market value of the NASDAQ and the Standards & Poors (S&P500)[5]. What is evident from the figure is that both the S&P500 and the NASDAQ move in line with each other. It can be seen that there is the run up of the market value of the NASDAQ around the end of the 90s also known as the Dotcom bubble.

[5] Data is obtained via Bloomberg terminal at the Erasmus University.

After the bubble collapsed the NASDAQ dropped back to realistic levels and continued to move in line with the S&P500 over the next years. During the financial crisis markets collapsed which can be seen from de indexed market values. Interesting in this figure is the run up in relative market value of the NASDAQ since 2012 compared to the S&P500. It indicates increasing capital on the NASDAQ which is in line with increased capital detected during previous bubbles. The fact that there has been an increase in capital is part of one of the phases elaborated on by Stiglitz[6] which is typical for bubbles.

Figure 3: Indexed Market Value NASDAQ and S&P500

The figure shows the indexed market value of both the NASDAQ and S&P500. This market value is based on the total market capitalization. The total market cap is the combination of the values of the individual company's part of the index. Data acquired via Bloomberg source. The Y-axis represents the indexed market value where both indexes start at 100.



Underlying earnings have always been a popular metric when investigating stocks. Price earnings (PE) ratios are often used to assess the attractiveness of a potential stock. When looking at the earning per share there are some factors that can undermine the reliability of the PE ratios. One of the problems is an accounting problem. The earnings are based on accounting earnings and these differ due to the different accounting standards for countries. The earnings are not the cash earnings part of the business.

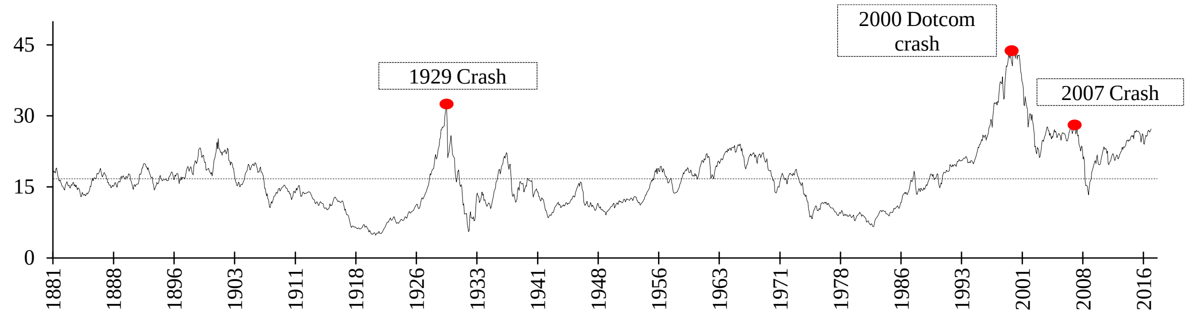
Professor Robert Shiller came up with a solution for this problem. A strong measurement in forecasting long-term future stock return is the Robert Shiller's Cyclically Adjusted PE ratio (CAPE Ratio). The ratio compares stock prices to earnings over the course of 10 years. Some hedge fund managers state that this CAPE ratio is a strong indicator about an impending downturn and low-returns era coming up. The ratio is adjusted for business cycles and inflationary pressure on earnings. Looking at historical CAPE ratios it becomes evident that high ratio trends highly correlate with boom periods. From 1881 till 2015 the average CAPE ratio for the US was around 17. The current CAPE ratio is much higher with a value of over 27. Professor Shiller found that previous crashes in 1929, 2000 and 2007 returned higher CAPE ratios. These years were all periods where the economy boomed at peaks followed by periods of recession and downward markets. Where the CAPE ratio is a technical indicator and reflects fundamentals of the economy it is not solid prove for potential bubbles. The metric does not tell us anything about an upcoming crash, just that the expected returns for the next period are much lower than average. It eliminates fluctuation of the ratio caused by the variation of profit margins during business cycles. From figure 8 it becomes evident that the CAPE ratio for the S&P500 is currently over

[6] See theory of Stiglitz in the first part of the theoretical framework.

27. This has only been higher three times the last 150 years. This was in 1929, 2000 and 2007 which are all dates around bubbles.

Figure 4: CAPE Ratio

Annual distribution of IPOs. Sample includes IPOs from January 2010 to November 2016 in the USA. The dotted line indicates the average number of IPOs over the past 6 years while solid line is historical CAPE ratio. Y-axis represents CAPE ratio and X-axis the years.



Besides earnings another interesting metric is that of debt levels. Conditions on capital markets play an important role in the run-up period of bubbles. The current market is in a strange situation with interest rates being close to zero making borrowing money very cheap. Central banks around the world have flooded stock markets with cheap money. In this way, they hope to stimulate the economic recovery after the financial crisis of 2007. When looking at the gap between available cash and debt in the US corporate sector this gap has been, and still is increasing. Leverage ratios have risen across almost all US market segments. While economic growth levels are low equity markets are doing remarkably well.

Corporations have used the debt financed cash for share buybacks and takeovers in order to improve profitability and create the illusion of growth for shareholders. "*In fact, Lapthorne said, companies are spending 35% more than their incoming cash flows, higher than previous peaks in 1998 and 2008"* (Business insider, 2016). Besides buybacks companies have also been involved in increased dividend payouts to reassure investors of the financial position. Looking at historical data payouts have never exceeded earnings for longer than two years in a row. This only happened before the Dotcom in 2000 and the housing bubble in 2007.

3. Hypotheses Development

With the academic background covered in the previous section it is important to get a clear understanding of how to connect the identifiers and signals of bubbles to a set of hypothesis. In April 2003 Alexander Ljungqvist and William J. Wilhelm wrote an article about IPO pricing during the Dotcom bubble (Ljungqvist & Wilhelm, 2003). In the article, they focused on IPO pricing during the Dotcom bubble and changes in ownership structure of companies performing an IPO. Their focus was mainly on IPO underpricing and price revision. They measured underpricing by comparing the stock price after the first trading day with the offer price. This research investigates if there is a difference between underpricing for tech firms versus non-tech firms and compare changes in underpricing and performance over the past years.

Besides the article of Lungqvist and Wilhelm there is a scope of other literature that tries to determine the drivers of bubbles. An interesting article in the Journal of Finance in August 2011 wrote specifically about who and what drove the tech bubble (Griffin, et al., 2011). There are a lot of theoretical models explaining bubbles but it is hard to find rigorous empirical work. Previous research proved that an increase in invested capital leads to increased trading volume and increased volatility. The focus will be on an increase in trading volume and increased volatility of stocks traded on the NASDAQ and will be compared to the stocks on the S&P500. Relative changes will be taken in consideration. An important metric which investors look at is that of the PE ratio. The PE ratio gives a strong indication of prices and underlying earnings. In this research the PE ratio of the stocks on the NASDAQ and the S&P500 is used to see what the influence of the different bubble indicators like underpricing, trading volume and volatility is on the PE ratios. For this I will use propensity score matching (PSM) to create a matched sample.

The first two hypotheses focus on increased volatility and trading volume detected during previous bubbles. This symptom is part of one of the phases described by Stiglitz.

> ***Hypothesis 1:*** *The stocks on the NASDAQ index experience increasingly higher trading volume compared to stocks on the S&P500 and this increase is significant.*

> ***Hypothesis 2:*** *The stocks on the NASDAQ index experience increasingly volatility compared to stocks on the S&P500 and this increase is significant.*

The third hypothesis is based on the relative simple indication of underpricing as seen from the article by Ljungvist and Wilhelm and more specifically on the increase of underpricing over the past years.

> ***Hypothesis 3*****:** *Just as seen during the Dotcom bubble in 1999 and 2000 IPOs are currently experiencing significant IPO underpricing which could indicate a potential bubble.*

During the Dotcom bubble the increase in average underpricing could mainly be explained by the increase in underpricing of tech stocks. Therefore, it is relevant to look at these high-tech companies and investigate their initial returns (underpricing) compared to those of other stocks.

> ***Hypothesis 4:*** *Companies performing an initial public offering which are active in the high-technology industry show significant higher underpricing.*

During the Dotcom bubble and other bubbles, there were several indicators related to the firm and deal characteristics. These involved a change in the offer price, firms age, deal value and accounting values of the firm. The next hypothesis will focus on these symptoms.

Hypothesis 5: *Over the past two years the average offer price and deal value increased significantly where the average firm age decreased. IPOs over the last two years also show significant lower accounting performance compared to previous years.*

Lastly, it is relevant to compare all the acquired data and look at the first five hypotheses. Based on the results I will try to answer the question if we are currently experiencing the next technology bubble.

Hypothesis 6: *Based on the symptoms detected we are currently experiencing the run up of markets which is not in line with fundamental values and indicating the forming of a potential bubble.*

All the above hypotheses will help to get a better understanding of the current market situation and give an indication of the current situation on the IPO markets in the US. The research questions are set up in way to compare the current situation in the US tech sector to that seen during the Dotcom bubble and other bubbles and investigate if the economy is currently experiencing a bubble. The next chapter focusses on the dataset and methodology used to answer the hypotheses.

4. Data and Methodology

This chapter further elaborates on the dataset and the methodology used to answer the hypotheses mentioned in the previous chapter. In the first part, the dataset is described including all the different data sources used. The second part will focus on the underpricing section after which I will elaborate on the other symptoms. The methodology part focusses the different statistical tests and regressions performed.

4.1 Data

The sample of this research consists of firms completing an IPO between January 2010 and November 2016. Thomson One lists a total of 1423 IPOs between that period. Thomson One also provides other IPO information like the offer price, underwriters and IPO date. The list of all the companies that performed an IPO are identified through their Ticker and CUSIP8-code. All related trading prices were available at the Datastream computers (CRSP) at the Erasmus University. Accounting data is collected via the Bloomberg terminal at the Erasmus University Rotterdam. After collecting all the basic information regarding the IPOs several dummies were created that will be used in the regressions performed later in this research. The first dummy created is that for high-technology (high-tech) companies. High-tech companies are selected based on research done by Charles O. Kile and Mary E. Phillips regarding industry classification codes to sample high-tech firms (Kile & Phillips, 2009). The exact codes can be found in the appendix and in table 1. The second and third dummy created are dummies for venture capital and private equity involved. This data is collected via the Wharton Database which collects data regarding PE en VC parties involved. Private equity focusses on companies which have a proven business model and generate cash. Venture capital focusses on young startups in which heavy investments is required to potentially become a successful business. Because of the different type of target company's VC and PE search for it is relevant to separate the two dummies.

Financial institutions (SIC code 60 to 63 and code 67) performing an IPO are removed from the sample based on their SIC codes just as is done in the research by Ljungqvist and Wilhelm (2009). Financial IPOs are bounded to different regulations. Secondly, all penny stocks with an offer price below $5 are removed from the dataset. Lastly, companies that are listed in their home country, limited partnerships are removed from the sample. The cleaning of the dataset is in line with the research of Ljungqvist and Wilhelm. Looking at the annual IPO distribution in the table 1 it should be noticed that relative to non-tech firms the amount of tech companies performing an IPO increased. The number of VC backed firms performing an IPO remained stable over the past six years. There has been a slight decrease in PE backed firms performing an IPO relative to non-PE backed IPOs. Overall 2016 has been a bad year for the IPO markets with low amount of companies performing a public offering.

Table 1: Sample Size

Annual distribution of IPOs. Sample includes IPOs from January 2010 to November 2016 in the USA. Internet stocks are classified with the sane method used in the article of Ljungqvist and Wilhelm (2003). High-technology companies are active in SIC codes 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825, 3826, 3827, 3829, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7378 and 7379. VC and PE backed IPOs are marked as such via Thomson One.

	2010 - 2016	2010	2011	2012	2013	2014	2015	2016
Initial Sample								
Total Sample	1423	199	180	179	256	307	189	113
Tech Stocks	547	58	52	52	88	149	93	55
Non-Tech Stocks	876	141	128	127	168	158	96	58
Fraction Tech Stocks	0.38	0.29	0.29	0.29	0.34	0.49	0.49	0.49
Final Sample								
Total Sample	857	100	91	100	163	213	126	64
Tech Stocks	483	47	45	45	83	137	85	41
Non-Tech Stocks	374	53	46	55	80	76	41	23
Fraction Tech Stocks	0.56	0.47	0.49	0.45	0.51	0.64	0.67	0.64
VC Backed IPOs	418	47	43	47	80	104	67	30
Fraction	0.49	0.47	0.47	0.47	0.49	0.49	0.53	0.47
PE Backed IPOs	370	62	44	54	68	77	41	24
Fraction	0.43	0.62	0.48	0.54	0.42	0.36	0.33	0.38

Figure 5: IPO Distribution over the Years

Annual distribution of IPOs. Sample includes IPOs from January 2010 to November 2016 in the USA. The dotted line indicates the average number of IPOs over the past 6 years. Y-axis represents the number of IPOs

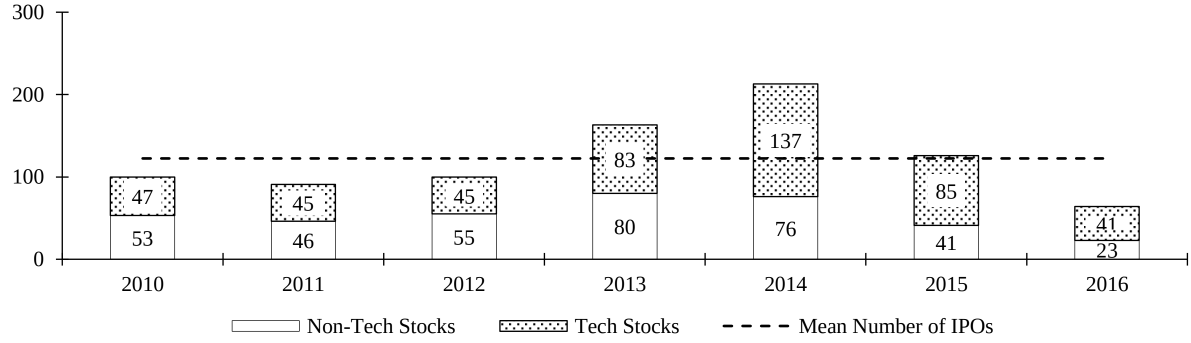


Figure 5 gives an overview of the IPO distribution over the past six years. Looking at the dotted line which indicates the mean number of IPOs over the past six years it becomes clear that for 2016 the IPO markets has not been as active as over the past five years. This downward trend started in 2015. For 2013 and 2014 there were a significantly higher number of IPOs compared to the average. The last three years also showed that an increased percentage of the IPOs were active in the tech sector.

The first part of the research focusses on the underpricing aspect of the different IPOs and uses the paper written by Ljungqvist and Wilhelm as a guideline. The regressions performed on the underpricing can be found in appendix 1 and are like those in the research of Ljungqvist and Wilhelm. The regressions are performed to see if the findings in their paper are in line and to control if the dataset is sound. Both in the results (chapter 5) and discussion (chapter 6) section of this paper I will shortly elaborate on the findings and implication of these findings and compare the results to the finding of the article by Ljungqvist and Wilhelm in 2003.

The second part of the research focusses on the trading volume, volatility, and the PE ratios of the different stocks on the indexes. For this part of the research stocks on the NASDAQ composite index are compared relative to stocks on the S&P500. The NASDAQ composite index is a stock market index of the common stocks and similar securities listed on the NASDAQ stock market. This stocks on the NASDAQ index are relevant because it is heavily weighted towards technology companies. By using the stocks on the two different indexes I can compare the market for technology focused stocks to stocks of companies active in different industries. As mentioned in the theoretical framework another symptom is that of credit expansion. With historical low interest rates borrowing is extremely cheap and this can be seen from the public debt ratios which are at levels seen before the financial crisis in 2007. Economist noticed that much of the borrowings are done by big corporate firms who use the borrowed capital to repurchase shares. This pushes share prices up due to scarcity. Past literature showed that equity markets that are in a ‘bull’ state experience increased debt levels. During previous bubbles, exceptional expansion of debt levels occurred and it will therefore be relevant to look at those debt levels at this moment.

On the next three pages, there are the descriptive statistics of the data used in this research. The first two tables contain information regarding the IPO data and the different variables analyzed in this research. Table 2 summarized the total IPO dataset used for the underpricing regressions. Table 3 summarizes the same dataset and the same variables as in table 2 but the only difference is the fact that in this table there is a split between high-tech and non-tech firms. The last descriptive table is table 4 which summarizes the dataset regarding the stocks on the indexes and their trading volume and volatility used for the regressions on the PE ratio. In table 3 and 4 significant levels are given which represent the statistical significance of the differences between the variables for tech versus non-tech stocks within the year and over the entire sample. In these tables the significance is represented with the stars.

Table 2: Descriptive Characteristics Total IPO Sample

Table 2 shows the descriptive statistics of sample data. Age is described as the IPO year minus the founding date[7]. Accounting data is collected via Bloomberg and is based on the last year available pre-IPO. Both revenue, total assets, book value of equity and net income are given in millions of dollars.

Variables		2010 - 2016	2010	2011	2012	2013	2014	2015	2016
Number of sample firms		857	100	91	100	163	213	126	64
Fraction high-technology companies		0.56	0.47	0.49	0.45	0.51	0.64	0.67	0.64
Gross Proceeds ($m)	Mean	287.8	325.8	342.1	347.8	275.0	301.4	228.0	194.2
	Median	126.9	119.5	170.0	123.2	137.3	109.3	120.8	107.9
	Std. Dev.	160.9	140.2	441.2	159.2	198.0	86.9	116.4	189.8
Underwriter Size	Mean	3.1	2.4	2.9	3.1	3.4	3.2	3.3	3.4
	Median	2.7	2.0	2.0	3.0	3.0	3.0	3.0	3.0
	Std. Dev.	1.9	1.2	1.5	1.5	2.3	2.2	2.3	2.2
Underwriter Ranking[8]	Mean	8.5	8.7	8.7	8.7	8.5	8.2	8.4	8.4
	Median	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0
	Std. Dev.	1.1	0.6	0.6	1.0	1.3	1.4	1.3	0.8
Offer Price ($)	Mean	14.9	13.2	15.6	15.3	16.0	14.5	15.0	14.5
	Median	14.5	12.0	15.0	15.0	15.8	14.0	15.0	15.0
	Std. Dev.	5.6	3.8	6.2	6.1	5.9	5.1	6.5	5.0
Age	Mean	19.5	20.8	13.9	24.8	22.6	18.2	13.8	22.5
	Median	11.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0
	Std. Dev.	26.3	27.7	16.8	29.9	30.1	24.1	13.7	27.5
Revenue ($m)	Mean	515.4	476.3	526.5	773.3	679.4	430.5	259.1	460
	Median	86.8	143.7	110.8	151.1	86.8	68.7	45.8	60.8
	Std. Dev.	898.5	840.0	1222.0	1438.2	1901.1	1125.7	598.5	968.2
Total Assets ($m)	Mean	785.3	658.8	975.2	985.4	1129.8	637.9	514.2	596.1
	Median	125.3	155.1	165.5	187.8	125.3	73.9	68.3	93.2
	Std. Dev.	751.9	658.8	3377.3	985.4	1699.2	1016.5	609.0	596.1
Book Value of Equity ($m)	Mean	172.2	148.7	229.7	179.3	135.6	135.6	197.4	177.5
	Median	32.5	63.1	58.2	39.8	17.7	17.7	25.5	32.5
	Std. Dev.	566.8	35.9	1091.8	610.7	585.9	1015.9	781.0	1071.0
Net Income after Taxes ($m)	Mean	20.7	-0.5	28.7	50.9	43.2	-6.7	9.4	19.2
	Median	-0.2	5.2	8.6	11.2	-0.2	-4.1	-8.5	-6.9
	Std. Dev.	111.7	101.2	139.0	141.3	201.1	464.5	125.9	171.2
Amount of shares sold (%)	Mean	29.9	29.4	29.6	29.6	29.5	30.4	31.8	28.1
	Median	27.7	25.7	25.5	25.5	26.5	29.0	26.8	24.1
	Std. Dev.	10.8	13.3	9.7	10.6	13.3	11.3	10.9	8.5
Underpricing Overall (%)	Mean	14.0	8.8	13.6	16.5	18.0	13.0	15.7	12.4
	Median	6.1	3.5	6.5	10.1	8.4	4.5	6.2	3.5
	Std. Dev.	26.5	19.7	25.5	25.3	29.8	29.9	32.1	23.2
Fraction EPS ≤ 0		0.68	0.38	0.35	0.30	0.47	0.56	0.66	0.63

[7] Founding date is collected via https://site.warrington.ufl.edu/ritter/ipo-data/

[8] Ranking based on scale from 0 to 9 where highest rank is 9 and lowest 0. Full list of underwriters and ranking can be found in the appendix.

Table 3: Descriptive Characteristics IPO Tech vs Non-Tech

Table 3 shows the descriptive statistics of sample data, divided in tech and non-tech companies. Age is described as the IPO year minus the founding date[9].

		2010 - 2016		2010		2011		2012		2013		2014		2015		2016	
		Tech	Non-Tech	Tech	Non-Tech	Tech	Non-Tech	Tech	Non-Tech	Tech	Non-Tech	Tech	Non-Tech	Tech	Non-Tech	Tech	Non-Tech
Number of sample firms		480	377	47	53	45	46	45	55	83	130	136	77	84	42	41	23
Fraction high-tech		0.56		0.47		0.49		0.45		0.51		0.64		0.67		0.64	
Deal Value ($m)	Mean	192.2	297.3	133.0	176.3	196.2	378.8	471.3	232.9	181.7	348.0	120.3	318.4	138.3	323.6	100.0	300.2
	Median	92.9	194.1	93.8	129.4	104.7	200.5	103.0	187.5	92.6	253.7	84.2	199.1	86.6	197.9	85.1	190.9
	Sign.	***		***		***		***		***		***		***		***	
Underwriter Size	Mean	2.6	3.9	2.3	2.4	2.6	2.9	2.8	3.4	2.7	4.2	2.5	4.6	2.6	4.9	2.9	4.9
	Median	2.3	3.7	2.0	2.0	2.0	3.0	3.0	3.0	2.0	4.0	2.0	4.0	2.0	5.0	3.0	5.0
	Sign.	***		-		-		**		***		***		***		***	
Underwriter Ranking	Mean	8.5	8.7	8.6	8.4	8.7	8.8	8.8	8.6	8.4	8.7	8.1	8.5	8.2	8.9	8.0	8.5
	Median	8.9	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	8.5	9.0
	Sign.	***		-		-		-		-		-		-		-	
Offer Price ($)	Mean	13.5	16.1	13.0	12.1	13.0	17.7	14.1	15.2	14.6	17.7	13.0	16.5	13.9	17.2	15.8	13.9
	Median	13.1	16.5	12.2	12.0	13.0	18.0	13.0	16.0	14.0	18.0	12.0	16.3	14.0	17.0	18.0	14.0
	Sign.	***		***		***		***		***		***		***		***	
Age	Mean	15.7	24.0	22.2	19.5	11.4	16.3	17.2	31.0	14.2	31.3	14.7	22.7	13.0	15.4	17.1	32.0
	Median	10.6	13.6	15.0	12.0	10.0	8.0	9.0	19.0	10.0	20.5	12.0	14.0	10.0	8.0	13.0	16.0
	Sign.	***		-		-		**		***		-		-		**	
Revenue ($m)	Mean	223.2	879.6	388.5	554.1	227.0	813.3	215.6	1229.5	315.2	1057.1	175.6	890.0	118.2	551.3	122.4	1061.9
	Median	54.5	319.1	118.0	199.0	68.5	186.1	91.1	410.6	45.2	269.7	17.9	320.4	5.1	262.3	35.7	585.9
	Sign.	***		***		***		***		***		***		***		***	
Total Assets ($m)	Mean	311.0	1112.9	613.0	699.5	290.3	1631	311.7	1536.6	315.3	105.1	257.3	1324	175.4	1216.7	214.0	1277.2
	Median	61.1	487.3	103.0	235.5	71.9	452.2	61.9	484.5	45.2	269.7	42.4	552.4	38.2	477.2	65.1	939.5
	Sign.	***		-		***		***		-		***		***		***	
Book Value of Equity ($m)	Mean	73.1	349.4	137.7	158.5	-17.7	466.6	173.5	184.1	114.2	341.1	25.5	345.1	28.7	556.5	49.9	394.0
	Median	22.0	97.8	44.0	68.3	35.0	111.7	14.0	107.7	15.6	102.3	9.5	88.4	8.5	151.8	27.3	54.4
	Sign.	***		-		***		-		***		***		***		***	
Net Income after Taxes ($m)	Mean	-4.4	51.3	-24.5	19.5	-17.7	71.9	26.5	71.4	18.8	68.5	-3.7	-10.1	-15.7	58.9	-14.7	79.2
	Median	-8.7	18.8	0.3	7.7	-1.9	22.6	-1.9	26.3	-13.6	20.0	-12.4	18.6	-13.5	22.8	-17.8	13.8
	Sign.	***		*		**		***		***		***		***		***	
Fraction EPS ≤ 0		0.68	0.25	0.43	0.34	0.50	0.21	0.57	0.09	0.70	0.24	0.73	0.28	0.84	0.29	0.78	0.35
Amount of shares sold (%)	Mean	26.3	27.1	28.2	28.2	24.8	26.5	23.9	28.3	27.1	30.6	28.8	29.9	27.9	26.9	23.0	19.0
	Median	25.3	25.4	25.9	23.5	23.6	25.0	23.7	26.5	25.1	29.7	27.8	29.0	28.1	24.8	23.0	19.2
	Sign.	***		-		-		-		-		-		-		-	
Underpricing (%)	Mean	17.9	11.9	10.6	8.4	18.8	11.2	18.2	14.5	24.2	14.1	15.0	9.3	18.1	19.6	20.1	6.4
	Median	11.5	5.3	4.8	3.5	13.4	5.8	14.5	10.2	18.5	4.0	6.4	3.2	9.3	7.9	13.6	2.3
	Sign.	***		**		**		-		**		-		*		*	

*,** and *** denote significance between the differences at the 10%, 5% or 1% level, respectively

[9] Founding date is collected via https://site.warrington.ufl.edu/ritter/ipo-data/

Table 4: Descriptive Characteristics

Table 4 summarizes data regarding trading volume, volatility and PE ratio regarding the indexes. Trading volume on both the S&P500 and the NASDAQ is given in millions. The CAPE ratio is obtained via the website of professor Shriller where he makes his data publicly available. The Domestic credit levels are based on data from the World Bank which makes debt data publicly available monthly. Volatility is based on the 30-days average return

Variables		2010 - 2016	2010	2011	2012	2013	2014	2015	2016
Trading Volume (S&P500) ('mln)	Mean	655.0	944.6	802.8	589.1	527.4	517.5	600.3	603.2
	Median	596.8	935.1	788.6	596.8	526.1	523.7	591.3	626.4
	Std. Dev.	242.8	270.3	224.4	149.6	150.7	157.0	182.7	178.7
Trading Volume (NASDAQ) ('mln)	Mean	484.5	602.1	535.4	431.3	416.7	494.4	462.9	449.0
	Median	458.9	614.1	536.1	432.0	419.2	493.7	458.9	458.7
	Std. Dev.	144.9	158.1	141.9	101.4	110.1	129.4	137.7	130.4
Return Volatility (S&P500) (%)	Mean	14.1	16.5	20.4	13.1	11.2	10.7	14.7	11.4
	Median	13.0	16.7	15.4	13.0	11.1	10.4	12.9	11.4
	Std. Dev.	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.1
Return Volatility (NASDAQ) (%)	Mean	16.3	17.5	22.6	15.2	12.5	13.4	16.1	15.5
	Median	14.8	16.3	18.1	14.8	12.3	12.5	14.4	13.1
	Std. Dev.	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.1
Trading Volume Ratio (NASDAQ/S&P500)	Mean	0.76	0.64	0.67	0.74	0.80	0.97	0.78	0.71
	Sign.	***	***	***	***	***	***	***	***
Volatility Ratio (NASDAQ/S&P500)	Mean	1.16	1.11	1.14	1.16	1.13	1.27	1.11	1.21
	Sign.	***	***	***	***	***	***	***	***
CAPE Ratio (S&P500)	Mean	19.3	16.2	17.1	16.6	18.7	21.3	22.5	22.5
	Median	18.9	16.0	17.6	16.6	18.9	21.3	22.6	22.7
	Std. Dev.	2.6	0.9	0.7	0.6	1.7	0.7	0.8	1.2
PE Ratio (S&P500)	Mean	15.4	14.1	13.1	13.3	15.1	16.3	17.6	18.1
	Median	15.3	13.8	13.4	13.3	15.3	16.3	18.1	18.5
	Std. Dev.	1.9	0.7	0.7	0.5	0.9	0.6	0.5	0.9
PE Ratio (NASDAQ)	Mean	19.2	18.3	16.6	15.9	19.2	21.0	21.8	21.4
	Median	19.0	19.0	16.9	15.8	19.0	20.9	22.2	22.0
	Std. Dev.	2.5	1.2	0.8	0.6	1.8	0.8	0.9	1.3
Domestic Credit (% of GDP)	Mean	188.0	187.4	177.9	178.5	192.2	194.1	188.8	197.1
Observations	N	1649	239	240	239	239	241	239	240

*,** and *** denote significance between the differences at the 10%, 5% or 1% level, respectively

Table 2, 3 and 4 provide the descriptive characteristics of the different sample firms and make a split between tech and non-tech IPOs. A factor which could be of influence on the return of an IPO is the maturity of a firm. A company that is well-established in its industry, with well-known products and loyal customers would be labeled as a mature firm (Investopedia, 2015). Research done by David T. Clark shows that firm's age is positively correlated with the long-term return except for high-tech firms where it is the other way around (Clark, 2002). Company age is determined by subtracting the founding year from the IPO date. The problem with the age variable is that there is a lack of information regarding the founding date in the data resources available. A web page created by Jay R. Ritter from the UF Warrington Faculty created different IPO related datasets which contain information regarding all IPOs between 1975 and 2015.

To determine which IPOs can be marked as high-tech company's standard industrial classification (SIC) codes are used (Philips, 2009). Important in this research is the accounting data to get an idea about underlying earnings. For accounting performance, I have collected the following variables: sales, the book value of assets, the book value of equity and net income. I use medians, following Kaplan (1991), as there are firms with extreme values (e.g. very negative net income) which bias the sample. Outliers do not affect medians. Table 2 shows the descriptive statistics of the sample. Net income is in this case most relevant. I will use this to assess underlying earnings. When looking at the descriptive statistics from table 3 it becomes evident that both the mean and median age of high-tech companies performing an IPO is lower than the age of non-tech firms. The age of non-tech companies remained relatively stable over the years where the age of tech companies decreased. Last three years the fraction of IPOs active in the technology sector increased to around 65% compared to around 50% for the years before. Larger and more mature IPO firms experience lower or no underpricing (Ritter, 1998). Revenue figures are heavily right-skewed due to the presence of some well-established and big businesses. For the same reason, the total assets and book value of equity are heavily rights skewed. It therefore makes sense to focus on the median because of the big impact of these big firm on the means. Tech firms performing an IPO also show decreased median revenues, total assets, book value of equity and net income.

As can be seen from table 2 and 3 I looked at mean deal value of the IPO. For high-tech firms the deal values are on average lower than the proceeds for non-tech firms and the high-tech value decreased in 2015 and 2016 for tech firms. Underwriters play an important role in the IPO process. A well-known investment bank has more experience in performing the tasks necessary for an IPO which again can result in higher trust of the new investors. Secondly, they have a network of potential investors. Besides the prestige of the underwriter, the number of lead underwriters is also relevant. Companies will try to avoid issuing shares when markets are cold and the other way around. With the wide scope of literature available about underwriters and the importance of the underwriter in the IPO process it is relevant to examine the role of these underwriters over the past few years.

From the descriptive statistics, it can be found that both the mean and median of the offer price remained stable over the sample period with a value of between $14-$15. When looking at underpricing both the adjusted and non-adjusted the results indicate that the initial returns fluctuated between 2010 and 2016 with higher first-day returns than long-term average for 2012, 2013, 2015 and 2016. When looking at the split in table 3 it becomes evident that underpricing for tech firms is almost always higher than for non-tech firms and this underpricing increased over the years. The fluctuations in initial returns between 2010 and 2016 are not as extreme as during the Dotcom bubble. For the net income variable, the Wilcoxon test will be relevant because this variable is not normally distributed. Before diving into the regressions and analysis of the data some of the hypotheses can already be answered by performing simple mean tests. This testing can either be done with a t-test or a Wilcoxon-Mann-Whitney test. The Wilcoxon test is a nonparametric test and is an alternative for the t-test and is added to the research.

For the number of book runners involved in the IPO process the difference between this amount for tech and non-tech stocks differs significant from 2012 onwards. This amount does not differ for the first two years 2010 and 2011. The average ranking of these underwriters is significantly different between tech and non-tech companies from 2011 onwards. The last but very important variable to investigate is net income. Because I suspect a bubble, prices detected must be unrealistically high compared to the underlying earnings. Net income is this case is a metric for earnings. For the net income of the tech and non-tech companies the differences between these net incomes differ significantly from each other for each year.

From table 4 looking at both volatility and trading volume levels for stocks on the NASDAQ and the S&P500 I find that within each year the numbers differ significant from each other. For 2010, 2011, 2013, 2015 and 2016 the differences between underpricing for tech and non-tech IPOs is significant. For the age variable, the age between tech and non-tech companies differ significant for 2012, 2013, 2013 and 2016. For the other years, the companies age does not differ significant but this is in line with expectations because the age in these years was similar between the two groups. For the gross proceeds also known as the deal value only the differences for 2010 do not differ significant. The other years all show significant results.

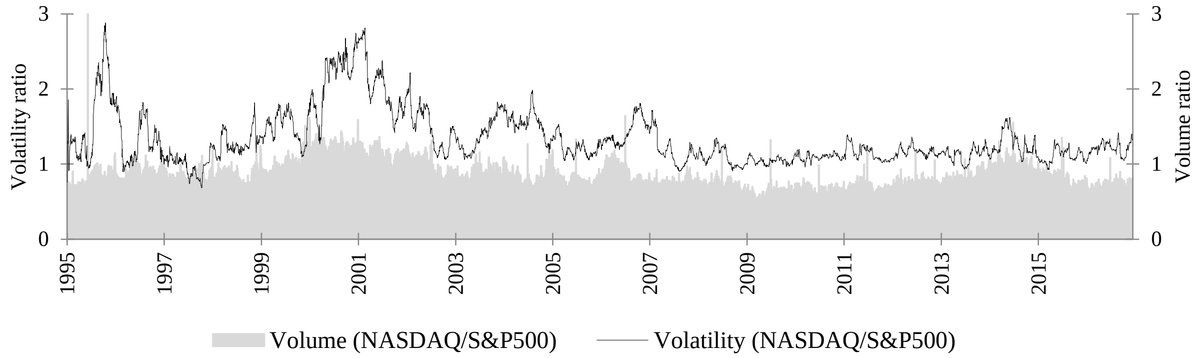
4.2 Index Performance

Bloomberg contained the summarized averages on volatility and trading volume of all stocks traded on the indexes. The stocks on the two indexes are compared with each other to see development over time. The NASDAQ which contains technology stocks is expected to show increased trading volume and volatility. Bloomberg contained information on average daily trading volume and volatility on these indexes. The volatility is based on the returns. This is calculated by taking the standard deviation of the returns of the last 30 trading days and multiplying this with the square root of 252. This because there are 252 trading days in a year. A 30-day period is a standard time-frame when looking at volatility. To be able to compare the stocks on the two indexes and especially the development over time I created different ratios on volume and volatility. The variables of both indexes are divided (NASDAQ/S&P500).

On trading volume, I found a long-term average ratio of 0.76 indicating on average more trading volume on the S&P500[10]. This is in line with expectation due the fact that the S&P500 is a bigger index which covers a greater variety of stocks. For the average long-term volatility, I found a ratio of 1.21 indicating that on average the NASDAQ is more volatility than the S&P500. Figures on both indexes can be found in the appendix. The fact that the volatility tends to be higher for the NASDAQ indicates that investors perceive stocks on average to be riskier that are traded on the NASDAQ. From figure 6 it becomes evident that both the S&P500 and the NASDAQ are sensitive for crashes and market situations. Interesting to see is that the increase in volume and volatility mostly occurred after the burst of the bubble due to investors trying to get rid of their stocks.

Figure 6: NASDAQ/S&P500 Volume and Volatility

Annual distribution of IPOs. Sample includes IPOs from January 2010 to November 2016 in the USA. The dotted line indicates the average number of IPOs over the past 6 years. This gives a good overview on the situation in the IPO markets.



Via Bloomberg I also collected data on the PE ratios of the stocks on both indexes. Next to earnings another metric that is further investigated is that of debt levels. In the run-up phase of previous bubbles there were high amounts of capital available which help to inflate the bubble. Currently there is an economic landscape with low interest rates making borrowing very cheap. To see if corporates use these low interest rates and increased borrowings data is collected on the debt levels of corporates in the US.

Because it is suspected that the amount of borrowings increased also data on share repurchases and dividend levels is collected. The reason for collecting data on these two variables is to investigate what companies use the borrowings for. During previous bubbles, scholars found that companies increased dividends and share repurchase to further push stock prices. It will therefore be interesting to see if markets are currently experiencing the same trend.

10 Ratios can be found in appendix 4.

4.3 Methodology

This section covers the methodology behind the different tests performed to answer the hypotheses. The first section focusses on the adjustments in the dataset and the regression on underpricing based on the research by Ljungqvist and Wilhelm. Secondly, the focus will be on the methodology behind the different mean tests. A difference-in-differences (DD) approach is used which will be explained. Lastly to test if markets are in a bubble several regressions are run. To reduce effects of differences in observable variables this regression will be run with a matched sample based on propensity score matching (PSM). This regression with the matched will be compared to the same regression with the full sample. In this way, I am able to test if the findings from the regression with the full sample are not caused by differences in observables.

4.3.1 Underpricing

An important metric in this research is that of underpricing. This underpricing is calculated according to the following formula.

$$IRi = Pi,t - Ei,t \quad \textbf{(1)}$$

IR_i means the initial return (IR) of the share (i). In this case, P is the price after the first trading day and E is the offer price of the share. To make this initial return comparable to others it is customary to convert this into the proportional return.

$$IRi = \frac{(Pi,t - Ei,t)}{Ei} * 100 \quad \textbf{(2)}$$

The variable initial return, which measures the amount of underpricing like in formula (2) above, is defined as a percentage change in return on the first trading day of the IPO. In the above equation, the first-day closing price is the official closing price at the end of the first trading day. The offer price is the price at which the shares got issued at the IPO. The formula at (2) does show the initial return but it is not adjusted initial return or excess return. It is usual that the initial returns of shares (IR) are adjusted for the return of ´'’the market”. Determining the excess returns requires the subtracting of the riskless rate, or benchmark rate, from the actual rate achieved (Wikipedia, 2016).

The market, in this case, would be the return of the S&P500 at the same day[11].

$$IRi = \frac{(Pi,t - Ei,t)}{Ei} - \frac{(Mt - Mt,0)}{Et,0} * 100 \quad \textbf{(3)}$$

11 According to Barber and Lyon (1996), cumulative abnormal returns give positively biased test statistics, while buy-and-hold abnormal returns give negatively biased test statistics. This occurs because of new listing, rebalancing, and skewness biases

After determining the first-day initial return compared to the offer price I performed several regressions on this initial return to test what influences the underpricing and see if the results are in line with earlier findings. Several interaction terms are used. An interaction occurs when an independent variable has a different effect on the outcome depending on the values of another independent variable. In the research by Ljungqvist et al they found some results on underwriter's reputation and VC/ PE backing. To test if my dataset is sound I added these variables as control variables. I should find that underpricing is positively related to underwriter's reputation and this correlation increased over the past years. I would expect an increasing number of companies performing an IPO which are backed by venture capital and private equity funding. Also, I should find that venture capital backed companies that perform an IPO experience significantly higher underpricing compared to non-and private equity backed companies. To control for this the following regression is run.

$$\textit{Underpricing: } \beta_0 + \beta_1 * \textit{Ln (age)} + \beta_2 * \textit{Number of Underwriters} + \beta_3 * \textit{Underwriter Ranking} + \beta_4 * \textit{VC Backed Dummy} + \beta_5 * \textit{PE Backed Dummy} + \beta_6 * \textit{Non-backed Dummy} + \beta_7 * \textit{High-tech Dummy} + \beta_8 * \textit{Year Dummies} + \beta_9 * \textit{Bubble Dummy} + \beta_8 * \textit{Deal value} + \beta_9 * \textit{Percentage Sold} \quad \mathbf{(4)}$$

For the age variable, the natural logarithm is taken. To the entire sample 1 years is added so that the natural logarithm of firms that perform an IPO in their founding year does not become ln(0), as of the fact that $e^x=0$ is an undefined mathematical expression. So, in the ordinary lease regressions I will take the logarithm to solve for linearity problems. For the reputation and quality of the underwriters the ranking system introduced by Carter, Dark and Singh (1998) is used. This model got updated in 2012. As mentioned before this ranking scales each underwriter on a scale from 0.0 to 9.0. The higher the number the more prominent the underwriter. High-quality underwriters are expected to be positively correlated to underpricing as mentioned in the theoretical framework. From the entire set, there is a decent amount of companies which are backed by some form of venture capital or private equity. Previous research proved influences of different sort of backing on underpricing. These effects can be tested by creating different dummies.

4.3.2 Difference-In-Differences

In this research, all means between the tech and non-tech companies are compared within the years and I test if the difference between 2016 versus 2010 is significant. To test what the differences are between tech and non-tech companies for 2016 versus 2010 the difference-in-differences (DID) test comes in. DID is a popular non-experimental tool to estimate a 'treatment' comparing pre- and post-differences between two groups. DID estimation has become an increasingly popular way to estimate causal relationships. It compares the average change over time of the 'treatment group' versus the average change over time for the 'control group'. The idea behind the DID is that the two groups can be different but if this difference is constant this difference can be filtered out. This removes biases in second period comparisons between the treatment and control group that could be the result from permanent differences between those groups. *`One of the key assumptions for the DID approach is that the outcome in both groups would follow a similar time trend in the absence of the treatment´* (European Commission, 2015). This trend is hard to verify and you still need to take in consideration non-observed changes. In my case the tech companies will be the 'treatment group' and the non-tech companies will be the 'control group'. The differences between the two groups in 2010 and the differences between the two groups in 2016 are tested. Next the differences between the differences will be compared to see if I can detect an effect over time. In the case of my research I want to compare two IPOs *i* which is B if it is a tech IPO and A if it is a non-tech IPOs. The potential outcomes are defined as $Y_{i,t}$ for each IPO A,B and time=0,1. The effect can be written as seen below:

$$\alpha_{it} = E(Y_{B,1}-Y_{A,1}) - E(Y_{B,0}-Y_{A,0}) \quad \textbf{(5)}$$

Under this approach the two differences within parentheses eliminate the systematic effect of individuals. In this way, both for group- and time-specific effects are allowed for. This is also the reason that the DID method eliminates bias caused by time effects. It must be noticed that this DID approach assumes a common trend. This trend depends on the way the control group is constructed. It should be questioned if the 'treated' group is comparable to the 'non-treated' group. To solve for potential selection biases matching provides a solution. In the next section I elaborate on propensity score matching (PSM).

Besides taking in consideration a potential selection bias unobserved heterogeneity also needs to be touched upon. Where the DID assumes independence, this condition can in some cases not be met due to unmeasured characteristics that are expected to influence outcomes. The unobservable cofounders and their causal effect can be identified by using instrumental variables. Where these instrumental variables are in most cases hard to find the DID exploits the time or cohort dimension which allows to account for unobservable but fixed characteristics. Unobserved heterogeneity is always an issue which can partly be solved by matching. PSM is based on the matching of observable characteristics and variables. The problem of unobserved heterogeneity always needs to be taken in consideration and remains an issue. It can be said that many unobservable characteristics of individuals or companies remain relatively the same over time and that DID in that way solves for that unobservable heterogeneity by assuming this.

4.3.3 Propensity Score Matching

As mentioned in the previous section a potential issue in this research and in the general application of the difference-in-differences approach is that of a selection bias in the sample selection. Where I compare tech versus non-tech companies in two different years there is a chance that the groups differ significantly on a set of observable characteristics. A problem with the dataset is that the independence assumption in some cases cannot be met because differences in observable characteristics could influence outcomes (cofounders). Where creating, exact matches can be very hard propensity score matching (PSM) comes in. By using the PSM approach this bias caused by this observable pre-treatment disparities between the two groups can be eliminated. The goal is that the distribution of observed baseline covariates is similar between the untreated and treated sample.

This matching is done via a program in STATA which is based on a probit regression model with all known cofounders as predictors. It is based on the propensity score matching (PSM) by the *psmatch2* software and uses nearest neighbor matching procedure. This approach makes use of weighted averages of all individuals in the control group to estimate the counterfactual outcome based on the cofounders. The propensity score is defined as: '*Probability of participating in the interception, conditional on the characteristics X'* (European Commission, 2015). So, in own words it is defined as the probability of receiving the treatment given the covariates. This is expressed as

$$p(x) = \Pr[D = 1 \mid X] \quad \textbf{(6)}$$

In this research this probability of participation is the probability of being a tech company. This matching assumes that there are no systematic differences in unobserved characteristics between tech and non-tech companies. With the *pscore* function in STATA the success of the matching can be tested. The issue of potential unobserved heterogeneity is a problem where other relevant unobservable variables correlate with observable variables influencing the results.

The advantage of using the propensity score is that it can correct for more cofounders that other matching techniques. It must be noticed that this matching can correct for observed cofounders and not for non-observed cofounders which could results in unobserved heterogeneity. The matching procedure goes in steps where the first step is to estimate the propensity score. The second step is to check if the assumptions hold. Thirdly the groups are matched after which a graphical representation can indicate if the matching has been successful. Lastly the new regressions can be run with the matched sample.

To summarize: the goal of matching is to balance the distribution of characteristics between the control and treatment group. The aim behind this is to minimize selection biases and allow for heterogeneous treatment effects and overcome fundamental evaluation problems.

Where the initial non-matched sample is used to run several regressions on the PE Ratio to see what the effect is of the different bubble indicators on this earnings ratio this regression will be repeated with the matched sample. The reason to run the regression with the matched sample is to assure that the found effects are not explained by differences in cofounders. By eliminating other potential influences on the coefficients, I try to isolate certain effects. The goal of the OLS is to predict correlations of the dependent variable with independent variables.

According to different research papers price and the underlying earnings are strong indicators of performance and future earnings. During previous stock market bubbles, it was always the case that stocks had very high PE ratios just before the burst. In the first regressions, the independent variable is the PE ratio of the stock performing the IPO. Several interaction terms are added. The idea behind interaction terms is detecting significant relations between a set of variables. With three variables interacting with a dummy variable, which equals 1 for tech companies performing an IPO in 2016, and underpricing, trading volume and volatility as variables I want to test if for the suspected bubble year any unusually interactions are in place. As mentioned before markets are currently experiencing low interest rates resulting in a favorable lending environment and this results in debt levels increasing. The debt levels are added as an independent variable to see what the influence is on the PE ratio. Both the variable treasury rate and dividends are added as control variables. The following regression will be run with the full sample and the matched sample.

$$PE(t){:}\ \beta_{0\,+} + \beta_1 * Underpicing(t) + \beta_2 * Volatility(t) + \beta_3 * Trading\ Volume(t) + \beta_4 * Dividends(t) + \beta_5 * Treasury\ Rate(1) + \beta_6 * Public\ Debt/\ GDP(t) + \beta_7 * TechDummy + \beta_8 * 2016TechDummy + \beta_9 * Underpricing(t) * 2016TechDummy + \beta_9 * Volatility(t) * 2016TechDummy + \beta_9 * Trading\ Volume(t) * 2016\ Tech\ Dummy \quad \textbf{(7)}$$

With the matched sample regressions, I want to make my results more robust and correct for potential biases. Multiple regression analyses rely on several assumptions as normal distribution of the independent variables and uncorrelated error terms. It is important to test the variables for multicollinearity. Multicollinearity arises when two or more independent variables are highly correlated reducing overall reliability of the model. A good method to detect multicollinearity is to look at variance inflation factors (VIFs). VIFs tell us to what extent to which the coefficients standard error ad been inflated upwards. The rule of thumb is that when the VIFs value exceeds the number 5, multicollinearity is likely to be a problem. One would expect the VIFs for the matched sample to be lower than those of the non-matched sample.

Correcting for heteroscedasticity is done in Stata by correcting robust standard errors with the White heteroscedasticity method. Heteroscedasticity occurs when the variance of the error term is not constant. This is the case when for example the error terms of large firms have larger variances than error terms for small firms. Robust standard errors do not remove heteroscedasticity, but correct standard errors to make them consistent.

5. Results

In this section the different results are summarized. Where in chapter 4 the data is described I already looked at the differences between tech and non-tech companies and tested if these differences are significant. These results already answer some hypotheses but with the results covered in this chapter I can eventually answer all hypothesis. The first step in this chapter is to look at the correlation between the different variables and check if the found correlations are in line with expectations. The second section focusses on the regression on underpricing which is mainly performed to test of the finding are like those seen during the Dotcom bubble and test if the dataset is reliable. The results of that regression can be found in the appendix and will be touched upon very shortly due to the fact that it is not relevant for the rest of the paper. The third part of this chapter looks at the DID and PSM results. The matching procedure is summarized and the quality of the matching is graphically represented after which I run a regression with the matched sample.

5.1 Data Description

Table 5 presents correlation matrices to describe the relationship between the variables which will later be used in the regressions. The first table represents the correlation between the firm characteristics and the second table looks at the correlation of other variables like trading volume and volatility.

From table 5 it can be found that the PE ratios of both stocks on the S&P500 and the NASDAQ show negative correlation with the volatility. The volatility is based on the average 30-day return. Historically, high volatility levels have been negatively correlated with prices so my results are in line with expectations. For the trading volume, a positive correlation with prices is found which is also in line with expectations. Higher trading volume means that a stock is more liquid which makes it more desirable and thus increases prices. For the indexed trading volume and volatility, the coefficients have the same sign as the single variables. What also becomes evident from the correlation matrices is the positive correlation between the PE ratio of both indexes. Also, the volume and volatility between the indexes shows positive correlation. Looking at the underpricing variable I find this variable to be significant positively correlated to underwriter ranking and the offer price. Underpricing is negatively correlated with revenues. Notably, there is a positive correlation between net income and deal value, underwriter size, offer price, age and revenue. Older companies performing an IPO show positive correlation with deal value and offer price which is in line with historical findings. The research by Ljungqvist and Wilhelm found similar results in their research from 2002. The high correlation between the different stocks is also in line with expectations. In the tables the stars represent the significance level at the 5% level.

Table 5: Correlation Matrices

The correlation matrix includes the sample of in total 857 IPOs between 2010 and 2016 and data on the stocks on the NASDAQ and S&P500 index. All the IPO data was obtained via the Thompson One and Bloomberg database. Underpricing is based on the first-day returns which is the price after the first trading day divided by the offer price and adjusted for the market.

	Coefficients of correlation											
	1	2	3	4	5	6	7	8	9	10	11	12
1. Deal Value	1.00											
2. Underwriter Size	0.35*	1.00										
3. Underwriter Ranking	0.13*	0.35*	1.00									
4. Offer Price	0.37*	0.48*	0.38*	1.00								
5. Age	0.19*	0.21*	0.08*	0.10*	1.00							
6. Revenue	0.33*	0.43*	0.16*	0.23*	0.40*	1.00						
7. Net Incomes	0.25*	0.07*	0.03	0.12*	0.07*	0.36*	1.00					
8. Underpricing	-0.01	-0.03	0.11*	0.21*	-0.01	-0.09*	-0.03	1.00				
9. Number of shares sold	-0.07*	-0.16*	-0.18*	-0.23*	-0.05	-0.11*	-0.01	-0.21*	1.00			
10. Trading Volume	0.02	-0.03	0.07*	0.00	0.05	0.10*	0.05	-0.12*	0.05	1.00		
11. Volatility	-0.03	-0.16*	0.02	-0.09*	-0.09*	-0.12*	-0.06	-0.09*	-0.02	0.31*	1.00	
12. PE Ratio	-0.13*	-0.16*	-0.17*	-0.15*	-0.15*	-0.26*	-0.12*	0.11*	-0.04	0.09*	-0.43*	1.00

* denote significance at the 5% level

	Coefficients of correlation							
	1	2	3	4	5	6	7	8
1. Trading Volume NASDAQ	1.00							
2. Trading Volume S&P500	0.90*	1.00						
3. Volatility NASDAQ	0.50*	0.44*	1.00					
4. Volatility S&P500	0.24*	0.34*	0.83*	1.00				
5. Trading Volume (NASDAQ/S&P500)	0.49*	0.11*	0.27*	-0.09*	1.00			
6. Volatility (NASDAQ/S&P500)	0.45*	0.22*	0.41*	-0.12*	0.57*	1.00		
7. PE Ratio (S&P500)	0.51*	0.38*	-0.21*	-0.33*	0.43*	0.45*	1.00	
8. PE Ratio (NASDAQ)	0.23*	0.04*	-0.29*	-0.41*	0.46*	0.42*	0.74*	1.00

* denote significance at the 5% level

5.2 Underpricing

In this section of the paper I further examine the result of effect on the underpricing (dependent variable) of different independent variables. The regressions can be found in the appendix 1 and is based on the research performed by Ljungqvist and Wilhelm. The regression can partly be considered as a robustness check for the IPO dataset. The values in the first line are the coefficients and the second line shows their corresponding p-value. As can be seen in the descriptive statistics there has been an increase in underpricing over the past six years. In the 1st regression (OLS 1) the influence of different firm characteristics is examined. Most interesting in this regression is a high positive correlation between VC-backed firm (VC backed dummy) and the initials returns. I find that VC-backed firms performing an IPO show significant higher initial returns and thus underpricing than non-and private backed companies and this effect is bigger for non-tech firms. This finding confirms the control variable regarding higher underpricing for VC-backed IPOs. In the last regression, all variables are tested together to measure the different effects. I find that firm's age is positively correlated to the initial returns. Looking at the other firm characteristics it becomes evident that the VC dummy is again highly significant with a high correlation with the initial returns. The number of book runners and percentage number of shares sold are negatively correlated to the initial returns. The offer price is again positively correlated to underpricing just as seen in regression two. As suspected from the 3rd regression I find the interaction variable not be significant anymore. For the different year dummies, I only find significant results for non-tech stocks in 2016. The offer price is positively and significant related to underpricing and this effect is biggest for tech-stocks. From the regression, I also find that tech stocks do experience significant higher underpricing because of the positive significant coefficient for the tech dummy. This again confirms hypothesis 3.

When testing for multicollinearity with the VIF analysis I find that for the coefficients none of the VIF numbers is close to 5 indicating an acceptable low degree of multicollinearity in the model. The regressions are made robust with the robust function in STATA.

5.3 Difference-In-Differences

Table 6 on the next page represents the difference-in-differences table. The means of tech versus non-tech stocks are tested within the same year and the differences in means between 2016 vs. 2010. First, I tested if the results for tech and non-tech stocks differ from each other in each year. The difference-in-differences estimation is an experiment that helps to estimate a causal effect. If there is a difference between means for 2016 versus 2010 I can explain what the reason for this change could be and compare them to observations from previous bubbles. In appendix 3 extra tables can be found with different mean tests and extra DID models looking at differences between other years to see the development of the differences over different time frames. In the table, standard errors of the means are the numbers in parentheses.

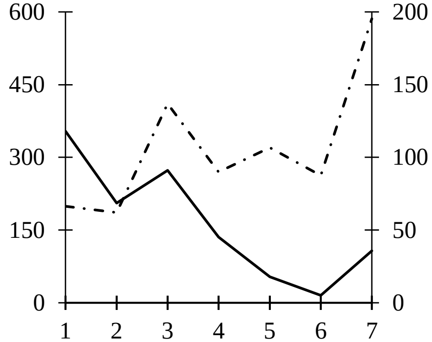
Table 6: Difference-in-differences

Analysis on 2016 versus 2010 where non-technology companies are the control group versus the high-tech companies which is the test sample relevant for this research. Standard error represented in parentheses. For the test between the differences significant is tested and represented with the stars. Column (9) indicated the relative change between tech and non-tech companies between 2016 and 2010.

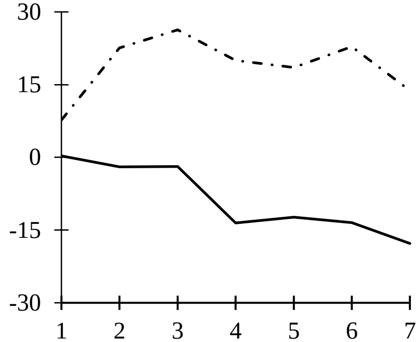
	2010		2016		Differences		Difference-in-differences
Variable	Non-Tech (1)	High-Tech (2)	Non-Tech (3)	High-Tech (4)	[(2) - (1)] (5)	[(4) - (3)] (6)	[(6) - (5)] (7)
Underpricing (%)	8.4	10.6	6.4	20.1	2.2	13.7**	11.5*
	(2.72)	(2.31)	(3.31)	(4.98)	(3.73)	(4.73)	(4.86)
Age	19.5	22.2	32.0	17.1	2.7	-15.0**	-17.7*
	(3.38)	(5.14)	(7.66)	(2.98)	(5.49)	(7.14)	(9.00)
Deal Value ($m)	176.3	133.0	300.2	100.0	-33.0	200.2***	-167.2***
	(21.55)	(16.93)	(38.65)	(17.55)	(34.54)	(45.65)	(56.91)
Offer Price ($)	12.1	13.0	13.9	15.8	0.9	1.9**	1.0
	(0.72)	(0.50)	(1.14)	(0.74)	(0.86)	(1.11)	(1.41)
Bookrunners	2.4	2.3	4.9	2.9	-0.1	-2.0***	-1.9***
	(0.18)	(0.16)	(0.54)	(0.24)	(0.31)	(0.41)	(0.52)
Ranking	8.4	8.6	8.5	8.0	0.2	-0.5	-0.7*
	(0.35)	(0.20)	(0.19)	(0.26)	(0.25)	(0.32)	(0.40)
Net Income ($m)	19.5	-24.5	79.2	-14.73	-44.0	-94.0***	-49.9
	(11.35)	(18.31)	(55.46)	(8.18)	(28.01)	(34.89)	(44.75)
Volume (m)	944.6	602.1	603.2	449.0	-342.5***	-154.2***	188.4***
	(24.89)	(8.35)	(5.32)	(6.68)	(16.39)	(21.31)	(26.88)
Volatility (%)	16.5	17.5	11.4	15.5	-0.9***	4.1***	3.2*
	(0.40)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
N (observations)	53	47	23	41	53	41	94

*,** and *** denote significance between the differences at the 10%, 5% or 1% level, respectively

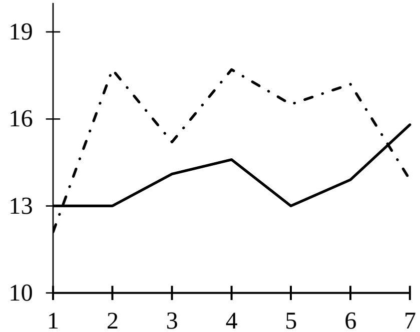
In column (5) and (6) I compare the difference between the tech groups versus the non-tech group in 2010 and then in 2016. The last column (9) captures the difference-in-differences. For the differences tests between 2016 versus 2010 and tech versus non-tech the significance is represented with the stars. Looking at the findings for the DID significant changes are detected in underpricing, age, deal value, offer price, amount of book runners, ranking, net income, trading volume and volatility. Underpricing of tech stocks increased significantly between 2016 and 2010. Underpricing and trading volume for tech stocks increased relatively to the non-tech stocks. For deal value, amount of book runners, ranking of the book runners and volatility it is the other way around. The age of tech companies decreased significantly. Looking at net income I find net income to have decreased for tech stocks but this decrease is not significant when comparing 2016 versus 2010. I do find that the net income difference for tech versus non-tech stocks in 2016 differs significant. Comparing above DID with the other DID analysis in the appendix I find that especially the last two years the gap between tech and non-tech companies have increased for most variables where it remained relatively stable in the earlier years indicating an unexplainable acceleration. This increasing gap which seems to gather speed is remarkable. On the next page, several plots show the development of different relevant independent variables over the years. Elaboration on the axes can be found in the descriptive of the figure.



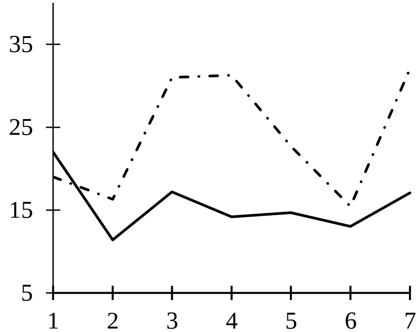
(a) Revenue



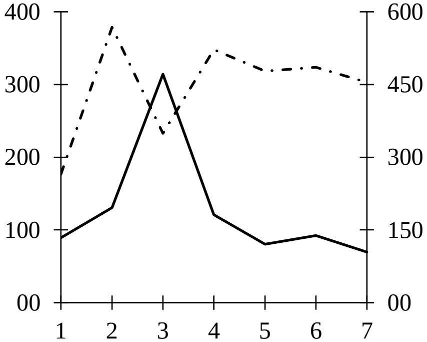
(b) Net Income



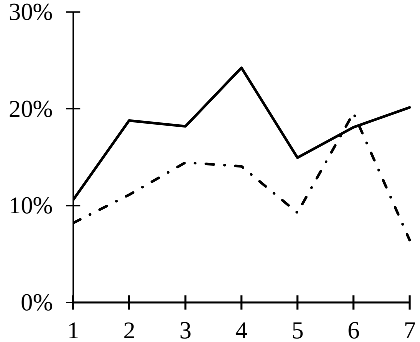
(c) Offer Price



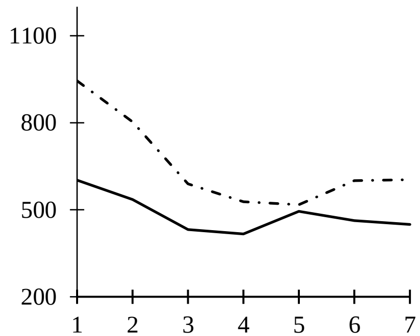
(d) Company Age



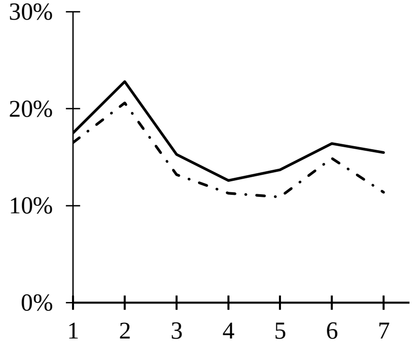
(e) Deal Value



(f) Underpricing



(g) Trading Volume



(h) Volatility

Figure 7: Differences Between Tech and Non-Tech Companies

The graphs above show the development of eight different variables for year 2010 till year 2016 for tech and non-tech companies. Horizontal axis represents the years with 1 being 2010 and 7 being 2016. Tech companies are shown as the solid line, while the dashed line represents the non-tech companies. Figure (a), (b) and (e) are presented in millions of US dollars. The offer price (c) is given in US dollars. Figure (f) and (h) represent the value in percentages. The trading volume (g) is given in millions. The volatility is based on the 30-day average return of the stocks. For figure (a) and (e) the secondary axis represents the values for tech stocks.

With the test results on the previous pages I can answer some of the hypothesis stated earlier in the paper. From the data, it becomes clear that stocks on the NASDAQ index experienced increasingly higher trading volume relatively compared to stocks on the S&P500 and this increase is significant. This confirms the 1st hypothesis. When looking at the difference-in-differences test from table 7 I find that for both indexes the trading volume decreased but this decrease was lower for the NASDAQ and therefor the ratio between the NASDAQ and S&P500 did change in favor of the NASDAQ. For the 2nd hypothesis, I find that for both indexes the volatility decreased significantly since 2010 and when looking at the ratio I find that the NASDAQs volatility decreased less than that of the S&P500. I can thus confirm that the stocks on the NASDAQ index experiences increasingly volatility compared to stocks on the S&P500 and this increase is significant but the overall volatility decreased.

When looking at the underpricing I find that for both tech and non-tech stocks IPOs experience significant underpricing and this underpricing increased over the past years. When comparing 2016 versus 2010 I find that this increase is only significant for tech stocks. In the sample tech stocks, overall experience higher underpricing compared to non-tech stocks. The different underpricing between the two groups is significant when looking at the entire sample. From the results, I can answer hypothesis 3 that markets are currently experiencing significant IPO underpricing which could indicate a possible bubble. I can also confirm hypothesis 4 which states that tech IPOs experience significant higher underpricing. In the discussion section of this paper I will further elaborate on the implication of this finding and compare current underpricing to underpricing during the Dotcom bubble. Companies performing an initial public offering which are active in the high-tech industry show significant higher underpricing when looking at total underpricing for all years but when looking at separate years this underpricing only differs significant from each other for 2011, 2013, 2015 and 2016.

Looking at other company and IPO characteristics I find that the average age of tech companies performing an IPO decreased significantly since 2010. I do find that tech companies tend to be younger when performing an IPO and this different is mostly significant comparing it to non-tech firms in the same year but the changes between 2016 and 2010 are not significant. The average offer price per share increased for both tech and non-tech stocks since 2010 and this increase is significant. The offer price for non-tech stocks tends to be higher than the offer price of tech stocks. Looking at the deal value I find that non-tech stocks have higher deal value and this deal value has increased significantly since 2010. For tech stocks, it is the other way around where the average deal value has decreased significantly since 2010. Overall the deal value tends to be lower for tech stocks. When looking at accounting standards of the companies performing an IPO the tech companies show significant lower accounting standards compared to non-tech stocks. Tech stocks do show significant lower net income where non-tech stocks did not. This might be in line with expectations since tech stocks are more risky and active in technologies that might have not proven yet. It is remarkable that much of the tech stocks performing an IPO have negative net income. With these findings hypothesis 5 can partly be confirmed.

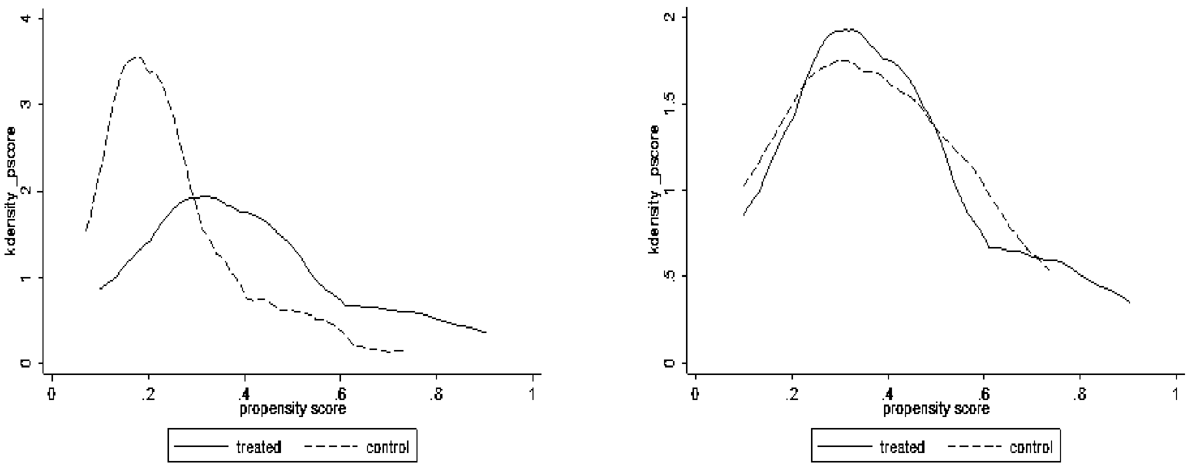
5.4 Propensity Score Matching

Where I investigate the differences between tech and non-tech IPOs I did not take in consideration any size or other variable effects. As mentioned in the methodology I will use PSM to solve for differences in cofounders. The matching is based on the nearest neighbor matching procedure. In appendix 6 the sample characteristics before and after the matching can be found indicating the success of the matching procedure. Where the PSM is often used to capture the effect of a treatment I followed the guidelines and adjusted this test for my dataset. In this case the causal part is just the difference between the years.

The first step is to create the actual PSM which is done via the Stata comment psmatch2. It is created to test the conditional chance that an observation is part of a specific group based on a set of covariance's. This is done automatically in STATA and is based on a probit regression model where all known cofounders are used as predictors. The matching is based on the companies age, net income, underpricing, trading volume, volatility, and deal value. After matching I find that differences between the matched covariates not to be significant anymore expect for the trading volume variable (appendix 6). Figure 7 shows the distribution of the propensity score before and after matching. As can be seen from the figure the distribution of cofounders was high before matching. After matching this residual imbalance decreased which solves the issue of taking in consideration extra cofounders in the model.

Figure 8: Propensity Score Plots

Graphs below represent the propensity score plots of the non-tech (control) versus tech (treated) group. The plots give a graphical representation of the propensity score distribution. It can be seen that there is a remarkable improvement in the match between the two distributions after matching.



(a) Before matching (b) After Matching

Now that the matching solved for the differences between the cofounder it is time to look at the regressions run on the PE Ratio with both the full and matched sample. This make sure that the results found are not explained by differences in cofounders.

When looking at trading volume, volatility and underpricing as indicators of a bubble it is important to link these indicators to the PE Ratio. As mentioned in the theoretical framework the PE ratios during previous bubbles has always been high compared to underlying earnings. From the collected data, I spot a trend for the tech stocks where prices keep on increasing while underlying earnings do not increase. Where the decrease is not significant I suspect these earnings to show significant decrease with a bigger dataset. To further investigate what influences this PE ratios I collected data on the PE ratio and debt levels in the US. I already mentioned the fact that during previous bubbles in almost all cases high amounts of capital were available which fueled the bubble. In our current landscape with the aftermath of the financial crisis interest rates are artificially kept low giving individuals and companies the opportunity to borrow money at low cost. Next to the PE ratios as dependent variables I added public debt/GDP, underpricing, volume, volatility, and interest rates as independent variables.

In the 1st regression, the influence of the dummies is tested on the PE ratio. The 2nd regression includes all indicators of a bubble and includes the control variable treasury rate and debt. It is widely recognized that a lower treasury rates results in increased stock prices. This is due to several reasons. One of them is that investors are trying to make returns on their portfolio and with low treasury rates these returns are hard to realize by buying bonds and other relatively riskless products. They therefor move to the equity markets to make higher returns. This increases the volume and liquidity of stocks on the equity market resulting in higher prices. In the 3rd regression, I added three interaction variables where I look at the interaction between the bubble indicators and the technology sector in 2016. This to detect differences between tech and non-tech companies in 2016. Because I suspect a bubble forming I believe that 2016 will show different results compared to previous years. The final regression (4) combines regression 2 and 3. In regression 2,3 and 4 a dummy is incorporated for each year to adjust for the fixed effects. It indicates the deviation for that year compared to an average year and adjusts for unobservable time-invariant differences among the data.

When running multivariate regressions like the one on the next page there are several assumptions made. These assumptions need to be tested. Firstly, I tested the assumption of no multicollinearity. With the results from the VIF I believe that the data contains no indication of multicollinearity. In the implementation of the robust estimate of variance, Stata is scaling the estimated variance matrix to make it less biased. The robust option relaxes the assumption that the errors are identically distributed and solves for the potential problem of heteroscedasticity.

Table 7 on the next page summarizes the results of the multivariate regressions on the PE ratio with the full sample and the matched sample

Table 7: Least-Squares Regressions Matched Sample versus Non-Matched Sample

The dependent variable in all the regressions is the PE ratio. Column (1) depicts the regression with the technology firm dummy and the technology firm with the year dummies. Column (2) depicts the regression with all the variables mentioned as bubble indicators. The column (3) contains interaction variables with the tech 2016 dummy. The last column (4) combines regression (2) and (3). Probabilities are shows in italics. I use *,** and *** to denote significance at the 10%, 5% or 1% level (two-sided), respectively. The total number of observations is 857. The last two rows represent the adjusted R^2 and number of observations N.

Dependent Variable: PE Ratio	(1)		(2)		(3)		(4)	
	Full Sample	Matched Sample	Full Sample	Matched Sample	Full Sample	Matched Sample	Full Sample	Matched Sample
Tech dummy	3.37*** *0.000*	6.30*** *0.000*	4.23*** *0.000*	5.98*** *0.000*	-7.00 *0.106*	6.91*** *0.000*	15.01*** *0.000*	4.98*** *0.000*
2016 Tech Dummy	1.12*** *0.000*	0.29*** *0.00*						
2015 Tech Dummy	0.78*** *0.005*	0.35 *0.176*						
2014 Tech Dummy	1.32*** *0.000*	0.48** *0.048*						
2013 Tech Dummy	0.75*** *0.005*	-2.25*** *0.000*						
2012 Tech Dummy	-0.79** *0.005*	-5.55*** *0.000*						
2011 Tech Dummy	0.08 *0.787*	-4.84*** *0.000*						
2010 Tech Dummy	0.85*** *0.003*	-3.14*** *0.000*						
Underpricing			0.29 *0.120*	-0.65* *0.060*			-0.27 *0.477*	-0.68* *0.055*
Log Trading Volume			9.25*** *0.000*	0.00 *0.625*			20.97*** *0.000*	-0.01 *0.518*
Volatility			-6.16*** *0.000*	-4.29** *0.050*			-21.69*** *0.000*	-3.76** *0.036*
Debt/GDP			43.48*** *0.000*	1.40*** *0.000*			38.48*** *0.000*	1.20 *0.826*
Treasury Rate			13.79*** *0.000*	4.27 *0.887*			27.34*** *0.000*	10.08 *0.826*
Underpricing x 2016 Tech					0.21 *0.572*	1.43*** *0.000*	0.18 *0.701*	1.72*** *0.00*
Trading Volume x 2016 Tech					-69.61*** *0.000*	-0.01* *0.080*	-34.56*** *0.000*	0.01 *0.518*
Volatility x 2016 Tech					34.01** *0.011*	10.31** *0.021*	21.96*** *0.000*	6.82* *0.093*
Constant	15.1*** *0.000*	19.21*** *0.000*	-55.82 *0.401*	19.60*** *0.003*	-50.81*** *0.000*	19.56*** *0.000*	-69.56*** *0.000*	19.38*** *0.003*
Year Fixed Effect	NO	NO	YES	YES	YES	YES	YES	YES
N	857	857	857	857	857	857	857	857
Adjusted R^2	79.49%	68.98%	77.74%	73.54%	25.94%	19.34%	78.30%	81.68%

*,** and *** denote significance at the 10%, 5% or 1% level, respectively

From regression 1 I find that the PE ratio overall is significant higher for tech stocks compared to non-tech stocks and that this is the case for both the full and matched sample. This is in line with what can be seen when comparing the NASDAQ with the S&P500. The average PE ratio of the NASDAQ is in general higher than the PE ratio of the S&P500. Remarkable to see is that in the matched sample there is a negative correlation for the 2010, 2011, 2012 and 2013 tech dummy and that this correlation became positive in the following years with an increasing coefficient.

Looking at the 2nd regression with the different bubble indictors and control variables I find the underpricing to be negatively correlated to the PE ratio for the matched sample while this showed the opposite sign in the correlation matrix of the full sample. In the full sample regression, this underpricing is not showing significant result. Looking at the different bubble indicators I find that both the trading volume and debt levels are positively correlated to the PE ratio but that in the matched sample the trading volume coefficient is close to zero and having low significance. The volatility indicated a negative relation with the PE ratio in both the full and matched sample meaning an increase in volatility leads to a lower PE ratio.

In regression 3 the three indicators of a bubble are all separately multiplied with the technology 2016 dummy creating different interaction variables. For the interaction term regarding underpricing I find positive correlation with the PE ratio in the matched sample. Looking at the other interaction terms I find opposite effects to those in the 2nd regression and these effects remain in the matched sample. When looking at technology stocks in 2016 and more specifically the interaction terms of this dummy with the independent variables of underpricing, volatility and trading volume I find these coefficients to be the opposite of those in regression 2. The trading volume coefficient is close to zero in the matched sample but does show a negative coefficient. The interaction variable regarding the volatility shows high positive correlation indicating that for 2016 an increase in volatility resulted in an increase in the PE ratio of tech stocks. The results are remarkable and go against assumptions of rationality.

The final regression (4) combines regression 2 and 3. Most of the results found in the 2nd and 3rd regression also show in regression 4. In the matched sample the debt variables loses significance and so does that interaction variable for the 2016 tech dummy with the trading volume. The other interaction variables show the same sign.

In regression 2,3 and 4 I took in consideration a time fixed effect. These effects clearly indicate the PE ratio to increase over the years in the form of an exponential growth. The interpretations of the results from the regression analysis when comparing the matched versus the non-matched sample seem to be in line with each other. Where the effect in most cases declined for the matched sample the effects point in the same direction. The R-squared of the models is relatively high indicating high explanatory power. The models are made robust in stata via the *robust* command.

5.5 Hypotheses Testing

To summarize the findings, I will reflect on the results and link them to the different hypothesis stated in chapter 3. From the data, the first two hypotheses can be confirmed. Stocks on the NASDAQ labeled as tech stocks in this research show increased trading volume and volatility compared to the stocks on the S&P500. While trading volume and volatility decreased for both groups this was less severe for tech stocks. Just as seen from historical research we have experienced significant underpricing of IPOs over the past six years for both tech and non-tech stocks. This underpricing is higher and has increased significantly for tech stocks during the past six years. These findings confirm hypothesis 4 and 5. Hypothesis 5 can partly be confirmed where I find that technology companies performing an IPO became younger while non-tech companies perform IPOs at a later age. Remarkable is the big increase in the age gap between tech and non-tech stocks. The offer price remained stable for both tech and non-tech companies. For 2016 net income is negative for tech stocks where it is positive for non-tech stocks. A trend can be spotted indicated tech stocks performance to have worsened. Based on the findings it can be concluded that prices for tech stocks are rising while underlying earnings do not grow in line with this price increase. From the matched regression, it can be found that the bubble indicators, trading volume and volatility, show opposite effects in 2016 of what is expected in normal markets and what is seen in the regression on all years. These findings are confirmed both when running the regression with the full and matched sample.

6. Discussion

This section provides an in-depth analysis and a subsequent discussion of the results. First, the results pertaining the descriptive statistics are considered followed by an examination of the different independent variables as bubble indicators. The results will be cross-examined with other papers written about financial bubbles. The focus is on the trading volume, volatility and underpricing as bubble indicators and the influence of these variables on the PE ratio. This is discussed by going over the regression results and compared the results of the regression with the full and matched sample. In the last part, all findings are combined and a conclusion regarding a potential bubble in the tech sector will be formulated.

6.1 Implication results

Looking at the firm and transaction specific descriptive statistics there are a few observations that require further elaboration. When looking at the number of public offerings over the past years it becomes clear that for 2013 and 2014 the number of offerings was significantly higher compared to previous years and long term average. After this peak, there has been a slowdown in the number of IPOs. This is in line with reports in the media of a slowdown in the public offering market. Reported 2016 has been the worst year for IPOs since the height of the financial crisis. There are several explanations for this decrease in the number of IPOs. Firstly, as mentioned before companies stay private longer due to the availability of private capital. Many of the firms seek funding though a form of private funding like PE or VC. Secondly, companies that went public in 2015 performed bad, making companies intending to float in 2016 conservative.

From the dataset, I find that both in the tech and non-tech sector companies experience significant underpricing when performing an IPO. Over the years this underpricing increased for tech stocks while the underpricing for non-tech stocks did not change significantly since 2010. When comparing underpricing between the two different groups it becomes evident that underpricing is significantly higher for high-tech stocks. Previous literature already showed tech stocks to be more prone to higher underpricing than non-tech stocks. The underpricing of all IPOs is above long-term averages. Levels of underpricing are not as extreme as during the Dotcom bubble in 2000 but it is above the long-term average. An interesting finding from the regressions on underpricing is that I find that VC backed companies experience significantly higher underpricing. Looking at the dataset I find the overlap between tech companies en VC backing to be very high. The high underpricing for VC backed firms is in line with the research done by Peggy Lee and Sunul Wahal in 2003. The amount of venture capital invested in companies almost reached similar levels as around the Dotcom bubble and is still increasing. Companies active in the tech sector performing a public offering are on average younger than non-tech firms and their age has decreased significant over the past few years. High-tech companies are often active in an industry which requires a lot of R&D and this is expensive. This is one of the reasons tech companies perform IPOs at a relative young age. They need capital to grow and the equity market is one way of obtaining capital.

When focusing on the transaction characteristics there is a clear difference between tech and non-tech stocks. For non-tech stocks, average revenues, net income, assets and equity remained relatively stable and sometimes even increased where for tech IPOs the accounting performance worsened over the years. Looking at the median net income of tech stocks it is now the case that most tech companies performing an IPO have on average negative earnings. This is not a good development and is similar to that experienced during previous bubbles. The average IPO deal value increased for the non-tech group where it decreased for tech companies. This is in line with what you would expect during a slowdown of the IPO market as experienced in 2016. When markets are down firms will only issue as a last resort. With low appetite from the investors side, this is represented in the deal value. It is interesting that this decrease in deal value on average only occurred for tech stocks where for non-tech stocks this deal value increased. It could be a sign of investors questioning the negative earnings trend for tech companies. The offer price at which both groups price their stocks when going public increased with around 1.5 dollar and this increase is the same for both groups. The age gap between tech and non-tech companies increased enormously just as seen during the Dotcom bubble.

Looking at trading volumes and volatility of stocks both on the NASDAQ and the S&P500. What I find is that for both indexes the average trading volume and volatility decreased the past few years but this decrease has been less extreme for stocks on the NASDAQ. Therefor the relative trading volume and volatility of the NASDAQ increased compared to the S&P500. To get an indication on the trading and volatility levels on the NASDAQ index versus the S&P500 I created a ratio. This ratio proved that for both volume and volatility the NASDAQ experienced increased numbers compared to the S&P500. Historical bubbles always show signs of increased volatility and trading volume but this increase often occurs after the burst so the fact that markets are currently not experiencing increased trading volume or volatility does not implicate stock markets are not in a bubble.

In the literature review is explained what conditions are needed to define a specific market boom as a bubble and what are the different phases which can be pointed out during a bubble. Initially, there must be a rise in stock prices and a continuing increase in expectations by investors. Then there must be a point at which investors start to realize that stocks are not priced according to the fair value after which they start pulling out their money. This drastic change in investor behavior results in a shock followed by a market collapse. Market volume and volatility have decreased for stocks on both indexes when comparing 2016 versus 2010. Looking at prices it is clear that they have seen an enormous increase, especially in 2016. From the market capitalization of the NASDAQ and the S&P500 I find that the NASDAQ has grew exponentially since 2012 compared to the S&P500. This year stock markets have been on a record tear. Looking at this development from an academic perspective this is strange. Taking in consideration that net income for tech stocks have not increased over the years the finding of rising prices is even more questionable. It does explain the increase in the PE ratio when prices increase and earnings remain the same the ratio is pushed upwards. But how can it be that when trading volume and thus liquidity decreased, prices increase.

After the financial crisis in 2007 governments around the world tried to kick start the economy by providing artificial solutions. A big problem that occurs just after a crisis is the fear among investors and consumers resulting in low spending. Due to low spending an economy cannot grow and you need economic growth to get out of a recession. One of the artificial solutions provided by the FED was a decrease of the interest rates. Interest rates dropped to historically low levels making borrowing money extremely cheap. In this way, the FED hoped to stimulate consumers and companies to spend more and boost the economy. As a results of this low interest rate companies did increase their borrowings. Historically low interest rates have been fueling stock markets since the crisis. The lending increased so much that in 2016 it reached levels like those seen just before the financial crisis in 2007. The enormous increase in available capital is one of the first phases many scholars describe as being part of an economic bubble. An increase in borrowings is not the issue. The roots of the problem lie at the way companies spend this borrowed money. As can be seen from appendix 10 the amount of share buybacks and dividend payments of publicly listed companies increased exponentially with the increased borrowings. Moderate levels of debt and buybacks are not a bad thing when they are used for the right cause. Both share buybacks and dividend payments are perceived as positive signals by investors but it should be questioned if it is sustainable when these actions are financed with borrowed money. Since 2009 over $2.5 trillion worth of stocks has been repurchased by American corporates. It does explain the fact that prices increased while volume has been down. Logically buybacks decrease the number of outstanding shares and therefore increase the earnings per share and pushing prices. A potential problem with the high corporate debt levels due to buyback schemes would be rising interest rates. The problems with the buybacks are that companies might be better off when they would reinvest this capital in their business. Secondly corporate profits might look better than they really are. The growth in stock markets is based on financial engineering and not on actual growth. This problem is especially relevant for the tech sector because here underlying earnings have been decreasing over the years. Changes in economic engineering by the FED could be a trigger that changes investors behavior.

Looking at my dataset I find that the three indicators of a bubble all show normal correlation with the PE ratio over the entire sample for both the regression on the full and matched sample. So, increased volume leads to higher prices and higher volatility leads to lower prices. The strange thing is that this is different for 2016. From the interaction variables in my regressions I find that the coefficients changes sign for 2016 and is thus the other way around. This is not rational from an academic perspective and indicates markets to behave irrational. Earnings did not improve for tech stocks while price have been climbing.

6.2 The next bubble?

When looking at the findings of my research I find that current markets are behaving irrationally. Stock markets are experiencing a rally with stock prices reaching high levels like those seen before the financial crisis in 2007. Where the IPO market has not been very active in 2016 this is expected to change in 2017. The finding that prices have been rising while trading volume levels have been low is not a normal development. For tech stocks, it is specially worrying because when looking at underlying earnings of companies performing a public offering this have been becoming worse and companies age has been decreasing. The data tells us that accounting performance of technology stocks have not been increasing and IPO underpricing increased. Equity markets have been booming partly due to availability of cheap capital in the form of debt. When interest rates for safer instruments like treasury bonds rise, the relative attractions of corporate debt and corporate leverage will fall. This will have impact on the corporate debt levels and thus share prices. There are signals indicating equity markets to be overpriced and behaving irrational. I do believe that if there would be a bubble this bubble would be partially concentrated around the VC backed stocks and more specifically around the unicorn companies going public. A bubble in this sector and a potential burst would influence the entire equity market. Equity markets are not yet at the point of slowdown but I expect this to happen in the future when investors realize that equity markets and prices have been fueled due to economic engineering and prices do not represent underlying value.

7. Conclusion

To conclude, the scope if this paper was to examine if symptoms of a bubble in the technology sector similar to those seen during historical bubbles could be detected which could potentially indicate a new bubble in the tech sector. When looking at the findings of the research it becomes evident that the current stock markets are behaving unusual. Equity markets are experiencing a rally with stock prices reaching high levels like those seen before the financial crisis in 2007. One of the reasons equity markets have been booming is partly due to availability of capital in the form of debt with low interest rates. Where IPO markets dried up in 2016 economist expect markets to heat up again in 2017. Big unicorn companies backed by private funding are expected to perform initial public offerings.

From the dataset, it becomes evident that private funding and the number of companies valued over a billion dollar have increased exponentially without significant increase in underlying earnings. The amount of invested capital by VCs reached levels similar to those seen before the Dotcom bubble and these levels continue to grow. With enormous amounts of public money invested in these unicorns a potential bubble in this sector would have a major impact on the American economy.

In short, this research examines different indicators of a stock market bubble and tries to understand what drives stock prices to current levels. An important metric investors and scholars use when investigating stocks is the PE ratio. This research is geared towards this PE ratio and the effect of different bubble indicators on the PE ratio. Underpricing, trading volume and volatility have in previous bubbles shown unexpected movements during which makes them potential indicators.

A large part of the research focusses on the IPO markets between 2010 and 2016. Where underpricing is a recurring IPO symptom I find current underpricing to be above long term average. The underpricing is significantly higher in the tech sector. Underpricing in the tech sector increased over the past 6 years. When comparing tech versus non-tech IPOs it is found that for tech stocks the deal value has decreased and accounting standards have not increased with many of the companies performing an IPO having negative earnings. The numbers are not as extreme as during the Dotcom bubble but it is a negative trend similar to that seen during the Dotcom bubble. Non-tech companies on the other hand show increased deal value and underlying earnings remained stable over the past 6 years. Tech companies performing an IPO are on average younger than non-tech firms and this average age at IPO date decreased for tech stocks increasing the age gap between the two groups.

Equity market have in general been doing very well so both for tech and non-tech stocks prices have been increasing. Trading volume and volatility are below long term average for both tech and non-tech stocks. After using propensity score matching to solve for differences in cofounders I ran a regression on the PE ratio with the different bubble indicators as independent variables. The finding that prices in 2016 have been rising while trading volume levels have been low is not something you would expect. For 2016 I find the regressions coefficients when regressing volatility and trading volume on the PE ratio to be the exact opposite of what one would expect assuming rational markets both in the full and match sample regressions. These findings indicate irrational behavior. From my data, it seems like underlying earnings have been keeping up with increasing prices for non-tech stocks where this is not the case for tech-stocks.

For 2017 I expect markets and prices to further rise until investors realize that many of the public companies, of which some unicorns that performed an IPO in 2017, are not priced in line with underlying earnings and markets will correct. This will be mostly the case for tech stocks. With interest rates expected to further increase in 2017 it is highly likely both institutional and private investors will adjust investment behavior making equity markets less attractive resulting in a decrease in capital on the equity markets.

8. Shortcomings & Recommendations

8.1 Shortcomings

In this section the focus will be on the limitation of the research and describes different shortcomings. Where I have been planning this research carefully I am aware of the fact that there are several limitations in this research which I will further discuss in this chapter.

The first shortcoming of this research is the fact that there is a lack of information on the private funding landscape. I still believe that a bubble is growing but I also believe that estimating the size is very hard due to the fact that financial information is kept private. When looking at the different bubble indicators I find none of them to provide solid evidence proving a bubble because my main focus is on public available data. Where I do find worrying signals, I have not been able to provide solid proof. A next research should focus on the private landscape and the development of unicorn companies.

In this research a predicting model should be added to see if future PE ratios can be predicted based on historical data. Therefore, the dataset should be increased in size and more stocks should be covered. Especially interesting is to see what the development is of underlying earnings of a wider variety of stocks has been compared to prices. In my data, I see that net income for tech stocks have decreased but unfortunately this decrease is not significant. I believe this not be significant since net incomes have a wide spread making the standard error wide. An increase in the amount of observation N could potentially solve this problem giving a better idea what underlying earnings are really doing for tech stocks.

8.2 Recommendations and Perspective

The question is if the IPO market is a good representative of the current situation in the high-technology sector as of the fact that this sector is mainly built on private funding. Even though markets experience a lot of private funding the numbers are not as extreme as compared to during the Dotcom bubble in 1999 and 2000. The volatile IPO markets and big differences in underpricing indicate that financing reached a new era where firms changed. Due to regulations companies prefer to stay private and do this by attracting private funding. Private funding is much more of a closed book. An indicator of this are the housing prices in San Francisco which are among the highest in the entire country. As an example, look at Uber Technologies Inc. which is valued over $60 billion. Uber is spending huge amounts of capital to capture markets all around the world while their business plan has not proven itself. Just imagine a startup like this curtailing its ambition and the shock wave it that would follow through the entire system. This is precisely the weakness in the current system. It is a race where startups are judged on their growth and not their financials and underlying earnings. At some point growth, will screech to a hold and I question what will happen with the billions of private funding into the tech sector and fast-growing firms. This makes it very hard or even impossible to estimate the consequences of a bubble in the private funding sector. All the private investors at some point want to cash on their investments and need to find a suitable way to exit. Where the unicorn companies are far too big to be acquired by a strategic firm or another financial sponsor the private investors will seek for an exit through a public offering.

For future research, it would be very interesting to keep track of the IPO markets. I would expect underpricing and deal value to increase in the next few years. In addition to looking at the public market following research should focus on the private funding sector. As discussed above there has been an unseen increase in unicorn companies in the US alone. The unicorn phenomenon used to be so rare and therefore new to us that there is a limited literature covering this topic.

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Appendix 1: Least-Squares Underpricing Regressions

The dependent variable in all the regressions is the initial return (the first-day closing price relative to the offer price) and is adjusted to normalize. Number 1 represents the full sample, number 2 represents non-tech stocks and number 3 high-tech stocks. Probabilities are shows in italics. We use *,** and *** to denote significance at the 10%, 5% or 1% level (two-sided), respectively. The total number of observations is 857. The last two rows represent the adjusted R^2 and the F-test with again the notation of significance.

Dependent Variable	Underpricing (OLS 1)			Underpricing (OLS 2)			Underpricing (OLS 3)			Underpricing (OLS 4)		
Firm characteristics	1	2	3	1	2	3	1	2	3	1	2	3
ln(1+age)	1.571*	1.448*	1.397							1.832*	1.562	1.224
	0.098	*0.084*	*0.489*							*0.032*	*0.130*	*0.534*
Revenue	-0.002**	-0.002*	-0.004							-0.002**	0.000	-0.005*
	0.034	*0.073*	*0.123*							*0.019*	*0.337*	*0.051*
VC backed dummy	10.325***	13.728***	8.415**							11.950**	13.538***	7.289**
	0.000	*0.000*	*0.016*							*0.029*	*0.001*	*0.036*
PE backed dummy	0.284	5.177*	-4.181							-1.105	6.135**	-5.721*
	0.893	*0.059*	*0.182*							*0.573*	*0.025*	*0.062*
SIC code	0.002***	0.001**	0.003***							0.002***	0.001*	0.002***
	0.000	*0.031*	*0.000*							*0.000*	*0.057*	*0.002*
Offer characteristics												
Number of bookrunners				-3.036***	-1.519**	-3.282***				-1.554***	-0.901	-2.048***
				0.000	*0.023*	*0.004*				*0.008*	*0.231*	*0.002*
Underwriter ranking				1.083*	1.641	0.206				0.399	0.600	-0.328
				0.091	*0.164*	*0.832*				*0.552*	*0.572*	*0.741*
Deal value				0.000	0.000**	0.000				0.000*	0.000	0.000
				0.229	*0.049*	*0.374*				*0.097*	*0.117*	*0.435*
Offer price				1.535***	0.950***	2.265***				1.625***	1.035***	2.176***
				0.000	*0.001*	*0.000*				*0.000*	*0.000*	*0.000*
Shares offered (%)				-0.390***	-0.185*	-0.474***				-0.269***	-0.089	-0.406***
				0.000	*0.072*	*0.001*				*0.001*	*0.394*	*0.007*
Lockup period				0.315***	0.313*	0.294**				0.299	0.285	0.267**
				0.001	*0.091*	*0.015*				*0.119*	*0.115*	*0.025*
Bubble years												
2013							5.549*	2.669	8.465*	4.483*	3.584	6.240
							0.053	*0.45*	*0.058*	*0.100*	*0.304*	*0.135*
2014							-1.1	-2.145	-0.827	-0.636	-2.177	0.045
							0.677	*0.55*	*0.831*	*0.789*	*0.522*	*0.991*
2015							-4.307	8.165*	2.302	2.225	2.778	1.806
							0.168	*0.070*	*0.603*	*0.509*	*0.524*	*0.674*
2016							1.479	-4.965	4.37	-1.539	-10.788**	1.530
							0.714	0.386	0.444	*0.590*	*0.046*	*0.779*
Constant	-4.815	-0.729	-6.502	-52.140***	-60.199*	-45.857*	11.361***	11.408***	15.779***	-70.345***	-66.446*	-58.556*
	0.485	*0.846*	*0.329*	*0.000*	*0.086*	*0.055*	*0.000*	*0.000*	*0.000*	*0.000*	*0.057*	*0.014*
Adjusted R	7.59%	7.37%	6.81%	13.38%	4.55%	18.40%	1.96%	1.64%	1.08%	18.70%	11.72%	20.43%
F-test all coeff. = 0	6.94***	5.86***	6.98***	12.35***	3.68***	17.48***	17.10***	1.5	1.3	9.95***	3.99***	9.06***

*,** and *** denote significance at the 10%, 5% or 1% level, respectively

Appendix 2: Underwriter Ranking

Underwriter	Rank	Underwriter	Rank	Underwriter	Rank	Underwriter	Rank	Underwriter	Rank	Underwriter	Rank
Goldman Sachs & Co	9	China Renaissance (CRS)	7	Canaccord Genuity	6	Knight Capital Markets	5	Kirlin Securities	3	Blackmont Capital Inc	2
JP Morgan (JPM)	9	Cowen	7	BMO Capital Markets	6	Renaissance Securitities	5	Anderson & Strudwick	3	National Securitiries Corp	2
Morgan Stanley & Co	9	Evercore	7	KeyBanc Capital Markets	6	Tudor-Pickering	5	Joseph Stevens & Company	3	Dundee Securities Corporation	2
Morgan Stanley International	9	Guggenheim Securities	7	Moelis	6	Feltl & Co	4	Dominick & Dominick Inc	3	Bathgate Capital	2
BAML	8.5	ICBC-Int	7	Simmons & Co	6	Johnson Rice & Co	4	Legend Merchant Group	3	Gunnar	2
Credit Suisse	8.5	Itau	7	Ladenburg Thalman & Co	6	MDB-Capital	4	Sunrise Capital	3	Security Research Associates	2
Deutsche Bank Securities Corp	8.5	JMP-Sec	7	Leerink Swann & Co	6	Wunderlich Securities, Inc.	4	EKN Bank	3	West Park Capital	2
UBS Investment Bank	8.5	John Nuveen Co	7	Cantor Fitzgerald	6	Morgen Joseph & Co	4	Aegis Capital	3	Sunrise Securities	2
Allen & Co Inc	8	Keefe Bruyette & Woods Inc	7	BB&T Capital markets	6	Wedbush Securities	4	Barrett	3	Gilford Securities	1
Barclays Capital	8	Leerink Swann & Co.	7	Key Banc Capital Markets	6	Merriman Curham	4	Burnham Securities Inc	3	A. G. Becker Paribas Inc.	1
HSBC	8	Macquarie Bank	7	Global - Hunter	6	DA Davidson & Co	4	Chardan Capital Markets, LLC	3	A. J. Michaels & Co., Ltd.	0
Jefferies & Co Inc	8	Nuveen (see John Nuveen)	7	Unterberg Harris	6	Pacific Growth Equities	4	Maxim Group LLC	3	A. L. Havens Securities	0
KKR Capital	8	Oppenheimer & Co Inc	7	Friedman Billings Ramsey Group	5	First Albany Capital	4	Paulson Investment Co	3	A. M. Levine	0
Lazard	8	Pacific Crest Securities Inc	7	Roth Capital Partners Inc	5	Craig Hallum	4	Summer Street	3	A. T. Brod & Co.	0
RBC Capital Markets	8	Raymond James & Associates Inc	7	FBR Capital Markets Corp	5	Imperial Capital LLC	4	Earlybirdcapital Inc	2	A.R. Baron & Co., Inc.	0
Santander Investment Bank	8	RBS Securities (Royal Bk Scotland)	7	Ferris Baker Walts	5	Baird Patrick & Co	4	Pali Capital	2	A.S. Goldmen & Company	0
Wells Fargo	8	Societe Generale	7	ThinkEquity Partners	5	Griffin Financial	4	I-Banker Securities	2	AB Capital Markets	0
CIBC Oppenheimer	7.5	Stephens Inc	7	Needham & Co LLC	5	Mutual-Sec	4	C&Co/PrinceRidge LLC	2	ABD Securities	0
Piper Jaffray Inc	7.5	W.R. Hambrecht & Company	7	Janney Montgomery Scott Inc	5	Seidler Corp	4	Dawson James Securities	2	ABN AMRO Chicago Corp	0
Sandler O'Neill Partners	7.5	William Blair & Co	7	CL King & Assiciates Inc	5	capital Growht Financial LLC	3	Newbridge Securities	2	ABN AMRO Incorporated	0
Ameriprise-Fin	7	Cowen & Co	6.5	Stanford Group Company	5	Jesup & Lamont Securities	3	Cohen & Co	2	ABN AMRO Rothschild	0
Banco Itau-BBA	7	SunTrust Robinson Humphrey	6.5	Scott & Stringfellow Financial	5	GunnAllen Financial	3	MDB Capital Corp	2	ABN-AMRO Holding NV	0
China International Capital Co	7	Zelman	6.5	Sterne Aggee & Leach Inc	5	Joseph Gunnar & Co	3	TAGLICH BROTHERS INC	2	Access Securities	0

Appendix 3: Mean test

This table represent an overview of the different means tests run on the variables where the means within years are compared and tested on significant difference. Probabilities are represented in italic. Low p values indicate that H_0 can be rejected indicating the variables to differ significant from each other. The Wilcoxon is added because it cannot be assumed that all variables are normally distributed.

high versus non-tech		2010 - 2016	2010	2011	2012	2013	2014	2015	2016
Volume NASDAQ/S&P500	T-test (t-score)	26.267	39.929	38.808	41.012	36.234	33.032	35.448	39.636
	p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
	Wilcoxon test (Z-score)	13.761	13.761	13.761	13.707	13.761	13.761	13.761	13.402
	p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Volatility NASDAQ/S&P500	T-test (t-score)	8.944	2.835	2.301	7.016	7.351	9.348	3.232	5.541
	p-value	*0.000*	*0.005*	*0.022*	*0.000*	*0.000*	*0.000*	*0.001*	*0.000*
	Wilcoxon test (Z-score)	35.845	13.708	13.761	13.707	12.489	13.761	13.084	13.402
	p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Underpricing	T-test (t-score)	2.783	0.527	1.408	0.767	2.176	1.287	-0.208	1.889
	p-value	*0.006*	*0.020*	*0.163*	*0.445*	*0.031*	*0.200*	*0.836*	*0.064*
	Wilcoxon test (Z-score)	2.746	1.069	2.094	0.299	2.379	0.994	1.665	0.639
	p-value	*0.006*	*0.085*	*0.036*	*0.765*	*0.017*	*0.320*	*0.096*	*0.083*
Age	T-test (t-score)	5.613	0.481	1.397	2.353	4.380	2.587	0.946	2.150
	p-value	*0.000*	*0.631*	*0.166*	*0.021*	*0.000*	*0.010*	*0.346*	*0.036*
	Wilcoxon test (Z-score)	4.324	0.386	0.158	1.806	3.917	1.196	0.402	1.871
	p-value	*0.000*	*0.699*	*0.874*	*0.071*	*0.000*	*0.232*	*0.688*	*0.061*
Deal Value	T-test (t-score)	2.469	1.368	1.995	0.669	3.680	5.351	3.066	2.964
	p-value	*0.014*	*0.178*	*0.022*	*0.507*	*0.000*	*0.000*	*0.004*	*0.007*
	Wilcoxon test (Z-score)	7.680	1.556	2.692	3.573	5.343	-5.685	3.293	2.808
	p-value	*0.000*	*0.120*	*0.007*	*0.000*	*0.000*	*0.000*	*0.001*	*0.005*
Offer Price	T-test (t-score)	6.899	1.104	4.127	0.589	3.385	3.927	2.390	0.769
	p-value	*0.000*	*0.275*	*0.000*	*0.559*	*0.001*	*0.000*	*0.022*	*0.450*
	Wilcoxon test (Z-score)	7.489	1.065	3.875	1.458	3.494	4.278	2.290	-0.807
	p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Bookrunners	T-test (t-score)	9.431	0.178	1.086	1.903	5.115	7.292	5.482	3.989
	p-value	*0.000*	*0.860*	*0.284*	*0.064*	*0.000*	*0.000*	*0.000*	*0.001*
	Wilcoxon test (Z-score)	8.867	0.098	1.389	2.162	4.969	5.879	4.431	3.116
	p-value	*0.000*	*0.922*	*0.165*	*0.031*	*0.000*	*0.000*	*0.000*	*0.002*
Ranking	T-test (t-score)	2.074	0.579	0.273	1.309	1.142	2.186	0.653	1.596
	p-value	*0.039*	*0.122*	*0.787*	*0.198*	*0.258*	*0.037*	*0.518*	*0.125*
	Wilcoxon test (Z-score)	2.952	1.877	0.273	1.283	1.923	2.577	1.289	1.878
	p-value	*0.000*	*0.120*	*0.007*	*0.000*	*0.000*	*0.000*	*0.001*	*0.005*
Net Income	T-test (t-score)	2.897	1.949	2.921	1.470	2.024	0.146	2.198	1.824
	p-value	*0.004*	*0.057*	*0.006*	*0.149*	*0.046*	*0.884*	*0.034*	*0.082*
	Wilcoxon test (Z-score)	9.033	1.757	3.194	3.731	4.333	4.365	3.479	2.585
	p-value	*0.000*	*0.090*	*0.007*	*0.000*	*0.000*	*0.000*	*0.001*	*0.005*

Appendix 4: Difference-in-differences

Analysis on 2016 versus 2010, 2013 and 2015 where non-technology companies are the control group versus the high-tech companies which is the test sample relevant for this research. Standard error represented in parentheses. For the test between the differences significant is tested and represented with the stars. Column (9) indicated the relative change between tech and non-tech companies.

	High-tech		Non-tech		Differences		Difference-in-differences
	2015	2016	2015	2016	[(2) - (1)]	[(5) - (4)]	[(7) - (8)]
Variable	(1)	(2)	(4)	(5)	(7)	(8)	(9)
Underpricing (%)	18.1	20.8	19.6	6.0	2.1**	-13.6***	15.7**
	(3.98)	(4.98)	(2.78)	(3.31)	(4.03)	(3.11)	(4.76)
Age	13.0	19.9	15.4	26.0	6.9	10.6	-3.7
	(2.57)	(2.98)	(7.35)	(7.66)	(7.66)	(9.05)	(10.01)
Deal Value ($m)	138.3	100.0	323.6	300.2	-38.3***	-23.4***	-14.9*
	(16.78)	(17.55)	(38.13)	(38.65)	(39.74)	(42.58)	(44.38)
Offer Price ($)	13.9	13.9	17.2	15.8	0.0	-1.4	1.4
	(0.55)	(0.74)	(0.79)	(1.14)	(0.01)	(1.59)	(2.98)
Bookrunners	2.6	2.9	4.9	4.9	0.3*	0.0**	0.3
	(0.10)	(0.24)	(0.63)	(0.54)	(0.74)	(1.10)	(1.79)
Ranking	8.2	8.5	8.9	8.6	0.3	-0.3	0.6
	(0.13)	(0.26)	(0.17)	(0.19)	(0.09)	(0.23)	(0.24)
Net Income ($m)	-15.7	-14.7	58.9	79.2	1.0	20.3	-19.3
	(8.23)	(8.18)	(41.02)	(55.46)	(45.03)	(55.88)	(57.98)
Volume (m)	462.9	449.0	600.3	603.2	-13.9***	2.9***	-16.8***
	(7.03)	(6.68)	(4.31)	(5.32)	(5.98)	(5.79)	(5.97)
Volatility (%)	14.4	15.5	12.9	11.4	1.1***	-1.5***	2.6***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.03)	(0.05)
N (observations)	85	41	41	23			

*,** and *** denote significance between the differences at the 10%, 5% or 1% level, respectively

	High-tech		Non-tech		Differences		Difference-in-differences
	2013	2016	2013	2016	[(2) - (1)]	[(5) - (4)]	[(7) - (8)]
Variable	(1)	(2)	(4)	(5)	(7)	(8)	(9)
Underpricing (%)	24.2	20.8	14.1	6.0	3.4	8.1***	-4.7*
	(4.73)	(4.98)	(2.78)	(3.31)	(4.03)	(3.11)	(3.13)
Age	14.2	19.9	31.3	26.0	5.7*	-5.3**	11.0*
	(2.88)	(2.98)	(6.98)	(7.66)	(7.01)	(8.01)	(8.41)
Deal Value ($m)	181.7	100.0	348.0	300.2	-81.7***	-47.8**	33.97**
	(14.33)	(17.55)	(22.13)	(38.65)	(23.14)	(41.98)	(42.01)
Offer Price ($)	14.6	13.9	17.7	15.8	-0.7	-1.9	1.2
	(0.71)	(0.74)	(0.77)	(1.14)	(0.91)	(1.39)	(2.03)
Bookrunners	2.7	2.9	4.2	4.9	0.2***	0.7***	-0.5***
	(0.12)	(0.24)	(0.13)	(0.54)	(0.23)	(0.66)	(0.87)
Ranking	8.4	8.5	8.7	8.6	0.1	-0.1	0.2***
	(0.13)	(0.26)	(0.13)	(0.19)	(0.38)	(0.21)	(0.27)
Net Income ($m)	18.8	-14.7	68.5	79.2	-33.5	10.7	44.2
	(5.01)	(8.18)	(51.13)	(55.46)	(45.03)	(55.88)	(54.77)
Volume (m)	416.7	449.0	527.4	603.2	32.3***	75.8***	-43.5***
	(5.47)	(6.68)	(4.88)	(5.32)	(4.98)	(6.01)	(7.96)
Volatility (%)	12.5	15.5	11.2	11.4	3.0***	0.2***	2.8***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.03)	(0.05)
N (observations)	83	41	80	23			

*,** and *** denote significance between the differences at the 10%, 5% or 1% level, respectively

Appendix 5: Fixed Effect Estimation

Full Sample:

Dependent Variable: PE Ratio	(1)	(2)	(3)	(4)
2016	4.92	4.82	4.79	3.98
2015	4.49	5.01	4.79	4.01
2014	3.11	3.69	3.09	3.13
2013	0.17	0.19	0.21	0.15
2012	1.92	1.98	2.03	1.77
2011	0.89	0.93	0.89	0.71
2010	0.93	0.99	0.89	0.94

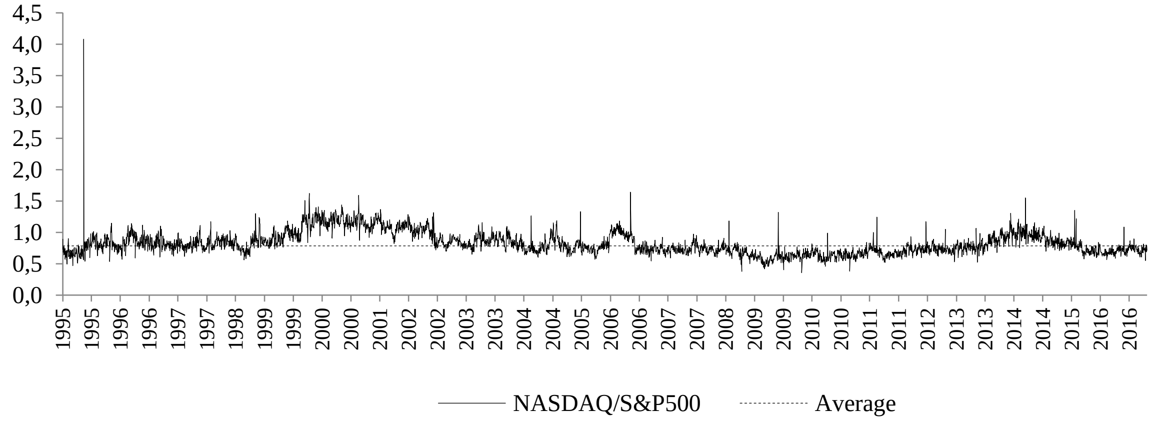
Appendix 6: T-test

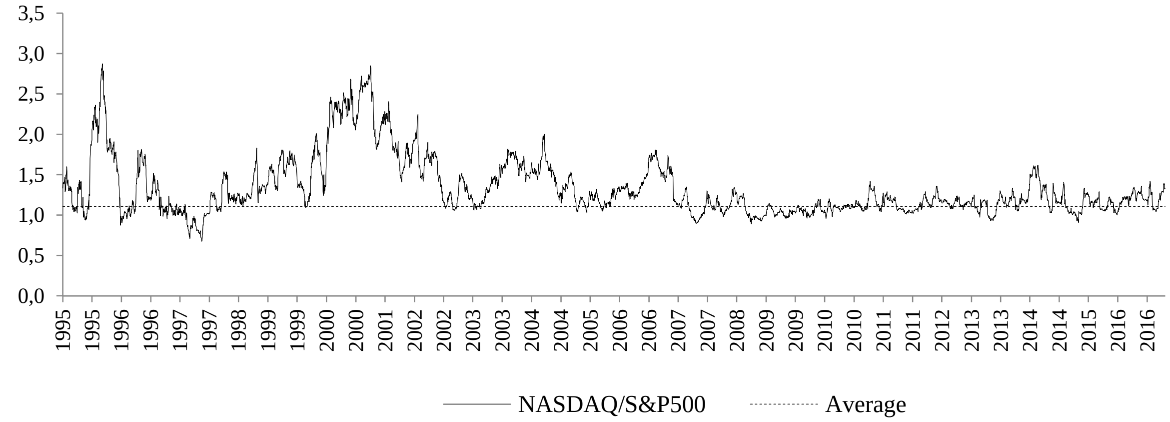
		2016 vs 2010		2015 vs 2010	
Variables		high-tech	non tech	high-tech	non tech
Volume NASDAQ/S&P500	T-test (t-score)	2.373	-	9.150	-
	p-value	*0.009*	-	*0.000*	-
	Wilcoxon test (Z-score)	2.403	-	8.386	-
	p-value	*0.016*	-	*0.000*	-
Volatility NASDAQ/S&P500	T-test (t-score)	17.253	-	3.123	-
	p-value	*0.000*	-	*0.002*	-
	Wilcoxon test (Z-score)	11.528	-	2.770	-
	p-value	*0.000*	-	*0.006*	-
Underpricing	T-test (t-score)	2.232	0.153	0.380	2.180
	p-value	*0.088*	*0.880*	*0.706*	*0.035*
	Wilcoxon test (Z-score)	1.821	0.182	0.042	2.093
	p-value	*0.098*	*0.855*	*0.966*	*0.036*
Age	T-test (t-score)	0.580	1.558	2.031	0.711
	p-value	*0.565*	*0.134*	*0.048*	*0.481*
	Wilcoxon test (Z-score)	1.102	1.475	1.011	0.991
	p-value	*0.271*	*0.140*	*0.312*	*0.322*
Gross Proceeds	T-test (t-score)	1.505	2.719	0.525	2.720
	p-value	*0.140*	*0.013*	*0.602*	*0.010*
	Wilcoxon test (Z-score)	2.715	2.549	0.254	2.231
	p-value	*0.007*	*0.011*	*0.800*	*0.026*
Offer Price	T-test (t-score)	2.099	2.643	1.711	2.940
	p-value	*0.042*	*0.015*	*0.094*	*0.005*
	Wilcoxon test (Z-score)	1.953	2.405	1.827	2.840
	p-value	*0.051*	*0.016*	*0.068*	*0.005*
Bookrunners	T-test (t-score)	1.796	4.919	0.854	6.072
	p-value	*0.080*	*0.000*	*0.398*	*0.000*
	Wilcoxon test (Z-score)	1.384	3.669	0.612	4.739
	p-value	*0.166*	*0.000*	*0.540*	*0.000*
Ranking	T-test (t-score)	2.146	1.535	2.064	0.431
	p-value	*0.040*	*0.140*	*0.045*	*0.669*
	Wilcoxon test (Z-score)	2.535	1.629	1.914	1.370
	p-value	*0.011*	*0.103*	*0.056*	*0.171*
Net Income	T-test (t-score)	0.620	0.613	0.002	1.112
	p-value	*0.539*	*0.546*	*0.999*	*0.273*
	Wilcoxon test (Z-score)	1.380	0.000	1.545	0.823
	p-value	*0.088*	*1.000*	*0.122*	*0.411*

Appendix 7: Matching procedure

Variable		Mean		%Reduct		t-test	
		Treated	Control	Bias (%)	bias	t	p>t
CAR01	Unmatched	0.18	0.12	22.4		3.09	0.002*
	Matched	0.18	0.02	56.3	-151.4	7.85	0.15
AGE	Unmatched	15.7	25.2	-39.5		-5.7	0.000*
	Matched	15.7	15.2	1.9	95.2	0.4	0.687
DealValueUSD	Unmatched	1.8	3.1	-21.3		-2.87	0.004*
	Matched	1.8	1.1	11.3	46.7	1.85	0.065
OfferPrice	Unmatched	13.7	16.5	-51.2		-7.18	0.150
	Matched	13.7	15.1	-25.5	50.1	-5.07	0.230
Bookrunners	Unmatched	2.7	3.9	-69.1		-9.92	0.000*
	Matched	2.7	2.4	13.0	81.1	2.88	0.150
Netincomeaftertax	Unmatched	-3.0	46.7	-23.3		-3.43	0.001*
	Matched	-3.4	0.4	-1.3	94.6	-0.51	0.613
Volatility30day	Unmatched	0.15	0.13	47.2		6.57	0.068*
	Matched	0.15	0.11	92.5	-96.1	17.3	0.237
Volume30DaysAverage	Unmatched	478.9	625.4	-123.6		-18.14	0.000*
	Matched	478.9	467.2	9.9	92.0	3.48	0.001*

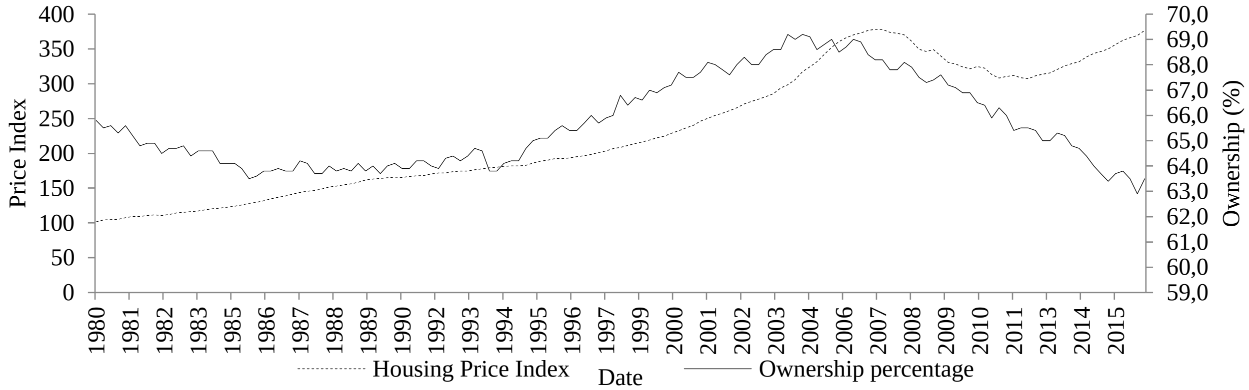
Appendix 8: Volume (1) and volatility (2) ratios on the NASDAQ/S&P500





Appendix 9: Housing Market

The figure shows the housing market price index of the US and the ownership percentage.



Appendix 10: Share Buybacks and Dividend