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UNICORNS: THE NEXT BUBBLE?

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Abstract

The current stock market, that is experiencing all-time low interest rates, provides a great environment for a potential asset price bubble to develop. As a consequence, venture capital-backed start-up companies reach billion dollar valuation in a short period of time. The development of these unicorn companies shows great resemblance to the events that led to the dot-com bubble of the late 1990s. This research attempts to fill the gap in the empirical literature, by assessing the extent to which unicorns exhibit similar characteristics to historical asset price bubbles, like the dot-com bubble. A multivariate regression model and propensity score matching method indicate that unicorns experience a higher degree of underpricing than non-unicorns at their initial public offering with up to 23 percent larger returns. Right-tailed forward recursive augmented Dickey-Fuller tests detect explosive price behavior in stocks of unicorns and this explosiveness appears to be positively related to trading volume and price volatility. The unicorn events show great analogy to the dot-com bubble of the late 1990s, which strengthens the presumption that an asset price bubble is emerging in the current stock market.

Keywords: Asset price bubble, Unicorns, Venture capital, Underpricing, Explosive price behavior

JEL Classification: G01, G12, G24, G32, G41

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How do we know when irrational exuberance has unduly escalated asset values, which then become subject to unexpected and prolonged contractions? – Alan Greenspan, December 1996.

1 Introduction

Throughout its history, the economy has suffered multiple asset price bubbles. A bubble can be described as a rapid asset price increase in the short-term, followed by a sudden contraction. During the run-up of a bubble, asset prices exceed their fundamental value to such an extent that it does not justify views about the future. The earliest asset price bubble, known as Tulip mania, comprises the events of speculation on Dutch tulip bulbs futures in the seventeenth century (Mackay, 1841). In February 1637, at the peak of the bubble, contracts resembled a value of tenfold the annual income of a skilled craftsmen (Thompson, 2007). The most famous bulb, the Semper August, traded at a price of 5,500 guilders, which represents a value of $50,000 in gold. Eventually, many buyers were expected to default and the proposition of a conversion from futures to call options caused a contraction in prices. The bursting of the bubble resulted in value losses of more than 99 percent for several bulb types (Garber, 1989).

The first events of speculation on stocks involved the conversion of French government debt into shares of the Mississippi Company. Shares initially resembled a value of 500 livres, but prices quickly rose to a value of 10,000 livres at the peak in October 1719. John Law, initiator of the plan, decided that the shares were overvalued and proposed a devaluation, which led to the collapse of the bubble. By September 1721, share prices returned to the initial price level of 500 livres, losing 95 percent of its peak value within two years (Garber, 1990). A contemporary situation occurred in Great Britain, where the share price of the South Sea Company rapidly increased from £120 to the peak value of £950 in June 1720. Subsequently, the Bubble Act was passed and banned the formation of similar corporations as the South Sea Company. This increased demand for South Sea Stock and eventually led to the bursting of the bubble. As a result, prices reverted to their par value of £100, losing 90 percent of its peak value (Temin & Voth, 2004).

More recent examples constitute the dot-com bubble of the late 1990s and the United States housing bubble of 2008. During the dot-com bubble, technology stocks were severely overvalued as measured by traditional valuation standards. When the bubble burst in 2000, the NASDAQ Composite Index experienced a drop of 78 percent, which resulted in a global financial crisis (Kiplinger, 2015). Nowadays, similar events are occurring in the current stock market as many venture capital-backed private start-ups, while mostly unprofitable, have grown to the highest valued corporations of the world in a very short time. The term *unicorn*, a start-up company that is worth at least $1 billion, resembles this exuberant growth because 'unicorns' are extremely rare and magical (Lee, 2013).

The sky-high valuations of these unicorns are analogous to the events that led to the dot-com bubble. Unicorns that went public exhibit high first-day returns, but show long-run underperformance. For example, Uber and Lyft respectively trade 35 and 50 percent under their offer price. Another striking example is WeWork, that saw her initial public offering revoked in September 2019 (Trainer, 2019). This indicates a turning point in the public market as investors start to notice that most unicorns are overvalued. The bubble therefore seems to converge to its peak (The Economist, 2020).

Timing an asset price bubble (let alone identifying one) is a hard practice. As Isaac Newton, who lost £20.000 in the South Sea Company bubble, famously claimed: "*I can calculate the motions of the heavenly bodies, but not the madness of the people*." (Kindleberger, 1978). Stanley Druckenmiller, manager of a 8.2 billion fund during the dot-com era, held his technology stocks too long, even though he was aware of the overvaluation. He intended to 'ride the bubble', but it burst too soon: "*We thought it was the eighth inning, and it was the ninth*." (Norris, 2000).

The bursting of a bubble can result in a major financial crisis affecting not only investors in long positions, but also the society as a whole. Because the market experienced several significant changes since the late 1990s, it is important to assess the extent to which the current market exhibits the characteristics of historical asset price bubbles. The unicorn phenomenon is relatively new and therefore empirical research on this topic is scarce. This research aims to fill this gap in the literature by measuring bubble characteristics for unicorns and compare them to the events that led to the dot-com bubble. The research question therefore states:

"*To what extent do unicorns exhibit the characteristics of an asset price bubble like the dot-com bubble?*"

The most important characteristics that are measurable are underpricing and explosive price behavior. The estimation of a multivariate regression model and propensity score matching method show that unicorns yield a higher first day-return than non-unicorns of up to 23 percent at their initial public offering. Explosive price behavior is detected by right-tailed recursive ADF-tests and a logistic regression model is estimated to examine the effects of trading volume and price volatility on explosiveness. It follows that stocks of unicorns exhibit explosive price behavior and that explosiveness is positively driven by trading volume and price volatility.

The remaining part of the text is structured as follows. Section 2 presents the literature overview on asset price bubbles, the dot-com bubble, unicorns, and develops the hypotheses. Section 3 explains the data and sample construction. Section 4 discusses the methodology and section 5 reports the corresponding results. Section 6 concludes, discusses the limitations, and provides recommendations for further research.

2 Literature overview

This section presents a framework of the relevant asset price bubble literature. The first subsection focusses on the definition of bubbles and their characteristics, which provides guidance for the identification of potential bubbles. Subsequently, an elaboration on the dot-com bubble and the unicorn phenomenon follows. The last subsection formulates the hypotheses that are constructed to answer the research question.

2.1 Definition of a bubble

There exists a lot of debate concerning the definition of asset price bubbles and their existence[1]. Stiglitz (1990) and Fox (2014) provide a great overview of the divergent views on bubbles. A bubble can be defined as "*loosely a sharp rise in the price of an asset in a continuous process, which is followed by a reversal of expectations and a sharp decline in prices, often resulting in a financial crisis*" (Kindleberger, 1991). A more common interpretation is given by Fox (2014): "*Bubbles arise if the price far exceeds the asset's fundamental value, to the point that no plausible future income scenario can justify the price*".

The efficient market hypothesis states that stock prices fully reflect all available information (Fama, 1970). This implies that any form of mispricing by irrational market participants would be resolved by rational arbitrageurs. Therefore, stock prices should reflect their fundamental value. In this point of view, high returns could be justified by a high degree of uncertainty.

However, two problems arise in determining the fundamental value of an asset: estimation of future cashflows and establishing the appropriate discount rate. Market efficiency is weakened in case the fundamentals do not justify the asset's price. Some apparent examples of mispricing in the stock market cannot be explained by market efficiency, which caused critics to argue that prices could not have been plausibly set by rational investors (Malkiel, 2003). Hence, many economists emphasized the role of irrational behavior[2]. This led to the sunspot theory, which refers to variables that have an impact on the economy, but do not reflect fundamentals of the economy. Psychological factors as investor behavior can therefore be classified as sunspots.

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[1] Garber (1990) states that speculative events can only be defined as a bubble when all reasonable economic explanations have been exhausted. Historical speculative events, like Tulip mania and the Mississippi / South Sea Company bubble, contained prices that were consistent with market fundamentals from the viewpoint of contemporary investors. Accordingly, from this perspective these events cannot be categorized as bubbles.

[2] There also exists a wide literature concerning rational asset price bubbles (Blanchard & Watson, 1982).

Shleifer (2000) states that human behavior can influence asset prices if irrational investors are present and there are limits to arbitrage such that rational investors cannot correct the mispricing. Asset prices may thus exceed their fundamental value in case investors have heterogeneous beliefs and short selling restrictions exist. Scheinkman and Xiong (2003) contemplate overconfidence as a potential cause of heterogeneous beliefs. Investors are too confident if they believe that their obtained information is more reliable than it is in reality. In that case, asset prices might deviate from their fundamental value, because short-sale constraints cause prices to reflect the most promising beliefs.

Moreover, asset price bubbles may even persist when rational arbitrageurs are present and no short-selling constraints exist (Abreu & Brunnermeier, 2003). Investors become sequentially aware of the mispricing and thus trading strategies are commenced at different points in time. The inability of investors to coordinate short-selling strategies prevents the correction of the mispricing. Hence, in the intermediate term, significant deviations from fundamental values may persist, which undermines market efficiency.

Bubbles seemingly follow a pattern, in which different phases can be distinguished (Kindleberger, 1978; Minsky, 1986). The run-up of a bubble is initiated through a shift in paradigm that promises to 'change the world'. Existing firms are displaced by new promising corporations and stock prices start to rise at an increasing rate. Widespread media coverage in combination with the fear of missing out among investors induces more speculation. More investors enter the market and provide a large influx of capital. At this point, the bubble is starting to gain momentum and asset prices expand rapidly (Greenwood, Shleifer & You, 2019).

The market then enters a state of exuberance, wherein stocks reach sky-high valuations. Traditional valuation measures are neglected and investors deny what they are doing. This state of 'euphoria' is characterized by positive feedback on prices and investors that are willing to acquire the asset at any cost, which essentially leads to a self-fulfilling prophecy (Malkiel, 2003). This relates to the reflexivity theory, which states that the perceptions of investors influence the stock market fundamentals, which in their turn alter the perceptions of the investors (Soros, 2013). Although some investors recognize the existence of the bubble and believe it will eventually burst, they still choose to ride the bubble because the 'greater fool' always has a higher willingness to pay.

However, prices do not reflect their fundamental value anymore and smart money starts to close their positions. Changes in systemic risk, the bubble's probability of bursting, produces volatile price movements. In case the perceived systemic risk increases, prices will fall (Wang & Wen, 2012). Timing the bubble is very difficult and as more investors start to incur profits, prices start to fall more rapidly. Investors become caught up in emotion and disbelief creates panic in the stock market. Eventually, the bubble bursts and prices plummet.

Classic bubbles, like Tulip mania, the Mississippi / South Sea Company bubble, and the dot-com bubble all have shown similar characteristics. First of all, trading volume and price volatility reach elevated levels during bubbles phases (Scheinkman & Xiong, 2003). During the run-up of the bubble, volatility is higher and markets produce high returns, which attracts more investors. As a result, asset prices skyrocket and exhibit explosive growth rates.

Furthermore, valuation measures, such as the price-to-earnings (P/E) ratio, exhibit high numbers relative to their historical levels. P/E ratios are calculated by dividing the price of a stock by the earnings of the last twelve months. High P/E ratios convey that investors have a higher willingness to pay for each dollar of earnings. Shiller's cyclically adjusted price-to-earnings (CAPE) ratio provides a more robust measure as it uses the average earnings over a 10-year period instead of a 1-year period to smoothen out business cycle fluctuations. CAPE ratios measure whether a stock is overvalued. A high CAPE ratio could therefore indicate that prices deviate from their fundamental values, and can serve as a good identifier for bubbles (Campbell & Shiller, 1998). However, in the current market share repurchases are more common than dividends, which influences the growth rate of earnings. This change in corporate payout policy may thus be a cause for bias. To reduce this bias, the Total Return CAPE (TR CAPE) ratio is created, by reinvesting dividends in the price index (Jivraj & Shiller, 2017). Additionally, during preceding bubble episodes, interest rates were at a historically low level. Low interest rates increase the level of borrowing. This cash is partly invested and the resulting capital influx increases asset prices.

Moreover, Greenwood, Shleifer, and You (2019) state that companies take advantage of windows of opportunities during the events of mispricing through an initial public offerings (IPOs). At the IPO, a private company offers stock to the general market for the first time. After the issue, the stock is publicly traded and listed on an stock exchange. Firms perform an IPO to acquire more capital and to provide an exit for the existing shareholders that incur their profits. When the firm goes public, the first day of trading represents the beliefs of the investors (Ofek & Richardson, 2003).

However, IPOs tend to exhibit high first-day returns and suggest that new stock issues are underpriced. Usually, IPOs are clustered in periods with high and low first-day returns, the so-called hot and cold issue periods (Ibbotson & Jaffe, 1975). Overvalued firms will therefore try to take advantage of these high-return periods. Loughran and Ritter (1995) state that many IPOs show long-run underperformance. The underpricing phenomenon could therefore indicate a potential asset price bubble.

There are several explanations for the underpricing phenomenon. One explanation is the winner's curse (Rock, 1986). Investors possess heterogeneous information about the value of the issue. Uninformed investors will subscribe to every issue, while the informed investors will only subscribe to the profitable issues. This automatically generates a winner's curse for the investors that lacked information. Therefore, the offer price must be discounted in order to attract uninformed investors as well. Shiller (1990) formulates the finding that underwriters underprice IPOs to attract attention as the impresario hypothesis.

Ritter (1991) states that underpricing typically occurs in a market where investors are too optimistic about the prospects of the earnings growth of young companies. This can be linked to the grandstanding hypothesis: underpricing is a result of a higher degree of risk exposure that young firms experience when they go public in an early stage of their life (Gompers, 1996). Because venture capital (VC) usually is invested in early-stage companies, VC-backed IPOs exhibit a higher degree of underpricing than non-VC IPOs (Lee & Wahal, 2004). Alternatively, underpricing can be the consequence of irrational behavior from investors that overreact to the IPO (Ofek & Richardson, 2003).

To summarize, bubbles are characterized by a large influx of capital, which lead to exploding stock prices with high trading volume and price volatility. Furthermore, valuation measures are significantly large relative to their historical levels and interest rates are historically low. Finally, IPOs show significant underpricing.

2.2 Dot-com bubble

The events that led to the dot-com bubble elapsed analogous to the aforementioned process described by Kindleberger (1978). The enormous growth of the internet during the 1990s and the corresponding emergence of many internet based companies caused the 'internet fever'. Although companies were unprofitable, the internet served great potential and promised to 'change the world'. Fundamentals, such as cash flows, were neglected and this led to irrational exuberance (Shiller, 2000).

August 14, 1995, is usually viewed as the start of the bubble when the Netscape IPO produced first-day returns that exceeded 100 percent of the offer price (Tuckett & Taffler, 2005). Between the period of 1995 to 1998 there were many internet IPOs which caused the NASDAQ Composite Index, the most renowned technology stock index, to increase rapidly. The index peaked at 5,048.62 points on March 10, 2000, coming from 1,114 points in August 1996 (Pástor & Veronesi, 2006). Valuation metrics, such as the TR CAPE ratio, reported high levels compared to the past.

In February 2000, the internet sector possessed 6 percent of the market capitalization of all U.S. listed public companies, while pertaining 20 percent of the public trading volume and producing a two-year return of 1000 percent (Ofek & Richardson, 2003). Phillips, Wu, and Yu (2011) find evidence that the NASDAQ Composite Index exhibited explosive price behavior during the dot-com bubble.

The bull run generated a hot issue period. As a result, many companies tried to take advantage of this period with high first-day returns and the number of IPOs increased drastically. Loughran and Ritter (2004) document a rise in first-day returns from 15 percent in 1990-1998 to 65 percent during the dot-com bubble years 1999-2000. A possible explanation could be provided by the changing issuer objective function hypothesis. During the dot-com bubble, issuers changed their willingness regarding leaving money on the table. Another explanation is the realignment of incentives hypothesis of Ljungqvist & Wilhelm (2003), which states that owners put in less bargaining effort due to higher fragmented ownership.

Several examples reflect the exorbitant mispricing in the late 1990s. First of all, the merest association with the internet would inflate valuations to sky-high levels. Adding a '.com' suffix would produce cumulative abnormal returns of 74 percent over a window of ten trading days surrounding the date of announcement and would increase trading activity significantly (Cooper, Dimitrov, & Rau, 2001).

Another example constitutes Priceline, an online travel company, that earned first-day returns of 330 percent on their IPO. A few weeks later, the company had a valuation that was higher than the combined valuation of the entire United States airline industry. After the bubble burst, the entire market capitalization would not even have covered the cost of two Boeing 747s (Cassidy, 2002). Theglobe.com would set the record of highest first-day returns when the stock price closed at a 606 percent return (Hamilton, 1998).

Finally, one of the most prominent examples of mispricing during the late 1990s are the equity carve-outs that were followed by spin-offs. 3Com, owner of subsidiary Palm, announced that it would sell 5 percent of the Palm shares through an IPO and that the remaining shares would spin-off later that year (each owner of a 3Com share would receive 1.5 Palm shares). The first day close price of Palm was $95.06, while the share price of 3Com totaled $81.81. 3Com's stub value, the value of 3Com minus the assets of Palm, equaled minus $63 per share after the first day of trading. This is a striking example of a violation of the law of one price, as a 3Com share should at least exceed the share price of Palm by a factor of 1.5 (Lamonth & Thaler, 2003).

Two reasons are usually connected to the explanation of the extraordinary high stock prices of internet companies during the dot-com bubble. First of all, investors were subject to short-sale constraints. Ofek & Richardson (2003) show that optimistic investors tend to cause a dramatic rise in stock prices and that pessimistic investors cannot correct the mispricing due to short-sale constraints. Then, as more and more optimistic investors enter the market, too much new capital flows to technology stocks and prices exceed fundamental values. Alternatively, even if short-sale constraints were not present, rational investors would require large sums of capital to compete with the optimistic investors.

Secondly, heterogeneous beliefs and the high demand for technology stocks gave a convenience yield, which means that holding the asset would provide benefits. This argument would explain the price development, the high trading volume, the long-run underperformance after the IPO, and especially the short-sale frictions during the dot-com bubble as investors were not willing to lend out their stocks (Cochrane, 2002).

Pástor and Veronesi (2006) find that the high degree of uncertainty and the downward revision of NASDAQ's expected profitability caused prices to fall. The high uncertainty was partially taken away by the reputation of the underwriters and lock-up agreements. Usually prestigious underwriters avoided high-risk issuers, but this changed in the late 1990s when many internet IPOs were underwritten by prestigious underwriters (Schultz & Zaman, 2001). Additionally, the 180-days lock-up agreements would prevent the owners from selling the shares on the first days of trading (Ofek & Richardson, 2003). During this time frame, investors were unaware of the mispricing. However, the owners knew that the stocks were overvalued and they sold their shares when the lock-up period expired. Institutional investors rode the bubble and captured technology stocks in the upturn, but reduced positions in the down-turn as soon as they noticed the sell-off (Brunnermeier & Nagel, 2004). Prices fell as more investors started to incur profits. Eventually, the bubble burst and the NASDAQ closed at 1,114 points on October 9, 2002, experiencing a drop of 78% from its peak value (Kiplinger, 2015).

2.3 Unicorns

Several legal revisions have been made since the late 1990s to prevent the development of similar bubbles from happening in the future. The Sarbanes-Oxley Act, that was passed in 2002, requires public companies to declare that their financial statements comply with the Act. As a result, less IPOs were performed after the dot-com era (Zimmerman, 2016).

However, the upsurge in technology and social media after the 2000s resulted in the emergence of many start-up companies (Kerai, 2017). Many venture capital funds invest in these early-stage start-up companies in exchange for equity. The Jumpstart Our Business Startups Act, that was passed in 2012, is developed to ease the IPO process for private companies. The Act enlarged the maximum amount of investors that were allowed to remain the private status from 500 to 2000 (Kenney & Zisman, 2019). VCs were able to raise an adequate amount of capital through what essentially are private IPOs (PIPOs), which postpone IPO events (Brown & Wiles, 2015). As a result, start-ups remained private for a longer period of time and were able to attain their unicorn status without bearing the burden of public companies (Fan, 2016).

At the start in 2013, the ‘Unicorn Club’ consisted out of 39 companies, which were predominantly based in the technology sector and grew rapidly through network effects (Lee, 2013). However, the Unicorn Club is not so magical and rare anymore as it contains 434 companies as of January 1, 2020, and is rapidly expanding (CB Insights, 2020). Many private companies desire the unicorn status and are trying to obtain a valuation of just above $1 billion. Most unicorns are based in the San Francisco Bay Area, which fuels the hype surrounding these start-ups. Fear of missing out prevailed among VCs and a large capital influx caused the amount of decacorns (valuation of at least $5 billion) and super-unicorns (valuation of at least $100 billion) to increase at a fast pace (Lee, 2015).

If the initial investors want to capture their profits, the unicorn must go public or the firm must be sold to another company. However, there is a large dispersion in pre-IPO and post-IPO valuations (Cogman & Lau, 2016). This phenomenon is referred to as the tech bubble puzzle. A potential explanation is that unicorns only go public if the PIPOs would not supply the desired amount of capital, and therefore signal that the unicorns are overvalued (Brown & Wiles, 2015). There exists a lot of valuation uncertainty and many of the unicorns are not yet profitable.

The events surrounding unicorns shows reminiscence to the late 1990s and unicorns may thus be the cause of a new asset price bubble. Despite the increase of VC funding, the number of IPOs has declined over the recent years (Kenney & Zisman, 2019). Unicorns create more value by staying private, which also preceded the dot-com bubble and The Great Recession (Clabaugh & Peters, 2019). In contrary, the ones that perform an IPO experience high first-day returns, with long-run underperformance.

Finally, unicorns that remain private experience down rounds – new private funding rounds which value the company at a lower level than previous rounds (Erdogan et al., 2016). As a consequence, many private unicorns will want to push for their IPO while they can still take advantage of the high first-day returns.

2.4 Hypotheses development

In this section, the hypotheses will be formulated and linked to the relevant literature. Although the formal definition of an asset price bubble is straightforward, the operational definition is hard to interpret as identification of a bubble can only be confirmed afterwards: "*one must wait a sufficient period of time to see how the future plays out before anyone can identify a bubble. It is virtually impossible to know immediately after a price falls whether there was a bubble or not*" (Siegel, 2003). On the other hand, Greenwood, Shleifer, and You (2019) state that historical bubbles exhibit identical characteristics. Thus, to assess whether the unicorn events can be addressed as a bubble, one must determine to what extent the events exhibit similar characteristic as other bubbles, like the dot-com bubble[3].

First of all, the underpricing phenomenon is present during the run-up of many bubbles. During the peak years of the dot-com bubble, the average company experienced first-day returns of 65 percent (Loughran and Ritter, 2004). Furthermore, the grandstanding hypothesis states that underpricing is a result of a higher degree of risk exposure that young firms experience when they go public in an early stage of their life (Gompers, 1996). Moreover, VC-backed IPOs yield higher first-day returns than non-VC IPOs (Lee & Wahal, 2004). Unicorns are venture capital-backed start-up companies, mostly active in the technology sector, that face a lot of valuation uncertainty. According to previous research, unicorns are therefore more susceptible to underpricing than non-unicorns. To this end, the following hypothesis is formulated:

Hypothesis 1: "Unicorns experience the underpricing phenomenon at their initial public offering to a significantly higher degree than non-unicorns."

[3] Some economists, such as Garber (1990), question the existence of asset price bubbles as all reasonable economic explanations should have been exhausted before a speculative event can be identified as a bubble. Although these hypotheses do not identify the unicorn events as an asset price bubble with 100 percent certainty, they strengthen the presumption of a potential bubble.

Secondly, trading volume and price volatility reach higher levels during the run-up phase of many bubbles (Scheinkman & Xiong, 2003). During the late 1990s, trading volume of internet companies rose to 20 percent while they only possessed 6 percent of the market capitalization (Ofek & Richardson, 2003). The fear of missing out among investors provides a huge capital influx, which elevates trading volume. High price volatility ensures that markets are able to produce large returns. Phillips, Wu, and Yu (2011) find evidence that during the dot-com bubble, the NASDAQ Composite Index exhibited explosive price behavior. Previous research suggests that increased trading volume and price volatility of unicorns are likely to yield large returns, even to the level of explosivity. To this end, the second hypothesis is formulated:

Hypothesis 2: "Unicorn stocks exhibit explosive price behavior and this explosiveness is positively driven by trading volume and price volatility."

Greenwood, Shleifer, and You (2019) claim that: "*The paradigm shift is to some extent measurable in financial data. And because one can measure it, one can also identify, imperfectly, asset price bubbles in advance*". The two hypotheses are the main indicators of individual asset price bubbles. The first hypothesis assesses the bubble characteristics when the unicorns go public and the second hypothesis evaluates the post-issue bubble characteristics. In case these insights are combined with bubble indicators for the stock market, such as TR CAPE ratios and interest rates, there is sufficient evidence to identify, although imperfectly, a bubble.

3 Data

This section presents the data that is used to test the hypothesis. The first subsection defines a unicorn and presents the unicorn list. The second subsection elaborates on the construction of the data sample and the variables. The last subsection describes several market indicators for a bubble.

3.1 Unicorn definition

Researchers have not been able to agree on an universally accepted definition of a unicorn as the phenomenon is relatively new. For the purposes of this research, only public unicorns are relevant. Private companies do not have the obligation to publish their financial statements, which brings challenges for gathering data about unicorns (Brown & Wiles, 2015). Besides the Prime Unicorn Index (2020), which measures the share performance of private companies with a valuation of at least $500 million and is compiled from company filings and other disclosure data, there are no other price performance measures of private unicorns available. Private unicorns that have not gone public yet, such as Airbnb and SpaceX, are therefore not covered in the analysis. Performance is thus entirely examined on the basis of public unicorns.

For the purposes of this research a unicorn will be defined as a venture capital-backed start-up company, founded since 2003, with a valuation of at least $1 billion at the time of the initial public offering, and is listed as common stock on the New York Stock Exchange (NYSE) or NASDAQ. This definition combines those of previous researches and allows for the assemblance of a comprehensive unicorn list (Lee 2013; Clabaugh & Peters, 2019).

The construction of the unicorn list is based on the unicorn exits that are reported by CB Insights (2018) and Intelligize (2020). The list is restricted to the following criteria. First of all, companies founded before January 2003 are excluded from the analysis. Secondly, All non-IPO exits, such as the acquisitions of Instagram and WhatsApp and the direct listings of Spotify and Slack, are excluded from the sample. Furthermore, several companies are not active as of December 2019, because they filed for bankruptcy or have been acquired after they went public. Examples are respectively A123Systems and LinkedIn and these companies have been removed from the sample. Finally, only companies that are listed as common stock on the NYSE or NASDAQ are included in the analysis. American Depositary Receipts (ADRs), such as the ADR of Alibaba Group, are therefore removed from the sample. ADRs are identified through the databases of JPMorgan and Bank New York Mellon. Only stocks with share codes 10 and 11 in CRSP are included in the sample as outlined in Greenwood, Shleifer, and You (2019). The final unicorn list contains 73 companies and is presented in Appendix 1.

3.2 Data sample

The data sample contains IPOs from 1 January 2010 until 31 December 2019. IPO data is obtained from the Thomson Financial Securities Data Corporation (SDC) database. SDC documents 2820 IPOs on the NYSE and NASDAQ over this time period. Several corrections for the data of unicorns have been made, and missing data for unicorns is manually collected by inspecting the prospectuses in the Electronic Data Gathering and Retrieval (EDGAR) system of the SEC and the database of Ritter (2020)[4].

The sample is restricted to the following criteria based on Loughran and Ritter (2004). First of all, all non-common share issues, such as ADRs, closed-end funds, real estate investment trusts (REITs), financial institutions, unit offerings and limited partnerships are excluded from the analysis[5]. Moreover, small offerings and penny stocks are less attractive to institutional investors. Therefore offerings with an offer price under $5 are excluded from the sample. Following Carter, Dark and Singh (1998), offerings with proceeds under $2 million are precluded from the sample. Finally, observations with missing values for the key variables (e.g. offer price, first-day close price etc.) have been removed. The final data sample contains 584 IPOs from 1 January 2010 until 31 December 2019, of which 73 are identified as unicorns and 511 as non-unicorns. Descriptive statistics are presented in Table 1.

The most important determinants of underpricing are mainly based on Loughran and Ritter (2004). Underpricing is measured by the market-adjusted return, which equals the difference between the first-day return and the market return on the respective day of issue (Carter, Dark, & Singh, 1998):

$$U_{i,t} = \left(\frac{(P_i^c - P_i^o)}{(P_i^o)} - \frac{(I_t - I_{t-1})}{(I_{t-1})} \right) \times 100\%$$

Where U_i denotes the degree of underpricing. $\frac{(P_i^c - P_i^o)}{(P_i^o)}$ represents the first-day return of stock i, which equals the percentage change from the offer price P_i^o to the first-day close price P_i^c. The market return of the S&P 500 Composite Index on issue date t, I_t, is calculated analogously through the percentage change of the index level from time $t-1$ to t.

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[4] Loughran and Ritter (2004) state that although some variables have missing observations, there is no evidence of backfilling bias. Thus, IPOs of winners are not covered more extensively or accurately than the IPOs of losers and there is no need to consider survivorship bias for the sample of non-unicorns. Observations with missing values for key variables can therefore be excluded from the sample without any violation.

[5] Closed-end funds and REITs are identified through the following Standard Industrial Classification (SIC) codes: 6726 and 6798. Furthermore, financial institutions are bounded by financial regulations and identified by the following SIC codes (Ritter, 1991): 602, 603, 612, and 671.

Table 1: Descriptive statistics of the data sample

High-tech companies are classified as in Kile and Phillips (2009) with the following SIC codes: 283, 357, 366, 367, 382, 384, 481, 482, 489, 737, and 873. Age is defined as the difference between the calendar year of offering and founding. Revenue is measured over the last twelve months period prior the issue or the maximum reported period of time prior the issue. Firms with a trailing revenue of zero are assigned a value of $10,000. Companies with a prestigious underwriter are defined as those where the lead underwriter has a ranking of at least 8.0 on the 0.0 – 9.0 reputational ranking scale of Carter and Manaster (1990). Number of underwriters includes the lead underwriter as well as co-underwriters. Gross proceeds exclude over-allotments. Withdrawals equals the fraction of issues that were cancelled divided by the total attempted issues. Price revisions denote the percentage change between the midpoint of the file price to the offer price. Money left on the table equals non-adjusted first-day returns multiplied by the total amount of shares offered. Post-issue valuation is defined as the post-issue number of shares outstanding multiplied by the offer price. Market capitalization equals the post-issue number of shares outstanding multiplied by the first-day close price. Market-to-revenue ratios denote respectively the median post-issue valuation (offer price) and median market capitalization (close price) divided by revenues. Initial returns are defined as the percentage change from the offer price to the close price on the first day of trading, adjusted for market returns (return on S&P 500 Composite Index) and measure the degree of underpricing. All dollar values are reported in millions of dollars.

Panel A: Descriptive characteristics of firms

		Unicorns	Non-unicorns	Full sample	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
No. of sample firms		73	511	584	27	15	39	107	125	65	34	55	65	52
Fraction unicorns		1.00	0.00	0.13	0.04	0.27	0.13	0.04	0.05	0.09	0.15	0.18	0.18	0.38
Fraction VC-backed		1.00	0.49	0.55	0.56	0.80	0.51	0.50	0.52	0.55	0.56	0.51	0.58	0.65
Fraction high-tech companies		0.81	0.53	0.56	0.41	0.87	0.51	0.50	0.56	0.58	0.47	0.49	0.66	0.69
Age	Mean	8.3	19.3	17.9	12.0	13.7	27.0	23.1	16.0	15.6	14.7	20.7	15.4	14.8
	Median	8	13	12	10	7	12	13	11	11	10	14	13	10
Revenue	Mean	411	708	671	296	2,316	774	720	549	647	274	938	634	556
	Median	193	105	113	112	105	185	115	90	92	110	267	116	118
Fraction with EPS ≤ 0		0.86	0.66	0.68	0.48	0.60	0.46	0.64	0.70	0.69	0.71	0.73	0.80	0.77

Panel B: Descriptive characteristics of IPOs

		Unicorns	Non-unicorns	Full sample	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Fraction prestigious underwriters		1.00	0.82	0.84	0.85	0.80	0.90	0.88	0.79	0.85	0.82	0.85	0.78	0.90
Number of underwriters	Mean	4.8	3.4	3.6	2.2	3.5	3.3	3.5	3.3	3.6	3.8	3.9	4.0	4.3
	Median	4	3	3	2	2	3	3	3	3	3	3	4	3
Gross proceeds	Mean	755	211	279	138	468	592	242	208	194	129	278	290	499
	Median	243	102	115	92	106	124	122	96	110	94	131	153	178
Withdrawals	Frequency	-	-	0.15	0.23	0.30	0.14	0.08	0.15	0.17	0.13	0.07	0.11	0.06
	Fraction high-tech	-	-	0.36	0.31	0.32	0.36	0.17	0.52	0.44	0.29	0.06	0.38	0.56
Price revision	Mean	8.54	-2.63	-1.23	-4.76	5.87	0.00	0.51	-5.21	-2.42	-2.67	0.61	1.14	1.12
	Median	8.11	0.00	0.00	-2.17	5.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.70
Money left on the table	Mean	796	182	258	106	267	243	281	167	195	198	310	379	432
	Median	539	91	116	23	188	136	155	75	62	83	103	168	285
Post-issue valuation	Mean	5,435	1,113	1,654	649	3,083	3,063	1,342	1,131	1,060	718	1,529	1,438	4,359
	Median	1,955	476	556	426	740	598	551	443	558	543	694	536	1,378
Market capitalization	Mean	6,605	1,301	1,964	729	3,618	3,363	1,716	1,291	1,277	954	1,799	1,817	5,082
	Median	3,023	554	686	443	986	680	678	562	715	511	779	660	1,687
Market-to-revenue	Offer	10.13	4.53	4.92	3.80	7.05	3.23	4.79	4.92	6.07	4.94	2.60	4.62	11.68
	Close	15.66	5.28	6.07	3.96	9.39	3.68	5.90	6.24	7.77	4.65	2.92	5.69	14.30
Initial returns	Mean	43.04	16.92	20.19	14.15	24.82	22.39	23.52	16.56	15.19	20.89	15.44	22.85	29.65
	Median	39.07	11.53	14.24	4.10	20.50	18.45	15.57	8.70	8.79	12.72	13.41	17.88	27.80
Mean initial returns	EPS < 0	44.14	18.39	22.47	14.10	25.28	36.67	25.32	17.89	14.82	21.62	17.59	25.72	33.07
	EPS > 0	36.15	14.12	15.30	14.20	24.14	10.15	20.26	13.39	16.02	19.13	9.71	11.40	18.22

SDC is the primary data source for venture capital issues. However, the Crunchbase database is used as primary source to retrieve venture capital data about the unicorns, because this database lists the several funding rounds. High-tech companies are identified as in Kile and Phillips (2009) with the following sic-codes: 283, 357, 366, 367, 382, 384, 481, 482, 489, 737, and 873.

Age is defined as the difference between the calendar year of offering and founding. The founding date is defined as the date of incorporation and acquired from Ritter (2020). Data on the number of shares offered and number of primary shares offered is obtained from SDC. The market value is defined as the offer price multiplied by the post-issue number of shares outstanding.

Furthermore, accounting data pertaining earnings per share (EPS), net income after tax, and revenue is acquired from SDC. Data lists the numbers of the most recent last twelve months period or the maximum reported period of time before the issue. Firms will be assigned a value of $10,000 as their revenue if they have a trailing revenue of zero. In that case, the natural logarithm of revenue is mathematically defined. When it is unclear whether observations of revenue are zero or missing, they are treated as missing.

Information on lead underwriters and managing underwriters are acquired through the SDC database. Underwriter reputation rankings are obtained through Ritter (2020), who provides updated rankings of the original Carter and Manaster (1990) 0.0 - 9.0 scale. Prestigious underwriters are defined as those with a score of at least 8.0. The list of prestigious underwriters is presented in Appendix 2.

Price revisions are defined as the percentage change between the midpoint of the file price to the offer price. The midpoint of the file price is obtained through SDC. The positive price revision from a midpoint file price of $0.05 to an offer price of $6.00 of ShiftPixy, Inc. is an outlier and is adjusted to 100%.

Stock data of daily and monthly close prices and trading volume are obtained from the Center for Research in Security Prices (CRSP). Individual companies are identified through Ticker symbols, 8-CUSIP codes, and PERMCO codes. PERMCO codes are particularly useful as these take corporate name changes and Ticker symbol changes into account. For example, Demand Media, Inc. changed its name to Leaf Group Ltd. In 2016. Asset price volatility equals the standard deviation of the natural logarithm of returns and is determined on a rolling window of 30 days.

The descriptive statistics outlined in Table 1 show an upward trend in price revisions, money left on the table, and market-to-revenue ratios. Meanwhile, the amount of profitable firms and withdrawn IPOs has decreased over the last couple of years. These findings are similar to those of the run-up of the dot-com bubble. The median level of underpricing for a unicorn is 39 percent, while the median level of underpricing was 32 percent during the dot-com bubble (Loughran & Ritter, 2004). This suggests that unicorns exhibit a higher degree of underpricing than companies from the dot-com era. Moreover, unicorns are younger and more unprofitable than non-unicorns. Finally, the median price revision is 8 percent higher for unicorns compared to non-unicorns.

Appendix 3 plots the annual volume and average degree of underpricing over the twenty-tens. It becomes evident that less companies went public in the years that followed the Great Depression. In 2017, unicorns started to become more dominant in the IPO market. During this upsurge of unicorns that went public, average initial returns doubled.

3.3 Market indicators

The NASDAQ Composite Index to the S&P 500 Composite Index ratio is constructed to assess the performance of the NASDAQ as opposed to the performance of the market. The NASDAQ is chosen because it measures the performance of technology stocks and lists the most unicorns. TR CAPE ratios are used to evaluate overvaluation in the stock market. TR CAPE ratios are equal to P/E ratios, but use the average earnings over the last ten years instead of one-year earnings to smoothen out business cycle fluctuations. Share repurchases are more common in the current market rather than dividends. This may be a potential cause for bias and therefore dividends are reinvested into the price index. TR CAPE ratios are obtained through the database of Shiller (2020). Interest data is acquired from the database of the Federal Reserve Bank of St. Louis. The federal funds rate is the interest rate at which commercial banks and other institutions trade overnight. The rate is determined on the preceding economic conditions and therefore a common interest rate measure. The development of the NASDAQ / S&P 500 Composite Index ratio, TR Cape ratio, and interest rates over time examine the performance of the stock market and are indicators for bubbles. The development of the market indicators over time are documented in Appendix 4-6.

As follows from Appendix 4 and 5, the NASDAQ-to-S&P 500 and TR CAPE ratios are steadily increasing and converging towards levels that were only observed during the late 1990s. Historically, lowering interest rates resulted in recessions according to Appendix 6. During the twenty-tens, interest rates reached their all-time low and were slightly above zero.

4 Methodology

This section will explain in further depth which tests will be performed to assess the hypotheses. Section 4.1 will elaborate on the methodology of the first hypothesis, which states that unicorns experience the underpricing phenomenon to a significantly higher degree than non-unicorns. Section 4.2 discusses the methodology for the second hypothesis, which states that unicorn stocks exhibit explosive price behavior and that the explosiveness is positively driven by trading volume and volatility.

4.1 Underpricing phenomenon

The first hypothesis, which states that unicorns experience the underpricing phenomenon to a significantly higher degree than non-unicorns, will be tested through two procedures. First of all, a multivariate regression model will be estimated in subsection 4.1.1 based on the analysis of Loughran and Ritter (2004). Secondly, unicorns will be matched to non-unicorns through propensity score matching to estimate the causal effect of unicorns on the degree of underpricing. This procedure is outlined in subsection 4.1.2.

4.1.1 Multivariate regression model

The first hypothesis states that unicorns experience the underpricing phenomenon to a significantly higher degree than non-unicorns. To test the hypothesis, the following multivariate regression model is estimated through ordinary least squares (OLS) based on the analysis of Loughran and Ritter (2004):

$$U_i = \alpha + \beta_1 Unicorn_i + \beta_2 VentureCapital_i + \beta_3 HighTech_i + \beta_4 \ln(1 + Age)_i + \beta_5 PurePrimary_i + \beta_6 \ln(\frac{MarketValue}{Revenue})_i + \beta_7 PrestigiousUnderwriter_i + \beta_8 NumberUnderwriters_i + \beta_9 LaggedNASDAQ_i + \beta_{10} NegativePriceRevision_i + \beta_{11} PositivePriceRevision_i + \varepsilon_i$$

Where the degree of underpricing U_i is the dependent variable and denotes the degree of underpricing. The $Unicorn_i$ dummy equals one if the issue concerns a unicorn as previously identified and zero otherwise. The coefficient of the $Unicorn_i$ dummy estimates the causal effect of unicorns on the degree of underpricing.

The $VentureCapital_i$ dummy equals one if the issue is VC-backed and zero otherwise. The $HighTech_i$ dummy equals one if the company is active in a high-tech industry according to the classification of Kile and Phillips (2009), and zero otherwise. A value of one is added to the Age variable, such that the natural logarithm of age is mathematically defined throughout the sample. The $VentureCapital_i$ dummy and the Age variable measure the grandstanding hypothesis of Gompers (1996), which states that young venture capital-backed firms are more likely to experience underpricing.

The $PurePrimary_i$ dummy equals one if the offering issues solely primary shares and measures the realignment of incentives hypothesis of Ljungqvist and Wilhelm (2003). The hypothesis states that underpricing is higher because fragmented ownership causes less bargaining effort over the offer price. Valuation uncertainty, which is partly caused by information asymmetry, predicts that a high risk is related to firms with a high market-to-revenue multiple. The natural logarithm of the $(\frac{MarketValue}{Revenue})_i$ ratio is therefore added to the regression. Furthermore, the $PrestigiousUnderwriter_i$ dummy captures the willingness to accept a higher degree of underpricing from the changing issuer objective function hypothesis. The $PrestigiousUnderwriter_i$ dummy equals one if the lead underwriter has a ranking of at least 8.0 on the Carter and Manaster (1990) scale and zero otherwise.

The following control variables are added to the regression. Prior research of Loughran and Ritter (2002) has shown that market performance in the three weeks before the issue can predict the degree of underpricing. Therefore, the lagged return on the NASDAQ Composite Index over the three weeks that preceded the issue is added the regression. The $NegativePriceRevision_i$ and $PositivePriceRevision_i$ variable capture the effect of changes in interest on the part of the investors.

4.1.2 Propensity score matching

A more econometrically sound method to estimate the causal effect of unicorns on the degree of underpricing is to match a unicorn with a non-unicorn that has similar characteristics. This can be achieved through Propensity Score Matching (PSM). PSM is a method that assigns an observation from the treatment group to an observation from the control group based on several observed covariates (Rosenbaum & Rubin, 1983). In this case, being a unicorn is viewed as 'receiving the treatment'. Assigned treatment for unit i is denoted by $z_i = 1$, whereas $z_i = 0$ represents assignment to the control group. Hence, being a unicorn is viewed as being part of the treatment group with $z_i = 1$ and being a non-unicorn as part of the control group with $z_i = 0$.

The propensity score is the conditional probability of assignment to the treatment group given its set of observed pre-treatment characteristics x and is estimated through a probit regression. The probability to be assigned into the treatment group, given its set of characteristics, is denoted by:

$$e(x) = P(z = 1 \mid x)$$

The outcome variable y represents the degree of underpricing and is denoted as follows:

$$y = \begin{cases} y_1 \; if \; z = 1 \\ y_0 \; if \; z = 0 \end{cases}$$

When units are matched on the basis of their propensity scores, the average treatment effect on the treated (ATET) can be modelled as follows (Cerulli & Potì, 2012):

$$ATET = E(y_1 \mid e(x), z = 1) - E(y_0 \mid e(x), z = 1)$$

The term $E(y_0 \mid e(x), z = 1)$ is counterfactual and not observable. However, $E(y_0 \mid e(x), z = 0)$ is observable and due to the PSM procedure, which states that units with the same propensity scores can be viewed as matches, the following equation holds: $E(y_0 \mid e(x), z = 0) = E(y_0 \mid e(x), z = 1)$. This means that the ATET can be estimated through the PSM procedure. The PSM procedure mitigates selection bias and therefore provides an adequate estimate of the causal effect of unicorns on the degree of underpricing.

4.2 Explosiveness

The second hypothesis claims that unicorn stocks exhibit explosive price behavior and that the explosiveness is positively related with trading volume and price volatility. The assessment of this hypothesis consists of two parts. First of all, right-tailed forward recursive ADF-tests as outlined in Phillips, Wu, and Yu (2011), further referred to as PWY, are performed to detect explosive behavior in the stock prices of unicorns. On the basis of the PWY methodology, a binary variable is constructed that equals one if there is explosiveness in prices and zero otherwise. The underlying methodology will be explained in section 4.2.1. The binary outcome of this test is used as the dependent variable of a logistic regression model on trading volume and price volatility to test the second part of the hypothesis. This model is further discussed in section 4.2.2.

4.2.1 Explosive price behavior

The following subsection elaborates on the detection of explosive price behavior as outlined in Phillips, Wu, and Yu (2011). The fundamental asset price is determined by the expected price in the future plus dividends:

$$P_t = \frac{1}{1+R} E_t \left(P_{t+1} + D_{t+1}\right)$$

By taking the log-linear approximation as in Campbell and Shiller (1988), the price of an asset at time t can be split in a fundamental value component and a bubble component:

$$p_t = p_t^f + b_t$$

Diba and Grossman (1988) state that, in case the discount rate is time invariant, any explosivity in prices with non-explosive behavior in the dividend series, would imply that the explosive behavior of prices arises from the existence of a bubble. Right-tailed unit root tests, as for example the augmented Dickey-Fuller test (ADF), are implemented to detect explosive behavior. However, standard unit root tests are not able to differentiate between stationary processes and periodically collapsing bubbles (Evans, 1991). A forward recursive estimation model is employed as it has the power to locate explosiveness and periods of exuberance in subsamples of the data and it is therefore not subject to this criticism.

The dividend series does not exhibit any explosive behavior and therefore emergence of explosivity in prices would indicate an asset price bubble. For time series x_t (the natural logarithm of the stock price) the ADF test for an unit root against the right-tailed alternative is applied. That is, the null hypothesis $H_0 : \delta = 1$ is tested against the alternative hypothesis $H_1 : \delta > 1$. The autoregressive specification is repeatedly estimated by ordinary least squares (OLS), where a subset of the sample is used in each regression, which is incremented by one observation each time:

$$x_t = \mu_x + \delta x_{t-1} + \sum_{j=1}^{J} \emptyset_j \Delta x_{t-j} + \varepsilon_{x,t}, \varepsilon_{x,t} \sim \text{NID}\ (0, \sigma_x^2)$$

Where J represents the amount of implemented lags and NID denotes the independent and normal distribution. The optimal lag length is determined by the Ng-Perron sequential t-test at a significance level of 5 percent and the maximum lag length is set to 12. The corresponding t-statistic is denoted as ADF_r. The first regression involves $[nr_0]$ observations with n representing the number of observations in the full sample and r_0 denoting the fraction of the sample used in the particular regression. Subsequent regressions supplement the previous regression with the successive observation, resulting in sample size $[nr]$, with $r \in [0{,}1; 1]$ if an initial sample size of 0.10 (10 percent) is chosen. For each increment in observation, the supremum ADF test statistic is obtained. For example, $ADF_{0,1}$ represents the supremum ADF test statistic with $r \in [0,1; 1]$ and equals $sup_{r\in[0,1;1]}ADF_r$. Periods that exhibit explosive behaviour are located by estimating the following intervals:

$$\widehat{r_e} = inf_{s\geq r_0}\{s: ADF_s > cv_{\beta_n}^{adf}(s)\}$$

$$\widehat{r_f} = inf_{s\geq \widehat{r_e}}\{s: ADF_s < cv_{\beta_n}^{adf}(s)\}$$

Where $\widehat{r_e}$ denotes the origin date of explosive behavior and $\widehat{r_f}$ its subsequent collapse. $cv_{\beta_n}^{adf}(s)$ represents the critical value around the 4 percent significance level and equals $\ln(\ln(ns))\,/100$.

4.2.2 Trading volume and volatility

To test what the effects of trading volume and asset price volatility are on the explosive behavior of asset prices, the following empirical logistic regression model is estimated:

$$b_{it} = \alpha + \beta_{1i}\ln(TV_{it}) + \beta_{2i}\ln(PV_{it}) + v_{it}\,,\ v_{it} = c_i + \varepsilon_i$$

Where the dependent variable bubbles b_{it} is regressed on the natural logarithm of trading volume in thousands TV_{it} and the natural logarithm of asset price volatility PV_{it}. Asset price volatility equals the standard deviation of the natural logarithm of returns and is determined on a rolling window of 30 days. c_i is the individual observation error term and ε_i captures the heterogeneity in the cross-sectional dimension.

The binary bubble variable is constructed on the basis of the PWY methodology. The right-tailed forward recursive ADF-tests will be conducted on the daily close prices of the unicorns, considering an initial sample size of $r_0 = 0.1$. This means that the period of IPO is omitted from the analysis and that the data thus less sensitivity shows towards the initial starting values. Narayan, Mishra, Sharma and Liu (2013) state that whenever the test statistic of the right-tailed forward recursive ADF test exceeds its critical value, the stock price surpasses its fundamental value. Based on this reasoning, there is an asset bubble b_{it} = 1 at time t when the $\widehat{r_e} = inf_{s\geq r_0}\{s: ADF_s > cv_{\beta_n}^{adf}(s)\}$ condition is satisfied and b_{it} = 0 otherwise. The following logit regression is estimated to examine the effects of trading volume and price volatility on explosiveness:

$$l = \log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 ln(TV_{it}) + \beta_2 ln(PV_{it}) + e_{it}$$

Where l represents the log-odds of the event that a bubbles occurs, which is denoted by $p = P(b_{it} = 1)$.

5 Results

This section presents the results of the outlined methodology. The results of the multivariate regression model and the PSM method, which both assess the first hypothesis, are presented in section 5.1. The results of the right-tailed forward recursive ADF-tests and the logistic regression, which both evaluate the second hypothesis, are outlined in section 5.2.

5.1 Underpricing phenomenon

The first hypothesis states that unicorns experience the underpricing phenomenon to a significantly higher degree than non-unicorns. It is therefore important to assess the causal effect of unicorns on the degree of underpricing. As outlined in section 4.1, this is accomplished by estimating a multivariate regression model and applying the PSM method. The results are respectively presented in section 5.1.1 and section 5.1.2.

5.1.1 Multivariate regression results

To estimate the causal effect of unicorns on the degree of underpricing, the multivariate regression outlined in 4.1.1 is estimated. The results are presented in Table 2. The unicorn dummy is statistically significant at the one percent significance level and the coefficient implies that being a unicorn increases the degree of underpricing with 15.30 percent. Additionally, the venture capital dummy is significant at a significance level of one percent and the coefficient implies that first-day returns increase with 7.72 percent if the issue is venture capital-backed. On the basis of previous research, it is expected that young high-tech firms with a high market-to-revenue ratio experience higher underpricing. However, the coefficient of the high-tech dummy and the age variable both show an opposite sign than expected. Therefore, the grandstanding hypothesis of Gompers (1996) is not an adequate explanation for the higher degree of underpricing.

The realignment of incentives hypothesis implies that issues with solely primary shares have a higher degree of underpricing. However, the sign for the primary shares dummy is negative and therefore not much supportive evidence for this hypothesis is found. The impresario hypothesis implies that firms that hire prestigious underwriters, experience higher first-day returns. Although the sign of the coefficient of the prestigious underwriter dummy is correct, it is not statistically significant and the impresario hypothesis is therefore not an adequate explanation for the higher degree of underpricing.

Table 2: Results multivariate least squares regression model on underpricing

The dependent variable is the degree of underpricing measured by the market-adjusted first-day returns. The unicorn dummy equals one is the issue concerns a unicorn and zero otherwise. The venture capital dummy equals one if the issue is VC-backed and zero otherwise. The high-tech dummy equals one if the company is active in a high-tech industry according to the classification of Kile and Phillips (2009) and zero otherwise. Age is defined as the difference between the calendar year of offering and founding. A value of one is added to the age variable, such that the natural logarithm of age is mathematically defined. The pure primary dummy equals one if the offering issues solely primary shares and zero otherwise. Market value equals the post-issue number of shares outstanding multiplied by the offer price. Revenue is measured over the last twelve months period prior the issue or the maximum reported period of time prior the issue. Firms with a trailing revenue of zero are assigned a value of $10,000. The prestigious underwriter dummy equals one if the lead underwriter has a score of at least 8.0 on the Carter and Manaster (1990) scale and zero otherwise. The lagged NASDAQ returns equals the return over the three weeks that preceded the issue. Price revisions denote the percentage change between the midpoint of the file price to the offer price. Standard errors are reported in parentheses and calculated using heteroskedastic-consistent White standard errors (White, 1980). *, **, and *** indicate significance at respectively 90 percent, 95 percent, and 99 percent and correspond with p-values < 0.10, 0.05, and 0.01.

Regressors	**Model 1**	**Model 2**
Intercept	5.28	5.25
	(5.08)	(4.60)
Unicorn	23.29***	15.30***
	(5.09)	(4.99)
VentureCapital	7.46**	7.72***
	(3.21)	(2.88)
HighTech	-0.58	-0.50
	(3.07)	(2.77)
ln(1+Age)	3.09**	2.92**
	(1.34)	(1.24)
PurePrimary	-4.21*	-1.71
	(2.47)	(2.21)
ln(MarketValue/Revenue)	0.40	-0.30
	(0.69)	(0.62)
PrestigiousUnderwriter	5.96*	3.89
	(3.14)	(2.94)
NumberUnderwriters	-0.72	-0.72
	(0.57)	(0.52)
LaggedNASDAQ	--	0.71**
	--	(0.29)
NegativePriceRevision	--	0.56***
	--	(0.09)
PositivePriceRevision	--	1.10***
	--	(0.32)
N	584	584
Adj. R-squared	0.11	0.26

The adjusted R^2 increases from 0.11 to 0.26 when the control variables are added to the regression. This indicates that market performance and price revisions clearly have explanatory power. The lagged NASDAQ coefficient conveys that an increase of the returns on the trailing 15 trading days increases underpricing with 0.71 percent. This implies that first-day returns are predictable on the basis of previous market performance. The positive price revision coefficient reveals that a positive price revision of one percent increases initial returns with 1.10 percent.

The correlations of the regression variables are reported in the correlation matrix in Appendix 7. The variance inflation factor (VIF) is used to identify multicollinearity issues, where a VIF > 5 indicates that coefficients are highly correlated. All VIFs are < 2.0 for all regressors and the chosen variables therefore do not introduce multicollinearity issues. Adding year dummies and industry dummies based on three digits SIC-codes (and thereby dropping the high-tech dummy) for robustness does not alter the inferences.

Altogether, the results suggest that unicorns experience 15 percent higher first-day returns at their initial public offering than non-unicorns. The first hypothesis, which states that unicorns experience underpricing to a higher degree than non-unicorns, is therefore confirmed on the basis of the multivariate regression model.

5.1.2 Propensity score matching results

The results of the PSM procedure are presented in Table 3. Unicorns are matched to non-unicorns on the basis of the covariates age, size, and industry. Industries are defined on the basis of the first three digits of the SIC codes. The nearest neighbor matching method matches a unicorn to the non-unicorn with the closest propensity score. The kernel matching method matches a unicorn to a weighted average of non-unicorns, where weights are inversely proportional to the distance in propensity scores. For robustness, the following two assumption are tested. First of all, the balancing condition states that the assignment to the treatment group is independent of the set of characteristics x, given an equal propensity score: $z \perp x \mid e(x)$. Secondly, the common support condition states that, given x, there are observations in the treatment and control group: $0 < P(z = 1 \mid x) < 1$. The balancing condition is found to be satisfied. Furthermore, the region of common support equals [0.001, 0.986] and thus there is sufficient overlap in the covariates x of unicorns and non-unicorns to ensure an adequate match.

The Average Treatment Effect of the Treated (ATET) is the estimator of the causal effect of being a unicorn on the degree of underpricing. The coefficient of ATET for the nearest neighbor matching method implies that being a unicorn increases the degree of underpricing with more than 19 percent. When applying the kernel matching method, the effect of being a unicorn increases underpricing with more than 23 percent. All results are statistically significant at a significance level of one percent. Therefore, the first hypothesis that states that unicorns experience underpricing to a higher degree than non-unicorns, can be accepted on the basis of the PSM procedure.

Table 3: Results of the propensity score matching procedure

Unicorns are matched to non-unicorns based on their propensity score. The propensity score is estimated by a probit regression with the chance of being a unicorn as the dependent binary variable based on the characteristics age, size and industry. Age is defined as the difference between the calendar year of offering and founding. Size is measured by the offer price multiplied by the post-issue number of shares outstanding. Industries are distinguished on the basis of three digits SIC codes. For the probit regression, the natural logarithm of age plus one is taken, as well as the natural logarithm of size, to ensure that the balancing condition holds. Standard errors are bootstrapped with 10,000 replications. *, **, and *** indicate significance at respectively 90 percent, 95 percent, and 99 percent and correspond with p-values < 0.10, 0.05, and 0.01.

Matching method	Obs. Treatment	Obs. Control	ATET	Standard Error	T-Statistic
Nearest Neighbor Matching	73	44	19.093***	6.18	3.09
Kernel Matching	73	448	23.471***	4.97	4.73

5.2 Explosiveness

The second hypothesis states that unicorn stocks exhibit explosive price behavior and that explosiveness is positively driven by trading volume and volatility. As outlined in section 4.2, right-tailed forward recursive ADF-tests will be conducted to detect explosivity in the stock prices of unicorns. The binary outcome of this test is used as the dependent variable in a logistic regression on trading volume and price volatility. The results of the right-tailed forward recursive ADF-tests and the logistic regression are respectively presented in sections 5.2.1 and 5.2.2.

5.2.1 PWY test results

First of all, the findings of Phillips, Wu, and Yu (2011) are replicated using monthly data on the NASDAQ Composite Index from January 1990 until December 2019. The results are presented in Appendix 8. The $sup_{r\in[0,1;1]}ADF_r$ test with an initial sample size of 36 observations (three years) is able to locate the dot-com bubble. The index started to exhibit explosive price behavior in July 1995 and it took until February 2001 for the market to return to a non-explosive state. This conforms the findings of Phillips, Wu, and Yu (2011), who document explosive price behavior of the NASDAQ Composite Index from July 1995 until March 2001.

The subsample of January 2010 until December 2019 is analyzed to examine whether any explosivity occurred during the decade of the unicorn. The results are presented in Appendix 9. The $sup_{r\in[0,1;1]}ADF_r$ with an initial sample size of 12 observations (one year) is able to locate two explosive periods. The NASDAQ Composite Index exhibited explosive price behavior from July 2013 until August 2015 and from October 2017 until October 2018.

To construct the binary variable for the logistic regression, the right-tailed forward recursive ADF-tests are conducted on the daily close prices of individual unicorns that went public before 2019. An initial sample size of 0.1 is selected to exclude the initial public offering from the sample. For robustness, the S&P 500 Composite Index is tested on explosivity as well. Due to the sensitivity of the start values, there is always explosive behavior at the start of the test that fades away after a couple of observations. These observations are omitted from the analysis. The results are presented in Table 4.

A significant high amount of unicorns exhibit explosive price behavior. However, in ten years of data on the S&P 500 Composite Index, only 40 bubble days are detected with a maximum continuous number of 15 bubble days. Considering an initial sample size of 0.1, there was thus explosivity in the S&P 500 Composite Index on 1.77 percent of the trading days. For comparison, 30 out of 53 unicorns exceed this explosivity percentage and only 8 out of 53 unicorns do not exhibit any explosive behavior. Moreover, 11 out of 53 unicorns exhibit highly explosive behavior and show explosiveness in more than 10 percent of the trading days. The first part of the second hypothesis, which states that unicorns exhibit explosive price behavior, can therefore be confirmed on the basis of the PWY methodology.

Table 4: Explosive price behavior of individual unicorn stocks

The total number of bubble days is obtained by adding the number of observations for which the $sup_{r\in[0,1;1]}ADF_r$ test statistic surpasses the critical value, as described in Phillips, Wu, and Yu (2011). The continuous number of bubble days is calculated by taking the maximum number of continuous days for which the $sup_{r\in[0,1;1]}ADF_r$ test statistic exceeds the critical value, as described in Phillips, Wu, and Yu (2011). Trading days represent the total trading days on 31 December 2019 since the IPO minus the number of trading days in the initial sample. Explosivity equals the total number of bubble days divided by the amount of trading days. Unicorns that went public in 2019 are excluded from the analysis, which means that 53 unicorns remain in the sample.

		Bubble days			
Unicorn	**Year of IPO**	**Total**	**Continuous**	**Trading days**	**Explositivity**
Tesla Motors, Inc.	2010	343	135	2,155	15.92%
Demand Media, Inc.	2011	38	26	2,023	1.88%
Ubiquiti Networks, Inc.	2011	51	12	1,859	2.74%
Groupon, Inc.	2011	15	7	1,846	0.81%
Zynga, Inc.	2011	1	1	1,820	0.05%
Splunk, Inc.	2012	7	2	1,744	0.40%
Facebook, Inc.	2012	100	51	1,725	5.80%
ServiceNow, Inc.	2012	2	1	1,699	0.12%
Palo Alto Networks, Inc.	2012	197	127	1,687	11.68%
Workday, Inc.	2012	4	2	1,634	0.24%
FireEye, Inc.	2013	32	28	1,423	2.25%
Veeva Systems, Inc.	2013	132	70	1,407	9.38%
Twitter, Inc.	2013	90	32	1,392	6.47%
Chegg, Inc.	2013	521	406	1,389	37.51%
Castlight Health, Inc.	2014	54	16	1,315	4.11%
GrubHub, Inc.	2014	209	178	1,301	16.06%
Arista Networks, Inc.	2014	307	247	1,263	24.31%
LendingClub Corporation	2014	31	13	1,145	2.71%
New Relic, Inc.	2014	140	100	1,144	12.24%
On Deck Capital, Inc.	2014	0	0	1,141	0.00%
Box, Inc.	2015	0	0	1,120	0.00%
Etsy, Inc.	2015	214	189	1,068	20.04%
Fitbit, Inc.	2015	10	3	1,029	0.97%
Sunrun, Inc.	2015	3	3	999	0.30%
Pure Storage, Inc.	2015	5	3	959	0.52%
Square, Inc.	2015	377	363	932	40.45%
NantHealth, Inc.	2016	80	36	812	9.85%
Twilio, Inc.	2016	250	169	798	31.33%
The Trade Desk, Inc.	2016	14	12	743	1.88%
Nutanix, Inc.	2016	9	3	736	1.22%
Coupa Software, Inc.	2016	207	71	733	28.24%
Snap, Inc.	2017	21	11	643	3.27%
Okta, Inc.	2017	111	21	619	17.93%
Cloudera, Inc.	2017	29	15	607	4.78%
Blue Apron Holdings, Inc.	2017	15	11	568	2.64%
Redfin Corporation	2017	3	2	550	0.55%
Cargurus, Inc.	2017	2	2	502	0.40%
MongoDB, Inc.	2017	4	2	498	0.80%
Stitch Fix, Inc.	2017	14	12	479	2.92%
Denali Therapeutics, Inc.	2017	13	13	466	2.79%
Casa Systems, Inc.	2017	39	19	462	8.44%
Zscaler, Inc.	2018	0	0	407	0.00%
Dropbox, Inc.	2018	0	0	402	0.00%
Zuora, Inc.	2018	0	0	391	0.00%
DocuSign, Inc.	2018	2	2	381	0.52%
Pluralsight, Inc.	2018	17	14	368	4.62%
Greensky, Inc.	2018	3	2	364	0.82%
Rubius Therapeutics, Inc.	2018	6	6	330	1.82%
Eventbrite, Inc.	2018	0	0	290	0.00%
Guardant Health, Inc.	2018	16	12	281	5.69%
Allogene Therapeutics, Inc.	2018	0	0	276	0.00%
Anaplan, Inc.	2018	0	0	275	0.00%
Moderna, Inc.	2018	3	3	241	1.24%

5.2.2 Logistic regression results

The Hausman test is performed to examine whether the fixed effects or random effects estimator is more appropriate for the logistic regression. The results of the test are presented in Appendix 10 and indicate that the fixed effects estimator is consistent. The results of the logistic regression and corresponding average marginal effects are outlined in Table 5. The coefficients are statistically significant at a significance level of one percent and imply that elevated trading volume and price volatility increase the probability of an asset price bubble. The average marginal effects can be interpreted as follows. An one percent increase in trading volume increases the probability of an asset price bubble, measured through the binary explosivity variable, by 5 percent. An one percent increase in price volatility increases the probability of a bubble with 4 percent. The second part of the explosivity hypothesis, which states that trading volume and price volatility positively drive explosive price behavior for unicorn stocks, can be accepted on the basis of the results of the logistic regression. As follows from section 5.2.1 and section 5.2.2, the sup-ADF tests and logistic regression indicate that unicorn stocks exhibit explosive price behavior and that the explosiveness is positively related to trading volume and price volatility. The second hypothesis is therefore confirmed.

Table 5: Binary logit regression with fixed effects of trading volume and volatility on bubbles

The dependent variable is the binary bubble dummy, where $b_{it} = 1$ if the stock of unicorn i exhibits explosive price behaviour at time t, and $b_{it} = 0$ if the stock does not show explosivity. Trading volume denotes the natural logarithm of trading volume in thousands. Volatility represents the natural logarithm of price volatility, calculated as the standard deviation of returns on the basis of a 30-day rolling window. Marginal effects represent the average marginal effect (AME). Standard errors are reported in parentheses and calculated using heteroskedastic-consistent White standard errors (White, 1980). *, **, and *** indicate significance at respectively 90 percent, 95 percent, and 99 percent and correspond with p-values < 0.10, 0.05 and 0.01.

Regressors	Coefficients	Marginal effects
Intercept	-6.44***	--
	(0.35)	--
Trading volume	0.83***	0.05***
	(0.03)	(0.00)
Volatility	0.63***	0.04***
	(0.05)	(0.00)
N	44,802	
McFadden R-squared	0.28	

6 Conclusion

This research aimed to fill the gap of empirical research on the unicorn phenomenon. The current market situation surrounding unicorn companies shows great resemblance to the events that led to the dot-com bubble of the late 1990s. This research investigates the contribution of unicorns to the potential run-up of a new asset price bubble by examining the following research question:

"*To what extent do unicorns exhibit the characteristics of an asset price bubble like the dot-com bubble?*"

The research question is answered by assessing the hypotheses of the measurable bubble characteristics underpricing and explosive price behavior. The first hypothesis states that unicorns experience the underpricing phenomenon at their initial public offering to a significantly higher degree than non-unicorns. This is examined by estimating a multivariate regression model and applying the propensity score matching method. The multivariate regression model estimates that the causal effect of unicorns on the degree of underpricing is more than 15 percent. Furthermore, matching a unicorn to non-unicorns with similar observable characteristics, such as age, size, and industry, shows that the causal effect of being a unicorn increased the degree of underpricing by up to 23 percent. The results provide sufficient evidence for the statement that unicorns experience the underpricing phenomenon to a higher degree than non-unicorns and the first hypothesis is therefore accepted.

The second hypothesis states that unicorn stocks exhibit explosive price behavior and that this explosiveness is positively driven by trading volume and price volatility. This is assessed on the basis of right-tailed forward recursive ADF-tests and a logistic regression model. The right-tailed forward recursive ADF-tests indicate that many unicorns exhibit explosive price behavior to a high degree, while the S&P 500 Composite Index exhibited almost no explosivity during the unicorn era. The logistic regression model implies that an one percent increase in trading volume and price volatility increased the probability of a bubble with respectively 5 and 4 percent. The results indicate that unicorns exhibit explosive price behavior and suggest that trading volume and price volatility have a positive effect on this explosiveness. The second hypothesis is therefore accepted.

The current stock market provides a good environment for a potential asset price bubble to develop. The NASDAQ-to-S&P 500 and TR CAPE ratio, which were good predictors for historical bubbles, almost have reached similar levels as in the late 1990s. Interest rates were at all-time lows during the twenty-tens, which resulted in more borrowing and therefore a larger influx of capital. Large sums of this capital is invested in unicorns and valuations of these young start-up companies inflated rapidly. Unicorn companies exhibit the typical asset price bubble characteristics to a high degree and the current events show great analogy to those of the dot-com bubble of the late 1990s. This strengthens the presumption that an asset price bubble is currently developing in the stock market. However, these findings do not affirm a bubble with 100 percent certainty and they merely allow for the presumption of a bubble. It is hard to state whether there is irrational exuberance in the current stock market or that there is a temporary overreaction. Though, many new unicorns are emerging at a rapid pace and they still have to obtain their public status. As more and more investors start to question the sky-high valuations, it is expected that in case there is a bubble, it is converging to its peak.

This research has several limitations. First of all, data on private unicorns is not widely available. The down rounds that many private unicorns are currently experiencing convey valuable information. For example, the down round tracker of CB Insights (2020) provides information on private companies that have not been able to meet their expectations. However, due to the lack of information on fundamentals, private companies are not included in the analysis. Presumption of a bubble is therefore entirely examined on the basis of public unicorns. It is therefore hard to determine which characteristics causes unicorns to pre-select on going public, while others choose to remain private. The tech bubble puzzle, the gap between private and public capital market valuations of technology companies, therefore stays (yet) unsolved. Moreover, as the unicorn phenomenon is relatively new and literature on this topic is scarce, identification of unicorns is not straightforward. Although the unicorn list is assembled on the basis of consistent selection criteria, it may suffer from selection bias as for example only U.S. companies are analyzed.

New unicorns emerge at a fast rate and many of them are expected to go public in the coming years while they still can take advantage of the hot issue period. Future research could keep track of all the public unicorns to examine the trends in underpricing and explosive price behavior over time. This would lead to a more valid conclusion and it would be more clear whether there is irrational exuberance or an temporary overreaction in the current stock market. An interesting extension is to explore the emergence and development of private unicorns to solve the tech bubble puzzle. Another possibility is to extend the analysis by including Chinese unicorns, which are on track to surpass the number of U.S. unicorns. All suggestions stress the importance of a more extensive unicorn database, which will lead to more substantiated conclusions.

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Appendices

Appendix 1: List of unicorns

For the purposes of this research a unicorn will be defined as a venture capital-backed start-up company, founded since 2003, with a valuation of at least $1 billion at the time of the initial public offering, and is listed as common stock on the New York Stock Exchange (NYSE) or NASDAQ. In total, 73 unicorns exited through an initial public offering in the time frame of January 2010 until December 2019.

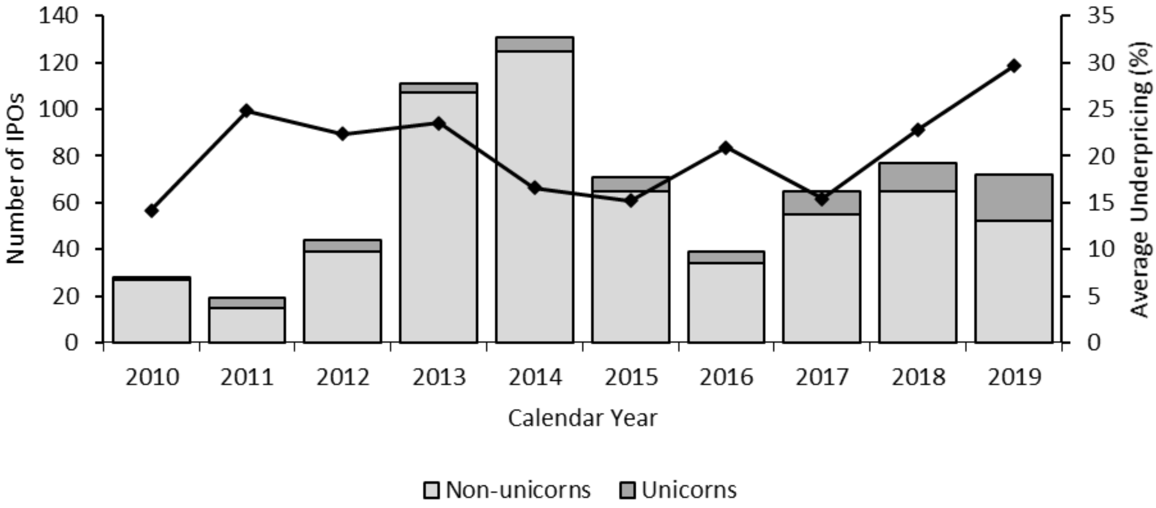
10X Genomics, Inc.	Demand Media, Inc.	NantHealth, Inc.	The RealReal, Inc.
Adaptive Biotechnologies Corporation	Denali Therapeutics, Inc.	New Relic, Inc.	The Trade Desk, Inc.
Alector, Inc.	DocuSign, Inc.	Nutanix, Inc.	Twilio, Inc.
Allogene Therapeutics, Inc.	Dropbox, Inc.	Okta, Inc.	Twitter, Inc.
Anaplan, Inc.	Etsy, Inc.	On Deck Capital, Inc.	Uber Technologies, Inc.
Arista Networks, Inc.	Eventbrite, Inc.	Pagerduty, Inc.	Ubiquiti Networks, Inc.
Beyond Meat, Inc.	Facebook, Inc.	Palo Alto Networks, Inc.	Veeva Systems, Inc.
Bill.com Holdings, Inc.	Fastly, Inc.	Peloton Interactive, Inc.	Vir Biotechnology, Inc.
Blue Apron Holdings, Inc.	FireEye, Inc.	Pinterest, Inc.	Workday, Inc.
Box, Inc.	Fitbit, Inc.	Pluralsight, Inc.	Zoom Video Communications, Inc.
BridgeBio Pharma, Inc.	Greensky, Inc.	Pure Storage, Inc.	Zscaler, Inc.
Cargurus, Inc.	Groupon, Inc.	Redfin Corporation	Zuora, Inc.
Casa Systems, Inc.	GrubHub, Inc.	Rubius Therapeutics, Inc.	Zynga, Inc.
Castlight Health, Inc.	Guardant Health, Inc.	ServiceNow, Inc.	
Chegg, Inc.	Health Catalyst, Inc.	Snap, Inc.	
Cloudera, Inc.	LendingClub Corporation	Splunk, Inc.	
Cloudflare, Inc.	Livongo Health, Inc.	Square, Inc.	
Coupa Software, Inc.	Lyft, Inc.	Stitch Fix, Inc.	
Crowdstrike Holdings, Inc.	Moderna, Inc.	Sunrun, Inc.	
Datadog, Inc.	MongoDB, Inc.	Tesla Motors, Inc.	

Appendix 2: List of prestigious underwriters

Companies with a prestigious underwriter are defined as those where the lead underwriter has a ranking of at least 8.0 on the 0.0 – 9.0 reputational ranking scale of Carter and Manaster (1990). Data is retrieved from the database of Ritter (2015). The data lists scores of the periods 2010-2011 and 2012-2015. All scores remained constant over time, except for the Santander Investment Bank who joined the list in 2012 when the score was upgraded from a 7.5 to 8.0.

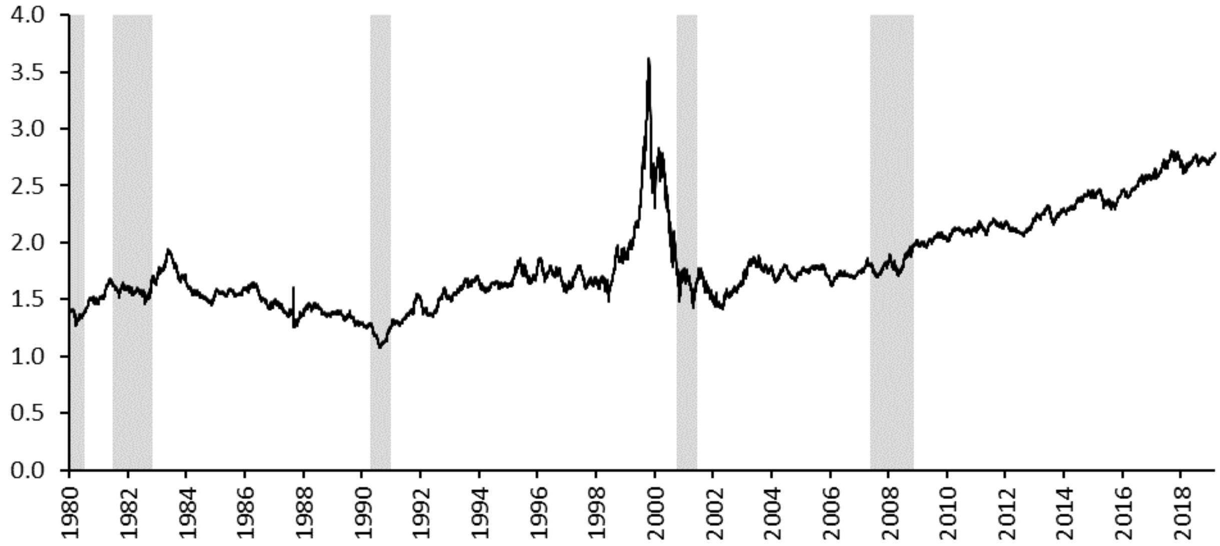
Underwriter	Ranking	Underwriter	Ranking
Citicorp Securities Inc.	9.0	Allen & Co. Inc.	8.0
Citigroup	9.0	Barclays Capital	8.0
Citigroup Global Market Inc.	9.0	Barclays Investment, Inc.	8.0
Goldman Sachs & Co.	9.0	BNP Paribas SA	8.0
Goldman Sachs Asia	9.0	Credit Agricole Securities	8.0
Goldman Sachs International	9.0	HSBC	8.0
JP Morgan	9.0	HSBC Investment Banking Ltd.	8.0
Morgan Stanley & Co.	9.0	HSBC James Capel & Co.	8.0
Morgan Stanley International	9.0	HSBC Securities Inc.	8.0
Bank of America - Merrill Lynch	8.5	Jefferies & Co. Inc.	8.0
Credit Suisse	8.5	KKR Capital	8.0
Credit Suisse First Boston	8.5	Lazard	8.0
Deutsche Bank Securities Corp.	8.5	Lazard Capital Markets	8.0
Merrill Lynch & Co. Inc.	8.5	Lazard Freres & Co. LLC.	8.0
UBS	8.5	RBC Capital Investments	8.0
UBS Investment Bank	8.5	Santander Investment Bank	8.0
UBS Securities Inc.	8.5	Wells Fargo	8.0

Appendix 3: Annual volume and average degree of underpricing over the twenty-tens



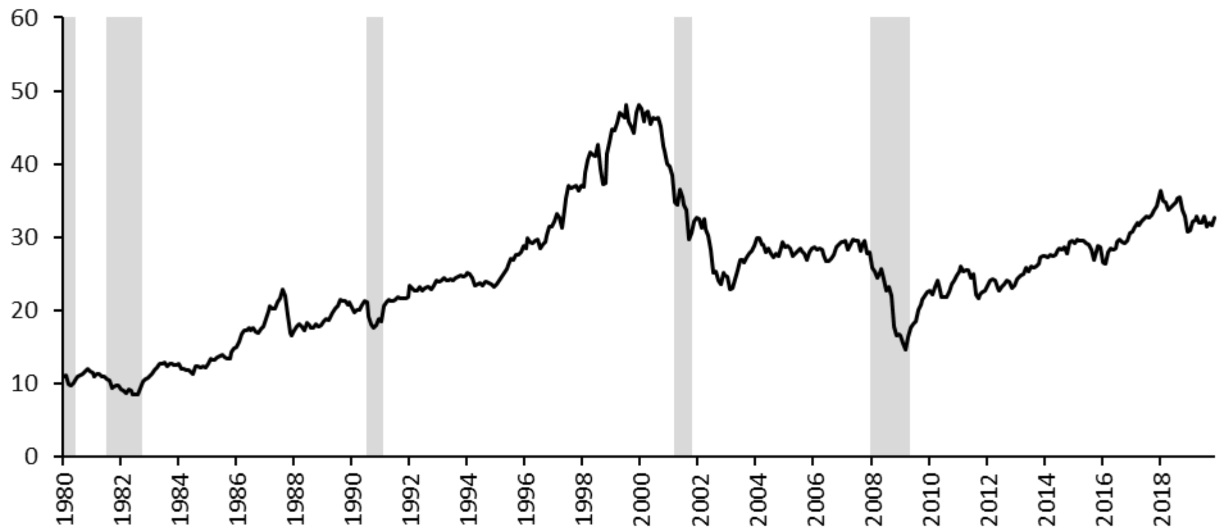
Appendix 4: NASDAQ to S&P 500 Composite Index ratio from January 1980 until December 2019

The NASDAQ Composite Index divided by the S&P 500 Composite Index over the period 1 January 1980 until 31 December 2019 is determined using daily stock prices. The shaded areas indicate recessions in the United States based on data of the National Bureau of Economic Research (NBER).



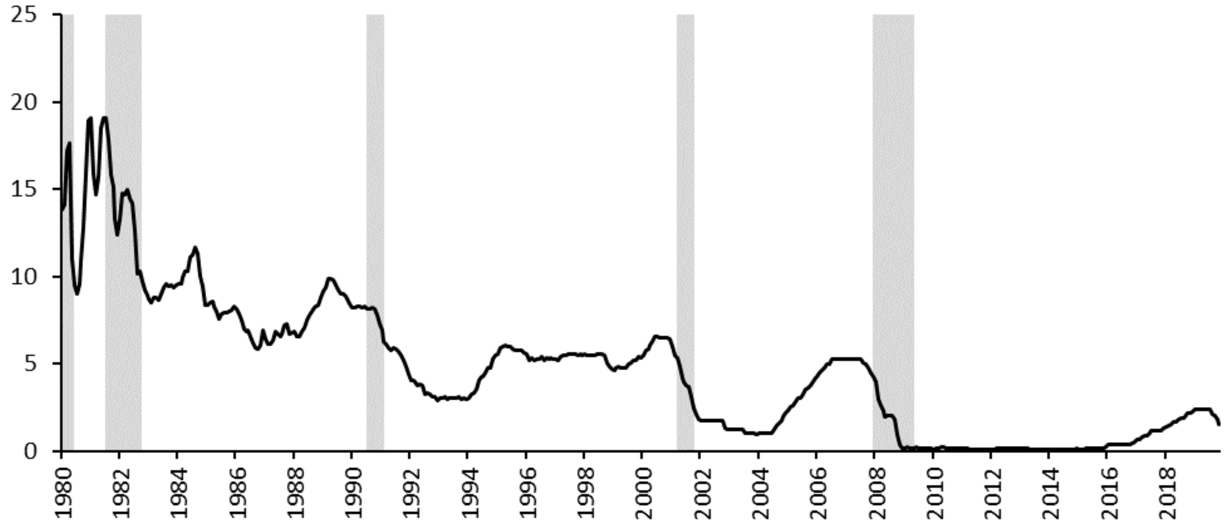
Appendix 5: Development of TR CAPE ratio from January 1980 until December 2019

TR Cape ratios represent the regular price-to-earnings ratio with two important adjustments. Instead of the earnings over the last twelve months, the average earnings over the last ten years are considered to smoothen out business cycle fluctuations. Secondly, dividends are reinvested in the price index to mitigate bias for changes in corporate payout policies. TR CAPE ratios are retrieved from the database of Shiller (2020). The shaded areas indicate recessions in the United States based on data of the National Bureau of Economic Research (NBER).



Appendix 6: Development of interest rates from January 1980 until December 2019

Interest rates are measured by the federal funds rate. The federal funds rate is the interest rate at which commercial banks and other institutions trade overnight. The rate is determined on the preceding economic conditions and therefore a common interest rate measure. Interest data is acquired from the database of the Federal Reserve Bank of St. Louis. The shaded areas indicate recessions in the United States based on data of the National Bureau of Economic Research (NBER).

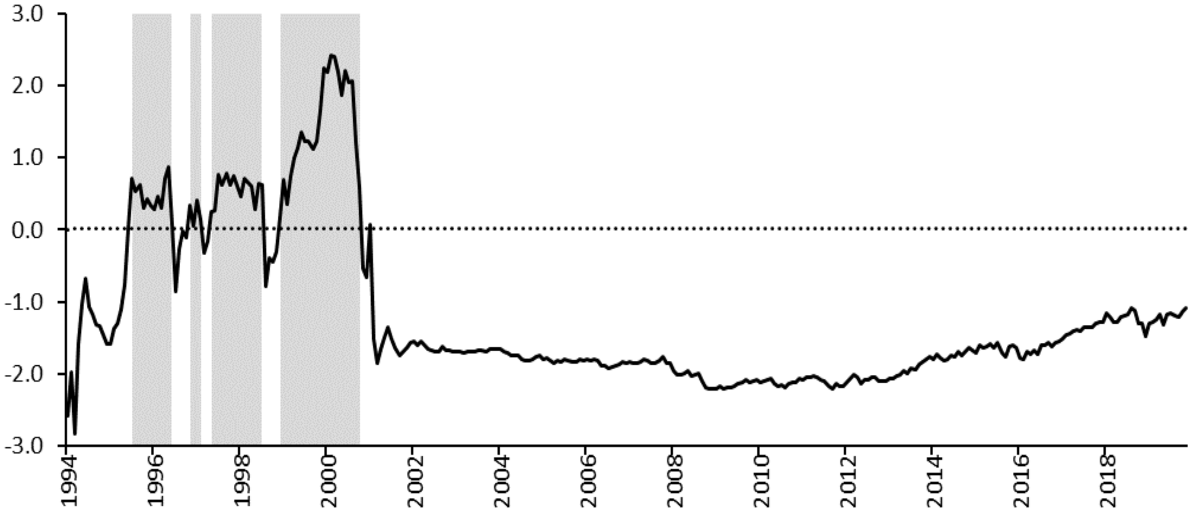


Appendix 7: Correlation matrix of the variables used in the multivariate regression

Variable		1	2	3	4	5	6	7	8	9	10	11	12
1	Underpricing	1.00											
2	Unicorn	0.30	1.00										
3	VentureCapital	0.21	0.34	1.00									
4	High-tech	0.11	0.19	0.57	1.00								
5	ln(1+Age)	-0.01	-0.18	-0.31	-0.25	1.00							
6	PurePrimary	-0.07	-0.02	0.09	0.12	-0.12	1.00						
7	Market-to-revenue	0.08	0.21	0.40	0.41	-0.49	0.19	1.00					
8	PrestigiousUnderwriter	0.12	0.16	0.08	0.08	0.05	-0.11	0.00	1.00				
9	NumberUnderwriters	0.01	0.21	-0.30	-0.21	0.24	-0.06	-0.19	0.32	1.00			
10	LaggedNASDAQ	0.09	-0.03	0.02	0.02	0.04	-0.02	-0.02	0.00	-0.05	1.00		
11	NegativePriceRevision	0.33	0.19	0.09	0.06	-0.07	-0.03	0.16	0.10	0.08	0.05	1.00	
12	PositivePriceRevision	0.41	0.24	0.08	0.05	-0.05	-0.10	0.08	0.09	0.04	0.03	0.34	1.00

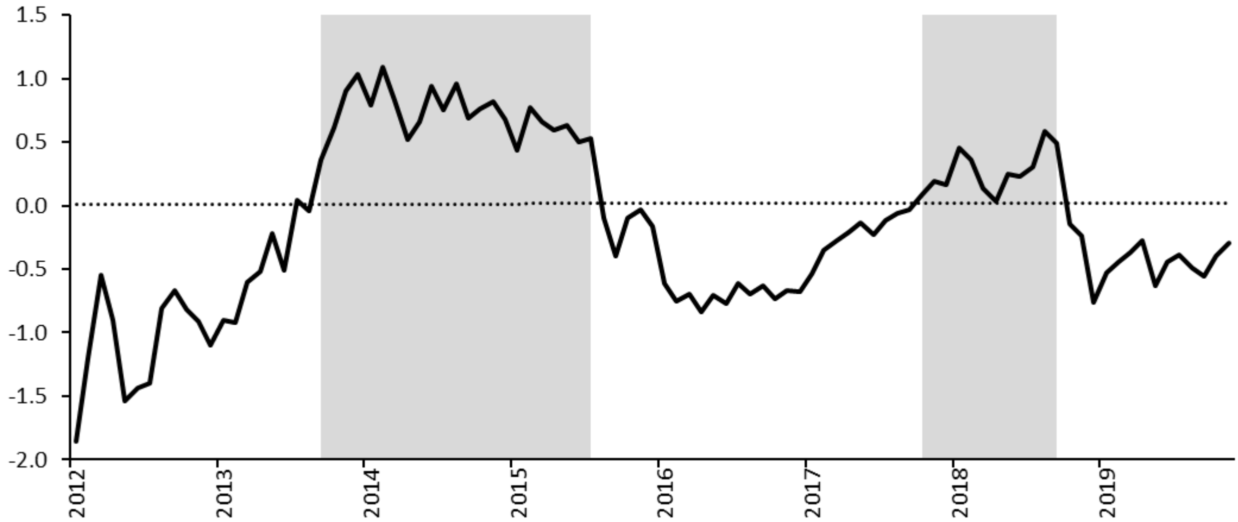
Appendix 8: Time series of the $sup_{r\in[0,1;1]}ADF_r$ test-statistic on NASDAQ Index from 1990-2019

The $sup_{r\in[0,1;1]}ADF_r$ test statistic is acquired from the right-tailed forward recursive ADF-test with January 1990 as the first observation and an initial sample size of $r \in [0,1;1]$. The test statistic is measured over the time period January 1994 until December 2019**.** The $sup_{r\in[0,1;1]}ADF_r$ test-statistic is denoted by the solid line. Critical values equal $\ln(\ln(ns))$ / 100 and are represented by the dotted line. Shading represents time periods in which the NASDAQ Composite Index experienced explosive price behavior.



Appendix 9: Time series of the $sup_{r\in[0,1;1]}ADF_r$ test-statistic on NASDAQ Index from 2010-2019

The $sup_{r\in[0,1;1]}ADF_r$ test statistic is acquired from the right-tailed forward recursive ADF-test with January 2010 as the first observation and an initial sample size of $r \in [0,1;1]$. The test statistic is measured from 2012 until December 2019. The $sup_{r\in[0,1;1]}ADF_r$ test-statistic is denoted by the solid line. Critical values equal $\ln(\ln(ns))$ / 100 and are represented by the dotted line. Shading represents time periods in which the NASDAQ Composite Index experienced explosive price behavior.



Appendix 10: Hausman test for fixed and random effects

The Hausman test examines whether fixed or random effects are more appropriate for the binary logistic regression model. The corresponding test-statistic equals 6.41, and the p-value of 0.04 indicates that the null hypothesis is rejected and fixed effects can assumed to be consistent.

	Coefficients	
	Fixed effects	**Random effects**
Trading volume	0.83	0.82
Volatility	0.63	0.63