Master Thesis

Firm age-at-IPO and the long-term performance of Internet companies

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Abstract

Since the burst of the dot-com bubble in 2000, there has been an ongoing debate around the long-term viability of Internet-specific business models. Quick IPOs with lacking profitability and high failure rates have put many investors off in the aftermath of the crisis. In this thesis, I therefore analyze how Internet companies' age-at-IPO relates to long-term stock performance. The sample consists of 116 Internet firms that went public on NASDAQ between 2003 and 2010. As predicted, I find that there is a significant U-shaped relationship between age-at-IPO and 5-year post-IPO performance. This implies that, on average, very young and old firms are most successful in the long run. The rationale for this finding is that Internet companies with quick IPOs have outstanding business models and can gain first-mover advantages, whereas older companies benefit from learning effects and already maintained a competitive advantage – even without public funding. Severe underperformance is mainly found for medium-aged Internet companies going public (age of 6 to 10 years). Furthermore, this thesis provides evidence that profitable Internet firms that have an IPO perform better in the long run than their unprofitable counterparts. Still, in contrast to most academic research, I do not find a significant relationship between profitability in the year of the IPO and long-term firm survival. A possible explanation is that most studies include the burst of the dot-com bubble and thus contain a large number of quick IPOs with high failure rates, whereas this thesis focuses on Internet IPOs in the more stable years 2003 to 2010. The findings underline the importance of first-mover advantages, especially in winner-takes-all Internet markets. Furthermore, they emphasize benefits from learning effects and the solid market position of older IPO companies. Overall, investors should carefully assess the IPO's strategic implications and treat hot markets with caution – especially in the Internet sector.

Keywords: Internet, age-at-IPO, time-to-IPO, profitability, long-term, post-IPO performance

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List of abbreviations

AMEX	American Stock Exchange
ANOVA	Analysis of variance
df	Degrees of freedom
IPO	Initial Public Offering
Log	Logarithm / Logarithmic
ln	Natural logarithm
Max.	Maximum
Min.	Minimum
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OLS	Ordinary least squares
SD	Standard deviation
SE	Standard error
SEC	Securities and Exchange Commission
SIC	Standard Industry Classification
U.S.	United States
VC	Venture Capital
WTA	Winner-Takes-All

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1. Introduction

Since the late 1990s, the Internet has been a main driver of new venture formation and worldwide economic development (Chang, 2004; Zacharakis, Shepherd & Coombs, 2003). As many Internet companies[1] offer a lot of growth potential, they attract large amounts of investments (Johnston & Madura, 2002; Zarzecki, 2010) and can ultimately achieve an initial public offering (IPO). Sometimes firms achieve an IPO despite being very young, not profitable and thus, not yet financially sustainable. The phenomenon of companies going public before achieving profitability exists especially in the Internet industry and has therefore been increasingly observed during the last two decades (Jain, Jayaraman & Kini, 2008; Lashinsky, 2006).

The IPO is generally seen as an early-performance measure for startups, especially as pre-IPO performance metrics are seldom available (Chang, 2004). But even though going public marks a milestone success for Internet ventures, it is not clear from academic literature what the relationship between firm age-at-IPO[2] and long-term stock performance are. On the one hand, Chang (2004) shows that promising startups with credibility through venture capital (VC) financing and strategic alliances attain an IPO more quickly. A quick IPO might therefore indicate a stronger business model. Following this line of argumentation implies that companies with great VC investments and low age-at-IPO have more future potential and will, on average, perform better in the long run. Furthermore, capital is needed in order to grow and to achieve long-term success (Bessler & Seim, 2012). Thus, receiving large cash injections from the equity market and using the money for further growth could also lead to a low age-at-IPO indicating better long-term performance for Internet ventures.

[1] *Internet companies* are defined in section 4.1 of this report.
[2] *(Firm) age-at-IPO* indicates the time that it takes a company from its date of legal incorporation to the IPO-date. Occasionally, I use the term *time-to-IPO* in an interchangeable manner.

On the other hand, founders and early-investors of firms are incentivized to get cash for their equity as quickly as possible (Kim & Heshmati, 2010). When the business model of the company is less promising and shows significant weaknesses to these parties with internal knowledge, the motivation for a fast payout is even greater. Thus, a fast IPO might actually signal weak long-term potential rather than a bright future for the firm. Additionally, firm age-at-IPO highly reflects the general market conditions where going public is more likely in "hot markets" (Plotnicki & Szyszka, 2014, p. 49). The burst of the dot-com bubble in 2000 has highlighted that fast IPOs – especially in the Internet industry – are often the consequence of tremendous overvaluation (Chang 2004; Jain et al., 2008; Zook, 2008).

Older companies in contrast benefit from learning effects and have proven financial viability in the market (Jain et al., 2008; van der Goot, van Giersbergen & Botman, 2009). Wagner and Cockburn (2010) find that older companies have a lower risk to fail. Overall, this might indicate that a higher firm age-at-IPO is associated with better long-run performance.

Following the above, the research question that this thesis aims to answer reads as follows:

What is the relationship between firm age-at-IPO and the long-term performance of Internet companies?

Furthermore, the overall research question is divided into three sub-questions.

1) *What is the relationship between firm age-at-IPO and the 5-year post-IPO stock performance of Internet companies?*
2) *What is the relationship between firm age-at-IPO and 5-year post-IPO survival of Internet companies?*
3) *What is the impact of profitability in the IPO-year on the long-term performance of Internet companies?*

In order to answer the above questions, a sample of 116 Internet companies that had an IPO on the NASDAQ stock exchange between 2003 and 2010 has been compiled and analyzed. The data was mainly collected from Datastream and Zephyr, two major databases providing general company and IPO-specific data. For each company in the sample, age-at-IPO has been measured as the months that passed from the date of legal incorporation until the IPO-date. To analyze the companies' performance, 5-year post-IPO excess returns have been calculated for each stock. I use the NASDAQ Composite Index[3] as the benchmark portfolio to calculate excess return. Besides excess returns, I employ 5-year post-IPO firm survival as a dependent variable. Other variables that have been retrieved for each Internet firm in the sample are profitability, revenues and number of employees in the IPO year.

This thesis consists of five parts that altogether aim at providing the reader with a coherent picture on the topic and a substantiated answer to the research question. First, I provide further theoretical background on Internet IPOs, company age-at-IPO, and the association with long-term performance and firm survival. Second, I develop several concrete, testable hypotheses on the relationship between Internet firms' age-at-IPO and the 5-year past-IPO performance based on insights from existing literature. Third, the final sample and the methodology of this study are explained. Fourth, I present the results of the statistical data analysis, which mainly consists of multivariate regression models. The last section concludes this thesis with a discussion on the final results, including theoretical contributions, managerial implications, limitations and suggestions for future research.

[3] The NASDAQ Composite Index is the market capitalization-weighted index of approximately 3,000 companies listed on the NASDAQ stock exchange.

2. Theoretical background

Ritter (1991) shows that the long-term performance of public offerings is heavily industry-dependent. Also, Ritter (1991, p. 4) illustrates that IPO underperformance is mainly "concentrated among relatively young growth companies", particularly highlighting computer and data processing companies. In line with Ritter's findings on industry-dependence, Clark (2002) reports that the relationship between age-at-IPO and aftermarket returns is significantly different for a sample of technology and non-technology firms. The author shows that young technology firms perform better, whereas for non-technology companies higher age-at-IPO is correlated with higher post-IPO stock performance (Clark, 2002). It can be assumed that the findings are even more distinct for listed Internet firms in particular as they usually attract extremely large early-stage investments and have even higher growth prospects than technology firms in general (Demers & Lewellen, 2003).

For Internet ventures, growth is a "strategic imperative", especially in so-called "winner-takes-all" (WTA) markets (Eisenmann, 2006, p. 1184). WTA markets refer to sectors where companies rely on first-mover advantages and network effects, such as the social media industry (Noe & Parker, 2005). Internet firms in these markets, e.g. Facebook and Twitter, therefore acquire large amounts of capital in order to develop quickly and to outperform competition. As acquiring financial resources for growth is of utmost importance for Internet ventures, an IPO constitutes a crucial strategic move for many of these firms (Eisenmann, 2006; Gill & Walz, 2016). Schultz and Zaman (2001) show that young IPO companies usually gain first-mover advantages and outperform competition. Furthermore, since financial information from periods previously to the IPO is usually not available, going public is generally often used as an early success measure (Chang, 2004; Kim & Heshmati, 2010).

It has been shown that Internet companies with greater VC investments and more reputable investors attain IPOs more quickly (Chang, 2004; Johnston & Madura, 2002). As venture capitalists carefully select their investments, it can be argued that the heavily funded, fast-IPO firms have better business models in general. Therefore, quick-IPO Internet stocks seem to be more likely to show greater performance in the long run. Banerjee, Güçbilmez, & Pawlina (2016) further argue that it is optimal for companies with high growth opportunities to go public as early as possible. According to Clark (2002, p. 385), "holding all else equal, the better a firm's idea, product or business model, the greater the opportunity cost of delay, and the earlier the firm will go public". He further argues that the low average age-at-IPO during the 1990s might thus be an indication for an era of "unusually promising firms" (Clark, 2002, p. 385).

The general view that the IPO event by itself denotes a success, that capital is needed for growth and that investors selected the best businesses for an IPO may lead to the assumption: *The faster the IPO, the better the company and the more successful it will be in the long run.* Even though it is intuitive, there are also several arguments opposing this assumption.

Jain et al. (2008) show that VC-financing has a negative effect on the likelihood of post-IPO profitability.[4] These findings indicate that there might be also negative implications from heavy early-stage funding for growth with regards to the long-term development of Internet firms. The crisis of 2000 serves as an illustrative example. Not only were Internet firms that went public before the burst of the dot-com bubble much younger than in previous decades (Clark, 2002), but also the percentage of unprofitable firms having an IPO rose significantly in the late 20th century (Doffou, 2014; Jain et al., 2008). This growing tendency to have a fast IPO "on the basis of a promise of profitability rather than actual profitability" can mainly be attributed to an increase in the percentage of technology companies going public, especially

[4] The result from Jain et al. (2008) might be due to the fact that the authors studied a sample from 1996 to 2000, which is strongly associated with the Internet boom and the burst of the dot-com bubble in 2000. In contrast to Jain et al. (2008), Rosenbusch et al. (2013) find that profitability is not affected by pre-IPO VC investments. Still, this also indicates that there would be no significantly *positive* impact of VC-funding on profitability.

Internet firms (Jain et al., 2008, p. 166). Rajgopal, Venkatachalam and Kotha (2000) argue that traditional accounting rules do not apply for the valuation of Internet businesses. The authors indicate that for these firms, significant market valuations usually coexist with negative accounting earnings (Rajgopal et al., 2000)[5]. Ritter and Welch (2002) show that the percentage of unprofitable firms going public rose from 19% in the 1980s to 37% during 1995-1998. Schultz and Zaman (2001) even find that only 8.72% of the Internet firms that went public between January 1999 and March 2000 were profitable in the quarter prior to the IPO. Yet this phenomenon is not specific to the dot-com bust as just a few years later the trend of being unprofitable at IPO accelerated again (Jain et al., 2008; Lashinsky, 2006).

Despite enjoying the early success of going public, unprofitable, young companies often show disappointing long-term performance after the hyped IPO (Jain et al., 2008). This is in line with Peristiani and Hong (2004) who find that pre-IPO profitability serves as a good predictor for post-IPO survival. Consequently, many of the hyped young and unprofitable Internet companies going public are likely to get into financial difficulties, as the burst of the dot-com bubble has illustrated.

The level of IPO underpricing is often used as a proxy for firm risk, with higher IPO underpricing indicating greater risk (Engelen & van Essen, 2010; Loughran & Ritter, 2004). Engelen and van Essen (2010) find additional evidence to confirm the findings of Loughran and Ritter (2004) that younger IPOs usually come with greater underpricing due to the high level of uncertainty regarding future returns. Thus, this serves as an indication that older firms, which have a longer history and more available accounting information, are less risky and more stable regarding their long-term performance (Engelen & van Essen, 2010; van der

[5] In contrast to Rajgopal et al. (2000), Bhattacharya, Demers and Joos (2010) find that accounting information is relevant for the valuation of Internet companies. Still, the authors show that there was a significant increase in IPO valuations in the years of the Internet bubble (Bhattacharya et al., 2010).

Goot, van Giersbergen & Botman, 2009). In line with this, previous studies find that going public at a later stage might be ideal because the pre-IPO learning process is very important for companies as it may reduce the chance of making "costly mistakes" (Clark, 2002, p. 385).

In accordance with the previous discussion, research on the relationship between age-at-IPO and post-IPO performance shows divergent results. Wagner and Cockburn (2010) find that older companies perform better since they have a lower risk of failure. The authors show that the chance of firm survival increases with an additional year of pre-IPO existence by roughly 3% (Wagner & Cockburn, 2010). Ritter (1991, p. 20) also analyzes the long-run performance of IPOs and finds a significant positive "monotone relation" between firm age-at-IPO and aftermarket performance. In line with the results from Ritter (1991), Clark (2002) finds that overall, there is a positive relationship between age-at-IPO and post-IPO performance, indicating that, on average, older firms show better 3-year post-IPO stock returns.

Nevertheless, when dividing the sample into non-technology and technology firms, results diverge in Clark's study. For non-technology firms, the pattern of higher age-at-IPO anticipating better performance is even more significant, whereas for the technology firms the opposite relationship occurs and younger firms perform significantly better (Clark, 2002). More recently, Andriansyah, and Messinis (2016) also find evidence for a negative association between firm age and financial post-IPO performance, especially with regards to profit margin. Banerjee, Güçbilmez, & Pawlina (2016) further show that young first-mover companies grant higher underpricing at IPO and have stronger operating performance in the long run compared to their older counterparts.

Kim and Heshmati (2010) investigate the relationship of age-at-IPO and the 3-year post-IPO performance for a set of Korean IT hardware firms. Their findings show no significant effect of age-at-IPO on post-IPO performance, but they suggest further research to be conducted with different samples and longer-term horizons (Kim & Heshmati, 2010).

Figure 1 below summarizes the major findings from past academic literature regarding the relationship between age-at-IPO and post-IPO performance.

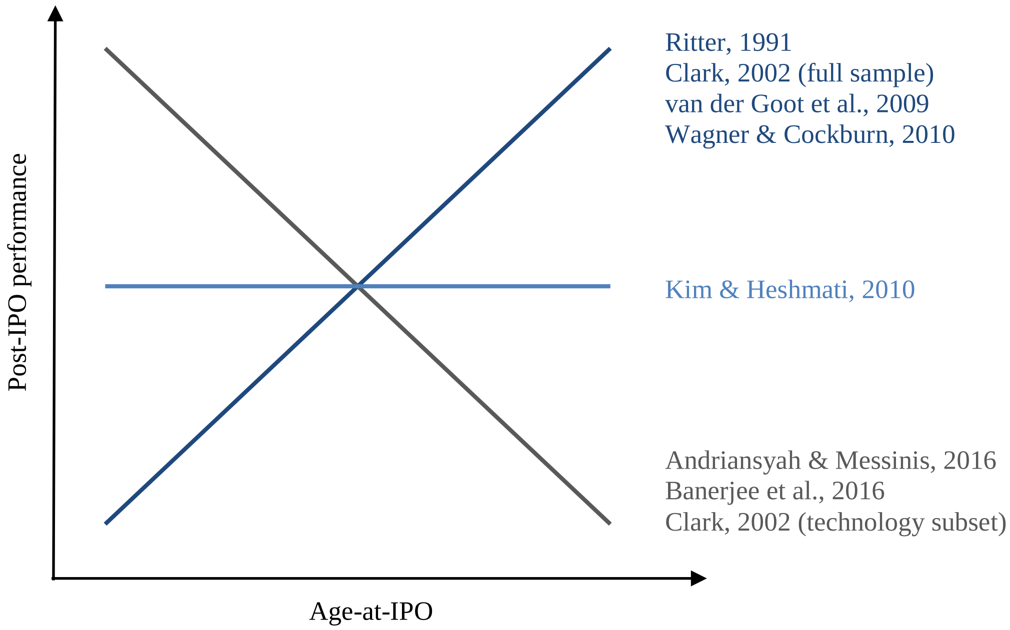

Figure 1: Relationship between age-at-IPO and post-IPO performance from literature

This thesis makes the research on the relationship between age-at-IPO and post-IPO performance not only more specific by focusing on Internet companies, but also analyzes 5-year post-IPO performance and thus has a significant long-term focus. Ritter (1991) studies the long-run performance of IPOs by investigating only 3-year post-IPO performance. He shows that the third year leads to the overall significant underperformance of IPOs, whereas the first two years do not show significant results. Also, Ritter (1991, p. 5) presents evidence from previous research that suggests “positive performance in the fifth year” after the public offering. Therefore, investigating five years can add additional insights when analyzing the long-term performance of tech-IPOs.

Concerning the time range of Internet IPOs, Bessler and Seim (2012, p. 216) argue to study a period from 1996 to 2010 as this includes two “IPO waves and stock market cycles”. Still, the authors present empirical evidence for the existence of major differences between the “new economy period”, which describes the years 1996 to 2003, and the following period (Bessler

& Seim, 2012, p. 231). To illustrate these differences, figure 2 shows the total number of Internet IPOs in the U.S. per year for the time period from 1992 to 2013 (data source: Ritter, 2016).[6]

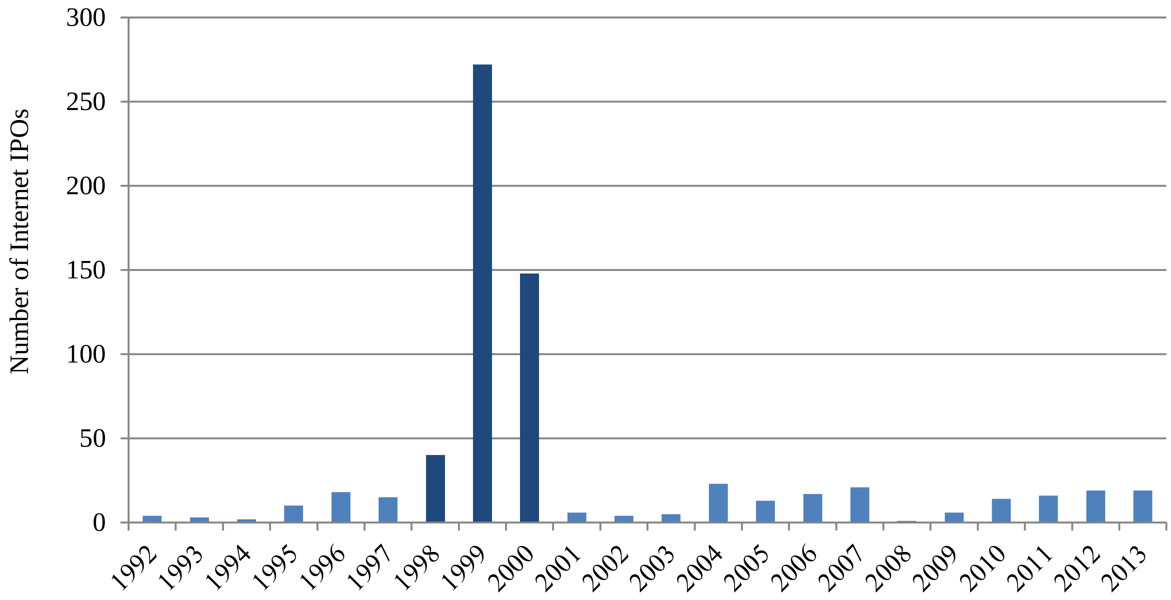

Figure 2: Number of Internet IPOs per year, 1992-2013

The chart clearly shows that the years 1998 to 2000 (highlighted in the figure) are not representative with a total number of 460 Internet IPOs – 153.33 per year on average. Between 2003 and 2010, in contrast, there were 14.5 Internet IPOs per year on average. Also, due to the hype from 1998 to 2000, dot-com IPOs happened extremely fast and companies were very young in this period (Zacharakis et al., 2003). Additionally, the percentage of unprofitable companies that went public based on uncertain growth expectations and the accompanying high failure rate were much more significant in the years of the dot-com crisis (Jain et al., 2008; Lashinsky, 2006).

Because of these major differences, I exclude these years from the analysis, as this would

[6] Appendix A shows an overview of the annual number of U.S. IPOs from 1992 to 2013 across industries and highlights Internet IPOs for comparison. It becomes clear that the proportion of Internet companies going public was much higher in the years of the dot-com bubble (1998-2000) and fell significantly afterwards.

give a distorted picture on the association between Internet companies' age-at-IPO and post-IPO performance. Not only the years until the burst of the dot-com bubble in 2000 are excluded, but also the two following years 2001 and 2002, since the crisis aftermath was highly affected by investor restraint and general skepticism towards Internet ventures (Bessler & Seim, 2012). Furthermore, the Internet sector and many business models around it were still pre-mature and investor understanding was often not well developed (Zook, 2008). Starting in 2003 therefore gives a more representative sample to analyze the research question at hand.

Overall, the IPO of a venture constitutes an important strategic move (Gill & Walz, 2016) and lays the foundation for following decisions and future financial performance. Still, there is a research gap in the academic literature on the relationship between age-at-IPO and the long-term performance of Internet companies. This thesis aims at closing that research gap.

3. Hypotheses development

In this section, I will develop testable hypotheses in order to answer the research question with substantiated evidence. The hypotheses are based on arguments from existing academic literature that are briefly summarized and related to the more specific context of Internet companies.

3.1 Age-at-IPO and 5-year post-IPO stock performance

As I have shown in section 2, the findings from academic literature on the relationship between age-at-IPO and long-term performance diverge significantly.

Most research shows that overall, older IPO firms perform better in the years after the public offering (Clark, 2002; Ritter, 1991; van der Goot et al., 2009; Wagner & Cockburn, 2010). The pre-IPO learning process associated with refining the business model as described by

Clark (2002) is one major reason why older firms perform better on average. Also, older companies have already shown that they can survive in the market and that they have a viable business model. Current examples from the Internet sector are Airbnb, Uber, and Spotify – three companies that have market leadership and already went through several rounds of large-scale VC-funding (Basulto, 2015; Braithwaite, 2016). Still, it seems like they are waiting for the strategically optimal timing for their IPO in order to avoid costly mistakes. For example, in the case of Uber, there are still legal issues in some countries with regards to the firm's service offering. Clarifying these elements prior to an IPO will increase certainty around the business model and give the firm the opportunity of a higher valuation (Basulto, 2015). Overall, these companies already have a competitive advantage even without the cash injection from the capital market. Also, founders and early-investors seem to be comfortable with waiting for payout as they have trust in the long-term viability of their business model associated with recurring positive cash flows. In general, it can therefore be expected that a higher age-at-IPO is associated with better post-IPO performance for Internet companies.

Still, there are also important findings with regards to young IPO companies. For a subset of technology firms, Clark (2002) finds that firm age-at-IPO is negatively associated with 3-year post-IPO performance. As Internet companies clearly fall into this sector, the findings from Clark are of significant importance for this study. The rationale behind quick IPO companies being most successful is that the opportunity costs of a delay would be too high if the business model and the growth opportunities are promising (Banerjee et al., 2016; Clark, 2002). Andriansyah and Messinis (2016) emphasize this rationale by showing that firm age is negatively associated with long-term financial performance, taking into account several financial performance indicators like profit margin. Banerjee et al. (2016) also document that IPO first-movers have higher investments, more growth and enhanced profitability after the public offering. As significant first-mover advantages are found (Schultz & Zaman, 2001), it can be assumed that these are even more prominent in the Internet sector that is often associated with so-called winner-takes-all (WTA) markets (Eisenmann, 2006; Noe & Parker, 2005). In WTA markets, network effects and first-mover advantages often leave one company with a monopoly position, as observed e.g. in the search engine market. Thus, there is also evidence to argue for young companies having better financial performance in the long run after an IPO.

Internet firms with a medium age-at-IPO may likely stand for the phenomenon of making the decision to go public depend more on general market conditions than on internal strategic choices. In other words, they might represent the willingness of investors to maximize returns during "hot market conditions" (Plotnicki & Szyszka, 2014, p. 49). Wagner and Cockburn (2010) find that companies going public in phases of enormous market valuations in the high-tech sector have significantly lower long-term performance and a higher chance of failure.

In general, young Internet IPO companies perform very well due to their high-potential business models, first-mover advantages and investment capacities for growth. Companies with high age-at-IPO perform very well on average due to their proven business models and the already existing competitive advantage. Medium-aged companies are sometimes "stuck in the middle" and tend to go public mainly based on the general market conditions and pressure from investors. This line of argumentation goes well with Kim & Heshmati (2010) who do not find a significant *linear* association between age-at-IPO and post-IPO performance.

Following the above, I hypothesize:

H1: The relationship between Internet companies' age-at-IPO and the 5-year post-IPO stock performance is U-shaped. On average, Internet companies with low and high age-at-IPO perform better in the long run.

3.2 Age-at-IPO and 5-year post-IPO survival

As shown before, Internet companies stand for high growth prospects and quick IPOs. Yet, they also are noted for higher risk and great failures as represented mainly by the burst of the dot-com bubble in April 2000 (Zook, 2008). Therefore, I do not only analyze long-term performance based on 5-year stock returns, but also on post-IPO firm survival. In case that a company was delisted due to negative reasons (bankruptcy or ceased operations), I will use the term *exit* to indicate non-survival (Hensler et al., 1997; Park & Steensma, 2012)[7].

Ritter (1991) explains that initial returns[8] are higher for young IPO-firms due to the higher risk that they inhibit. Other authors validate the findings from Ritter and show a significant negative relationship between firm age and IPO underpricing (Engelen & van Essen, 2010; Loughran & Ritter, 2004). Age-at-IPO therefore constitutes a viable "proxy for risk" (Ritter, 1991, p. 20). Similarly, Johnston and Madura (2002) find that initial returns are higher for Internet companies than for non-Internet IPOs. The authors show that Internet IPOs involve higher risk and that underwriters therefore could be "forced to allow for additional underpricing at the time of issue" (Johnston & Madura, 2002, p. 526). This goes in line with Ritter's explanation and underlines the high risk of fast Internet IPOs more specifically. Despite positive initial returns, the young firms in Ritter's sample show not only worse long-term stock performance, but also a much higher bankruptcy rate. Clark (2002) describes similar findings. Even though Clark (2002) shows that young technology firms perform better than their older counterparts on average, his results also indicate higher distressed delisting rates for young companies. In particular, the author presents significant evidence that *young* tech-companies are "more likely to suffer extreme financial difficulty" (Clark, 2002, p. 386).

[7] The only reasons for delisting that do not indicate failures are mergers and moving to another exchange, e.g. from NASDAQ to NYSE or to AMEX (Hensler et al., 1997).

[8] *Initial returns* refer to the stock returns on the first day of trading.

Other authors also find that increasing firm age lowers the risk of bankruptcy after a public offering (Hensler, Rutherford & Springer, 1997). Hensler et al. (1997) further indicate that the chance of survival is reduced significantly if the respective company is in the computer and data industry.

The reason for the lower risk of older firms is twofold. First, older companies are more steady and mature. Thus, they inhibit less uncertainty about the future performance (van der Goot et al., 2009). Second, with a longer history, managers of more mature businesses can easily reduce information asymmetry before the IPO (van der Goot et al., 2009), which is highly important from an investor perspective.

Following the evidence from existing literature on the relationship between age-at-IPO and post-IPO firm survival for companies in general and for technology firms in particular, I hypothesize the following:

H2: There is a positive relationship between age-at-IPO and 5-year post-IPO survival for Internet companies.

3.3 Profitability in the IPO year and post-IPO performance

Jain et al. (2008) state that there is a general trend for companies to go public without having achieved profitability. The authors attribute this tendency to have an IPO "on the basis of a promise of profitability" mainly to the growing number of technology firms going public (Jain et al., 2008, p. 166). Especially Internet companies in WTA markets are often valued based on growth prospects and not on the basis of existing positive cash flows (Doffou, 2014; Lashinsky, 2006). Nonetheless, profitability serves as an important indicator of the long-term viability and financial performance of a business (Jain et al., 2008). Therefore, I hypothesize:

H3: There is a positive relationship between profitability in the year of the IPO and the 5-year post-IPO stock performance for Internet companies.

Overall, investors often underestimate the risk of unprofitability at IPO, overestimate the expected growth potential and many high-risk Internet ventures are doomed to fail (Jain et al., 2008; Peristiani & Hong, 2004). According to Peristiani & Hong (2004, p. 1) pre-issue profitability is highly correlated with aftermarket firm survival. As this holds true for firms in general, I assume that profitability in the IPO-year is highly relevant for higher-risk Internet ventures. Consequently, I hypothesize that profitable Internet firms going public are significantly more likely to survive than those with negative net income.

H4: There is a positive relationship between Internet firm profitability in the IPO year and the likelihood of 5-year post-IPO survival.

Furthermore, the relationship between age-at-IPO and post-IPO firm survival, as predicted in hypothesis H2, is likely to be impacted by the profitability in the year of the IPO. Very young Internet companies that are already profitable might be more likely to survive post-IPO than young firms that are not profitable. Therefore, I hypothesize that a moderation effect of profitability on this relationship exists.

H5: Profitability in the IPO year has a moderating effect on the relationship between age-at-IPO and 5-year post-IPO survival of Internet companies, with greater profitability decreasing the strength of this relationship.

4. Data and methodology

In this section, I will describe the data that has been used for this study as well as the applied methodology. First, I will shed light on the classification of Internet companies as used for this study. This is of great importance since a universal definition and categorization of Internet firms does not exist. Second, I will describe the sample of this study and the data collection procedure. Third, the dependent variables and the explanatory variables are introduced and explained. In section 4.5, I will introduce the control variables used for this study. In the last section of this part, I describe the empirical approach of this thesis.

4.1 Classification of Internet companies

The unit of analysis in this study is *Internet companies*. Even though the term is widely used, Zook (2008) recognizes that it cannot be applied only to one specific business model or sector. Therefore, Zook (2008, p. 6) broadly describes Internet companies as "fast-growing companies which use the Internet as an integral part of their business model". Hand (2000) also uses a general description and simply investigates a set of firms that would not have been established without the existence of the Internet. For the purpose of this thesis, I define an Internet company as a firm that receives more than 50% of its revenues due to the existence of the Internet (Bhattacharya et al., 2010; Demers & Lewellen, 2003). In case of doubt, I further apply the broader definitions by Zook (2010) and Hand (2000).

Since there is no Standard Industrial Classification (SIC) code for Internet companies (Bhattacharya et al., 2010; Demers & Lewellen, 2003), I have consulted different sources in order to come up with a sound dataset. First, I used various keywords like "Internet", "dot-com", "online" and "e-commerce" on siccodes.com to retrieve a list of SIC codes that include Internet-specific companies. Some of the major code categories are 737 (Computer programming, data Processing, and other computer related services), 4812 (Radiotelephone communications), 4899 (Communication services – not elsewhere classified), 8999 (Services – not elsewhere classified) and 52-59 (Retail trade). Second, I retrieved the relevant data on companies with the identified SIC codes from Datastream and Zephyr. Third, I enriched the dataset with a list of Internet IPOs between 1990 and 2013 from Ritter (2016) that can be downloaded in Excel format on the website of the Warrington College of Business Administration. Fourth, I went through the preliminary dataset and checked companies where

I had doubt on matching the definitions for Internet companies by Demers and Lewellen (2003) and Zook (2008). For many companies such as Alphabet (formerly Google), it was clear that they belong to the dataset of Internet companies. When I was unsure about the classification based on company name and SIC code, I went to the short business profile on nasdaq.com to judge whether could be defined as Internet companies or not. Here, I applied the broad definitions stated earlier. If there were further doubts, I searched for information on the company website and reviewed SEC filings. This procedure does not only guarantee for a highly relevant dataset of Internet companies, but also gave me a better understanding of the sample. Table 1 shows an overview of the sample distribution in terms of simplified industry segments. Most Internet companies have the SIC code 737 (Computer Programming, Data Processing, and Other Computer Related Services), accounting for 58.62% of the final sample.

Table 1: Sample distribution in simplified industry segments

SIC code	Description	Total	Percentage
27	Printing, Publishing, and Allied Industries	1	0.86%
35; 36; 38	Electronics	9	7.76%
47	Transportation Services	3	2.59%
48	Communications	6	5.17%
55; 59	Retail	7	6.03%
60; 62; 64	Finance	7	6.03%
73	Business Services	79	68.10%
736	*Personnel Supply Services*	*1*	*0.86%*
737	*Computer Programming, Data Processing, and other Computer Related Services*	*68*	*58.62%*
738	*Miscellaneous Business Services*	*10*	*8.62%*
80	Health Services	1	0.86%
82	Educational Services	3	2.59%
	TOTAL	116	100%

Some remarkable exceptions to the general classification schema exist. For example, Cimpress (went public as Vistaprint in 2005) has the SIC code 2750, which stands for *Commercial Printing*. Still, according to the definitions applied, the company must be considered an Internet company. The firm profile on nasdaq.com includes the following:

> "… We seek to offer compelling value to our customers through an innovative use of technology, a broad selection of customized printed products, low pricing and personalized customer service. Through our use of proprietary **Internet-based** graphic design software, 16 localized **websites**, proprietary order receiving and processing technologies and advanced computer integrated printing facilities, we offer a meaningful economic advantage relative to traditional graphic design and printing methods. …"

The company's strategy of providing services via Internet-based software, which is key to its value proposition and brings the majority of revenues, clearly makes it an Internet firm.

4.2 Sample and data collection

The final sample consists of 116 Internet companies (as defined and selected in the previous section) with IPOs on NASDAQ between 2003 and 2010.[9] NASDAQ was chosen as the stock exchange for the sample since it hosts the vast majority of technology-IPOs worldwide (Clark, 2002) and because data on stocks, as well as on a benchmark index can be obtained in a reliable manner. The data for the final sample was retrieved from Datastream and Zephyr, which are two major business and IPO databases. Further information was collected from the listing information on nasdaq.com, from the technology database crunchbase.com and from SEC filings like annual reports.

Most importantly, the final dataset includes SIC code, companies' date of legal incorporation, IPO date, and total revenues, net income and number of employees in the IPO year. It also contains monthly closing stock prices for the five years after going public. From all this information, age-at-IPO and 5-year post-IPO stock returns are calculated.

In the 5-year post-IPO performance analysis, it occurs that companies get delisted from the NASDAQ stock exchange. A delisting might occur for different reasons. Some of these reasons, like bankruptcy, denote failure events, whereas others such as mergers can have

[9] An overview of the final sample can be seen in Appendix B.

different implications (Hensler et al., 1997). Out of the 116 Internet companies going public on NASDAQ between 2003 and 2010, 34 were delisted in the five years after the IPO. From these 34 companies, 24 were delisted due to mergers or moving to the NYSE. The remaining 10 companies were delisted for negative reasons, which are bankruptcy and ceased operations (Hensler et al., 1997). All the 34 companies that were delisted are still included in the sample. The stock price return from the month of listing until delisting is then carried forward to the end of the 60th month (end of the 5-year period) and used for the subsequent analysis.

4.3 Dependent variables

Excess log return

As suggested by Ritter (1991), I use stock returns as a proxy for the 5-year post-IPO performance. In particular, I employ the variable *Excess log return* as a dependent variable in linear regression models. Therefore, I first calculate logarithmic stock returns after 60 months, $r_{i,t=60}$, for each individual stock in the sample as shown in equation 1.

$$r_{i,t=60} = \ln\left(\frac{p_{i,t=60}}{p_{i,t=0}}\right) - 1 \tag{1}$$

I use logarithmic returns in order to obtain a (close to) normally distributed dataset since general holding period returns have large outliers (e.g. maximum of 937% return for Baidu Inc.). These outliers are only found for positive returns since the minimum possible holding period return is -100%. The use of the natural logarithm basically treats returns as cumulative stock returns over time.

Next, I calculate excess returns, er_i, as suggested by Clark (2002) and Ritter (1991). This ensures that the influence of general market swings is minimized. Excess returns are calculated as the excess return of each stock, $r_{i,t=60}$, compared to the return of a benchmark portfolio, $r_{b,t=60}$.[10] The benchmark portfolio that I chose for the purpose of this study is the NASDAQ Composite Index, which is the market capitalization-weighted index of all companies listed on the NASDAQ stock exchange[11]. The benchmark portfolio's return was calculated in the same way as the individual stock returns (equation 2).

$$r_{b,t=60} = \ln\left(\frac{p_{b,t=60}}{p_{b,t=0}}\right) - 1 \tag{2}$$

Then, for each stock, the representing 5-year period benchmark return was subtracted in order to get the excess stock return (equation 3).

$$er_{i,t=60} = r_{i,t=60} - r_{b,t=60} \tag{3}$$

Survival

The long-term performance of companies is often measured by post-IPO firm survival (Hensler et al., 1997; Banerjee et al., 2007). This variable is binary, meaning that it can either have the value 0 or 1. For the purpose of this study, 1 denotes firm *survival* and 0 denotes *exit* within the five years after the initial offering. Throughout this thesis, *exit* stands for a firm turning *defunct*, which According to Park and Steensma (2012) describes a delisting due to negative reasons, i.e. bankruptcy and ceased operations. Only 10 companies in the final sample had an exit within the 5-year post-IPO period (8.62%).

4.4 Explanatory variables

Age-at-IPO

The time that it takes an Internet company from date of incorporation until the IPO is the primary explanatory variable in this study. I measure this variable in months. Figure 3 shows

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[10] Excess returns are typically calculated through market models (e.g. CAPM) to account for companies' betas (MacKinlay, 1997). According to Ritter (1991), post-IPO firms' betas to respective indexes do usually not have significant economic effects on the outcomes. Therefore, I determine excess returns without adjusting for betas.

[11] The monthly 5-year returns of the NASDAQ Composite Index (01/2008 - 12/2015) are shown in Appendix C.

that the data on age-at-IPO in this dataset is highly skewed to the right. The observations on the far right (age > 15 years) represent older companies that adapted their business strategy only after the appearance of the Internet. Thus, in their years of incorporation (before 1990) they would not have been Internet companies. Only later, these firms created product lines and services based on the web, which let them grow and attain an IPO. Nevertheless, these firms are defined as Internet companies since the majority of their revenue is made due to the Internet. As the data is skewed to the right, I decide to reduce the influence of older companies by conducting the analyses with two different age-at-IPO variables.

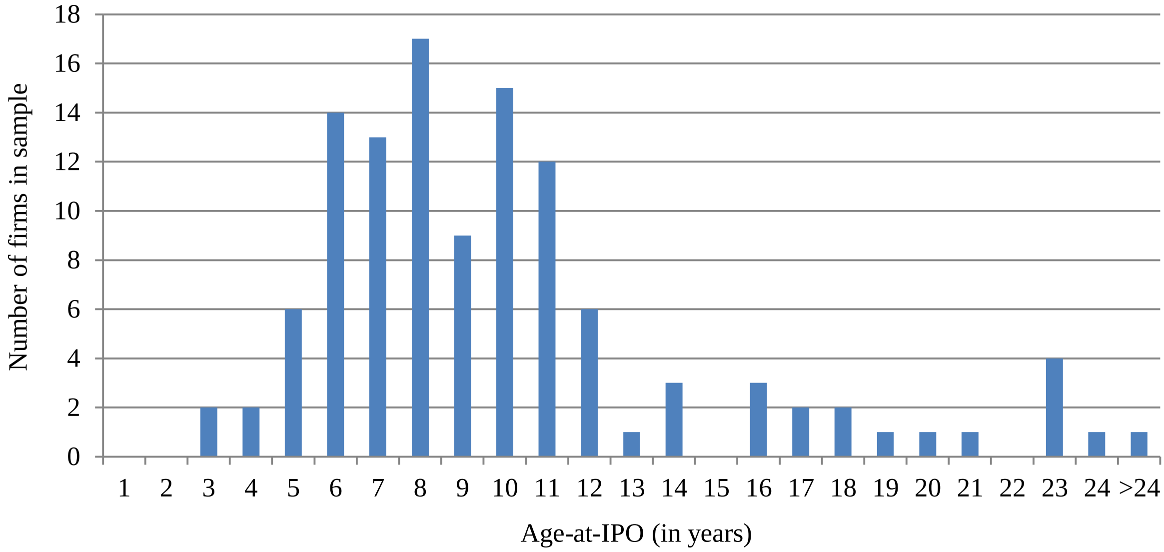

Figure 3: Distribution of the dataset in terms of age-at-IPO

First, I take the natural logarithm of the age-at-IPO variable. The log-transformation of the variable standardizes the distribution and erases the influence of existing outliers. Second, I make a breakdown of the sample in terms of quintiles with regards to the age-at-IPO as applied by Clark (2002).[12] Thus, five age-at-IPO groups are compared based on average 5-year post-IPO excess log returns (see table 2). The youngest quintile has a maximum age-at-IPO of 71 months (6 years), whereas firms in the oldest quintile are at least 138 months (11.5

[12] I applied the breakdown of companies into quintiles in SPSS through the function “Rank Cases”.

years) old. The medium quintile has an age-at-IPO-range of 94 to 112 months.

Table 2: Age-at-IPO quintiles

Quintile	Age-at-IPO (in months)	Number of firms
1	28-71	22
2	72-92	24
3	93-112	23
4	113-137	24
5	138-317	23
	TOTAL	116

Profit margin

Several authors describe a significant impact of firm profitability on the long-run performance of listed companies (Jain et al., 2008; Peristiani & Hong, 2004). Therefore, I assume that the profit margin in the year of the IPO is positively associated with long-term post-IPO firm performance (H3) and post-IPO firm survival (H4). Furthermore, since I assume that the relationship between age-at-IPO and post-IPO survival is impacted by a firm's profitability, I use the variable *Profit margin* as a moderating variable in hypothesis H5. It is hypothesized that profitability decreases the strength of the relationship in a sense that younger firms, which are profitable are more likely to survive, whereas older firms with less profitability are more likely to fail.

For each firm in the sample, I retrieve profits in the year of the IPO as well as revenues. Through this, the variable *Profit margin* is calculated and used in the subsequent analysis. The profit margins of firms in the sample do not have severe outliers and the data is not skewed. Due to the relatively normal distribution, I do not standardize this variable. In order to investigate the moderating effect of profitability, I create an interaction variable by multiplying profit margin in the IPO year with the independent variable age-at-IPO.

4.5 Control variables

Hensler et al. (1997) show that large IPOs have a better position in the market and a stronger base of resources than smaller IPOs in order to prosper despite bad investments or declining market valuations. Size is thus positively associated with companies' post-IPO performance, in particular with post-IPO survival (Hensler et al., 1997). Ritter (1991) also finds that smaller firms have worse aftermarket performance.

In order to reduce the influence of firm size on the long-run performance of Internet IPOs, I control for firm size in this study. The two control variables that I use for this purpose are revenues in the year of the IPO (*Revenues*) and number of employees in the year of the IPO (*Employees*).

4.6 Empirical approach

This thesis focuses on the quantitative analysis of collected secondary data. In order to investigate the hypothesized relationships, I construct several regression models and analyze them. The two dependent variables used in this study are different variable types. *Excess log return*, which is used as a proxy for 5-year post-IPO performance is a continuous variable, whereas *Survival* (5-year post-IPO firm survival*)* is a binary variable. For the continuous variable *Excess log return*, I use ordinary least squares (OLS) regression models (H1 & H3). First, I analyze the U-shaped relationship between age-at-IPO and the post-IPO performance as predicted in hypothesis H1. Second, I investigate the hypothesized positive association between profitability and post-IPO performance (H3). The significance of the regression models is tested mainly by looking at the overall F-statistic and through looking at the significance of the predictors' coefficients.

Since the second dependent variable *Survival* is either 0 (exit) or 1 (survival), a binary logistic regression model has to be applied. Binary logistic regression makes it possible to analyze how well predictor variables explain a dependent variable that is categorical (Pallant, 2013). It further indicates how adequate the model is by “assessing goodness of fit” (Pallant, 2013, p. 171). Pallant (2013) explains that in logistic regression, the distribution of the explanatory variables is not important, but that these models are sensitive to multicollinearity, which arises when high correlations between predictors exists. Since outliers might influence the results of binary logistic regression (Pallant, 2013), it is important to apply the normalization procedures for the explanatory variable age-at-IPO as discussed in section 4.4 of this thesis.

Besides the regression models, I will compare the age-at-IPO quintiles based on their average post-IPO performance and the rate of firm survival within each group. For a proper analysis of the quintiles, I conduct a one-way analysis of variance and a chi-square test.

All of the analyses in this thesis have been conducted with the statistics computer software IBM SPSS 24.

5. Results

In this part of the thesis, I am presenting the results of the empirical analysis that has been conducted as described previously. First, I show the descriptive statistics for the sample. Second, I present the results of linear regression models against the dependent variable *Excess log return*, which is used as a proxy for 5-year post-IPO performance. Third, the results for binary logistic regression models against the dependent variable *Survival* are highlighted. Fourth, I analyze the age-at-IPO quintiles based on their respective excess log returns and survival rates. In section 5.5, I will discuss several robustness tests in order to increase the strengths of the outcomes from previous analyses.

5.1 Descriptive statistics

Table 3 shows the summary statistics of the final sample. The median age-at-IPO is 102 months, which translates to 8.5 years. Nevertheless, the mean age-at-IPO is 115.53 months (9.6 years). The mean is significantly higher than the median due to the fact that the data is skewed to the right as presented in section 4.4. This emphasizes the importance of standardizing age-at-IPO and creating age-at-IPO quintiles from the dataset. The same phenonemon as for age-at-IPO can also be observed for the excess returns: the data has severe outliers on the right part of the data. The median excess return is only -13%, whereas the mean is 18%.

Table 3: Summary statistics

Variable	Description	N	Mean	Median	SD	Min.	Max.
Age-at-IPO	In months	116	115.53	102	58.19	28	317
Age-at-IPO log	Natural logarithm of Age-at-IPO	116	4.64	4.62	0.46	3.33	5.76
Excess return	5-year post-IPO excess return	116	0.18	-0.13	1.49	-2.18	9.36
Excess log return	Natural logarithm of excess return	116	-0.43	-0.14	1.46	-6.76	2.33
Survival	1 if survival, 0 if exit; 5-year post IPO	116	0.91	1	0.28	0	1
Employees	Number of employees; In year of IPO	116	567.76	325	697.02	14	4,400
Revenues	In year of IPO; in 000s	116	214,407	91,405	538,072	813	3,947,105
Profit	In year of IPO; in 000s	116	12,915.69	4,532.50	58,578.53	-135,169	399,119
Profit margin	In year of IPO	116	0.02	0.05	0.28	-1.07	0.77

The minimum and maximum values for *Employees* and *Revenues* in the year of the initial public offering show that there are big differences in the sample with regards to company size. The smallest company in terms of employees just employed 14 people (software company Copsync), whereas the largest already counted 4,400 employees when going public (travel platform Expedia). In terms of revenues, the smallest company in the sample had sales of less than one million U.S. dollars (advertising platform Sito Mobile), wheres the largest made almost four billion U.S. dollars in revenues in the IPO year (travel platform MakeMyTrip). The vast differences in the sample are further highlighted by the large standard deviations for these two variables (697.02 for employees; 538,072 for revenues).

Correlations between the variables used in this thesis can be seen in the correlation matrix of table 4. The two explanatory variables of this study, *Age-at-IPO (log)* and *Profit margin* are not significantly correlated with each other, so that multicollinearity is not a problem (Pallant, 2013). For control variables – in this thesis *Employees* and *Revenues* – multicollinearity is generally not an issue (Pallant, 2013). Naturally, the variables *Age-at-IPO* and *Excess return* are highly correlated with their own natural logarithms.

The dependent variables *Excess log return* and *Survival* are correlated significantly at the 1% confidence level with a correlation coefficient of 0.695. This is intuitive as both are measures of long-term corporate performance. It also confirms the logic behind including the two variables in this study to identify different aspects of Internet firms' sustainable development.

Table 4: Correlation matrix

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Age-at-IPO	1.000								
(2)	Age-at-IPO log	0.949**	1.000							
(3)	Excess return	0.078	0.027	1.000						
(4)	Excess log return	0.125	0.057	0.710**	1.000					
(5)	Survival	0.111	0.074	0.276**	0.695**	1.000				
(6)	Employees	0.203*	0.198*	0.125	0.171	0.160	1.000			
(7)	Revenues	0.094	0.120	0.041	0.057	0.087	0.395**	1.000		
(8)	Profit	0.002	0.000	0.107	0.125	0.078	0.299**	0.584**	1.000	
(9)	Profit margin	0.017	-0.01	0.109	0.150	0.004	0.092	0.045	0.110	1.000

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

5.2 Linear regression

In this section, I will employ linear regression models in order to assess the hypothesized U-shaped relationship between age-at-IPO and the 5-year post-IPO stock performance (H1). Additionally, I will analyze whether a positive association between profitability in the year of the IPO and long-term stock returns exists as predicted in hypothesis H3. Table 5 provides an overview of the results from linear regression models with the dependent variable *Excess log return.*

Table 5: Results of linear regression models

Dependent variable: Excess log return

Variable	Model 1A	Model 2A	Model 3A	Model 4A	Model 5A	Model 6A
Constant	-0.884***	-0.989	0.173	20.081**	-0.622***	16.769*
	(0.307)	(1.396)	(0.666)	(8.883)	(0.171)	(8.883)
Age-at-IPO	0.002		-0.014			
	(0.002)		(0.010)			
Age-at-IPO²			0.005*			
			(0.000)			
Age-at-IPO log		0.078		-9.023**		-7.666**
		(0.303)		(3.803)		(3.798)
Age-at-IPO log²				0.974**		0.837**
				(0.406)		(0.405)
Profit margin					1.151**	1.027**
					(0.479)	(0.483)
Employees	0.001*	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Revenues	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	116	116	116	116	116	116
R-squared	0.038	0.030	0.065	0.078	0.077	0.114
df	2	2	3	3	2	4
F-statistic	1.467	1.147	1.915	2.338	3.111	2.834
P-value	0.227	0.333	0.113	0.060	0.029	0.019

Standard errors in parentheses
*** Significant at the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

First, I test for a linear relationship between *Age-at-IPO* and *Excess log returns*. Model 1A and 2A include only the control variables *Employees* and *Revenues*, as well as an age-at-IPO variable as predictor (Model 1A: *Age-at-IPO*; Model 2A: *Age-at-IPO log*). In both of these two models, there is no significant relationship between age-at-IPO and post-IPO performance, as indicated by statistically insignificant coefficients for the age-at-IPO variables. Overall, models 1A and 2A also show very low F-statistics (1.467 and 1.147) and high p-values (0.227 and 0.333). Thus, these two models do not indicate a significant positive or negative linear association between age-at-IPO and post-IPO performance for Internet companies.

Next, I test for a U-shaped relationship between age-at-IPO and post-IPO excess returns as predicted in hypothesis H1. Therefore, I include a squared term of the age-at-IPO variables in the models 3A and 4A. Model 3A includes age-at-IPO in months and an age-at-IPO squared term. The overall model is not statistically significant (F-statistic = 1.915, $p > 0.10$), but the squared predictor variable (ß = 0.005, $p < 0.10$) is significant at the 90% confidence level. Even though the overall log-linear model is not statistically significant, interestingly the two independent variables go into the direction of a U-shape, with the linear term being negative and the squared term being slightly positive.

This U-shaped relationship is much more apparent and statistically significant in the log-log model 4A, which uses the natural logarithm of age-at-IPO and its squared term as predictor variables. In this model, the coefficients of both independent variables are significant at the 0.05 level. The linear age-at-IPO log variable is negative (ß = -9.023, $p < 0.05$), whereas the quadratic variable is positive (ß = 0.974, $p < 0.05$). Therefore, a U-shaped relationship between firm age-at-IPO and post-IPO stock performance exists for Internet companies as predicted in hypothesis H1. The graphical output from SPSS in figure 4 illustrates this relationship.

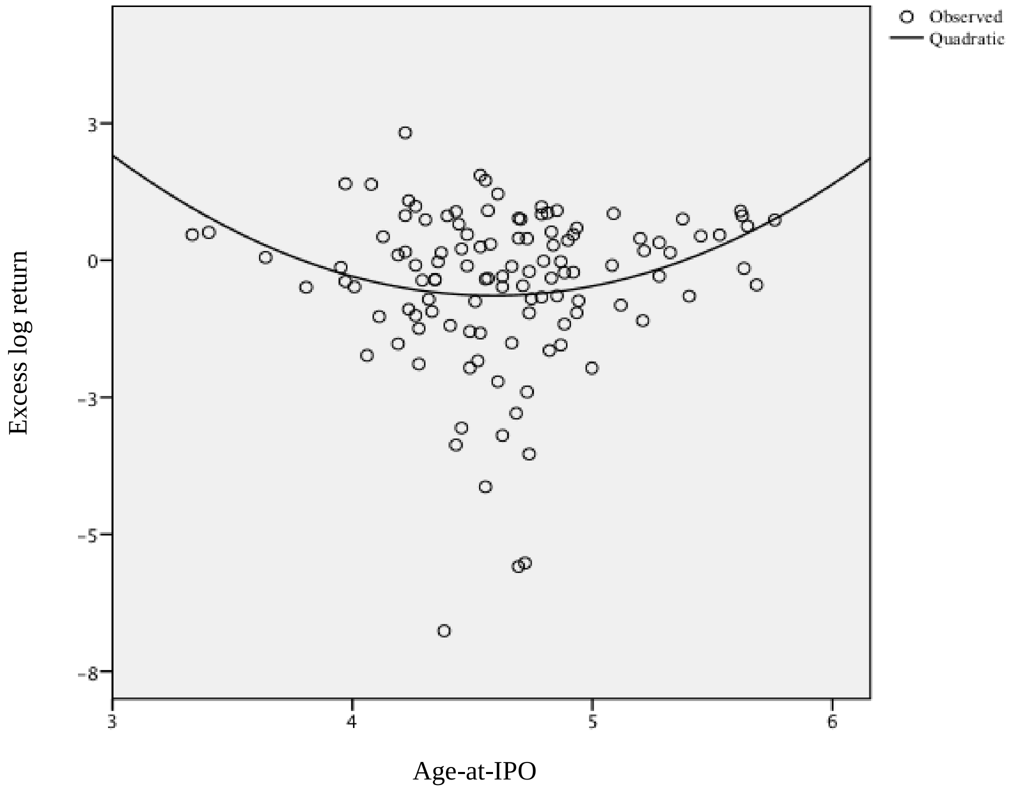

Figure 4: U-shaped relationship between age-at-IPO and excess returns

The equation of regression model 4A that describes the U-shaped relationship between *Age-at-IPO log* and *Excess log return* is shown below.[13]

$$Excess\_log\_return = 20.081 - 9.023 * Age\_at\_IPO\_log + 0.974 * Age\_at\_IPO\_log^2 \quad (4)$$

The negative coefficient of the linear age-at-IPO term makes the regression line downward sloping initially. By setting the first derivative of the equation equal to zero, I find that the minimum of the slope is at *Age-at-IPO log* of 4.63 (approximately 102 months/ 8.5 years).[14] The representing expected excess log return at this point is -81.6%. After the minimum point, the curve is upward sloping, indicating that firms older than 8.5 years, on average, start

[13] This formula does not include the control variables, but as their coefficients are very close to zero and statistically insignificant, I omit them in the equation.

[14] The first derivative of the equation gives the slope of the curve: $\frac{d_y}{d_x} = -9.023 + 1.948x$. Setting the derivative equal to 0 give the minimum point of the curve, which is at $x = 4.63193$.

performing better again. Other expected values for excess log returns from regression model 4A can be obtained from table 6 below. The table also shows conversions of the values for age-at-IPO log into the original age-at-IPO values given in months.

Table 6: Expected excess log returns from regression model 4A

Age-at-IPO log	3.25	3.50	3.75	4.00	4.25	4.50	4.75	5.00	5.25	5.50	5.75	6.00
Age-at-IPO	25.8	33.1	42.5	54.6	70.1	90.0	115.6	148.4	190.6	244.7	314.2	403.4
Excess log return	**1.04**	**0.43**	**-0.06**	**-0.43**	**-0.67**	**-0.80**	**-0.80**	**-0.68**	**-0.44**	**-0.08**	**0.40**	**1.01**

Model 4A has an overall p-value of 0.06 (F-statistic = 2.338) and an R-squared of 7.8%. Even though the individual regression coefficients are statistically significant at the 0.05 level, the overall model is only significant at the 0.10 level (p = 0.06).

The relationship between profitability in the year of the IPO and the 5-year post-IPO performance of Internet companies is investigated with log-linear model 5A. As predicted in hypothesis H3, I find a significant positive relationship between profit margin in the year of the IPO and 5-year post-IPO excess returns. The regression coefficient of the independent variable *Profit margin* has a value of 1.151 (SE = 0.479) and is statistically significant ($p < 0.05$). Thus, holding all else equal, a 1% increase in profit margin is associated with a 1.151% increase in excess log returns.[15] Also, model 5A is significant with an F-statistic of 3.111 (2 degrees of freedom) and a p-value of 0.029. The model is not only significant, but also has a relatively high R-squared of 7.7%.

Model 6A combines models 4A and 5A and thus includes three independent variables: *Age-at-IPO log*, *Age-at-IPO log squared* and *Profit margin*. All of these variables are significant at the 95% confidence level, which provides evidence for hypothesis H1 and hypothesis H3.

[15] To calculate the exact change in the non-log-transformed dependent for a one-unit change in the independent variable in log-linear models, one needs to calculate $e^{ß}$ (Benoit, 2011). To calculate the 1% change, the formula is $e^{0.01*ß}$. Thus, when *Profit margin* increases by 1%, holding all else equal, *Excess return* increases by 1.158%.

Model 6A shows the highest significance of all models (p = 0.019) and has the highest value for goodness of fit with an R-squared of 11.4%. This means that the independent variables in model 6A explain 11.4% of the variability in the dependent variable *Excess log return*.[16]

Surprisingly, none of the control variables in the model is highly significant, which means that firm size does not relate to post-IPO performance in the Internet sector. This is contrasting past research on firms in general (Hensler et al., 1997). Regarding *Employees* this finding is intuitive since Internet companies are generally less asset-heavy, including human resources (Not & Parker, 2005). The result concerning *Revenues* could indicate that for Internet firms, post-IPO growth is more important than pre-IPO sales (Eisenmann, 2006).

Overall, the results of the linear regression analyses provide evidence that there is a U-shaped relationship between firm age-at-IPO and the 5-year post-IPO performance of Internet companies. Therefore, Hypothesis H1 is supported. Furthermore, I find that Internet firms' profit margins in the year of the IPO are positively associated with the 5-year post-IPO performance. Thus, hypothesis H3 is also supported.

5.3 Binary logistic regression

I use binary logistic regression models in order to assess the hypothesized relationship between the independent variables *Age-at-IPO* (hypothesis H2) and *Profit margin* (hypothesis H4) and the binary dependent variable *Survival*. Furthermore, the hypothesized moderation effect of *Profit margin* (hypothesis H5) on the relationship between age-at-IPO and Internet firm survival is tested. Table 6 provides an overview of the results from six different binary logistic regression models.

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[16] This study does not aim at predicting the dependent variable, but rather it aims at explaining the relationship between independent and dependent variables. Thus, the R-squared is not my primary focus when analyzing the models. Nevertheless, a high R-square is still desirable and indicates that the independent variables are useful to explain the variation in the dependent variable (Pallant, 2013).

Table 7: Results of binary logistic regression models

Dependent variable: Survival

	Model 1B	Model 2B	Model 3B	Model 4B	Model 5B	Model 6B
Constant	0.239	-0.002	16.572*	1.012	0.366	0.200
	(1.086)	(4.142)	(9.243)	(0.680)	(1.131)	(1.156)
Age-at-IPO	0.006		-0.336*		0.007	0.008
	(0.009)		(0.194)		(0.009)	(0.009)
Age-at-IPO²			0.002*			
			(0.001)			
Age-at-IPO log		0.181				
		(0.900)				
Profit margin				1.112	1.132	6.550
				(1.050)	(1.033)	(5.432)
Profit margin*Age-at-IPO						-0.059
						(0.058)
Employees	0.003	0.003	0.004	0.003	0.003	0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Revenues	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	116	116	116	116	116	116
Log Likelihood	58.703	59.154	51.818	58.051	57.476	56.203
Cox & Snell R-squared	0.078	0.074	0.131	0.083	0.088	0.098
Nagelkerke R-squared	0.176	0.168	0.295	0.187	0.198	0.220
Omnibus Tests of Model Coefficients	9.429	8.979	16.314	10.081	10.656	11.929
P-value	0.024	0.030	0.003	0.018	0.031	0.036
Hosmer and Lemeshow Test	7.740	18.090	4.441	7.321	2.839	4.470
P-value	0.459	0.021	0.815	0.502	0.944	0.812

Standard errors in parentheses
*** Significant at the 0.01 level
** Significant at the 0.05 level
* Significant at the 0.10 level

Model 1B and 2B investigate whether a linear relationship between age-at-IPO and 5-year post-IPO survival exists for Internet companies. Both models pass the *Omnibus Tests of Model Coefficients* ($p < 0.05$), indicating the overall goodness of fit for the model (Pallant, 2013). Nevertheless, the *Hosmer and Lemeshow Test* does not support model 2B.[17] When looking at the regression coefficients of model 1B and 2B, it becomes apparent that none of

[17] The Hosmer-Lemeshow Goodness of Fit Test indicates poor fit of the model when it is significant ($p < 0.05$), whereas the Omnibus Tests are significant when the model fits well (Pallant, 2013).

the independent variables in the model are significant. Thus, a linear relationship between age-at-IPO and 5-year post-IPO firm survival does not exist for the sample. Consequently, hypothesis H2 is not supported.

Model 3B adds a quadratic age-at-IPO term to model 1B to test for a U-shaped relationship between *Age-at-IPO* and *Survival*. This follows from the evidence found for the dependent variable *Excess log return* (hypothesis H1) that was tested with the linear regression model 1A. In fact, model 3B shows improvements with the independent variables being significant at the 0.10 level. The regression coefficient of the linear age-at-IPO term is negative (ß = -0.336, $p < 0.10$), whereas the squared age-at-IPO term is positive (ß = 0.002, $p < 0.10$). Model 3B has a highly significant result for the Omnibus Tests ($p = 0.003$) and insignificance for the Hosmer-Lemeshow test ($p = 0.815$). The *Cox & Snell* and *Nagelkerke R-squared* values indicate that between 13.1% and 29.5% of the variability in post-IPO firm survival is explained by the model, which is the highest range of all binary regression models that I conducted.

Overall, the findings indicate that rather than the predicted negative linear relationship between age-at-IPO and post-IPO survival, there is a U-shaped relationship with Internet firms in the medium age-at-IPO range being most likely to fail. This is contradicting the academic literature, where most authors find evidence that age-at-IPO is associated positively with aftermarket survival (Engelen & van Essen, 2010; Loughran & Ritter, 2004). The upward-sloping part of the U-shape is thus easily explained through previous studies. Still, the authors stated explicitly that young firms are more likely to fail since they inhibit a higher risk (Engelen & van Essen, 2010; Loughran & Ritter, 2004; Ritter, 1991). Nevertheless, past research does not focus on Internet companies in particular. As discussed previously, many Internet firms are part of winner-takes-all markets where being a first-mover on the stock market actually increases the chances of survival (Engelmann, 2006; Noe & Parker, 2005).

Model 4B assesses the relationship between the independent variable *Profit margin* and the dependent variable *Survival*. Hypothesis H4 predicts that a positive relationship exists, which would imply that firms with higher profitability in the IPO year are more likely to survive in the long term. Even though the variable's regression coefficient is positive, it is not statistically significant (ß = 1.112, $p > 0.05$). Also in model 5B, *profit margin* is not significant (ß = 1.132, $p > 0.05$). Consequently, hypothesis H4 is not supported.

Model 6B tests for a moderation effect of *Profit margin* on the relationship between *Age-at-IPO* and *Survival.* Therefore, the interaction variable *Profit margin*Age-at-IPO* is added to model 5B. The coefficient for Age-at-IPO in this model is 0.008, which means that for every additional month of age-at-IPO, the likelihood of survival increases by 0.8%. The coefficient of the interaction variable is negative (-0.059), which would indicate that profitability decreases the strength of the relationship between *Age-at-IPO* and *Survival* as predicted. Nevertheless, none of the coefficients in this model are significant and thus, there is no evidence for a moderation effect. Therefore, insufficient support is found for hypothesis H5.

As in the linear regression models of section 5.2, the control variables are not significant for any of the models. This further suggests that for Internet companies, size in the year of the IPO is not associated significantly with post-IPO performance, in particular firm survival.

5.4 Quintile analysis

In order to validate previous findings, I conduct an analysis of age-at-IPO quintiles as suggested by Clark (2002). Table 5 shows that the youngest quintile (28-71 months) and the oldest quintile at IPO (138-317 months) have the best post-IPO performance overall with average excess returns of 68.39% and 37.06% respectively. Firms in the second quintile (72-92 months) have the lowest average stock performance in the five years after going public with an average 5-year post-IPO excess return of -29.16%.

When looking at the average excess log returns in table 5, which are used as the primary measure of long-term performance in this study, the same pattern is evident. Quintile 1 and 2 have the highest average excess log returns with 8.63% and -0.18% respectively. On the opposite side, quintiles 3 and 4 show the worst performance with -93.03% and -90.19% average excess log returns. The average excess log return of quintile 3 (-90.19%) is much lower relatively to its average excess return (15.02%). As period holding returns of individual stocks can have a minimum value of -100%, whereas there is no theoretical maximum, average excess returns are highly influenced by large positive returns above 100%. Through the log-transformation of excess returns, the magnitude of companies with very good performance is decreased and more emphasis is on firms that perform badly (Hudson & Gregoriou, 2015). Evidently, in the third quintile, there are more firms with negative holding period returns than in other quintiles, which makes the log-transformed values worse.[18]

Table 8: Long-term performance of age-at-IPO quintiles

Quintile	Number of firms	Age-at-IPO (in months)	Average excess return	Average excess log return	Number of firms surviving	Percentage of firms surviving
1	22	28-71	68.39%	8.63%	21	95.45%
2	24	72-92	-29.16%	-93.03%	20	83.33%
3	23	93-112	15.02%	-90.19%	20	86.96%
4	24	113-137	5.27%	-36.29%	22	91.67%
5	23	138-317	37.06%	-0.18%	23	100%
TOTAL	116	115.53	18.35%	-43.04%	106	91.34%

These findings confirm the evidence presented from linear regression models and they are in line with hypothesis H1, which predicts a U-shaped relationship between age-at-IPO and the post-IPO performance. Figure 4 illustrates this relationship.

[18] For a detailed overview of observations for age-at-IPO and excess log returns see the scatterplots in Appendix D and E. Low average excess log returns of firms with an age of 80 to 120 months stand out in Appendix D.

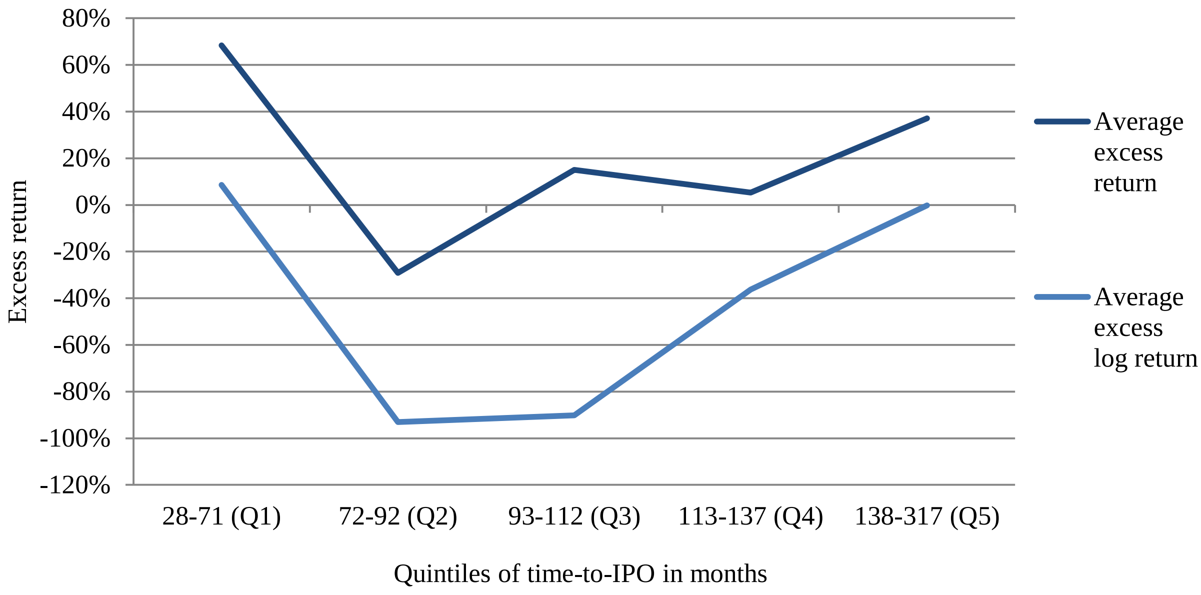

Figure 5: Excess (log) return per quintile of age-at-IPO

Furthermore, I conducted a one-way analysis of variance (ANOVA)[19] in order to analyze whether the differences between the five groups with respect to *average excess log returns* are statistically significant. Overall, the analysis shows that the groups differ significantly at the 0.05 level.[20] Levene's test for homogeneity of variances, which assesses if the variance in scores is equal for each group, shows a significance level of 0.001 (Pallant, 2013). This means that the homogeneity of variance assumption is violated (Pallant, 2013). Therefore, I consult the *Robust Tests of Equality of Means* as suggested by Pallant (2013).[21] Both, the Welch and the Brown-Forsythe test are significant at the 0.05 level. Thus, I find sufficient evidence that the quintile groups' means differ significantly with respect to the variable average excess log returns.

[19] A one-way ANOVA is used in order to investigate whether more than two groups differ significantly with regards to their mean scores of a continuous dependent variable. The test compares the variance *between* the groups to the variance *within* each group. An F-statistic is calculated through dividing the total variance between the groups by the total variance within the groups. Thus, the larger the F-statistic, the more variance exists between the different groups as caused by the independent variable (Pallant, 2013).

[20] Detailed results of the ANOVA can be seen in Appendix F.

[21] The two Robust Tests of Equality of Means, *Welch* and *Brown-Forsythe*, should be used when the assumption of the homogeneity of variance is violated (Pallant, 2013).

In order to find out which particular quintiles differ significantly, I conducted the post-hoc tests *Tukey Honestly Significant Difference* (HSD) and *Fisher's Least Significant Difference* (LSD). Tukey HSD does not show any significant differences between the groups. But Fisher's LSD indicates that there are significant differences between quintiles 1 and 2/3, and quintiles 5 and 2/3. This provides evidence that the above-average performance of Internet firms in the youngest and the oldest quintile is significant and that companies with average age-at-IPO in quintile 2 and 3 perform significantly worse.

The quintile groups do not only differ in terms of average excess (log) returns, but also show different percentages of firms surviving the five years after going public (see table 7). As explained by the binary logistic regression model 3B in section 5.3, firms in the medium age ranges have the lowest survival rate. In the oldest quintile (age-at-IPO > 137 months) all firms survive, which is in line with past academic literature. Several authors present evidence that older firms that go public are less risky and have a lower chance of failure (Engelen & van Essen, 2010; Loughran & Ritter, 2004; Ritter, 1991). Nevertheless, authors have also highlighted that young companies inhibit a higher risk and are thus more likely to exit in the long run (Clark, 2002; Engelen & van Essen, 2010). In the sample of this study, only one of the Internet firms that were younger than 72 months (6 years) at the initial offering did not survive the 5-year post-IPO period.

In order to analyze whether the differences between the quintiles with regards to post-IPO firm survival are statistically significant, I use a *Chi-square test for independence*.[22] The Chi-square test statistic shows a value of 5.180 with 4 degrees of freedom.[23] This test statistic results in a p-value of 0.269, which means that the differences between the groups are not

[22] The Chi-square test for independence is used when the relationship between two categorical variables is explored. The test compares the observed frequencies in each category to the values that are expected if there would be no relationship between the variables under investigation (Pallant, 2013).

[23] The SPSS outputs of the Chi-square test can be seen in Appendix G.

statistically significant. Furthermore, the criterion of expected values higher than 5 (Pallant, 2013) is not fulfilled. This is due to the overall low number of companies that do not survive. Due to the failed criterion of values greater than 5, I also consult the more precise alternative test, *Fisher's Exact Test,* which is also highly insignificant (Pallant, 2013).[24]

Overall, the analysis of age-at-IPO quintiles underlines previous findings: Internet companies with low age-at-IPO and those with high age-at-IPO perform better in the long run. Internet firms that need 72 to 112 months (6 to 9.33 years) from date of incorporation until initial public offering show the worst average post-IPO performance. When looking at the long-term survival of Internet companies, no statistically significant conclusions can be drawn.

5.5 Robustness tests

Throughout the data analysis, I have applied several measures to ensure robust results and validated findings. I used logarithmic stock returns and the natural logarithm of age-at-IPO in order to standardize the data and to exclude outliers. Furthermore, I tested several different regression models and presented the results of each model. Still, further robustness tests have been conducted.

As discussed in section 4.1, Internet companies are not easily classified. Companies that were actually founded before the existence of the Internet can only be considered as such after they started providing new additional services and products or by readjusting their business model. This might influence the results of this study since the true nature of some companies might not be represented by the original date of incorporation. Therefore, I exclude all companies from the sample that were founded before the 1990s, as this was the century when the Internet started to be used in the commercial space (Chang, 2004; Zacharakis et al., 2003).

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[24] Fisher's Exact Test has to be used when the Chi-square test does not meet the criterion of (at least 80%) expected values above 5 (Pallant, 2013).

In fact, ten companies in the sample were incorporated before 1990 and are consequently excluded in this linear regression. Again, as in section 5.2, I use *Excess log return* as the dependent and *Age-at-IPO*, as well as its squared term, as independent variables. The model is still significant, but the predictor variables are now only significant at the 0.10 level. This indicates that these very mature companies that adjusted their business models after the rise of the Internet have significant influence on the results. Still, a U-shaped relationship between age-at-IPO and post-IPO performance exists since the regression coefficients are slightly significant.

The scatterplot in Appendix E shows three negative outliers with excess log returns of more than -500%. As these outliers are part of the medium-aged Internet companies, I exclude them from the analysis to observe whether they affect the results. The linear regression without the excluded firms still indicates a significant U-shaped relationship between age-at-IPO and post-IPO excess log returns. The model is significant at the 0.10 level and the regression coefficients of *Age-at-IPO log* and its squared term are significant at the 0.05 level. Thus, I provide further evidence that a U-shaped relationship between age-at-IPO and post-IPO performance exists for Internet firms. Table 8 summarizes the results of this thesis.

Table 9: Summary of results

Hypothesis	Dependent variable	Explanatory variables	Test	Outcome
H1	Excess log returns	Age-at-IPO (log)	Linear regression	Supported
		Age-at-IPO (Quintiles)	Analysis of variance	Supported
H2	Survival	Age-at-IPO (log)	Binary logistic regression	Not supported
		Age-at-IPO (Quintiles)	Chi-square of independence	Not supported
H3	Excess log returns	Profit margin	Linear regression	Supported
H4	Survival	Profit margin	Binary logistic regression	Not supported
H5	Survival	Age-at-IPO & Profit margin (mediation)	Binary logistic regression	Not supported

6. Discussion

In this final chapter of the thesis, I will summarize the main findings, compare them to the proposed hypotheses and relate the results to both, academic literature and business practice. First, I give an overview of the theoretical contributions of this study. Second, practical implications are presented. Third, I outline several limitations of this thesis and make suggestions for future research. The last section concludes this study.

6.1 Theoretical contributions

Academic scholars have found contradicting evidence regarding the relationship between age-at-IPO and the long-term performance of companies. Some authors find that older companies that go public perform better in the long run and are less likely to fail (Ritter, 1991; van der Goot et al., 2009; Wagner & Cockburn, 2010). Others do not find significant results (Kim & Heshmati, 2010), whereas some even find that there is a negative relationship between firm time-to-IPO and post-IPO performance (Andriansyah & Messinis, 2016; Banerjee et al., 2016; Clark, 2002). This thesis adds to the existing research by providing insights on Internet IPOs in the post-dot-com-bubble period from 2003 to 2010.

For these particular firms an alternative view, contrasting previous research, is offered regarding the relationship between firm age-at-IPO and post-IPO performance. I find evidence for a U-shaped relationship, which indicates that very young companies and older companies show the best performance in the five years after the IPO. Thus, I provide an alternative to past research. Still, my findings incorporate many elements of existing theories. Mainly, young companies in the Internet sector (age-at-IPO < 6 years) that achieve an IPO gain can finance further growth and attain a competitive position in the market. Furthermore, common WTA Internet markets often leave first-movers with a long-term competitive advantage and even monopoly positions. Older Internet companies (age-at-IPO > 10 years) benefit from learning effects and have already maintained a competitive market position previously even without being publicly funded. A possible explanation for the overall underperformance of medium-aged Internet companies that go public (approximately 6-10 years) is that they are neither the outstanding first-movers, nor the solid incumbents with a lasting competitive advantage. Often, the management of these firms might either wait for the market to provide higher valuations or they push the company to market quicker than strategically rational because of pressure from impatient investors and founders.

Further, in line with past research, I find that profitability in the year of the IPO is positively associated with 5-year post-IPO performance. Even though Internet businesses have a lot of growth potential, traditional accounting measures should not be neglected, which is in line with Bhattacharya et al. (2010). Profitability is a sign for the long-term viability of a business. Thus it makes intuitive sense that a positive relationship with long-term performance exists.

Surprisingly, there is no significant relationship found between age-at-IPO/ profitability and the long-term survival of Internet companies. This contrasts existing research that provides evidence for a positive relationship between firm age-at-IPO and survival (Engelen & van Essen, 2010; Loughran & Ritter, 2004; Ritter, 1991). One reason is the overall low number of exits in the sample. Furthermore, after the dot-com bust, investors were skeptical and the Internet sector has become more mature. This led to a careful selection of IPOs and emasculated the over-ambitious growth expectations that existed during the years of the bubble. Thus, this study adds to the existing literature on Internet companies and makes the discussion more recent.

Overall, surprisingly little research has been conducted so far regarding the relationship between firm age-at-IPO and post-IPO performance. Even though several authors (Banerjee et al., 2016; Clark, 2002; Kim & Heshmati, 2010; Ritter, 1991; Wagner & Cockburn, 2010) investigated the effect of age-at-IPO on post-IPO performance, they did so for firms in general. By focusing on Internet ventures, this research adds significant value, particularly because Internet companies have distinguishing characteristics, such as enormous growth potential and great volatility (Johnston & Madura, 2002). So far, studies on the relationship between firm age-at-IPO and aftermarket performance looked at 3-year post-IPO performance (Clark, 2002; Kim and Heshmati, 2010), whereas this research investigates a time horizon of five years after going public. Thus, the long-term focus of this study allows for more insights on the relationship between age-at-IPO and performance. This is very interesting in the relatively young domain of Internet ventures. The long-term viability of Internet business models is an often-debated topic and besides growth, a sustainable performance is more and more in the focus of attention. Thus, this research contributes significantly to the discussions around the sustainability of Internet ventures.

6.2 Practical implications

This thesis sets the focus of managers and investors towards the long-term implications of Internet IPOs. As Gill & Walz (2016, p. 357) argue, "going public is one of the most important corporate governance decisions in a firm's lifetime". It is therefore a key strategic decision that does not only provide a company with funds, but also comes with liabilities such as more detailed reporting and the influence of institutional investors. This is especially important in the Internet sector, where oftentimes hype and general market conditions have determined the actions of companies and investors.

In general, the finding that both young and old Internet IPOs are most successful on average makes a concrete investment recommendation challenging. Nevertheless, it becomes obvious that what matters is how the Internet company is strategically positioned in the market. Investors should therefore carefully analyze the conditions in the respective market niche instead of throwing money at companies during hot IPO markets. It might be that an old company with low external investments proves financial sustainability for a long time in a niche market. Through an initial public offering it could extend its position and gain further stakes in related markets. Very young companies on the other hand might present less risk to investors than usually assumed. When a young Internet firm is a first-mover and has the chance to dominate a WTA market for example, it might be a great target for investments and the risk of failure might be actually low.

The enormous scalability that comes with the World Wide Web and the existence of WTA markets made growth the Holy Grail for Internet firms. Still, other measures of corporate performance should be equally relevant to investors in this sector. The significant relationship between profitability and post-IPO performance, which was found in this study, indicates that Internet companies need to show signs of long-term financial viability in order to prosper. Profitability certainly is one of those signs (Jain et al., 2008). In the long-term, a company should make profits and provide returns to its shareholders. This can only happen if it generates positive cash flows from operations in the long term.

6.3 Limitations and future research

Even though, I have conducted a robust empirical study, several limitations have to be revealed. First, I simply carried forward the last stock prices of companies that had a delisting during the five years after the IPO. Thus, it happens that for some companies, only two years of true performance are obtained. This might affect the results slightly, especially since general market conditions are heavily influencing the stock prices of Internet firms.

Furthermore, I did not control explicitly for hot market conditions and crises, which would be an important measure to test the reasons for underperformance of medium-aged Internet IPOs. The only way that I account for market conditions, such as the 2008 financial crisis, is by calculating excess returns above the market index.

One of the main arguments for the, on average, superior performance of young companies is the existence of winner-takes-all (WTA) Internet markets where only one firm attains a competitive advantage. Nevertheless, I do not analyze the markets of all firms in the sample in order to validate this reasoning further. Future studies should thus review the respective markets of the firms in the sample to investigate the effect of WTA markets on the superior performance of quick Internet IPOs.

The lack of significant findings for the dependent variable *Survival* is partially due to the fact that only 10 out of the 116 companies in the sample had an exit, which equals 8.6%. Thus, the prediction of firm survival through the constructed regression models is not better than predicting that all companies would survive. Taking a larger sample might therefore be helpful in order to investigate this relationship meaningfully. Including companies from the New York Stock Exchange or even exchanges from other countries are examples of valid options to enlarge the sample.

Even though it is evident that firm size might impact the post-IPO performance, it has to be noted that the control variables number of employees and revenues, which I use in all regression models, are not significant. This is surprising and it might be wise to include another control variable in future studies. For example, the amount of venture capital investments prior to the IPO might be an interesting indicator for Internet firms that future research should take into account.

Last, Internet companies are still broadly defined in this thesis. Since Internet-based business models can be vastly distinct, it is interesting to separate future samples into different kinds of Internet firms, e.g. e-commerce, social media, advertising and software infrastructure. All these types have very different characteristics, e.g. regarding first-mover advantages and network effects. A distinction between business-to-consumer and business-to-business Internet firms might also add value.

6.4 Conclusion

This thesis provides evidence for a U-shaped relationship between age-at-IPO and 5-year post-IPO stock performance for Internet companies. This implies that Internet firms with low age-at-IPO and high age-at-IPO perform better in the long run than their medium-aged counterparts. Older companies that go public mainly benefit from learning effects and already have a solid positioning in the market even though they were not publicly funded yet. This is in line with most research that suggests that age-at-IPO is positively associated with long-term stock performance. The main explanation for young companies performing well is that they can grow quickly with the acquired cash from an IPO and attain first-mover advantages in their respective market. This is especially important in winner-takes-all Internet markets, which is a main reason for the novelty of this outcome in this particular study. Furthermore, an Internet company with a quick IPO usually obtained large amounts of venture capital funding because investors believe in its superior business model. For these high-potential first-movers, the costs of delaying the IPO is likely to be higher than the benefits from learning effects or higher market valuations over time.

Additionally, as hypothesized, I have shown that profitability in the year of the IPO is positively associated with the long-term stock performance of Internet companies. A company that is profitable shows long-term viability and thus, on average, is more likely to perform better. This finding is important as it adds to the ongoing debate around the sustainability of Internet companies, which are still often associated with overvalued growth opportunities and hyped IPOs despite significant losses at the bottom line. Also, it shows that traditional accounting metrics still apply for the Internet sector.

Above all, I conclude that managers and investors should mainly emphasize the strategic implications of an IPO, which has an impact on future investment capabilities, internal processes and the overall market positioning.

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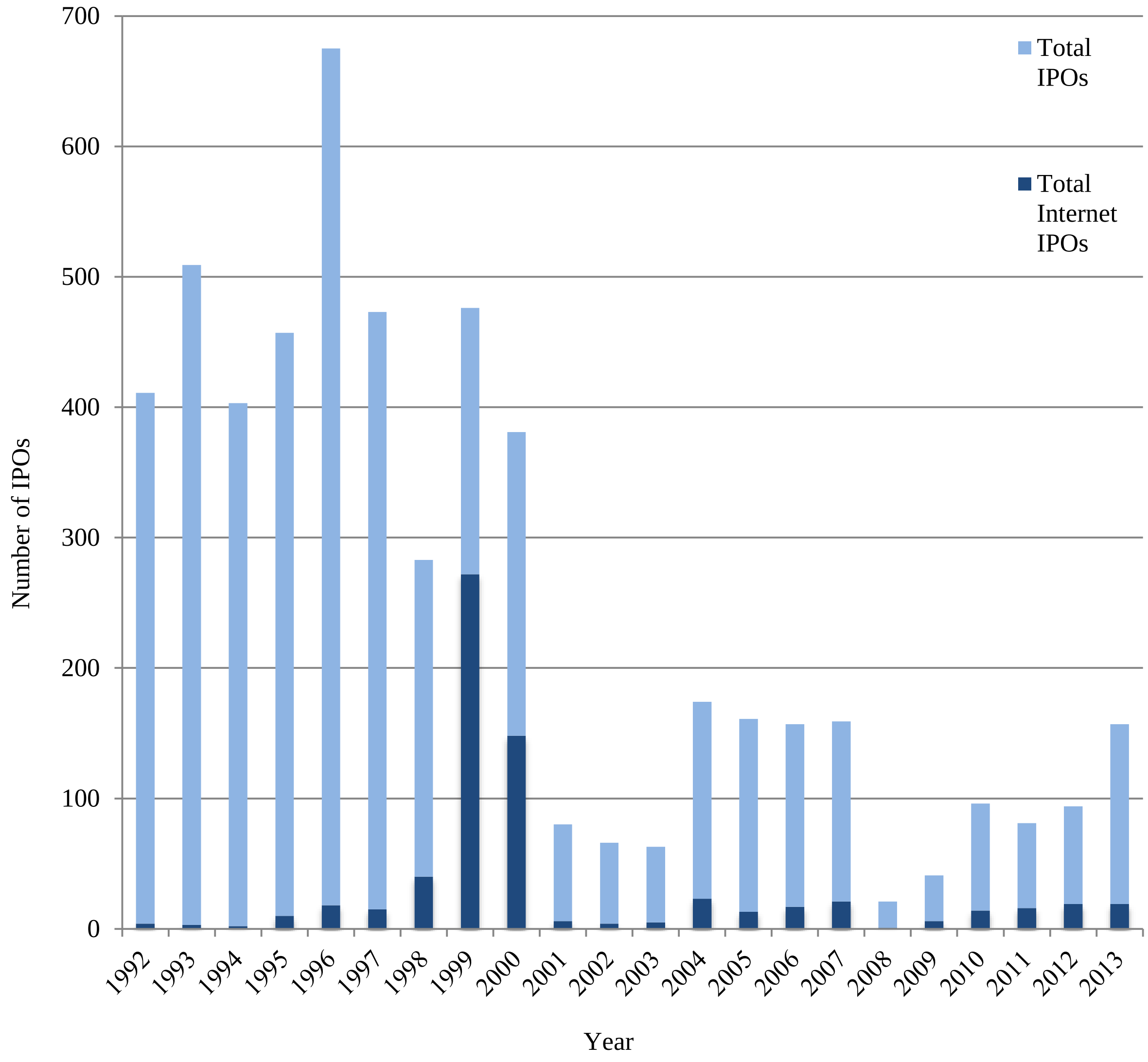
Appendix

Appendix A: Total number of (Internet) IPOs in the U.S. from 1992 to 2013

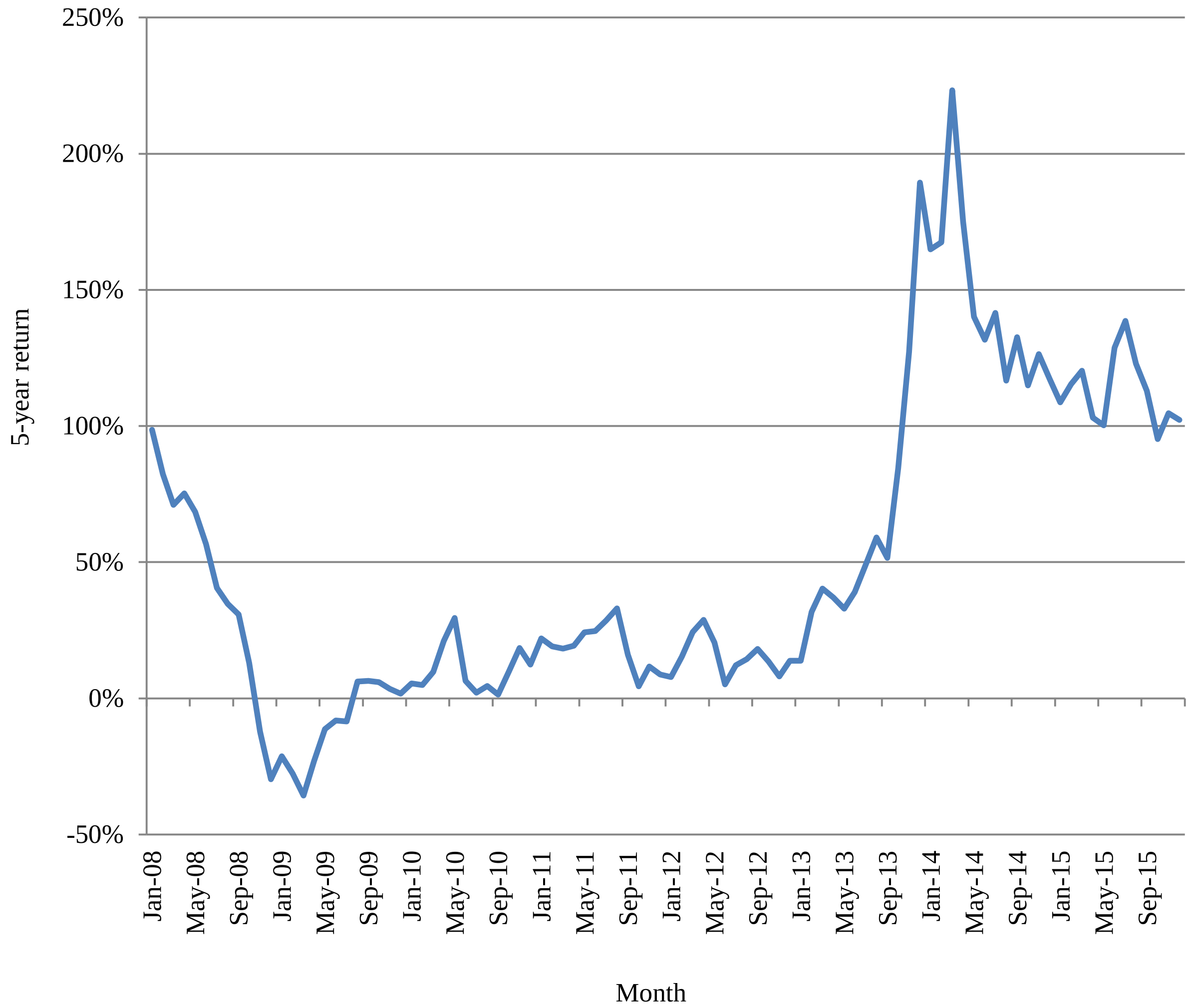


Data source: IPO data (Ritter, 2016)

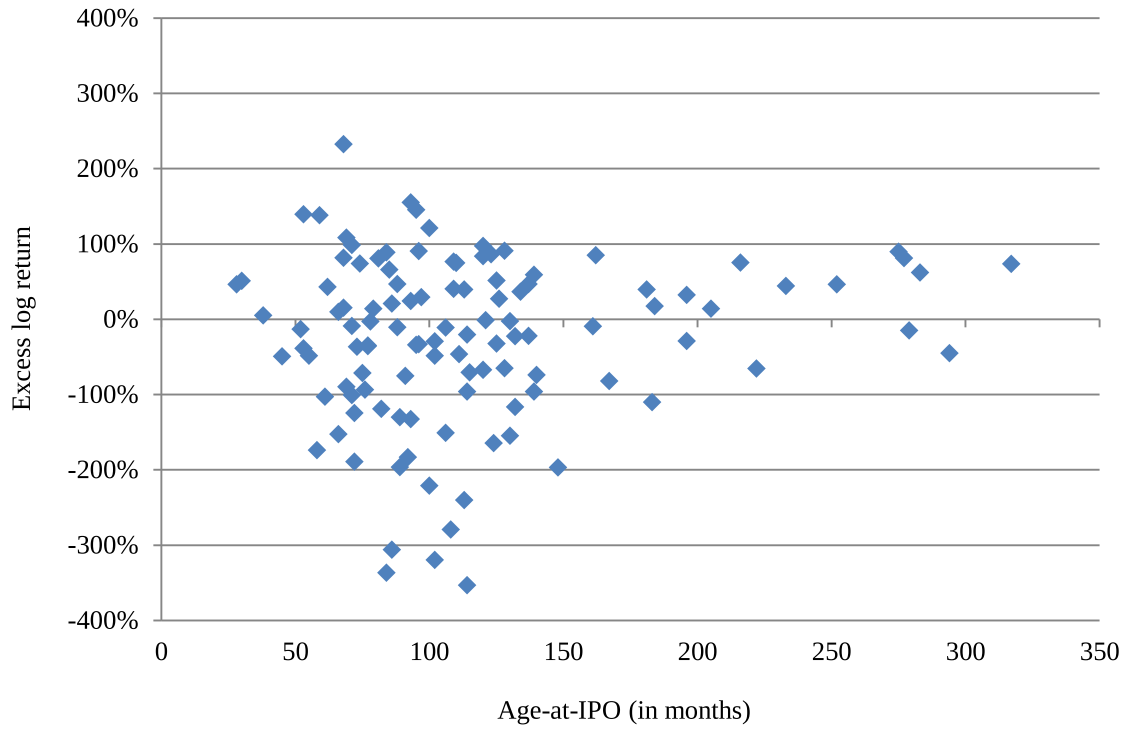
Appendix B: Sample

1	51Job	40	Fortinet	79	Phase Forward
2	Acme Packet	41	Global Defense Technology & Systems	80	PlanetOut
3	Airvana	42	Glu Mobile	81	PowerDsine Ltd.
4	Allot Communications	43	Gravity	82	Provide Commerce
5	Alphabet	44	Greenfield Online	83	Qlik Technologies
6	American Public Ed.	45	Guidance Software	84	Quinstreet
7	Ancestry.Com	46	Interactive Brokers	85	Realpage
8	Archipelago Learning	47	Internet Brands	86	RightNow Technologies
9	Arcsight	48	Ipass	87	RigNet
10	Athenahealth	49	Isilon Systems	88	Sajan
11	Baidu	50	Kanbay International	89	Salary.Com
12	Blackbaud	51	Kingtone Wirelessinfo Solution Holding Ltd	90	Shanda Interactive Entertainment Ltd.
13	Blackboard	52	Knology	91	Shoretel
14	Blue Nile	53	Kongzhong Corp.	92	Shutterfly
15	Bofi Holding	54	Limelight Networks	93	Sirf Technology Holdings
16	Bridgeline Digital	55	Liquidity Services	94	Sito Mobile
17	Broadcom Limited	56	Logmein	95	Sky-Mobi Limited
18	Broadsoft	57	Loopnet	96	Smartpros
19	Callidus Software	58	Makemytrip	97	Soundbite Communications
20	Capella Education	59	Marchex	98	Sourcefire
21	Changyou.Com Limited	60	Marketaxess Holdings	99	SPS Commerce
22	China Finance Online	61	Medassets	100	SS&C Technologies Holdings
23	Chinacache International Holdings Ltd.	62	Medecision	101	Starent Networks Corporation
24	Cimpress	63	Mediamind Technologies	102	Synchronoss Technologies
25	Commvault Systems	64	Medidata Solutions	103	Taleo Corporation
26	Comscore	65	Mercadolibre	104	TechTarget
27	Comverge	66	Monotype Imaging Holdings	105	Telenav
28	Convio	67	Morningstar	106	Traffic.Com
29	Copsync	68	NCI	107	US Auto Parts Network
30	Ctrip Com International Ltd.	69	Netsol Technologies Ltd	108	Virtual Radiologic Corporation
31	Dealertrack Holdings	70	Ninetowns	109	Virtusa Corporation
32	Deltek	71	Odimo	110	Visual Sciences
33	Demandtec	72	Omniture	111	Vitacost.com
34	Digimarc	73	Open Solutions	112	Vocus
35	Divx	74	Opentable	113	Voltari
36	eCOST.com	75	OptionsXpress Holdings	114	Web.Com Group
37	eFuture Holding	76	Orbitz	115	WebMD Health
38	EHealth	77	Palmsource	116	Xyratex
39	Expedia	78	Perion Network		

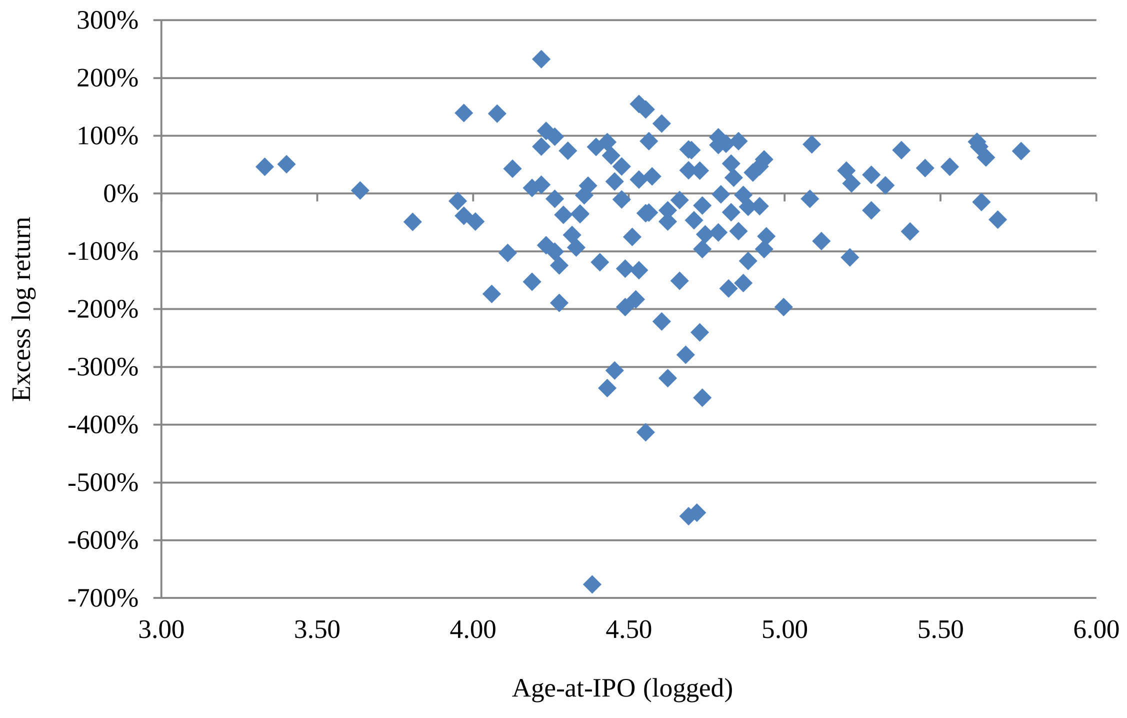
Appendix C: NASDAQ Composite 5-year return (monthly)



Appendix D: Scatterplot of age-at-IPO vs. excess log returns



Appendix E: Scatterplot of age-at-IPO logged vs. excess log returns



Appendix F: ANOVA outputs for age-at-IPO quintiles

ANOVA

Variable		Sum of Squares	df	Mean Square	F-statistic	Sig.
Excess log return	Between Groups	21.318	4	5.329	2.633	0.038
	Within Groups	224.68	111	2.024		
	Total	245.998	115			

Test of Homogeneity of Variances

Variable	Levene Statistic	df1	df2	Sig.
Excess log return	4.913	4	111	0.001

Robust Tests of Equality of Means

Variable	Test	Statistic	df1	df2	Sig.
Excess log return	Welch	2.622	4	54.188	0.045
	Brown-Forsythe	2.649	4	74.665	0.04

Descriptives

Variable	Quintile	N	Mean	SD	SE	95% Confidence Interval for Mean		Min.	Max.
						Lower Bound	Upper Bound		
Excess log return	1	22	0.086	1.011	0.216	-0.362	0.535	-1.738	2.326
	2	24	-0.930	1.697	0.346	-1.647	-0.214	-6.763	0.887
	3	23	-0.902	2.090	0.436	-1.806	0.002	-5.587	1.550
	4	24	-0.363	1.107	0.226	-0.830	0.104	-3.534	0.974
	5	23	-0.002	0.760	0.159	-0.331	0.327	-1.967	0.897
	Total	116	-0.430	1.463	0.136	-0.699	-0.161	-6.763	2.326

Multiple Comparisons

Dependent Variable	(I) Quintile	(J) Quintile	Mean Difference (I-J)	SE	Sig.	95% Confidence Interval	
Excess log return						Lower B.	Upper B.
Tukey HSD (Honestly Significant Difference)	1	2	1.017	0.420	0.117	-0.148	2.181
		3	0.988	0.424	0.143	-0.188	2.165
		4	0.449	0.420	0.822	-0.715	1.614
		5	0.088	0.424	1.000	-1.088	1.265
	2	1	-1.017	0.420	0.117	-2.181	0.148
		3	-0.028	0.415	1.000	-1.180	1.123
		4	-0.567	0.411	0.641	-1.706	0.572
		5	-0.928	0.415	0.174	-2.080	0.223
	3	1	-0.988	0.424	0.143	-2.165	0.188
		2	0.028	0.415	1.000	-1.123	1.180
		4	-0.539	0.415	0.693	-1.690	0.612
		5	-0.900	0.420	0.209	-2.064	0.263
	4	1	-0.449	0.420	0.822	-1.614	0.715
		2	0.567	0.411	0.641	-0.572	1.706
		3	0.539	0.415	0.693	-0.612	1.690
		5	-0.361	0.415	0.907	-1.512	0.790
	5	1	-0.088	0.424	1.000	-1.265	1.088
		2	0.928	0.415	0.174	-0.223	2.080
		3	0.900	0.420	0.209	-0.263	2.064
		4	0.361	0.415	0.907	-0.790	1.512
LSD (Fisher's Least Significant Difference)	1	2	1.017*	0.420	0.017	0.184	1.849
		3	0.988*	0.424	0.022	0.147	1.829
		4	0.449	0.420	0.287	-0.383	1.281
		5	0.088	0.424	0.836	-0.753	0.929
	2	1	-1.017*	0.420	0.017	-1.849	-0.184
		3	-0.028	0.415	0.946	-0.851	0.794
		4	-0.567	0.411	0.17	-1.381	0.246
		5	-0.928*	0.415	0.027	-1.751	-0.106
	3	1	-0.988*	0.424	0.022	-1.829	-0.147
		2	0.028	0.415	0.946	-0.794	0.851
		4	-0.539	0.415	0.197	-1.362	0.284
		5	-0.900*	0.420	0.034	-1.731	-0.069
	4	1	-0.449	0.420	0.287	-1.281	0.383
		2	0.567	0.411	0.17	-0.246	1.381
		3	0.539	0.415	0.197	-0.284	1.362
		5	-0.361	0.415	0.386	-1.184	0.462
	5	1	-0.088	0.424	0.836	-0.929	0.753
		2	0.928*	0.415	0.027	0.106	1.751
		3	0.900*	0.420	0.034	0.069	1.731
		4	0.361	0.415	0.386	-0.462	1.184

* The mean difference is significant at the 0.05 level.

Appendix G: Chi-square outputs for age-at-IPO quintiles

Crosstabulation: Quintile Group of Age-at-IPO * Survival

Quintile		Exit	Survival	Total
1	Count	1	21	22
	Expected Count	1.9	20.1	22
2	Count	4	20	24
	Expected Count	2.1	21.9	24
3	Count	3	20	23
	Expected Count	2	21	23
4	Count	2	22	24
	Expected Count	2.1	21.9	24
5	Count	0	23	23
	Expected Count	2	21	23
Total	Count	10	106	116
	Expected Count	10	106	116

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	5.180a	4	0.269
Likelihood Ratio	6.789	4	0.147
Linear-by-Linear Association	0.961	1	0.327
N of Valid Cases	116		

a. 5 cells (50.0%) have expected count less than 5. The minimum expected count is 1.90.