IPO Underpricing and tech valuation

An empirical study of the Swedish IPO market

DENNIS BERGGREN
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by

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Master of Science Thesis INDEK 2017:31

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Approved 2017-06-12
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Abstract
The closing price first day of trading has historically been found to exceed the offer price set in IPOs, implying that many issuing firms tend to leave money on the table in their IPO. This thesis examines the level of IPO underpricing in Sweden using unique data of IPO transactions on the largest Swedish stock exchanges during 2010-2016. It further discusses the valuation difficulties using the most common valuation methods for firms exhibiting characteristics commonly shared by technological firms.

Univariate and multivariate tests confirm the existence of underpricing on Swedish stock exchanges during the period of study. Firms in the technological sector are found to experience both high average levels of underpricing and great variance in initial returns, suggesting potential difficulties valuing technological firms. Robust univariate tests do however not yield a significant result of greater variance in initial returns compared to rest of the sample. By using regression analysis, I find capital raised relative to market capitalization to have significant negative effect on initial returns.

Key-words: IPO Underpricing, Corporate Finance, Technology firms, Valuation
Acknowledgement

I would like to thank my supervisor Gustav Martinsson for his support during the entire project. I would also like to express my gratitude towards Redeye for advising on the topic as well as providing access to the data necessary to fulfill my research objective.
# Contents

1. **Introduction** .......................................................... 1

2. **Theoretical framework** .............................................. 5
   2.1 Valuation methods .................................................. 5
   2.2 Underpricing in initial public offerings .......................... 7
      2.2.1 Information asymmetry ....................................... 9
      2.2.2 Signaling .................................................... 10
      2.2.3 Cyclicality and “Hot issue markets” ......................... 11
      2.2.4 Other reasons for underpricing to arise ..................... 12
      2.2.5 Firm-specific variables and IPO outcome .................... 13
      2.2.6 Long run performance ........................................ 13

3. **Data and methods** .................................................. 15
   3.1 Sample construction ............................................... 15
   3.2 Dependent variable ............................................... 18
   3.3 Industry classifications .......................................... 19
   3.4 Extreme values .................................................. 21
      3.4.1 Distribution of data ......................................... 22
   3.5 Statistical methods ............................................... 23
      3.5.1 T-test ...................................................... 24
      3.5.2 Kruskal Wallis ............................................... 24
      3.5.3 Levene’s test of variances .................................. 25
      3.5.4 Regression analysis ......................................... 26

4. **Empirical analysis** ............................................... 31
   4.1 Descriptive statistics ............................................. 31
   4.2 Industry comparison ............................................... 33
   4.3 Exchange characteristics ........................................ 36
   4.4 Time series variation ............................................. 38
   4.5 Test of variance between industries ............................ 41
4.6 Regression analysis .............................................. 43
4.7 Technology specific regression ............................... 48

5 Conclusions ......................................................... 51

6 Appendix .......................................................... 59
1 Introduction

There are numerous different valuation techniques used by professionals to estimate values of corporate ventures. However, there exist no magical formula applicable to all ventures as firms differ from each other. Companies differ in age, size, objectives, markets, growth cycles among endless other matters. Depending on firm and current business phase, particular valuation methods are likely to be more appropriate than others. This becomes especially evident valuing firms expected to experience substantial growth. The reason for rapid growth might differ between firms, but they often possess particular attributes that are expected to bolster their future advancement. An example of such attribute is technology, which often is expected to generate significant future firm growth.

As with any other industry, firms differ, but there might exist general firm characteristics that hold for a majority of firms within each industry and thereby needs to be considered for valuation purposes. Many highly technological firms are often expected to experience high sales growth while making negative earnings, often assumed only to be transitory (Bartov et al., 2002). Internet firms, in particular, are often found to be young and thereby lack historical financial data. The available data is moreover often found irrelevant as many of these firms seldom report positive profits and the underlying market growth is expected to be substantial (Trueman et al., 2000). Not only are business conditions potentially different, but shares of publicly traded internet firms are also often found to be affected by serious volatility (Ofek and Richardsson, 2003).

This demonstrates that shares of technology firms potentially are affected by high levels of uncertainty. It partly arises due to volatility and lack of historical revenues and profits, but is further bolstered through large investments into Research & Development, often found burdensome for investors to value (Bartov et al., 2002). It is therefore reasonable to expect high levels of information asymmetry in the case of technology firms, where companies
possess better information and knowledge about the venture than investors. Altogether, this indicates that technology firms could be difficult to value.

I therefore find it interesting to examine whether technology firms are subject to higher degrees of uncertainty compared to other industries. The uncertainty would thus be illustrated by large valuation differences among market actors. One method of examining variation in valuations is to review how investment banks (underwriters) and the stock market differ in their valuation of firms by studying initial public offerings (IPOs).

There should be no difference in the valuation of common shares offered in an IPO and shares already traded on an exchange (Ritter, 1998). Yet, there exists vast research confirming the historical difference in IPO offer price and closing price first day of trading - a phenomenon defined as underpricing. By manually gathering recent data I enabled the possibility to examine whether the pattern of underpricing still is present in the largest Swedish stock exchanges. I further had an interest in examining whether firms belonging to the technology industry exhibit greater variance in the level of underpricing, which would suggest a difficulty in valuing technology firms. I have moreover used regression analysis to investigate if the degree of underpricing could be explained by several firm-specific variables.

It is of significant importance to examine the efficiency of capital markets as capital is vital for companies to fund their future business operations. If markets are inefficient, it is important to understand why and how it affects market actors. High degrees of underpricing are negative for issuing firms as they leave money on the table\footnote{Expression used to illustrate that firms forego capital by issuing shares at offer prices lower than the market’s valuation.}. Underpricing is also costly for pre-IPO shareholders if shares are offered at too low prices. It is therefore important to investigate whether the phenomenon of underpricing exist as well to understand why it arises.

Prior research on the topic of underpricing is mainly focused on confirming
the existence of underpricing (for example Ibbotsson (1975) and Ljungkvist (2007)) and providing theoretical explanations for underpricing to exist, as seen in Rock (1986) and Michaely and Shaw (1994). There are studies comparing underpricing across industries but not with a particular focus to examine valuation variances. I further contribute to previous research by using unique data with recent observations from the Swedish IPO market. I moreover use the data to investigate whether the degree of underpricing could be affected by several firm-specific variables.

I have studied the Swedish IPO market during 2010-2016, and it is thereby possible that I examined the IPO market during a cyclical peak due to my rather narrow time frame. Apart from investigating the existence of underpricing, I am also focused on examining whether it is harder to estimate the value of technology companies compared to other industries. A potential cyclical IPO trend is thus a negligible obstacle given that all examined sectors experience similar cyclical patterns. My research is heavily dependent of industry classifications as my incentive is to compare technology firms to firms within other industries. It is thus possible that use of another classification system would yield different results.

My research objective has no direct relationship to sustainability issues. However, many of the firms included in the data set possess technologies and strategic objectives that could come to have positive effects on environmental sustainability. For example, the data set cover several companies classified as cleantech\textsuperscript{2} which could come to have positive effect on the environment. It is therefore important to investigate the capital markets as capital is required to achieve the potential positive effects on environmental sustainability. It is possible that poorly functioning capital markets may deter firms from achieving such effects.

I start by presenting and discussing the most common valuation tech-

\textsuperscript{2}Products or services classified as clean technology are expected to have a positive impact on environmental sustainability by either being more energy efficient or by reducing negative impacts on the environment.
niques and their relevance for companies with common characteristics of technology firms. This is followed by a brief explanation of the IPO procedure and a review of previous research on the topic of IPO underpricing. Then follows an introduction to the data, presentation of the methodology used and its empirical implications. My results are then summarized and discussed in the final section of conclusions.
2 Theoretical framework

2.1 Valuation methods

The most classical and common valuation methods are the dividend discount model (DDM), relative valuation and discounted cash flow analysis (Berk and DeMarzo, 2014). The DDM is a rather simple method of calculating the fair share value by estimating the expected dividend payment which then is discounted by the expected return subtracted by the expected future growth rate of dividends. This method is cumbersome to apply in the case of high growth technology firms as they generally need to use its available capital to finance their growth. They thereby lack the capital needed to distribute dividend payments. DDM is therefore inapplicable on most high growth firms.

Relative valuation is a technique used to compare valuation multiples between firms and industries. It is often used to compare the valuation of a firm to corresponding multiples of competitors within a similar industry or market. There are numerous multiples used by professionals. Some common multiples are price-to-earnings (P/E) which is calculated as current share price divided by earnings per share, price-to-sales (P/S) and enterprise value divided by earnings before interest, taxes, depreciation and amortization (EV/EBITDA). The relative valuation method becomes rather difficult to apply to high growth firms as they often are found in a phase characterized by high sales growth while still making negative earnings. Another downside of relative valuation is that firms are unique, which might be even more plausible in the technology industry where firms possess technologies that are considerably different from their competitors. Thus, relative valuation could be regarded as rather difficult to apply to high growth technology firms. Relative valuation, however, has several benefits when the accessibility of data is good as it is a fairly easy and straightforward method to apply when comparing firms. Relative valuation has for example been found to be useful in
preliminary valuations when historical financial information often is missing (Ritter, 1998). Moonchul and Ritter (1999) have further found that specific multiples based on predicted earnings yield higher accuracy than comparing multiples based on historical data. Relative valuation can thus be useful even when the accessibility of historical data is poor.

In discounted cash flow (DCF) analysis one estimates the enterprise value of a firm by forecasting the free cash flows the company is estimated to generate. These are then discounted by the firm's weighted average cost of capital (WACC). The advantage of using DCF is the capacity to impose various assumptions which will affect the forecast of future cash flows and ultimately the intrinsic value of the firm. It further allows for adjustments in growth rate assumptions over a wide time horizon and thereby becomes useful for valuing high growth technology ventures as the investor can adjust the DCF-model according to the specific firm. An additional advantage of DCF analysis is that it is solely based on fundamentals and thus is independent of the current market mood, compared to relative valuation where a majority of the commonly used multiples are directly affected by the market's valuation. Coakley and Fuertes (2006) conclude that share prices might deviate from fundamentals in the short run, but that prices will match fundamentals in the long run.

During the IT boom in 1995-2000 practitioners came up with complementary valuation measures specifically appropriate for internet companies. Business magazine Fortune mentions the example of market capitalization per pair of eyeballs\(^3\) as a new approach for researchers to compare valuations of internet firms, indicating a need to incorporate more than merely financial information in valuations of internet stocks (Schonfeld, 2000). Trueman et al. (2000) have found that internet usage measures such as website page views and number of unique visitors have great explanatory value on the

\(^3\) Used to calculate firms value per customer by dividing the firm’s market value of outstanding shares by the number of customers/users.
share price of internet companies.

Apart from being difficult to value, high-tech firms are also found to be atypical regarding investor sentiment. Baker and Wurgler (2007) have found evidence of that stocks with particular characteristics are anticipated to be heavily affected by investor sentiments. Shares of firms experiencing high growth and negative earnings, low capitalization and high volatility among other characteristics are found to be mostly affected by investor sentiment. Several of these characteristics are typically ascribed to technology firms expected to experience high growth.

Having stated that particular methods are more applicable than others when valuing growth firms does not necessarily imply that investors will estimate identical values as they are heavily affected by the underlying assumptions. One should also be careful in rejecting certain valuation methods as they all have benefits and drawbacks. The intention of this review is to illustrate the difficulty in valuing ventures exhibiting common characteristics of technology firms using common valuation methods since my research objective is to examine if valuation differences do exist in the market of IPOs and if the variance of this valuation difference is especially great for technology firms.

2.2 Underpricing in initial public offerings

An IPO is a process where a firm (issuer) raises capital by issuing shares to the public and becomes publicly traded on a stock exchange. An advantage of being publicly traded is better access to capital as it becomes easier to raise high amounts of capital both during the IPO and possible subsequent seasonal equity offerings. It is also advantageous for the firm’s shareholders as the liquidity increases, which implies that it becomes easier to trade (buy or sell) the company’s share. In general, this comes at the cost of decreased ownership concentration, often found negative for the company as owners lose their ability to control management of the firm (Berk and DeMarzo,
To become publicly traded firms hire investment banks (underwriters) to help them through this process. The offering is either done through issuance of new shares (primary offering) or through a secondary offering where current shareholders sell their already existing shares. The underwriter will help the issuer to setup the IPO transaction based on the issuer’s demands. The underwriters will perform numerous of duties associated with the IPO, such as writing prospectus, market the IPO, valuing the firm and its shares and thereby suggest the price at which the issues shares will be offered. The underwriter will furthermore assist to distribute the offered shares to investors. The issuing firm will then pay the underwriter for undertaking the IPO project, most often a percentage of the capital raised known as gross margin.

The valuation is often based on DCF valuation and relative valuation through the use of valuation multiples. It is most often also complemented by valuation multiples of comparable recent IPO transactions (Berk and DeMarzo, 2014). As previously mentioned, there should be no difference between the valuation of shares offered in an IPO and common shares (Ritter, 1998). Yet, the closing price first day of trading has on average been found to be 17% higher than the offer price in the US stock market during the period 1960-2011 (Berk and DeMarzo, 2014). Ljungqvist (2007) confirms this pattern, but further notes that there have been great fluctuations in the level of underpricing. During 2000-2004 the average level of underpricing was found to be as high as 40%. Ljungqvist further finds that underpricing is not only cyclical but also differs geographically, where the differences often could be explained by institutional differences. The average level of underpricing in Sweden was found to be around 15% between the years 1990-2003 (ibid).

This implies that issuing firms tend to leave money on the table and forego capital that could have been used to fund their businesses. As an example, firms in the U.S. left $62 billion on the table only during the years 1999
and 2000 when average levels of underpricing were as high as 71% and 57% respectively (Ljungkvist, 2007). In their extensive study of IPO underpricing, Loughran and Ritter (2004) finds that the average first day return was 65% during 99-00. The authors also found that technology and internet related businesses, in general, are subject to greater degrees of underpricing, which was particularly evident during 1990-2000 where average initial returns were found to be 80.6% for tech and IT companies and 23.1% for other firms. The difference has however seemed to decrease over time. They furthermore conclude that the fraction of young firms going public was at its peak during the same period. Only during the period between the beginning of 1998 until February 2000 publicly traded internet companies yielded stock returns over 1000 percent (Ofek and Richardsson, 2003). This indicates that 1995-2000 was a spectacular stock market period with an exceptional demand for young high-tech companies, which held until the Dot-com bubble crashed during 2000-2001.

Altogether, this illustrates the historical existence and cyclicality of underpricing. It is, however, unclear what drives the level of underpricing. There exist a vast amount of research suggesting different theoretical explanations for underpricing to arise. I will briefly present the most recognized theories mentioned in the existing literature on IPO underpricing.

2.2.1 Information asymmetry

There is ample scientific literature suggesting that underpricing arise from the economic problem of asymmetric information where sellers and buyers possess different levels of knowledge and intelligence about the issuing venture. This becomes relevant in IPOs as sellers (issuing firms or prior shareholders) are likely to have an informational advantage about the issuing venture whereas potential buyers possess less information about the company.

One of the most well-known theories to explain the outcome of IPOs is the winner’s curse proposed by Rock (1986). The winner’s curse stems
from the problem that to win an auction, the winner has to outbid other potential acquirers which imply that the winner of the auction ends up with the highest valuation of the object. The winner’s curse is relevant in the case of IPOs where aftermarket performance tends to be greater when there is high demand of the issued stock, implying that each bidder gets fewer amounts of shares. Respectively, the allotment of shares is larger when the demand is low, and aftermarket performance is thus worse (Berk and DeMarzo, 2014). Rock (1986) suggests that informed investors will refrain from investing in an IPO where the price exceeds the value of the firm and the shares will then be allocated to the uninformed investors. Rock therefore argues that underpricing arise as underwriters compensate uninformed investors for the asymmetric information dilemma they face by setting low IPO prices.

Chang and Su (2010) suggests that information asymmetries in the IPO process are especially common for high technology firms and firms with high research and development (R&D) expenditures. They also find evidence of high levels of underpricing for high-tech firms in Taiwan. The authors thereby reach the conclusion that R&D investments induce information asymmetries and thereby raises the level of underpricing. The relationship between R&D expenditure and level of underpricing has been confirmed in numerous studies (Guo, Lev and Shi, 2006; Chin et al., 2006; Lu, Kau and Chen, 2011). Lowry and Schwert (2002) have also found that there is a high level of information asymmetry in the case of high-tech firms and that this often leads to high levels of underpricing.

2.2.2 Signaling

Apart from compensating uninformed investors for asymmetric information, IPO underpricing has also been suggested to work as a signaling function for firms of high quality (Welch, 1989). By incorporating seasonal offerings (SO) Welch constructs a multiperiod model with both IPOs and SOs and concludes that high degrees of IPO underpricing should not be problematic
for high quality firms as they can raise the offer price in subsequent SOs. The relatively low offer price in the IPO could thus be used by firms as a signal of confidence for companies of high quality. Welch further argues that low quality firms cannot imitate this behavior as the market will be able to distinguish the true firm quality during the period between the IPO and potential subsequent seasonal offerings.

Allen and Faulhaber (1989) support the theory of signaling by arguing that the issuer is best informed about their prospect. Thus, if the firm knows that it is a favorable prospect, it has an incentive to request a low offer price as a signal of high quality to potential investors which then will understand that the firm is of high quality and expects to be compensated for the IPO underpricing in subsequent equity issues.

2.2.3 Cyclicality and “Hot issue markets”

As mentioned earlier the degree of underpricing has historically varied over time. Not only does the level of underpricing change over time, but the number of performed IPOs is also subject to great cyclicality. Ritter (1998) finds that high initial returns are succeeded by greater IPO volumes - a phenomenon referred to as hot issue markets. This is based on the reasoning that high initial returns illustrate a great demand for shares of new companies. It should thus be more tempting for firms to exploit the opportunity to raise capital and become publicly traded in such a positive climate. Ritter states that the pattern of high levels of underpricing and increasing IPO volume has been noticed in the U.S. and other countries. It is thus plausible to assume that high initial stock market returns spur IPO volume. The great variation in IPO volume is further supported by Ibbotson, Sindelar and Ritter (1994). The authors provide a table of average initial returns and IPO volume for the US market between 1960-1992 which illustrates that IPO volume varies greatly between single years. The IPO volume was for example found to increase from 198 to 848 between 1982 and 1983. Apart from great
variation in total IPO volume, there is also a substantial variation in IPO volume within industries. Lowry (2004) illustrates this by examining the number of IPOs within industries by decades. For example, the number of public communication and computer firms increased by 92.1% during 1980s whereas the corresponding measure for oil and gas firms was 18.2%. Thus, previous research has shown patterns of great cyclicality of initial returns and IPO volume (both in total and between industries), where high initial returns historically have been found to favor high IPO volumes.

2.2.4 Other reasons for underpricing to arise

Loughran and Ritter (2004) also provide several suggestions as to why underwriters could benefit from underpricing. Apart from receiving transaction fees from the issuer, underwriters often also receive trading commissions from investors. By setting a low offer price and allocating more shares to investors with a history of paying high commission fees, underwriters could expect to increase commission revenues when the shares become traded the first day.

Beatty and Ritter (1986) argue that underwriters have an incentive to underprice to retain clients. If the underwriter sets too high offer prices, they will lose potential IPO investors as the offer is relatively expensive. If the offer price is too low (high degree of underpricing) there is a possibility of losing issuing clients as the issuing firms leave capital on the table. The authors thereby suggest that underwriters have incentives to find an optimal degree of underpricing that will not hurt their reputation and client relationships. Beatty and Ritter further find that underwriters deviating too much from the desired level of underpricing will lose clients in the subsequent period.

\[^4\text{Measured as IPO volume during the decade divided by number of public firms at the beginning of the decade.}\]
2.2.5 Firm-specific variables and IPO outcome

Some researchers have also examined whether firm-specific variables affect the outcome of IPOs. By comparing IPOs of internet and non-internet firms, Bartov et al. (2002) found that initial prospectus valuations of non-internet firms are based on traditional measures such as positive earnings and positive cash flows while positive earnings are not being priced for internet companies. Furthermore, they find that negative cash flows are being priced in the valuation of internet firms. The authors are also examining the difference between the offer price and closing price, and finds the difference to be significantly affected by sales growth, positive cash flows, R&D, high-risk warnings and float (number of outstanding shares available to the market) for internet firms, while the only significant factor for non-internet firms is float.

Firm age has also been suggested to affect the outcome of IPOs. Loughran and Ritter (2004) finds that younger firms (classified as 0-7 years) on average yield higher initial returns. During 99-00 the average underpricing was found to be 75.2% for young firms, compared to 45.2% for older firms. One should, however, bear in mind that this was a rather spectacular stock market period.

2.2.6 Long run performance

Although IPOs tend to perform very well in the short run, several researchers have found that IPOs tend to perform worse in the long run. Ritter (1998) concludes that the long run (5 years) average annual return for an investor buying stocks at the closing price first day of trading was found to be 7.9 percent for companies going public between 1970-1993, which was significantly lower than the benchmark returns during the period. Ritter (1991) finds that the long-run underperformance is even larger for younger firms and suggest that it is likely due to overoptimism in the IPO.

Carter, Dark and Singh (1998) have found that the long run returns are less negative for IPOs held by prestigious underwriters. Michaely and Shaw
(1994) have also shown that IPOs performed by more prestigious underwriters tend to perform better in the long run. Thus, the reputation of the underwriter is an additional variable that has been suggested to influence the outcome of IPOs. I have, however, decided to only examine firm-specific characteristics when examining the outcomes of IPOs as the variables are more closely related to my interest in valuations.
3 Data and methods

3.1 Sample construction

I gathered a majority of my data from Bloomberg, Bloomberg Finance L.P. I collected data for IPOs performed between 2010-2016 on the largest Swedish stock exchanges Nasdaq Stockholm, Nasdaq First North and AktieTorget. I chose only to study IPOs where there have been share issues held in relationship with the listing, which implies that I have excluded listings, list changes\(^5\) and separate listings\(^6\). I have furthermore excluded offerings of preferential shares and thereby only studied IPOs of common shares. This is preferable as I am examining variables such as market capitalization.

In order to avoid missing transactions, I reviewed reported corporate actions from the researched exchanges and the website nyemissioner.se. Transactions that were missing in Bloomberg have been gathered manually by using information from prospectus, memorandums, annual reports as well as press releases. I have further used the website of Avanza Bank\(^7\) to gather and control for historical share prices and number of outstanding shares.

IPO offer price and closing price first day of trading have been extracted from Bloomberg, which has been complemented by adjusted IPO offer price and adjusted closing price for companies that have performed corporate actions that affect the price per share (for example stock splits). I have also used data from AktieTorget’s website\(^8\) as they provide adjusted prices for shares traded on their exchange. I have further used the Swedish Tax Agency’s website\(^9\) to verify information regarding corporate actions.

Data regarding company age is based on businesses registration date. This has been collected from Bloomberg, allabolag.se, company websites,\(^5\) When a firm is moved from one exchange to another exchange.
\(^6\) Separate listing is when an already public company joins an additional exchange.
\(^7\) http://www.avanza.se
\(^8\) http://www.aktietorget.se
\(^9\) https://www.skatteverket.se/privat/skatter/vardepapper/aktiehistorik
annual reports and memorandums. Age is presented as the difference in years between the year of going public and registration date. Revenues and earnings before interest rates and taxes (EBIT) have been gathered from Bloomberg, annual reports and IPO memorandums. I have used full year figures the fiscal year before going public. For example, revenue and EBIT from FY 2015 are used for a company listed in June 2016. Shares offered and capital raised is gathered from Bloomberg, memorandums and press releases. Capital raised is then calculated as number of subscribed shares times offer price. This implies that the costs related to the transaction have not been excluded. Market capitalization is extracted from Bloomberg and is calculated as the total number of outstanding shares first day of trading times the closing price first day of trading.

I have in total gathered 216 observations of IPOs between 2010-2016. 86 of these were listed on Aktietorget, 76 on Nasdaq First North and 54 on Nasdaq Stockholm. I have also compiled data of GDP and OMXSPI growth to examine whether the IPO volume could be explained by the economic climate. I find it plausible to assume that the number of IPOs increase during positive economic times, reflected in high GDP and OMXSPI growth and decrease during worse economic conditions. OMXSPI is an all-share price index of all companies listed on the Stockholm exchange. Annual growth is then calculated as:

\[
OMXSPI \text{ Growth}_{t+1} = \frac{Index \text{ closing value}_{t+1} - Index \text{ closing value}_t}{Index \text{ closing value}_t}
\]  

(1)

As noticed in previous studies on IPOs, the number of IPOs varies tremendously between years. I notice the same pattern for my data set, where there has been a significant increase in IPO volume during the last three years. It is important to keep in mind that the first day of trading is regarded as IPO

\[10\] Outcomes of IPOs often are presented in press releases.
date as this is when the transaction is considered complete. There might, for example, have been more IPO processes started in 2012, but where the shares were not traded before 2013. It is also important to remember that my period of study is following the financial crisis of 2007-2008. Thus, it is reasonable to expect a rather weak IPO climate the years following the crisis and an increase in IPO volume during subsequent years characterized by a more positive financial climate. It is moreover possible that some companies have been delisted or gone bankrupt since their initial public offering which obstructs the access to data. Thus, transactions performed by such firms have not been included in the data set.

![Figure 1: Number of performed IPOs vs. GDP and OMX All-share index (OMXSPI) growth (%) during 2010-2016.](image)

The relation between IPO volume, GDP growth (%) and OMXSPI growth
The number of IPOs seem to follow GDP growth fairly well during the period but not sufficiently enough to explain the great increase between 2013-2014. OMXSPI growth does not appear to be a good indicator for IPO volumes during the period of study. It is possible that the growth variables should be lagged to fit IPO volumes better. The OMXSPI index is furthermore not a perfect index to explain the entire data set as numerous firms exhibit characteristics that differs significantly from the firms included in the OMX index. However, my primary interest is not to investigate drivers of IPO activity but rather to study the outcome of the performed transactions. I can thereby only state that there is no visible pattern from GDP or OMXSPI growth that works as an efficient indicator of IPO volume using this data. Price adjusted GDP growth have been collected from Statistics Sweden (2017) and historical OMXSPI index values are gathered from Nasdaq OMX Nordic (2017).

### 3.2 Dependent variable

Initial return is calculated as the simple return during the first day of trading, which is the percentage difference between the IPO offer price and the closing price first day of trading.

\[
Initial\; return\; (\%) = \frac{Closing\; price - offer\; price}{Offer\; price}
\]

Positive initial returns illustrate that the IPO price is lower than the market price and thus implies that the IPO valuation is lower than the market’s valuation. Setting a price lower than the market’s valuation is the definition of underpricing and positive initial returns will therefore also be referred to as underpricing.

I have not calculated excess returns\(^{11}\) as my interest is to compare the

\(^{11}\)The difference between the initial return and corresponding index return the same time period.
valuation of the IPO, reflected in the offer price, and the market’s valuation reflected in the closing price first day of trading. Furthermore, the time frame between offering date and the first day of trading is in general short. Market returns during that period are therefore assumed to have remote effects on the initial returns (Ljungkvist, 2007). Moreover, a substantial share of the firms included in the study exhibit low levels of market capitalization, high volatility and are deeply affected by investor sentiment among other things, which makes it difficult to find a suitable index to use when calculating excess returns. Use of market adjusted returns will be of greater importance if one is interested in examining the long-run performance.

3.3 Industry classifications

The choice of industry classification is an important factor of consideration as my research objective is to compare valuation and characteristics between sectors. Common industry classifications used in research are Standard Industry Classification (SIC) and Industry Classification Benchmark (ICB). However, neither SIC or ICB was available for all firms included in my data set. SIC codes have further been found to frequently misclassify firms (Kim and Ritter, 1999). I therefore decided to use Bloomberg Industry Classification Systems (BICS). Apart from being global and available for all firms included in the data set, it is also available for up to 7 different levels (such as sector name and industry group name) which were helpful in controlling that firms were placed in plausible categories. The BICS is a market based classification system identifying companies by the sectors of their primary income. This implies that firms classified as technology are primary addressing a segment belonging to the technology industry. The initial distribution of observations by industry is found in Table 1 below.
With few observations within Consumer Staples, I decided to merge this group with Consumer Discretionary into one Consumer goods category. I also moved the single observation (Arise Windpower) from Utilities to Energy as the firm is a wind power company. After adjusting the classifications, I have the following number of observations in each industry classification.

<table>
<thead>
<tr>
<th>Industry classification</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Communications</td>
<td>9</td>
</tr>
<tr>
<td>Consumer Discretionary</td>
<td>36</td>
</tr>
<tr>
<td>Consumer Staples</td>
<td>6</td>
</tr>
<tr>
<td>Energy</td>
<td>7</td>
</tr>
<tr>
<td>Financials</td>
<td>20</td>
</tr>
<tr>
<td>Health care</td>
<td>74</td>
</tr>
<tr>
<td>Industrials</td>
<td>26</td>
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<td>Materials</td>
<td>7</td>
</tr>
<tr>
<td>Technology</td>
<td>30</td>
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<tr>
<td>Utilities</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 2: Number of observations in each sector after adjustments.

Fewest (7) observations are found within materials, and 74 (34% of the data) observations are found within the healthcare industry.

The classification of technology companies is rather cumbersome. For example, there might be companies exhibiting certain characteristics often
found among technology firms, but that are classified as companies of other industries because they are specifically targeting a particular sector. The same reasoning holds for numerous healthcare businesses that often are found to be young, exhibiting high R&D expenditures and often possess patents relying on technological improvements. Yet, the companies are regarded as healthcare firms since their business technology is used within the healthcare industry. These firms are often classified as Biotech due to the combination of technology and healthcare specialization. With better access to data, it would have been desirable to construct a classification system by combining variables such as BICS, SNI (Swedish equivalent of SIC), R&D expenditure, and patenting activity for example. Although the discussion of defining technology companies is highly interesting, I decided to use an established classification system to avoid ending up with arbitrary results.

3.4 Extreme values

As one of my research objectives is to study the average effect of underpricing, it is important to handle extreme values as these have a significant impact on descriptive statistics. As I am interested in studying variables such as mean and variance, it is of utmost importance to take care of extreme values to avoid skewed results. I will furthermore apply OLS regression which is rather sensitive to outliers, and it is thereby important to adjust for extreme values. I decided to use the technique of winsorizing which is used to set the extreme values to the value of observations at a certain percentile. In my case, I decided to use a 1% winsorization fraction, implying that observations below the 1st percentile are set to the value of the observation at the 1st percentile and observations above the 99th percentile are set to the value at the 99th percentile. This implies that four variables have been adjusted as I have 216 observations in total. There is no clear rule to follow when considering extreme values of initial returns. These observations have been checked multiple times and have not arisen due to data entry errors. I
however had to adjust the most extreme variables to avoid skewed descriptive statistics.

<table>
<thead>
<tr>
<th>Adjustments</th>
<th>Average initial return</th>
<th>Adjusted variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>No winsorization</td>
<td>13.22%</td>
<td>0</td>
</tr>
<tr>
<td>0.5% winsorization fraction</td>
<td>12.91%</td>
<td>2</td>
</tr>
<tr>
<td>1% winsorization fraction</td>
<td>12.22%</td>
<td>4</td>
</tr>
<tr>
<td>2.5% winsorization fraction</td>
<td>11.85%</td>
<td>10</td>
</tr>
</tbody>
</table>

*Table 3: Winsorization fraction and the effect on average initial returns.*

Table 3 illustrates how the mean decreases as the winsorization fraction increases, implying that the upper extreme values have great positive impact on the average initial return. At 1% winsorization, I have adjusted initial returns of 311% and 230% to 147%, whereas -60% and -48% have been adjusted to -39% in the lower bound.

### 3.4.1 Distribution of data

As shown in Table 3, especially large positive extreme values have a great impact on the mean. This implies that the distribution of my data could be skewed by the large positive extreme values. It is reasonable to assume that the distribution of extreme values will be skewed due to the nature of mathematics since there is no theoretical upper limit for positive initial returns, whereas negative initial returns cannot exceed -100%. This is illustrated in the minimum observation of -60% and the maximum observation of 311%.
The distribution of underpricing demonstrates how large positive initial returns have great impact on the mean. It is also illustrated by the skewness of the distribution which exhibits a longer right tail, indicating that significant positive initial returns are more common than large negative returns. It further illustrates that underpricing is not symmetrically distributed around its mean.

### 3.5 Statistical methods

As I am interested in investigating whether IPO underpricing is still present in the Swedish stock markets, a significant amount of information is provided by studying descriptive statistics. Apart from reporting summary statistics, I will compare these between industries to investigate whether sector specific differences exist.
I am further interested in examining if technology companies are subject to great valuation variances by comparing the variance of initial returns against other industries. A significant difference would not explicitly imply that technology firms are harder to value as the variance merely is an aggregated measure of the observations deviation from the mean. It would, however, illustrate that technology firms are subject to greater differences in valuations between investment banks and investors, which could be interpreted as an indicator of valuation difficulty.

3.5.1 T-test

I have used Student’s t-test to examine whether the average level of underpricing is significant. The null-hypothesis is that the average level of underpricing is 0, implying that the pattern of underpricing is non-existing. If the observed t-statistic is greater than the critical value, I will reject the null-hypothesis which would significantly prove that underpricing exist. As indicated in the discussion of extreme values, the distribution of underpricing seems to be affected by some skewness. The skewness does not however seem to be severe, and the effect the potential skewness could have on the power of the t-test should not be great enough for the t-test to lose its practicality. Furthermore, t-tests do not require the assumption of normality in larger samples as t-tests have been found to be useful even for extreme non-normal data in sufficiently large samples (Lumley et al., 2002).

3.5.2 Kruskal Wallis

The t-test is an appropriate method to compare the difference in means, but I am furthermore interested in testing whether differences in underpricing between industries exist. The Kruskal Wallis is a nonparametric version of the ANOVA test which allows for comparisons of more than two groups. Even if ANOVA is not extremely sensitive to the assumption of normality, I chose to apply a nonparametric test as my data exhibits patterns of being
slightly skewed. The Kruskal Wallis tests whether the sampled groups are taken from the same population. It is thus often used as a test of medians between industries. Using a nonparametric test like Kruskal-Wallis is for example advantageous when the means are affected by extreme values. The test-statistic is calculated accordingly:

\[
H = (N - 1) \frac{\sum_{i=1}^{k} n_i (\bar{r}_i - \bar{r})^2}{\sum_{i=1}^{k} \sum_{j=1}^{n_i} (r_{ij} - \bar{r})^2}
\]  

(3)

\(N\) is number of total observations, \(n_i\) is observations in group \(i\), \(r_{ij}\) is the rank of observation \(j\) from group \(i\), \(\bar{r}_i\) is the average rank of observations in group \(i\) and \(\bar{r}\) is the average of \(r_{ij}\). The Kruskal Wallis follows a Chi-Square distribution with \(k-1\) degrees of freedom. If the observed test-statistic \(H\) is greater than the critical value, I will reject the null-hypothesis that the groups follow the same distribution. This would imply that underpricing is differently distributed across industries. If not significant, I can only conclude that the phenomenon of underpricing is present but that the statistical nonparametric test suggests that there is no significant difference between industries.

3.5.3 Levene’s test of variances

The test of variance between industries is related to my hypothesis of valuation difficulties. To examine whether technology firms are affected by higher valuation variances compared to other industries, I will apply Levene’s test of variances which is a two-sample variance-comparison test using groups. The test is thus used to examine differences in standard deviations between groups. The groups will be categorized as technology firms against rest of the sample.

\[
W = \frac{(N - k)}{(k - 1)} \frac{\sum_{i=1}^{k} N_i (Z_{it} - Z..)^2}{\sum_{i=1}^{k} \sum_{j=1}^{N_i} (Z_{ij} - Z_i)^2}
\]  

(4)
Where \( N \) is total number of observations, \( N_i \) is number of observations in group \( i \), \( k \) is number of groups, \( Z_{ij} = |Y_{ij} - \bar{Y}_i| \) where \( Y_{ij} \) is the value of observation \( j \) from group \( i \), \( Z_i \) is the mean of \( Z_{ij} \) for group \( i \) and \( Z_\cdot \) is the average for all \( Z_{ij} \). The test statistic \( W \) will then be compared to the critical value taken from the F-distribution with \( k-1 \) and \( N-k \) degrees of freedom. This implies that the test is sensitive to the assumption of that the data is normally distributed. Since my data seem to be affected by some skewness, I will also apply a robust version of Levene’s test to check for this.

I will thus apply a second test which is a robust version of the Levene’s test using a test-statistic that has been found to be robust for non-normality (Levene, 1960). Apart from using a robust test statistic, the robust test will also examine how the results differ if one replace the mean with the median which might be useful in cases of nonnormality as proposed by Brown and Forsythe (1974). It will also report the test statistic where the mean has been replaced by a 10% trimmed mean.

I will thereby test whether the robust test statistic is greater than the critical value. This would, in turn, imply that the variance in underpricing is greater among technology firms than rest of the sample, implying that technology firms are subject to greater valuation variance than rest of the sample. It would, therefore, suggest a potential difficulty in valuing technology firms relative to firms of other industries.

### 3.5.4 Regression analysis

To examine whether the degree of underpricing can be explained by several firm-specific variables, I will apply Ordinary Least Squares (OLS) regressions. OLS is an estimation technique used to examine linear relationships between a dependent variable (response) and independent (explanatory) variables. Initial return will be employed as the dependent variable and firm-specific variables as independent variables. I do not anticipate to fully explain the degree of underpricing but rather to control if underpricing is affected by
some firm-specific attribute. I have used the following regression model:

\[
\begin{align*}
\ln(\text{Initial return}_i + 1) &= \beta_0 + \beta_1 \ln(\text{age}_i + 1) + \beta_2 \text{Revenue}_i + \beta_3 \text{EBIT}_i + \\
&\quad + \beta_4 \sqrt{\text{Capital raised}_i} + D_j \text{Industry}_j + D_t \text{Year}_t + \varepsilon_i
\end{align*}
\]  \tag{5}

Where Revenue, EBIT and Capital raised have been adjusted for firm size by dividing the variables by the firm’s market capitalization. Revenue for firm \(i\) is for example calculated as:

\[
\text{Revenue}_i = \frac{\text{Revenue}_i}{\text{Market Cap}_i}
\]  \tag{6}

I have also added two sets of dummy variables to control for industry and yearly fixed effects. These are included to check that a potential explanatory effect on underpricing is not generated through a specific industry or year. The fixed effect variables are normalized to the category that represented the overall sample best. I for example decided to add dummy variables for all industries except financials, which was found to represent the sample best.

As noticed in section 3.4.1, initial returns are not symmetrically distributed around its mean but rather slightly skewed to the right. I will therefore use the natural logarithm of initial returns, which made the distribution more symmetrical. I have further added the constant one before taking the natural logarithm to avoid undefined observations.\(^{12}\)

The variable age has previously been found to affect the initial returns positively during some periods and to affect long-run returns negatively in other studies. It is possible that age has an impact on the level of underpricing in a market heavily affected by investor sentiment. Age shows patterns of being log-normally distributed which is why I also chose to use the natural logarithm of age as well. Once again I added the constant one before taking

\(^{12}\)Some observations exhibit initial returns of 0%. As the natural logarithm of 0 is undefined one has to add a constant sufficiently large to define all variables.
the natural logarithm as firms with age 0 would have been dropped otherwise. The same setup for age is used in Carter, Dark and Singh (1998).

I included revenue and EBIT in the regression to control that the variables have been incorporated into the offer price. If revenue or EBIT would show to have positive effects on initial returns, it is possible that the variables have not been fully incorporated into the offer price or reflect a scenario where the market has a greater demand for mature firms of high quality. On the contrary, if revenues and EBIT have a significant negative effect on initial returns, it would be reasonable to assume that underpricing arises due to high expectations of future growth as negative revenues and EBIT evidently would be assumed to only be transitory. My hypothesis is that both revenues and EBIT have been incorporated in the offer price and I thereby anticipate the variables not to have an impact on the level of underpricing.

I have further added capital raised in the IPO in relation to market capitalization in the regression. I expect the market capitalization adjusted level of capital raised to have a negative impact on initial returns. This is based on the reasoning that higher capital raised implies a greater supply of shares and thus I expect the initial return to be lower. Apart from using a standard supply/demand framework, higher capital raised relative to firm size implies some uncertainty. For example, compare a business that needs to raise 5% of its market capitalization to fund its operations to a firm that needs to raise 40% of its expected market value. Obviously depending on the firm, its business and strategic objectives, but I find it plausible to assume that raising more capital relative to the firm size implies uncertainty. I further noticed that capital raised/market capitalization showed patterns of being log-normally distributed. I however found the data to become more symmetrical and normally distributed by using the square root of capital raised/market capitalization in the regression. By transforming the variables according to the above, I have increased the goodness of fit and gained more symmetrical distributions of the regression residuals as illustrated in Figure
To control that the data is not affected by heteroskedasticity, I ran the regression presented above and plotted the residuals vs. fitted values (Figure 4).

Figure 3: Distribution of predicted regression residuals.
Figure 4 illustrates that the data seem to be affected by heteroskedasticity as the residuals seem to increase as the fitted values increases which is a sign of heteroskedasticity. I further performed a Breusch-Pagan test which showed that the data is subject to heteroskedasticity. I will, therefore, use robust standard errors in the subsequent regressions.
4 Empirical analysis

4.1 Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>p10</th>
<th>p90</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial return</td>
<td>12.22%</td>
<td>5.07%</td>
<td>-39.23%</td>
<td>-20.06%</td>
<td>53.17%</td>
<td>147.33%</td>
</tr>
</tbody>
</table>

*Table 4: Initial return: mean, median and percentiles.*

The average level of initial return is 12.22% for the winsorized data set, which is in line with the level presented in Ljungqvist (2007). This indicates that underpricing is an existing phenomenon and illustrates a great difference between the valuation in the IPO and the market’s perceived valuation. It further implies that stocks on average tend to perform well the first day of trading. The median (5.07%) is however substantially lower than the mean. This highlights the fact that average initial return is highly affected by significant returns of several well performing stocks.

Apart from the positive mean and median, the fraction of transactions with positive initial returns is found to be 60.19%. This indicates that a majority of the IPOs tend to be profitable for investors and further highlights the potential skewness of the distribution. The pattern of high average initial returns and modest fractions of positive IPO outcomes have been found in previous studies. Ibbotson (1975) found the average initial return to be 11.4% while the probability of a random gain was found to be approximately 50%.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>T-statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial return</td>
<td>216</td>
<td>12.22%</td>
<td>32.83%</td>
<td>5.4718</td>
<td>0.000</td>
</tr>
</tbody>
</table>

*Table 5: The observed t-test statistic indicates that the mean initial return is significantly different from zero.*

The outcome of the t-test is presented in Table 5. Although the data seem to be affected by some skewness, t-tests are argued to be valid in sufficiently
large samples and therefore applicable even in cases where data could exhibit patterns indicating non-normality. The t-statistic is calculated to 5.4718 which corresponds to a p-value of 0.00. I can thus conclude that the average initial return is significantly greater than 0 and thereby confirm the existence of underpricing.

Apart from confirming the general existence of underpricing, it is moreover interesting to examine whether the level of underpricing differs between industries.

<table>
<thead>
<tr>
<th>Industry classification</th>
<th>Mean</th>
<th>Median</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industrials</td>
<td>28.86%</td>
<td>12.30%</td>
<td>46.14%</td>
</tr>
<tr>
<td>Technology</td>
<td>15.66%</td>
<td>2.85%</td>
<td>43.79%</td>
</tr>
<tr>
<td>Health care</td>
<td>12.63%</td>
<td>3.06%</td>
<td>32.73%</td>
</tr>
<tr>
<td>Financials</td>
<td>10.30%</td>
<td>5.28%</td>
<td>14.59%</td>
</tr>
<tr>
<td>Materials</td>
<td>7.09%</td>
<td>1.67%</td>
<td>26.56%</td>
</tr>
<tr>
<td>Consumer</td>
<td>6.41%</td>
<td>5.98%</td>
<td>21.26%</td>
</tr>
<tr>
<td>Communications</td>
<td>2.85%</td>
<td>7.30%</td>
<td>23.13%</td>
</tr>
<tr>
<td>Energy</td>
<td>-4.25%</td>
<td>-3.00%</td>
<td>18.67%</td>
</tr>
<tr>
<td>Total</td>
<td>12.22%</td>
<td>5.07%</td>
<td>32.83%</td>
</tr>
</tbody>
</table>

*Table 6: Underpricing across industries.*

The best performing IPOs regarding average initial return are found within industrials where the average initial return was found to be 28.86%. This is followed by an average initial return of 15.66% in the technology sector and 12.63% in the healthcare industry. This implies that the average initial return among technology firms is substantially lower than what has been found in earlier studies. The industrial sector further exhibits the highest median (12.3%), followed by communications (7.3%) and consumer goods industry (5.98%). The worst performing IPOs are on average found within the energy industry, reflected in an average initial return of -4.25% and median of -3%.

Interestingly, there is a great difference between the mean and the median in almost all observed industries. It is especially evident in the case of
technology firms where the median (2.85%) is substantially lower than the mean (15.66%). Technology firms further seem to exhibit large standard deviation relative to all other industries except the industrial sector. At first glance, this appears to support my hypothesis of great valuation differences for technology firms.

4.2 Industry comparison

There appear to exist differences in the degree of underpricing across industries as indicated in Table 6. It is, therefore, interesting to investigate whether differences do exist in other variables that might affect the attractiveness of a specific sector. For example, if companies within the industrial sector are characterized as more profitable compared to other industries, it might be plausible to expect a greater demand for their shares reflected by higher initial returns. To make this comparison, I have summarized the average market capitalization, capital raised, revenues, earnings before interest rates and taxes (EBIT) and company age. All figures except firm age are presented in million SEK.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Market cap</th>
<th>Capital raised</th>
<th>Revenues</th>
<th>EBIT</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>Communications</td>
<td>1805.18</td>
<td>775.48</td>
<td>533.06</td>
<td>76.20</td>
<td>6.67</td>
</tr>
<tr>
<td>Consumer</td>
<td>1648.06</td>
<td>610.13</td>
<td>1594.01</td>
<td>95.72</td>
<td>13.00</td>
</tr>
<tr>
<td>Energy</td>
<td>370.12</td>
<td>133.10</td>
<td>5.89</td>
<td>-12.46</td>
<td>9.00</td>
</tr>
<tr>
<td>Financials</td>
<td>3328.49</td>
<td>1149.58</td>
<td>751.75</td>
<td>280.67</td>
<td>19.90</td>
</tr>
<tr>
<td>Health care</td>
<td>636.08</td>
<td>223.43</td>
<td>501.18</td>
<td>37.69</td>
<td>7.73</td>
</tr>
<tr>
<td>Industrials</td>
<td>1359.03</td>
<td>517.62</td>
<td>1842.90</td>
<td>119.27</td>
<td>13.12</td>
</tr>
<tr>
<td>Materials</td>
<td>735.27</td>
<td>425.71</td>
<td>913.03</td>
<td>88.22</td>
<td>20.57</td>
</tr>
<tr>
<td>Technology</td>
<td>685.41</td>
<td>188.00</td>
<td>138.23</td>
<td>11.99</td>
<td>10.30</td>
</tr>
<tr>
<td>Total</td>
<td>1218.10</td>
<td>441.08</td>
<td>844.30</td>
<td>79.11</td>
<td>11.31</td>
</tr>
</tbody>
</table>

Table 7: Industry averages of firm-specific variables.

The largest firms in terms of greatest average market cap are found within the financial industry (3328 mSEK), followed by communications
(1805 mSEK) and consumer (1648 mSEK). The financial industry is characterized by large absolute values of capital raised and further exhibit the highest average absolute earnings as well as highest EBIT relative to revenues. The average level of capital raised differs between industries in absolute terms but is approximately the same for all industries when calculated relative to market capitalization.

Interestingly, companies within the industrial sector which exhibited highest initial returns, seem to be rather average in terms of average market capitalization and average capital raised. Average revenue and EBIT are however found to be higher than the total average. It is therefore interesting to examine whether the level of underpricing could be derived from high revenues and earnings. It could in such case illustrate that the variables have not been fully incorporated into the offer price or reflect a greater demand for stable and profitable businesses.

The youngest firms are on average found within communications, energy, healthcare and technology. There is a substantial difference in mean age between communications, where the average company went public 6.67 years after registration and materials where the corresponding number is 20.57 years.
Figure 5: Distribution of initial returns by industry.

The distribution of underpricing seem to exhibit rather different patterns in all sectors. Notice that industrials and technology appear to be the sectors that are most likely to affect the skewness of the total sample distribution as they contain several observations with large initial returns. Similar skewed patterns seem to be noticeable in the consumer and healthcare industry where large positive initial returns have a great impact on the mean. It is rather difficult to state something about communications, energy and materials other than that the observations seem to be distributed around the mean and that these industries contain too few observations to draw any further conclusions.

As the distribution of initial returns appears to be rather skewed, it becomes necessary to examine more statistics than just the mean. The median was for example found to be lower than the mean in most sectors and fur-
thermore seemed to differ between sectors. I therefore found it interesting to examine whether the distribution of underpricing differs between industries. As the data show signs of skewness, I applied the nonparametric Kruskal-Wallis test. As mentioned in the methodology section, Kruskal-Wallis test whether groups exhibit similar distributions. Thus, it can also be used to compare medians between groups.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Obs</th>
<th>Rank Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Communications</td>
<td>9</td>
<td>912.00</td>
</tr>
<tr>
<td>Consumer</td>
<td>42</td>
<td>4308.50</td>
</tr>
<tr>
<td>Energy</td>
<td>8</td>
<td>559.50</td>
</tr>
<tr>
<td>Financials</td>
<td>20</td>
<td>2354.50</td>
</tr>
<tr>
<td>Health Care</td>
<td>74</td>
<td>7972.50</td>
</tr>
<tr>
<td>Industrials</td>
<td>26</td>
<td>3402.00</td>
</tr>
<tr>
<td>Materials</td>
<td>7</td>
<td>709.00</td>
</tr>
<tr>
<td>Technology</td>
<td>30</td>
<td>3218.00</td>
</tr>
<tr>
<td><strong>Observed Chi-Square statistic</strong> = 7.416</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Probability</strong> = 0.3869</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 8: Kruskal-Wallis test of distributions between industries. Observed test statistic implies that the null hypothesis of an equal distribution between industries cannot be rejected.

According to the Kruskal-Wallis test statistic (7.416), we cannot reject the null hypothesis that the distributions are equal across industries. This indicates that there is no significant difference in distributions between the groups. Hence, I can only state that the phenomenon of underpricing exists but the distribution of underpricing is not significantly different between industries using a nonparametric test.

4.3 **Exchange characteristics**

Not only are there differences in industry characteristics, but there are also differences between stock exchanges. Differences between exchanges are ex-
pected as the examined exchanges apply different rules and requirements for companies applying for listing. One would, for example, expect companies listed on Nasdaq Stockholm to exhibit higher revenues and EBIT as Nasdaq Stockholm incorporate larger firms compared to Nasdaq First North, where I use market capitalization as the primary variable defining the size of a company. It is in general reasonable to expect larger firms to be listed on larger exchanges. It is thereby plausible to expect that the largest companies in terms of market capitalization are traded on Nasdaq Stockholm and smaller companies are traded on Nasdaq First North and AktieTorget.

<table>
<thead>
<tr>
<th>Exchange</th>
<th>Market cap</th>
<th>Capital raised</th>
<th>Revenues</th>
<th>EBIT</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nasdaq Stockholm</td>
<td>4230.42</td>
<td>1590.29</td>
<td>3279.74</td>
<td>314.41</td>
<td>20.56</td>
</tr>
<tr>
<td>Nasdaq First North</td>
<td>392.82</td>
<td>110.24</td>
<td>63.40</td>
<td>3.36</td>
<td>9.32</td>
</tr>
<tr>
<td>AktieTorget</td>
<td>55.97</td>
<td>11.85</td>
<td>5.17</td>
<td>-1.70</td>
<td>7.26</td>
</tr>
<tr>
<td>Total</td>
<td>1218.10</td>
<td>441.08</td>
<td>844.30</td>
<td>79.11</td>
<td>11.31</td>
</tr>
</tbody>
</table>

*Table 9: Average levels of firm-specific variables by exchange.*

This is supported by the data where the average market capitalization is 4230 mSEK for Nasdaq Stockholm, 392 mSEK for First North and 56 mSEK for AktieTorget. There are moreover substantial differences in average levels of revenue, EBIT and age. AktieTorget is especially deviating as the average revenues are low (5 mSEK), earnings are on average negative (-1.7 mSEK) and the firms are in general younger than the firms listed on Nasdaq Stockholm and First North. Apart from being consistent with expectations, it also illustrates the possibility that a majority of companies listed on AktieTorget are in an earlier stage of business as revenues are low and earnings are negative. As stated in the theoretical framework, these are typical characteristics of companies expected to experience significant growth. I find this consistent with my data as the average market capitalization is still large relative to revenues and earnings.
### Table 10: Average, median and standard deviation of initial return by exchange.

<table>
<thead>
<tr>
<th>Exchange</th>
<th>Average</th>
<th>Median</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nasdaq Stockholm</td>
<td>9.79%</td>
<td>6.94%</td>
<td>13.24%</td>
</tr>
<tr>
<td>Nasdaq First North</td>
<td>9.18%</td>
<td>1.94%</td>
<td>33.02%</td>
</tr>
<tr>
<td>AktieTorget</td>
<td>16.44%</td>
<td>5.76%</td>
<td>40.31%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>12.22%</td>
<td>5.07%</td>
<td>32.83%</td>
</tr>
</tbody>
</table>

Interestingly, AktieTorget is exhibiting the largest average level of underpricing (16.44%). According to the exchange characteristics, this would imply that underwriters seem to value some firms listed on AktieTorget substantially lower than the investors. It is possible that the high average initial return among firms listed on AktieTorget is driven by several firms affected by high expectations from investors. The slightly skewed distribution is also visible in all exchanges. The median for AktieTorget is for example 10.69 p.p. lower than the corresponding mean. The highest median is found on Nasdaq Stockholm (6.94%). It is also interesting to note that the standard deviation of underpricing among firms listed on Nasdaq Stockholm seem to be substantially lower compared to First North and AktieTorget.

I further found it interesting to examine the proportion of IPOs with positive initial returns across exchanges. For AktieTorget, 56.98% of the initial returns are positive. The similar measure for First North is 55.26% and 72.22% for Nasdaq Stockholm. This implies that IPOs performed on Nasdaq Stockholm, in general, have been profitable for investors by yielding the highest median and greatest proportion of positive initial returns.

#### 4.4 Time series variation

I noticed that there seemed to exist some differences among industries and exchanges, which is why I also wanted to examine whether there are yearly differences in the level of underpricing. As mentioned in the theoretical framework, underpricing has historically been found to vary greatly between
periods. It is, however, important to remember that the period of study is rather narrow and that the number of observations between 2010-2013 is few compared to the number of observations in the subsequent years.

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Median</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>2.04%</td>
<td>-0.31%</td>
<td>27.19%</td>
</tr>
<tr>
<td>2011</td>
<td>22.49%</td>
<td>0.50%</td>
<td>44.18%</td>
</tr>
<tr>
<td>2012</td>
<td>-13.08%</td>
<td>-5.03%</td>
<td>21.68%</td>
</tr>
<tr>
<td>2013</td>
<td>30.47%</td>
<td>25.09%</td>
<td>38.58%</td>
</tr>
<tr>
<td>2014</td>
<td>5.41%</td>
<td>3.06%</td>
<td>24.39%</td>
</tr>
<tr>
<td>2015</td>
<td>16.63%</td>
<td>10.75%</td>
<td>30.83%</td>
</tr>
<tr>
<td>2016</td>
<td>13.13%</td>
<td>5.28%</td>
<td>36.48%</td>
</tr>
</tbody>
</table>

Table 11: Average, median and standard deviation of initial returns by year.

Table 11 illustrates that underpricing seem to vary greatly between years. The average level of underpricing was found positive in all years except 2012. Not only was the average initial return negative, but the number of observations was also fewest during that year. 2012 was further characterized by the lowest median (-5.03%) which altogether illustrates that 2012 was a bad year for IPOs in Sweden. It was followed by the year of highest average level of underpricing (30.47%) and a median of 25.09%. This indicates that the level of underpricing varies considerably between years as the difference in average initial return between 2012-2013 is 43.55 p.p.
I have further plotted the data to examine whether the initial return (underpricing) seem to follow IPO volume as suggested by the hot issue markets theory. The relationship between average initial returns and IPO volume is not obvious by studying Figure 6. It might illustrate a relationship between initial return and IPO volume during specific years, such as 2012 where both the number of IPOs and the average initial return decreased substantially compared to 2011. This was then followed by an increase of average initial return and IPO volume in 2013. The figure illustrates that IPO volume follows the level of underpricing fairly well during some specific years, but underpricing is in general a weak indicator of IPO volume in such a narrow time frame. In order to examine whether this is consistent with the hot issue markets theory, it would be more reasonable to introduce more years or to compare the entire data set against other time periods of similar length.

Figure 6: Mean initial return and IPO volume between 2010-2016.
4.5 Test of variance between industries

To test whether specific companies are subject to greater valuation variances, I am interested in examining if the standard deviation significantly differs between industries. To perform this comparison, I created a binary variable given the value 1 if the firm belongs to the technology industry and 0 for all other firms. This variable was then used to separate the groups in the performed variance ratio test.

<table>
<thead>
<tr>
<th>Group</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology</td>
<td>30</td>
<td>15.66%</td>
<td>43.79%</td>
</tr>
<tr>
<td>Rest of the sample</td>
<td>186</td>
<td>11.67%</td>
<td>30.81%</td>
</tr>
</tbody>
</table>

F-statistic = 0.4954
P-value = 0.0058

Table 12: Output table of variance ratio test. The P-value implies that the variance in initial returns among technology firms is significantly greater than the variance for the aggregated rest of the sample.

By comparing firms classified as technological to the rest of the sample I conclude that the average underpricing is greater for technology firms than the aggregated average for all other industries. Interestingly, the variance is also significantly greater for firms within the technology industry compared to rest of the firms according to the variance ratio test presented in Table 12. This indicates that the hypothesis that technology firms, in general, are subject to great valuation differences holds. Assuming that the offer price and closing price first day of trading solely are based on the investment banks and market’s valuation, the great variance suggests a difficulty in valuing technology companies relative to other firms as the difference in valuation between market actors is significantly large compared to other sectors. It is important to remember that technology firms have historically been found to be heavily affected by investor sentiment and that the greater variance could be a result of this. Great variance is per definition implying that the
initial return of technology firms, in general, differs much from the industry average.

The F-test is however sensitive to non-normality. As I have previously noticed that the distribution of my observations is rather skewed, I have to check that the result is robust and significant in tests adjusted to capture effects of non-normality data, which is why I also apply Levene’s robust test for equality of variances.

<table>
<thead>
<tr>
<th>Group</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology</td>
<td>30</td>
<td>15.66%</td>
<td>43.79%</td>
</tr>
<tr>
<td>Rest of the sample</td>
<td>186</td>
<td>11.67%</td>
<td>30.81%</td>
</tr>
</tbody>
</table>

W0 = 3.6719, Pr > F = 0.0567
W50 = 2.3116, Pr > F = 0.1299
W10 = 2.6647, Pr > F = 0.1041

*Table 13: Output table of Levene’s robust test of variances. The p-value indicates that the null hypothesis of equal variances cannot be rejected at 5% level of significance.*

The robust test presented in Table 13 indicates that the difference in variance is not significant at 5% level of significance. This is especially evident when replacing the mean with the median to calculate the variance, which is illustrated in the W50 statistic. Remember that this is a test of variance between technology firms and all other firms, which only implies that technology firms do not exhibit greater variance than the rest of the sample. It is still possible that technology firms are affected by higher variance than other specific sectors. If I, for example, excluded the industrial sector from the data, the robust variance test would have been significantly different (see appendix). This implies that industrials is subject to great variance which obviously affects the variance of the full sample. Technology firms are in general subject to great valuation variances, but the variance is not however significantly greater than the variance of the rest of the sample using robust test statistics.
4.6 Regression analysis

As I previously noticed that there are some industry differences in average levels of underpricing, market capitalization, capital raised, revenues and EBIT, I found it interesting to examine whether these variables affect the level of underpricing. In order to adjust for firm size differences, reflected in the large absolute differences in capital raised, revenues and EBIT, I have used the variables relative to the firms market capitalization. To investigate whether the degree of underpricing is affected by the mentioned variables I ran the regression presented in the methodology section (equation 6).

Both revenue and EBIT relative to market capitalization are significant when capital raised relative to market capitalization is excluded. Interestingly, the beta coefficient for revenues is negative, indicating that the higher the revenues, the less the degree of underpricing. However, one should be careful interpreting this as the effect does not remain significant after introducing capital raised as the dependent variable. The significance of EBIT will also disappear after controlling for both industry and yearly fixed effects. The p-value of the EBIT coefficient in regression (4) is 0.093. Hence, it is not significant at 5% level of significance.

Although it is appealing to find relationships that significantly explain occurring phenomenon, I also find it interesting to reject the hypothesis that revenues and EBIT could account for the degree of underpricing. The primary intention to include revenue and EBIT was to control for that these have been incorporated into the offer price. I would, in general, expect high revenues and positive EBIT to be desired in a climate where many firms exhibit low levels of revenues and profits. It is reasonable that these variables have already been incorporated in the offer price. Furthermore, it could also be offset by a strong demand for firms that are expected to experience high sales growth and a profitable future, but with low current levels of revenues and profits.

In contradiction to previous studies, age was found not to be significant.
<table>
<thead>
<tr>
<th></th>
<th>(1) ln(ir+1)</th>
<th>(2) ln(ir+1)</th>
<th>(3) ln(ir+1)</th>
<th>(4) ln(ir+1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(age+1)</td>
<td>-0.0028 (0.0194)</td>
<td>-0.0019 (0.0181)</td>
<td>-0.0076 (0.0177)</td>
<td>-0.0047 (0.0177)</td>
</tr>
<tr>
<td>Rev</td>
<td>-0.0510* (0.0251)</td>
<td>-0.0146 (0.0154)</td>
<td>-0.0186 (0.0191)</td>
<td>-0.0202 (0.0192)</td>
</tr>
<tr>
<td>EBIT</td>
<td>0.4957** (0.1544)</td>
<td>0.3135 (0.1819)</td>
<td>0.3294* (0.1595)</td>
<td>0.2768 (0.1594)</td>
</tr>
<tr>
<td>sqrt(cap raised)</td>
<td>-0.2397*** (0.0330)</td>
<td>-0.2397*** (0.0318)</td>
<td>-0.2459*** (0.0327)</td>
<td>-0.2459*** (0.0327)</td>
</tr>
<tr>
<td>Financials</td>
<td>0.0000 (. )</td>
<td>0.0000 (. )</td>
<td>0.0000 (. )</td>
<td>0.0000 (. )</td>
</tr>
<tr>
<td>Communications</td>
<td>-0.1400 (0.0795)</td>
<td>-0.1131 (0.0807)</td>
<td>-0.1131 (0.0807)</td>
<td>-0.1131 (0.0807)</td>
</tr>
<tr>
<td>Consumer</td>
<td>-0.0286 (0.0381)</td>
<td>-0.0067 (0.0561)</td>
<td>-0.0157 (0.0377)</td>
<td>-0.0157 (0.0377)</td>
</tr>
<tr>
<td>Energy</td>
<td>-0.0699 (0.0587)</td>
<td>-0.0615 (0.0561)</td>
<td>-0.0615 (0.0561)</td>
<td>-0.0615 (0.0561)</td>
</tr>
<tr>
<td>Healthcare</td>
<td>-0.0251 (0.0354)</td>
<td>-0.0157 (0.0377)</td>
<td>-0.0157 (0.0377)</td>
<td>-0.0157 (0.0377)</td>
</tr>
<tr>
<td>Materials</td>
<td>-0.0319 (0.0543)</td>
<td>-0.0342 (0.0686)</td>
<td>-0.0342 (0.0686)</td>
<td>-0.0342 (0.0686)</td>
</tr>
<tr>
<td>Industrials</td>
<td>0.1111* (0.0554)</td>
<td>0.1339* (0.0568)</td>
<td>0.1339* (0.0568)</td>
<td>0.1339* (0.0568)</td>
</tr>
<tr>
<td>Technology</td>
<td>-0.0259 (0.0584)</td>
<td>-0.0229 (0.0580)</td>
<td>-0.0229 (0.0580)</td>
<td>-0.0229 (0.0580)</td>
</tr>
<tr>
<td>year=2010</td>
<td>0.0000 (. )</td>
<td>0.0000 (. )</td>
<td>0.0000 (. )</td>
<td>0.0000 (. )</td>
</tr>
<tr>
<td>year=2011</td>
<td>0.0679 (0.0848)</td>
<td>0.0679 (0.0848)</td>
<td>0.0679 (0.0848)</td>
<td>0.0679 (0.0848)</td>
</tr>
<tr>
<td>year=2012</td>
<td>-0.2799** (0.0913)</td>
<td>0.0201 (0.0931)</td>
<td>-0.2799** (0.0913)</td>
<td>0.0201 (0.0931)</td>
</tr>
<tr>
<td>year=2013</td>
<td>0.0201 (0.0931)</td>
<td>0.0277 (0.0675)</td>
<td>0.0277 (0.0675)</td>
<td>0.0277 (0.0675)</td>
</tr>
<tr>
<td>year=2014</td>
<td>0.0836 (0.0681)</td>
<td>0.0836 (0.0681)</td>
<td>0.0836 (0.0681)</td>
<td>0.0836 (0.0681)</td>
</tr>
<tr>
<td>year=2015</td>
<td>0.0170 (0.0676)</td>
<td>0.0170 (0.0676)</td>
<td>0.0170 (0.0676)</td>
<td>0.0170 (0.0676)</td>
</tr>
<tr>
<td>year=2016</td>
<td>0.0170 (0.0676)</td>
<td>0.0170 (0.0676)</td>
<td>0.0170 (0.0676)</td>
<td>0.0170 (0.0676)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.1065* (0.0448)</td>
<td>-0.2326*** (0.0605)</td>
<td>-0.2055** (0.0664)</td>
<td>-0.2497*** (0.0925)</td>
</tr>
<tr>
<td>Observations</td>
<td>216</td>
<td>216</td>
<td>216</td>
<td>216</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0472</td>
<td>0.3195</td>
<td>0.3600</td>
<td>0.4142</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 14:** Regression output table where $ir =$ initial return, $Rev =$ Revenue/Market Capitalization, $EBIT =$ EBIT/Market capitalization and $Cap$ raised = Capital raised/Market capitalization. The industry dummy variable has been normalized to the financial industry.
I find this reasonable as I would assume the valuation of a firm to be based on its possibilities to generate future cash flows, which should be depending on business opportunities rather than age. I primarily chose to include age to investigate whether investor sentiment could have an impact on initial returns. I find it reasonable to assume that the age variable had a greater impact during the IT-boom in 1999-2000 compared to the IPO market between 2010-2016.

The variable that I assumed to be most likely to affect the level of underpricing was in fact found to be significant. As illustrated in the regression table, capital raised in terms of market cap is significant at 0.1% level of significance. The beta coefficient is negative which indicates that the more capital a firm raise in their IPO relative to their size the less is the degree of underpricing. I find this result plausible as it implies that the initial return decreases as the relative size of capital raised increases. An economist could potentially visualize this as a lower equilibrium price (initial return) resulting from a relative increase in supply (of equity). The coefficient of determination, $R^2$, increases substantially after introducing the capital raised/market capitalization variable, indicating its importance in determining outcomes of IPOs.

In regression model (3) and (4), I introduce industry and yearly dummy variables to examine whether the results remain robust for industry and yearly fixed effects. Capital raised/market capitalization is robust for these fixed effects and is still significant at a 0.1% level of significance. This finding is expected and consistent with Rock’s (1986) theories of how allotment affect the outcome of an IPO. If the supply of equity is greater, the chances of getting a higher allotment of shares increases and the initial return is likely to be lower. When controlling for industry and yearly effects, I normalized the industry dummies to the financial sector as it represented the average and median degree of underpricing very well relative to other sectors. For yearly fixed effects, I normalized to the year 2010 based on that it is the
starting point of the data and that it was a rather average year regarding underpricing.

The coefficient for industrials is significant at 5% level of significance, indicating substantial levels of underpricing for this industry. Regarding yearly effects, 2012 was found to be the single year where initial returns were significantly less compared to other years. One should, however, bear in mind that the number of observations during this year is low.

The careful reader might notice that the market capitalization (first day of trading) is affected by the initial returns first day of trading. It thus exists a feeding mechanism between the dependent and independent variables. To ensure that my results are robust for this, I remove the effect of initial returns on market capitalization by simply reversing the percentage return.

\[
\text{Adjusted market capitalization} = \frac{\text{Market capitalization first day of trading}}{(1 + \text{initial return})}
\]  
(7)

Running the regressions with revenues, EBIT and capital raised relative to market capitalization adjusted for initial returns yields is presented in Table 15.

After adjusting market capitalization for initial returns, I find that size adjusted EBIT is still significant in regression (1). Revenues are no longer significant after adjusting for initial returns effect on the market capitalization. Neither is capital raised. Both revenue and capital raised remain insignificant at 5% level of significance after introducing industry and yearly fixed effects. The p-values of size adjusted EBIT and capital raised/market capitalization are 0.066 and 0.065 respectively. This implies that the findings in the previous regression are not robust to adjustments for initial returns. The only significant variable is the industrials industry fixed effect which significantly affects the level of underpricing positively.

The goodness of fit (0.13) is substantially lower than in the previous re-
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(age+1)</td>
<td>-0.0046 (0.0194)</td>
<td>-0.0045 (0.0194)</td>
<td>-0.0087 (0.0199)</td>
<td>-0.0059 (0.0197)</td>
</tr>
<tr>
<td>Rev adj</td>
<td>-0.0276 (0.0144)</td>
<td>-0.0226 (0.0141)</td>
<td>-0.0276 (0.0181)</td>
<td>-0.0261 (0.0209)</td>
</tr>
<tr>
<td>EBIT adj</td>
<td>0.2374* (0.1088)</td>
<td>0.2252* (0.1121)</td>
<td>0.2805* (0.1158)</td>
<td>0.2398 (0.1242)</td>
</tr>
<tr>
<td>sqrt(cap adj)</td>
<td>-0.1648 (0.1256)</td>
<td>-0.1925 (0.1301)</td>
<td>-0.2445 (0.1363)</td>
<td></td>
</tr>
<tr>
<td>Financials</td>
<td>0.0000 (.)</td>
<td>0.0000 (.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Communication</td>
<td>-0.1055 (0.0848)</td>
<td>-0.0719 (0.0838)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumer</td>
<td>-0.0117 (0.0414)</td>
<td>0.0134 (0.0444)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>-0.1169 (0.0694)</td>
<td>-0.0970 (0.0699)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthcare</td>
<td>0.0067 (0.0402)</td>
<td>0.0132 (0.0444)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Materials</td>
<td>-0.0207 (0.0816)</td>
<td>-0.0317 (0.0861)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industrials</td>
<td>0.1450* (0.0705)</td>
<td>0.1668* (0.0721)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technology</td>
<td>0.0190 (0.0659)</td>
<td>0.0268 (0.0688)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>year = 2010</td>
<td>0.0000 (.)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>year = 2011</td>
<td></td>
<td>0.1406 (0.1094)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>year = 2012</td>
<td></td>
<td>-0.2286 (0.1230)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>year = 2013</td>
<td></td>
<td>0.1653 (0.1263)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>year = 2014</td>
<td></td>
<td>0.0180 (0.0841)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>year = 2015</td>
<td></td>
<td>0.1217 (0.0844)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>year = 2016</td>
<td></td>
<td>0.0613 (0.0850)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.0997* (0.0450)</td>
<td>0.1877* (0.0813)</td>
<td>0.2027* (0.0893)</td>
<td>0.1470 (0.1268)</td>
</tr>
<tr>
<td>Observations</td>
<td>216</td>
<td>216</td>
<td>216</td>
<td>216</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0117</td>
<td>0.0178</td>
<td>0.0680</td>
<td>0.1304</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Regression output where $ir$ = initial return, $Rev\ adj$ = Revenue/Adjusted market capitalization, $EBIT\ Adj$ = EBIT/Adjusted market capitalization and $Cap\ adj$ = Capital raised/Adjusted market capitalization.
gression (0.42). This is reasonable as the initial return was feeding from underpricing into the market capitalization which was used as size adjusting variable of revenues, EBIT and capital raised. I however find the previous setup more reasonable as market capitalization per definition is the market value of firms outstanding shares. It is yet important to notice the feeding mechanism and its impact on causality. Thus, one can conclude that capital raised has a significant impact on the outcome of IPOs if it is adjusted according to the market capitalization at the closing price first day of trading. The more capital a firm raise in relation to its size (market capitalization) the less is the degree of underpricing. However, if one adjust the size adjusting variable (market capitalization) by removing the effect of the initial returns, capital raised will no longer significantly explain the level of underpricing on 5% level of significance. It is, therefore, difficult to conclude the suggested causal relationship between capital raised and initial returns as the effect disappears after adjusting the size variable according to the response variable.

4.7 Technology specific regression

56.67% of the technology firms in the data set generated positive returns on their first day of trading. Yet, the average level of underpricing was found to be 15.66%. This indicates that the distribution potentially is slightly skewed. The skewness is further illustrated by the median which is merely 2.85% for technology firms. As I am specifically interested in examining valuations of firms within the technology sector, I decided to run the same regression specifically for the technology sector. The technology industry was found to exhibit both the second highest average underpricing and second greatest variance. A high average level of underpricing was expected based on previous underpricing studies. However, I had no expectations of the level of underpricing compared to other sectors. Even though none of the firm-specific variables except market capitalization was found to affect the level
of underpricing significantly in the previous regressions, it is possible that the firm-specific variables affect the initial returns in the case of technology firms. Technology firms have previously been found to be young and exhibit great levels of average underpricing. I therefore apply the same regression technique as earlier but without adjusting market capitalization for initial returns. I have also removed the industry dummies.

\[
\begin{align*}
\text{ln}(\text{initial return}+1) & \quad 0.0303 (0.0600) \\
\text{ln(age}+1) & \quad -0.2566 (0.3128) \\
\text{Rev} & \quad 0.3113 (1.0661) \\
\text{EBIT} & \quad -0.1707 (0.1559) \\
\text{sqrt(cap raised)} & \quad 0.0000 (.) \\
\text{year=2010} & \quad -0.2947 (0.3786) \\
\text{year=2011} & \quad -0.4809 (0.4572) \\
\text{year=2014} & \quad -0.0014 (0.4987) \\
\text{year=2015} & \quad -0.2920 (0.4990) \\
\text{year=2016} & \quad -0.0873 (0.6208) \\
\end{align*}
\]

<table>
<thead>
<tr>
<th>Observations</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>(R^2)</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Table 16: Technology industry specific regression where \(\text{Rev} = \text{Revenue/Market capitalization}, \text{EBIT} = \text{EBIT/Market capitalization and Cap raised = Capital raised/Market capitalization.}\)

The beta coefficients for revenue and capital raised are negative while age and EBIT are positive. However, none of the variables are significant and it is thus impossible to draw any conclusions. The only conclusion one can make is that none of the included variables can significantly explain why underpricing arise among firms within the technology sector. Technology firms have been found to be rather young and exhibit relatively low revenues and earnings, but these variables are not able to significantly explain higher
degrees of underpricing. The level of underpricing is therefore either likely to be derived from variables that I have not examined or could simply represent a general high demand for shares of technology firms which drives high levels of underpricing.

I further found a level of underpricing among technology firms that is lower compared to previous studies. This is especially obvious if you compare it to the levels of underpricing during the IT-boom. I find this reasonable as investors probably are likely to be more cautious compared to the situation during 1999-2000. The number of listed technology companies is also greater than ever, implying that the industry might grow towards reaching its maturity (in the sense all technology firms could be assumed to belong to one industry). It would, therefore, be reasonable to expect lower levels of underpricing compared to earlier periods. Either because underwriters have adjusted offer prices according to previous levels of underpricing, a greater supply of technology issuers or due to lower demand for shares of technology firms.
5 Conclusions

My empirical analysis confirms that underpricing still is an existing phenomenon in the Swedish market of initial public offerings, where the closing price first day of trading on average has been found to be 12.22% higher than the offer price set in the IPO. Descriptive statistics indicate that underpricing differs between industries, with the highest levels (both in terms of mean and median) of underpricing observed within the industrial sector. Technology firms exhibit average initial returns of 15.66% which is relatively low compared to the level found in previous studies. This is, however, reasonable as the technology industry has developed and no longer is in its infancy. I further noticed that the distribution of underpricing is slightly skewed, which implies that one has to be cautious in interpreting the average level of underpricing as it is highly affected by large positive initial returns. The performed nonparametric Kruskal Wallis test does not yield significant results of differences in the distribution of underpricing between industries.

Firms within the technology industry seem to experience high degrees of variance in valuations. I find the variance of the technology sector to be significantly greater than the variance of rest of the sample, but the significant difference, however, disappears after introducing robust statistics. This implies that technology firms, in general, are subject to high levels of valuation differences but not significantly greater than rest of the industries using robust statistics. The variance in initial return for rest of the sample is mainly driven by the industrial industry, which I have no plausible explanation for. The high variance among technology firms was expected and is consistent with my review of the most common valuation techniques. As argued in the theoretical background, the most commonly used valuation techniques should often be found difficult to apply to high growth ventures. I argue that discounted cash flow analysis is a suitable method to apply to firms expected to experience high future growth, while the dividend discount model and relative valuation have some drawbacks in the same matter. Even if a
majority of investors use the same valuation method, it would not be reasonable to expect identical valuations as the models are heavily dependent on assumptions. Altogether this suggests that high growth technology firms should be subject to great valuation differences. It is possible that there are some industrial firms exhibiting characteristics that impose some uncertainty in valuation matters. Descriptive statistics indicate that numerous firms listed on the smaller exchanges AktieTorget and First North are likely to be assumed to experience future growth as average levels of revenue and earnings are found to be low compared to the average market capitalization. I furthermore find it important to emphasize that my research is heavily dependent on industry classifications. With better access to data, it would have been possible to construct a certain definition of technology firms by using a combination of variables.

As IPO underpricing has been shown to be an existing phenomenon, it implies that companies and pre-IPO shareholders generally are negatively affected by the relatively low offer price set in IPOs, while new investors benefit from the low offer price. Companies affected by high underpricing could have raised more capital by increasing the offer price and thereby avoiding leaving money on the table. Pre-IPO shareholders are also hurt by relatively low offer prices in secondary offerings as their ownership would have been worth more with higher IPO offer prices. IPO investors benefit from underpricing as they exploit the opportunity to invest in an instrument that on average will yield high positive returns in a short time frame. It is however important to remember that IPOs with positive outcomes often are oversubscribed, indicating that the allotment of shares is lower. Thus, apart from the fact that an investor has to choose an IPO with positive initial returns, the allotment of shares will most likely be low in the case where the outcome is positive and opposite when the IPO yields a negative outcome where the allotment of shares will be greater. This implies that one should be cautious in interpreting the high average levels of underpricing as an indicator of a prof-
itable investment strategy, especially since only 60% of the IPO transactions included in the data yield positive initial returns.

There is no clear relationship between initial returns and IPO volume during my period of study as suggested by the hot issue markets theory. I noticed variation in the average level of underpricing, but it is not clearly related to the variation in IPO volume, which has increased substantially during the last three years of the study compared to the first four years of study. I suggest one to introduce more years in the period of study to examine the hot issue markets theory.

By using regression analysis to examine if firm-specific variables affect the outcome of IPOs, I found that capital raised relative to market capitalization to have a negative impact on the initial return. This indicates that the more capital a firm raise in its IPO relative to its size (market capitalization) the less is the level of underpricing. This significant effect, however, disappears after adjusting the size variable by removing the effect of initial returns on market capitalization. None of the firm-specific variables age, revenues or EBIT seem to be good indicators of the level of underpricing. Age, which previously has been found to affect the level of underpricing positively, is not significant. Results from the regression analysis indicate that both revenues and EBIT have been incorporated in the offer price as they are not able to significantly explain the general difference between the offer price and closing price first day of trading.

I can thereby confirm the existence of underpricing but not derive the effect of underpricing to any of the examined firm-specific variables. I have neither found evidence that contradicts any of the theories presented in earlier research. It is possible that underpricing exist to compensate uninformed investors for asymmetric information in the IPO process, where technology firms, in particular, possibly exhibits a high average level of underpricing due to R&D investments which bolster the effect of asymmetric information. I have, however, not been able to include R&D expenditures to confirm this.
It is also possible that high levels of underpricing works as a signal of high quality, where the issuer signals confidence about its future operations and ability to raise the offer price in subsequent equity offerings.

As I chose to use recent data to study IPO underpricing, I lost the ability to study the long run performance of the issuing firms. I would, therefore, suggest future researchers to follow up on the long-run performance of the observed companies to examine whether Ritter’s (1998) finding that long-run performance from the closing price at IPO date is lower than the corresponding index performance. It would also be interesting to observe the fraction of companies that succeed in meeting (or beating) the high growth expectations and also how many businesses that fail to do so. Furthermore, it would be interesting to see whether underpricing as a phenomenon will persist and in particular, to see if this decreases for technology firms as the market matures (will it ever?).
References


6 Appendix

![Boxplot of underpricing by industry.](image)

**Figure 7:** Boxplot of underpricing by industry.

<table>
<thead>
<tr>
<th>Breusch-Pagan test results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-square</td>
</tr>
<tr>
<td>P-value</td>
</tr>
<tr>
<td>H0: Constant variance</td>
</tr>
</tbody>
</table>

**Table 17:** Breusch-Pagan test for heteroskedasticity. *P*-value suggests that the null hypothesis should be rejected, implying that the data is affected by heteroskedasticity.
Figure 8: Bar chart of initial returns.

<table>
<thead>
<tr>
<th>Group</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology</td>
<td>30</td>
<td>15.66%</td>
<td>43.79%</td>
</tr>
<tr>
<td>Rest of the sample</td>
<td>160</td>
<td>8.88%</td>
<td>26.72%</td>
</tr>
</tbody>
</table>

$W_0 = 7.4473, \Pr > F = 0.0070$

$W_{50} = 4.6903, \Pr > F = 0.0316$

$W_{10} = 5.4619, \Pr > F = 0.0205$

Table 18: Levene’s robust test of variance where the industrial sector is excluded.