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Simen Hestnes

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The Effect of Investor Sentiment on IPO-Underpricing

Evidence from the Nordic Market

Simen Hestnes

Supervisor: Thomas K. Poulsen

MSc in Finance – Master Thesis
BI NORWEGIAN BUSINESS SCHOOL

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Abstract

The heavily researched, yet unsolved, IPO underpricing phenomenon has been by investigated by academics for decades and offered multiple explanations as to why it exists. Analysing a sample of 526 IPOs in the Nordic market between 2005 and 2018 which is found to be underpriced by 8.13%, this thesis explores whether investor sentiment is a determinant of this observed underpricing. It does so by applying Baker and Wurgler's recognized sentiment index as a measure of investor sentiment and tests its relationship to underpricing while controlling for multiple IPO characteristics. Furthermore, periods of positive and negative investor sentiment, hot and cold market periods, and industry classifications are considered to shed further light on the relationship. Using multiple linear regression models, I find evidence of a statistically significant relationship between investor sentiment and underpricing. Additionally, underpricing is found to be considerably higher for companies debuting during periods of investor optimism, but the application of multiple regression models on sub-samples as well as t-tests on the displayed mean difference, fail to statistically prove the effect. Obtained results show some contradictions to previous studies as well. I find that underpricing decreases during hot market periods and that this effect is strengthened during periods of positive investor sentiment. This thesis provides some supporting evidence to previous literature's findings that investor sentiment and underpricing are related, and adds to the existing research by using an approach not yet tested on the Nordic Market.

Key words: IPO underpricing, Investor Sentiment, Nordic, Hot IPO Markets, Cold IPO Markets, Industry Classifications

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1.0 Introduction and Motivation

Underpricing of initial public offerings (IPOs) is a well-known, and heavily researched phenomenon which has been proved to exist in markets all around the world (Ritter, 2003). With that in mind, the first trading day underpricing phenomenon is still an unsolved mystery. There are, however, several theories which have proved to have an effect on IPO underpricing. One of the more dominant among these theories are asymmetric information models, which are based around the idea of someone posessing superior knowledge over others. Both Ljungqvist (2007) and Ritter & Welch (2002), however, agree that the asymmetric information theories are insufficient in explaining the underpricing puzzle due to certain periods, such as the internet bubble, with astonishing first-day returns, and therefore believe that the answer is likely to come from either share allocation issues which are based around how shares are distributed in the IPO process, or behavioral explanations which seeks to explain underpricing based on the behavior displayed by any of the main “players”. Share allocation is highly relevant among researchers today, but the lack of available data has made it challenging (so far) to reach sufficient conclusions. From a behavioral perspective, there are a few different theories regarding behavioral biases of investors, where investor sentiment is one of the more prominent. According to Baker and Wurgler (2006), there is no doubt that investor sentiment affects stock prices, and the real question one should ask is how to account for its effect. Thus, it may have even more of an effect on IPOs which are difficult to value in the first place due to lack of publicly available information. Ljungqvist, Nanda and Singh (2006), Derrien (2005), and Cornelli, Goldreich and Ljungqvist (2006) all found evidence suggesting that underpricing increases simoultanously with demand from sentiment investors.

Research has been conducted on the basis of several different markets and its data, but there has not, however, been done an extensive amount on the Nordic market. Due to its proven existence, it is important for all parties involved to understand why underpricing occurs so that they can optimize their benefits. From an investors point of view, IPOs present investment opportunities that, if selected carefully, can yield excess returns. Having a better understanding of which factors effect underpricing gives the investor a higher chance of identifying underpriced IPOs. The main purpose of this thesis is therefore to use an under-investigated market to test whether the impact of investor sentiment reflects the findings from more heavily researched markets, so that investors are better suited to successfully select underpriced IPOs.

1.1 Research Question and Aim

Throughout this thesis, I explain the first-day underpricing of IPOs in the Nordic market from the perspective of investor sentiment, which translates into the following research question.

Does investor sentiment explain first-day underpricing in the Nordic market?

Multiple studies have provided evidence that companies seek to exploit periods of higher valuations by timing their entrance into the markets. Both Lee, Shleifer, and Thaler (1991), and Loughran, Ritter, and Rydqvist (1994) found that more companies go public in periods of excessive investor optimism which explains the existence of hot market periods with a higher volume of new issaunces. Moreover, Ljungqvist, Nanda, and Singh (2006) argue that investors tend to show an irrational amount of optimism towards IPOs within certain industries, indicating that some industries are more exposed to underpriced offerings than others. Ibbotson and Jaffe (1975) claim that hot IPO market periods are closely related to positive investor sentiment, and that these periods provide a higher degree of underpricing. Based on these findings, I investigate the effects of investor sentiment on first-day underpricing in the Nordic market by accounting for both industry specific characteristics and periods of investor optimism. Morevoer, to create a better understanding of the effects, I explore if there exists a relationship between hot market periods and positive sentimen periods, and test whether these periods can be proven to have higher underpricing.

As more traditional explanations seem to come short in explaining IPO underpricing. Behavioral theories have become a hot topic of interest when trying to explain the anomalies related to the first trading day. Both Loughran and Ritter (2004), and Ljungqvist, Nanda, and Singh (2006) are among the researchers that have been able to produce evidence suggesting that investor sentiment has a significant effect on underpricing. The majority of the research has been focused on the US market, but the effect has been proven in the European and Asian markets as well. Investor sentiment is clearly acknowledged in other markets, which motivates the investigation of the extent it explains underpricing in the Nordic market. Moreover, there exists empirical evidence suggesting that underpricing is more pronounced among smaller firms. IPOs in the Nordic market are likely to be smaller than IPOs in the US, meaning that one could expect a stronger role for sentiment when investigating the Nordic market. Although interesting, the effect of investor sentiment on the long-run performance of the IPOs in the sample is not considered. Ljungqvist (2007) states that there are many potential pitfalls of abnormal return estimates over longer time horizons, such as an increasing return-variance which can negatively affect the rejection of the null hypothesis.

2.0 Theory

2.1 Defining Initial Public Offerings and the Main Players

"The initial public offering (IPO) represents the first significant stage in the evolution of a public company" (Jain and Kini, 1999). Taking a firm public is generally thought of as a natural part of its growth process. It allows the company to raise additional capital from outside investors to further finance investment opportunities. The IPO process is quite complex as there are several necessary steps to be taken and it involves different parties with different objectives and bias. The main players involved are the issuer, the underwriter, and the investor.

2.1.1 The Issuer

The issuer in an IPO is the party responsible for issuing shares to the public. The process of an IPO begins with the issuer filing for a public issuance through an exchange commission (Lowry and Schwert, 2004). From this point forward, the task of pricing the shares correctly is initiated. The issuing firm will seek to maximize the offer price potential because it is directly correlated to the amount of capital being raised. Deciding on offer price, however, is a fine balance because you want to attract as many investors as possible without leaving any money on the table. To ensure a fair offer price is being offered, management hires an underwriter to help guide the process.

2.1.2 The Underwriter

The underwriter is typically an investment bank can be thought of as a middleman between the issuer and the investor. Hired by management, the underwriter cooperates with and help guide the company through the process of deciding an offer price. This process includes everything from valuations, researching market conditions and financial advice, to necessary paperwork and documentation (Corwin and Schultz, 2005). After agreeing on offer price, the underwriter buys all shares before distributing them out to the public market. The underwriter makes money on the difference between the offer price and the price they purchased the shares for, meaning that there is incentive for the underwriter to reach a price reflecting the market. Furthermore, underwriters work on multiple IPOs leaving them with a reputation to uphold with both issuers and investors.

2.1.3 The Investor

The remaining player in the IPO process is the investor. The role of the investor is simply to invest in new share issuances by paying the offer price. Each investor seeks to secure as many shares as possible of underpriced IPOs and avoid the ones that are overpriced. Here, we separate between large institutional investors and smaller retail investors. Institutional investors have an advantage over the retail investor in terms of information superiority, close relationship to underwriters, and available capital, which gives them an advantage in securing large allocations of in-demand offerings.

2.3 The Nordic Stock Exchanges

Throughout this thesis, I refer to the Nordic markets. When doing so, I refer to the stock exchanges of the Nordic countries in which I have gathered data. These countries are Norway, Sweden, Denmark, and Finland, and their respective main stock exchanges are Oslo Stock Exchange (OSE), Stockholm Stock Exchange (SSE), Copenhagen Stock Exchange (CSE), and Helsinki Stock Exchange (HSE). All the exchanges began trading during the 1800s, but in 1998 the SSE and CSE entered into the NOREX alliance. This was a strategic alliance where the exchanges continued to operate independently but with a similar system of rules and regulations with the purpose of simplifying trading across exchanges. Oslo stock exchange joined the alliance a year later. In 2003, OMX AB which was a merger between Optionsmäklarna AB (OM) and HSE, was created. OM refers to the SSE which they acquired in 1998. OMX AB went on to acquire CSE in 2005 and has since then been renamed Nasdaq AB and is also known as Nasdaq Nordic. As of today, OSE is the only exchange which is not a part of Nasdaq. Nasdaq are, however, a large stakeholder and has publicly announced its interest in a takeover which is not unlikely to happen in the near future.

2.2 Underpricing

Previous research on the IPO process shows that new offerings tend to be priced too low in relation to market demand, which has resulted in abnormal short-term returns, and thus the well-known underpricing phenomenon. Underpricing happens when the IPO price is lower than the stock price observed at its first market close. Moreover, since return data on public companies is publicly available, the amount of underpricing can be easily observed. The complexity of underpriced IPOs does not come from the concept itself but rather the reasoning of why we experience abnormal first day returns. Academics have, for a long time, intended to answer this question by by applying and testing different theories, but still disagree as to the exact reason of why it exists. Reviewing the existing literature on the issue, however, helps get an overview of where the research is headed as well as what results to expect.

3.0 Literature review

3.1 Background

Pricing of goods and services has always been a complex task due to the uncertainty of demand. Under assymmetric information, the supplier and consumer usually disagree when it comes to valuing a specific good or service. This same concept of supply and demand has been found to apply well to stock prices where the information asymmetry stems from different classes of investors (Lowry and Michelle, 2002). Reasonably enough, this rationale has made asymmetric information theories a particularly attractive field of research for academics', and one of the most prominent for explaining underpricing.

One can say that the limitations of results obtained in the academic literature on information asymmetry has led to a growing underpricing literature where several other theories intend to explain the phenomenon. Ljungqvist (2007) put the underpricing literature into four groups: institutional factors, ownership, behavioral theories, and asymmetric information. Each of these groups, again, contain several other theories which have been constructed on the base of the parent group. Theories such as the signaling theory, the winner's curse, and the agency theory, for instance, are based on the existence of asymmetric information. Others, such as the behavioral theories, are taking a complete different starting point in explaining the anomaly. As pointed out by Ljungqvist (2007), some theory-groups are not as heavily researched and especially underinvestigated in certain markets, but also believed likely to help solving the puzzle. One of these are the behavioral theories, and more specifically, investor sentiment. Most financial models assume that investors are rational, but it is also known that irrationality exists. Since the investor is a major player in the IPO process and the existence of irrationality, the idea of studying underpricing on the basis of investor sentiment is certainly appealing. Investor sentiment is often used in explaining why prices diverge from their fundamental values, but also a concept which, according to Baker and Wurgler (2006) cannot be measured directly. However, applying relevant proxies such as previously constructed sentiment indexes make it, to some degree, possible to empirically test its effect on underpricing.

As pointed out by Ritter and Welch (2002), the underpricing puzzle is not likely to be solved from a single theory because of the complexity in determining the IPO price. There are different market forces that work in relation to several firm specific, issue specific, and economy specific forces which results in a complexity that lessens the likelihood of explaining underpricing through a specific theory. Digging deeper into investor sentiment in the Nordic market will contribute to a topical research question and could therefore help in both affirming and adding to the already existing underpricing literature on investor sentiment.

3.2 Empirical Evidence

Empirical studies in the existing literature have tried to model the short-term underpricing, but as suggested by Ljungqvist, Nanda, Singh (2006), the majority of these models assume the existence of an efficient market with rational investors. According to Ritter and Welch (2002), the asymmetry in information between individual and institutional investors, results in individual investors being less rational and more likely to overreact. It is also important to note that the existing literature on IPOs tend to take hot-issue and cold-issue markets into account as they are significant with regards to understanding market and investor behavior during certain time periods.

3.3 Hot-Issue Markets

A hot-issue market is defined as a period where investor demand for IPOs is higher than normal. In the existence of a hot market, investors display a disproportionate optimism which increases demand and pushes up the IPO prices (Shefrin, 2002). The concept was first introduced by Ibbotson and Jaffe (1975) and taken further by Ritter (1984) who studied a 20-year sample period of the US stock market and found that a hot-issue market significantly outperformed a cold-issue market in terms of initial returns. Hot market periods have a higher volume of firms going public and show greater average underpricing as compared to cold periods. Moreover, as pointed out by Brailsford (2000), both issuers and underwriters take advantage of this information in the IPO process.

3.4 Information Asymmetry

Asymmetric information has both been a leading, and the origin of many theories in the effort of explaining first-day underpricing. The issuing firm, the underwriter, and the investor are the main parties involved in an IPO, and the idea of information asymmetry originates from the basic idea that one party involved in the IPO process possesses superior knowledge, and thus have an edge. As with hot-issue markets, Ibbotson (1975) was one of the first to conduct a study which highlighted underpricing in initial IPO returns in the US. Since then, his findings have been confirmed through similar studies such as Ljungqvist (2007), and Cohen and Dean (2005). Information asymmetry was quickly introduced as a possible explanation for the phenomenon and a few main theories are leading today's literature. These are the winner's curse and the signaling theory.

3.4.1 The Winner's Curse

The winner's curse, also known as Rock's theory (1986), was the very first trying to tackle the underpricing puzzle. It takes base in that there exist two types of investors, being informed investors and uninformed investors. Moreover, the theory reasons that the informed investors will bid only for the IPOs which are attractively priced, while the uninformed investors bid unselectively. The winner's curse term comes from the "faith" of uninformed investors in the sense that the informed investors will scoop up a portion of the shares in all attractive offerings, while they receive all the shares they bid for in unattractive offerings. As a result, the uninformed investors can end up with negative returns even though IPOs are, on average, underpriced. If uninformed investors experience negative returns, they will not be willing to place bids which leaves the IPO market with informed investors only. Rock argues, however, that the market needs uninformed investors, meaning they must at minimum break-even from their bids. For that to be possible, Rock argues that IPOs must be underpriced.

3.4.2 The Signaling Theory

As discussed in Allen and Faulhaber (1989), above-average firms in possession of more information than the investor, will try to separate themselves from below average firms through underpricing of the initial share issuance. The purpose is for the above-average firms to distinguish themselves by essentially throwing money away to signal their quality. This prevents below-average firms from imitating because they would not be comfortable selling shares below the market price. Quality issuers, on the other hand, are confident that they eventually will make up for the money left on the table. Allen and Faulhaber propose that quality firms could recoup their “lost money” through future dividend announcements, but others have suggested that it also could happen through analyst coverage (Chemmanur 1993), or future issuances (Welch 1989). With regards to Allen and Faulhaber’s model on future dividend announcements, new dividend policies update the beliefs of investors. High dividends positively influence firm valuation, while low dividends have the opposite effect. Above-average firms will therefore signal their quality by underpricing more, announce higher earnings, and use those to pay out dividends early.

The model in Welch (1989) takes the stance that above-average firms underprice to leave a good taste in investors’ mouths for more favorable future issuances. As in Allen and Faulhaber (1989), Welch predicts that above-average firms signal its quality by leaving money on the table through underpricing, which will be recouped at the time a higher priced issuance is presented. Similarly to Allen and Faulhaber, the idea is to impose an imitation cost on the below-average firms by giving up money as a signal, but the quality of the firm is rewarded through a subsequent issue rather than dividend policy. In alignment with the above two models, Chemmanur (1993) predicts that above-average firms use underpricing to signal quality. In contrast to the other models, the “lost money” from an underpriced issue will be recouped through a maximization of outsider information production. Firms of high quality in possession of more information than investors, would benefit from reducing this information asymmetry. Producing information, however, is costly and the idea is that the money left on the table covers this production cost because it incentivizes outsiders to produce information.

3.5 Behavioral Theories

Behavioral theories came to life when researchers started doubting whether the substantial amounts of money left on the table from underpricing could be explained entirely from existing theories. In recent literature, behavioral theories have been very attractive in terms of explaining IPO underpricing for a few reasons. Firstly, Behavorial theories assumes the existence of irrational investors, and as pointed out by Ljungqvist (2006), IPO shares have no prior price history and tend to be young, immature, and informationally opaque. This makes them hard to value and leaves room for interpretation, especially with the presence of irrational investors. Investor sentiment is arguably the most well-known and researched behavioral theory in the existing literature, but others such as the use of information cascades have been prominent as well.

3.5.1 Investor sentiment

Along with the recent developments in behavioral finance, the literature on IPO underpricing from the perspective of investor sentiment has increased and taken more and more ground. Investor sentiment basically means that we have irrational investors who have a belief that does not align with obtainable facts. Ljungqvist, Nanda, and Singh (2006) were one of the first to bring forth a model on investor sentiment. The model measured the optimal response of an IPO company in the presence of sentiment or irrational investors. They take the stance that sentiment investors are overly optimistic of the prospects of IPO companies. Cornelli, Goldreich, and Ljungqvist (2006) studied the irrational behavior among retail investors and related that behavior to post-IPO prices. They used prices from the grey market and found that high grey market prices (overoptimism) are a good indicator of first-day initial returns as overly optimistic investors are willing to pay above the fundamental value. Dorn (2009) also studied the behavior of retail traders by using a sample from a large German retail broker in the early 2000's. He found that sentiment has a significant effect on retail trading decisions as a result of willingness to overpay and aggressively buy at sentiment-affected prices.

Cook, Jarrell, and Kieschnick (2003) and others have found evidence suggesting that IPOs trade at higher values exclusively in hot-issue markets when IPO volume is high. Interestingly, Lowry (2002) found that IPO volume fluctuates over time and that investor sentiment plays an important role with regards to the IPO volume. This manifests the assumption that investor sentiment can help explain underpricing when there is a significant difference between hot-issue and cold-issue markets. Ofek and Richardson (2003) found that the first-day underpricing phenomenon happens when institutional investors sell shares to retail investors on the first day, and that the returns follow significant reversals. This prediction had help being confirmed when the 'dot-com bubble' burst and the IPO volume decreased. Zhu (2021) studied the impact of investor sentiment on underpricing by studying the Chinese IPO market. He found evidence suggesting that investor sentiment has a significant effect on underpricing and that the effect of investor sentiment depends on the issuing price. Baker and Wurgler (2006) studied investor sentiment and how it affects the cross-sectional returns of stocks. By running a set of five relevant metrics against different macroeconomic variables, they constructed an investor sentiment index which most certainly has proved helpful in later studies on the impact investor sentiment.

More niche studies have intended to explain underpricing from the perspective of investor sentiment with regards to certain events or conditions. Chen, Goyal, and Veeraraghavan (2019) studied the effect of terrorist attacks and discovered it causing variations in investor sentiment, and thus reduced underpricing. Shao, He, Jiang, and Liao (2015) studied the impact on underpricing when IPO companies take advantage of mainstream media to reach out to investors. However, they were unable to reach any sufficient conclusions as mainstream media is regarded differently within different investor classes.

Shleifer, and Summers (1990) discussed the investor sentiment theory on the basis of noisy investors. The term noisy investors stem from the efficient market theory, and is a term used in describing investors who tend to react on emotions and thus make biased and irrational decisions. Having a few noisy investors, however, is not a major issue, but too many noisy traders coming together could increase demand significantly and push up prices. This rationale is especially relevant within IPOs as one could argue that new listings are overly hyped, specifically in hot-issue markets when there is overall market euphoria.

3.5.2 Informational cascades

As mentioned, the amount of underpricing varies over time (see section 3.3). As with investor sentiment, the informational cascades theory do not assume that all investors are rational and non-biased which is the case in many of the theories mentioned. In Welch (1992), a model of what he refers to as informational cascades among investors and how it may affect underpricing is presented. The model uses a scenario of sequential sales where the early investors impact the bids of later investors. The later investors believe that early investors possess some information they do not and disregard their own information. If early investors have several positive initial sales, later investors believe that they possess favorable information and invest thereafter. Essentially, later investors basically invest in what early investors invest in which leaves early investors with the power to control a stock's direction through an assumed superiority in information. The cascades created from the events described above allow early investors to request higher underpricing in order to buy shares such that the cascades created are positive rather than negative. Welch's model is statistically tested by Amihud, Hauser and Kirsh (2003) who found evidence of cascades in the Israelian market.

4 Research Methodology and Data

This section mainly describes the thesis' empirical methodology and data sources. It discusses how the effects of investor sentiment will be tested, as well as the collection of data, how it was obtained, and all the modifications applied to construct the final data sample.

4.1 Methodology

Cornelli, Goldreich, and Ljungqvist (2006) were able to study underpricing on the basis of investor sentiment by investigating data from the grey market. The grey market is an unofficial marketplace where you can buy or sell shares of companies before they go public. This gives potential to an in-depth study of IPO dynamics but obtaining data from the grey market is rather difficult as there is no official platform. Although it would be interesting to study the premiums in the grey market, it would be challenging to obtain a sufficient sample, especially for the Nordic markets. Moreover, Cornelli, Goldreich, and Ljungqvist (2006) already found, using a grey market sample, that investor sentiment has a significant impact on the demand for IPOs.

The investor sentiment index which was constructed by Baker and Wurgler (2006), has both been used and proved helpful in studies similar to this. The index has, among other things, helped form the argument that investor sentiment has a significant impact on first-day underpricing of IPOs. With the help of the investor sentiment index as the measurement of investor sentiment over time, I investigate what, if any, impact it has on the observed underpricing of IPOs in the Nordic market. The index is constructed on the basis of US data, but the US and Nordic stock markets are highly correlated meaning that the time-series variation in IPOs is likely to be similar in the US and Nordic markets, its inclusion seem theoretically sound.

The effects of investor sentiment on underpricing are investigated through a set of multiple linear regression models which test how well the sentiment index and a set of control variables are able to explain underpricing. It does so by running the independent variables on the market-adjusted underpricing rate seen in (3). A similar regression on the standard underpricing rate in (4) as well as four other regression models intended to capture the effects are also performed, but these are mainly used for comparison and robustness reasons. Both the sentiment index and the control variables are carefully selected through existing literature confirming their relevance (see section 5 for variable descriptions). The sentiment index originally included six metrics, but the turnover ratio metric was recently dropped which leaves us with an index based on the following five metrics; the value-weighted dividend premium, IPO volume, the first-day initial return of IPOs, the equity share in new issues, and the closed-end fund discount. The investor sentiment index data is gathered from a publicly available dataset located at Wurgler's NYU website (Wurgler, 2022). The control variables used are company age, number of employees at the time of the IPO, offering price, offering size**,** a dummy variable for hot and cold IPO markets, and six industry variables for the following industries. Energy, industrial, financial, consumer (cyclical), consumer (non-cyclical), and technology.

4.2 Measuring Degree of Underpricing

The various sentiment and information variables mentioned above are to be tested against a measurement of IPO underpricing. In the existing literature, different methods have been used to measure first-day underpricing, but perhaps the most common underpricing metric is simply the difference between first day closing price and offer price. Following this methodology, the underpricing rate, UPR, is simply expressed as.

$$UPR = \frac{First\ day\ closing\ price - IPO\ price}{IPO\ price} \tag{1}$$

Simply by changing the first day closing price term, the above formula can easily be applied to discover IPO price relations for the longer periods as well. Dependent on the time period of interest, the underpricing rate can be applied to studies of underpricing for any time horizon. For the purpose of this thesis, however, only the first-day closing price is to be considered.

The underpricing rate (1) however, only explain whether the IPOs in question are underpriced or overpriced, meaning that it does not take the overall market performance into account. An IPO could, for instance, debut on a day or even during a period where the overall market is performing exceptionally well or vice versa. More companies feel incentivized to go public when markets are performing well and overall sentiment is high. To adjust for the market effect, at least to some degree, the underpricing rate should take the market returns into account. Doing so, introduces the market adjusted underpricing rate, MAUP, expressed as follows.

$$MAUP = UPR - \frac{CP_1 - CP_0}{CP_0} \qquad (2)$$

Where CP_1 is the closing price of the index in question on the date of the IPO and CP_0 is the closing price of the day prior to the IPO. The market returns are gathered from the corresponding exchanges of Norway, Finland, Denmark, and Sweden and added to (2) depending on which exchange each IPO debuted on.

4.3 Data Sample Selection

From the Bloomberg database, I collected an initial sample of 646 IPOs listed on the main exchanges of Norway, Sweden, Denmark, and Finland[1] between 2005 and 2018 (see Appendix 1 for the full list of IPOs included in the sample). The reasoning behind using this 13-year sample period is the desire to investigate the most recent time-period while making sure the dataset accounts for both hot and cold-issue periods, and all available IPOs during that time period were gathered. These hot and cold issue markets are determined in alignment with the findings of Ibbotson and Jaffe (1975), where the number of new issuances each year moves in

[1] The IPOs are mainly from the Stockholm Stock Exchange, Oslo Stock Exchange, Helsinki Stock Exchange, and Copenhagen Stock Exchange. However, some IPOs debuted on the Spotlight exchange located in Sweden and the Nordic Growth Market operateing in all the Nordic countries.

cycles. Furthermore, compared to some of the largest markets for IPOs, the volume of new issuances in the Nordic countries are rather low. Using data from the entirety of the Nordic market along with a fairly large sample period, however, allows for a sufficient sample size. Iceland is regarded as a part of the Nordic market, but due to a limited number of Icelandic companies going public during the sample period, it is left out (see Appendix 2 for the number of IPOs from each country represented in the sample). Moreover, I only use data through 2018 as the investor sentiment index used does not contain data subsequent to 2018.

Bloomberg allows for filtering out IPOs based on a set of optional inputs and creates a downloadable dataset based on these. This dataset includes, but is not limited to, initial offer price, first-day closing price, country of origin, exchange, sector, the number of shares offered, number of employees and performance since the IPO. All variables used throughout this thesis are either gathered directly from the Bloomberg database or calculated using data available in the dataset.

However, some supplementary data has been added from independent sources. The investor sentiment index is gathered directly from Wurgler's NYU website (Wurgler, 2022). Company age at the time of publicly entering the market is not available from Bloomberg so a proxy in alignment with Ritter's (2021) list of median age for IPOs is used. Daily market returns for the all countries represented in the sample are gathered from a publicly available database (www.tradingeconomics.com) and used in calculating the market-adjusted underpricing rate.

4.3.1 Criteria and Regulations

Only successfully, first time issued IPOs which offered common stock are to be considered. Offerings of class B-shares, units, and American depositary receipts are filtered out. They are mainly filtered out for simplicity as they have certain characteristics differentiating them from a traditional offering. However, as IPOs of common shares are by far the most common, the exclusion of all other types of share issuances only reduces the sample size to 545 IPOs.

The sample consists of data from stock exchanges in the Nordic market. All countries have their own set of trading rules and financial regulations, but some differ more than others. The major stock exchanges in Norway, Sweden, Denmark, and Finland have a similar set of trading rules and regulations and no significant differences affecting the empirical study. Furthermore, trading practices on the SSE, HEX, and CSE are under the Nasdaq OMX, meaning that all new listings undergo the same listing procedure. Markets today are also highly digitalized and globalized, meaning that companies can easily get listed on exchanges across borders. As this thesis aims at investigating underpricing in the Nordic market, the sample should consist of companies with similar firm characteristics so that any issuances deviating from the sample are avoided. For this reason, all non-Nordic companies listed on any of the relevant exchanges are excluded from the final sample. In addition to the reasonings above, a small number of companies were lacking information critical to further analysis. In the cases I was unable to obtain that data from other independent sources, the respective IPO was eliminated from the sample. After adjusting for non-Nordic companies and missing data, the sample size was reduced to 526, which is the final sample used in analysing the aim of the thesis.

4.3.2 Sample Selection Biases and Robustness

Empirically testing the selected sample opens for the obtained results being influenced by potential biases. It is important to address potential biases as they have the potential to limit the validity of the study.

Outliers

The chosen sample size of the study is large in relation to the number of firms actually going public during the sample period. However, it is not that large with regards to the effect of outliers in the variables which, if significant enough, have the potential to affect the results. First-day returns are especially exposed to extreme outliers as they have proved to be volatile and, in some cases, produce extreme returns. When considering returns, the downside is limited, but there are no limits on the upside. Since regression estimates are known to be sensitive to extreme values, there runs a risk of these having an unwanted impact on the results. In the case of multiple outliers of extreme values, there are ways to limit their effects. One way is through the application of winsorization. As proposed by Dixon (1960), winsorization transforms a specified percentile of extreme values to less extreme values such that there influence is limited. Based on the data, however, one should carefully select when to winsorize because the modification of data just for the sake of it is not beneficial.

Omitted Variables

Another potential bias is the endogeneity issue occurring as a result of omitted variables. In the case where these are left out but relevant to the dependent variable and correlated to any of the independent variables, the resulting regression coefficients will be biased (Clarke 2005). Since existing literature suggests that several variables not included in this study have a significant impact on underpricing, the models presented are likely to not be perfect. Moreover, there is a high chance of these omitted variables being correlated to any of the included variables, which increases the likelihood of an omitted variable issue. As discussed throughout this paper, the underpricing phenomenon is complex and thus difficult to capture in its entirety. In fact, it is so complex that the literature intends to explain it through many different models and theories, and the optimal regression would have to account for all of these. For this reason, I expect the model to have a low R-squared suggesting that the independent variables only captures underpricing to a relatively small degree. The relationship that cannot be explained by the model is stored in the error term which is assumed to be uncorrelated with the regressor. Omitted variables, however, violate this assumption. So, the inclusion of omitted variables in form of control variables would most likely increase R-squared. Following the standard teachings (add source), the amount of relevant variables included in the regression model should be maximized. Futhermore, it states that including irrelevant variables yields inefficient estimates, but the model will be better off including irrelevant variables as opposed to exluding relevant variables. However, as pointed out by Clarke (2005) the standard teachings do not apply in practice since we rarely find ourselves in precise situations. For this reason, they argue that the bias effect of adding even relevant variables cannot be known and that omitted variable bias is a "phantom menace", and, control variables should be selected carefully.

Missing Data

As discussed in relation to the sample selection, certain new issuances had to be left out of the final sample due to missing data. The IPOs in question were lacking data necessary to either calculate first-day underpricing or any of the control variables. Missing data can affect the analysis either through bias or inefficiency, or both. The most efficient solution to this issue is maximizing the data in the collection process. (Kang, 2013) However, there are also other approaches that can be used to deal with this issue where the most common are imputation, likelihood, weighting approaches, and listwise deletion (Horton & Kleinman, 2007). Listwise deletion which is simply the deletion of the cases with missing data, is the most common. However, it is also the most criticized as it has shown to produce bias in the estimates. For convenince, listwise deletion was used to deal with the cases where data related to the first-day return calculations where missing. Conveniently, the missing cases are missing completely at random (MCAR) and accounts for less than 2% of the total sample, making it plausible to assume the data elimination have a limited impact on the estimates.

After eliminating the missing cases related to first-day returns, the final sample was set. However, the data on a few of the variables had several missing cases. Eliminating these would account for a more significant amount of the total sample and significantly increase the likelihood of bias. As a result, an imputation process was used. Imputation is a way of replacing missing data through an estimation of the missing values, often by using values from other included variables. (Kang, 2013) The advantage of this technique is that all data cases are retained, meaning that the sample size is not affected. Moreover, the distributional shape and standard deviation are not affected to the same degree as in an eliminating process. The way in which the missing values for the variables effected were estimated are explained in the following variable section.

5 Variables and Regression Model

To verify whether the initial first-day returns are influenced by investor sentiment, a number of multiple regression models which tests the effect of investor sentiment and a set of control variables on underpricing, is applied to the already established cross-sectional data sample. All control variables included in the models have previously been shown to have some type of effect on IPO underpricing, and chosen accordingly. Furthermore, they strengthen the models by helping to avoid omitted variable issues as well as improve the fit and validity of the empirical study as a whole. Table 1 gives a brief overview of the variables used in the regression models, and is followed by a detailed description of each.

Table 1

Variable Introduction

Variable name	Abbreviation	Description
IPO underpricing rate	UPR	$UPR = \frac{First\ day\ closing\ price - IPO\ price}{IPO\ price}$
IPO market-adjusted underpricing rate	MAUP	The uderpricing rate adjusted for market returns, see (1)
Baker and Wurgler's Investor sentiment index	LN ISI	Measurement of sentiment among investors
Company age	LN AGE	Company age at time of IPO
Employees	EMPL	Number of employees at time of IPO
Issue size	SIZE	Market capitalization at time of IPO
Issue price	LN PRICE	Share price at time of IPO
Hot and Cold market dummy	HOT/COLD	Dummy variable for hot and cold markets. "1" = hot, "0" = cold
Six industry dummies	$\mathbf{IND_i}$	Six industry dummy variables

Note. This table serves only as an overview and introduction to the variables included in the study. More detailed explanaitions are found below.

5.1 Dependent Variable - Market-adjusted Underpricing Rate

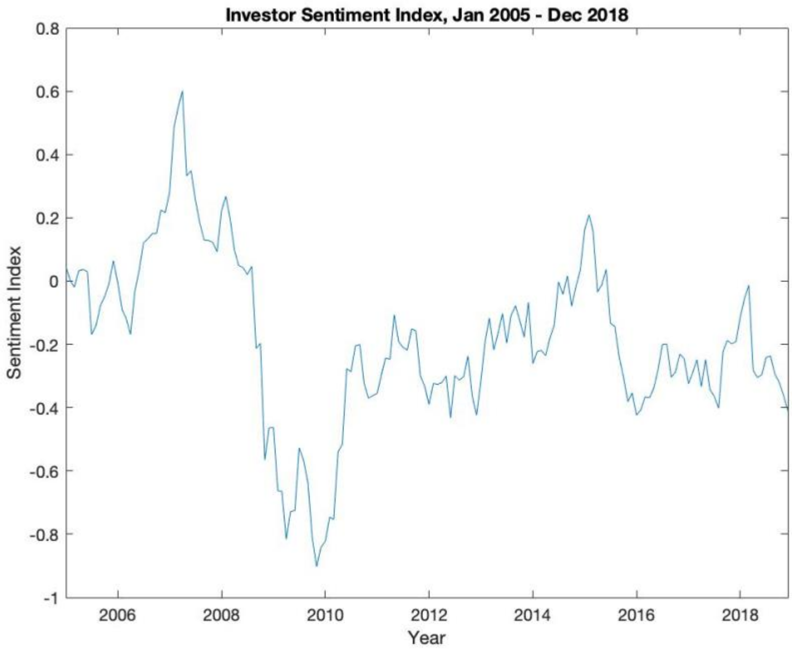
The market-adjusted underpricing rate given in (2) is used as the main dependent variable in the regression models (see section 4.2 for justifications). This allows for determining which variables, and to what degree they affect the underpricing rate of IPOs after being adjusted for market effects. However, the market-adjusted underpricing rate of 8.13% and the standard underpricing rate of 8.23% are close to identical, indicating that the results and conclusions are likely to be similar regardless of which measurement of underpricing is used as the dependent variable. To check whether the results are, in fact, coherent and not affected by small changes in the dependent variable, two separate regression models are conducted. For the purpose of this study however, the model using the standard underpricing rate is only meant for comparison.

5.2 Baker and Wurgler Investor Sentiment Index

The investor sentiment index, also known as the Baker-Wurgler (2006) sentiment index is a measurement of the monthly overall investor sentiment constructed on the basis of five different proxies. These are the value-weighted dividend premium, IPO volume, the first-day initial return of IPOs, the equity share in new issues, and the closed-end fund discount, and further explained in the sub-section below. As these sentiment proxies are hand-picked on the basis of previous research and highly recognized among academics, the sentiment index with a one day lag will be used as an independent variable in the empirical testing. This simply means that each IPO gets assigned the investor sentiment index value observed one day prior to its issuance. Classical finance theory does not include the impact of investor sentiment, but Baker and Wurgler (2006) challenges that view by proving its significant cross-sectional effects. Moreover, existing literature has produced evidence of both a positive and significant impact of the sentiment index on underpricing. As mentioned, the index includes IPO specific variables which leads to an underlying relationship between underpricing and sentiment. Zhan (2010) deals with this issue by eliminating some of these variables, and use a reduced Baker and Wurgler index to study investor sentiment on a sample of US IPOs. For the purpose of this thesis, I decided to keep the original index without adjusting for any variables, with the main reason being that this paper studies the Nordic market as opposed to the US market in which the index is based upon.[2] In her US study using the reduced index, Zhan (2010) found that there is a positive and statistically significant relationship between investor sentiment and IPO underpricing. These findings indicate that the original Baker and Wurgler index does a better job at capturing investor sentiment, and since the IPO related variables are based on US IPOs, it is not as directly related to the underpricing observed in the Nordic market.

Figure 1

Baker and Wurgler's Investor Sentiment Index During Sample Period



Note. This figure depicts the sentiment among investors during the selected sample period. It ranges from -1 to 1, where 1 represents extreme optimism and -1 represents extreme pessimism.

5.2.2 Sentiment Proxies

The explanation of each of the five proxies below are aligned with their explanations in Baker and Wurgler (2006). Each of the five proxies reflect investor sentiment in some way, but also include other sentiment unrelated and

[2] The justification of using a US based index on the Nordic market is described in section 4.1

idiosyncratic components. To highlight the common sentiment component, Baker and Wurgler uses a principal component analysis when forming the index.

The value-weighted dividend premium, VWDP, is calculated as the log difference of the average market-to-book ratios of payers and nonpayers. It is represented in the index with the purpose of representing investor demand for dividend paying stocks. Following Fama and French's (2001) argument, the payers are typically larger, more profitable, and less scalable firms, meaning that the VWDP could be a reliable proxy for the relative demand for certain dividend-paying characteristics.

The equity share in new issues is basically just the share of equity of the total equity and debt. This proxy that could reflect sentiment because high values of the equity share have typically been generating low market returns. Baker and Wurgler (2006) calculates it as gross equity issuance divided by gross equity and gross long-term debt issuance.

A closed-end fund is a variation of a mutual fund which uses an IPO to issue a fixed number of shares in order to raise capital. Moreover, closed-end funds tend to trade at a discount to their net asset values, but they can also trade at a premium. The closed-end fund discount, CEFD, is calculated as the average difference between the net asset values of closed-end fund shares and their market prices. Lee, Shleifer, and Thaler (2001) argue that fluctuations in CEFD are affected by changes in investor sentiment.

The last two proxies reflecting sentiment in the sentiment index are IPO volume and average first day returns. It is common knowledge that the IPO market is sensitive to investor sentiment, and first day returns and volume are perhaps the best indicators of the level of investor enthusiasm. In their index, Baker and Wurgler uses first day returns and volume which are gathered directly from publicly available data without any further adjustments or calculations.

5.3 Control variables

In addition to the sentiment index, a set of related control variables are included in the regression models. The control variables used are not necessarily of interest to the aim of the study itself but are controlled by holding them constant because they could potentially affect the outcomes. Moreover, the inclusion of control variables helps increase the stability of the regression model because it isolates the relationship between the variables of interest from the effects of the control variables. As pointed out by Clarke (2005), the logic behind control variables boils down to four points. First, the inclusion does not lead to inefficiency as they have real effects. Second, due to the real effects, their absence may cause bias when correlated to other included variables. Third, since including every relevant variable is impossible, as many as possible should be included to reduce bias. Last, omitted variables bias is an aggregation of the individual omitted variable bias. The control variables used in this study are carefully selected based on existing literature validating their relevance and correlation. Others were considered and could have been included, but I wanted to minimize the risk of including irrelevant variables. The control variables included in the regression model are company age, number of employees, issue size, issue price, a dummy variable for hot and cold IPO markets, and discussed below.

5.3.1 Company Age

The company age used as a control variable is simply a monthly measure of how long it has been in existence up until the IPO date. Previous studies have used age as a control variable with the reasoning that it has an influence on underpricing. Baker and Wurgler (2006) found an inverse relationship between sentiment and age. When sentiment is high, demand in young companies increase and the opposite when sentiment is low. Moreover, Ritter (1984) suggests that age reflects several characteristics of a company. Older companies are more established, pose less uncertainties, and thus do not find it necessary to leave extra “money on the table” for investors as compared to less established companies who might use attractive prices to lure in investors. Ritter (2021) has conducted a list of the median age of all IPOs in each year from 1980 to 2021. Since the age of a company at the point in time it went public is not, to my knowledge, a standard metric of any database, it would be time consuming to gather this data. For this reason, the median age reported by Ritter is used to create a proxy generating the age of all firms going public each year.

5.3.2 Employees

As company age is considered to be an important control variable for this study, the same arguments support the inclusion of employees as a control variable as well. It speaks to the same set of firm characteristics discussed above. The employee control variable is simply the number of employees employed in the company at the time of its IPO. This build on the rationale regarding company age as more established firms tend to have more employees. The employee variable initially had several missing datapoints. Rather than deleting all the missing datapoints which would significantly decrease the sample size, they were replaced by a number selected on the basis of the mean and standard deviation of the present variable data.

5.3.3 Issue Price and Issue Size

The issue price and issue size variables are also used as control variables in the regression models. The issue price is the price per share at the time of listing and was gathered directly from the database. The issue size refers to the total transaction value of the IPO. It is calculated as the issue price times the number of shares offered, but the calculation was not necessary to conduct as it was available directly from the database. Since the IPOs in the sample stem from exchanges of countries with different currencies, both the issue price and issue size variables had to be modified to follow one common currency. By applying the relevant currency exchange rates, all values were adjusted to reflect the Norwegian krone (NOK). Both these variables have been used as control variables in similar studies because they are thought have explanatory relevance to investor sentiment. As with the other control variables, they help increase the stability of the model by reducing the impact of omitted variables.

5.3.4 Hot and Cold Market Dummy Variable

Aligned with the evidence discussed in previous sections suggesting hot and cold issue markets having an effect on underpricing as well as showing correlation to sentiment among investors, a hot and cold market dummy variable is included in the regression models. The use of dummy variables allows the regression model to account for variables that are not numerical in nature (Suits, 1957). The hot and cold market dummy variable takes the value of "1" when the IPO in question debuted during a hot market period, and the value of "0" otherwise.

5.3.5 Industry dummy variables

In addition to the variables discussed above, six industry dummy variables are added to the regression models. The sample consists of companies within nine industries, but only five are represented in variable form as "dropping out" one or more of the categories have estimation benefits such as preventing multicollinearity between dummies (Suits, 1957). Each IPO is assigned an industry in accordance with Bloomberg´s industry specifications and takes the value of "1" if included in the industry and the value of "0" otherwise. Different industries pose different levels of risks as well as containing industry specific risks. To account for these risks as well as the differences in underpricing across industries, the inclusion of industry specific dummy variables are useful due to their properties. The industries represented in the form of dummy variables are energy, industrial, financial, consumer (cyclical), consumer (non-cyclical), technology. The utility, communications, and basic materials industries have been left out as they contain a very limited number of observations, making it difficult to capture the industry effects. These industries are captured in the intercept term.

5.3.5 Logarithmic Treatment of Variables

The LN ISI, LN AGE, and LN PRICE variables have all been subject to a logarithmic transformation, with the main reason being a desire to transform skewed variables into a more normal distribution. Linear regression models improve on the features of variables being normally distributed and the said variables did not show that when testing for normality. Variables that show non-normal relationships are more likely to produce errors that are skewed negatively, meaning that logarithmic treatment can help improve the overall fit and reduce the presence of heteroscedasticity and multicollinearity by producing a smaller amount of error (Benoit, 2011).

5.4 Regression Models

The parameters of the regression models to be are estimated through an ordinary least squares (OLS) method, meaning that the relationship is linear in parameters and given as follows.

$$\gamma_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \ldots + \beta_k x_{ik} + \varepsilon_i$$

After applying the above set of variables to this model (see section 5), the following regression model is to be used when testing the established hypothesis.

$$\begin{aligned} MAUP_i = \beta_0 + \beta_1 (ISI)_i + \beta_2\,(AGE)_i + \beta_3 (EMPL)_i + \beta_4 (SIZE)_i \\ + \beta_5 (LNPRICE)_i + \beta_6 (HOT/COLD)_i + \textstyle\sum_{i=7}^{11} \beta_i (IND)_i \; + \varepsilon_i \end{aligned} \tag{3}$$

For comparison reasons, the exact same regression model will be perfromed on the standard underpricing rate, UPR.

$$\begin{aligned} UPR = \beta_0 + \beta_1 (ISI)_i + \beta_2\,(AGE)_i + \beta_3 (EMPL)_i + \beta_4 (SIZE)_i \\ + \beta_5 (LNPRICE)_i + \beta_6 (HOT/COLD)_i + \textstyle\sum_{i=7}^{11} \beta_i (IND)_i \; + \varepsilon_i \end{aligned} \tag{4}$$

5.4.1 OLS Regression

OLS is arguably the most used method for estimating linear models, and it does so by minimizing the number of squared residuals. The reason for it being the most used estimation model is simply because it yields the best estimates. In order to produce the best estimates, however, there are certain assumptions on the unobservable error terms (residuals) that has to be met. These assumptions are described briefly in table 2.

Table 2

OLS assumptions

Technical notation	Interpretation
$\gamma_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} \ldots + \beta_k x_{ik} + \varepsilon_i$	Model is linear in parameters
$E[u_t] = 0$	The error mean is zero
$Var\ [u_t] = \sigma^2 < \infty$	Constant and finite variance of errors for all observations (homoscedasticity)
$Corr[u_i, u_j \mid X] = 0$	Uncorrelated error terms (no autocorrelation)
$\rho_{x_i, x_j} \not\approx 1$	No multicollinearity
$u_t \sim N(0, \sigma^2)$	Normal distribution of u_t

Note. Table 2 shows the technical notation and interpretation of the OLS assumptions.

Most of the assumptions describe some property of the error term. However, as this term is not available, the residuals become the focus of attention. Thus, to make sure that these assumptions hold, several tests had to be performed on the basis of the residuals. A White's test was conducted to check for heteroscedasticity, a Breusch-Godfrey test using ten lags was used to test for autocorrelation, a Jarque-Bera test for normality, and a correlation matrix were used to test for multicollinearity between variables. Furthermore, to assess the assumptions of the OLS linear regression models, residual plots were used to check for patterns (see Appendix 4 for plotted residuals of all regression models performed).

5.5 White's Test for Heteroskedasticity

Heteroscedasticity simply means that the variance of the errors is non-constant. It occurs when there are certain subsets of the residuals where the variability amounts are significantly larger than in other subsets. To test for heteroscedasticity, a test must therefore look for this type of pattern in the residuals. The ultimate goal is population errors which are homoscedastic, meaning that the variance of the error term is equal to a constant σ^2. Using an OLS estimator when there is a significant amount of heteroscedasticity present in the data could result in inappropriate standard errors and thus misleading results. To avoid this issue, a White's test for heteroscedasticity was conducted. The test was introduced by Halbert White and uses a covariance matrix estimator that does not depend on a specific formal model, and thus is consistent in the presence of heteroscedasticity (White, 1980). White's test is one of the best approaches to use since it does not make many assumptions about the form of the heteroscedasticity. Consequently, the hypothesis testing becomes more conservative as more evidence against the null hypothesis is required prior to rejection. The dataset was tested as proposed by White and the results are given in table 3.

5.6 Breusch-Godfrey Test for Autocorrelation

As stated in the fifth assumption for the OLS estimator above, the error terms must be uncorrelated, i.e. no autocorrelation. The assumption states that there is no pattern in the true residuals, u_t. However, there is no way to know the true residuals, meaning that an estimated set of residuals, $\hat{u}_t$, are to be used. Autocorrelation occurs if there are patterns in the estimated residuals. The reasoning for using the Breusch-Godfrey test is that it tests for the r^{th} order autocorrelation which makes it one of the most efficient. In the presence of autocorrelation, the coefficient estimates will still be unbiased, but inefficient, meaning that the OLS estimators are not the best linear unbiased estimators. In case the standard errors are inappropriate, wrong inferences could be drawn as the r-squared has a high probability of being inflated.

Table 3

Results from White's test for heteroscedasticity and Breusch-Godfrey's test for autocorrelation

	1%	5%	10%
White test	false	false	false
Breusch-Godfrey test	false	false	false

*Note.*This table shows the results obtained after performing a white's test for heteroscedasticity and a Breusch-Godfrey test for autocorrelation at the 1%, 5% and 10% significance level. For White's test ,"False" refers to a failure of rejecting the null hypothesis that the data is homoscedastic. For Breusch-godfrey's test, "False" refers to a failure of rejecting the null hypothesis that there is no serial correlation.

5.7 Multicollinearity

The issue regarding multicollinearity takes place when there is high correlation between the explanatory variables. We distinguish between perfect multicollinearity, such as $x_1 = x_2$ and $x_1 = 2 * x_2$, and near multicollinearity (high correlation). In the case of perfect collinearity, all the coefficients cannot be estimated which obviously calls for an inefficient model. In the presence of near multicollinearity, issues that might result in inappropriate conclusions will occur. R-squared will be high, but standard errors of the individual coefficients will also be high. In addition, small changes in the specification will have significant effects on the regression. To test for multicollinearity, a correlation matrix which showcases the correlation between each of the variables was created. As table 4 displays, there is no presence of multicollinearity between variables used in the model. A correlation coefficient between two or more variables larger than 0.7 is typically said to indicate multicollinearity. The only variables with a correlation above this threshold are the two different metrics of underpricing. However, these are naturally correlated and not used simultaneously in the regression model.

Table 4

Correlation matrix of variables

	UPR	MAUP	ISI	Issue Size	Issue Price	Age	Employees
UPR	1	0.999	0.031	0.020	-0.043	-0.025	-0.108
MAUP	0.999	1	0.029	0.018	-0.040	-0.023	-0.107
ISI	0.031	0.029	1	0.054	0.019	-0.010	0.202
Issue Size	0.020	0.018	0.054	1	0.031	-0.056	0.024
Issue Price	-0.043	-0.040	0.019	0.031	1	0.455	0.210
Age	-0.025	-0.023	-0.010	-0.056	0.455	1	0.314
Employees	-0.108	-0.107	0.202	0.024	0.210	0.314	1

Note. This table shows the correlation between variables. Except for the undepricing variables which are known to be correlated, there are no signs of significantly high correlation and no presence of multicollinearity is concluded.

5.8 Jarque-Bera Test for Normality

To determine whether the dataset is following a normal distribution, a Jarque-Bera test for normality was conducted. The test checks for normality by testing whether the excess kurtosis and skewness are jointly equal to zero. It does so by estimating the skewness and the excess kurtosis of the estimated residuals, $\hat{u}_t$, obtained from the OLS regression. Normality is either confirmed or rejected from a simple hypothesis test. As one of the assumptions for best linear unbiased estimators requires normality, it is critical to conduct the test to secure for the validity of the conclusions drawn. Evidence of non-normality is not optimal, but there are ways to get around it. One way to solve the problem is through the application of dummy variables. Non-normality is often caused by a few large outliers in the plotted residuals and replacing these outliers with a dummy variable basically eliminate the observations. After applying logarithmic treatment to the non-normally distributed variables, the Jarque-Bera test showed a normal distribution of the dataset.

6 Descriptive statistics

This section mainly discusses key statistics of the variables used in the study. Previous sections have defined all variables, but this part of the study offers more of an in-depth analysis regarding different statistics and results that can be drawn from underlying data. The statistics put numbers to the variable definitions which provides a deeper understanding of the data as well as allowing for comparisons with similar studies using a different dataset.

6.1 Descriptive statistics of variables

Looking at the reported underpricing in table 5, it shows that the average standard underpricing rate (UPR) of 8.23% and average market-adjusted underpricing rate (MAUP) of 8.13% are more or less the same. The small difference is due to the limited effect of market returns in relation to the large variations in first-day returns. This is within the range of the underpricing reported in similar research done on different samples. Ritter (2003) looks at the average underpricing reported in different studies, and found that the degree of underpricing varies significantly between different countries and periods, but tend to range all the way from 5% to upwards of 100%. The two different underpricing metrics were expected to be in the same range, but they were even more similar than initially thought. This could be explained in a few different ways using intuition. Firstly, exchanges do not typically provide large daily movements in either direction. IPOs on the other hand, present, on average, larger movements in both directions, meaning that the daily market return would not adjust significantly for a highly underpriced or overpriced IPO. This can be seen from the minimum underpricing rate of -95% and the maximum underpricing rate of 135% in table 5. Secondly, approximately half of the sample IPOs debuted on a day where the prior daily market return was negative, and the other half debuted when the prior daily market return was positive. The average daily market return of the days prior to all the sample IPOs were 0.10%, which means one can argue that the returns are close to cancelling each other out.

Table 5

Descriptive statistics of key variables

Variable	Mean	Median	Std.Dev	Minimum	Maximum
UPR	0.082	0.018	0.664	-0.956	13.500
MAUP	0.081	0.018	0.665	-0.956	13.530
ISI	-0.149	-0.165	0.287	-0.902	0.601
Issue Size (mln NOK)	818.861	148.926	1990.338	0.065	24366.900
Issue Price (NOK)	348.093	29.876	5018.796	0.430	112075.894
Age (Years)	11.210	11.289	2.459	4.604	18.597
Employees	1258.163	306	3038.481	1.000	36345

Note. This table cosists of simple calculations which derive variable statistics important for the aim of the study.

Taking a closer look at the descriptive statistics for the investor sentiment index in table 5, which is arguably the most important independent variable regarding the aim of this thesis, the average sentiment among investors during the sample period is -0.148 with a median of -0.168. This implies that the sentiment among investors was, on average, negative during the sample period, and is a potential argument for why the underpricing rate reported is in the lower range. According to Ljungqvist, Nanda & Singh (2006) stating that more underpricing exist when there is exuberance among investors, the underpricing rate of 8.13% should see an increase in a sample where the average investor sentiment is positive. However, only looking at the average sentiment over a period is not enough to verify the effect of investor sentiment. It requires a closer look at the positive and negative investor sentiment periods.

6.2 Positive vs Negative Investor Sentiment Periods

The investor sentiment index ranges from -1 to 1, where -1 indicates that investors are exclusively negative, and 1 indicating exclusive positiveness. For all observations occurring during positive sentiment periods, the average investor sentiment is 0.1758. The average during negative sentiment periods is -0.2611. The complete sample produces, as mentioned earlier, an average market-adjusted underpricing rate of 8.13%. Looking at positive and negative investor sentiment periods separately, however, the average underpricing among the observation differs.

Lee, Shleifer, and Thaler (1991) found that more companies go public when investor sentiment is high, and the same investor optimism plays a role in underpricing being larger during periods of positive investor sentiment, which is shown to be consistent with this sample. This, however, introduces the paradox of why issuers are not more aggressive when determining offer price and thus lower underpricing. Ljungqvist, Nanda, and Singh (2006) argue that investors, sometimes, are irrationally optimistic and thus “outcompete” the optimism of rational issuers. As described in table 6, the average market-adjusted underpricing for positive investor sentiment periods is approximately twice as large as for negative investor sentiment periods, which translates to a difference in means of 6.62%. Furthermore, the standard deviation is substantially higher when sentiment is positive which indicates higher volatility in first-day returns. To test whether the mean differences between the variables of the two subsamples are statistically significant, independent sample t-tests are applied. As both samples are extracted from the same population, equal variance is assumed and the test statistic is calculated as seen in (5).

$$t = \frac{\overline{x_1} - \overline{x_2}}{s_p\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}} \tag{5}$$

With

$$s_p = \sqrt{\frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1+n_2-2}} \tag{6}$$

Where $\overline{x_i}$ refers to the mean of the i_{th} sample, n_i refers to the sample size of the i_{th} sample, s_i refers to the standard deviation of the i_{th} sample, and s_p is the pooled standard deviation.

The difference in means between two samples does not tell a whole lot in itself, but running a hypothesis test on the reported differences allows for meaningful conclusions. The t-test assumes a null hypothesis that the true difference between the two subsample means is zero, and an alternativ hypothesis that the mean difference of the two subsample means is different from zero. Using the calculated t-statistics depicted in table 6 and t-distribution values calculated as in (5), the null hypothesis is either rejected and found to be statistically significant or not rejected and insignificant. Rejection of the null is interpreted as the true mean difference not being equal to zero. Failing to reject the null hypothesis, however, means that the mean difference between the supsamples is likely to be zero.

Table 6

Summary Statistics of Variable Data Split into Positive and Negative Sentiment Periods

	Positive			Negative			Mean Difference	
Variable	**Mean**	**Median**	**Std.Dev**	**Mean**	**Median**	**Std.Dev**	**Mean Difference**	**t-Stat**
UPR	0.128	0.010	1.124	0.062	0.021	0.297	0.066	0.052
MAUP	0.129	0.017	1.122	0.063	0.023	0.297	0.066	0.052
ISI	0.176	0.160	0.130	-0.287	-0.261	0.199	0.463	1.072
Issue Size (mln NOK)	685.104	157.336	2122.428	875.026	143.526	1931.479	-189.922	-3.452
Issue Price (NOK)	934.759	25.000	8282.732	34.237	21.500	39.627	900.522	8.303
Age (Years)	11.654	11.692	2.827	11.020	11.210	2.260	0.634	0.316
Employees	1244.294	628.000	2757.097	1264.118	219.500	3155.162	-19.824	-0.316

Note. This table shows descriptive statistics for all variables when each observation is split into positive and negative investor sentiment periods. 158 IPOs debuted in a period of positive investor sentiment, while the remaining 368 IPOs debuted when investor sentiment was negative.

The t-statistics in the last column of table 6 are the determinants of whether the mean differences are statistically significant or not. At the 5% significance level, the number of employees, issue size, and issue price report mean differences with statistical significance. With a high level of confidence, there is enough evidence to conclude that the reported mean differences of these variables are a result of whether the IPOs debuted during a positive or negative investor sentiment period. Underpricing, the investor sentiment index, and company age report insignificant differences. This indicates that the difference reported in the means of the two samples are most likely due to chance or random variations.

As can be seen in table 6, the number of employees working at the time of issuance has a notable difference in means, suggesting that firms going public during negative sentiment periods, on average, have more employees than firms going public during positive sentiment periods. Furthermore, the issue size of firms going public during negative sentiment periods are, on average, significantly less than of firms going public during postitive sentiment periods. These findings support Lee, Shleifer, and Thaler (1991), and Loughran, Ritter, and Rydqvist (1994) stating that less mature firms are timing the market and seek to exploit periods where investors are overly optimistic. The number of employees are an indicator of the size of a firm. A firm with a large amount of employees are likely to be larger and more mature than a firm with few employees. Issue size is also directly related to the maturity of a firm because it speaks directly to the value at issuance.

6.4 Industry Specific Underpricing

Table 7 displays underpricing in each of the nine industries in which the IPOs of the sample falls under. Both the number of IPOs and the average underpricing varies substantially within each industry, strengthening the proposed argument that one should account for industry classifications when discussing the underpricing phenomenon. The industrial sector displays the highest amount of underpricing by far, but a high maximum value along with a large standard deviation implies extreme values having an impact. The energy industry shows that IPOs, on average, are slightly overpriced, while the communications industry reports the lowest amount of underpricing out of all industries. From the last two columns of the tables, all industries except basic materials and utilities, display large values in both directions. These results, along with the average underpricing, confirms that some degree of underpricing exists in almost all industries, and thus validates the inclusion of all industries.

Table 7

Underpricing based on industries

Industry	Number of Observations	Mean Underpricing	Mean Sentiment	Median Underpricing	Standard Deviation	Minimum Underpricing	Maximum Underpricing
Energy	37	-1.18%	-0.12	1.23%	0.24	-95.59%	60.00%
Industrial	90	20.64%	-0.15	2.67%	1.48	-86.34%	1353.00%
Financial	70	8.91%	-0.07	0.51%	0.35	-52.33%	212.89%
Consumer, Cyclical	56	10.35%	-0.20	4.31%	0.36	-41.39%	212.67%
Consumer, non-cyclica	144	5.67%	-0.18	2.71%	0.29	-60.02%	147.66%
Technology	77	4.12%	-0.18	0.31%	0.23	-83.90%	81.89%
Communications	34	1.14%	-0.12	2.53%	0.22	-84.44%	53.29%
Basic Materials	15	5.21%	0.02	4.18%	0.12	-16.68%	28.36%
Utilities	3	2.44%	-0.16	-1.47%	0.11	-6.41%	15.18%

Note. This table splits all IPOs into their belonging industry, and reports the number of observations in each category as well as the average sentiment and underpricing statistics.

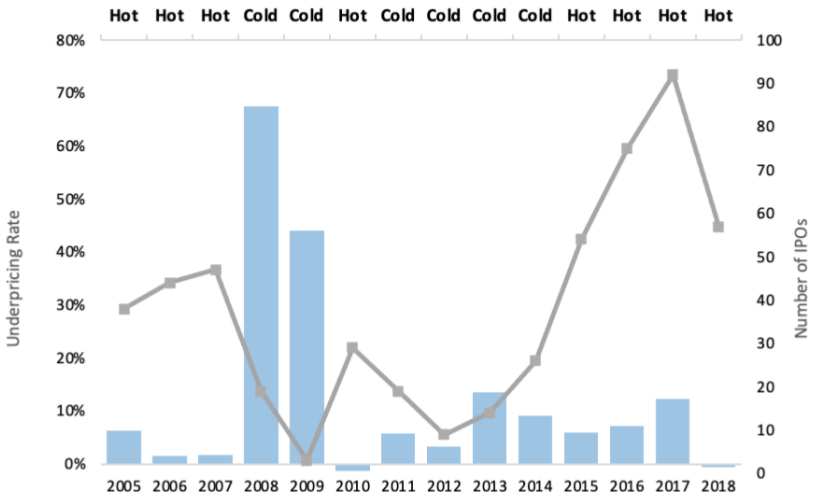
Loughran and Ritter (2003) found evidence suggesting the risk-compensation theory is applicable to underpricing, meaning that high-risk industries display a higher degree of underpricing compared to lower-risk industries. Additionally, Ljungqvist, Nanda, and Singh (2006) states that investor are irrational based on industries. By assuming that these findings of first-day returns being affected by industry classification are applicable to this study, and thus supporting the investor sentiment theory, the different industries have both relevance and correlation to the variables of interest in this study. Looking at the average sentiment within each industry in table 7, there is no immediate evidence suggesting that industries with higher underpricing display more investor optimism. Furthermore, industries often classified as high-risk does not seem to show correlation with higher underpricing. The technology sector is often classified as high-risk and has previously been proven to be affected by investor sentiment, but in the technology related IPOs in the Nordic market show an underpricing towards the lower end. It is important to note, however, that the modest sample size leads to a limited number of observations for each industry which limits the explanatory power of the statistics. The literature claiming a relation between industries, and sentiment and underpricing are based on much larger samples with a narrower focus.

6.5 Hot Issue vs Cold Issue Markets

It is known that IPO markets move in cycles where certain periods have a significant increase in the number of new offerings. According to both Ibbotson and Jaffe (1975) and Ritter (1984), these periods are known as hot issue markets, and are the opposite of cold issue markets where the number of new offerings is limited. Furthermore, they find that hot issue markets are characterized by higher underpricing, smaller offerings in terms of total transaction value, and overoptimistic investors. Figure 2 shows the average underpricing and the number of IPOs each year. It also classifies each year as either hot or cold, depending on whether the number of IPOs are above or below the average of the entire sample period. As the hot and cold periods are determined based on new listings volume, there is an obvious relationship between the two. What is of particular interest, is the amount of underpricing observed during the hot and cold periods. There seems to be no consistency between the amount of underpricing and hot/cold market periods reported in existing literature. The highest amount of underpricing is actually observed during cold market periods, but due to the low amount of IPOs during these periods, the findings are of minor importance as a few observations are likely to drive the results.

Figure 2

Per Year Underpricing, Number of IPOs, and classification of Hot/Cold periods



Note. This figure shows the underpricing rate, represented by columns, per year on the left y-axis, and the number of companies going public, represented by lines, each year on the right y-axis.

Figure 2 classifies each year represented in the sample as either “hot” or “cold” along with the number of IPOs during that specific year. A year is considered hot if the number of IPOs a specific year is above the average number of IPOs each year across the entire sample. Figure 1 which models investor sentiment, exhibits some correlation between positive investor sentiment periods and hot issue markets which supports the idea that investors are overly optimistic during hot issue market periods, and thus investor sentiment’s importance with regards to underpricing. However, the specific sample data contradicts this correlation as the number of IPOs during positive sentiment periods is substantially lower than for negative sentiment periods. Moreover, table 6 displays a large and statistically significant difference in means for the number of employees in companies going public during positive and negative investor sentiment periods. On average, companies going public during positive sentiment periods have fewer employees than companies going public during negative sentiment periods. Furthermore, this is backed up by the significant difference in means for issue size. These findings support the claims of both Ibbotson and Jaffe (1975), and Ritter (1984 and 1991) that smaller, more risky firms seek to exploit the advantages related to going public when investors are overly optimistic.

7 Empirical Analysis and Results

To create an overview of the relationship between the market-adjusted underpricing rate (MAUP) and Baker & Wurgler's investor sentiment index (LN ISI), the empirical analysis was initiated by running a simple linear OLS regression without the inclusion of any additional variables. It is helpful for comparison reasons as it shows the effect of adding control variables in terms of how well the model fits and is able to explain underpricing. The results of this simple model, seen in table 9, were as expected. It shows a positive, but insignificant, relation between investor sentiment and underpricing, meaning that there is no existence of conclusive evidence that investor sentiment has any effect on underpricing. Moreover, the fit of the model is extremely low.

Using these results as the starting point for the analysis, all the already discussed variables were added to the regression to control for certain IPO characteristics. Two, almost identical models, seen in (3) and (4), using the exact same independent- and control variables but two different measures of underpricing as the dependent variable were ran. Table 9 shows the results gathered from all the different regression models that were performed. Model 1 is the simple linear regression that only tests for the effect of investor sentiment on underpricing without including any additional variables. Model 2 and model 3 presents the results of the regression models using the market-adjusted underpricing rate (MAUP) and the standard underpricing rate (UPR) as the dependent variable. Model 3 is intended for both comparison purposes and as a robustness check, mainly to see whether different measurement methods of underpricing cause the model to display any significantly different results. Model 4 tests for the effect after winsorizing the dependent variable at the 1^{st} and 99^{th} percentile. Additionally, two regression models, model 5 and model 6, were conducted. These models separate the IPO data into two subsamples of positive and negative investor sentiment periods and perform an identical regression on each using the exact same variables as model 2-4. This allows for testing and comparing how the impacts on underpricing differ when sentiment among investors is high versus low.

Table 9

Regression results

	No Control Variables	Main Models		Winsorization	Positive/Negative Sub-Samples	
	MAUP	MAUP	UPR	MAUP	MAUP	MAUP
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
LN ISI	0.046	0.135*	0.137*	0.031	1.280	0.059
	(0.503)	(0.061)	(0.065)	(0.304)	(0.195)	(0.171)
AGE		-0.017	-0.011	-0.016	0.117	-0.007
		(0.938)	(0.902)	(0.778)	(0.803)	(0.932)
EMPL		0.000	0.000	0.000	0.000	0.000
		(0.445)	(0.468)	(0.135)	(0.843)	(0.193)
SIZE		0.000	0.000	0.000	0.000	0.000
		(0.472)	(0.464)	(0.402)	(0.427)	(0.961)
LN PRICE		-0.067***	-0.068***	-0.020**	-0.133**	-0.026*
		(0.006)	(0.006)	(0.048)	(0.038)	(0.088)
d. Hot/Cold		-0.201**	-0.201**	-0.047	-0.689**	-0.056
		(0.014)	(0.014)	(0.163)	(0.019)	(0.182)
d. Energy		-0.022	-0.022	-0.027	0.162	-0.020
		(0.879)	(0.879)	(0.639)	(0.681)	(0.808)
d. Industrial		0.206*	0.207*	0.038	0.780**	0.003
		(0.075)	(0.074)	(0.421)	(0.023)	(0.964)
d. Financial		0.119	0.119	0.066	0.266	0.105
		(0.332)	(0.332)	(0.189)	(0.429)	(0.140)
d. Consumer,		0.132	0.131	0.081	0.231	0.116*
cyclical		(0.302)	(0.307)	(0.127)	(0.566)	(0.097)
d. Consumer,		0.064	0.063	0.041	0.068	0.046
non-cyclical		(0.555)	(0.562)	(0.364)	(0.832)	(0.441)
d. Technology		0.041	0.041	0.021	0.112	-0.001
		(0.730)	(0.735)	(0.672)	(0.763)	(0.983)
Intercept		0.457	0.446	0.175	0.420	0.206
		(0.235)	(0.245)	(0.269)	(0.759)	(0.343)
R-squared	0.000	0.038	0.039	0.025	0.110	0.042
Adj. R-squared	0.00	0.015	0.016	0.002	0.036	0.009
N	526	526	526	526	158	368

Note. This table shows the results of the total six regression models that were performed. Model 1 only tests the investor sentiment (ISI) variable and excludes all control variables. Models 2 and 3 are of the whole sample and includes all the control variables as well as ISI. Model 2 uses MAUP as the dependent variable, and model 3 uses UPR as the dependent variable. Model 4 is similar to model 2, but applies winsorization on the dependent variable, MAUP, at the 1st and 99th percentile. Models 5 and 6 are regressions on subsamples created based on positive and negative investor sentiment periods. Model 5 uses a sample containing all IPOs debuting during positive investor sentiment periods, while model 6 does the same for negative investor sentiment periods. They both use MAUP as the dependent variable. Corresponding p-values are in parentheses.

* p<0.1, ** p<0.05, ***, p<0.01

As the measurement methods of model 2 and model 3 are similar, table 9 displays close to identical values for both models, indicating that the results are entirely due to the impacts of the independent and control variables. The inclusion of control variables to model 1 can thus be seen to significantly improve the overall quality of the model. The R-squared increases substantially meaning that the goodness-of-fit is now higher, although still at the lower end. Due to the already discussed omitted variables issue and the complexity of the underpricing phenomenon, however, this was to be expected. After the addition of variables, the reported F-statistic is now statistically significant meaning that the added variables are jointly significant, improve the fit of the model, and allows for interpretations. Adding control variables increased the positive relationship between the investor sentiment variable and underpricing variable, but more importantly, it changed the statistical significance. Based on the reported p-value, the investor sentiment variable is significant at the 10% level and shows a positive relation with underpricing in alignment with the thesis question.

The reported standard deviation for the underpricing metrics reported in table 5 are rather large. Due to the large movements often seen with IPOs, this was not unexpected. However, it raises the question of the potential effect of outliers on the regression results. First-day returns are exposed to extreme outliers in both directions which can be seen in in the last two columns of table 5. Since regression estimates are known to show sensitivity towards outliers, an additional model was added to test for the effects. Model 4 is performed using the exact same variables as model 2, but the dependent variable, MAUP, is winsorized at the 1st and 99th percentile meaning that the top and bottom 1% data points are assigned a lower weight. Table 9 indicates that the winsorization approach produce a substantial change in the results. The model fails to show any significance between investor sentiment and underpricing and the overall validity of the model drops which limits the interpretations that can be made. This speaks to the fact that outliers may have an effect on the overall model efficiency. As expected with underpricing data, the plotted dependent variable displays outliers, but it is important to keep in mind that extreme values are an influencing factor of why underpricing exists. However, there is only one observation that stands out as particullarly extreme. To test the effect of this single outlier, I modified it to align with the more normal-looking outliers. Although it slightly changed some of the variable coefficients, it had no effect on the overall significance of the model and variables, which is why no modifications was made to the original model. In the case of a limited amount of extreme values, winsorization influences outliers not seen as extreme which could negatively affect the relationship.

When separating between IPOs debuting during positive or negative investor sentiment periods and running one regression on each, the overall fit of the model drops. The purpose of these models was to elaborate on the results of the previous models by testing and comparing whether the impacts on underpricing differ when sentiment among investors are high or low. These sub-sample models fail to show any significant effect between investor sentiment and underpricing. However, it is worthwhile to note that the LN ISI coefficient experience a sharp increase in the positive sub-sample and a sharp decrease in the negative sub-sample as compared to the other models. One could argue that the sub-sample models should show a significant LN ISI variable as it is plausible to assume they are set up to capture the significant effects seen in the previous models even better due to the difference in means. However, the fit of the models is weak compared to the other models indicating that they cannot be properly supported. The obvious reason as to why that might be the case is that each sample size decreases, meaning that the likelihood of having statistically significant variables decreases as well. Another explanation is the lower-end degree of underpricing, which alongside a smaller sample size might not be able to capture the effects. This sample shows an average underpricing of 12.83% during positive sentiment periods, 6.25% during negative sentiment periods, and 8.13% for the entire period, which is at the lower end compared to similar research done on different samples. Parts of the moderate degree of underpricing could be explained by sample characteristics such as not including data from the bull-run leading up to the dot-com bubble during the 1990s.

As discussed already, the main regression model finds the investor sentiment variable to be statistically significant. Another variable found to be significant in several of the models is the hot/cold dummy variable. With a negative coefficient, it is found statistically significant at the 5% level in the main regression model and in the model of positive sentiment. The negative coefficient obtained in the main regression implies that underpricing in the Nordic market is less likely to occur during hot market periods. Interestingly, the coefficient is even more negative in the positive sentiment sub-sample model, which indicates that the combination of positive sentiment and hot market periods is more likely to have less underpricing. These findings are contradicting to evidence obtained in previous studies.

The only variable to show significance across all models is the offering price (LN PRICE) variable. The coefficient is negative across all models, but the most negative during positive sentiment periods. These findings state that an increase in offering price tends to lead to lower underpricing. Offering price does not say anything about the value of an IPO alone, but its significance from a behavioural perspective is rather interesting. There is no logical reason as to why a low offering price should lead to higher demand among sentiment investors, but a possible explanation is that it “appears” cheaper to the already irrational investor. Moreover, the higher implied change in underpricing during positive sentiment periods strengthen this argument.

Another aspect of the regression results worth mentioning are the effects of the industry dummies. As already discussed, the underpricing varies within different industries due to risk and other industry specific factors, and some of these differences are reflected in the regressions. The industrial dummy variable shows a positive and statistically significant coefficient in the main model and the model of positive sentiment which can be explained by it being the industry with the highest observed underpricing. Apart from the industrial dummy, none of the industry dummies show a statistical relationship with underpricing and there is no concluding evidence suggesting that investor sentiment has a significant effect on the different amounts of underpricing within different industries.

8 Conclusion

By accounting for positive and negative sentiment periods, hot and cold IPO markets, and industry classifications, this thesis explores and tests the effect of investor sentiment on first-day IPO underpricing in the Nordic market. It does so through different descriptive statistics as well as six different regression models using the Baker and Wurgler (2006) sentiment index as the measure of underpricing.

With the help of several variables controlling for IPO characteristics and industry effects, the main regression model finds a statistically signifcant and positive relationship between the investor sentiment index and first-day underpricing. This indicates that an increase in investor sentiment tend to increase the average underpricing in the Nordic market which positively answers the research question. These findings also confirm the existence of sentiment investors in the Nordic market, as well as sophisticated investors generating profits at their expense.

The application of t-tests on the differences in means between positive and negative sentiment periods find that smaller firms in the Nordic market are timing their IPOs to exploit periods of optimism among investors. These findings add to the similar claims made by others such as Lee, Shleifer, and Thaler (1991), Loughran, Ritter, and Rydqvist (1994) that smaller firms, in general, view investor optimism as a window of opportunities.

The sample includes 436 companies going public in a hot-issue market and only 90 companies going public in a cold-issue market. However, only a total of 158 IPOs occurred when investor sentiment was positive, compared to 368 IPOs when there was negative sentiment. The application of multiple regression models find that underpricing in the Nordic market tend do decrease during hot market periods Furthermore, I find evidence suggesting that this negative correlation is strengthened during hot market periods where positive sentiment is present. This is contradicting to Ibbotson and Jaffe (1975) and Ritter (1984) who found that hot issue markets are characterized by overly optimistic investors and higher underpricing.

In alignment with previous literature, this study finds that IPOs in the Nordic market, on average, are underpriced by 8.13%. I also find a first-day underpricing rate of 12.87% for firms going public when there is positive sentiment among investors, and only 6.25% for firms going public during times where sentiment is negative. These findings do not prove anything, but they help strengthen the argument of Ljungqvist, Nanda, and Singh (2006) that issuers fail to integrate investor optimism in the offering price because investors are more irrational compared to issuers. The difference in means also suggest that investor sentiment might effect the displayed variations.

8.1 Limitations

There are certain limitations to this thesis that is worth mentioning. Firstly, the selected sample size is somewhat small compared to many of the similar studies investigating the same relationship. Using a longer sample period would result in a larger sample and the inclusion of periods where the Baker and Wurgler sentiment index display high volatility (see Appendix 3 for the devolpment of the index since its construction). Increasing the sample period to include the 1990s would, for instance, account for both the burst of the Dot-Com bubble as well as the bull run leading up to it. For further reasearch, it would therefore be interesting to use a similar approach on a larger sample period in the Nordic market to test whether the effects found in this study are heightened. Second, The Baker and Wurgler index is constructed on the basis of US market data. This thesis justifies its use on the Nordic market, but the construction of a similar index on the basis of Nordic market data could increase the power of the study.

Additionally, it should be noted that the R-squared of all the regression models are low. This indicates that the proven effects of the investor sentiment variable is not explaining a whole lot of the variation in underpricing.

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Appendices

Appendix 1

List of all IPOs in the sample

Issuer Name	Country	Underpricing
COSL Holding AS	NORWAY	1.23%
Exploration Resources ASA	NORWAY	0.81%
APL ASA	NORWAY	-19.95%
Neste Oyj	FINLAND	21.50%
Berry Packaging Norway AS	NORWAY	310.08%
Oslo Areal AS	NORWAY	57.53%
Havfisk AS	NORWAY	-9.96%
Allianse ASA	NORWAY	-2.55%
Havila Shipping ASA	NORWAY	-12.86%
Affecto OY	FINLAND	45.48%
Seadrill X ASA	NORWAY	-95.59%
Nemi Forsikring AS	NORWAY	-19.44%
VIA Travel Group ASA	NORWAY	-8.16%
TopoTarget A/S	DENMARK	-0.14%
DOF Subsea AS	NORWAY	-17.91%
Wintershall Norge AS	NORWAY	2.68%
American Shipping Co ASA	NORWAY	45.16%
Multipower AS	NORWAY	22.82%
Deep Sea Supply ASA	NORWAY	-0.48%
Norstat ASA	NORWAY	-16.64%
Indutrade AB	SWEDEN	-25.47%
Hemtex AB	SWEDEN	1.68%
Unison Forsikring ASA	NORWAY	7.70%
Tryg A/S	DENMARK	8.67%
Aker Drilling ASA/Old	NORWAY	-13.00%
Wayfinder Systems AB	SWEDEN	0.31%
Cermaq Group AS	NORWAY	10.20%
Powel AS	NORWAY	1.02%
BW Gas AS	NORWAY	-2.74%
ArcticZymes Technologies ASA	NORWAY	3.03%
TradeDoubler AB	SWEDEN	-84.44%
Orexo AB	SWEDEN	17.25%
NorGani Hotels ASA	NORWAY	5.67%
ODIM ASA	NORWAY	7.89%
ICA Gruppen AB	SWEDEN	-3.81%
Agility Group AS	NORWAY	5.82%
Funcom Se	NORWAY	-32.07%

Norda ASA	NORWAY	29.22%
Direct Conversion AB	SWEDEN	-6.94%
KapitalPleje AS	DENMARK	6.36%
Odfjell Invest Ltd	NORWAY	-0.01%
cBrain A/S	DENMARK	0.65%
KappAhl AB	SWEDEN	-1.20%
Saipem Discoverer Invest SARL	NORWAY	-11.80%
Salcomp plc	FINLAND	-22.11%
Ahlstrom Oyj	FINLAND	-37.40%
BWG Homes ASA	NORWAY	-22.64%
Gant Co AB	SWEDEN	20.20%
Formuepleje Safe A/S	DENMARK	11.55%
FIM Group Oyj	FINLAND	32.10%
Dios Fastigheter AB	SWEDEN	-38.36%
BW Offshore Ltd	NORWAY	28.79%
Curalogic A/S	DENMARK	0.64%
Swedol AB	SWEDEN	14.87%
Teekay Petrojarl ASA	NORWAY	-86.34%
Petroleum Services Group ASA	NORWAY	-0.83%
Trolltech ASA	NORWAY	-0.94%
Karo Pharma Norge AS	NORWAY	12.43%
RusForest AB	SWEDEN	11.02%
Melker Schorling AB	SWEDEN	-2.55%
Swedish Orphan Biovitrum AB	SWEDEN	-3.00%
AlphaHelix Molecular Diagnosti	SWEDEN	39.23%
Metso Outotec Oyj	FINLAND	11.14%
Austevoll Seafood ASA	NORWAY	13.69%
Marine Farms ASA	NORWAY	16.59%
Arctic Seafood Group AS	NORWAY	0.83%
Formuepleje Merkur A/S	DENMARK	-3.32%
AKVA Group ASA	NORWAY	11.38%
Det Norske Oljeselskap ASA/OLD	NORWAY	17.79%
Veloxis Pharmaceuticals A/S	DENMARK	5.15%
Norwegian Property ASA	NORWAY	-0.93%
Team Tankers Management Holdin	NORWAY	19.62%
BE Group AB	SWEDEN	-16.68%
Lindab International AB	SWEDEN	-2.95%
Rovsing A/S	DENMARK	-1.00%
Scirocco AB	SWEDEN	12.95%
Faktor Eiendom ASA	NORWAY	-2.96%
Aker BioMarine ASA/Old	NORWAY	7.51%
Allenex AB	SWEDEN	10.58%
Nordic Mines AB	SWEDEN	20.14%

Tilgin AB	SWEDEN	2.82%
Aker BP ASA	NORWAY	-1.47%
Tribona ASA	SWEDEN	-1.57%
Scandinavian Private Equity A/	DENMARK	-1.60%
Enalyzer	DENMARK	14.52%
Yinson Production AS	NORWAY	-11.59%
Obos Danmark AS	NORWAY	-1.41%
NEAS ASA	NORWAY	-6.73%
Algeta ASA	NORWAY	3.98%
Electromagnetic Geoservices AS	NORWAY	18.65%
Terveystalo Healthcare Oyj	FINLAND	-33.57%
Datum Opportunity AS	NORWAY	-12.10%
Y.C.O. BUSINESSPARTNERS AB	SWEDEN	36.61%
Salmar ASA	NORWAY	20.21%
ScanArc ASA	NORWAY	22.60%
Powerflute Oyj	FINLAND	4.30%
Nederman Holding AB	SWEDEN	7.60%
Protector Forsikring ASA	NORWAY	0.43%
Arrow Seismic ASA	NORWAY	15.43%
Exiqon A/S	DENMARK	9.97%
Ahtium PLC	FINLAND	12.61%
Grieg Seafood ASA	NORWAY	13.33%
Novus Group International AB	SWEDEN	2.00%
SRV Group Oyj	FINLAND	-8.05%
Nordic Shipholding A/S	DENMARK	27.32%
Hunter Group ASA	NORWAY	-1.83%
Aerocrine AB	SWEDEN	-25.96%
DIBS Payment Services AB	SWEDEN	-7.11%
Endomines AB	SWEDEN	0.38%
EnergyO Solutions Russia AB	SWEDEN	1.82%
SeaNet Maritime Communications	SWEDEN	-15.35%
Berlin IV A/S	DENMARK	5.55%
Water Jet Sweden AB	SWEDEN	-15.29%
Jojka Communications AB	SWEDEN	81.89%
C-RAD AB	SWEDEN	-0.14%
Amnode AB	SWEDEN	4.93%
German High Street Properties	DENMARK	1.63%
Pronova BioPharma ASA	NORWAY	0.55%
Systemair AB	SWEDEN	7.21%
HMS Networks AB	SWEDEN	2.87%
Copenhagen Capital A/S	DENMARK	-41.38%
Eastnine AB	SWEDEN	-13.27%
KIF Handbold Elite A/S	DENMARK	-41.39%

Duni AB	SWEDEN	38.52%
Sparekassen Hvetbo A/S	DENMARK	-30.99%
Infratek AS	NORWAY	-8.59%
Philly Shipyard ASA	NORWAY	2.74%
Trifork A/S	DENMARK	2.61%
Fodboldalliancen AC Horsens AS	DENMARK	-0.86%
Eriksson Development and Innov	SWEDEN	1353.00%
NattoPharma ASA	NORWAY	3.48%
Cryptzone AB	SWEDEN	-16.75%
EWII Production A/S	DENMARK	-5.13%
GlobalFun AB	SWEDEN	11.87%
EgnsINVEST Ejd. Tyskland A/S	DENMARK	-0.67%
FormueEvolution II	DENMARK	-0.54%
FormueEvolution I	DENMARK	32.22%
Vestum AB	SWEDEN	15.40%
eWork Group AB	SWEDEN	26.42%
Trygga Hem Skandinavien AB	SWEDEN	-5.47%
World Class Seagull Internatio	SWEDEN	-0.29%
Hexpol AB	SWEDEN	2.12%
DGC One AB	SWEDEN	-2.98%
PCI Biotech Holding ASA	NORWAY	-1.60%
Senzime AB	SWEDEN	-8.40%
H1 Communication AB	SWEDEN	-34.59%
Prime Office A/S	DENMARK	-52.33%
Vopium A/S	DENMARK	-34.45%
Arctic Minerals AB	SWEDEN	-1.11%
EXINI Diagnostics AB	SWEDEN	4.46%
Cimber Sterling Group A/S	DENMARK	128.75%
North Energy ASA	NORWAY	7.72%
Sportjohan AB	SWEDEN	16.30%
Arise AB	SWEDEN	-28.58%
Brandworld Sverige AB	SWEDEN	0.34%
Solvtrans AS	NORWAY	4.75%
Hartelex AB	SWEDEN	-0.12%
Ekomarine AB	SWEDEN	9.60%
LunchExpress i Sverige AB	SWEDEN	-33.38%
Syncro Group AB	SWEDEN	-1.50%
Layerlab AB	SWEDEN	-60.02%
Byggmax Group AB	SWEDEN	10.82%
Chr Hansen Holding A/S	DENMARK	4.18%
Parans Solar Lighting AB	SWEDEN	18.50%
EcoRub AB	SWEDEN	-2.07%
NetConnect ASA	NORWAY	-2.84%

Mabi Rent AB	SWEDEN	-50.99%
MQ Holding AB	SWEDEN	8.57%
Morpol ASA	NORWAY	38.13%
PharmaLundensis AB	SWEDEN	-7.57%
Safe Lane Gaming AB	SWEDEN	13.77%
Lyyn AB	SWEDEN	17.83%
Pandora A/S	DENMARK	-19.99%
CellCura ASA	NORWAY	7.09%
Circle K AS	NORWAY	-10.41%
Novavax AB	SWEDEN	5.56%
Vard Holdings Ltd	NORWAY	4.09%
Zealand Pharma A/S	DENMARK	7.33%
Gjensidige Forsikring ASA	NORWAY	1.74%
WntResearch AB	SWEDEN	3.28%
Abelco Investment Group AB	SWEDEN	-30.17%
Umida Group AB	SWEDEN	-0.01%
Transocean Norway Drilling AS	NORWAY	28.60%
Kancera AB	SWEDEN	-0.19%
Koggbron Fastigheter AB	SWEDEN	-3.17%
Norway Royal Salmon ASA	NORWAY	3.05%
FX International AB	SWEDEN	21.00%
Sevan Drilling ASA	NORWAY	12.66%
Bulten AB	SWEDEN	-0.69%
Bridge Energy AS	NORWAY	17.65%
AroCell AB	SWEDEN	6.23%
Moberg Pharma AB	SWEDEN	-0.87%
Transmode AB	SWEDEN	0.89%
Enzymatica AB	SWEDEN	35.18%
Boule Diagnostics AB	SWEDEN	-9.47%
Hoegh LNG Holdings Ltd	NORWAY	24.75%
Danske Andelskassers Bank A/S	DENMARK	-10.47%
NordIQ Goteborg AB	SWEDEN	4.20%
EfB Elite A/S	DENMARK	9.27%
Brighter AB	SWEDEN	-2.10%
Medfield Diagnostics AB	SWEDEN	5.16%
Selvaag Bolig ASA	NORWAY	-3.37%
Gullberg & Jansson AB	SWEDEN	5.25%
Respiratorius AB	SWEDEN	-1.58%
FDT System Holding AB	SWEDEN	10.21%
Siili Solutions Oyj	FINLAND	1.27%
Borregaard ASA	NORWAY	9.56%
STYLEPIT A/S	DENMARK	5.15%
Recyctec Holding AB	SWEDEN	28.36%

Asetek A/S	DENMARK	29.49%
EAM Solar ASA	NORWAY	4.97%
MultiClient Geophysical ASA	NORWAY	16.80%
Matas A/S	DENMARK	24.64%
Ocean Yield AS	NORWAY	-1.73%
Odfjell Drilling Ltd	NORWAY	-1.65%
Ovaro Kiinteistosijoitus Oyj	FINLAND	26.42%
REC Solar ASA	NORWAY	-1.94%
Bulk Invest ASA	NORWAY	8.64%
NoHo Partners Oyj	FINLAND	-14.50%
Napatech A/S	DENMARK	10.09%
Geberit Production Oy	FINLAND	42.10%
Link Mobility Group ASA	NORWAY	17.59%
Aurora LPG Holding AS	NORWAY	16.91%
Bufab AB	SWEDEN	0.43%
ISS A/S	DENMARK	-37.69%
Hemfosa Fastigheter AB	SWEDEN	0.63%
OW Bunker A/S	DENMARK	0.32%
Verkkokauppa.com Oyj	FINLAND	-7.77%
Insr Insurance Group ASA	NORWAY	-4.27%
Vow ASA	NORWAY	10.53%
Envirologic AB	SWEDEN	9.95%
Herantis Pharma Oyj	FINLAND	9.37%
Besqab AB	SWEDEN	6.37%
Com Hem Holding AB	SWEDEN	16.54%
Zalaris ASA	NORWAY	-1.22%
Scandi Standard AB	SWEDEN	15.09%
Havyard Group ASA	NORWAY	3.43%
Cxense ASA	NORWAY	1.21%
Serendex Pharmaceuticals A/S	DENMARK	118.19%
Inwido AB	SWEDEN	-3.85%
Scatec ASA	NORWAY	11.53%
XXL ASA	NORWAY	31.39%
Granges AB	SWEDEN	1.59%
Entra ASA	NORWAY	13.86%
Nexstim Oyj	FINLAND	11.06%
Thule Group AB	SWEDEN	-3.83%
NP3 Fastigheter AB	SWEDEN	46.46%
RenoNorden ASA	NORWAY	-28.81%
Eltel AB	SWEDEN	23.26%
Multitude SE	FINLAND	-1.14%
Dustin Group AB	SWEDEN	10.04%
OrganoClick AB	SWEDEN	-2.61%

NNIT A/S	DENMARK	-1.14%
Detection Technology Oy	FINLAND	-30.35%
Evolution AB	SWEDEN	-1.01%
Nordic Nanovector ASA	NORWAY	-0.51%
Hoist Finance AB	SWEDEN	39.65%
Enento Group Oyj	FINLAND	10.91%
Troax Group AB	SWEDEN	-1.31%
Hancap AB publ	SWEDEN	9.35%
Tobii AB	SWEDEN	14.47%
ICE Group AS	NORWAY	-7.93%
Robit Oyj	FINLAND	13.78%
Transtema Group AB	SWEDEN	-0.69%
Multiconsult ASA	NORWAY	-6.18%
Scibase Holding AB	SWEDEN	-2.53%
Pihlajalinna Oyj	FINLAND	11.17%
Magnolia Bostad AB	SWEDEN	-3.38%
Collector AB	SWEDEN	64.46%
Talenom Oyj	FINLAND	3.19%
Studentbostader i Norden AB	SWEDEN	8.91%
Coor Service Management Holdin	SWEDEN	-7.02%
Nordax Group AB	SWEDEN	65.95%
Alimak Group AB	SWEDEN	-1.89%
Nobina AB	SWEDEN	-24.49%
Europris ASA	NORWAY	-10.96%
5th Planet Games A/S	DENMARK	-9.92%
Capio AB	SWEDEN	13.15%
Fit Biotech Oy	FINLAND	23.39%
Kotipizza Group Oyj	FINLAND	41.35%
Footway Group AB	SWEDEN	5.58%
Oncology Venture Sweden AB	DENMARK	-3.12%
Headsent AB	SWEDEN	41.96%
Sinch AB	SWEDEN	-1.45%
Bravida Holding AB	SWEDEN	16.22%
Hamlet Pharma AB	SWEDEN	5.36%
Sbanken ASA	NORWAY	-5.93%
Kid ASA	NORWAY	4.87%
Waystream Holding AB	SWEDEN	16.69%
Faron Pharmaceuticals Oy	FINLAND	21.56%
Photocat A/S	DENMARK	-7.80%
Maxkompetens Sverige AB	SWEDEN	2.97%
Dometic Group AB	SWEDEN	6.95%
Attendo AB	SWEDEN	4.29%
Immunovia AB	SWEDEN	-5.73%

Scandic Hotels Group AB	SWEDEN	-10.38%
Camurus AB	SWEDEN	-0.41%
Zenergy AB	SWEDEN	-30.87%
Stillfront Group AB	SWEDEN	-2.14%
Sparekassen Sjaelland-Fyn A/S	DENMARK	0.55%
Consti Oyj	FINLAND	-34.38%
Toleranzia AB	SWEDEN	51.07%
Randviken Fastigheter AB	SWEDEN	0.14%
FastOut Int AB	SWEDEN	24.19%
Sleepo AB	SWEDEN	11.20%
Xbrane Biopharma AB	SWEDEN	11.83%
Scandinavian Tobacco Group A/S	DENMARK	-45.48%
Invent Medic Sweden AB	SWEDEN	1.95%
GARO AB	SWEDEN	4.52%
LeoVegas AB	SWEDEN	33.79%
Humana AB	SWEDEN	73.93%
Xintela AB	SWEDEN	-39.96%
Hoivatilat Oyj	FINLAND	0.48%
Plejd AB	SWEDEN	-62.14%
Nepa AB	SWEDEN	4.29%
Lehto Group Oyj	FINLAND	4.11%
Resurs Holding AB	SWEDEN	42.84%
Tokmanni Group Corp	FINLAND	-0.22%
Vadsbo SwitchTech Group AB	SWEDEN	1.96%
Wilson Therapeutics AB	SWEDEN	11.66%
Clean Motion AB	SWEDEN	-19.78%
Paradox Interactive AB	SWEDEN	-18.94%
Litium AB	SWEDEN	0.81%
Cyxone AB	SWEDEN	-32.11%
B2Holding ASA	NORWAY	31.16%
Orsted AS	DENMARK	15.18%
PiezoMotor Uppsala AB	SWEDEN	10.23%
Nordic Waterproofing Holding A	SWEDEN	-29.67%
Enorama Pharma AB	SWEDEN	22.62%
B3 Consulting Group AB	SWEDEN	-16.85%
TF Bank AB	SWEDEN	84.66%
SwedenCare AB	SWEDEN	1.73%
AcadeMedia AB	SWEDEN	-10.88%
Redwood Pharma AB	SWEDEN	-22.38%
GomSpace Group AB	SWEDEN	-5.88%
Shortcut Media AB	SWEDEN	5.05%
Alelion Energy Systems AB	SWEDEN	-22.96%
Dignita Systems AB	SWEDEN	-0.04%

BrandBee Holding AB	SWEDEN	53.29%
Lauritz.com Group A/S	DENMARK	-20.60%
Provide IT Sweden AB	SWEDEN	-3.15%
MaxFastigheter i Sverige AB	SWEDEN	4.76%
Skarta Group Oyj	FINLAND	2.60%
SynAct Pharma AB	SWEDEN	1.93%
Meltron AB	SWEDEN	11.90%
Maha Energy AB	SWEDEN	2.50%
Expres2ion Biotech Holding AB	SWEDEN	0.31%
PEN Concept Group AB	SWEDEN	122.88%
Sustainable Energy Solutions S	SWEDEN	-26.31%
Cyber Security 1 AB	SWEDEN	34.80%
WilLak AB	SWEDEN	-4.75%
Nets A/S	DENMARK	-3.63%
Internationella Engelska Skola	SWEDEN	-5.49%
Index Pharmaceuticals Holding	SWEDEN	-3.30%
Vincit Oyj	FINLAND	41.77%
Gasporox AB	SWEDEN	85.44%
Ahlsell AB	SWEDEN	32.74%
Tobin Properties AB	SWEDEN	0.05%
Heeros Oyj	FINLAND	8.34%
Crunchfish AB	SWEDEN	-0.11%
Alligator Bioscience AB	SWEDEN	-0.87%
Serneke Group AB	SWEDEN	24.16%
Swedish Stirling AB	SWEDEN	1.79%
DNA Oyj	FINLAND	7.09%
Volati AB	SWEDEN	3.75%
Arcus ASA	NORWAY	11.34%
Adderacare AB	SWEDEN	24.48%
ByggPartner I Dalarna Holding	SWEDEN	19.30%
Smart Eye AB	SWEDEN	-23.46%
Edgeware AB	SWEDEN	16.02%
Finepart Sweden AB	SWEDEN	26.18%
Transiro Holding AB	SWEDEN	13.42%
Aino Health AB	SWEDEN	2.30%
Acarix AB	DENMARK	1.71%
Appspotr AB	SWEDEN	2.31%
Vo2 Cap Holding AB	SWEDEN	2.54%
SeaTwirl AB	SWEDEN	3.97%
Unified Messaging Systems AS	NORWAY	-17.32%
AcouSort AB	SWEDEN	2.93%
Multidocker Cargo Handling AB	SWEDEN	10.08%
MenuPay AB	SWEDEN	-1.71%

Oncopeptides AB	SWEDEN	-0.79%
SARSYS-ASFT AB	SWEDEN	-1.85%
Medclair Invest AB	SWEDEN	94.37%
Acosense AB	SWEDEN	11.07%
MIPS AB	SWEDEN	0.63%
Next Games Oy	FINLAND	10.52%
EatGood Sweden AB	SWEDEN	7.71%
Ambea AB	SWEDEN	3.00%
Isofol Medical AB	SWEDEN	46.02%
Fondia Oyj	FINLAND	-1.23%
SSM Holding AB	SWEDEN	-3.63%
Tangiamo Touch Technology AB	SWEDEN	-1.13%
Actic Group AB	SWEDEN	26.93%
Bergenbio ASA	NORWAY	-18.39%
Annexin Pharmaceuticals AB	SWEDEN	-7.53%
AcuCort AB	SWEDEN	3.68%
XmReality AB	SWEDEN	54.84%
Compare-IT Nordic AB	SWEDEN	-0.43%
Mantex AB	SWEDEN	-0.34%
Bambuser AB	SWEDEN	-5.83%
Northern CapSek Ventures AB	SWEDEN	212.89%
Instalco AB	SWEDEN	-1.46%
Secits Holding AB	SWEDEN	36.88%
Kamux Corp	FINLAND	212.67%
Nexar Group AB	SWEDEN	3.54%
Munters Group AB	SWEDEN	8.37%
Mobiplus AB	SWEDEN	-1.82%
BioServo Technologies AB	SWEDEN	145.30%
Fjord1 AS	NORWAY	22.16%
Saferoad Holding AS	NORWAY	14.30%
Remedy Entertainment Oyj	FINLAND	-0.11%
Boozt AB	SWEDEN	-5.97%
Zaplox AB	SWEDEN	-3.75%
Silmaasema Oy	FINLAND	2.33%
TCECUR Sweden AB	SWEDEN	0.08%
Paxman AB	SWEDEN	-5.15%
Sparebank 1 Oestlandet	NORWAY	-1.04%
Grong Sparebank	NORWAY	1.93%
Enersize Oyj	FINLAND	-83.90%
GreenMobility A/S	DENMARK	1.13%
Nitro Games Oyj	FINLAND	8.21%
Surgical Science Sweden AB	SWEDEN	-9.47%
Evry AS	NORWAY	-9.36%

BoneSupport Holding AB	SWEDEN	2.49%
Sedana Medical AB	SWEDEN	147.66%
Conferize A/S	DENMARK	2.61%
OXE Marine AB	SWEDEN	-1.57%
Promore Pharma AB	SWEDEN	6.69%
NextCell Pharma AB	SWEDEN	-1.67%
OmniCar Holding AB	SWEDEN	-4.03%
Realfiction Holding AB	DENMARK	8.12%
Enrad AB	SWEDEN	0.94%
Senzagen AB	SWEDEN	-0.04%
XSpray Pharma AB	SWEDEN	6.48%
Inhalation Sciences Sweden AB	SWEDEN	-33.94%
Rovio Entertainment Oyj	FINLAND	5.88%
Infront ASA	NORWAY	4.49%
SpareBank 1 Nordmoere	NORWAY	-12.21%
Balco Group AB	SWEDEN	-5.96%
Titanium Oyj	FINLAND	-16.20%
Terveystalo Oyj	FINLAND	15.43%
Webstep AS	NORWAY	-6.46%
Qiiwi Games AB	SWEDEN	29.75%
Global Gaming 555 AB	SWEDEN	-8.04%
Ferronordic AB	SWEDEN	-16.00%
Self Storage Group ASA	NORWAY	17.66%
BibbInstruments AB	SWEDEN	4.17%
Crayon Group Holding ASA	NORWAY	-0.19%
Komplett Bank ASA	NORWAY	0.91%
Orphazyme A/S	DENMARK	3.17%
Gofore Oyj	FINLAND	15.81%
Seafire AB	SWEDEN	11.67%
IRRAS AB	SWEDEN	7.27%
Touchtech AB	SWEDEN	24.23%
TCM Group A/S	DENMARK	-21.07%
2cureX AB	SWEDEN	21.11%
Awardit AB	SWEDEN	38.61%
Tempest Security AB	SWEDEN	0.14%
Time People Group AB	SWEDEN	16.11%
MAG Interactive AB	SWEDEN	1.88%
Efecte Oyj	FINLAND	-14.05%
Acconeer AB	SWEDEN	1.93%
Lyko Group AB	SWEDEN	-10.54%
Colabitoil Sweden AB	SWEDEN	60.00%
Bio-Works Technologies AB	SWEDEN	0.22%
Flexqube AB	SWEDEN	53.55%

Topright Nordic AB	SWEDEN	-4.26%
24SevenOffice Group AB	NORWAY	15.98%
Hubso Group AB	SWEDEN	12.49%
ObsteCare AB	SWEDEN	16.70%
Infracom Group AB	SWEDEN	-2.18%
SPENN Technology A/S	DENMARK	-0.02%
Admicom Oyj	FINLAND	38.57%
Coegin Pharma AB	SWEDEN	-7.08%
LIV Ihop AB	SWEDEN	-0.44%
Smoltek Nanotech Holding AB	SWEDEN	-9.23%
BBS-Bioactive Bone Substitutes	FINLAND	4.64%
OptiMobile AB	SWEDEN	12.94%
BBS-Bioactive Bone Substitutes	FINLAND	-10.78%
Cibus Nordic Real Estate AB	SWEDEN	30.14%
BuildData Group AB	SWEDEN	-9.71%
Fjordkraft Holding ASA	NORWAY	-1.47%
Elkem ASA	NORWAY	5.36%
Harvia Oyj	FINLAND	-3.53%
Agillic A/S	DENMARK	78.10%
Anora Group Oyj	FINLAND	-4.17%
Green Landscaping Group AB	SWEDEN	-3.99%
BHG Group AB	SWEDEN	-4.03%
Iconovo AB	SWEDEN	-0.35%
Fluicell AB	SWEDEN	56.88%
Infrea AB	SWEDEN	-0.96%
Enersense International Oyj	FINLAND	5.88%
Happy Helper A/S	DENMARK	-28.55%
Ovzon AB	SWEDEN	2.46%
Bodyflight Sweden AB	SWEDEN	36.40%
Jondetech Sensors AB	SWEDEN	31.01%
I-Tech AB	SWEDEN	-39.31%
Africa Resources AB	SWEDEN	-0.34%
NCAB Group AB	SWEDEN	-19.61%
Netcompany Group A/S	DENMARK	3.79%
Better Collective A/S	DENMARK	-44.94%
SpectrumOne AB	SWEDEN	-4.19%
Gomero Group AB	SWEDEN	-9.98%
Freetrailer Group A/S	DENMARK	-23.39%
Kojamo Oyj	FINLAND	-1.61%
Eezy Oyj	FINLAND	14.52%
Dicot AB	SWEDEN	2.37%
Midsummer AB	SWEDEN	1.82%
Virogates A/S	DENMARK	-11.16%

Calliditas Therapeutics AB	SWEDEN	-26.52%
Odico A/S	DENMARK	-3.48%
Risk Intelligence A/S	DENMARK	23.15%
poLight ASA	NORWAY	-8.87%
Sparebanken Telemark	NORWAY	2.38%
Fellow Finance Oyj	FINLAND	24.60%
Stenocare A/S	DENMARK	3.36%
Viafin Service Oyj	FINLAND	-6.41%
Alzecure Pharma AB	SWEDEN	16.82%
Oma Saastopankki Oyj	FINLAND	-25.49%
Nordic ID Oyj	FINLAND	-12.51%
Jetpak Top Holding AB	SWEDEN	-31.62%
Lime Technologies AB	SWEDEN	-16.99%
Q-Linea AB	SWEDEN	-47.19%
Azelio AB	SWEDEN	-34.43%
CAG Group AB	SWEDEN	-8.99%

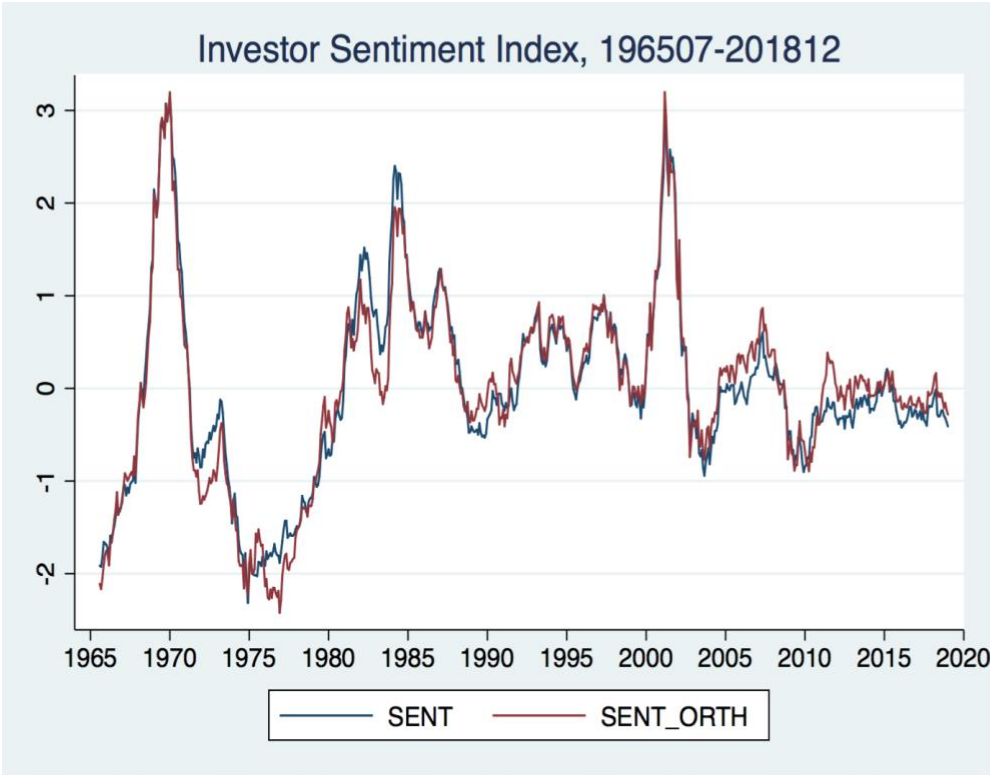
Appendix 2

Number of IPOs and the corresponding underpricing in each Nordic country

	Number of IPOs	Underpricing
Norway	121	4.83%
Sweden	283	11.29%
Denmark	64	1.55%
Finland	58	6.84%

Appendix 3

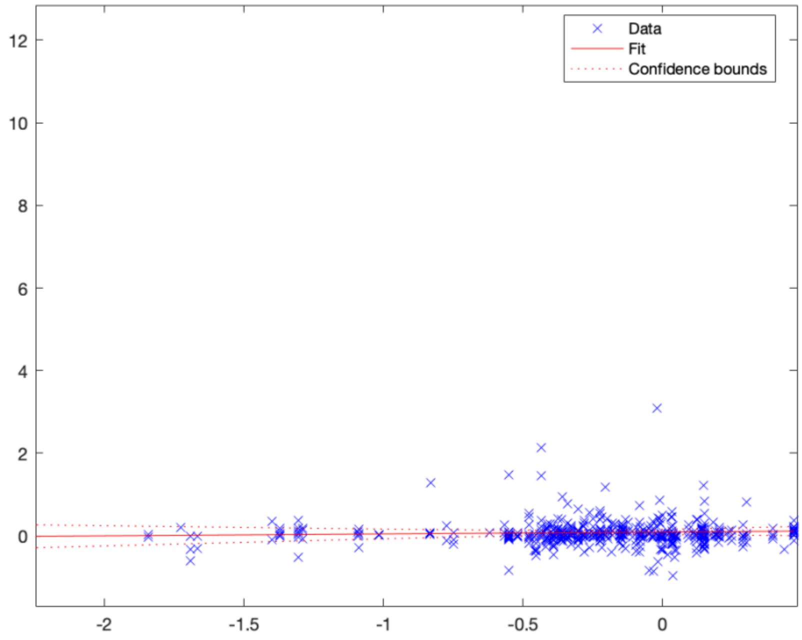
The Baker and Wurgler sentiment index since 1965



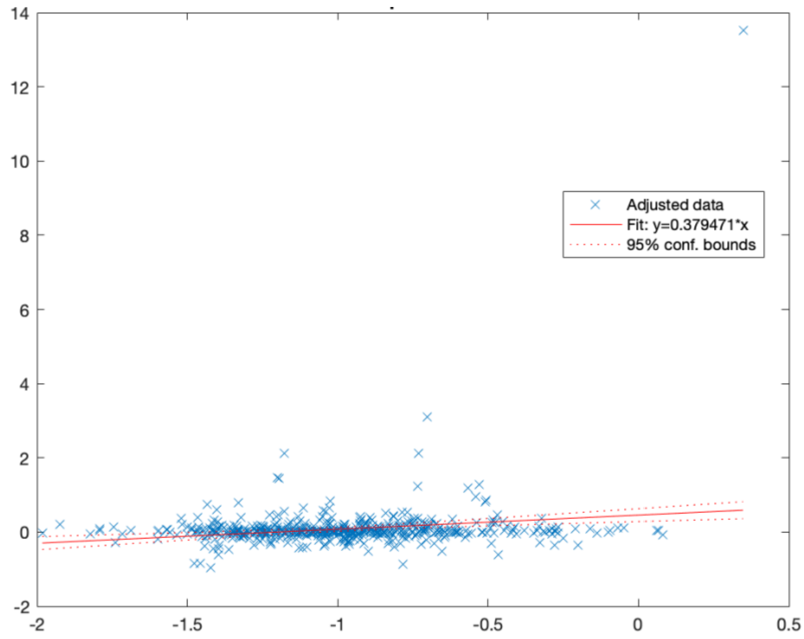
Appendix 4

Plotted regressions

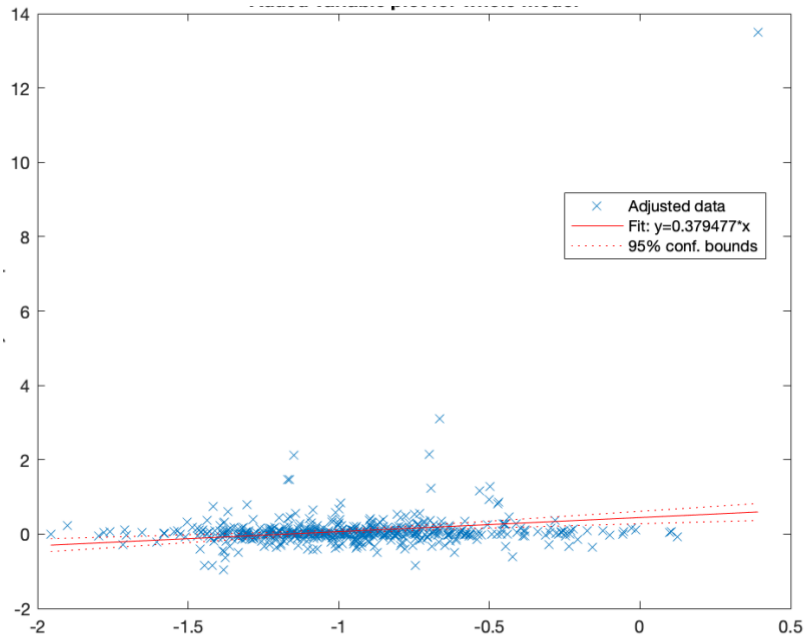
Model 1



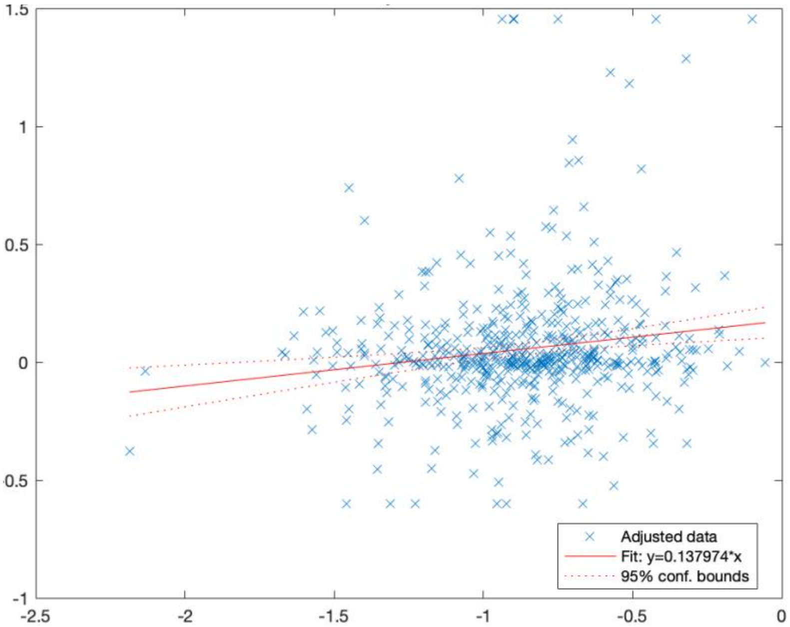
Model 2



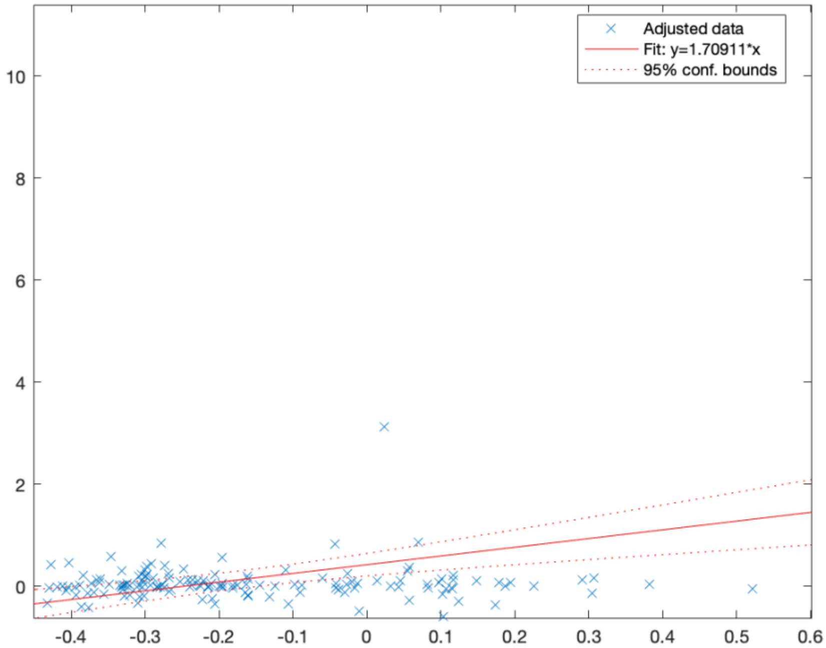
Model 3



Model 4



Model 5



Model 6