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IPO Underpricing in Norway

Testing of existing underpricing theories in the Norwegian stock markets

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Abstract

In our thesis we have analysed the pricing for 202 IPOs in Norway from 2003 to 2019. A well-known phenomenon for IPOs known as underpricing is a trend where IPO stocks are offered at a lower price than what the market perceives as the true value of the IPO stocks. This results in a capital loss for the previous shareholders. The objective of this thesis is to check if some of the established underpricing theories are valid for new listings on two of the Norwegian stock exchanges.

We have found an average underpricing of 3.475% in the Norwegian stock exchanges from 2003 to 2019, which is similar to results from other studies in Norway. Our results provide support for theories such as underwriter quality theories from Carter and Manaster (1990) and Michaely and Shaw (1994), and Ibbotson and Jaffe's (1975) study on hot and cold markets. Loughran and Ritter's (2003) study on industries with higher underpricing due to risk compensation is also supported by our findings. More known theories such as investor sentiment and information revelation theory are also supported by our findings. However, Rock's (1986) "*The Winner's Curse*" does not explain underpricing with our use of proxies for valuation uncertainty. We have corrected our analysis for econometric issues with robust standard errors and have performed the necessary econometric testings. Even though most of our selected theories explain some of the underpricing in Norway, there are still theories or approaches that would be suitable for further research.

We want to thank our supervisor, Johann Reindl, who has contributed with relevant insight, solutions to our problems and constructive feedback for our work. Oslo Stock Exchange has also been helpful by providing data. In addition, we want to thank Finanstilsynet for adding the missing prospectuses from Oslo Stock Exchange. To summarize, we would like to thank the library staff at OsloMet for the opportunity to access and retrieve data from Thomson Reuters and Datastream.

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Part I: Introduction

In this part we will introduce the background for our research and present our problem statement. Furthermore, we will present delimitations around our thesis and our research contribution. We will conclude this part with the outline for the rest of our study.

1.1. Background

An initial public offering (referred to as "IPO" for the rest of the thesis) is a process where a company lists new and existing shares at an exchange traded market for the public to be able to take part in ownership of the company. Thus, the company raises funds by new or existing investors investing in the company's shares. On average, a quite special phenomenon occurs during the IPO process; *underpricing*. The underpricing phenomenon occurs when the offer price during the IPO process is lower than what the market perceives as the real market value of the shares. This means that the previous shareholders experience a loss in value as their shares are sold at a lower price during the IPO compared to what they would receive in the market when the shares are publicly listed. Underpricing of IPO's in the United States averaged over 20% in the 1990s (Ljungqvist, 2007). We will get back to different levels of underpricing on a global basis in section 2.2.1.

1.2. Problem Statement

Because the underpricing phenomenon in the Norwegian stock markets have been confirmed by several previous studies, we want to investigate what causes underpricing in Norway. Before we test for different existing theories, we will measure the level of underpricing with an updated dataset. There are several underpricing theories, but due to data availability we will only research the most relevant theories for our selected market in our study. The theories we have chosen will be elaborated in section 2.4. With our updated data, we will elucidate existing literature from a different point of view. Confirming a theory would show that some of the underpricing observed in Norway is explained and will provide better understanding to the academia. Our thesis is based on the following problem statement:

"Can IPO underpricing in Norway be explained by existing theories in the time frame 2003 to 2019?

The choice of the 17-year time frame is explained in the section below. To answer our problem statement, we have created and tested six hypotheses, where each of them will provide support for or against our chosen theories.

1.3. Delimitations

Due to the fact that IPO underpricing concerns several different theories and hypotheses, it is necessary to delimit the range of this thesis. As some theories might not be applicable for other countries and markets, our main focus will be on Oslo Stock Exchange and Oslo Axess. A smaller alternative for growing companies is the Merkur Market. The IPOs on Merkur Market are present in our sample but will be excluded from our analysis by using dummy variables for the exchanges, due to more lenient requirements for companies on this exchange. The differences in requirements would have resulted in more outliers in our sample and made our analysis biased if Merkur Market was included.

The IPOs we have observed took place from the beginning of 2003 until the end of 2019, meaning our time frame is 17 years. We could have taken the study even further back, but 2003 is the earliest publicly available IPO data we could extract from Oslo Stock Exchange. This makes 2003 a natural point of departure for our study. It is also worth mentioning that including IPOs earlier than 2003 would increase the sample size and ease our statistical analysis. However, with over 200 IPO listings in our sample, we consider the sample size sufficient. It has been time-consuming to collect the significant amount of data we need to perform our analysis and acquire IPO data for our sample. Our dataset has taken all observable IPOs into the analysis, which makes it the most updated sample possible as of January 2020.

As mentioned above, there are many theories which attempt to explain the phenomenon of underpricing. To suit the scope if this thesis, we have selected some of these theories. Another issue we have taken into consideration when choosing the theories that we want to test is data availability. The theories we have chosen to exclude require confidential data, have little academic support or seem to not be suitable for the Norwegian IPOs. We have chosen theories that we perceive as most relevant for the Norwegian stock market. A small sample of the IPO literature focus solely on the Norwegian stock market and we believe our testing of the selected theories will contribute further to the literature.

1.4. Our contribution

We contribute to the existing literature on underpricing in several ways. Some of the theories we have chosen for our study have not been tested thoroughly for the Norwegian market and could provide us with some interesting answers. Additionally, our selection of proxies and variables is a mixture of proxies used in older research and new interesting variables, which has given us a good starting point for new findings.

The second contribution in our study is that our entire dataset is uniquely collected. This allows us to gather different results than what have been explored by our predecessors. We have manually collected the data ourselves by gathering information from Oslo Stock Exchange, assessing the individual IPO prospectus of each of the IPOs in our sample. We have worked our way through over 400 prospectuses, ending up with a sample size of 202. Any additional information we have thought would assist our study, is gathered from financial terminals such as Yahoo Finance, Bloomberg and Datastream. To our knowledge, as of 2019, our unique dataset contains more observations than any other studies that involve Norwegian IPOs in recent history. With this unique dataset, we have found results that could potentially not have been revealed before, and which may strengthen previous findings from other studies.

Finally, our results will contribute to academia such as supporting or abandoning existing theories of underpricing as possible explanations for the underpricing phenomenon in Norway.

1.5. Outline

We have organized the remainder of our thesis with the following setup; part two will introduce the theoretical aspects of IPOs, the market for IPOs in Norway and relevant theories of IPO underpricing literature. The methodology for our thesis will be described in part three, which also highlights what we will research and how the research will be conducted. This is followed by our analysis in part four where we present our results in regard to underpricing and the pricing process from the underwriters. Finally, we explain what our econometric results imply regarding our research hypotheses and theories in part five, followed by our conclusion to the thesis in part six. This part will also contain limitations to our thesis and suggestions for further research.

Part II: Theory

In this part of the thesis, we present information regarding initial public offerings in order to give a comprehensive picture of our topic. We will explain the motives behind the phenomenon called initial public offerings. This will provide a better understanding about initial public offerings and help when we further elaborate previous findings and theories from IPO literature.

2.1. Initial public offerings

An initial public offering refers to the first time that a company's shares are sold to public investors and subsequently traded on the stock exchange. The shares offered to public investors are usually a mix of primary shares, which are newly issued common stocks, and secondary shares, which are already existing shares. This results in two methods of stock offerings in an IPO: Primary offering is where new shares are sold to raise supplementary cash for the company, or a secondary offering, where the prevailing shareholders opt to take advantage by selling a part of their holdings (Brealey, 2011). In both cases, the company ownership is going to be transferred when involving an IPO, because the shares are sold or thinned out by new issued shares. The shares that are sold within the IPO will be sold at an offer price, which is determined by a bookbuilding period or as a fixed price.

According to the life cycle theory (Mueller, 1972), firms go through four phases during its lifespan. The first phase is called the start-up phase which is where companies are financed. Usually that happens through the owner's own private equity or venture capital. Ritter and Welch (2002) suggest that firms should go public during or after a certain stage in their life cycle and that is the second phase, the growth phase. This phase is when the firms are thinking of expanding. The companies need additional capital in order to expand, which can be acquired through an IPO. Initial owners could also use the IPO as an exit strategy. Additionally, it is not certain that the IPO firms remain on a stock exchange forever. There may arise situations where buyouts, bankruptcy or delisting could be the reality. If the company is delisted, it is usually noncompliant with the regulations of the stock exchange.

2.1.1. Why companies go public

Underpricing is costly to a firm's owner, where shares are sold from personal accounts and at a price which is too low. Value of the shares usually stabilizes after the IPO is diluted (Reiche, 2014). In the following paragraphs we will present the incentives for companies to go public. Going public provides the firm with more capital while at the same time allowing the original owners to diversify their holdings. The decision of going public is usually done by small and young companies seeking to expand their capital, but also large privately-owned companies which aspire to become publicly traded (Reiche, 2014). Investing in the IPO is not limited to investors from the country in which the listing takes place, foreign investors can also fund and invest in the company. Being listed makes it easier to acquire capital from banks as explained by Rajan (2012). Rajan claims the banks hold an informational advantage in loan negotiation before the company is listed. This asymmetrical information is decreased when the company goes public, which makes it easier for the company to access bank loan and lower interest rates.

There are also many other reasons for being a company accessible for the public. Being listed could signal the company's performance. The company's stock price gives a readily available measure of performance, which could be used as an incentive for the management to perform better. Rewarding the management with stock options to adjust management incentive in accord with owners' incentives, would benefit both the company and the management (Brealey, 2011). Since the stock exchanges have regulations that demand a large amount of financial reporting and publishing, an IPO increases transparency in the company. As there are many parties dependent on the performance of a company, this information is monitored. If the management makes mistakes, the stock price will quickly reflect the inaccuracy. This monitoring that occurs when being listed creates a need for disciplinary mechanisms ensuring proper conduct by the management (Brealey, 2011). According to Brealey (2011), by going public the company will protect themselves against hostile takeovers and it will increase the possibility for the initial owners to use the IPO as an exit strategy.

Underpricing alone is not the only cost for the firm concerning an IPO, but the entire IPO process results in costs for the issuing firm. Underwriters charge a fee which can be substantial depending on the size of the IPO. There are also a lot of administrative costs. The process with the registration statement and prospectus involves legal counsel, accountants, advisors and the management's time and attention. The stock exchange charges fees for listing companies as well (Brealey, 2011).

2.1.2. IPOs in Norway

When firms choose to go public in Norway, their shares are listed on Oslo Stock Exchange, Oslo Axess or Merkur Market. Companies which do not fulfil the required necessities and regulations of a listing on the Oslo Stock Exchange, lists on Oslo Axess. Merkur Market is the smallest exchange and has more simplified ongoing obligations than the other two. It is not a regulated market, but a so-called multilateral trading facility (MTF) where stocks can be purchased through the stocks trading system and under the stocks market surveillance. Hence, Merkur Market is a place used by relatively small or new companies (Oslo Børs, 2020a). The development in listings on all the three exchanges from 1996 to 2019 is illustrated in the diagram below.

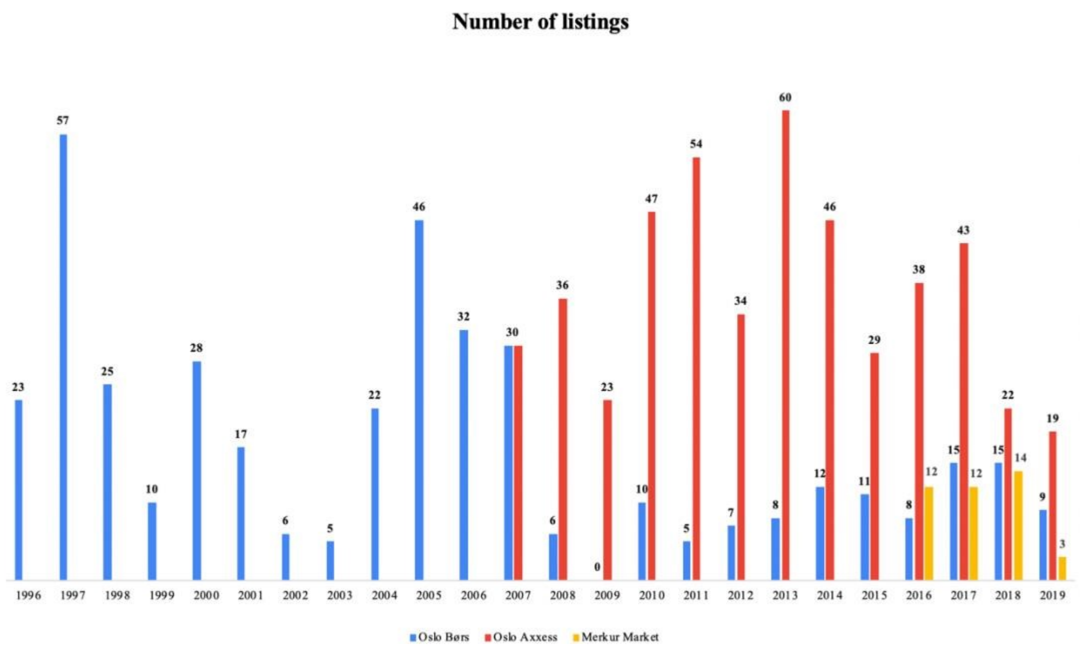

Chart 1: Number of new listings on the Norwegian Stock Exchanges from 1996 to 2019. Source: (Oslo Børs, 2020b)

The chart shows the number of listings each year for all three exchanges for a 24-year time period. The diagram illustrates that the IPO market remained cyclical over our time frame. The number of listings on Oslo Stock Exchange seems to be linked to the state of the world economy. One can see both the burst of the dot-com bubble and the financial crisis where there were many IPOs in the years before. By the looks of the chart, the entrance of Oslo Axess may have taken over some of the listings which would normally occur on Oslo Stock Exchange. Our interpretation is that companies do not wait until they meet the necessary requirements for Oslo Stock Exchange when they can list on Oslo Axess. In addition, IPO activity has shown to vary greatly over time, supporting Ibbotson and Jaffe (1975) findings around hot and cold markets, which will be explained in section 2.2.2.

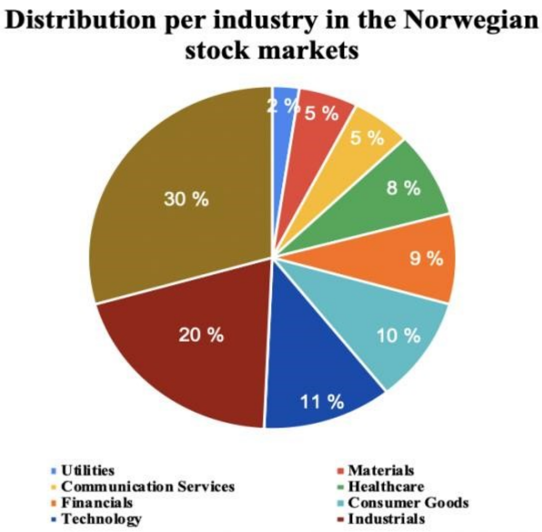

Chart 2: The industries from the stock exchanges are according to ICB classification.

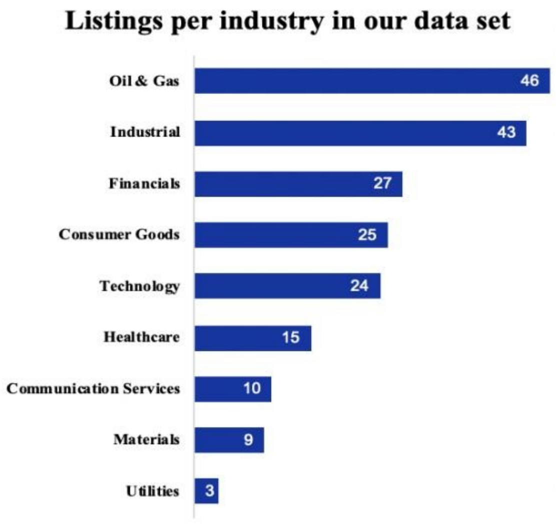

Chart 3: IPOs from our dataset per industry.

Norway's economy is highly energy dominant, where the oil and gas industry hold a large share of the total Norwegian stock market. Our pie chart highlights that the oil and gas industry correspond to 28% of firms listed on the Norwegian stock exchange. The second largest industry is Industrials, providing 19% of the companies listed in Norway. Oil & Gas and Industrials are followed by technology, consumer goods and financials providing roughly 10% per industry. To categorize the IPO firms to relevant industries, we have used the industry classification benchmark codes (ICB). ICB codes are used for the categorization and comparison of companies by industry and sectors. This allows us to compare the companies through four hierarchical levels of industry classification, where we have chosen to use two of them (ftserussell.com).

The bar chart shows the number of new listings for each industry in our timeframe. This chart is in line with our pie chart, where oil and gas are the largest industry contributor. However, there are some differences between the two charts. In the bar chart, industrials have an increased number of IPOs, which will clearly affect the distribution, especially if it is going to be an upward trend. Several of the other industries are over-represented among the IPOs, which will show over time in the distribution. Instead of using an industry category named "other", consumer goods are a combination of consumer staples and consumer discretionary.

2.1.3. Listing regulations in Norway

The companies that want to be listed need to satisfy strict requirements from Oslo Stock Exchange. Commercial criteria, share specific, activity and management specific and general criteria are among the requirements the companies need to meet before the listing (Oslo Børs, 2020b). Additionally, it is a requirement that the stocks should be of public interest and the stocks should be expected to be subject to regular trading. The main commercial criteria state the market value of the IPO shares should be no less than NOK 300 million. As for Oslo Axess, the market value criteria are NOK 8 million, which makes it easier for smaller companies to get listed. There are also commercial criteria involving liquidity, equity capital, financial leverage and frequency and quality of the company's financial reports (Oslo Børs, 2020b). The activity and management criterion require that the company must have existed and been running for a minimum of three years. Oslo Stock Exchange may grant an exemption if the company can signify continuity in its activities for three years forward instead. In addition, management needs expertise around proper management, distribution of information and production of financial accounts as well as composition of the board of directors must be in order to get accepted on the exchange (Oslo Børs, 2020b). Oslo Axess does not have the same three years requirement as Oslo Stock Exchange. The requirement on Oslo Axess is to have submitted at least one annual or interim report (Oslo Børs, 2020c).

The main requirement involving the share specific criteria is that at least 25% of the shares in the company needs to be distributed around in the general public, this applies for both trading platforms. In other words, no more than 75% of a company's shares can be held by insiders. In addition, there must be at least 500 shareholders holding shares with a value of at least NOK 10,000. Oslo Axess has leaner requirements; 100 different shareholders are required to hold the same par value. The listed shares must be freely transferable. These are the main listing regulations and the, "Listing Rules for equities on Oslo Børs" (Oslo Børs, 2020b) include several other requirements. Companies which do not satisfy these requirements and still want to go public, can apply for an IPO on Merkur Market.

2.1.4. Players involved in an IPO

Three main parties are needed to perform an IPO. These are the issuer, the underwriter and the investor. In this section, each of the parties' roles and goals are presented.

The issuer

The issuer is the company going public. The issuer's main role is to make the decision of going public, provide the stocks which will be offered in the IPO and to choose the most suitable underwriter to perform the IPO.

One of the issuers' main target for the IPO is to get the highest possible offer price, without influencing the success of the IPO. If the issuer and the underwriter come to an agreement with an offer price which is too low, the issuer will not realize its full potential to raise capital. This is referred to as leaving money on the table (Ibbotson, Ritter & Sindelar, 1988). Raising new capital is one of the most important cases for the issuer in the offering as the companies will use the funding to grow and become more established. The issuer cannot set the offer price too high due to the relationship to the investors. An offer price which is set too high indicates lower underpricing and therefore; not rewarding the investors taking the risk in the IPO.

The underwriter

The firm that wants to go public will usually seek an underwriter or a syndicate of underwriters. The underwriters are the investment banks performing the IPO on behalf of the issuing company. Underwriters are usually major investment or commercial banks, where their success depends on financial muscles and experience (Brealey, 2011). The underwriter's main role is to buy the stock from the issuer and resell the entire issue to the public. They also assist in deciding the offer price and the price range, where their goal is to satisfy both their clientele; the issuer and the investors. A more prestigious underwriter is preferable for the issuer, because this prestige gives the market a favourable signal. But the underwriter has to maintain their prestige, meaning they will choose which firms they will take public. Thus, new issuers search for the best underwriter at the most favourable conditions possible (Ibbotson, 1988).

The underwriters make their money from acquiring the issuers' shares at a discount to the offer price. This is where the underwriters' margin is created. A study from Chen and Ritter from 2000 found that more than 90% of all IPOs had a spread of exactly 7% of the proceeds, regardless of the size of the IPOs. Underwriters' margins are therefore larger when the IPO is related to a big firm and consequently more attractive for the underwriters. In order to earn their 7%, the underwriter needs to sell out all of the issued stocks. This creates an incentive to set the offer price low to increase demand of the stock. Issuers usually raise capital through an IPO once in their life. The underwriters are involved in the IPO business, meaning they cannot price the offer too low in fear of ruining their reputation. By decreasing their position as reputable underwriters, they might lose business from other issuing companies in the future.

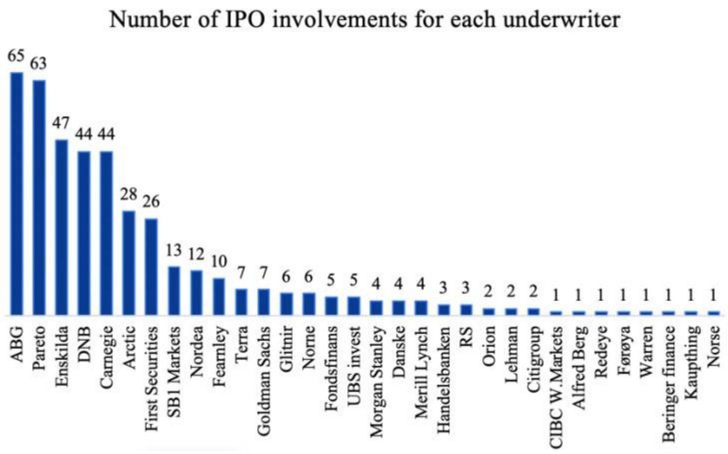

Chart 4: Underwriter involvements in IPOs in our dataset.

The investor

Investors can be divided into two groups; institutional and retail investors. Institutional investors are hedge funds, banks, pension funds, mutual funds or insurance companies. Their returns from IPOs can exceed the retail investors' returns as they often receive larger allocations and contribute with larger investments in IPOs. Institutional investors have the superior informational advantage about valuation and financial insight (Hanley & Wilhelm, 1995). In addition, institutional investors could be in business with the underwriter or be known associates from earlier, which could be beneficial for allocation of shares in popular underpriced IPOs. Retail investors are usually small, regular and private investors; hence they would not have the same buying power as institutional investors.

The two groups of investors have the same main goal and incentives when entering and investing in IPOs; they want large allocations in underpriced IPOs and stay clear of overpriced IPOs. To succeed with this strategy, they need relevant information about the IPO and allocations of stocks from the underwriter. With a popular stock, where many investors compete for the same number of shares, it could be difficult acquiring the demanded number of shares. Since allocating shares is the underwriter's responsibility, it could be an advantage for the investors to have a good relationship with the underwriter (Brealey, 2011).

2.1.5. The IPO process

The IPO process starts long before the listing date and the issuing companies need to account for 15 - 20 weeks according to Reiche (2014). This time period will vary due to dependency on actual market conditions and other factors. The IPO process is in detail summed up by Oliver Reiche (2014) as a timeline of four phases that can be applied to all IPO processes.

Phase I: Preparation of the IPO

The first step is to select an appropriate underwriter. As mentioned before, a syndicate of underwriters is the most common approach, where the lead underwriter is in charge of the process. The lead underwriter will coordinate the involved parties in the process and also choose which method to use regarding the offering and date of the IPO.

Phase II: Structuring & Valuation

When the issuer and its underwriters move into the second phase, the preparation of conducting due diligence and a company's prospectus becomes the main task. In order to be best prepared, due diligence is needed to provide accuracy, completeness and truthfulness concerning the company's registration statement (Reiche, 2014, p. 23). Due diligence will help the underwriters and other advisors to fully understand the company's prospects before going public. The prospectus presents an official version of the offer price for the investors and contains the financial statements as well. The lead underwriter has the full responsibility of gathering all relevant information through the due diligence and to express it in the prospectus.

Valuation uncertainty is one of the challenging steps in this phase for the underwriter. To set a suitable price range, the issuer needs a valuation of the stock. A method used by the underwriters is called roadshow. Roadshows are viewed as a sales pitch and a presentation in various locations to reach out to different investors, where the investors can make non-binding bids, in order to determine the price range and later the offer price (Deloof, Maeseneire & Inghelbrecht, 2009). The underwriter will get a sense of the demand for the IPO after the non-binding bids. This process is called bookbuilding process. Without a market value for the shares, the underwriter has to value the shares based on information about the issuer, demand from the bookbuilding process and the current market state. These factors will impact the valuation of the firm and makes the valuation and eventual price setting a crucial part.

The most common valuation methods are the discounted free cash flow method and the multiple method, which is valuation that rely on multiples from comparable companies that are already listed (Reiche, 2014, p. 25). Most of the lead underwriters choose the multiple method as it is less time-consuming, flexible and it is able to deal with firm characteristics. The most used multiple is price-earnings ratio (Reiche, 2014, p. 25).

Phase III: Marketing & Roadshow

After the valuation, the marketing process begins. This process has four stages where preparing the media is the first stage. The next stage is a research analyst briefing. Underwriters arrange meetings where the company presents detailed financial and strategic information to prepare research analysts for detailed research (Reiche, 2014, p. 26). This is an important stage where analysts take the company's prospectus into consideration which will eventually reflect the investor's opinion. Pre-marketing to key investors and the media through “warm up” meetings is the next stage. Here, the underwriter will get feedback known as the “investor education” phase (Reiche, 2014, p. 26), which is essential for the success of the roadshow. This feedback is used to identify the company’s critical aspects and to set a final price range in the IPO. The last step in this phase is the actual roadshow, which usually happens two weeks before the IPO.

Phase IV: Pricing & Trading

In phase four, all the underwriters combine the gathered information to set the offer price. There are three pricing options, where bookbuilding is the most common option for the Norwegian exchanges. The remaining options are auction or fixed price, which is rarely used in Norway and therefore only mentioned. After the offer price is set, investors subscribe to the share (Reiche, 2014, p. 26). If the IPO is in high demand with many subscribing investors, the IPO will be oversubscribed. Underwriters will then allocate the shares based on the bids from the bookbuilding process, which will be elaborated at section 2.3.1.

When the company and its underwriters are through the four phases, the issuer is ready to go public on the listing date. Usually, it is investors which did not receive shares in the bookbuilding process that buy shares. Due to recurring underpriced IPOs, investors take advantage of the situation and sell after the first day of trading, hopefully at a higher price. This activity is known as "flipping" (Chen, 2018).

2.1.6. IPO Underpricing

Since the early 70s, academics and enthusiasts within the financial markets have raised awareness around IPO underpricing. A simplified version of underpricing is that newly issued companies have set an offer price which is too low. This will usually lead to significant price appreciations on the first day of trading. In other words, this results in a large wealth loss, where the issuer leave money on the table instead of valuing the stocks to their true value. From a financial perspective this seems irrational, but IPO underpricing has been a clear phenomenon all around the world and has been proven by a vast number of empirical evidences. IPO underpricing is a direct violation of the efficient market hypothesis, which indicates that the market prices reflect all knowledge, implying zero or low deviation on the first day closing price. (Reiche, 2014, p. 41).

In order to measure underpricing, one can simply take the difference between the offer price and first day closing price and multiply it with the number of shares involved in the offering (Adams, Thornton & Hall, 2011). This is referred to as money left on the table. It is also possible to measure it as the percentage return on the first day of trading relative to the offer price. It is important to adjust the return for market movements to separate the underpricing from market effects. This measure is called adjusted initial return.

2.1.7. Disadvantages with IPOs

Companies take risk exposure into consideration during the IPO process. Prior to the IPO, there are direct and indirect costs related to the IPO. The direct costs are more or less predictable such as stock exchange and registration fees, pre-marketing activities, investor relation activities, legal and underwriter fees. A study from Draho (2004) argued that these costs vary between 5-10% in Germany, and 7% for issues up to $80 million in the U.S. (Reiche, 2014, p. 18). Indirect costs involve publicity costs and management time for regulations and restrictions in the IPO market. The most significant and discussed issue containing indirect costs is the costs of the actual underpricing. It is also important to know that the company goes from being controlled by a handful of shareholders to a vast number of shareholders. The original owners and founders voting rights will be thinned out with the entrance of new investors and will lose some of the control of the company.

2.2. Empirical findings of underpricing

For the underpricing theories to be relevant, they need to be supported by empirical evidence. Many authors have studied the underpricing phenomenon all over the world, which we will elaborate below. There is also evidence that IPO activity varies in different periods following the world trends and differs between industries. This section will describe the different empirical findings.

2.2.1 Empirical findings of underpricing on a global basis

The first observations of underpricing were done by Reilly and Hatfield in 1969. Their study found 20.2% average short-term return related to DJIA on the New York Stock Exchange for newly issued shares in the time period 1963-1966. They argue that some of the reasons for underpricing is the same we use to explain underpricing today. Valuation uncertainty and the probability that the issue will be successful is higher due to underpricing. It is defined as successful if it is oversubscribed and/or increases in price soon after the offering (Reilly, Hatfield, 1969). At a later point in the mid-seventies, Logue (1973) and Ibbotson's (1975) findings highlighted that offer prices were set too low, which caused large returns in the U.S at the first day of trading.

More recent studies have further investigated how underpricing works in the U.S. Ritter and Welch's (2002) further research found the initial return to vary greatly. Their study started in the 80s where they found an average of 7.4% that had increased to 11.2% in the early 90s. The initial return peaked in the millennium shift at 65%, before it drastically dropped to 14% in 2001 due to the burst of the dot-com bubble (Ritter & Welch, 2002). There is also evidence of underpricing outside the U.S, smaller samples could make the research more questionable. Ritter has also done studies abroad in order to compare how initial IPO returns vary from country to country. His study from 2003 put Norwegian IPOs on the low end of the mean, while observing extreme cases of IPO in China, Malaysia and Brazil with 256.9%, 104.1% and 78.6% respectively on average (Ritter, 2003). The chart below shows the average IPO return found in some selected countries from European countries with similarities to the Norwegian stock markets and some outliers to show how European countries underprice.

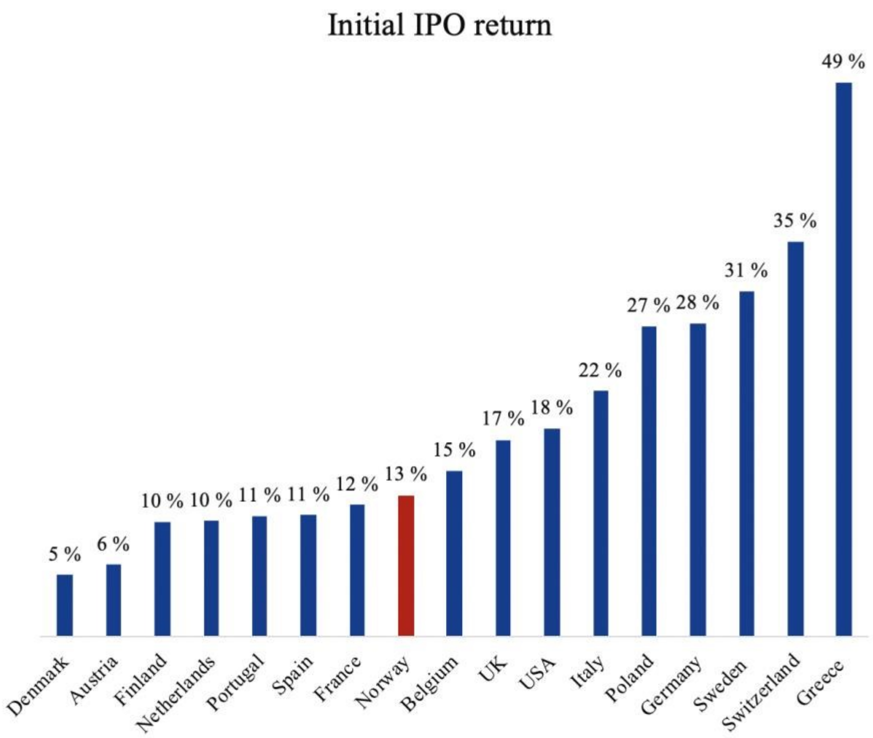

Chart 5: Percentages of underpricing in selected countries in Europe and the US. Source: (Ritter, 2003)

Many of the European countries are included in the chart with high variation in underpricing. The Swedish and Danish markets are regarded as similar to the Norwegian stock market, but the degree of underpricing is substantially different. Emilsen, Pedersen and Sættern (1997) studied underpricing from 1984 to 1996 in Norway and found an initial return of 12.5%. A more recent study with a bigger sample size from 1984 to 2006 by Loughran, Ritter and Rydqvist (2012) found an average underpricing of 9.6%. And the initial return kept decreasing in a working paper by Fjesme (2011) where he found an initial return of 8% from 1993 to 2007. The Norwegian stock exchange is relatively small compared to other stock exchanges which has been studied for IPO purposes, which means the variation in the degree of underpricing is highly related to the data used in the studies.

2.2.2. Empirical evidence of underpricing in different IPO activity periods

As mentioned earlier, Ibbotson and Jaffe (1975) highlighted that IPO activity has been cyclical over time. Schöber (2008) argues that this cyclical behaviour may occur as a result of the business cycle, market-timing regarding investor sentiment, information externalities, "pseudo market timing" of IPO firms and adverse selection costs. This behaviour of first day returns and IPO activity was first documented by Ibbotson and Jaffe (1975) and Ritter (1984). Their articles define "hot issue markets" as periods where new issues pay returns which are unusually higher than average returns, and "cold issue markets" as periods where new issues generate below average return. Ritter's study revealed that the average return on IPOs in a 15-month period in January 1980 was 48.4%, while average return during the period 1977-1982 was 16.3%. This indicates that the 15-month period was a "hot issue market".

Ritter and Loughran (2004) have a more recent study where they observed the same trends during the dot-com bubble. Prior to the burst of the dot-com bubble in the years of 1999-2000, the first-day return was 65% on the New York Stock Exchange, while after the burst in 2001-2003, the average return fell to 12% (Ritter & Loughran, 2004). Loughran, Ritter and Rydqvist (1995) argues that there is a correlation between market returns and IPO underpricing, implying that "hot issue markets" usually follow periods of high stock market returns. Irrational investors can reinforce the favorable market conditions known as "hot issue markets" (Ljungqvist, Nanda & Singh, 2006).

2.2.3. Empirical evidence of underpricing in industries

Earlier researchers argue that high risk industries underprice more to compensate for the risk. Tech and internet companies are often defined as high risk industries. Loughran and Ritters paper from 2004 investigated IPOs from 1980-2000 were regular risked companies underpriced with 11%, while IT and tech companies underpriced with 30% in the US. Alm, Berglund and Falk (2009) did a similar study in Sweden from 1998-2007. Their study found that Swedish IT companies had an initial return of 59% while the average initial return was 23%. The earliest study mentioned differences in industry is Ritter (1984). Ritter suggested that the degree of underpricing was industry dependent and the growth of industries varied over time.

Two of the three studies have included the years around the dot com bubble. Several IT companies went public in this period and investors had high expectations, creating high demand for these stocks. The high demand for IT stocks increased the underpricing for the majority of IT firms. In the burst of the dot com bubble in 2001, skepticism arose around these companies. The large differences could be explained by the periods of high demands for these companies. Christiansen (2011) refers to the risk as a cyclical behavior. From her study, there are no particular high-risk industries at the moment, and she argued that there are also large differences in underpricing of companies within the same industry.

2.3. Underpricing Theories

To summarize the most appropriate theories explaining the phenomena of IPO underpricing, we used Alexander Ljungqvists grouping from "IPO Underpricing" from the Handbook of Corporate Finance (2007). The theories of underpricing can be grouped under four categories: asymmetric information, institutional reasons, control considerations and behavioral approaches (Ljungqvist, 2007). We regard the institutional and control theories as nonapplicable for the Norwegian market and will not elaborate these further.

2.3.1. Asymmetric information

Asymmetric information theories are the best-established base models. The model assumes that one of the key parties in an IPO, issuing firm, underwriter or the investor, knows more than the others, which will in some way create underpricing.

Winner's Curse

One of the best-known asymmetric information models is Rocks paper from 1986. The idea behind this theory is that some IPO investors hold more information than other investors, creating asymmetry. Informed investors bid only on attractively priced IPOs and avoid the overpriced IPOs, whereas the uninformed investors bid equally for both IPOs as they do not have the required information. The underpriced IPOs will be highly attractive, leading to each investor being allocated fewer shares than they bid for. Only the uninformed investors will bid on the overpriced IPOs and will be allocated much more compared to the underpriced IPOs. This creates the phenomenon known as "*The Winner's Curse*". Uninformed investors receive all the shares they have bid for in unattractive offerings, but with the attractive offerings, they lose as they receive few of the attractive shares due to overcrowding. In the extreme cases, uninformed investors will receive 100 percent of its allocation in overpriced IPOs and nothing from the underpriced IPOs, leading to a negative average return. As uninformed investors require positive return, they would not participate in biddings of IPO allocations, which will make the IPO market only populated by equally informed investors.

In order for the demand in the market to be functional, Rock assumes the market is dependent on the participation of uninformed investors. Informed investors alone cannot acquire all shares on offer even in underpriced IPOs. With the intentions of getting uninformed investors involved, the expected returns need to be non-negative. This will get the uninformed investors to break-even, making it a lower-risk investment. Even though this assumption exists, the uninformed will still be crowded out by the informed at the most underpriced IPOs, but they are not expecting to make losses on average. Rock's model also assumes that firms seeking to go public benefit from underpricing, because it is the key to ensuring the uninformed investors continued participation in the IPO market. Since underpricing and leaving money on the table is costly for the issuing firm, an incentive to free ride by underpricing too little will arise. Beatty and Ritter (1986) argue that investment banks, as underwriters and regular players, have an incentive to ensure that new issues are underpriced enough lest they lose underwriting commissions in the future. There has to be a balance in the degree of underpricing. If they underprice too much, they could be losing their underwriter market share.

Tested implications for Winner's Curse

In the centre of this model, given the returns are adjusted for allocations, the winner's curse" could be tested by testing if uninformed investors' abnormal returns are zero on average. This will just be enough to ensure the uninformed investors continued participation (Ljungqvist, 2007). Koh and Walter's (1989) study argued that average initial returns fall significantly when adjusting for allocations in Singapore. Levis (1990) did a similar study in the UK.

Some studies show that uninformed IPO investors do not nearly break even. Amihud, Hauser & Krish (2003) tested the winner's curse and found that uninformed investors earned a negative allocation-weighted initial return in Israel. The challenge when studying this theory is how to distinguish uninformed and informed investors. One could use proxies such as institutional investors for informed investors and retail investors for uninformed investors. Acquiring such data would be time consuming and very hard to obtain. Another challenge is to find the cost of becoming informed. Costly information could be covered by the conditional underpricing return for the informed investors.

An additional way of testing the winner's curse is to analyse IPOs where the information asymmetry is likely to be low. Michaely and Shay (1994) model suggest that if the heterogeneity goes to zero, the winner's curse will perish and underpricing as well. In other words, if the information is equal for all groups of investors in Rock's (1986) paper, underpricing will not occur. Michaely and Shaw's study from 1994 highlighted a segment in the IPO market called master limited partnerships (MLPs). A segment where institutional investors try to avoid IPOs mainly because of tax reasons and therefore should only be invested by retail investors. The investors in the MLP should therefore involve low heterogeneity among investors. Results of the study show that IPO initial return among MLPs was -0.04% while non-MLP IPOs were 8.5% over the same time period (Michaely & Shaw, 1994). This supports the winner's curse.

There is also another way to test the winner's curse through testing underpricing against ex ante uncertainty. The proxies could be much more attainable than the proxies needed to check information heterogeneity. Beatty and Ritter (1986) suggest that underpricing should increase around the uncertainty about the valuation of the IPO firm before it launches. When an investor decides to take part in information production of the IPO, the investor implicitly acquires a call option on the IPO. The call option would be exercised if the investors valuation of the IPO shares exceeds the offer price. This option increases in value as a result of valuation uncertainty. As the role of producing information for the IPO will be highly demanded and thus worth more, uncertainty of the valuation will be higher. Thus, if there is high valuation uncertainty, the more investors will strive to be well informed. More informed investors will lead to higher underpricing, worsening the winner's curse problem. If underpricing is related to valuation uncertainty, the winner's curse could be tested depending on the right usage of proxies. Several company characteristics have been used as proxies for valuation uncertainty. Company age is used by Ljungqvist and Wilhelm (2003) and Megginson and Weiss (1991) or measures of size such as log sales and market capitalization is used by Ritter (1984). Older and larger companies are more experienced and will be low risk compared to newer companies and easier to value due to more information available. Company industry is also used as a proxy to determine uncertainty (Benveniste et al., 2003). The idea behind using the company's industry is that the uncertainty may be different between the groups.

Underwriters which underprice at a high level could lose business from issuers. Low levels of underpricing could also lead the underwriter to lose interest and demand from the investors involved in the IPO. Beatty and Ritter (1986) argue that underwriters put pressure on issuers to underprice in order to avert uninformed investors leaving the IPO market. Nanda and Yun (1997) found that overpricing affected the lead underwriters stock market value negatively, while moderate levels of underpricing increased the stock market value for the underwriter. Indicating that underwriters and investors obtain advantage of each other's actions as a quid pro quo. Dunbar (2000) supports these findings by identifying that banks lose IPO market share if they underprice too much or too little.

Information revelation theories

If some investors are better informed than either remaining investors or the company, their information becomes important for the underwriter before setting the price. This information is crucial and to gather it from the informed investors become one of the key tasks for the underwriter taking the company public. From the investors point of view, there are initially no incentives for revealing their information. Doing so would result in a higher offer price, affecting the expected return for the investor. There is in fact an incentive to misrepresent positive information to induce the underwriter to set a lower price. The challenge for the underwriter is to design a mechanism which will give the informed investor an incentive to reveal its information truthfully greater than the incentive of misleading (Ljungqvist, 2007).

Under certain conditions, bookbuilding could be such a mechanism. After collecting indications of interest from the investors, the underwriter allocates few or no shares to investors with low bids. Those who have misrepresented information and approach to buy stocks afterwards, would then be excluded from the IPO, removing the incentive of misrepresenting. Investors who reveal favourable information by bidding more aggressively are rewarded with large allocations of shares. Bidding aggressively will raise the offer price, advantaging the underwriter. In order for this to work there has to be a level of underpricing or the mechanism would not be incentive compatible (Benveniste & Spindt, 1989; Benveniste & Wilhelm, 1990; Spatt & Srivastava, 1991).

Issuers benefit to a certain degree from underpriced IPOs. Creating the incentive to truthfully reveal information, the bookbuilding period will give the issuer the opportunity to extract the positive information and raise their offer price as a response. They will still keep a degree of underpricing if they adjust the price, meaning that money still is left on the table. It is not only beneficial for the issuer, but also the investors. The investors are taking the risk, investing in IPOs where the valuation is uncertain, and are therefore rewarded with allocations of underpriced IPOs (Benveniste & Spindt, 1989).

Tested implications for information revelation theories

Cornelli and Goldreich (2001, 2003) observed two types of bids where they separated regular bids from price-limited bids. Price-limited bids specify the maximum price an investor is willing to pay for a number of shares and will provide valuable information for the underwriter. Investors with price-limited bids should be rewarded with larger allocations as stated in information revelation theory. Cornelli and Goldreich (2001, 2003) supports this assumption by exposing that price-limited bids receive 19% larger allocations than regular bids. Submitting price-limited bids will give investors larger allocations, but also depend on how much information the underwriter has already acquired from other investors. The type of bid is not the only thing affecting allocations. Frequent bidders will more often receive larger allocations compared to infrequent bidders, equivalent to the prediction that regular investors are chosen in front of random investors even if the latter bid more aggressively (Ljungqvist, 2007).

The study done by Cornelli and Goldreich (2001, 2003) is hard to reproduce as they had access to confidential data from an investment bank. The data contained information about institutional investors' bids and how the allocation went. Jenkinson and Jones (2004) did a similar study with the same confidential data from another investment bank, but their results were less supportive for the information revelation theory. In their case, price-limited bids were much rarer and were not associated with favourable allocations. According to Ljungqvist (2007), the results may differ due to the banks having differences in how they carry out bookbuilding. A bank's ability to extract information depends on how active they are in the IPO market. High activity levels will create an incentive for the investors to cooperate due to future deal flow. Benveniste and Spindt (1989) assumes that the bank has access to a set of informed investors who can use his information to gain favourable allocations of underpriced shares.

Hanley and Wilhelm's (1995) study have researched how underwriters allocate between informed institutional investors and retail investors. Their results show that underwriters clearly favour institutions over retail investors and are being more rewarded for revealing their information. Assuming that institutional investors are well informed, the study of Hanley and Wilhelm (1995) evidently supports the information revelation theory where informed investors are rewarded with larger allocations for their information. In order for the investor to want these allocations as a reward, the IPOs must be underpriced on average, which also supports the theory. This is all though hard to test because of the lack of information about allocation data.

Ljungqvists paper from 2007 explains that Benveniste and Spindt (1989) tests a key prediction without bid- or allocation data. This study uses corrections in offer price as a proxy in order to explain an investors' information revelations. They corrected the offer price towards the upper part of the price range. Number of shares issued during the bookbuilding is used as a proxy to reflect investors' level of interest. If the offer price is adjusted upwards, positive information has been revealed and vice versa. Even though the underwriter adjusts the price upwards, he only does it partially, to ensure he leaves enough money on the table to reward investors with valuable information. Hanley (1993) presented this as the "*Partial Adjustment Theory*". As offer price and price ranges are available for the public, this is more easily testable.

Principal-agent models

Loughran and Ritter (2004) highlights the relationship between the underwriter and the issuer, where there could be a potential agency problem. The price setting sequence is where the agency problem occurs. An incentive for underwriters to allocate underpriced IPO is the possibility to earn future business. If an underwriter allocates stocks to executives in large companies, they might win their future investment banking business, known as 'spinning' (Ljungqvist, 2007). Underpriced IPOs create high demand, leading to more trading. However, this might be disadvantageous for the issuer as the issuer will leave more money on the table than necessary, while highest possible proceeds remain preferable.

Baron and Holmström (1980) and Baron (1982) highlight how banks use their informational advantage over issuing companies to exert suboptimal effort in marketing and distribution of the stock. The informational advantage involves knowledge about stock demand and investor interests. For the underwriter's superior information to be used optimally, Baron's model assumes the bank gets the pricing decision. The underwriter self-selects a contract from a menu of combinations of IPO price and underwriting spreads (Ljungqvist, 2007). If they think demand is low, the underwriter selects a high spread and a low price, and vice versa if demand is expected high. Underwriter's unobservable selling effort is optimized by making it dependent on market demand.

Tested implications for principal-agent models

Ljungqvist (2003) studies the role of underwriter compensation in mitigating conflicts of interest between companies going public and their underwriters (Ljungqvist, 2007). Agency conflicts could be reduced if the bank's compensation is more sensitive to the issuers valuation and thus underpricing. Consistent with this prediction, Ljungqvists show that IPOs between 1991 to 2002 lead to significantly lower initial returns in the UK. This was done after controlling for other influences on underpricing and a variety of endogeneity concerns (Ljungqvist, 2007). These results indicate that the pricing behaviour of IPO underwriters is affected by the issuing firms' contractual choices.

A powerful way to test the agency models is to investigate IPOs where there is no or little informational asymmetry between issuer and underwriter. In order to find such a scenario, the company needs to underwrite its IPO itself or that the underwriter owns equity stakes in the IPO company. Muscarella and Vetsuypens (1989) studied this case by only containing investment bank IPOs, which is limited in Norway as only a few investment banks have gone public. When the issuer underwrites their own IPO, the agency problem would not be relevant as there will be no informational asymmetry. Muscarella and Vetsuypens (1989) results contradicted the principal-agent theory since the investment bank IPOs were underpriced at the same level as other new listings.

Signal theory

The final model that includes asymmetric information models reverses Rock's assumption that the companies know more than the investors. If companies have better information about present value of future cash flows, underpricing can be used as a signal to highlight the company's true value. The method is costly, but the reward of it being a success, can allow the issuer to return to the market to sell equity on better terms at a later date (Ljungqvist, 2007). A high-quality firm has incentive to signal its higher quality than a low-quality firm. This will give the high-quality firm an opportunity to raise capital on more advantageous terms. The low-quality firm has incentive to imitate whatever the high-quality firm does.

Before the post-IPO financing stage, a firm's true quality is revealed to the investors. This will expose the low-quality companies before they can benefit from imitating. The risk of detection and the consequences that will follow, stops the low-quality issuers from imitating. The low-quality issuers may not be able to recoup the cost of the signal later. High quality issuers can influence investors' beliefs in the aftermarket by leaving money on the table in the

IPO. This money is recouped at a later date when the firm returns to the market (Ljungqvist, 2007).

Tested implications for signal theory

Michaley and Shay's (1994) study is consistent with Jegadeesh, Weinstein and Welch's (1993) paper and does not support the signal theory for underpricing. Their findings show that the decision on how much to underprice is not significantly related to the decision of re-issuing more shares at a later time.

Underwriter's reputation could also be a signal for IPO underpricing, as a trustworthy underwriter indicates good signals to the stock market. Carter and Manaster study from 1990 show that underpricing and underwriter reputation is negatively correlated. Michaely and Shaw (1994) support these findings by having similar results. Their study found that underwriters with high reputation tend to underprice less than IPOs performed by underwriters with low reputation. Baron (1982) argues that underwriters encourage to underprice IPOs due to marketing costs and reduce risk.

2.3.2. Behavioural approaches theory

The fourth and last group of theories of underpricing involves behavioural theories. Behavioural theories are doubting that asymmetric information is severe enough to influence and affect underpricing on this scale. Researchers believe investors are irrational and bid the IPO prices above their true value, or that issuers are irrational and therefore, are not able to pressure underwriters to reduce underpricing.

Investor sentiment

Behavioural theories follow the notion that irrationality or sentiment of the investors could have a significant impact on the IPO prices. This effect is stronger for IPO where the companies are young, immature and have lack of information, making it harder to value. In Ljungqvist, Nanda and Singh's paper from 2004, sentiment investors are assumed to hold over-optimistic beliefs about IPO companies. The issuers would like to capture this enthusiasm but need to find the balance between maximizing the excess value and flooding the market. Overflow of stocks will depreciate the price, meaning that the optimal strategy is to hold back stocks to prevent a decreasing price. This is problematic in Norway, because of the regulatory constraints on firms' own stock. Oslo Stock Exchange and Oslo Axess require that the issuer lists at least 25% of the company's shares (Oslo Børs, 2020a). The theory says that issuers first sell to institutional investors, which will resell to sentiment investors. In order to keep the price up, the institutional investors hold back stocks and maintain the supply restricted. This is a high-risk strategy for institutional investors. If the stock depreciates, the institutional investors would be penalized for their attempt in limiting the supply of the stocks. For an investor to take this risk by doing this, they receive underpriced shares (Ljungqvist, Nanda & Singh, 2004).

Prospect theory

Loughran and Ritter (2002) propose an explanation for IPO underpricing that stresses behavioural biases from a different perspective. Instead of looking at biases among investors, they are looking at biases among the decision-makers of the IPO firm. This study is strongly linked with Thaler's paper from 1985 on mental accounting. To put it briefly, mental accounting for the issuing firm is that they only care about total wealth gain or loss. Loughran and Ritter suggest that even though the issuers want to raise as much capital as possible, the issuers fail to get upset about leaving money on the table in the form of first-day returns. The issuers tend to sum the wealth loss of underpricing with the wealth gain on retained shares in the aftermarket as of the price jump (Loughran, T. & Ritter, J. R., 2002). This difference tends to be positive. Issuers that do not get upset benefits the underwriters if investors take part in rent-seeking behaviour to increase their chances of being allocated underpriced stocks (Ljungqvist, 2007). By keeping public investors satisfied with their stock investment, they may want to buy more shares if the company is eager to raise capital at a later stage.

Tested implications for prospect theory

There is not extensive research concerning prospect theory, but Ljungqvist and Wilhelm (2005) tested this theory by investigating whether the CEOs of recent IPO firms are satisfied with their underwriter's performance. Their results show that the phenomenon of mental accounting could have some explanatory power to underpricing, but there could be other factors involved as well.

2.4. Theories we will test

There are several existing theories of underpricing as shown above. Out of the wide selection, we have chosen the most interesting theories and have eliminated the remaining due to the limitations of this thesis. One of the main reasons for eliminating some theories is data availability. Studies such as Muscarella and Vetsuypens (1989) on the principal agent case for underpricing use a sample only contained by investment bank IPOs. Such data is hard to obtain in Norway. For the last couple of years, only a few investment banks have gone public in Norway. In addition, other studies require data that is confidential or not publicly available which makes it difficult for us to research that specific theory. Another main reason for us to eliminate a theory is that we find the theory unlikely for the Norwegian stock market or do not have the necessary level of academic support.

Among the different theories, asymmetric information and behavioral approaches are the ones we find interesting and believe could potentially explain the underpricing phenomenon in Norway. Winner’s curse and information revelation from the asymmetric information theory will be tested in our analysis. The testing of winner’s curse will be based on Beatty and Ritter’s theory from 1986 on valuation uncertainty. We will use Hanley’s partial adjustment theory from 1993 to test the information revelation theory. This is supported by Benveniste and Spindt’s (1989) approach in the use of corrections in the offer price. The investor sentiment Theory from the behavioral approach is selected in combination with Ibbotson and Jaffe's (1975) theory on hot and cold markets. Loughran, Ritter and Rydqvist (1995) approach will be used in the aftermarket of hot markets to see if there is correlation in the Norwegian stock market. It might seem unclear mentioning all the authors and theories, thus we will explain each of the mentioned theories in addition to our hypotheses in part three.

Part III: Methodology and data

Part three starts with the introduction of our structure and the hypotheses we will test in order to see if there is correlation between underpricing and the chosen theories. Furthermore, a description of the data selection process will be presented and different ways of calculating underpricing. Regression analysis including assumptions, biases and traps we need consider will conclude this section.

3.1. Overview of our analysis

To test the selected theories from part two we have developed six hypotheses, which we will test through regression analysis. The data we have collected data was adjusted and optimized to create independent variables for the hypotheses. We determine the outcome of the hypotheses by regressing our dependent variable; underpricing, and all relevant independent variables will be included.

3.2. Hypotheses which we will test

Hypothesis 1:

IPO pricing in Norway has been fairly priced since 2003

In a scenario where an efficient market exists, hypothesis 1 could have been accepted. Like previously mentioned, underpricing is a direct violation of EMH. As we have shown in part two, many researches worldwide show that almost every developed country has significant underpricing, including Norway. This hypothesis will be rejected if we find some evidence of mispricing whether that is overpricing or underpricing.

As our dataset is among the most updated for Norwegian IPOs, it is relevant to research the existence of underpricing in Norway. Additionally, the data we obtain from researching hypothesis 1 will give us more information to test all the other hypotheses.

Hypothesis 2:

Underpricing is unaffected by underwriter quality and reputation.

If hypothesis 2 can be rejected, we can support that underwriter's quality has an effect on the level of underpricing. Studies from Nanda and Yun (1997) argue that lead underwriters' stock market values were affected negatively by overpricing, suggesting that an incentive for underpricing is present. If the underwriters underpriced to moderate levels it would result in increased stock market value for the underwriters. This could be perceived as mutually beneficial for underwriters and investors. Underwriters would achieve higher quality and reputation while investors would acquire underpriced shares.

We want to analyze the quality and reputation of underwriters' effect on the IPO process to determine underwriters influence on the underpricing phenomenon. This can be done by classifying the underwriters in a ranking system and then comparing it to the level of underpricing within issues they took to the market. This is based on Loughran & Ritters (2002) and Carter and Manasters (1990) classification on underwriters. The variables are described at section 4.2.2.

Hypothesis 3:

Underpricing is unaffected by hot and cold markets

If hypothesis 3 can be rejected, we expect a higher degree of underpricing in hot markets in contrast to the return in cold markets. The hypothesis is based on Ibbotson and Jaffe's theory on hot and cold markets from 1975. Studies from Loughran, Ritter and Rydqvist (1995) argue that hot issue markets will be followed by periods of high stock market returns, implying that a correlation exists. Testing this in the Norwegian market could give us a good indication of whether hot issue markets also exist in smaller markets. This hypothesis could also be linked to investor sentiment, where issuers take advantage of investors who are above average optimistic. In order for us to see if the investor sentiment holds, we need to see a positive and correlated relationship between underpricing and IPO activity.

Hypothesis 4:

Upward price revisions are not affecting underpricing

If hypothesis 4 can be rejected, we expect that the upward revisions in the price range will increase underpricing. It could be logical that a higher offer price produces lower underpricing, but information revelation theory contradicts this suggestion. This theory is based on Hanley's study from 1993, called partial adjustment theory. The theory says that if the price is revised upwards, positive information has been revealed about the IPO. In order for the investors to truthfully reveal their information, the price is partially adjusted only to leave some underpricing as a reward. Information revelation theory will be tested as described by Hanley's (1993) partial adjustment theory and provide explanation of underpricing in the Norwegian market, if hypothesis 4 is rejected. Beneveniste and Spindt (1989) use corrections in the offer price in order to explain information revelations, which we will test with this hypothesis.

Hypothesis 5:

Underpricing of IPO stocks is not affected by industry classification

Different industries involve different risks. Underpricing could therefore be an instrument to attract customers to high-risk industries, such as the tech industry. The companies that are involved in technology are usually young and dynamic companies with high growth during the first years of their life cycle, which requires a considerable amount of capital. Due to their high-risk business models and uncertainty, acquiring capital from banks will often be a struggle. This would make the tech companies riskier than other industries such as the finance industry. This is supported by Loughran and Ritter (2004), where high-risk industries underpriced more, especially around the dot com bubble. This can refer back to investor sentiment, where several investors have a higher belief in some industries than others in cyclical terms. By rejecting the null hypothesis, we can confirm that IPO stocks experience different underpricing due to industry differences and risk levels. The industry classifications are based on ICB.

Hypothesis 6:

Valuation uncertainty is not affecting underpricing

If we can reject hypothesis 6, IPO underpricing is expected to increase in valuation uncertainty. This hypothesis is based on Beatty and Ritter’s (1986) theory where underpricing should increase if the firm's valuation is uncertain. If proven right, Rock’s winner’s curse from 1986 explaining IPO underpricing would be supported. Information asymmetry increases the effect of the winner’s curse, meaning when more investors become informed, the effect gets stronger and underpricing increases. Information gathering to become an informed investor can be explained as buying a call option on the IPO. When the investor is informed, he/she can make up his mind about the valuation and choose to use his option depending on whether the valuation exceeds the offer price or not. The value of the call will increase when volatility increases, similarly to options. Due to this increase, more investors choose to become informed, strengthening the effect of the winner's curse. We will try to test the effect of the winner’s curse by using proxies for valuation uncertainty.

3.3 Dataset

The purpose of the dataset is to collect every new listing from Oslo Stock Exchange’s web page for our time period. We have created a unique dataset for our analysis by working through over 400 prospectuses from IPOs from Oslo Axess and Oslo Stock Exchange for the period 2003 until 2019. After careful analysis only 202 IPOs remain in our sample. Reasons of elimination will be described in section 3.3.2. Company name, underwriter name, company’s sector and subsector, price/price range, IPO date and number of shares listed have been extracted from each IPOs individual prospectus. This information has been retrieved from several sources including; Newsweb, underwriters’ webpage, some were shared by our guidance counsellor, and some were shared with us directly from the underwriter. Stock information, such as closing price on the first day of trading and adjusted closing price were gathered from Datastream. Some of the historical prices downloaded from Datastream were corrected for later stock splits or reverse stock splits. This gave quite extreme results in terms of underpricing as the prices did not match the historical offer prices in any sense. This problem was solved by gathering unadjusted prices from Datastream. Closing levels of indices were also gathered from Datastream.

3.3.1. Data selection

Most of our data is collected manually through Oslo Stock Exchange notifications, over 400 prospectuses, company websites, financial databases, Finanstilsynet and correspondence with some companies. This information gathering has helped us generate a unique dataset. Even though this has been extremely time consuming, we felt it was necessary to reach a large sample size in order to strengthen significance in our dataset. Information on the IPO's subscription period is crucial for us to calculate the return from the industry index from the end of the bookbuilding period and until the listing date. The return will be used to adjust the initial return for market movements, as we will describe in section 3.4.2.

3.3.2. Data exclusion

As we mentioned in section 3.3. there were numerous IPOs that were eliminated during our data collection process. Many of the companies that were listed during our timespan were actually listed with private placements, where only a selected set of investors are invited to participate in the offering and is therefore, not an *initial public offering*. Another reason for exclusion is missing data. This was mostly present with earlier IPOs where prospectuses were missing or Newsweb did not provide any relevant information about offer prices, price ranges or bookbuilding periods.

Some prospectuses had notices stating that the prospectus purpose was only as a listing document, where no shares were offered in connection with the listing. Without a specific offer price, we could not calculate the underpricing connected with the listing. This was mostly the case with companies listed on Oslo Axess or Merkur Markets where regulations and capital demands are quite lenient in contrast to Oslo Stock Exchange. There were also a few cases where the listing was connected with offerings of bonds to institutions and selected investors, and therefore not a regular *initial public offering*.

As explained in section 2.1.3, due to the listing requirements, the inclusion of companies from Merkur Markets would introduce larger variations in company characteristics and distort the information symmetry as these markets have leaner requirements concerning company specific reporting. Therefore, companies that were listed on Merkur Markets were excluded from the analysis.

The last instance where IPOs were excluded were connected with demergers and double listings. Demergers in this case refers to a company which is already listed, where an entity of that company is being demerged and then listed as a separate entity. In such a case, the company is already known to the public and has already had an IPO with the initial company. What we refer to as double listings is where a company already was listed at a Norwegian market platform, for example Oslo Axess, and then listed again at a later stage at the Oslo Stock Exchange. Such as the case with demerges, the company would already have had an IPO when it was originally listed and trading data is already known before the IPO to the new trading platform.

Due to the reasons presented above, our dataset now consists of 202 IPOs.

3.3.3. Outliers

An issue which occurs when analyzing IPO returns is the occurrence of extreme observations which will distort the results. According to Ljungqvist (2007), underwriters may underprice to earn future business and to attract investor demand. Beatty and Ritter (1985) also stated that underpricing occurs at a higher degree around valuation uncertainty around the IPO firm. Due to the risk associated with IPOs, underpricing is used as an incentive for investors to participate, which would result in our IPO sample to be right tailed. Despite having a sample which in theory should be right tailed, some IPO returns deviate far from what is normal and creates a problem when we analyze averages. To solve our problem with outliers, we have identified the 1% lower and upper levels of outliers and excluded these with the use of a dummy variable. This procedure eliminates four observations from the regression analysis.

3.4 Calculation of underpricing

A standard way of calculating underpricing is to use the first day's initial return. This is found by gathering the offer price from the IPO and the closing price from the same IPO on the first day of trading (Ibbotson, 1975). If the initial return is higher than zero, the IPO was underpriced, and new investors have gained profits on the first day of trading. And vice versa, a negative initial return would mean that the IPO was overpriced. A more precise way of calculating would be to correct the initial return with market returns according to Logue (1973).

3.4.1. Simple initial return

Simple initial return is calculated with the following formula:

$$R_i = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$$

Where;

Ri = initial return of stock i

$P_{i,t}$ = Closing price of first day of trading

$P_{i,t-1}$= Offer price from bookbuilding period

The quoted formula states that underpricing or simple initial return is given by the percentage change between the price at which the stock is traded on the first day of trading and the final offer price from the bookbuilding period (Ljungqvist, 2007). If we were to use later prices such as the end of the first week of trading, it would make little difference (Ljungqvist, 2007). Some capital markets are regulated by daily volatility limits, which would limit the first day of trading to for example a maximum of 8 or 10% (Ljungqvist, 2007). In the presence of such regulatory terms, it would be relevant to use a longer period than the first day of trading, but this is not the case for the Norwegian market and our analysis.

A relevant issue is the market movements between the end of the offer period and the listing date. According to Ljungqvist (2007) it is necessary to adjust for market movements when there is substantial delay between pricing date and first day of trading. In the U.S and increasingly in Europe, the offer price is often set just a few days or hours before the listing (Ljungqvist, 2007). This is not precise in our dataset, where the average number of days between the offer price is set and the listing date is 7.24 days. Therefore, we have chosen to adjust the simple initial return with market movements for the relevant period.

In our sample we encountered an issue for IPOs from 2005 where two offer prices were missing from Newsweb or the relevant prospectuses. Recent studies on the pricing process shows that the final offer price will be on average 1.4% below the midpoint of the initial price range from the IPO prospectus (Lowry & Schwert, 2003). As all other necessary information was gathered on these two IPOs, we chose to simulate the offer price by using Lowry and Schwert's estimate for the offer price.

3.4.2. Market adjusted initial return

We can adjust the simple initial return by subtracting the return from a relevant index for the period between price setting of the offer price and the listing date, thus correcting the issue of market movements for this period. Whether the underwriter incorporates all public information into the offer price is a matter of debate within the IPO literature (Lowry & Schwert, 2003). The extent of the market movements during the bookbuilding period until the listing date would be considered public information which could be incorporated into the final offer price. The findings of Loughran and Ritter (2002) suggests that the underwriter of a new issue partially incorporates publicly available information into the offer price.
The adjusted initial return is based on Logue (1973). He defines the adjustment with the following formula:

$$R_i^* = R_i - R_m = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} - \frac{I_{i,t} - I_{i,t-1}}{I_{i,t-1}}$$

Where;

R_i^* = marked adjusted initial return

R_i = return on stock i

R_m = return on relevant index

$I_{i,t}$ = closing value of index on the first trading day of stock i

$I_{i,t-1}$ = closing value of index on the final day of the bookbuilding period

As quoted in 3.4.1. the simple initial return gives only a price difference and gives no statement alone of whether the IPO is underpriced or overpriced as there is no comparison standard. An investor who may subscribe to an IPO has the option of alternative investments instead of the IPO. Adjusting the initial return with the return of an alternative investment such as a relevant index is a way of comparing the return to an alternative investment (Hunger, 2015). The choice of relevant market portfolio or index is of high importance so that it represents fairly the same risk level as the IPO stock. The alternative investment could be a wide share market index, which is the customary approach according to Hunger (2015).

It could be relevant to include a beta value for the IPO stock to correct for the stocks' risk level compared to the market movement. But a common problem here is that the beta value cannot be measured where there is no historical stock price. We have chosen to use the adjustment method of Logue (1973) since we cannot calculate the beta value of the IPO companies.

When we chose the market indices, we wanted to use relevant indices that were closely linked to the industry the IPO company operated in. In our dataset we have used the Industry Classification Benchmark codes (ICB) to categorize each company to their respective industry. We used the same industry classification to download the relevant indices to use for the market adjustments from Datastream. OSE35 Health Care were used as the relevant adjustment index for IPOs that were classified as Health Care. Examples of other relevant indices we used are OSE10 Energy, OSE40 Financials, OSE20 Industry and so on. By using industry relevant indices as an adjustment measure, we are able to portray the alternative investment to investing in the IPO stock more precisely as described by Hunger (2015). By using industry relevant indices, we're able to convey the risk associated with the company going public, compared to using a broad market index.

3.5 Regression analysis

In the interest of analysing the relationship between underpricing and the chosen theories it would be appropriate to perform a multiple regression analysis. The analysis gives us an equation that will help us describe the relationship between our variables in the regression. Multiple regression analysis will give us a more accurate picture of the causal factors behind our phenomenon.

Our variables are related to the six hypotheses that we are testing. More information on why we chose each independent variable to the regression will be shared in part four. Performing this analysis on our data sample will provide information about the relationship between the dependent and independent variables and their significance. In addition, the explanatory power of the model and other information we can use will be revealed.

3.5.1. Regression assumptions

Three of the OLS-assumptions, heteroscedasticity, multicollinearity and normal distribution will be tested manually in order to detect the previously mentioned issues. Due to the nature of our variables, heteroscedasticity might occur in our regression and can be managed with the use of robust standard errors. It is unlikely that we will incur a multicollinearity issue, but if we do, this will be controlled for when reading the regression output. The test results will be discussed in section 4.4. followed by violation consequences of the assumptions and solutions to the problems. It is not many advanced regressions which will fulfil all of the OLS-assumptions.

3.5.2. Sample selection bias

Data samples that are not normally distributed are discussed in Heckman's paper from 1997. Sample selection bias in the OLS-estimator is induced by using data that arise from endogenous sample selection (Wooldridge, 2018, p. 767). The bias appears when there is missing data in the data sample, which could be caused by self-selection of our data or selection decisions that were necessary during the process. With three different stock exchanges and requirements, some issues will arise, such as missing offer prices, price ranges and subscription periods. Fortunately, Newsweb has provided us with nearly all the necessary data and the missing data has been supplemented with Datastream.

3.5.3. Dummy variable trap

Dummy variable traps occur when too many dummy variables among the independent variable is included and arise when an overall intercept is in the model and a dummy variable is included for each group (Wooldridge, 2018, p. 759). We cannot include both variables in the regression because it will not be able to estimate both of the coefficients at the same time when they are perfectly multicollinear. This also violates assumption 3 involving imperfect collinearity in order to be a classical linear model. In our model, we have dummies for several explanatory variables and some control variables where we will take the necessary measures to prevent dummy variable traps.

3.5.4. Survivorship bias

Survivorship bias is a potential issue when studying IPOs performance (Ritter, 1991). Companies that have been delisted or bankrupt could simply be overlooked because of the absence of information, where we only consider the winners. The winners are defined here as companies that are still public. We will not go further into the effect of a possible survivorship bias, but we have tried to include as many delisted companies as possible to avoid survivorship bias.

Part IV: Analysis and presentation of results

In part four we present our findings around IPOs in the Norwegian market and relevant descriptive statistics. Furthermore, we present our explanatory variables and control variables, followed by the introduction and estimations of our three regression variables along with comments related to them. To conclude, we have mentioned potential econometric issues and applied measures that will fix the issue.

4.1. Results from underpricing

Our dataset of 202 recorded IPOs from 2003 to 2019 shows an initial return of 4.107%. As described in section 3.4.1, this is the unadjusted initial return. After correcting the returns for market movements, our sample's underpricing decreases to 3.475% on the first day of trading. The number of observations listed in our table below deviates from the total number of IPOs in our sample due to the exclusion of outliers as mentioned in section 3.3.3. and the removal of IPOs connected with Merkur Markets as stated in section 3.3.2.

4.1.1. Descriptive statistics

The descriptive statistics of our results are summarized in the table below.

Descriptive statistics	Simple initial return	Adjusted initial return
Observation	202	202
Mean	0.04107	0.03475
Std. Dev.	0.11630	0.11673
Variance	0.01352	0.01362
Max	64.33%	66.57%
Min	-23%	-24.67%
Skewness	1.75507	1.71263
Kurtosis	8.58864	9.02870
25th percentile	-1.79%	-2.69%
Median	0.965%	1.165%
75th percentile	7.27%	6.27%

Table 1: Descriptive statistics of our underpricing results

The table shows the difference between simple initial return and adjusted initial returns. Standard deviation, variance and skewness differ in small degree between the two returns. The adjusted initial return is slightly lower than the simple initial return, meaning that the market return from the subscription period to the IPO date is positive on average. Even though the difference between adjusted and unadjusted is relatively small, we think that the adjusted initial return would be most suitable to approach our research. Older studies from

Logue (1973) and Ibbotson and Jaffe (1975) have been using adjusted returns for their findings. Newer studies, such as Ritter and Rydqvist (2012) have also used this approach.

A simple t-test shows that the adjusted initial return of 3.475% is statistically significant at the 1% level. The critical value with 201 degrees of freedom is 3.13, where our t-stat is estimated to 4.23 and by far exceeding the critical value. Later on, this result proves important for our study as it confirms the presence of underpricing in our research period. The median of the adjusted initial return is 1.165%, meaning that half of our observations have a higher return than 1.165%. Because the median is lower than the mean, the sample will appear to be skewed towards the right. A few high return observations are the cause of the higher mean, which could be the reason for a positive skew. Our skewness is calculated to 1.71, confirming the positive skew. This indicates that there is more data in the right tail than what is usual in a normal distribution where the skewness is zero. The 25th percentile informs us that 25% of the observations are lower or equal to -2.69%, while the 75th percentile informs us that 75% of the observations are lower or equal 6.27%. This implies that the remaining 25% are 6.27% or higher. The percentiles suggest that there is significant underpricing in our sample, with the help of some observations which brings the mean higher.

Due to structural differences in industries, price changes for necessary commodities, variations in investors' view on the selected industries and others, our sample might have underpricing variations for the industries. Below we will present a chart which shows the average adjusted underpricing and return per industry on the first day of trading.

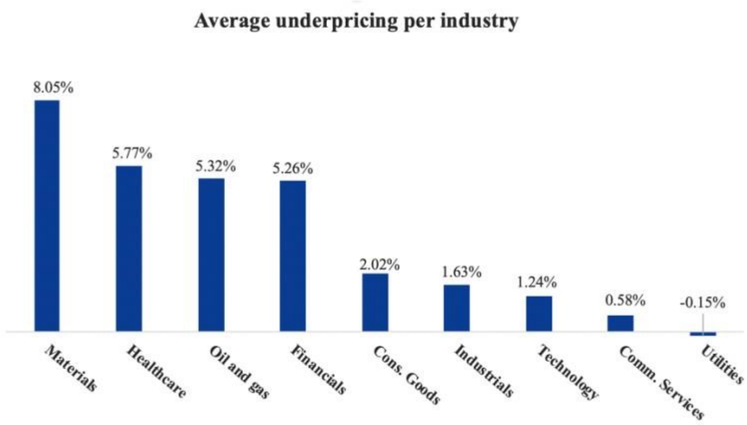

Chart 6: Average underpricing per industry in our dataset

The averages are calculated without the four outliers from our data sample to prevent distortion of the results. The utilities industry with its three observations is -0.15% overpriced on average as the only overpriced industry. The remaining industries provide support for underpricing, with varying degrees; materials, health care, financials and oil & gas all provide underpricing over 5%, while consumer goods, communication services, industrials and technology experience underpricing approximately between 0.6% and 2%. The materials industry only contains nine observations, which might explain why the average adjusted return deviates from the mean. This is also the case with utilities, which only have three observations.

Industry	Number of IPOs	Mean underpricing	Standard deviation
Materials	9	8.05%	0.10684
Healthcare	15	5.77%	0.21888
Oil and gas	46	5.32%	0.12103
Financials	27	5.26%	0.14095
Cons. Goods	25	2.02%	0.05407
Industrials	43	1.63%	0.07994
Technology	24	1.24%	0.10876
Comm. Services	10	0.58%	0.10276
Utilities	3	-0.15%	0.01440

Table 2:Number of IPOs and average underpricing per industry.

As mentioned in section 2.2.1., several studies have shown that underpricing varies greatly over different time periods. The more recent studies presented diminishing returns in contrast to the earlier studies of underpricing. These studies have been done in large IPO markets, but in a small IPO market like Norway, the results can vary due to fewer observations. This is applicable for the years where there have been few IPOs. The trend of diminishing returns is not present for the Norwegian market in our dataset. Underpricing per year is shown in the table below.

IPO Year	Number of IPOs	Mean underpricing	Standard deviation
2003	1	2.70%	.
2004	11	5.93%	0.09348
2005	32	3.73%	0.09969
2006	19	5.41%	0.11070
2007	38	1.17%	0.06549
2008	5	9.99%	0.08328
2009	3	-0.70%	0.03817
2010	14	3.32%	0.15281
2011	9	3.00%	0.10986
2012	3	5.62%	0.14665
2013	11	-2.99%	0.07628
2014	14	0.57%	0.12731
2015	9	5.65%	0.13326
2016	4	25.95%	0.27276
2017	12	0.69%	0.07015
2018	8	10.59%	0.23098
2019	9	0.72%	0.07532

Table 3:Underpricing per year

Table 3 illustrates that 2009 and 2013 deviates from the rest of the observations being the only years where the IPOs were overpriced. A possible explanation for this irregularity is that 2009 contained only a few observations, causing it to lose significance. 2013 contained more observations and seem to maintain its significance. The rest of the years have a fair amount of observations, showing a large distribution from 0.5% to 26%. 2016 stands out with extremely high levels of underpricing. This could be linked to a low number of observations. The fluctuations in underpricing from one year to another could introduce intertemporal variations in our data, which we can control later on in our regression analysis.

4.1.2. Comparison to other results

Our average underpricing of 3.475% is statistically significant at a 1% level. Studies of Norwegian underpricing seem to fit with our findings. Earlier findings have shown that underpricing has decreased slightly over the years, which has caused studies with newer datasets to show lower levels of underpricing. One of the first studies in the Norwegian market by Emilsen, Pedersen and Sættem (1997) found a 12.5% underpricing from 1984 to 1996. A more recent study from Loughran, Ritter and Rydqvist (2012) showed an underpricing level of 9.6% from 1984 to 2006, while Fjesme (2011) found 8% in a shorter time period from 1993 to 2007. Our dataset includes collected information from a more recent time period and shows even lower returns. Thus, the lower returns confirm our assumption that underpricing has decreased over the years. On a global basis, our results provide lower returns or underpricing than other international studies.

There are several student theses from the 20th century that have studied underpricing in the Norwegian market. Christiansen's (2011) study showed a 2% underpricing in Norway however, her results were not statistically significant. Falck (2013) studied underpricing of Norwegian IPOs from 2003 to 2012 and found a 3.17% underpricing that was statistically significant at a 1% level. Falck’s results were similar to our findings. Over an eight-year period, Barrera and Langmoen (2009) found an underpricing of 2.45% between 2000 and 2008.

Compared to the studies involving Norwegian IPOs, our results are not a deviation and compares well to existing findings. It is natural and a good sign that there are small differences due to the different time spans that are used for the IPO samples. Our study is one of few studies that has included the years post financial crisis and has included the uptick that occurred in the years after. To summarize, our results combined with more recent research and student studies highlights decreasing levels of underpricing.

4.2. Regression variables

In our linear regression model, we have chosen a total of eight explanatory variables. These relate directly to our hypotheses, whereas the rest of the variables would be used as control variables. A control variable is held constant to clarify the relationship between two other variables (businessdictionary.com). In other words, they might help explain our dependent variable and will not interfere with the explanatory variables. The control variables will also provide deeper validation to our results.

The remaining variables are carefully selected to help us with the testing on each hypothesis. Our hypothesis will be concluded when we have investigated the significance of these variables. One of the most common mistakes when handpicking variables is to select those that provides the highest R-squared (R^2) for the model, instead of a theoretical approach to pick the variables. This process is referred to as data mining and is important to avoid in order for the regression model to not lose theoretical relevance (Gujarati & Porter, 2009). For our study, where we investigate former theories, each variable needs to have theoretical relevance to fit in our regression. Therefore, each of our variables have a theoretical reason for being included in our regression. This will help us avoid the data mining issues. In this section, each of our variables will be explained including their theoretical relevance and which role they will play in the regression model.

4.2.1. Underpricing

The dependent variable in our regression is underpricing from the IPOs in our sample. It is a variable which is easily observable and calculated from publicly available data. To avoid the returns being interfered with market movements, we have used the market adjusted initial return as our measure of underpricing. The market movements are adjusted from the initial return using an industry index for the respective exchanges our observations are listed on. As this method seems to be the most theoretically correct approach (Logue, 1973), we apply it to each IPO when calculating the underpricing. Some of the observations were missing a subscription period, where we used the average from the other observations. Our choice of using an average will not affect our results noticeably because the difference between simple initial return and marked adjusted return is small. We will use our dependent variable to test hypothesis 1.

We have given the dependent variable the following name: *underpricing_dep.*

4.2.2. Underwriter quality and reputation

To test hypothesis 2, we have created two variables which we will use as proxies to measure the different underwriter's quality and reputation and potential influence on underpricing. The hypothesis is based on Carter and Manaster's study from 1990 and similar work from Michaely and Shaw (1994) where we want to research the relation between underwriter's quality and underpricing. The approaches we will use will be similar to the approaches of Carter & Manaster (1990) and Loughran & Ritter (2002).

The first variable concerning underwriters is one that lists how many different underwriters which contributed to the work of each IPO listing. We assign the number 1 if there was a single underwriter working on the IPO and 2 if there were two underwriters etc. This variable could help identify if underwriters in collaboration choose to underprice, and the extent a collaboration contributes to the degree of underpricing.

Our second variable is a combination of several conditions to measure the quality and reputation of underwriters. The first criterion is a measure of IPO size which each underwriter was involved with, in the time period of our dataset. This was calculated by adding up the proceeds per IPO each underwriter was involved in. Carter and Manaster (1990) suggested that more prestigious or reputable underwriters would be selected to handle larger offerings than less prestigious underwriters. The second criterion are the number of IPO involvements for each underwriter in our dataset. Similarly, the third criterion is based on the number of lead involvements for each underwriter. Each of these three criteria is summed up and underwriters with the highest level of proceeds, highest IPO involvements and highest lead role involvements receive the highest rank in each criterion and vice versa. Finally, we assign each underwriter a total rank which is the average rank of each criterion. For IPOs with underwriter participation, the highest rank received is 10, and the lowest rank received is 1. We have one observation without an underwriter, which is ranked 0.

It is expected that the coefficient in our regression will be negative as a higher rank and underwriter quality should prove to deliver less underpricing than lower ranked underwriters.

We have given the variables concerning underwriters the following names: *total_rank* and *nr_of_und*.

4.2.3. Hot market issues

To test hypothesis 3, we will use one variable for hot markets. This hypothesis is based on Ibbotson and Jaffe (1975) and their "hot" and "cold" markets theory. If hot markets exist in the Norwegian markets, the average underpricing for our total dataset should be lower than the average underpricing in these periods, according to Ibbotson and Jaffe (1975). There should also be more IPO listings during these periods.

We created a dummy variable to measure hot markets. This variable was defined periods as semi-annual. The choice of using semi-annual instead of a longer period was based on the notion that semi-annual captured the market state more precisely. Using an annual dummy would include periods too far back in time which would not be relevant for the current market state. The semi-annual variable was defined by using average return for all listings between 01.01.XX until 30.06.XX and average returns for all listings between 01.07.XX until 31.12.XX and comparing these returns to the average return of the entire dataset. If a semi-annual period had higher returns than the average return of all observations, this periods' observations were assigned 1 and 0 if returns were lower.

The sign of the coefficient in our regression is expected to be positive, as periods with high returns should reflect a higher level of underpricing per observation according to Ibbotson and Jaffe (1975).

Our proxy for hot and cold markets is named: *hot_cold_semi*

4.2.4. Price revision

For our test of hypothesis 4, we have included price revision in the regression. Hypothesis 4 is based on the asymmetric information model, where information revelation could be an explanation of underpricing. We have used price revision as a proxy for information revelation. As mentioned in section 2.3.1, if the offer price is revised upwards, positive information has been revealed during the bookbuilding process. The positive information revealed will partially adjust the offer price to reward the investors according to Hanley's (1993) partial adjustment theory. Hence, there is reason to include a variable for price revision due to the theoretical support.

Offer prices could also be revised downwards and if there are changes in the offer price, revised IPO prospectuses or Newsweb would include this information. We have created three dummies for price revision. These were assigned to observations where price was revised upwards, downwards or equal offer price and midpoint price range. The method of using the midpoint price range is similar to the method used by Lowry and Schwert (2004). They have designed the following formula:

$$\frac{(Offer\ price - Midpoint\ price\ range)}{Midpoint\ price\ range}$$

Not all IPO prospectuses include a price range. Some prospectuses will just present the offer price directly. As we do not have a price range for all of our observations, the number of observations will be 63% of the total number of observations when researching this hypothesis. Due to this issue, the price revision variables will be researched in a separate regression. To prevent an issue with perfect multicollinearity, only two of the dummies will be included in the regression.

The variables for price revision are named: *price_rev_up* and *price_rev_zero*.

4.2.5. Industry

To test hypothesis 5, we have created several dummy variables for the industries that will be researched. This hypothesis is based on Loughran and Ritter's (2004) study where we want to research the level of underpricing between industries. Loughran and Ritter assume that riskier industries would underprice more to compensate, and we can assume that the industry with the highest level of underpricing would likely include more risk. Earlier, the technology industry was regarded as riskier than other industries and as Christiansen (2011) mentioned, risk in industries evolves as a cyclical behavior. This implies that it is not given that the technology industry would underprice more than others in our dataset. As illustrated in chart 6, the degree of underpricing varies between industries. This chart also includes standard deviation to each industry. In order to prevent issues with collinearity, we have used eight of the nine dummies for the different industries.

The industry dummy variables are named according to each industry: *industrials, oil_and_gas, materials, financials, healthcare, consumer goods, utilities, consumer services* and *technology*

4.2.6. Valuation uncertainty

In order for us to test hypothesis 6, we have included two proxies for valuation uncertainty in the regression. Beatty and Ritter (1986) suggest that valuation uncertainty in connection with an IPO increases underpricing. If this is true, it will provide support to Rock’s (1986) winner's curse.

There is not a directly observable variable involving valuation uncertainty, so we will use proxies to research valuation uncertainty. Log sales, company age, company industry or market capitalization have been used by several researchers (see section 2.3.1.) as proxies. This can be linked to valuation uncertainty as bigger companies are viewed as less risky by both institutional and retail investors, which provides more coverage and analysis. Valuation uncertainty would therefore be lower for the bigger companies.

We have decided to use logarithmic market capitalization and age of company as proxies. We believe that the age measure will be a good proxy to determine the public’s knowledge of the company and therefore decrease valuation uncertainty. Market capitalization is calculated by multiplying the number of stocks in each company with the closing price of the first day of trading and then applied the logarithm of the number. The logarithmic market capitalization creates a less linear relationship to firm size and gives the absolute change in underpricing for a percentage change in market capitalization.

$$ln\_mrkt\_cap = ln\ (stocks\_listed * closing\ price\ first\ day\ of\ trading)$$

Due to the inclusion of the logarithmic market capitalization, we will not use regular market capitalization as a control variable when researching valuation uncertainty. Instead, we will research valuation uncertainty in a separate regression as shown in table 5.

The expectation is a negative sign on both coefficients as bigger and older companies should have lower degree of valuation uncertainty and therefore provide less underpricing.

We have given the variables for valuation uncertainty the following names: *ln_mrkt_cap* and *age_of_firm.*

4.2.7. Control Variables

The remaining variables in our regression are control variables. These variables will not be researched specifically but will be present in our regression as we believe they capture effects and provide explanatory power.

We have included control variables for the number of days for the subscription period, number of days between the end of subscription period until listing date and variables for which exchange the IPO was listed on. We also include a dummy variable to capture demand for IPOs where we assign the value of 1 if the IPO was oversubscribed. The oversubscription information is gathered from Oslo Stock Exchange's web page (Oslo Børs, 2020d). We have included two proxy variables to test for valuation uncertainty in the fourth regression. Market capitalization is used as a control variable for the first three regressions as a measure of firm size. Our final control variable for all our regressions is the dummy variable for outliers which was described in section 3.3.3. For the third regression we have also included a dummy variable for which year each IPO took place. This was done to control for intertemporal variation in our dataset. The approach of using yearly dummies is in line with the theories of

Cliff and Denis (2004). In order to prevent issues with collinearity, we will drop the dummy for the first year in our sample.

Our control variables are called: *daycount_subscr*, *daycount_subscr_list*, *dummy_OBX*, *dummy_merkur*, *dummy_axess, outliers, oversubscription, mrkt_cap and dummy_2004 to dummy_2019*

4.2.8. Overview

The table below represent the different variables:

Variable name	Expected sign	Min	Max	Mean	Standard deviation
Dependent Variable					
underpricing_dep		-24.67%	66.57%	3.47%	11.67%
Research Variables					
ln_mrkt_cap		14.86092	24.38398	20.0734	1.48635
age_of_firm	-	0.0027	150.46	9.5563	14.18384
price_rev_up	+	0	1	0.3125	0.46533
price_rev_zero		0	1	0.04687	0.21220
hot_cold_semi	+	0	1	0.37623	0.48564
nr_of_und	-	0	4	2.00495	0.87245
total_rank	-	0	10	8.21985	2.07023
industrial	+	0	1	0.20792	N/A
oil_and_gas	+	0	1	0.22772	N/A
technology	+	0	1	0.11881	N/A
healthcare	+	0	1	0.07425	N/A
communication_se	+	0	1	0.04951	N/A
utilities	-	0	1	0.01485	N/A
materials	+	0	1	0.04455	N/A
financials	+	0	1	0.13366	N/A
Control Variables					
dummy_OBX		0	1	0.74257	N/A
dummy_merkur		0	1	0	N/A
daycount_subscr		0	19	9.67822	2.58592
daycount_subscr_list		1	37	6.59406	6.01685
outliers		0	1		
oversubcsribed		0	1	0.42079	0.49491
mrkt_cap		2844574	3.89e+10	1.59e+09	4.14e+09
Yearly dummies					

Table 4: Summary of all variables and key figures

4.3. Results from our regression model

We have created 4 regression equations out of the variables we explained in the previous section. The base line regression (1) is described by the equation below:

$$(1)\qquad Underpricing = \beta_0 + \beta_1\, dummy\_OBX + \beta_2 dummy\_merkur + \beta_3 daycount\_subscr + \beta_4 daycount\_subscr\_list + \beta_5 outliers + \beta_6 mrkt\_cap + \beta_7 oversubscribed + \beta_8 hot\_cold\_semi + \beta_9 nr\_of\_und + \beta_{10} total\_rank + \sum \beta_n\, industry\_dummies + \mu$$

The second regression includes *price_rev_up* and is given by the following equation:

$$(2)\qquad Underpricing = \beta_0 + \beta_1\, dummy\_OBX + \beta_2 dummy\_merkur + \beta_3 daycount\_subscr + \beta_4 daycount\_subscr\_list + \beta_5 outliers + \beta_6 mrkt\_cap +$$

$$\beta_7 oversubscribed + \beta_8 hot\_cold\_semi + \beta_9 nr\_of\_und + \beta_{10} total\_rank + \sum \beta_n\, industry\_dummies + \beta_{19} price\_rev\_up + \beta_{20} price\_rev\_zero + \mu$$

The third regression include all of the yearly control variables. It is given by the following equation:

$$(3) \qquad Underpricing = \beta_0 + \beta_1 dummy\_OBX + \beta_2 dummy\_merkur + \beta_3 daycount\_subscr + \beta_4 daycount\_subscr\_list + \beta_5 outliers + \beta_6 mrkt\_cap + \beta_7 oversubscribed + \beta_8 hot\_cold\_semi + \beta_9 nr\_of\_und + \beta_{10} total\_rank + \sum \beta_n\, industry\_dummies + \beta_{19} price\_rev\_up + \beta_{20} dummy\_2004 + \cdots + \beta_{35} dummy\_2019 + \mu$$

The fourth regression exclude *mrkt_cap* in order to make place for *ln_mrkt_cap*. *Age_of_firm* is also included and is given by the following equation:

$$(4) \qquad Underpricing = \beta_0 + \beta_1 dummy\_OBX + \beta_2 dummy\_merkur + \beta_3 daycount\_subscr + \beta_4 daycount\_subscr\_list + \beta_5 outliers + \beta_6 ln\_mrkt\_cap + \beta_7 oversubscribed + \beta_8 hot\_cold\_semi + \beta_9 nr\_of\_und + \beta_{10} total\_rank + \sum \beta_n\, industry\_dummies + \beta_{19} price\_rev\_up + \beta_{20} age\_of\_firm + \mu$$

The 4 OLS-regressions give the following results:

	Regular standard error				Corrected standard error			
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Intercept	0.09569*	0.02297	0.07793	0.06996				
t-stat	(1.90)	(0.44)	(0.67)	(0.56)	(1.90)	(0.48)	(1.21)	(0.51)
dummy_OBX	0.02629	0.01683	0.03864*	0.02671				
t-stat	(1.44)	(0.93)	(1.85)	(1.42)	(1.40)	(0.81)	(1.88)	(1.44)
daycount_subscr	-0.005762*	-0.00188	-0.00401	-0.00585*				
t-stat	(-1.93)	(-0.63)	(-1.24)	(-1.95)	(-1.79)	(-0.70)	(-1.16)	(-1.82)
daycount_subscr_list	-0.00168	-0.00222	-0.00127	-0.00176				
t-stat	(-1.33)	(-1.58)	(-0.98)	(-1.39)	(-1.18)	(-1.70)	(-0.85)	(-1.24)
oversubscribed	0.04340***	0.00583	0.04730***	0.04341***				
t-stat	(2.88)	(0.41)	(2.94)	(2.85)	(2.83)	(0.41)	(2.73)	(2.74)
hot_cold_semi	0.08610***	0.03569**	0.09817***	0.08732***				
t-stat	(5.46)	(2.40)	(4.45)	(5.49)	(4.90)	(2.29)	(4.45)	(4.96)
mrkt_cap	1.97e-12	2.17e-12	2.80e-12					
t-stat	(1.06)	(1.34)	(1.45)		(1.76)	(2.14)	(1.89)	
nr_of_und	-0.02082**	-0.00658	-0.02420**	-0.01915*				
t-stat	(-2.26)	(-0.79)	(-2.41)	(-1.95)	(-2.34)	(-0.92)	(-2.20)	(-1.92)
total_rank	-0.00722*	-0.00352	-0.00896**	-0.00766**				
t-stat	(-1.93)	(-0.93)	(-2.28)	(-2.05)	(-1.77)	(-1.14)	(-2.04)	(-1.89)
industrial	0.02090	0.03652	0.03380	0.02316				
t-stat	(0.80)	(1.50)	(1.25)	(0.88)	(1.20)	(1.75)	(1.61)	(1.30)
oil_and_gas	0.05116*	0.04725**	0.06849**	0.05423**				
t-stat	(1.95)	(1.97)	(2.51)	(2.06)	(2.57)	(2.10)	(3.14)	(2.70)
technology	0.02511	0.02465	0.04844	0.02614				
t-stat	(0.85)	(0.99)	(1.52)	(0.85)	(1.04)	(1.13)	(1.72)	(1.02)
healthcare	0.06242*	0.05160	0.07430**	0.06359*				
t-stat	(1.85)	(1.55)	(2.14)	(1.84)	(1.31)	(1.15)	(1.65)	(1.29)
comm_services	-0.03273	-0.02846	-0.02229	-0.03062				
t-stat	(-0.86)	(-0.90)	(-0.57)	(-0.79)	(-1.19)	(-1.28)	(-0.87)	(-1.07)
utilities	0.00575	0.00192	0.02137	0.00643				
t-stat	(0.09)	(0.04)	(0.33)	(0.10)	(0.16)	(0.07)	(0.39)	(0.18)
materials	0.07587*	0.00418	0.08634**	0.08234**				
t-stat	(1.87)	(0.10)	(2.06)	(2.04)	(2.37)	(0.21)	(2.29)	(2.41)
financials	0.06091**	0.00765	0.05178*	0.06226**				
t-stat	(2.13)	(0.31)	(1.74)	(2.15)	(2.19)	(0.52)	(2.29)	(2.28)
price_rev_up		0.04576***						
t-stat		(2.89)				(2.87)		
price_rev_zero		-0.02814						
t-stat		(-0.82)				(-0.76)		
ln_mrkt_cap				0.00131				
t-stat				(0.22)				(0.19)
age_of_firm				0.00015				
t-stat				(0.29)				(0.38)
Yearly Variables	No	No	Yes	No	No	No	Yes	No
R-squared (R^2)	30.96%	30.36%	39.01%	30.58%				
Adjusted R-squared	24.98%	18.86%	27.46%	24.16%				
F-value	(5.18)***	(2.64)***	(3.38)***	(4.77)***				

Table 5: The table shows the OLS-coefficients of the 3 regressions and their t-stat in parentheses. The corrected standard error column represents White's heteroscedasticity-robust standard errors.
**** is significant on a 1% level, ** is significant on a 5% level and * is significant on a 10% level.*

The table above outlines the results of the four equations of the OLS-regressions. Every variables coefficient is linked to its t-stat below in the parenthesis. The asterisks (*) specify the level of significance of the coefficients, where the significance level is described below the table. The White's heteroscedasticity-robust standard error is applied in the right column for the four regressions.

4.3.1. Regression (1)

Our first regression includes every explanatory variable except variables for valuation uncertainty and price revision. Due to alteration of sample size, we will analyze the variables for price revision in regression (2) separately. The first regression will also include every control variable except the yearly dummies. Our regression model produces a R-squared of 30.96%, which translates to our model explaining 30.96% of the variation in adjusted underpricing. The adjusted R-squared at 24.98% is a bit lower, but this is expected due to the number of variables we have included and how the adjusted R-squared is designed. R-squared at 30.96% is a high degree of explanatory power compared to other similar studies, such as Falck (2013) with 7.05%. Despite having a model with a R-squared of 30.96%, there is still substantial unexplained variation in underpricing which our model does not capture.

The explanatory variables prove to be statistically significant in most of the cases, except some of the industry dummies, when studying the robust output. Only three out of eight industry dummies prove to be statistically significant. Our explanatory variables vary in significance levels from 10% to 1%. The variable with the highest significance level at 1% is *hot_cold_semi.* As predicted, the coefficient of the variable has a positive sign and the coefficient can be interpreted to hot market periods contribute with approximately 8.6% more underpricing, when controlling for our other variables.

The models F-statistic of 5.18 is statistically significant at a 1% level. This means that the regression model has significance in fitting the data, and the explanatory variables have influence on the dependent variable.

Due to the OLS-assumption of homoskedasticity, we have to consider the presence of heteroskedasticity. With the presence of heteroskedasticity, the estimators will no longer be efficient and BLUE (Wooldridge, 2018, p. 90). To adjust the heteroskedasticity issue, we have included White's heteroskedasticity robust standard errors in our regressions. The inclusion of robust standard errors alters the t-values in the regression illustrated in table 5. A key difference between the output from regular standard errors and corrected standard errors in regression (1) is the change in *mrkt_cap, oil_and_gas, healthcare* and *materials*. *Mrkt_cap*, *oil_and_gas* and *materials* become statistically significant at a higher significance level than the regular standard error output, while healthcare is no longer statistically significant at the 10% level. Heteroskedasticity will be elaborated further in section 4.4.1.

4.3.2. Regression (2)

Regression (2) includes two more research variables; *price_rev_up* and *price_rev_zero*. This inclusion substantially reduces the number of observations, which is emphasized when interpreting the results. As the number of observations decreases by almost 40%, the R-squared of 30.36% and R-squared adjusted of 18.86% are decreased compared to regression (1). These results imply that the new regression model provides decreased explained variance in underpricing, most likely due to a decreased number of observations and not the new included variable itself.

With a F-value of 2.64 the regression model is still statistically significant at the 1% level, but the F-value has decreased a lot compared to regression (1). The new included variable *price_rev_up* is statistically significant at 1% level with regular and robust standard errors, which interprets the variable being significantly different from zero at 1% level. The variables coefficient has a positive sign and can be interpreted as providing 4.57% higher underpricing given that the price was revised upwards after controlling for all other variables in the regression. The final dummy for price revision where offer price was equal to the midpoint price range has proven to be without significance. This can be linked to the few observations which took on this value.

As previously mentioned, when the price revision variables are included, the number of observations decreases severely. This infers with the results from the regression, especially the t-stat to each coefficient. The intercept, *oversubscribed*, *nr_of_und*, *total_rank*, *healthcare*, *materials* and *financials* are no longer statistically significant at 1%, 5% or 10%

when comparing the non-robust output of regression (2) and regression (1). The significance level of *hot_cold_semi* decreases from 1% to 5% when comparing the output of these regressions. One of the control variables *daycount_subscr_list* becomes statistically significant at 10% level in regression (2) robust output. This variable is not significant in our other regressions. When we study the results from regression (2) with corrected standard errors we see that *mrkt_cap* is statistically significant at the 5% level.

A clear visual trend in the results of regression (2) is decreased or absence of significance level for many of the variables that were statistically significant in regression (1). It is also noticeable that some of the coefficients have decreased compared to regression (1).

4.3.3. Regression (3)

Regression (3) is quite similar to regression (1), but also includes the yearly dummy variables for the year of each IPO to try to capture intertemporal variation within our sample. The dummy for 2003 is left out to avoid perfect multicollinearity. R-squared increases quite drastically in contrast to regression (1) and (2), with a R-squared of 39.01% in contrast to 30.96% and 30.36%. Due to the inclusion of 16 new control variables, it is relevant to compare the change in adjusted R-squared as the adjusted R-squared provides penalty for the number of variables included. While regression (1) provides an adjusted R-squared of 24.98%, the adjusted R-squared of regression (3) is only 2.48% higher at 27.46%. The inclusion of yearly dummies provides more explanatory power to the variation in underpricing than our previous regressions, but when adjusted for the number of new variables, the difference is not of significance compared to regression (1).

Our third regressions F-statistic is 3.38 which means that the regression is still significant at 1% level. The F-statistic has increased compared to regression (2) but is still lower than regression (1) F-statistics.

When all our control variables have been included in the regression, there are minor changes to the test statistics of the variables compared to regression (1). *Healthcare* and *technology* are now statistically significant at the 10% level in the robust output. *Industrial* have not been statistically significant in neither previous regressions nor regression (3) but have an increased test value in regression (3) which is close to being significant at the 10% level. *Total_rank*

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have gone from 10% significance to 5% significance level when comparing the robust result from regression (1) and (3). The dummy variable for Oslo Stock Exchange is also now statistically significant at the 10% level, while not being significant in previous regressions.

None of the yearly dummies are statistically significant which makes it hard to argue that they capture intertemporal variation. An interesting observation from this regression is the improvement in significance level and higher test values for many of the industry dummies. It is also interesting that the inclusion of yearly dummies contributes to statistical significance for *dummy_OBX*, which makes sense as stocks listed at Oslo Axess first emerged in our dataset in 2007.

4.3.4. Regression (4)

Regression (4) is produced to research valuation uncertainty separately. This regression included two new variables; *ln_mrkt_cap* and *age_of_firm.* The previous control variable for market capitalization was excluded due to the inclusion of the logarithmic market capitalization variable. Regression (4) was also produced without the yearly control variables. With these alterations of the regression, the R-squared maintained at a close level to regression (1) and (2) with a R-squared of 30.58%. The adjusted R-squared was reduced to 24.16% which is lower than the previous regressions, except regression (2).

Our final regressions F-value is 4.77 which means the regression is still significant at 1% level. When comparing the F-value to previous regressions it is higher than regression (2) and (3), but lower than our first regressions F-value.

As this regressions F-value and included variables have most resemblance with regression (1), it is natural to compare the variables between these regressions. The test statistics is quite similar for most of the variables which is used in both regressions. Regression (4) differs from regression (1) where the intercept is not statistically significant, *nr_of_und* is significant at 10% instead of 5% level and *oil_and_gas* is significant at 1% instead of 5%. The new proxies for valuation uncertainty have low t-values and are not close to being significant at the 10% level.

4.4. Econometric issues

The main rule for regression models is that they should meet the OLS-assumptions in order to be called valid. However, in general, most regression contain possible econometric issues and violations of the OLS-assumptions. We have tested for the most likely issues for our study and added measures if possible. In this section we will comment and provide test results for the potential econometric issues.

4.4.1. Heteroscedasticity

We suspect that our regressions error term could be heteroscedastic, where the residuals are subject to non-constant variance. A common issue for most regressions is heteroscedasticity and could potentially affect the inferences. Heteroscedasticity would violate OLS-assumption 5, which will reduce the efficiency of the OLS-estimators, resulting in non-BLUE estimators.

A possible reason for heteroscedasticity is that the sample has combined firms of different sizes in a cross-sectional analysis, which is the case for our data. In order for us to examine this issue, we can plot the squared residuals against each explanatory variable. These graphs are presented in appendix 5 and show that we have heteroscedasticity issues. If our sample is homoscedastic, the residuals should show systematic patterns and be distributed throughout the charts with a mean of zero. In our case, many of our variables seem to increase with the mean, implying that we have heteroscedasticity.

There are different heteroscedasticity tests, where the Breusch-Pagan-Godfrey test (Breusch & Pagan, 1979; Godfrey, 1978) assumes the errors are normally distributed (Wooldridge, 2018, p. 251). Theta (θ) is Chi-square distributed with degrees of freedom to the number of independent variables in the regression. If the critical Chi-square value is exceeded by θ, the null hypothesis is rejected, implying heteroscedasticity. The Breusch-Pagan-Godfrey test of our regression (1) gives the following results:

Breusch-Pagan-Godfrey Test for Regression (1)			
Θ	Critical value 5% significance	Critical value 1% significance	Critical value 0.1% significance
13.77	3.84	6.64	10.83

Table 6: Test statistics from Breusch-Pagan-Godfrey test for regression (1)

Our θ clearly rejects the null hypothesis, because the theta exceeds the critical Chi square value at the 1% level by far. Therefore, we can assume that regression (1) has evidently a heteroscedasticity problem, violating OLS-assumption 5. As our second regression includes a smaller sample size, we have performed the Breusch-Pagan-Godfrey test on regression (2) as well:

Breusch-Pagan-Godfrey Test for Regression (2)			
Θ	Critical value 10% significance	Critical value 5% significance	Critical value 1% significance
3.18	2.71	3.84	6.64

Table 7: Test statistics from Breusch-Pagan-Godfrey test for regression (2)

The smaller sample size decreases theta to the extent that it will accept the null hypothesis at a 10% significance level. This confirms our suspicion that the reduced sample size interferes with the result of the test, meaning that we still need to question the results. Thus, we will still look at this as a heteroskedasticity issue.

Robust standard errors could be either higher or lower than the regular standard errors, resulting in t-values which is altered in either direction. This may lead us to discover different statistical findings than the findings we made before we corrected for heteroscedasticity. We have used White's robust standard errors in all the statistical inferences in our analysis, to correct our results for heteroscedasticity.

4.4.2. Endogeneity and specification errors

When the explanatory variables seem to be dependent on the error term, endogeneity problems occur. If this assumption is violated, the OLS-regression coefficients will be biased, inconsistent and the inferences could not be valid. Thus, the regression model will not qualify as BLUE.

The Hausman test is one way to test for endogeneity. It examines if the explanatory variables are endogenous with instrument variables. An instrument variable is an extra variable that does not appear in the model which affects the dependent variable through one of the independent variables (Wooldridge, 2018, p. 761). However, the absence of good instrumental variables in our dataset prevents us from performing the Hausman test. We cannot rule out that some of the variables are endogenous, but we choose to believe that endogeneity is not going to be a big problem for the variables we have chosen. Endogeneity issues have several possible origins such as specification errors which includes underfitting or measurement errors.

It is important to not omit variables that could be relevant for the dependent variable to prevent omitted variable bias. An omitted variable will create an endogeneity problem. If the omitted variable is correlated with one or more of the independent variables, endogeneity problems are present (Gujarati & Porter, 2009). To elaborate, the error term includes the effect of the omitted variable, meaning the error term will correlate with the independent variable. This will cause inconsistent and biased regression coefficients. When the omitted variable is uncorrelated to the other independent variables, the intercept would still be biased.

In addition to a potential omitted variable issue, it is important to exclude variables that does not hold explanatory power to the dependent variable (Wooldridge, 2018, p. 79). Such variables will not create biased coefficients, but they could lead to unnecessary high variance and will cause the models adjusted R-squared to decrease. With a high number of variables and a low number of observations, some variables could experience effects that do not exist (noise) (Gujarati & Porter, 2009). The exclusion of relevant variables has a high probability in models where R-squared is limited. It is likely that our regression model is subject to this endogeneity issue due to our approach to the research problem. Since we have chosen a few theories of IPO underpricing, we believe there are variables that actually explain underpricing, which we have excluded.

Measurement error is the difference between an observed variable and the variable that belongs in a multiple regression model (Wooldridge, 2018, p. 763). The error term will be affected if one of the variables includes a measurement error. If the same measurement error affects an independent variable and the error term, they will correlate and cause endogeneity.

Measurement error will not cause biased estimates if it exists in the dependent variable. Although, if the errors were absent, the estimated variance would be smaller (Wooldridge, 2018, p. 479-481). One reason for measurement error is that we do not adjust for market movements where the timeframe between the offer period and the IPO is unknown, even if this is in line with Adrian Hunger's (2012) approach. Instead, we have chosen to use the average for these timeframes and adjust for the market movements. The variables we have selected in our models are supported by our chosen theories and we have avoided data mining. It should be mentioned that endogeneity and specification errors could be a potential source of error in our results.

4.4.3. Multicollinearity

If two or more of the explanatory variables have a perfect linear relationship, multicollinearity is present (Wooldridge, 2018, p. 764). It is worth mentioning that it is only perfect multicollinearity which violates the OLS-assumptions. One of the consequences with perfect multicollinearity is that the correlated variables will have high variance and the estimated coefficient in the sample will be far from the population's true value. However, imperfect multicollinearity, where the correlation coefficient between two variables is close to -1 or 1 will also create problems for the regression. The coefficients will still vary greatly from the population's true value, leading to large confidence intervals. Large intervals will often lead to acceptance of the null hypothesis, even when it should not be accepted, which is type II error.

As our regression output has been calculated without any significant problems and we have included variables without perfect correlation, we can exclude the case of perfect multicollinearity. High R-squared with few significant t-stats is one sign of multicollinearity, but this is not the case in our study as we have several significant t-stats even though our R-squared is relatively high compared to other master theses. Another way to detect multicollinearity is to look at the variance inflation factor (VIF). A VIF above 10 is quite problematic because it will increase the standard error of the coefficient with 10 (Ringdal, 2017, p. 147). This is not the case in our analysis as the highest VIF is at 3.84 (see appendix 9).

However, Bartlett's test shows that we have a degree of correlation. A correlation matrix will help us detect the source of multicollinearity. The correlation matrix for regression (1) is presented in appendix 7. We need to consider correlation in both directions and the highest correlation between coefficients is -0.2782 between the variables *oil_and_gas* and *industrial*. As 0.6 is referred to as a moderate positive relationship, our correlation matrix shows no signs of multicollinearity issues. Although, we could be misled due to low correlations that still have high multicollinearity in models with more than two variables (Wooldridge, 2018, p. 84-85). To be certain that we do not have a multicollinearity problem, we applied the "condition index".

The eigenvalues from appendix 8 can be used for each independent variable to diagnose multicollinearity. The following formula shows how the condition index is defined:

$$Condition\ Index = \sqrt{\frac{Maximum\ Eigenvalue}{Minimum\ Eigenvalue}}$$

Issues involving multicollinearity are severe when the condition index is above 30 and if the value is between 10 and 30, there are small multicollinearity issues. Acceptable values are below 10 (Gujarati & Porter, 2009). Our eigenvalues and condition indexes are included in appendix 8 The condition index is 11.75 and 3.34 for regression (1) and (2), respectively. Even though the condition index for regression (1) has some multicollinearity, we believe we don't have perfect multicollinearity because it is only present in one variable. Since a multicollinearity problem is not an issue for regression (2) and (3) and it is roughly an issue for regression (1) we will not investigate this problem any further.

4.4.4. Non-normal errors

Non-normal distribution is not a problem if the sample size is big, because the errors can be explained as a normal occurrence. With a sample size defined as large such as ours, OLS-assumption 6 will be violated without consequences (Wooldridge, 2018, p. 156). In order for us to test for non-normal errors, we have used the skewness and kurtosis test for normality. These tests clearly provide evidence of a normality issue as illustrated in appendix 7. However, due to our reasonably large sample size, we regard the normality absence as normal occurrence.

Part V: Interpretation of our results

In part five, we will use our results to interpret how the different underpricing theories hold for the Norwegian Stock Exchanges. Each hypothesis will be accepted or rejected based on our analysis from the previous part.

5.1. Test of underpricing in Norway

Hypothesis 1 says that Norwegian IPOs have been fairly priced from 2003 to 2019. Our results point us toward rejecting the null hypothesis. As expected, we have found evident signs of Norwegian IPO underpricing. After adjusting for market movements our adjusted initial return is 3.475%. Our regression models are statistically significant at the 1% significance level. The 75th percentile shows an adjusted initial return of 6.27%, meaning that 25% of the observations are underpriced with 6.27% or more. This implies that high levels of underpricing of IPOs in Norway are not uncommon. Earlier studies with earlier time frames have shown higher levels of underpricing, indicating that underpricing has slightly decreased over the years. Appendix 9 contains a t-test where:

$$H_0: underpricing\_dep = 0$$
$$H_a: underpricing\_dep \neq 0$$

H_0 is rejected in H_a when underpricing_dep ≠ 0 and when underpricing_dep > 0. Both are statistically significant at 1% level.

We have confirmed the existence of underpricing for our research period and can move on to the results from tests of the different theories to underpricing.

5.2. The effect of underwriter quality and reputation on underpricing

In order to test hypothesis 2, we have included *total_rank* and *nr_of_und* as proxies for underwriter quality and reputation. The expectation was that higher quality and reputable underwriters would be more accurate in their price setting. Carter and Manaster (1990) suggested that underwriters with good quality and reputation would be selected more often to handle large offerings, as they will provide less money on the table. Nanda and Yun (1997) found that moderate levels of underpricing increased the underwriters stock market value, again increasing underwriter quality and reputation. We expected the sign of the regression coefficient to be negative, as quality and reputation should decrease underpricing.

The results show both coefficients to the regression variables were negative, where *nr_of_und* was statistically significant at a 5% level, while *total_rank* was statistically significant at a 10% level in regression (1). These findings were changed in regression (2), but as mentioned earlier regression (2) includes *price_rev_up* and *price_rev_zero*, reducing the sample size by almost 40%. By estimating regression (3), which includes yearly control variables, both variables became statistically significant at a 5% level. This means that we reject the null hypothesis where underwriter quality and reputation does not affect IPO underpricing.

Our results provide support for the theories of Carter and Manaster (1990) and Michaely and Shaw (1994) as underwriter quality has the expected effect on underpricing levels. We have not researched specifically how underpricing levels contributed to underwriters' stock market values like Nanda and Yun (1997), but we expect this could be an underlying motive for moderate levels of underpricing.

5.3. The effect of hot and cold markets on underpricing

Hypothesis 3 states that IPO underpricing is unaffected by hot and cold markets. In order for us to test this hypothesis we have included the *hot_cold_semi* variable. If we can reject this hypothesis, it is expected that there is a positive relationship between *hot_cold_semi* and underpricing. This variable is given by setting up average underpricing per semi-annual period against average underpricing to illustrate the hot and cold markets, supported by the hot and cold markets theory by Ibbotson and Jaffe (1975).

As expected, the coefficient on the *hot_cold_semi* is positive in regression (1) and statistically significant at a 1% level. When adding the yearly control variables in regression (3) the t-value decreases but is still significant at a 1% level. The drop in the t-value could be a sign that the control variables capture intertemporal variation. This clearly suggests that we reject the hypothesis that hot markets are not affecting IPO underpricing. Thus, we see a positive and correlated relationship between underpricing and hot issue markets.

Our data support Ibbotson and Jaffe's (1975) study on hot and cold markets as underpricing seems to be significantly higher in hot market periods. This means that issuers choose to take advantage of the market conditions, while it gives importance to the investor sentiment theory. IPOs will be underpriced and investors, affected by the market conditions, will misjudge the valuation due to their over-optimistic beliefs about the IPO, bidding for more shares than actually needed. Issuers would like this to happen and sell as many shares as possible, but still need to take into consideration that overflowing the market with shares could decrease the price. In other words, the market conditions could potentially mislead the investors to overvalue an IPO.

5.4. The effect of price revisions

In order to test hypothesis 4, we included two dummy variables in regression (2). *price_rev_up* and *price_rev_zero* are included as proxies for the information revelation during the bookbuilding process. We expected that offerings with upward price revisions would indicate higher underpricing due to increased demand for the IPO and information revealed during this process. The coefficient is expected to be positive for *price_rev_up.*

The output revealed a positive coefficient for *price_rev_up* and the test-statistics which was significant at 1% level. By correcting the standard errors, we got the same result, but with a slightly lower t-value. The dummy *price_rev_zero* was not significant in both outputs and the coefficient had a negative sign. We can therefore reject the hypothesis that underpricing is unaffected by upward price revisions. partial adjustment theory from Hanley (1993) is supported by our findings where our regressions have shown that upwards revised offer prices provide more underpricing.

Although we can reject the null hypothesis of price revisions not affecting underpricing, the number of observations was drastically reduced as explained in section 4.2.4 and 4.3.2. The explanatory power of the regression is also reduced when we researched this hypothesis. Despite a lower R-squared adjusted, the regular R-squared is almost equal to the other regressions and the F-value of the regression is significant at 1% level.

5.5. The effect of industry classification

We wanted to test hypothesis 5 to verify if industry classification affected the level of underpricing. Dummy variables were included for 8 of the 9 industries in our dataset to test this hypothesis. Earlier studies have shown that high-risk industries were more underpriced (Loughran & Ritter, 2003) to compensate for the risk. Christiansen (2011) refers to risk as a cyclical behaviour and there were no high-risk industries in the period of her study. Since every industry, except utilities, provides positive average underpricing, we expected that most of the coefficients would show a positive sign. Should we fail to reject the null hypothesis, the level of underpricing would be equal between all industries, which would defy the results of Loughran and Ritter's study.

When studying the output from regression (3) we see that every industry variable is significant at 10%, 5% or 1% level, except *industrials, utilities* and *communication_services*. An interesting finding is the change where *utilities* get a positive coefficient despite a negative average underpricing and vice versa for *communication_services*. When adding more control variables as a robustness check in regression (3), the sign is still negative and insignificant for *communication_services*. As most of the companies on the Norwegian stock market are primarily within *industrials* and *oil_and_gas* we obtain a small number of observations in some of the remaining industries. The small sample in some of the remaining industries could be a possible reason for the insignificant coefficients for *utilities* and *communication_services*. These two variables are among the industries with the fewest number of observations.

The significant variables indicate that industry classification affects the level of underpricing, supporting the investor sentiment theory. However, according to Loughran and Ritter (2003) tech companies should be more underpriced than other industries due to different risk levels. In our findings, tech companies had lower levels of underpricing than several of the other industries, suggesting that there is no compensation. This could lead us to refer risk as a cyclical behaviour as claimed by Christiansen (2011). In our case, *materials* and *health_care* experience more underpricing than other industries. These results provide support for rejecting our hypothesis of industries not affecting IPO underpricing. This will re-validate Loughran and Ritter's study (2003) that underpricing varies between industries due to risk compensation. Moreover, we can assume that some of our industries involve more risk than other industries for different time periods.

5.6. The effect of valuation uncertainty

In order for us to test hypothesis 6, the proxies *ln_mrkt_cap* and *age_of_firm* were included in regression (4) as proxies for valuation uncertainty. The idea was that companies with higher market capitalization and longer lifespan contain more available information that would lower valuation uncertainty. Beatty and Ritter (1986) claimed that IPO underpricing would be higher if the valuation uncertainty was high. Therefore, we would expect the sign of the coefficients to be negative as higher market capitalization and lifespan would result in lower valuation uncertainty.

Although our expectations suggest that the sign should be negative, the output gives small, but positive coefficients for the proxies. This can be interpreted as underpricing will increase when the firms market value and age increases, resulting in more underpricing when valuation uncertainty is decreasing. The output without corrected standard errors and the output with corrected standard errors provide t-statistics for the variables which are not significant for either variable. We therefore fail to reject the null hypothesis for hypothesis 6. IPO underpricing is unaffected by valuation uncertainty. This becomes even more clear as the coefficients provided the opposite sign of what valuation uncertainty predicts.

Our results do not find support for one of the most famous theories, Rock's (1986) Winner Curse, as our results indicate that underpricing should increase when information asymmetry is decreasing, and the variables are not significant. Rock claims that underpricing should increase in information asymmetry, and the information asymmetry is increasing in valuation uncertainty according to Beatty and Ritter (1986).

Part VI: Limitations and conclusion

Conclusion and limitations will be the end of our thesis, where we link our conclusion to our problem statement. The conclusion is followed by limitations of our research.

6.1. Conclusion

We have confirmed the existence of underpricing in the Norwegian stock market as the IPOs are underpriced by 3.475% in our research period. Other studies on the Norwegian market provide similar results. It has been shown that underpricing levels has decreased in the last decades. Our interpretation of the decreasing underpricing in recent decades compared to earlier studies is the increasing information availability. Company information, characteristics, reports and analysis are more easily available for the public at a faster pace, than before. The cause of underpricing has been widely discussed through several underpricing theories, where we have selected the most relatable to the Norwegian stock market in our time frame. By testing several hypotheses, we could answer our problem statement:

"Can IPO underpricing in Norway be explained by already existing theories in the time frame 2003 to 2019"

We have researched our problem statement with the use of variables or proxies for each of the hypotheses. Regression analysis were used for the hypothesis testing, where we included relevant variables in order to test the different theories. Our results have been tested and corrected for econometric issues.

Our findings give support for several of the selected theories, as they provide explanation of the underpricing in Norway. Carter and Manaster's (1990) and Michaely and Shaw's (1994) theory involving underwriter quality and Ibbotson and Jaffe's (1975) study on hot and cold markets are supported by our findings. One of our chosen theories, Hanley's (1993) partial adjustment theory, is also supported, but should be questioned as our sample size were reduced in this regression. In addition, the investor sentiment theory by Ljungqvist, Nanda and Singh (2004) and Loughran and Ritter's (2003) study on industries with higher underpricing due to risk compensation is supported by our study. However, we do not find support to the most famous "Winner's Curse" theory by Rock (1986). Our suggestion for decreasing underpricing in recent decades could be linked to the lack of support for winner's curse" as valuation uncertainty should decrease with an increase in publicly available company information. Our analysis shows that several of our chosen theories provides explanation of the underpricing levels in Norway. It is worth mentioning that our intention never was to create a model which explained all of the variation in underpricing as this is regarded as data mining. Our goal was to test the relevance of existing underpricing theories in the Norwegian market.

6.2. Limitations

Despite our results giving support to several established underpricing theories, there might be reasons for the non-significant results for the winner's curse and some of the industry dummies not being significant. There could also have been econometric issues affecting our results as well. Firstly, there could potentially be other proxies for valuation uncertainty which could have given different results, such as log sales, price/book measures et cetera. As we wanted to avoid data mining, we did not test several proxies for valuation uncertainty. Therefore, we kept the chosen proxies as we perceived them to be suitable for the hypothesis. It is also a possibility that the theory is more applicable for less transparent stock markets than the Norwegian market.

Secondly, due to the size of the Norwegian market, the number of listings within each industry was limited for the smaller industries. This clearly affected the significance for some of the industry dummies. If we had been able to obtain a larger sample by increasing the timespan, this issue could potentially have been solved. This proved to be difficult as previously explained, due to the availability of data. Another potential issue concerning the industry hypothesis was each company's relevance to its respective industry classification by the ICB. This classification compiled companies within sportswear together with companies which produced marine nutrition in *consumer goods*. The differences in company characteristics and risk levels within this industry could have been a factor for the non-significant result for some of the industries. A possible solution could have been to split the industry in two and place the respective companies within the industry we found most suitable. This would again provide an even smaller sample within each industry and would force us to derail from the standardized classification we originally chose.

Another suggestion which could have strengthened our research was if we were able to obtain a larger sample which included price ranges for more IPOs. It would be interesting to compare the results of price revision with 128 observations to a larger sample with price revisions to check the inference with the remaining variables. As the model with price revision were significant at 1% level and the unadjusted R-squared were almost identical to the other models, we do not see this as a critical issue.

Other sources of limitations to our results are econometric issues. Our analysis show that endogeneity and specification errors are problems we most likely will have in our research. If the omitted variable is correlated with one or more of the independent variables, the error term will include the omitted variable's effect and endogeneity will be present. Our chosen theories were supported but we also had to exclude some theories due to the absence of necessary data. This could potentially have made our regressions underfitted. Some of the excluded theories could explain significantly more of the underpricing phenomenon. But the timeframe of our thesis would not allow us to research all known theory. In addition, confidential data were also needed to test some of the excluded theories.

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Appendix

Appendix 1: List of IPO companies

Company	Adjusted underpricing	Industry	Subsector	Date of offering
Norwegian Air Shuttle ASA	2,70 %	Industrial	Airlines	18.12.2003
Bjørge ASA	-0,28 %	Oil & Gas	Oil Equipment & Services	17.12.2004
Sevan Marine ASA	15,84 %	Oil & Gas	Oil Equipment & Services	13.12.2004
Active 24 ASA	5,65 %	Technology	Computer Services	12.11.2004
Odfjell Invest Ltd.	5,96 %	Oil & Gas	Oil Equipment & Services	11.10.2004
Conseptor ASA	-2,00 %	Consumer Goods	Clothing & Accessories	24.06.2004
Medistim ASA	3,04 %	Healthcare	Medical Equipment	28.05.2004
Findexa Limited	-3,31 %	Communication Services	Broadcasting & Entertainment	25.05.2004
Mamut ASA	1,01 %	Technology	Software	10.05.2004
Catch Communications ASA	-2,96 %	Communication Services	Media	29.03.2004
Yara International ASA	23,76 %	Industrial	Diversified Industrial	25.03.2004
Opera Software ASA	18,55 %	Technology	Software	11.03.2004
Scorpion Offshore Ltd	1,36 %	Oil & Gas	Oil Equipment & Services	20.12.2005
NorDiag ASA	-1,72 %	Healthcare	Biotechnology	14.12.2005
Funcom N.V.	-10,77 %	Communication Services	Electronic Gaming & Multimedia	13.12.2005
DeepOcean ASA	-10,40 %	Oil & Gas	Oil Equipment & Services	07.12.2005
Future Information Research Management ASA	-2,49 %	Technology	Computer Service	06.12.2005
Odim ASA	4,12 %	Industrial	Marine Shipping	18.11.2005
Norgani Hotels ASA	1,36 %	Financials	Real Estate	16.11.2005
Biotec Pharmacon ASA	-2,21 %	Healthcare	Biotechnology	04.11.2005
Rygge-Vaaler Sparebank	14,69 %	Financials	Banks	01.11.2005
BW Gas ASA	-6,27 %	Industrial	Marine Shipping	25.10.2005
Cermaq ASA	-0,81 %	Consumer Goods	Fishing & Farming	24.10.2005
Powel ASA	-0,01 %	Technology	Software	24.10.2005
Bluewater Insurance ASA	0,47 %	Financials	Insurance	13.10.2005
Deep Sea Supply ASA	3,98 %	Industrial	Marine Shipping	15.09.2005
Aker American Shipping ASA	-3,97 %	Industrial	Marine Shipping	11.07.2005
Eastern Drilling ASA	1,44 %	Oil & Gas	Oil Equipment & Services	28.06.2005
Revus Oil & Gas ASA	5,17 %	Oil & Gas	Exploration & Production	27.06.2005
Eidesvik Offshore ASA	9,90 %	Oil & Gas	Oil Equipment & Services	27.06.2005
Kongsberg Automotive Holding ASA	1,90 %	Consumer Goods	Auto Parts	24.06.2005
Questerre Oil & Gas Corporation	34,20 %	Oil & Gas	Exploration & Production	17.06.2005
VIA Travel Group ASA	-0,76 %	Communication Services	Travel & Leisure	09.06.2005
Norway Oil & Gas & Marine Insurance ASA	3,24 %	Financials	Insurance	07.06.2005
Havila Shipping ASA	4,06 %	Industrial	Transportation Services	24.05.2005
Aker Seafoods ASA	0,33 %	Consumer Goods	Food Products	13.05.2005
Vizrt Limited	-6,32 %	Technology	Software	12.05.2005
Awilco Offshore ASA	0,62 %	Industrial	Marine Shipping	11.05.2005
Oslo Areal ASA	0,37 %	Financials	Real Estate	03.05.2005
Polimoon ASA	-0,43 %	Industrial	Container & Packaging	26.04.2005
International Maritime Exchange ASA	25,93 %	Oil & Gas	Oil Equipment & Services	04.04.2005
Wilson ASA	16,08 %	Industrial	Marine Shipping	17.03.2005
Exploration Resources ASA	14,90 %	Oil & Gas	Oil Equipment & Services	09.03.2005
Petrojack ASA	21,41 %	Oil & Gas	Oil Equipment & Services	23.02.2005
Spits ASA	-10,22 %	Communication Services	Media	12.12.2006
Faktor Eiendom ASA	-2,74 %	Financials	Real Estate	08.12.2006
Norwegian Property ASA	5,29 %	Financials	Real Estate	15.11.2006
Det norske oljeselskap ASA	4,16 %	Oil & Gas	Exploration & Production	10.11.2006
AKVA group ASA	-0,27 %	Consumer Goods	Fishing & Farming	10.11.2006
Eitzen Chemical ASA	-3,74 %	Industrial	Marine Shipping	02.11.2006
Northland Resources Inc	1,16 %	Materials	Iron & Steel	23.10.2006
Codfarmers ASA	-2,75 %	Consumer Goods	Fishing & Farming	19.10.2006
Marine Farms ASA	-3,22 %	Consumer Goods	Fishing & Farming	12.10.2006
Austevoll Seafood ASA	-0,09 %	Consumer Goods	Fishing & Farming	11.10.2006
Trolltech ASA	10,32 %	Technology	Software	05.07.2006
Petrojarl ASA	-4,83 %	Industrial	Marine Shipping	30.06.2006
Telio Holding ASA (NEXTGENTEL)	-5,69 %	Communication Services	Telecommunications	02.06.2006
Renewable Energy Corporation ASA	21,69 %	Oil & Gas	Renewable Energy Equipment	09.05.2006
Dolphin Interconnect Solutions ASA	18,99 %	Communication Services	Media	20.04.2006
B+H Ocean Carriers Ltd.	22,35 %	Industrial	Marine Shipping	12.04.2006
SeaBird Exploration Ltd.	27,75 %	Oil & Gas	Oil Equipment & Services	11.04.2006
Block Watne Gruppen ASA	10,80 %	Consumer Goods	Home Construction	17.03.2006
Petrobank Oil & Gas and Resources Ltd.	13,87 %	Oil & Gas	Exploration & Production	08.02.2006
IGE Nordic AB	-7,77 %	Technology	Software	21.12.2007
Aker Philadelphia Shipyard ASA	0,00 %	Industrial	Heavy Construction	17.12.2007
Aker Exploration ASA	-9,28 %	Oil & Gas	Exploration & Production	17.12.2007
Hafslund Infratek ASA	-3,97 %	Communication Services	Telecommunications	05.12.2007
Scandinavian Clinical Nutrition AB	4,82 %	Healthcare	Medical Supplies	22.11.2007
Norwegian Oil & Gas Company ASA	5,50 %	Oil & Gas	Oil Equipment & Services	09.11.2007
Eastern Echo Holding Plc.	4,71 %	Oil & Gas	Oil Equipment & Services	30.10.2007
Nøtterø Sparebank	4,54 %	Financials	Banks	29.10.2007
Ability Drilling ASA	3,02 %	Industrial	Oil Equipment & Services	15.10.2007
Etman International ASA	-5,27 %	Industrial	Electronic Equipment	11.10.2007
Pronova BioPharma ASA	3,59 %	Healthcare	Biotechnology	11.10.2007
London Mining Plc	7,59 %	Materials	Iron & Steel	09.10.2007
Seajacks International Ltd.	3,60 %	Industrial	Renewable Energy	08.10.2007
Dockwise Ltd	1,34 %	Industrial	Marine Shipping	02.10.2007
Cecon ASA	2,85 %	Oil & Gas	Oil Equipment & Services	26.06.2007
24SevenOffice ASA	-14,44 %	Technology	Software	22.06.2007
Grieg Seafood ASA	1,50 %	Consumer Goods	Fishing & Farming	21.06.2007
Badger Explorer ASA	6,27 %	Technology	Hardware	12.06.2007

RomReal Ltd.	-1,33 %	Financials	Real Estate	11.06.2007
InvivoSense ASA	0,45 %	Healthcare	Medical Equipment	06.06.2007
SCAN Geophysical ASA	-8,42 %	Industrial	Oil Equipment & Services	31.05.2007
Arrow Seismic ASA	0,55 %	Industrial	Oil Equipment & Services	30.05.2007
Protector Forsikring ASA	9,44 %	Financials	Insurance	25.05.2007
Maritime Industrial Services Co Ltd. Inc	0,92 %	Oil & Gas	Oil Equipment & Services	22.05.2007
Bouvet ASA	-0,66 %	Technology	Computer Services	15.05.2007
Fred. Olsen Production ASA	-3,52 %	Industrial	Marine Shipping	11.05.2007
ScanArc ASA	2,37 %	Materials	Commodity Chemicals	10.05.2007
SalMar ASA	4,67 %	Consumer Goods	Fishing & Farming	08.05.2007
Klepp Sparebank	13,54 %	Financials	Banks	03.05.2007
Wega Mining ASA	16,77 %	Materials	Platinum & Precious Metals	02.05.2007
Rem Offshore ASA	4,64 %	Industrial	Marine Shipping	30.03.2007
Wavefield Inseis ASA	6,30 %	Oil & Gas	Oil Equipment & Production	30.03.2007
Nexus Floating Production Ltd	0,69 %	Industrial	Industrial Suppliers	30.03.2007
Electromagnetic Geoservices ASA	7,97 %	Oil & Gas	Oil Equipment & Production	30.03.2007
APL Plc	-10,86 %	Oil & Gas	Oil Equipment & Services	28.03.2007
Algeta ASA	-7,22 %	Healthcare	Biotechnology	27.03.2007
NEAS ASA	-4,53 %	Financials	Real Estate	23.03.2007
Copeinca ASA	4,05 %	Consumer Goods	Food Products	29.01.2007
Bergen Group ASA	0,04 %	Industrial	Business Support Services	30.06.2008
Remedial Offshore PCL	20,05 %	Oil & Gas	Oil Equipment & Services	27.06.2008
Norway Pelagic ASA	11,90 %	Consumer Goods	Fishing & Farming	24.06.2008
Camposol Plc.	2,99 %	Consumer Goods	Fishing & Farming	15.05.2008
NattoPharma ASA	-34,63 %	Healthcare	Biotechnology	30.01.2008
Aqua Bio Technology ASA	14,95 %	Consumer Goods	Nondurable Household Products	10.01.2008
FLEX LNG LTD	1,60 %	Industrial	Marine Shipping	30.10.2009
Golar LNG Energy Ltd	1,40 %	Industrial	Marine Shipping	08.10.2009
Polarcus Limited	-5,11 %	Oil & Gas	Oil Equipment & Services	30.09.2009
Gjensidige Forsikring ASA	1,02 %	Financials	Insurance	10.12.2010
Floatel International Ltd	-3,02 %	Oil & Gas	Oil Equipment & Services	01.12.2010
Statoil Fuel & Retail ASA	4,72 %	Oil & Gas	Integrated Oil & Gas	22.10.2010
CellCura ASA	-24,67 %	Healthcare	Medical Equipment	06.10.2010
Storm Real Estate ASA	-2,80 %	Financials	Real Estate	06.07.2010
Morpol ASA	-3,31 %	Consumer Goods	Farming & fishing	30.06.2010
Wilh. Wilhelmsen ASA	0,06 %	Industrial	Marine Shipping	24.06.2010
Dannemora Mineral AB	20,71 %	Materials	Iron & Steel	17.06.2010
Avocet Mining PLC	26,66 %	Materials	Gold Mining	16.06.2010
Bridge Energy ASA	-16,01 %	Oil & Gas	Exploration & Production	21.05.2010
Sølvtrans Holding ASA	-1,03 %	Consumer Goods	Fishing & Farming	30.03.2010
P/f Bakkafrost	9,86 %	Consumer Goods	Fishing & Farming	26.03.2010
IDEX ASA	32,11 %	Technology	Software	12.03.2010
North Energy ASA	2,17 %	Oil & Gas	Exploration & Production	05.02.2010
Hofseth BioCare ASA	24,55 %	Healthcare	Biotechnology	02.12.2011
Nordic Financials ASA	7,42 %	Financials	Industrial & Office REITs	07.11.2011
Awilco LNG ASA	-17,61 %	Industrial	Marine Shipping	06.09.2011
Asia Offshore Drilling Limited	-0,34 %	Oil & Gas	Oil Equipment & Services	15.07.2011
Höegh LNG Holdings Ltd.	4,12 %	Industrial	Marine Shipping	05.07.2011
Awilco Drilling Plc	6,55 %	Oil & Gas	Oil Equipment & Services	10.06.2011
Sevan Drilling ASA	1,82 %	Oil & Gas	Oil Equipment & Services	03.05.2011
Norway Royal Salmon ASA	3,03 %	Consumer Goods	Fishing & Farming	29.03.2011
Aker Drilling ASA	-2,52 %	Oil & Gas	Oil Equipment & Services	25.02.2011
Borregaard ASA	-1,37 %	Materials	Speciality Chemicals	18.10.2012
Spectrum ASA	22,48 %	Oil & Gas	Exploration & Production	02.07.2012
Selvaag Bolig ASA	-4,23 %	Financials	Real Estate	14.06.2012
Link Mobility Group ASA	-16,39 %	Technology	Software	12.12.2013
Atlantic Petroleum P/F	1,17 %	Oil & Gas	Oil Equipment & Services	12.12.2013
Napatech A/S	2,11 %	Technology	Electronic Equipment	06.12.2013
BW LPG Limited	6,14 %	Industrial	Marine Shipping	21.11.2013
REC Solar ASA	215,83 %	Utilities	Alternative Electricity	25.10.2013
Western Bulk ASA	-2,36 %	Industrial	Marine Shipping	25.10.2013
Odfjell Drilling Ltd.	-2,57 %	Oil & Gas	Oil Equipment & Services	27.09.2013
Ocean Yield ASA	2,74 %	Industrial	Marine Shipping	05.07.2013
MultiClient Geophysical ASA	-1,23 %	Oil & Gas	Oil Equipment & Services	02.05.2013
Serodus ASA	-18,40 %	Healthcare	Pharmaceuticals	09.04.2013
EAM Solar ASA	-1,81 %	Utilities	Alternative Electricity	26.03.2013
Asetek AS	-2,35 %	Technology	Computer Hardware	20.03.2013
RenoNorden ASA	-0,31 %	Industrial	Waste & Disposal Services	16.12.2014
RAK Petroleum plc	28,63 %	Oil & Gas	Oil Equipment & Services	07.11.2014
Entra ASA	-0,37 %	Financials	Real Estate	17.10.2014
XXL ASA	5,57 %	Consumer Goods	Personal Goods	03.10.2014
Scatec Solar ASA	0,77 %	Utilities	Alternative Electricity	02.10.2014
Aqualis Offshore Holding ASA	169,67 %	Oil & Gas	Business Support Services	13.08.2014
Havyard Group ASA	-5,90 %	Industrial	Aerospace & Defense	01.07.2014
Cxense ASA	-1,31 %	Technology	Software	01.07.2014
NEXT Biometrics Group ASA	-8,51 %	Technology	Electronic Equipment	25.06.2014
Zalaris ASA	7,78 %	Industrial	Business Training & Employment A	20.06.2014
Magseis ASA	19,80 %	Oil & Gas	Oil Equipment & Services	06.06.2014
African Petroleum Corporation Limited	-22,42 %	Oil & Gas	Exploration & Production	30.05.2014
Avance Gas Holding Ltd.	-1,24 %	Oil & Gas	Integrated Oil & Gas	15.04.2014
Vardia Insurance Group ASA	-13,94 %	Financials	Property & Casuality Insurance	08.04.2014
Tanker Investments Ltd	-0,53 %	Industrial	Marine Shipping	25.03.2014
Kid ASA	-3,04 %	Consumer Goods	Durable Household Products	02.11.2015

Skandiabanken	-7,29 %	Financials	Banks	02.11.2015
Hugo Games A/S	11,15 %	Communication Services	Electronic Gaming & Multimedia	26.06.2015
Pioneer Property Group ASA	3,00 %	Financials	Real Estate	19.06.2015
Europris ASA	-4,80 %	Consumer Goods	Food Retailers & Wholesalers	19.06.2015
Vistin Pharma ASA	33,31 %	Healthcare	Pharmaceuticals	10.06.2015
Multiconsult ASA	18,95 %	Industrial	Industrial Engineering	22.05.2015
Nordic Nanovector ASA	3,02 %	Healthcare	Biotechnology	23.03.2015
Team Tankers International Ltd.	-3,43 %	Industrial	Marine Shipping	09.03.2015
Solstad Offshore ser. B	-24,84 %	Oil & Gas	Oil Equipment & Services	13.12.2016
Pareto Bank ASA	40,75 %	Financials	Banks	12.12.2016
Arcus ASA	1,73 %	Consumer Goods	Distillers & Vintners	01.12.2016
Norwegian Finans Holding ASA	56,96 %	Financials	Banks	17.06.2016
B2Holding ASA	4,39 %	Financials	Consumer Finance	08.06.2016
Tysnes Sparebank	1,36 %	Financials	Banks	18.12.2017
Lillestrøm Sparebank	6,37 %	Financials	Banks	08.12.2017
Komplett Bank ASA	6,41 %	Financials	Banks	10.11.2017
Crayon Group Holding ASA	-5,29 %	Technology	Software	08.11.2017
Self Storage Group ASA	-4,15 %	Industrial	Diversified Industrials	27.10.2017
Northern Drilling Ltd.	-1,74 %	Oil & Gas	Oil Equipment & Services	26.10.2017
Webstep ASA	10,29 %	Technology	Computer Services	11.10.2017
SpareBank 1 Nordvest	0,31 %	Financials	Banks	02.10.2017
Infront ASA	-6,61 %	Technology	Software	29.09.2017
EVRY ASA	-8,22 %	Technology	Computer Services	21.06.2017
Grong Sparebank	0,72 %	Financials	Banks	14.06.2017
SpareBank 1 Østlandet	0,68 %	Financials	Banks	13.06.2017
Saferoad Holding ASA	0,17 %	Industrial	Building Materials & Fixtures	29.05.2017
BerGenBio ASA	1,00 %	Healthcare	Biotechnology	07.04.2017
Unified Messaging Systems ASA	15,46 %	Technology	Software	06.01.2017
Sparebanken Telemark	5,35 %	Financials	Banks	03.10.2018
poLight ASA	1,48 %	Technology	Electronic Equipment	01.10.2018
Shelf Drilling Ltd.	-2,81 %	Oil & Gas	Oil Equipment & Services	25.06.2018
TargetEveryOne AB	-1,16 %	Technology	Software	08.06.2018
SoftOx Solutions AS	33,64 %	Healthcare	Biotechnology	01.06.2018
PCI Biotech Holding ASA	66,57 %	Healthcare	Biotechnology	27.04.2018
Elkem ASA	-2,69 %	Materials	Speciality Chemicals	22.03.2018
Fjordkraft Holding ASA	0,59 %	Utilities	Conventional Electricity	21.03.2018
Sunndal Sparebank	22,52 %	Financials	Banks	15.03.2018
Salmones Camanchaca S.A.	4,77 %	Consumer Goods	Farming & Fishing	02.02.2018
MPC Container Ships ASA	11,44 %	Industrial	Marine Shipping Services	03.05.2018
Hafnia Limited	-0,56 %	Oil & Gas	Oil Equipment & Services	08.11.2019
SATS ASA	-6,23 %	Consumer Goods	Leisure	23.10.2019
Norske Skog ASA	1,23 %	Materials	Forestry & Paper	18.10.2019
Kahoot! AS	15,41 %	Communication Services	Entertainment	10.10.2019
Scanship Holding ASA	6,51 %	Industrial	Waste & Disposal Services	24.06.2019
NORBIT ASA	7,04 %	Technology	Electronic Equipment	21.06.2019
OKEA ASA	-3,96 %	Oil & Gas	Oil & Gas Producers	18.06.2019
Nidaros Sparebank	2,80 %	Financials	Banks	14.06.2019
Ultimovacs ASA	0,43 %	Healthcare	Biotechnology	03.06.2019
Klaveness Combination Carriers ASA	-11,40 %	Industrial	Marine Shipping Services	22.05.2019
Adevinta ASA	13,42 %	Communication Services	Mobile Telecommunications	10.04.2019
Zwipe AS	-5,97 %	Technology	Software	28.01.2019

Appendix 2: STATA regression output (1)

Regression output:

Source	SS	df	MS
Model	.847868151	16	.052991759
Residual	1.89110421	185	.010222185
Total	2.73897236	201	.013626728

Number of obs	=	202
F(16, 185)	=	5.18
Prob > F	=	0.0000
R-squared	=	0.3096
Adj R-squared	=	0.2498
Root MSE	=	.1011

underpricin~p	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
dummy_OBX	.0262997	.0182851	1.44	0.152	-.0097745	.0623739
dummy_merkur	0	(omitted)				
daycount_su~r	-.005762	.0029865	-1.93	0.055	-.0116539	.0001299
daycount_su~t	-.0016835	.0012664	-1.33	0.185	-.004182	.000815
outliers	0	(omitted)				
mrkt_cap	1.97e-12	1.86e-12	1.06	0.289	-1.69e-12	5.63e-12
oversubscri~d	.0434059	.0150688	2.88	0.004	.013677	.0731348
hot_cold_semi	.0861005	.0157627	5.46	0.000	.0550027	.1171983
nr_of_und	-.0208228	.0092172	-2.26	0.025	-.0390071	-.0026384
total_rank	-.0072217	.0037346	-1.93	0.055	-.0145895	.0001462
industrial	.0209003	.0259746	0.80	0.422	-.0303442	.0721448
oil_and_gas	.0511615	.026171	1.95	0.052	-.0004705	.1027935
technology	.0251141	.0295492	0.85	0.396	-.0331826	.0834109
healthcare	.0624234	.033795	1.85	0.066	-.0042497	.1290965
communicati~s	-.0327316	.0381778	-0.86	0.392	-.1080514	.0425881
utilities	.0057501	.0629397	0.09	0.927	-.1184218	.129922
materials	.0758772	.0405493	1.87	0.063	-.0041213	.1558758
financials	.0609174	.0286259	2.13	0.035	.0044422	.1173925
_cons	.0956975	.0503117	1.90	0.059	-.0035609	.1949559

Robust regression output:

Linear regression

Number of obs	=	202
F(15, 185)	=	.
Prob > F	=	.
R-squared	=	0.3096
Root MSE	=	.1011

underpricin~p	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
dummy_OBX	.0262997	.0187286	1.40	0.162	-.0106493	.0632488
dummy_merkur	0	(omitted)				
daycount_su~r	-.005762	.0032223	-1.79	0.075	-.0121192	.0005953
daycount_su~t	-.0016835	.0014274	-1.18	0.240	-.0044997	.0011327
outliers	0	(omitted)				
mrkt_cap	1.97e-12	1.12e-12	1.76	0.080	-2.36e-13	4.18e-12
oversubscri~d	.0434059	.0153604	2.83	0.005	.0131018	.0737099
hot_cold_semi	.0861005	.01758	4.90	0.000	.0514175	.1207834
nr_of_und	-.0208228	.0088896	-2.34	0.020	-.0383608	-.0032847
total_rank	-.0072217	.004083	-1.77	0.079	-.0152769	.0008336
industrial	.0209003	.0174355	1.20	0.232	-.0134977	.0552983
oil_and_gas	.0511615	.0199071	2.57	0.011	.0118873	.0904357
technology	.0251141	.0242246	1.04	0.301	-.0226779	.0729062
healthcare	.0624234	.0478062	1.31	0.193	-.031892	.1567388
communicati~s	-.0327316	.0276106	-1.19	0.237	-.0872039	.0217406
utilities	.0057501	.0349685	0.16	0.870	-.0632381	.0747383
materials	.0758772	.0320079	2.37	0.019	.0127298	.1390246
financials	.0609174	.0277708	2.19	0.030	.0061291	.1157056
_cons	.0956975	.050475	1.90	0.060	-.0038831	.195278

Appendix 3: STATA regression output (2)

Regression output:

Source	SS	df	MS
Model	.248461726	18	.013803429
Residual	.56999348	109	.005229298
Total	.818455206	127	.006444529

Number of obs	=	128
F(18, 109)	=	2.64
Prob > F	=	0.0010
R-squared	=	0.3036
Adj R-squared	=	0.1886
Root MSE	=	.07231

underpricing_dep	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
price_rev_up	.0457691	.0158181	2.89	0.005	.0144182	.07712
price_rev_zero	-.0281465	.0341731	-0.82	0.412	-.0958764	.0395834
dummy_OBX	.0168384	.0181599	0.93	0.356	-.019154	.0528307
dummy_merkur	0	(omitted)				
daycount_subscr	-.001888	.0029947	-0.63	0.530	-.0078234	.0040474
daycount_subscr_list	-.0022273	.0014095	-1.58	0.117	-.005021	.0005664
outliers	0	(omitted)				
mrkt_cap	2.17e-12	1.62e-12	1.34	0.183	-1.04e-12	5.38e-12
oversubscribed	.0058342	.0142433	0.41	0.683	-.0223955	.034064
hot_cold_semi	.0356955	.014857	2.40	0.018	.0062494	.0651416
nr_of_und	-.0065898	.0083417	-0.79	0.431	-.0231227	.0099431
total_rank	-.0035208	.0037728	-0.93	0.353	-.0109983	.0039567
industrial	.0365256	.0243593	1.50	0.137	-.0117537	.084805
oil_and_gas	.0472508	.0239519	1.97	0.051	-.0002211	.0947227
technology	.0246567	.024984	0.99	0.326	-.0248608	.0741741
healthcare	.0516009	.0333802	1.55	0.125	-.0145575	.1177593
communication_services	-.0284655	.0317197	-0.90	0.371	-.091333	.0344019
utilities	.0019262	.046347	0.04	0.967	-.089932	.0937843
materials	.0041897	.040976	0.10	0.919	-.0770235	.0854028
financials	.0076534	.0249135	0.31	0.759	-.0417244	.0570312
_cons	.0229735	.0519169	0.44	0.659	-.0799241	.1258711

Robust regression output:

Linear regression

Number of obs	=	128
F(17, 109)	=	.
Prob > F	=	.
R-squared	=	0.3036
Root MSE	=	.07231

underpricing_dep	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
price_rev_up	.0457691	.0159527	2.87	0.005	.0141514	.0773868
price_rev_zero	-.0281465	.0368739	-0.76	0.447	-.1012293	.0449364
dummy_OBX	.0168384	.0208243	0.81	0.421	-.0244348	.0581115
dummy_merkur	0	(omitted)				
daycount_subscr	-.001888	.0026868	-0.70	0.484	-.0072131	.0034371
daycount_subscr_list	-.0022273	.0013078	-1.70	0.091	-.0048194	.0003648
outliers	0	(omitted)				
mrkt_cap	2.17e-12	1.01e-12	2.14	0.035	1.61e-13	4.18e-12
oversubscribed	.0058342	.0143894	0.41	0.686	-.0226851	.0343536
hot_cold_semi	.0356955	.0155959	2.29	0.024	.004785	.0666061
nr_of_und	-.0065898	.0071308	-0.92	0.357	-.0207229	.0075432
total_rank	-.0035208	.0030936	-1.14	0.258	-.0096522	.0026106
industrial	.0365256	.0209066	1.75	0.083	-.0049105	.0779618
oil_and_gas	.0472508	.0225512	2.10	0.038	.002555	.0919465
technology	.0246567	.0217771	1.13	0.260	-.0185049	.0678182
healthcare	.0516009	.0450097	1.15	0.254	-.0376069	.1408087
communication_services	-.0284655	.0222826	-1.28	0.204	-.0726288	.0156977
utilities	.0019262	.0282074	0.07	0.946	-.05398	.0578324
materials	.0041897	.0196526	0.21	0.832	-.0347611	.0431405
financials	.0076534	.0147209	0.52	0.604	-.0215229	.0368297
_cons	.0229735	.0481028	0.48	0.634	-.0723647	.1183116

Appendix 4: STATA regression output (3)

Regression output:

Source	SS	df	MS			
				Number of obs	=	202
				F(32, 169)	=	3.38
Model	1.06841765	32	.033388052	Prob > F	=	0.0000
Residual	1.6705547	169	.009884939	R-squared	=	0.3901
				Adj R-squared	=	0.2746
Total	2.73897236	201	.013626728	Root MSE	=	.09942

underpricin~p	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
dummy_OBX	.0386404	.0208482	1.85	0.066	-.0025161	.0797969
dummy_merkur	0	(omitted)				
daycount_su~r	-.0040155	.0032427	-1.24	0.217	-.0104169	.0023859
daycount_su~t	-.0012759	.001308	-0.98	0.331	-.0038581	.0013063
outliers	0	(omitted)				
mrkt_cap	2.80e-12	1.94e-12	1.45	0.150	-1.02e-12	6.63e-12
oversubscri~d	.0473045	.0160803	2.94	0.004	.0155603	.0790487
hot_cold_semi	.0981775	.022074	4.45	0.000	.0546013	.1417537
nr_of_und	-.0242022	.0100619	-2.41	0.017	-.0440655	-.0043389
total_rank	-.0089612	.0039353	-2.28	0.024	-.0167299	-.0011925
dummy_2004	-.0725414	.1096028	-0.66	0.509	-.2889084	.1438255
dummy_2005	-.0384815	.1039123	-0.37	0.712	-.2436148	.1666518
dummy_2006	.0094268	.1053888	0.09	0.929	-.1986213	.2174749
dummy_2007	.0051263	.1034946	0.05	0.961	-.1991824	.2094351
dummy_2008	.0044578	.1152164	0.04	0.969	-.222991	.2319066
dummy_2009	-.0102698	.1172205	-0.09	0.930	-.2416748	.2211353
dummy_2010	-.0448252	.1087891	-0.41	0.681	-.2595858	.1699355
dummy_2011	.0373921	.1092561	0.34	0.733	-.1782904	.2530745
dummy_2012	-.0065917	.1209749	-0.05	0.957	-.2454083	.2322248
dummy_2013	-.0071897	.1068649	-0.07	0.946	-.2181518	.2037724
dummy_2014	-.0233002	.1071652	-0.22	0.828	-.234855	.1882546
dummy_2015	-.0005356	.1089893	-0.00	0.996	-.2156915	.2146202
dummy_2016	.1638374	.1175908	1.39	0.165	-.0682988	.3959735
dummy_2017	-.0065836	.1059424	-0.06	0.951	-.2157246	.2025574
dummy_2018	.0107723	.1092015	0.10	0.922	-.2048025	.226347
dummy_2019	.0170789	.1075635	0.16	0.874	-.1952622	.2294201
industrial	.0338008	.0270328	1.25	0.213	-.0195647	.0871662
oil_and_gas	.0684943	.0273028	2.51	0.013	.0145958	.1223928
technology	.0484405	.0318847	1.52	0.131	-.0145031	.1113841
healthcare	.074306	.0346947	2.14	0.034	.0058151	.1427969
communicati~s	-.022299	.0388799	-0.57	0.567	-.0990518	.0544539
utilities	.0213738	.0655172	0.33	0.745	-.1079638	.1507114
materials	.0863465	.0419141	2.06	0.041	.0036039	.1690891
financials	.0517858	.0298185	1.74	0.084	-.0070789	.1106505
_cons	.0779374	.1161101	0.67	0.503	-.1512755	.3071503

Robust regression output:

Linear regression			
	Number of obs	=	202
	F(31, 169)	=	.
	Prob > F	=	.
	R-squared	=	0.3901
	Root MSE	=	.09942

underpricin~p	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
dummy_OBX	.0386404	.0205003	1.88	0.061	-.0018292	.07911
dummy_merkur	0	(omitted)				
daycount_su~r	-.0040155	.0034631	-1.16	0.248	-.010852	.0028209
daycount_su~t	-.0012759	.0014985	-0.85	0.396	-.004234	.0016823
outliers	0	(omitted)				
mrkt_cap	2.80e-12	1.48e-12	1.89	0.060	-1.23e-13	5.73e-12
oversubscri~d	.0473045	.0173058	2.73	0.007	.0131412	.0814678
hot_cold_semi	.0981775	.0220863	4.45	0.000	.054577	.141778
nr_of_und	-.0242022	.0110163	-2.20	0.029	-.0459495	-.0024549
total_rank	-.0089612	.0043836	-2.04	0.042	-.0176149	-.0003075
dummy_2004	-.0725414	.0458584	-1.58	0.116	-.1630705	.0179877
dummy_2005	-.0384815	.0296317	-1.30	0.196	-.0969775	.0200145
dummy_2006	.0094268	.0313899	0.30	0.764	-.05254	.0713936
dummy_2007	.0051263	.0274522	0.19	0.852	-.049067	.0593197
dummy_2008	.0044578	.0552737	0.08	0.936	-.1046581	.1135737
dummy_2009	-.0102698	.0343753	-0.30	0.765	-.0781301	.0575905
dummy_2010	-.0448252	.0434886	-1.03	0.304	-.1306759	.0410256
dummy_2011	.0373921	.0516786	0.72	0.470	-.0646267	.1394108
dummy_2012	-.0065917	.0635744	-0.10	0.918	-.132094	.1189106
dummy_2013	-.0071897	.0334625	-0.21	0.830	-.073248	.0588685
dummy_2014	-.0233002	.0466819	-0.50	0.618	-.1154549	.0688545
dummy_2015	-.0005356	.0460272	-0.01	0.991	-.0913979	.0903266
dummy_2016	.1638374	.1039563	1.58	0.117	-.0413828	.3690575
dummy_2017	-.0065836	.0346663	-0.19	0.850	-.0750184	.0618511
dummy_2018	.0107723	.0661698	0.16	0.871	-.1198535	.1413981
dummy_2019	.0170789	.029447	0.58	0.563	-.0410524	.0752102
industrial	.0338008	.0210323	1.61	0.110	-.0077191	.0753206
oil_and_gas	.0684943	.0218425	3.14	0.002	.0253749	.1116136
technology	.0484405	.028207	1.72	0.088	-.0072429	.1041239
healthcare	.074306	.0451137	1.65	0.101	-.0147531	.1633651
communicati~s	-.022299	.0256384	-0.87	0.386	-.0729117	.0283137
utilities	.0213738	.0553653	0.39	0.700	-.0879229	.1306705
materials	.0863465	.0377261	2.29	0.023	.0118714	.1608216
financials	.0517858	.022571	2.29	0.023	.0072283	.0963433
_cons	.0779374	.064615	1.21	0.229	-.0496191	.2054939

Appendix 4: STATA regression output (4)

Regression output:

Source	SS	df	MS
Model	.837506551	17	.049265091
Residual	1.9014658	184	.010334053
Total	2.73897236	201	.013626728

Number of obs	=	202
F(17, 184)	=	4.77
Prob > F	=	0.0000
R-squared	=	0.3058
Adj R-squared	=	0.2416
Root MSE	=	.10166

underpricing_dep	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
dummy_OBX	.0267171	.018825	1.42	0.158	-.0104235	.0638577
dummy_merkur	0	(omitted)				
daycount_subscr	-.0058539	.0030035	-1.95	0.053	-.0117797	.0000719
daycount_subscr_list	-.0017684	.0012731	-1.39	0.166	-.0042802	.0007433
outliers	0	(omitted)				
age_of_firm	.0001557	.0005457	0.29	0.776	-.0009209	.0012323
ln_mrkt_cap	.0013164	.0058718	0.22	0.823	-.0102682	.012901
oversubscribed	.0434174	.0152227	2.85	0.005	.0133838	.073451
hot_cold_semi	.0873201	.0158965	5.49	0.000	.0559573	.118683
nr_of_und	-.0191596	.0098167	-1.95	0.052	-.0385274	.0002082
total_rank	-.0076682	.0037375	-2.05	0.042	-.015042	-.0002944
industrial	.0231697	.0262544	0.88	0.379	-.0286287	.0749681
oil_and_gas	.0542306	.0263596	2.06	0.041	.0022247	.1062366
technology	.0261443	.030653	0.85	0.395	-.0343321	.0866208
healthcare	.0635983	.0346189	1.84	0.068	-.0047027	.1318992
communication_services	-.030629	.0388602	-0.79	0.432	-.1072978	.0460399
utilities	.0064397	.0634002	0.10	0.919	-.1186451	.1315246
materials	.0823447	.0403233	2.04	0.043	.0027892	.1619003
financials	.0622615	.0289018	2.15	0.033	.0052399	.1192831
_cons	.0699607	.1250313	0.56	0.576	-.1767186	.3166401

Robust regression output:

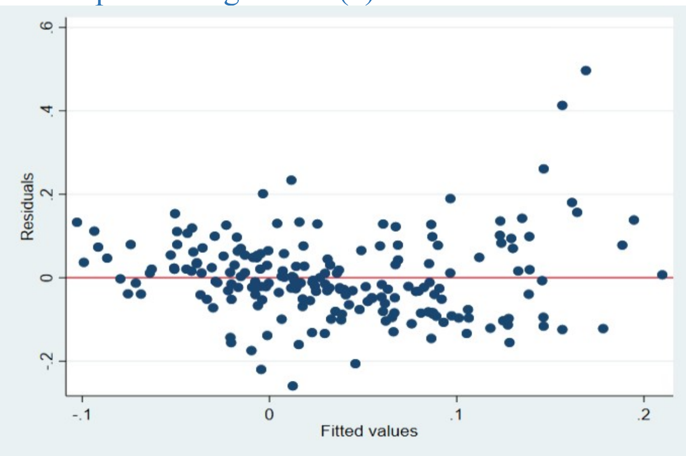
Linear regression

Number of obs	=	128
F(17, 109)	=	.
Prob > F	=	.
R-squared	=	0.3036
Root MSE	=	.07231

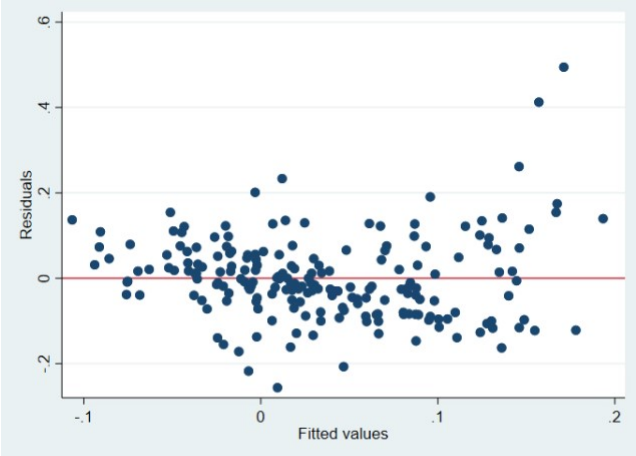
underpricing_dep	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
price_rev_up	.0457691	.0159527	2.87	0.005	.0141514	.0773868
price_rev_zero	-.0281465	.0368739	-0.76	0.447	-.1012293	.0449364
dummy_OBX	.0168384	.0208243	0.81	0.421	-.0244348	.0581115
dummy_merkur	0	(omitted)				
daycount_subscr	-.001888	.0026868	-0.70	0.484	-.0072131	.0034371
daycount_subscr_list	-.0022273	.0013078	-1.70	0.091	-.0048194	.0003648
outliers	0	(omitted)				
mrkt_cap	2.17e-12	1.01e-12	2.14	0.035	1.61e-13	4.18e-12
oversubscribed	.0058342	.0143894	0.41	0.686	-.0226851	.0343536
hot_cold_semi	.0356955	.0155959	2.29	0.024	.004785	.0666061
nr_of_und	-.0065898	.0071308	-0.92	0.357	-.0207229	.0075432
total_rank	-.0035208	.0030936	-1.14	0.258	-.0096522	.0026106
industrial	.0365256	.0209066	1.75	0.083	-.0049105	.0779618
oil_and_gas	.0472508	.0225512	2.10	0.038	.002555	.0919465
technology	.0246567	.0217771	1.13	0.260	-.0185049	.0678182
healthcare	.0516009	.0450097	1.15	0.254	-.0376069	.1408087
communication_services	-.0284655	.0222826	-1.28	0.204	-.0726288	.0156977
utilities	.0019262	.0282074	0.07	0.946	-.05398	.0578324
materials	.0041897	.0196526	0.21	0.832	-.0347611	.0431405
financials	.0076534	.0147209	0.52	0.604	-.0215229	.0368297
_cons	.0229735	.0481028	0.48	0.634	-.0723647	.1183116

Appendix 6: Residuals

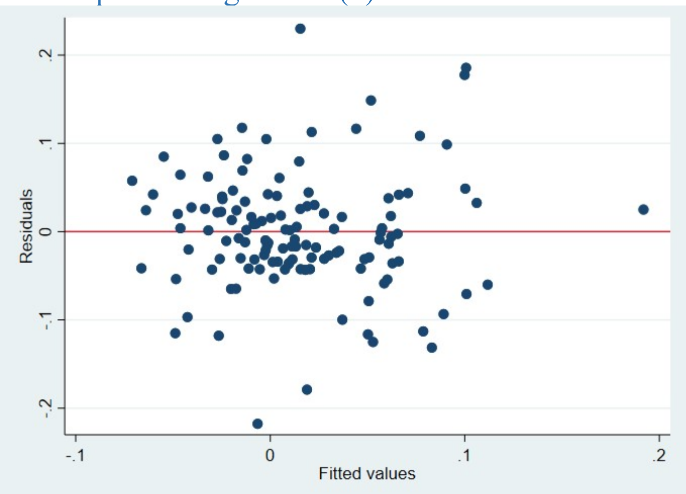
Scatter plot for regression (1):



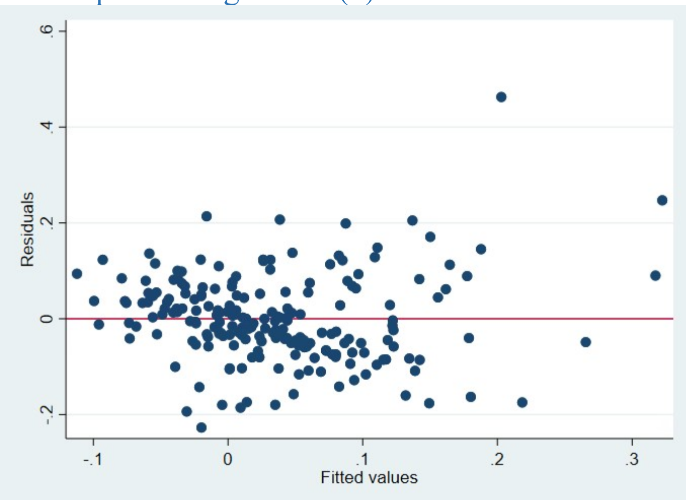
Scatter plot for regression (4):



Scatter plot for regression (2):

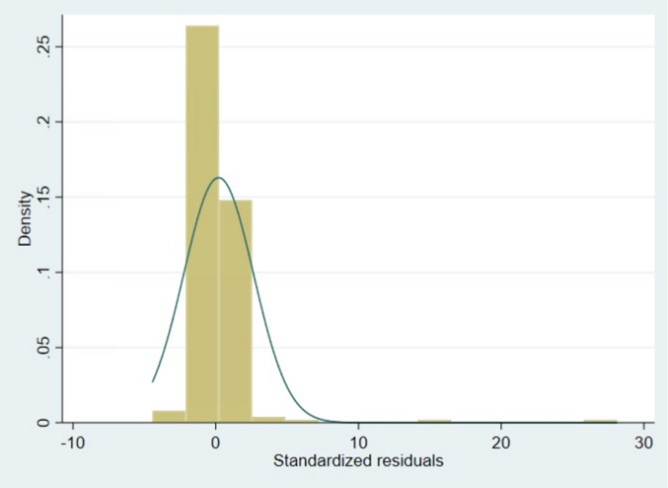


Scatter plot for regression (3):

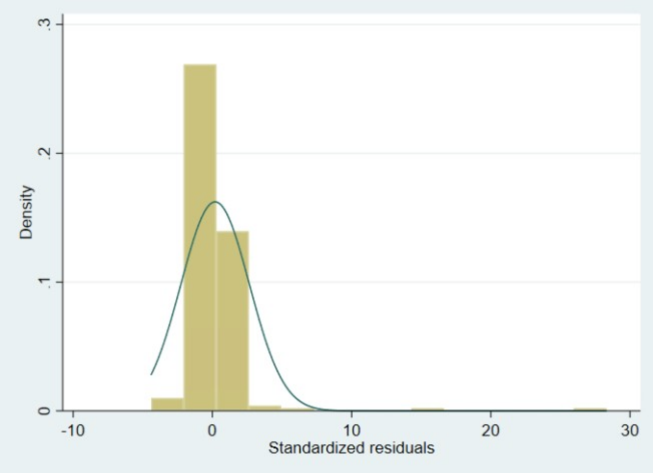


Appendix 7: Distribution

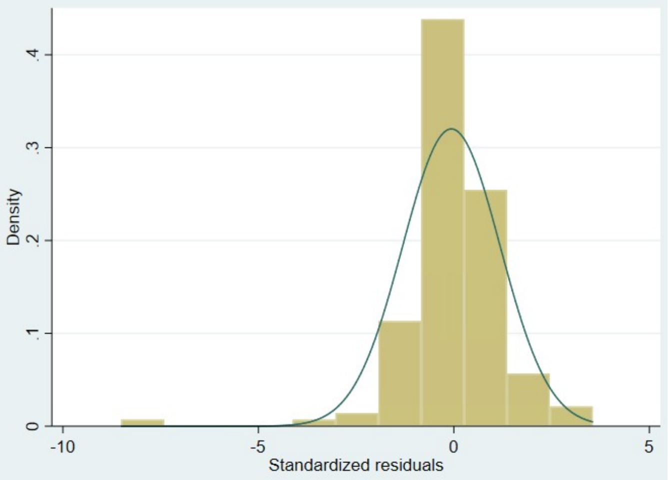
Normal distribution for regression (1):



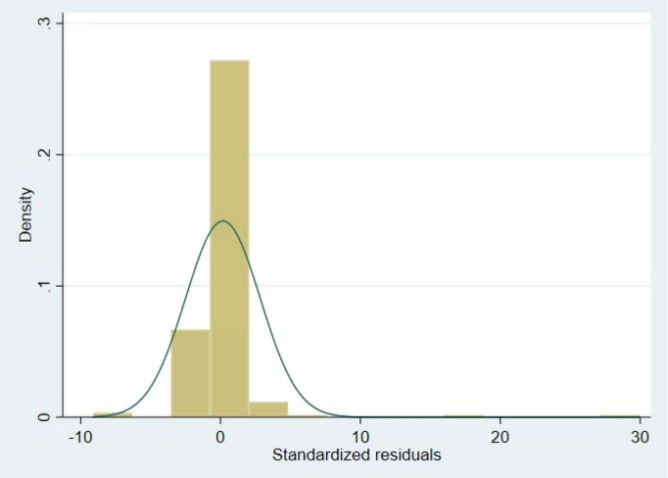
Normal distribution for regression (4):



Normal distribution for regression (2):



Normal distribution for regression (3):



Appendix 8: Correlation matrix

Correlation matrix for regression (1):

	mrkt_cap	hot_co~i	nr_of_~d	total_~k	indust~l	oil_an~s	techno~y	health~e	commun~s	consum~s	utilit~s
mrkt_cap	1.0000										
hot_cold_s~i	0.1021	1.0000									
nr_of_und	0.2658	0.0426	1.0000								
total_rank	-0.0450	0.0394	0.1914	1.0000							
industrial	0.0081	-0.0706	0.0251	0.0046	1.0000						
oil_and_gas	0.0790	0.0413	0.0919	0.1308	-0.2782	1.0000					
technology	-0.1144	-0.0957	-0.0724	0.0005	-0.1881	-0.1994	1.0000				
healthcare	-0.0890	-0.0641	-0.1101	-0.1520	-0.1451	-0.1538	-0.1040	1.0000			
communicat~s	0.0015	0.1054	-0.0013	-0.1165	-0.1169	-0.1239	-0.0838	-0.0646	1.0000		
consumer_g~s	-0.0135	0.1570	0.0155	-0.0341	-0.1881	-0.1994	-0.1348	-0.1040	-0.0838	1.0000	
utilities	-0.0280	0.0736	0.0463	0.1058	-0.0629	-0.0667	-0.0451	-0.0348	-0.0280	-0.0451	1.0000
materials	0.1245	0.0304	-0.0012	0.0777	-0.1106	-0.1173	-0.0793	-0.0612	-0.0493	-0.0793	-0.0265
financials	0.0191	-0.0948	-0.0357	-0.0487	-0.2012	-0.2133	-0.1442	-0.1112	-0.0896	-0.1442	-0.0482

	materi~s	financ~s
materials	1.0000	
financials	-0.0848	1.0000

Appendix 9: Eigenvalues

Eigenvalues and condition index for regression (1):

```
Factor analysis/correlation                        Number of obs    =      202
    Method: principal-component factors            Retained factors =        8
    Rotation: (unrotated)                          Number of params =       76
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.60120	0.28562	0.1232	0.1232
Factor2	1.31557	0.04660	0.1012	0.2244
Factor3	1.26897	0.05453	0.0976	0.3220
Factor4	1.21444	0.05130	0.0934	0.4154
Factor5	1.16314	0.06551	0.0895	0.5049
Factor6	1.09763	0.02094	0.0844	0.5893
Factor7	1.07669	0.01612	0.0828	0.6721
Factor8	1.06057	0.09566	0.0816	0.7537
Factor9	0.96491	0.11335	0.0742	0.8279
Factor10	0.85156	0.06899	0.0655	0.8934
Factor11	0.78256	0.19139	0.0602	0.9536
Factor12	0.59117	0.57959	0.0455	0.9991
Factor13	0.01159	.	0.0009	1.0000

LR test: independent vs. saturated: chi2(78) = 761.86 Prob>chi2 = 0.0000

$$CI = \sqrt{\frac{1.6012}{0.01159}} = 11.75$$

Eigenvalues and condition index for regression (2):

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.59972	0.33069	0.1333	0.1333
Factor2	1.26903	0.01182	0.1058	0.2391
Factor3	1.25721	0.07327	0.1048	0.3438
Factor4	1.18394	0.03937	0.0987	0.4425
Factor5	1.14458	0.06361	0.0954	0.5379
Factor6	1.08097	0.00827	0.0901	0.6280
Factor7	1.07269	0.10742	0.0894	0.7173
Factor8	0.96528	0.09794	0.0804	0.7978
Factor9	0.86733	0.05398	0.0723	0.8701
Factor10	0.81335	0.21471	0.0678	0.9378
Factor11	0.59864	0.45137	0.0499	0.9877
Factor12	0.14726	.	0.0123	1.0000

LR test: independent vs. saturated: chi2(66) = 280.77 Prob>chi2 = 0.0000

$$CI = \sqrt{\frac{1.59972}{0.14726}} = 3.3$$

Appendix 10: Different tests

Simple t-test for underpricing (Outliers and Merkur Market excluded):

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[99% Conf.	Interval]
underp~p	202	.034754	.0082133	.1167336	.0133951	.0561128

```
    mean = mean(underpricing_dep)                                 t =   4.2314
Ho: mean = 0                                     degrees of freedom =      201

    Ha: mean < 0                 Ha: mean != 0                 Ha: mean > 0
 Pr(T < t) = 1.0000         Pr(|T| > |t|) = 0.0000          Pr(T > t) = 0.0000
```

Simple t-test for underpricing:

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
underp~p	215	.0513372	.0149849	.2197216	.0218003	.0808741

```
    mean = mean(underpricing_dep)                                 t =   3.4259
Ho: mean = 0                                     degrees of freedom =      214

    Ha: mean < 0                 Ha: mean != 0                 Ha: mean > 0
 Pr(T < t) = 0.9996         Pr(|T| > |t|) = 0.0007          Pr(T > t) = 0.0004
```

White's test for heteroscedasticity:

```
. estat imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(107)    =    159.12
         Prob > chi2  =    0.0008

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	159.12	107	0.0008
Skewness	27.09	16	0.0405
Kurtosis	1.96	1	0.1619
Total	188.16	124	0.0002

Breusch-Pagan-Godfrey test for regression (1):

```
. estat hettest, iid

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of underpricing_dep

         chi2(1)      =    13.77
         Prob > chi2  =   0.0002

.
```

Breusch-Pagan-Godfrey test for regression (2):

```
. estat hettest, iid

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of underpricing_dep

         chi2(1)      =     3.18
         Prob > chi2  =   0.0747
```

Breusch-Pagan-Godfrey test for regression (3):

```
. estat hettest, iid

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of underpricing_dep_ln

         chi2(1)      =     6.44
         Prob > chi2  =   0.0112
```

Breusch-Pagan-Godfrey test for regression (4):

```
. estat hettest, iid

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of underpricing_dep

         chi2(1)      =    15.22
         Prob > chi2  =   0.0001
```

Test for multicollinearity (VIF):

```
. vif
```

Variable	VIF	1/VIF
oil_and_gas	3.98	0.250980
industrial	3.73	0.268307
financials	2.90	0.344397
technology	2.77	0.361483
consumer_g~s	2.66	0.376144
healthcare	2.17	0.461789
materials	1.79	0.557534
utilities	1.29	0.773877
nr_of_und	1.27	0.786100
dummy_OBX	1.27	0.790375
total_rank	1.17	0.856319
daycount_s~r	1.17	0.856910
mrkt_cap	1.16	0.862656
hot_cold_s~i	1.16	0.862763
daycount_s~t	1.14	0.876073
oversubscr~d	1.09	0.921394
Mean VIF	1.92	

Test for multicollinearity (Bartlett's test):

```
Bartlett test of sphericity

Chi-square          =          757.987
Degrees of freedom =               78
p-value             =            0.000
H0: variables are not intercorrelated
```

Test for normality for regression (1) and (3):

```
. sktest myresiduals
```

Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	joint adj chi2(2)	joint Prob>chi2
myresiduals	215	0.0000	0.0000	.	0.0000

Test for normality for regression (2):

```
. sktest myresiduals
```

Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	joint adj chi2(2)	joint Prob>chi2
myresiduals	129	0.0000	0.0000	.	0.0000