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# Aftermarket Liquidity and Performance of Initial Public Offerings

*Evidence from Oslo Stock Exchange*

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## Abstract

This thesis investigates abnormal returns in initial public offerings (IPOs) at the Oslo Stock Exchange during the time period of 2007 to 2018. By utilising four liquidity measures, we aim to identify the relationships between aftermarket liquidity and abnormal returns, both initially and long-run.

Through our sample of 125 observations, we confirm the existence of the underpricing phenomenon and the long-run underperformance of IPOs in the Norwegian market. We find aftermarket liquidity to be positively related to underpricing. When sorting the issues by sentiment, based on the previous two-month returns, the positive relationship solidifies for hot sentiment markets. Hence, underpricing positively affecting aftermarket liquidity seems to be amplified during bullish trends.

We find indications of a positive relationship between liquidity and long-run abnormal returns, the more illiquid the stock, the worse the performance, and vice versa. This contradicts the risk-return trade-off, which states illiquidity as an attribute of risk. Therefore, we further examine the long-run issue returns by separating between marketplaces. Thus, we discover Oslo Axess, the junior exchange, to be the driver of the counter-intuitive results. We suggest this is a consequence of the speculative nature of Oslo Axess. For the Oslo Stock Exchange, the relationship subsides.

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# 1. Introduction

Initial public offerings, in the modern sense, have existed ever since 1602, when The Dutch East India Company (VOC) became the first company to issue shares to a broad audience (Gelderblom, Jong & Jonker, 2013). Through the offering, they were able to raise 6.5 million guilders, and in the span of four years, the stock had appreciated by 200%. VOC shares were traded increasingly and subsequently grew to become the world's first multinational company.

However, the literature of recent times has found IPOs to underperform substantially; both compared to the market, and firms of similar size and structure. In 1991, Jay Ritter documented the three-year stock value appreciation of IPOs in America to be 34.47%. However, an industry and size-matched control sample produced a return of 61.86% over the same holding period. Thus, the IPOs, as compared to the matching firms, underperformed significantly. Thenceforth, several similar studies were conducted, evidencing similar results, uncovering a general underperformance of IPOs worldwide.

A few decades earlier, Reilly and Hatfield (1969) were the first to lay forth tangible evidence of IPO underpricing. Like Ritter, they paved the way for extensive research on the subject matter, results consistent with the 1969 finding. Thereafter, incentives and theories were established, moving on from identifying this underpricing phenomenon and confirming its existence, to attempting to explain and understand it.

Not until years later did researchers account for and consider liquidity a factor that affects the behaviour of IPOs and their abnormal returns. After adjusting for the risk associated with illiquidity, Eckbo and Norli (2005) were able to explain the long-run underperformance of IPOs in the American market, utilising the classic Fama-French three-factor model. Their evidence points towards the high liquidity profile of IPOs equalling less risk, resulting in lower returns.

Booth and Chua (1996) suggested that underpricing positively affects liquidity, the cause being broad ownership, as a result of oversubscription. Inspired by these claims, Ellul and Pagano (2006) went on to prove that expected secondary market liquidity affects the degree of underpricing, elucidating that investors demand compensation, in this case, in terms of a price discount, for the risk which accompanies uncertainty. Hence, a negative relationship was found; the more liquid an IPO stock was expected to be in the aftermarket, the less underpriced it seemed to be. Later, Hahn, Ligon and Rhodes (2013) confirmed the findings of Booth and Chua, adding to the ambiguity of underpricing's effect on aftermarket liquidity.

To begin our study, we select liquidity measuring techniques, from simple ones such as the NOK volume to methods developed by the likes of Datar, Naiv and Radcliffe (1998) and Amihud (2002). We keep in mind the elusive nature of liquidity, as well as half of our proxies in actuality measuring illiquidity rather than liquidity. Thereafter, we extract IPO data from the Norwegian market, construct the liquidity measures, as well as analyse the data sample. The construction of liquidity measures requires us to make decisions that influence the magnitudes of the proxies.

From our finalised models, we analyse liquidity's relation to initial and long-run abnormal returns in IPOs, and to which degree liquidity can explain these abnormal returns. Furthermore, we attempt to uncover the driver behind certain of our results differing from prior studies, through investigation of hot periods and marketplace specific IPO behaviour.

## 1.1 Research Question, Motivation and Value of Thesis

In this thesis, we seek to further understand the relationship between abnormal returns in initial public offerings, both initially and in the long-run, and the stock liquidity in the secondary market. More specifically, we attempt to ascribe meaning to the relationship between abnormal returns and implied liquidity in IPOs in the Norwegian market, analysing historical data from 2007 to 2018. High liquidity stocks are perceived as less risky because of the transaction advantage implications of their liquid nature. Thereby, according to the risk-return trade-off theory, as well as previous research,[1] highly liquid stocks, being less risky, should in turn yield lower expected returns. This relation implies a premium for illiquid stocks, also referred to as the liquidity factor premium. And we seek to potentially identify its existence in the Norwegian stock market, through inspecting initial public offerings.

Clearly, we are not the very first ones investigating liquidity and IPO returns, yet there are evident motivations for our study. Prior studies investigate either the American or the British market, which both differ significantly from the Norwegian one, most notably size-wise. Hence, we complement the existing literature with additional evidence from a new market,

[1] See for example Eckbo and Norli (2005).

documenting IPO behaviour, and its relationship with liquidity. Furthermore, we extend the literature by conducting a comparison analysis between the main- and junior marketplace.

The rest of the thesis is structured as follows. In Chapter 2, we review the existing literature. Chapter 3 elucidates our empirical method, including data sample, variable constructions, and factor relevancy. Chapter 4 presents and discusses the finalised models. Finally, in Chapter 5, we provide the conclusion of this thesis.

# 2. Literature Review

The following chapter presents theories and empirical findings on IPOs, underpricing, long-run performance, and liquidity, in conjunction with the relationships between them.

## 2.1 IPOs

An initial public offering (IPO) is in various ways defined as the process of offering shares of a private company to the general public for the first time (Berk & DeMarzo, 2014). Public share issuance allows firms to raise capital from public investors.

### 2.1.1 Motives to go Public

Ritter and Welch (2002) figure that the primary motivation to go public is a desire to raise more equity capital for the firm through dispersion of public investors, and thereby also creating a position in the public market where the founders and other shareholders can cash out some of their wealth. Furthermore, Draho (2004) points to the aspect of raising capital for expansion of operations, which focuses on company growth and increasing liquidity for shareholders, which is pervasive in the broad literature. Among nonfinancial motives, going public is beneficial for creating a valuable currency (stock), which can be used for mergers and acquisitions, or employee compensations.

The downsides of going public are costs associated with the IPO process, as well as the continuous process of being a publicly traded firm. Issuing firms experience costs associated with filing and registration, such as incremental auditing fees, financial reporting, legal matters and regulatory compliance, and compensation to investment banks managing the IPO process (PwC, 2014). Furthermore, Draho (2004) argues that the dispersion of investors, the lack of ownership concentration, weakens investors' ability to monitor the company's management.[2]

[2] See also Berk and DeMarzo (2014).

### 2.1.2 How to go Public in Norway

Going public is a comprehensive, several-step process. Typically, the first step is divided into two different procedures. Investors must be identified and buy shares, and shares must be admitted to a stock exchange. Regulations on stock exchanges and their national authorities vary, and the company needs to satisfy these regulations (Jenkinson & Ljungqvist, 2001). The Norwegian stock market is regulated by Oslo Stock Exchange (OSE),[3] and as of June 2019, Oslo Stock Exchange is controlled by Euronext, which operates multiple European stock exchanges (Euronext, 2019).

In the Norwegian market, issuers can choose between two marketplaces, OSE and Oslo Axess, differing in admission requirements and obligations, and the multilateral trading facility Merkur Market. OSE is the obvious choice for larger companies and represents a full stock exchange listing in accordance with EU requirements. Oslo Axess is more suitable for young companies seeking a quality stamp and benefits associated with listing on a regulated market. Merkur Market is an option for companies failing to satisfy the requirements for listing, or do not wish to be fully listed on a regulatory market (Oslo Stock Exchange, 2019).

OSE has stricter rules than Oslo Axess, and Oslo Axess has stricter rules than the trading facility Merkur Market.

| | Oslo Stock Exchange | Oslo Axess | Merkur Market |
|---|---|---|---|
| **Marketplace status** | Stock exchange listing in accordance with EU requirements and the Norwegian Securities Trading Act. | Authorised and fully regulated marketplace. | Multilateral trading facility. |
| **Market capitalisation** | NOK 300 million | NOK 8 million | No requirement |
| **Minimum price per share** | NOK 10 | NOK 1 | NOK 1 |
| **Minimum number of shareholders** | 500 | 100 | 30 |
| **Minimum proportion of share capital distributed among general public** | 25% | 25% | 15% |

*Table 1: This table depicts the most decisive differences in characteristics between the three marketplaces on OSE. The full table of requirements and regulations is found in Appendix 2.[4]*

[3] Oslo Stock Exchange refers both to the market operator as well as the main marketplace.
[4] Extracted directly from https://www.oslobors.no/ob_eng/Oslo-Boers/Listing/Shares-equity-certificates-and-rights-to-shares/Comparison-between-Oslo-Boers-Oslo-Axess-and-Merkur-Market

The choice of market is no longer constrained by national boundaries. The trend of recent times is national exchanges merging or forming joint ventures which create larger, hopefully more liquid markets (Jenkinson & Ljungqvist, 2001). OSE, as mentioned, is part of Euronext, a pan-European exchange operating the exchanges in Amsterdam (Netherlands), Brussels (Belgium), Dublin (Ireland), Paris (France), Lisbon (Portugal), London (UK) in addition to the Norwegian market.

*Producing a Prospectus*

After deciding the marketplace, the next step is to produce a prospectus. The prospectus is a legal document used to market shares to the public, a key component of the marketing process, helping investors make more informed investment decisions (Berk & DeMarzo, 2014).

Several intermediaries, such as auditors, lawyers, and investment banks are included in the process of producing the prospectus. One of the key decisions in the prospectus is to set the issue price (Jenkinson & Ljungqvist, 2001).

*Marketing*

The marketing process is a form of promotion of the issue. Kuhn (1990) points to the marketing campaign as a key to stimulate investor demand for the issue. Companies often take on so-called “roadshows”, presenting the issue, especially in locations with high concentrations of institutional investors (Jenkinson & Ljungqvist, 2001). For new issues at OSE with international offerings, the roadshows will take place in many different locations around the world (PwC, 2014).

*Pricing Mechanisms*

IPO pricing mechanisms define the procedure where issuers and underwriters sell the offering to investors (Draho, 2014). There are several methods to determine the price and allocations of IPOs, the two main types employed being book-building and fixed price. Book-building has become the most popular approach worldwide, as is the case in Norway (Jenkinson & Ljungqvist, 2001).

### 2.1.3 The Underpricing Phenomenon

A new issue is considered underpriced when the listing price for the IPO is below the real value; the stock market value, given by the first day's closing price (Berk & DeMarzo, 2014). The first tangible evidence of IPO underpricing was documented by Reilly and Hatfield (1969), analysing 53 American issues in 1963-1966, finding an average underpricing of 9.9%. Subsequently, the phenomenon was continuously researched and proved ubiquitous in nature.

Thirteen years later, Baron (1982) developed a model applying principal-agent analysis, which demonstrates that vertical informational asymmetry can explain the underpricing of new issues. Specifically, the asymmetric information between the issuer and external investors. This was the first empirical evidence supporting the hypothesis that underpricing is undertaken deliberately, and simultaneously an explanation as to why the phenomenon occurs to begin with.

Thenceforth, the growing IPO literature has also been able to explain underpricing in virtue of signalling and behavioural theories. The effect of the individual factors predominantly depends upon macroeconomic variations and country-specific regulations. Through these findings, further evidence was provided concerning both the time inconsistencies and international variations of the underpricing phenomenon.[5]

Through their research, Loughran, Ritter and Rydqvist (1994) were able to document the underpricing variation across countries, ranging from 4.2% in France to 80.3% in Malaysia (of the included countries). Today Jay R. Ritter runs a website, keeping track of IPO data and statistics for countries around the world.

[5] See Loughran and Ritter (2004) and Loughran, Ritter and Rydqvist (1994).

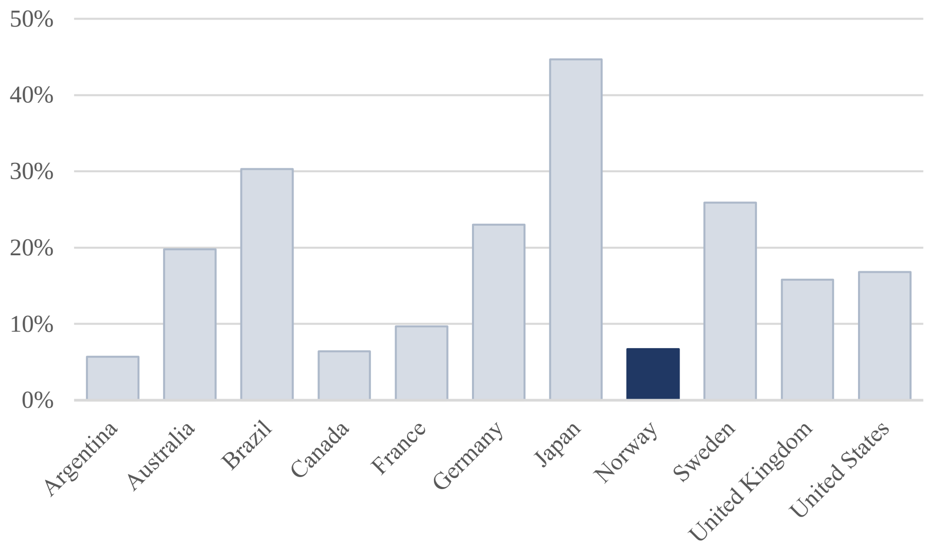


*Figure 1: Average historic underpricing given by country.*[6] *The statistics are extracted from different time periods and include only a narrow selection of countries. Knowingly, underpricing strongly varies with cyclical movements, and over time. Thus, the graph only provides us with an indication of the true levels of underpricing. China and Saudi Arabia are two of the excluded countries, with underpricing percentages of 157.7 and 239.8 respectively.*

### 2.1.4 Underpricing in the Norwegian Market

Loughran, Ritter and Rydqvist (1994) did not include OSE in their earliest research examining underpricing on an international basis. However, only three years after their results were published, Emilsen, Pedersen and Sættem (1997) documented the underpricing in the Norwegian market from 1984-1996, finding an average of 12.5%. In a working paper by Fjesme (2011), the initial return of 8% is found from 1993-2007. Even further research shows a trend of this percentage to be gradually decreasing with time, as is the case for most countries.

OSE scores in the very lowest percentiles of underpricing internationally. Low informational asymmetry is highlighted as the most decisive reason why some countries experience less underpricing than others, asymmetric information being recognised as the preeminent driver of offering price-to-market price deviations (Banerjee, Dai & Shrestha, 2011).

[6] Found at https://site.warrington.ufl.edu/ritter/files/2019/03/Int.pdf

### 2.1.5 Hot Issue Markets

Hot issue markets are characterised as periods where investor demand for IPOs is especially high and the optimism lead IPO prices to rise above issue price. The patterns of hot markets are cyclical, hot periods being identified through both high IPO volumes and average initial returns (Ibbotson & Ritter, 1995). Ljungqvist, Nanda and Singh (2006) assert that investor sentiment is particularly present in hot markets and Loughran and Ritter (2002) and Lowry and Schwert (2004) evidence that higher market returns leading up to the issue yields greater underpricing. The predictability is found puzzling since the market returns are publicly available information. Bakke, Leite and Thorburn (2017) amongst others calls this the demand effect where a positive public signal leads to a higher likelihood of sufficient investor demand, which will generate underpricing.

### 2.1.6 Long-run Performance

As evidenced in the early 90s, firstly by Ritter (1991), and later by Loughran and Ritter (1995), IPO stocks underperform significantly in the long run, providing shareholders with surprisingly low returns. As is the case with underpricing, long-run performance varies over time and across countries as well.

| Authors | Market | Time period | Average performance | Time-frame |
|---|---|---|---|---|
| Ritter, 1991 | USA | 1975-1984 | -29.13% | 3 years |
| Aggarwal and Rivoli, 1990 | USA | 1977-1987 | -13.73% | 1 year |
| Loughran, Ritter and Rydqvist, 1994 | Sweden | 1980-1990 | 1.20% | 3 years |
| Giudici and Roosenboom, 2004 | Europe | 1996-2000 | -32% | 3 years |

*Table 2: Prior research on IPO long-run performance. The average performances are index adjusted and sorted by time-period.*

The systematic long-run underperformance of IPO stocks questions the efficient market hypothesis (EMH) and motivates the use of behavioural models for the cause of asset pricing. However, counter-evidence to this notion was swiftly put forward, demonstrating that the underperformance-pattern is consistent with standard multifactor pricing, with a tendency to be concentrated in small growth stocks.[7] Thus, the underperformance could rather be a

[7] See Brav and Gompers (1997), Brav, Geczy and Gompers (2000) and Eckbo, Masulis and Norli (2000).

manifestation of the general finding of Fama and French (1992), stating that firms with low book-to-market ratios (growth stocks) tend to deliver low returns.

## 2.2 Liquidity

*"Liquidity is an elusive concept. It is not observed directly but rather has a number of aspects that cannot be captured in a single measure." (Amihud, 2002, p. 33)*

Stock liquidity can be defined as the ability to quickly buy and sell a large number of a certain stock without affecting the price (Næs, Skjeltorp & Ødegaard, 2008). A closer examination of this definition reveals a quantity dimension – how much can be traded, a time dimension – how quickly can the trade be executed, and an elasticity dimension – what is the price impact. Furthermore, liquidity is not directly observable, but rather a measure which must be estimated. And as Baker (1996) indicates, because of its complexity, different liquidity measures might lead to conflicting results.

### 2.2.1 Measuring Stock Liquidity

Measuring stock liquidity is either accomplished through trade-based or order-based measures, the measures being able to describe different aspects of the liquidity of a stock. Volume, for example, is a simple measure, which indicates whether a stock is actively traded. Trade-based measures, such as trading volume, are attractive due to its simplicity and widespread acceptance (Aitken & Comerton-Forde, 2003).

However, trade-based measures are ex-post, in the sense that they indicate what has been traded in the past rather than display the current liquidity picture. Therefore, with increasing data availability, spread-oriented measures are also increasingly used, accurately capturing the costs associated with immediate trades – the essence of liquidity.

Furthermore, liquidity measures are diverged into one-dimensional and multi-dimensional; where one-dimensional measures consider one factor, while multi-dimensional models attempt to consider several factors concurrently.

## 2.3 IPOs and Liquidity

Several studies have been conducted investigating IPO underpricing and its relation to aftermarket liquidity, albeit fewer than expected. Especially seeing as the ubiquitous nature of IPO underpricing is a unique phenomenon, making it highly topical for researching matters. Even fewer have investigated the relationship between the aftermarket liquidity of IPOs and their relative long-run performance.

### 2.3.1 Underpricing and Liquidity

Booth and Chua (1996) suggested that issuers underprice to promote oversubscription, allowing broader initial ownership, resulting in higher aftermarket liquidity. Hence, they argued underpricing to be positively related to secondary market liquidity. Hahn et al. (2013) later confirmed this finding, using eight liquidity measures to show that underpricing generally increases the aftermarket liquidity of IPOs.

Looking to extend the work of Booth and Chua, Ellul and Pagano (2006) proved that secondary market liquidity, or rather *expected* secondary market liquidity, and its implied risk, affects the degree of IPO underpricing. Investors demand to be compensated for the liquidity risk of the shares they are buying; the risk of an illiquid secondary market. Thus, based on their results, Ellul and Pagano determined the relationship between the two factors as negative; the more liquid the stock was expected to be in the aftermarket, the less underpriced it was during the offerings, and vice versa. The results of the research clearly contradict the findings of Booth and Chua, and Hahn et al.

### 2.3.2 Long-run Performance and Liquidity

After indicating that IPO stocks are highly liquid, exhibiting a high share turnover, Eckbo and Norli (2005) specify that the implied lowered liquidity risk of the IPO stocks may lower systematic risk exposures. Thus, their theory reveals that lowered liquidity risk, as a consequence of greater liquidity, may be a major factor contributing to the low post-listing returns of IPOs.

The hypothesis is examined by constructing a factor model based on the Fama and French (1993) three-factor model, augmented with a liquidity risk factor, in the form of share turnover, as well as a momentum factor. The liquidity risk factor consists of a portfolio containing share turnovers for each stock, sorted “low-minus-high”. Through this model, Eckbo and Norli manage to provide results in line with standard asset pricing models, and evidence which indicates that IPOs may be correctly priced, when considering the reduced systematic risk exposures of high liquidity stocks.

In summary, the high liquidity of IPO stocks seems to reduce the systematic risk, which further reduces the expected long-run returns. Essentially, IPO stocks seem to behave in line with risk-return theory.

# 3. Methodology

We have laid forth our desire to investigate the market behaviour of IPOs in relation to their aftermarket liquidity profiles. We now proceed to elucidate how we test this empirically; our methodology being fine-tuned to produce coherent measurements and models.

In the following chapter, we explain our data, discuss underway decisions and entailing biases, define essential variables and their construction, as well as investigate statistics and relationships between them. The selection of data is essential for producing an unbiased model, and therefore explanation and justification of our data selection is positioned in Subchapter 3.1. Subchapter 3.2 discusses potential biases our models might suffer from. Subchapter 3.3 elaborates our method for retrieving abnormal returns. In Subchapter 3.4 and 3.5, we present our selected liquidity measures and control variables, respectively. Subchapter 3.6 is dedicated to descriptive and inferential statistics. Lastly, Subchapter 3.7 and 3.8 are devoted to empirical strategy and econometric concerns, respectively.

## 3.1 Data

The following subchapter describes our choice of market and timeframe, data selection and collection process. We have constructed a unique dataset, being forced to obtain data mechanically, which proved to be a time-consuming process.

### 3.1.1 Choice of Market and Timeframe

We have chosen to use IPOs listed on both Oslo Stock Exchange and Oslo Axess to include a variety of firm sizes and to increase the sample size, due to the Norwegian IPO market being limited. The timeframe is set to twelve years and includes multiple economic periods and cycle stages. Our timeframe does not include the hot issue years enveloping the millennium, whereas it includes the cold issue years in the aftermath of the financial crisis of 2008. Regarding the Norwegian market being an energy-heavy stock market, the oil crash in 2014 is also worthy of mention. Furthermore, our timeframe is chosen based on the launching of Oslo Axess in 2007, as an alternative listing opportunity in the Norwegian market.

### 3.1.2 Sample Selection

Through the "New listings"[8] overview at OSE's website, we find 182 new listings between January 1st, 2007 and December 31st, 2018 on Oslo Stock Exchange and Oslo Axess. We only include new listings, excluding transfers from Oslo Axess to Oslo Stock Exchange, Merkur Market to Oslo Axess, or Merkur Market directly to Oslo Stock Exchange.

Our initial sample of 182 new listings is trimmed down due to a variety of reasons. We exclude 14 companies, due to already being priced in the market, for example through OTC-listings. Moreover, we only include companies issuing shares to the public or to increase share capital. Therefore, one offering is excluded due to secondary listing and 14 offerings because of a merger or demerger of an already listed company. Three further companies are excluded due to delisting and relisting. Finally, 22 offerings are excluded due to missing data, either because of missing issue prices and other essential information or due to missing data on equity prices after issue.

This leaves us with our final sample of 128 IPOs. For 125 of these observations we possess both one-day and one-year data. Three companies are missing yearly data due to acquisitions within the first year, and therefore all regressions are using 125 observations because the liquidity measures are based on yearly data.

### 3.1.3 Data Collection

OSE's official website and Børsprosjektet at NHH are our main sources for the collection of data. OSE's overview of "New listings" is utilised as an index to collect all new listings on OSE and Oslo Axess from 2007-2018. To depict the market as accurately as possible, we actively use the statistics published on issues and list changes.[9] For our collection of daily stock prices and trading volume, Børsprosjektet at NHH served us with satisfactory data. Additionally, Bloomberg Financial Terminal and Yahoo Finance are used to control for deviations in data and supplement missing information. Also, the prospectuses of each IPO have served as additional important sources of information.

[8] "New listings" are found at: https://www.oslobors.no/ob_eng/Oslo-Boers/Listing/Shares-equity-certificates-and-rights-to-shares/New-listings

[9] "Issues statistics" and "List changes" are found at: https://www.oslobors.no/ob_eng/Oslo-Boers/Statistics

## 3.2 Potential Biases

### 3.2.1 Selection Bias

Heckman (1990) states that sample selection bias is a specification bias because of problems with missing data. As our data consists of a trimmed down number of 182[10] original observations, there are definite risks of selection bias. The typically omitted companies are smaller firms with missing data, which could be due to for example early bankruptcy leading to a survivorship bias or information shortage towards the smallest issues. Thus, the models and results might be positively skewed in terms of abnormal returns, due to a substantial number of the worst-performing firms not being included, nor being statistically taken account for. The final dataset is a result of a self-collection process where data was collected from different sources to the best of our ability.

### 3.2.2 Outliers

Wooldridge (2015) argues that outliers are such influential observations, that dropping them lead to relatively large changes in the key OLS estimates. By examining box plots, we can detect significant outliers. These outliers could substantially affect mean values, as well as influence other variables of interest. We choose not to correct for outliers by removing them, but rather by logarithmically transforming our variables. Hence, the variables become increasingly normally distributed, and concurrently, the effect of outliers is decreased. By not entirely removing any outliers, but rather decreasing their presence and effect, we may still face increased probabilities of making Type I or Type II errors (Osborne & Overbay, 2004). We report box plots and kernel density estimation of distributions in Appendix 1.

We test our regression models and output when correcting for outliers, both manually and as an upper and lower percentile, in our dependent variables, liquidity measures, and multiple control variables. The results remain constant and confirm that outliers carry minimal leverage over the overall results of our analysis.

[10] Not all new listings are considered IPOs.

### 3.2.3 Calculation of Liquidity Measures

Our research depends greatly on the estimated liquidity measures. When calculating the measures, a shortage of data is a source of potential inconsistency. One specifically sobering observation is that several of the listings are illiquid to the degree that many trading days are without trades. Hence, with a trading volume of zero, the stock price remains constant, at the exact same price for several days. Especially the Amihud illiquidity ratio and high-low range are affected by this. Observations of non-existing trading volume lead to a lower Amihud ratio value and a higher high-low range value weighting in the direction of higher liquidity based on the formula for Amihud ratio and lower liquidity for high-low range. In reality, this is a sign of weak liquidity. It could be argued that exclusion of zero-volume days is more efficient, however, we have chosen to remain a formula consistent approach throughout the measure construction process.

### 3.2.4 Source Inconsistency

Throughout our collection process, we discover some minor errors; for example when cross-checking data between OSE and Bloomberg or Yahoo Finance, some mismatches are discovered. This could lead to statistically biased results. We consistently prioritise the data provided by OSE and Børsprosjektet when available and supplement or correct only when necessary. The data is manually collected, and errors due to misentering data may exist, even after cross-checking the data.

## 3. 3 Calculation of Abnormal Returns

*Initial Abnormal Return*

The existing literature uses several different methods to measure underpricing.[11] The initial return is the difference between the issue price and the price of the stock when efficiently priced in the market. Underpricing indicates positive initial returns. McGuinness (1992), Ritter and Welch (2002) and Loughran and Ritter (2004) are among many researchers arguing for stock prices being efficiently priced after the first day of trading, thus the first-day closing price being the accurate measure. Other studies on the other hand, calculate the underpricing based on more than the first trading day, arguing that the market needs more time to efficiently price the stock

[11] Also referred to as the initial return of the issue or first-day return throughout the thesis.

(Lowry, Officer & Schwert, 2010).[12] We apply the first-day closing prices as our method of calculating the initial returns, maintaining consistency with the efficient market hypothesis.

Ambiguity instances also emerge when confronted with whether to adjust for market returns. Beatty and Ritter (1986) argue that the average daily market return was less than 0.1 percent in their research period, and therefore, adjustments would only result in minor changes.[13] Logue (1973) on the other hand, presents an adjustment method where the simple initial return is adjusted by subtracting the return for the same period on a representative index. Several other scholars copy this method (e.g. Ibbotson & Jaffe (1975)). We decide on adjusting for index returns to ensure a correction for market movements, even if the movements are considered small in magnitude. We choose the Oslo Stock Exchange Index (OSEBX) as the adjustment index, being a broad Norwegian index, with historical price development dated back to 2007. This index gives a good indication of the overall performance in the Norwegian market. The Oslo Stock Exchange All-share Index (OSEAX) could potentially also be fitting, as a slightly broader index, but the differences are deemed insignificant.

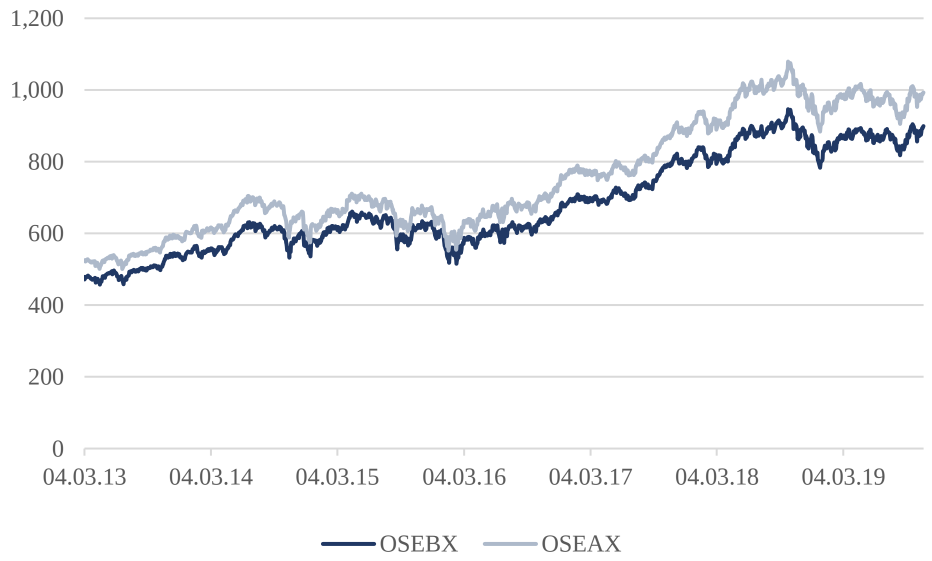


*Figure 2: Graphical presentation of the cumulative returns of OSEBX and OSEAX on OSE from March 2013 until late 2019. As mentioned, the differences in returns are small.*

[12] Lowry, Officer, and Schwert, 2010 uses the 21st day of trading to exclude the volatility before price stabilization.
[13] Example of other scholars using this method: Ljungqvist and Wilhelm (2003).

Our calculation of initial abnormal returns will therefore be calculated as follows:

$$Abnormal\ Return_{First-day} = \left(\frac{Close\ price_1 - Offer\ price_0}{Offer\ price_0}\right) - \left(\frac{OSEBX_1 - OSEBX_0}{OSEBX_0}\right) \quad (1)$$

$$Log\ Abnormal\ Return_{First-day} = ln\left(\frac{Close\ price_1}{Offer\ price_0}\right) - ln\left(\frac{OSEBX_1}{OSEBX_0}\right) \quad (2)$$

We use the (1) initial abnormal return when describing our data and inference statistics, and the (2) log-transformed initial abnormal return in our regression models.

*Long-run Abnormal Return*

The techniques of measuring long-run performance vary among researchers both with respect to the timeframe and general method. Normally, the long-run performance is measured with a timeframe of one to three years. Aggarwal and Rivoli (1990) use a one year frame on U.S. data, Ritter (1991) uses three years, while Ljungqvist (1997) looks at the German market using one-to-three years, and Chan, Wang and Wei (2004) use a timeframe of three years on the Chinese market. As Aggarwal and Rivoli, we use a long-run performance timeframe of one year.

Our data sample includes data over a twelve-year time period, and the internal market conditions differ substantially. Hence, it is necessary to adjust for these continuous movements, and therefore all one-year returns are adjusted for periodically matched movements in the OSEBX, as with the initial returns. Some studies use constructed benchmarks with the purpose of matching the IPO firm-characteristics with comparable public firms, including similar risk. Our benchmark, OSEBX, is a broad index for the Norwegian market and is easy to implement. A process matching comparable firms with all the sampled IPOs is too difficult in the small Norwegian market, and furthermore, the OSEBX works effectively as a benchmark.

The general calculation of long-run performance is mainly performed in two ways, differing with respect to the starting point. One is the closing price after the first trading day, and the other being the offer price. In this thesis, we measure the long-run performance relative to the offer price:

$$Abnormal\ Return = \left(\frac{Close\ price_{1\ year} - Offer\ price_0}{Offer\ price_0}\right) - \left(\frac{OSEBX_{1\ year} - OSEBX_0}{OSEBX_0}\right) \quad (3)$$

$$Log\ Abnormal\ Return_{Long-run} = ln\left(\frac{Close\ price_{1\ year}}{Offer\ price_0}\right) - ln\left(\frac{Closing\ price_{m_{1\ year}}}{Closing\ price_{m_0}}\right) \quad (4)$$

We use the (3) market adjusted long-run return when describing our data and inference statistics, and the (4) log-transformed long-run abnormal returns in our regression models.

## 3.4 Liquidity Measures

We use four different liquidity measures as our main explanatory variables, computed to signify the relationship between abnormal returns and liquidity. The measures are NOK volume, share turnover, Amihud illiquidity ratio and high-low range. Higher liquidity is generally associated with lower risk and thus expected to yield lower returns.

### 3.4.1 Average Trading Volume

The volume of a share is simply the total number of shares traded during a specific period. Trading volume is carefully investigated by Lee and Swaminathan (2000) in the context of momentum and value strategies. If the volume-related liquidity measures are high, this is a sign of high liquidity. Trading volume is the simplest form of liquidity measure, only considering the number of shares transacted.

$$ADV_t^i = \frac{1}{Days_t^i} \sum_{d=1}^{days_t^i} V_t \qquad (5)$$

*Where V is trading volume at date t, summed and divided by number of trading days.*

Trading volume can also be explained in dollar amount, or Norwegian kroner in our case.

$$ADV\ in\ NOK_t^i = \frac{1}{Days_t^i} \sum_{d=1}^{days_t^i} NOK\ Volume_t \qquad (6)$$

*Where NOK volume is trading volume measured in Norwegian kroner at date t, summed and divided by number of trading days.*

We use the average daily NOK volume on one-year data and log-transform this to normalise and account for extreme values. The NOK volume variable is thereby created and used as our simplest form of liquidity measure. The variable is positively correlated to liquidity. Higher (lower) NOK volume indicates higher (lower) liquidity.

### 3.4.2 Share Turnover

Share turnover measures trading volume while considering the number of shares outstanding. This method is considered superior to pure volume measures since it controls for trading demand – a function of the float, the number of shares outstanding (Datar et al., 1998). It is important to note that this ratio only explains how easily an investor can buy or sell stocks and that investors might avoid company shares with a low turnover ratio. The share turnover ratio is calculated by dividing the trading volume of the stock by the 'float'. The higher the turnover, the more liquid the stock. On the occasion of the number of shares outstanding changing over time, a time-weighted average is adopted.

The turnover ratio data (along with the volume data) are noisy and tend to produce outliers (Bekaert, Harvey & Lundblad, 2007). This might complicate modelling matters and prospective interpretation power of the variable unless taken care of.

$$Share\ Turnover_t^i = \frac{\sum_{d=1}^{days_t^i} V_t}{(\sum_{d=1}^{days_t^i}(d_1SO_1 + d_2SO_2 + \cdots d_nSO_n))/d_n} \tag{7}$$

*Where V is trading volume at date t, $d_n$ is number of days and SO is shares outstanding.*

The variable is positively correlated to liquidity. Higher (lower) share turnover indicates higher (lower) liquidity.

### 3.4.3 Amihud Illiquidity Ratio

The Amihud illiquidity ratio attempts to measure stock illiquidity by capturing the magnitude of the price movements given volume. It is interpreted as the daily stock price reaction to a dollar of trading volume (Amihud, 2002). Thus, the higher the Amihud ratio, the higher the degree of illiquidity of the stock.

$$ILLIQ_t^i = \frac{1}{Days_t^i}\sum_{d=1}^{days_t^i}\frac{\left|R_{td}^i\right|}{NOK\ Volume_{td}^i} \tag{8}$$

*Where R is return on stock i at date t, and NOK Volume is volume in Norwegian kroner on stock i. The values are summed and divided by number of trading days.*

The Amihud illiquidity ratio is log-transformed to normalise and account for extreme values. The Amihud measure takes values from $2.51^{-10}$ to 0.0001458 in our sample. The value is lower when the absolute change in return is low relative to the NOK volume. The value is expected to be low for liquid companies and higher for illiquid companies.[14]

### 3.4.4 High-Low Range

The high-low range is an attempt to capture the price movements and impact of trades. It is a simple measure of range, and since the high and low prices are buyer and seller initiated respectively, the measure may be an adequate proxy for the observed bid-ask spread.

$$Range_t^i = \frac{1}{Days_t^i} \sum_{d=1}^{days_t^i} ln \frac{H_{td}^i - L_{td}^i}{C_{t-1,d}^i} \tag{9}$$

*Where H is high price, L is low price, and C is previous day's close at date t. The measure is log-transformed, summed and averaged.*

High-Low Range takes values from -4.36 to -0.05 in our sample. The lower the value is, the smaller the spread between high and low, and the higher the volume. On this basis, we expect the most liquid companies to exhibit the lowest values.[15]

## 3.5 Control Variables

### 3.5.1 Offer Size

The offer size variable is constructed by multiplying the number of shares offered by the price per share.[16] Research suggests a positive relation between offer size and underpricing. The larger the issue, the higher the underpricing (Helwege & Liang (2004) and Low & Yong (2011)). In order to normalise the distribution of observations, the offer size variable is transformed logarithmically.

It could be argued that offer size, together with the other NOK-based measures,[17] should be inflation adjusted since the IPOs are listed during different years. The earlier an IPO was listed, the more deflated the values. Real values could be obtained using a CPI deflator and adjusting the sizes to a base year. Our sample period, a period of twelve years, is limited, and we suggest that deflating values only would lead to minor changes. Furthermore, several researchers use

[14] To exemplify the measure; Gjensidige and Fjordkraft are among the companies in the lower percentile of the sample, and thereby perceived as less illiquid, based on the Amihud illiquidity ratio.
[15] To exemplify the measure; one of the most negative high-low range values is exhibited by Gjensidige, which is considered as a very liquid company.
[16] The offer size is normally available in the data from OSE.
[17] NOK volume and market value (company size).

offer size as an independent variable without adjusting for inflation.[18] Moreover, elements of the time effects will be adjusted for by the inclusion of yearly dummies.

### 3.5.2 Age of Firm at Listing

Loughran and Ritter (2004) point to company age as a central variable in their research. Smaller issues are often younger companies. They find a higher underpricing level of young firms than of old firms. Younger firms imply less historic data and are normally described as riskier investments in the literature, based on the historical information being limited. Recall principal-agent theory, here implying a more substantial informational asymmetry for younger firms. Therefore, informed investors demand a discounted price for younger firms since the information is costlier (Ritter, 1984). In fact, Beatty and Ritter (1986) use company age as a direct proxy for risk.

To examine possible age-effects, we create an age variable. Age is measured as the time in years from the year of establishment to the year of the IPO. The initial sample has an average of 25.5 years and a median of 10.5 years. The sample variation is large, with the greatest observations being 211 and the smallest being listed in the same year as established. Company age is log-transformed to reduce the effect of outliers. Since some of the observations are zero, as the companies are established in their listing year, we add a constant of 1 to all observations.

### 3.5.3 Company Size

Company size is found as the market value at the listing date. OSE holds data on most companies, and when data is missing, the market value is estimated as the total number of outstanding shares multiplied by the first-day closing price. Company size is highly correlated with the offer size.[19] The variable is constructed into a dummy, which is equal to 1 if market capitalization exceeds one billion NOK, and 0 otherwise. Thus, our sample consists of 68 big companies and 60 small companies by market value.

[18] Drake and Vetsuypens (1993) and Loughran and Ritter (2004) are examples.
[19] See correlation matrix in Table 7.

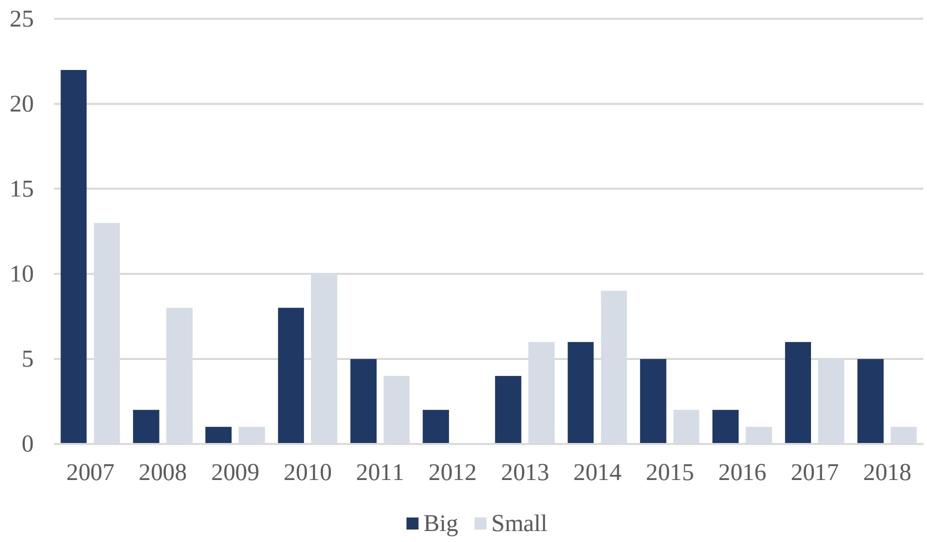


*Figure 3: Big- and small-cap companies going through the IPO process each year from 2007-2018.*

Large companies are generally associated with higher liquidity, which is also evident in our dataset, where company size is strongly positively correlated with NOK volume and share turnover, indicating higher liquidity. Furthermore, it is negatively correlated with the Amihud ratio and high-low range, also indicating higher liquidity in larger company stocks.

### 3.5.4 Volatility of the Market, VIX

Lowry, Officer and Schwert (2010) examine volatility in initial returns in IPOs and find that the *volatility fluctuates greatly over time*. The CBOE[20] Volatility Index[21] (VIX Index) has become a diligent variable for expressing investor sentiment (or fear). VIX is a forward-looking barometer measuring 30-day expected volatility of the broad U.S. stock market, based on S&P 500 options. The Norwegian Volatility Index (NOVIX) measures the implied volatility from 30-day options on OBX, a similar measure to the CBOE VIX, but for the Norwegian market. The calculation is based on the demand for put-options relative to call-options. NOVIX increases when the demand for put-options increases relative to call-options. An increase in the NOVIX relates to a higher fear of decline on OSE during the following 30 days. NOVIX only includes data from April 2016,[22] and is therefore not usable for our purpose. Since the VIX index measures the broad stock market in the U.S. and the Norwegian market is strongly

[20] Chicago Board Options Exchange.
[21] Also referred to as the fear index.
[22] Data on NOVIX are found at: https://novix.xyz/

influenced by international sentiments as a small and open economy (Gjerde & Sættem, 1999), CBOE VIX[23] serves as a good measure.

We conduct comparisons of correlations between the data with both VIX and NOVIX to examine the relationships. Since the data for NOVIX exists only from April 2016, the two indexes are matched for the period April 2016 to October 2019. We find a correlation of 0.476 with daily data, which indicates a positive relationship to some extent, but not perfectly. Further, we assume that this strong correlation persists for the remainder of our sample period.

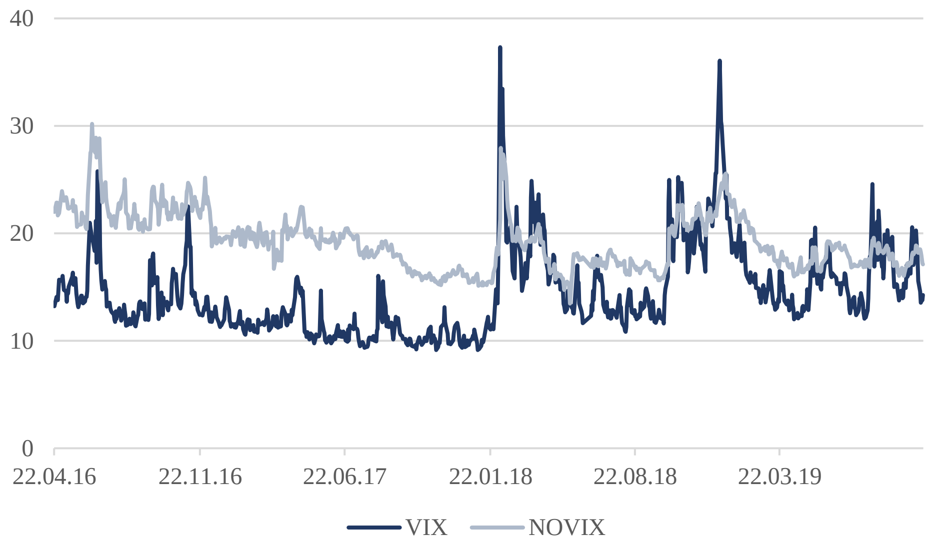


*Figure 4: Graphical presentation of VIX and NOVIX from April 2016 to October 2019.*

Patel (2013) points out that higher market volatility will hurt IPOs, as swings can make it difficult to set a price range for the offer. IPO conditions improve when market volatility is lower, VIX is lower, which normally increases financial activity. Hence, we create two different variables based on values on VIX. First, a daily VIX variable is constructed as the natural logarithm of the listing day value on VIX. The variable is created to explain some of the conditions in the market on the day of listing. Likewise, we construct a variable for the long-run sentiment on the VIX, defined as the average value on the index the first year of listing. The variable for the yearly average of VIX is log-transformed to normalise and account for extreme values.

[23] Data on the CBOE VIX are found at: http://www.cboe.com/vix

### 3.5.5 Brent

Knowingly, OSE is significantly exposed to the oil industry, a large proportion of companies being classified within the energy sector, and many related to the oil industry. An increase in oil prices is expected to be positive for the valuation of future earnings and thereby increased valuation of stocks exposed to oil prices (Næs, Skjeltorp & Ødegaard, 2009). Brent variables are based on Brent Spot oil prices denoted in American dollars.[24] We are interested in the changes in oil price and not the absolute value; hence we create one variable for the change from the day before listing to the day of listing, and another variable for change between the day of listing and price one year later. Both variables are log-transformed.

Increased oil prices are expected to be positively associated with market returns and thereby stock returns. Increased oil prices possibly lead to higher expectations of cash flows for stocks, and the variable is used to control for some degree of market sentiment in addition to VIX.

### 3.5.6 Standard Deviation of Returns

The standard deviation of returns explains the volatility of the returns on an annual basis. In order to construct the variable, annual standard deviations were found, based on calculations of daily returns. The standard deviations reflect risk, volatility in each stock. Thus, higher standard deviation corresponds to higher risk. And in line with traditional risk-return trade-off theory, higher risk is expected to yield higher potential returns. The variable for standard deviation is constructed as a log-transformed variable of the yearly standard deviation of returns for each company, and the variable is used to account for company risk in each IPO.

### 3.5.7 Sector Differences

We apply the global industry classification standards (GICS)[25] to categorise the IPOs into eleven sectors, which is used by OSE. The GICS is internationally practiced and developed by Morgan Stanley Capital International (MSCI) and Standard & Poor's (S&P). The eleven sectors include 24 industry groups, which are further divided into 69 industries. With our limited dataset, using the eleven sectors seem to be the best fit. The 11 sectors are energy, materials,

[24] Data on Brent Spot are found at: https://fred.stlouisfed.org/series/DCOILBRENTEU
[25] GICS division is found at: https://www.msci.com/gics

industrials, consumer discretionary, consumer staples, health care, financials, information technology, communication services, utilities and real estate.

In our regressions, we create a dummy variable for whether the company is an energy company or not. The dummy variable is constructed such that the dummy variable equals 1 if the company falls within the sector "Energy" and 0 otherwise.

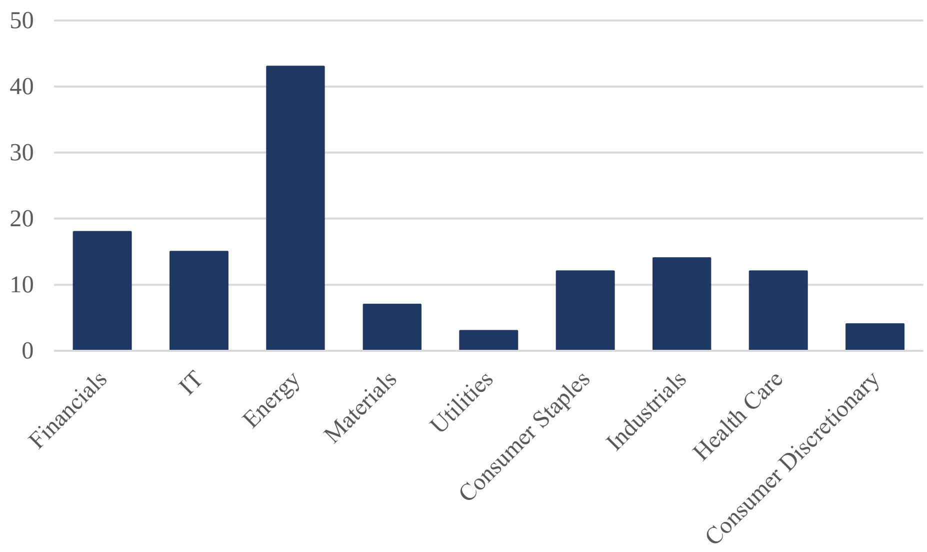


*Figure 5: Number of IPOs in each sector from 2007-2018. The energy sector, and especially oil-related listings, are prominent.*

#### 3.5.8 Yearly Dummies

Both first-day and first-year abnormal returns vary from year to year.[26] Since the degree of abnormal returns is cyclical and concentrated in periods (Ibbotson & Jaffe, 1975), we utilise yearly fixed effects to control for it. Ritter (1984) and Ibbotson and Jaffe (1975) both show apparent evidence of underpricing-differences in hot- and cold issue markets. An alternative solution to using year-fixed effects to control for time-effects would be constructing period-fixed effects based directly on market conditions. Implying the dummies would not be yearly, but rather periodically based, divided by cycles.[27]

[26] See Figure 7 and Figure 8.
[27] We test both yearly dummies and time-period dummies in our regressions without any substantial differences.

## 3.6 Descriptive Statistics and Inferential Statistics

### 3.6.1 Sample Characteristics

The frequency of IPOs varies substantially over time. It is well known that the IPO volume is cyclical. IPO volume is positively related to the level of investor sentiment (Lowry, 2003), an indication of IPO volume being highly affected by the economic sentiment. Figure 6 shows the IPO volume in the Norwegian market for our data period. The IPO activity is clearly highest in 2007, before the financial crisis. During and after the financial crisis, the IPO activity is low, and for the entire sample, the activity is substantially lower than the pre-crisis level.

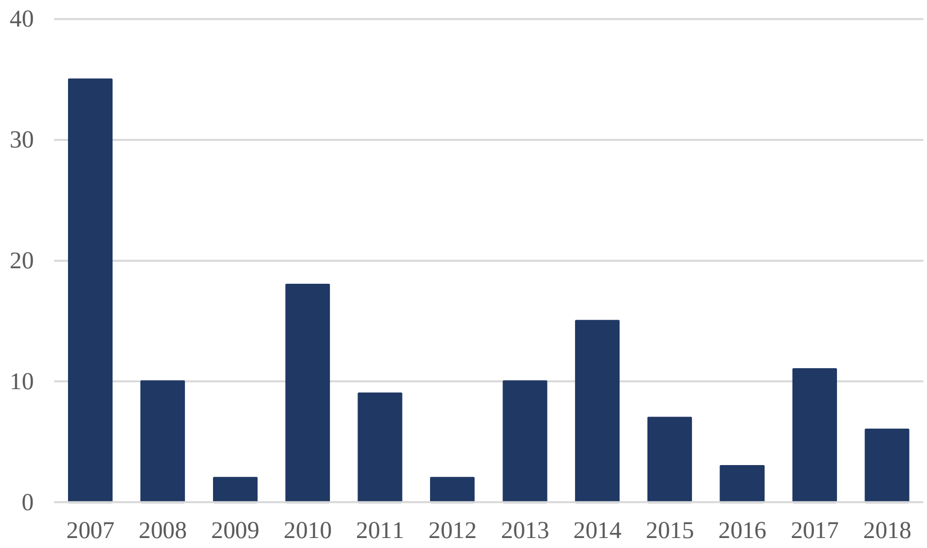


*Figure 6: Number of IPOs each year in the sample period.*

### 3.6.2 Initial Abnormal Returns

Figure 7 depicts the average initial abnormal returns graphically, revealing first-day returns to vary from year to year. Three of the years, IPOs are overpriced on average. According to Ibbotson and Jaffe (1975), periods with negative first-day returns are normal during cold periods. Several scholars find overpricing of IPOs in the period after the financial crisis, which may explain our findings.[28]

[28] See for example Fauzi, Wellalage and Locke (2012).

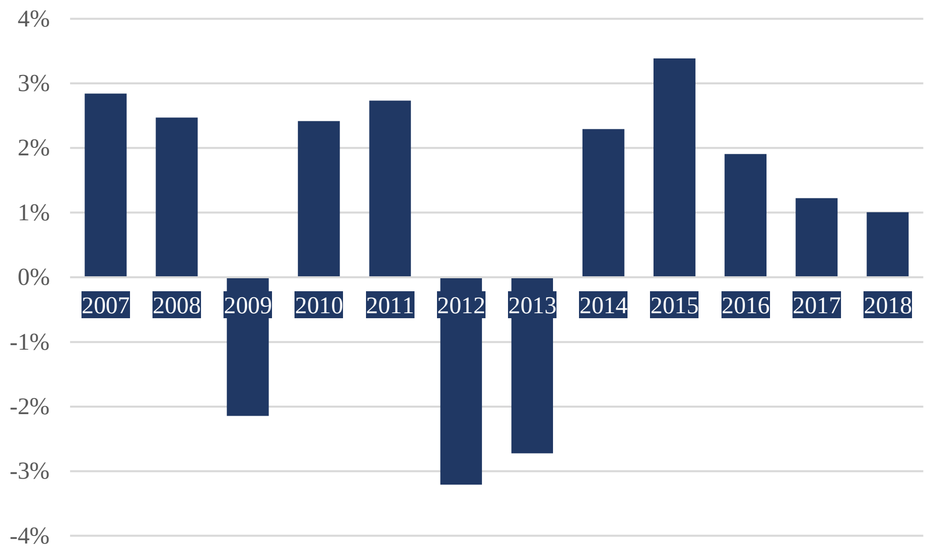


*Figure 7: Initial market-adjusted returns, given by listing year.*

Table 3 summarises the descriptive statistics for underpricing. The first column presents the first-day initial returns, the second presents first-day abnormal returns (adjusted for market movements), and lastly, we have included the log-transformed first-day abnormal returns.

| Descriptive statistics | Initial return | Initial AR | Log initial AR |
|---|---|---|---|
| Observations | 128 | 128 | 128 |
| Mean | 1.662% | 1.857% | 0.012 |
| Standard deviation | 11.782% | 11.827% | 0.100 |
| Skewness | 1.735 | 1.763 | 0.324 |
| Kurtosis | 10.175 | 10.288 | 5.693 |
| Min | -26.190% | -24.776% | -0.270 |
| $25^{th}$ percentile | -3.229% | -3.489% | -0.032 |
| Median | 0.000% | 0.434% | 0.008 |
| $75^{th}$ percentile | 5.000% | 4.787% | 0.051 |
| Max | 62.369% | 63.287% | 0.417 |

*Table 3: The table presents descriptive statistics on initial return, market-adjusted initial return and the log-transformed variable of market-adjusted initial return used in the regressions.*

The table shows that the differences between the simple initial return and the market-adjusted initial return is small with respect to mean, standard deviation, and remaining descriptive measures. The market adjusted initial abnormal returns are actually observed as higher than the unadjusted ones. These statistics support Beatty and Ritter (1986), who deem one-day market adjustments to be of insignificance. We conduct a simple t-test for significance of the average

1.857% underpricing and find it statistically significant at the 10% significance level.[29] Hence, we can reject the null hypothesis of zero underpricing.

The median observation indicates that half of the issues are more underpriced than 0.434%. The 25th percentile tells us that the 25% least underpriced issues are overpriced with 3.489% or more. The 75th percentile, on the other hand, tells us that the 25% greatest observations are underpriced with more than 4.787%. Substantial underpricing is therefore not uncommon. The median is lower than the mean, and the sample thereby appears to be skewed to the right, which is also confirmed by the skewness value of 1.763.[30] The kurtosis of 4.438 deviates from the indications of a normal distribution. The normal distribution has a kurtosis of 3; the kurtosis found, indicates a sharper distribution with fatter tails, also known as a leptokurtic distribution (Choi & Nam, 2008).

### 3.6.3 Long-run Abnormal Returns

As mentioned, the phenomenon of IPO long-run underperformance is widely acknowledged. This notion also appears in our data. Consistent with Ritter (2016) finding negative market-adjusted three-year average returns for the time period 1980-2015, our sampled firms are heavily underperforming on a yearly basis. Our long-run abnormal returns are graphically presented in Figure 8.

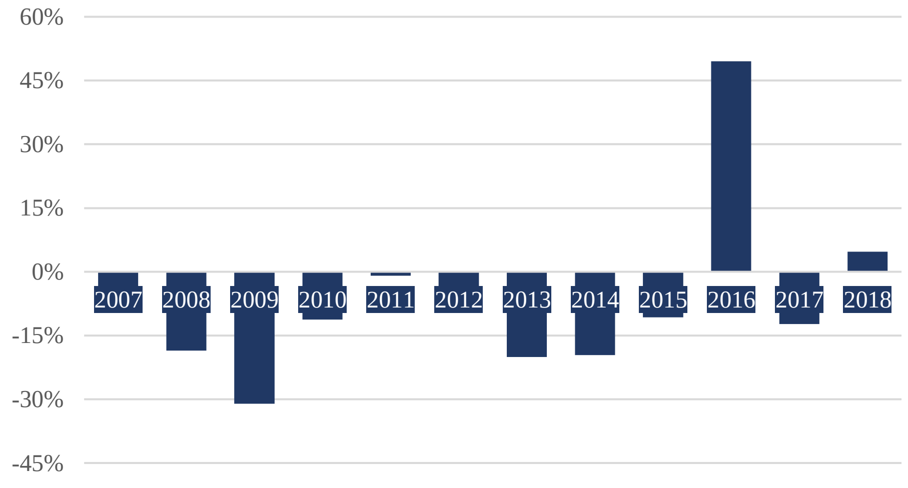


*Figure 8: Long-run market-adjusted return of sampled IPOs, given by year listed.*

[29] Two-sided t-test for null hypothesis where underpricing is different from zero.
[30] Skewness of 0 when normal distribution or any symmetric distribution.

Table 4 summarises the descriptive statistics for long-run performance, measured as the first year listed, in three different ways. The first column shows the first-year performance without adjusting for the market, the second column describes the first-year market-adjusted performance, and the last column shows statistics for log-transformed abnormal returns.[31]

| Descriptive statistics | Long-run performance | Long-run AR | Log long-run AR |
|---|---|---|---|
| **Observations** | 125 | 125 | 125 |
| **Mean** | -12.101% | -9.183% | -0.204 |
| **Standard deviation** | 43.443% | 41.175% | 0.524 |
| **Skewness** | 0.768 | 0.900 | -0.298 |
| **Kurtosis** | 4.169 | 4.438 | 3.089 |
| **Min** | -87.037% | -88.662% | -1.538 |
| **25th percentile** | -46.809% | -36.682% | -0.513 |
| **Median** | -14.615% | -14.078% | -0.135 |
| **75th percentile** | 14.031% | 11.031% | 0.121 |
| **Max** | 156.251% | 141.687% | 1.055 |

*Table 4: The table presents descriptive statistics for long-run returns, market-adjusted long-run returns and the log-transformed variable of long-run market-adjusted returns used in the regressions.*

By observing the table output, it is apparent that an index correction for market returns is more valuable and even necessary in the long-run compared to first-day returns. We focus on the abnormal return columns. The sample mean is -9.183%, a substantial negative first-year abnormal return. This is statistically tested through a simple t-test, which indicates that the coefficient is statistically significant at a 5% significance level. The significance strongly confirms the long-run underperformance of IPOs.

The median observation is -14.078%, indicating that half of the firms perform worse than -14% in the first year of listing, depicting substantial underperformance. The 25th and 75th percentiles also indicate a greater downside than the upside of observations. Skewness and kurtosis indicate a distribution skewed to the right, also indicated by the median being lower than the mean, and somewhat fatter tails than a normal distribution.

*Big vs. Small*

The differences between big- and small-cap firms' initial abnormal returns when going public are observably small for our sample. We find an average underpricing of 2.024% for big firms and 1.668% for small firms. A simple two-sided t-test shows that big firm underpricing is

[31] The different calculation methods can be found in Subchapter 3.2 about calculation of abnormal returns.

significantly different from zero at a 10% significance level, while small firm underpricing is insignificant.

However, the difference in yearly underperformance is substantial. On average, large companies yield -1.418% first-year abnormal returns, while small-cap companies deliver -17.524% in the first year. The big-cap firm underperformance is not significantly different from zero, while the small firm is significantly different from zero at a 1% significance level.

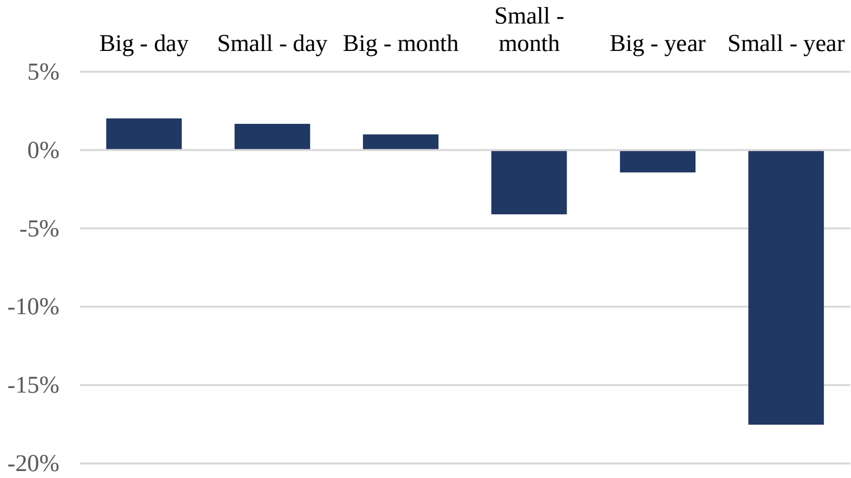


*Figure 9: Abnormal return for big and small companies; first day, first month and first year.*

*Yearly Time Effects*

As mentioned, average abnormal returns vary heavily over time.[32] In three of the twelve total years, we experience negative abnormal returns on average the day of listing. Only two years yield positive long-run abnormal returns. Since the dataset consists of a limited number of observations for each year, few of the years become significant when performing the simple t-tests on a yearly basis.[33]

| Year | # of IPOs | First day AR | First year AR |
|---|---|---|---|
| **2007** | 35 | 2.842%*** | -4.686% |
| **2008** | 10 | 2.470% | -18.517%** |
| **2009** | 2 | -2.146% | -31.083% |
| **2010** | 18 | 2.418% | -11.222% |
| **2011** | 9 | 2.734% | -0.905% |
| **2012** | 2 | -3.212% | -4.028% |
| **2013** | 10 | -2.724% | -20.064%* |

[32] See Figure 7 and 8 and Table 5.
[33] The tests suffer from a small n, which in turn requires the observations to be far more extreme to be deemed significant.

| | | | |
|---|---|---|---|
| **2014** | 15 | 2.295% | -19.639% |
| **2015** | 7 | 3.385% | -10.723% |
| **2016** | 3 | 1.905% | 49.566% |
| **2017** | 11 | 1.224% | -12.312% |
| **2018** | 6 | 1.007% | 4.743% |
| **Total** | 128 | 1.857%* | -9.183%** |

*Table 5: The table presents descriptive statistics on average yearly abnormal returns both initially and long-run. The returns are significance tested using a two-sided t-test to see if yearly observations are different from zero. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

*Sector Differences*

The sector classification of the company is yet another differentiating factor of abnormal returns. The sectors yield different results, both based on the initial- and long-run abnormal returns. Since some sectors consist of very few observations, the results are not statistically significant and should be interpreted with care.

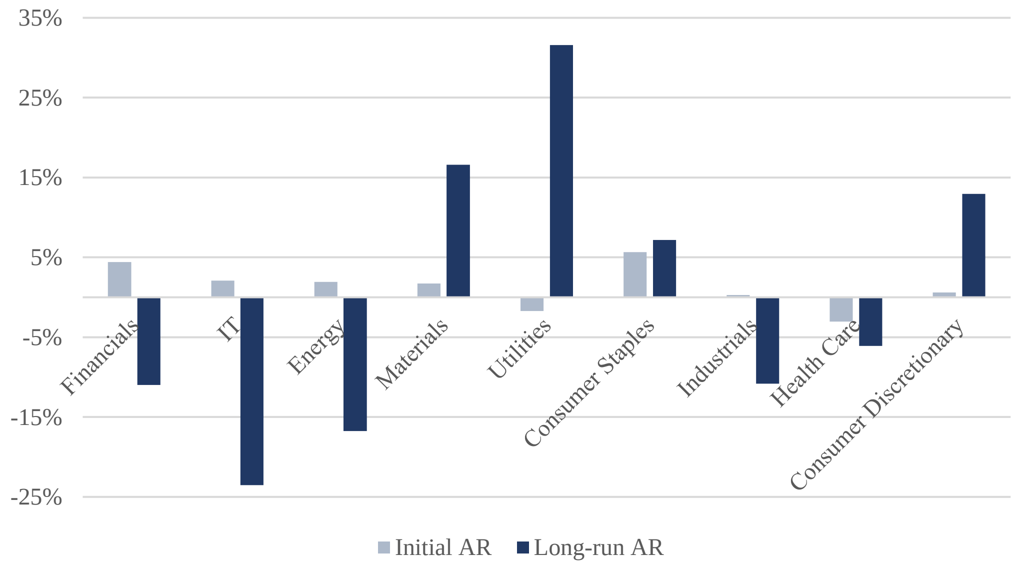


*Figure 10: Sector differences in underpricing and long-run performance.*

The differences in underpricing between the energy sector and the remaining sectors are small. The energy sector exhibits a mean underpricing of 1.935% compared to 1.817% for the rest of the IPOs. A two-sided t-test assessing whether underpricing is different from zero deems the results insignificant. However, long-run performance differences are larger. The energy sector depicts a mean of -18.029% compared to -5.020% for the remaining companies. Energy firms' abnormal return is different from zero at a 1% significance level, while the latter is insignificant.

### 3.6.4 Summary Statistics for Independent Variables

In the following subchapter, we present summary statistics for all liquidity measures and control variables. Some of our variables are both estimated based on daily and yearly observations. Table 6 shows numerical statistics for all variables.

| IPO characteristics | Mean | Std. Dev. | 25th% | Median | 75th% | N |
|---|---|---|---|---|---|---|
| **Market value (1 000)** | 2,393,796 | 3,749,577 | 475,379 | 1,122,851 | 2,550,279 | 128 |
| **Offer size (1 000)** | 840,473 | 1,485,335 | 72,580 | 253,700 | 897,092 | 128 |
| **Company age** | 25.48 | 43.57% | 4.00 | 10.50 | 19.00 | 128 |
| **VIX daily** | 18.06 | 6.62 | 13.16 | 16.09 | 22.11 | 128 |
| **VIX yearly average** | 20.81 | 6.92 | 14.93 | 20.34 | 23.51 | 125 |
| **Brent daily (change)** | -0.0004 | 0.0193 | -0.0104 | 0.0009 | 0.0109 | 128 |
| **Brent yearly (change)** | -0.0361 | 0.4537 | -0.4808 | -0.0049 | 0.3822 | 125 |
| **Std. dev. of returns** | 0.5293 | 0.3114 | 0.3061 | 0.4591 | 0.6440 | 125 |
| ***Liquidity measures*** | | | | | | |
| **NOK Volume yearly average (1 000)** | 5,889 | 11,766 | 216 | 1,022 | 4,412 | 125 |
| **Share turnover** | 0.3494 | 0.3412 | 0.1195 | 0.2335 | 0.4215 | 125 |
| **Amihud*$10^7$ - Illiquidity** | 3.3274 | 13.9091 | 0.0594 | 0.4118 | 1.6682 | 125 |
| **High-low-range** | -2.5633 | 1.0806 | -3.4576 | -2.8186 | -1.8152 | 125 |

*Table 6: The table presents summary statistics for all variables used in our regressions.*

Table 7 presents a correlation matrix for all the control variables. The correlation values denote the correlation between all variables connected to the time of each IPO.

| | Age | Offer size | Market value | VIX day | VIX year | Brent day | Brent year | Std. dev. | Float rate | Energy dummy |
|---|---|---|---|---|---|---|---|---|---|---|
| **Age** | 1.000 | | | | | | | | | |
| **Offer size** | 0.284 | 1.000 | | | | | | | | |
| **Market value** | 0.208 | 0.563 | 1.000 | | | | | | | |
| **VIX day** | -0.155 | -0.160 | -0.108 | 1.000 | | | | | | |
| **VIX year** | -0.201 | -0.370 | -0.111 | 0.604 | 1.000 | | | | | |
| **Brent day** | -0.015 | 0.005 | -0.015 | -0.090 | -0.015 | 1.000 | | | | |
| **Brent year** | 0.098 | 0.130 | 0.213 | -0.117 | -0.198 | -0.102 | 1.000 | | | |
| **Std.dev.** | -0.310 | -0.450 | -0.286 | 0.247 | 0.409 | -0.064 | -0.240 | 1.000 | | |
| **Float rate** | 0.216 | 0.739 | 0.061 | -0.107 | -0.319 | -0.003 | -0.003 | -0.280 | 1.000 | |
| **Energy dummy** | -0.256 | 0.098 | 0.179 | 0.179 | 0.186 | -0.032 | 0.039 | 0.228 | -0.092 | 1.000 |

*Table 7: The table presents a correlation matrix of all control variables.*

We observe multiple noteworthy relationships in the correlation matrix. We observe strong positive correlations between offer size and market value and offer size and float rate. This is in accordance with expectations, since bigger offer size is related to the overall size of the company and float rate being stocks issued as a percentage of total stocks. Hence, the variables rationally seem to collinear. We do not include market value and float rate in our final regressions but observe minimal differences when including them.[34] VIX day and VIX year are strongly correlated, but VIX day is exclusively used in the models for initial returns, while VIX year is exclusively used in the models for long-run returns; hence the correlation is uninteresting. The same applies to Brent day and Brent year.

## 3.7 Empirical Strategy

We have now defined a research question, extracted data, and identified relevant variables to conduct the analysis. Through the research question, we attempt to investigate how stock liquidity in the secondary market affects both initial and long-run abnormal returns. Further, we investigate variations in the data to look for potential drivers of our results. We diverge the observations into hot and cold sentiment market issues to inspect deviations in liquidity's relation to returns. Lastly, the sample is diverged by which marketplace the IPOs are issued at, OSE or Oslo Axess.

We now proceed to explain how we test this empirically. We perform regressions with the liquidity measures and a set of control variables. The four liquidity measures are presented in Subchapter 3.4, and the control variables are presented in Subchapter 3.5.

We estimate the following models for initial abnormal returns with the four liquidity measures.

$$Initial\ abnormal\ return_t = \beta_0 + \beta_1 Amihud + \sum_{m=1}^{M} \gamma_m Control_t^m + \mu_{t+k} \tag{10}$$

$$Initial\ abnormal\ return_t = \beta_0 + \beta_1 Share\ Turnover + \sum_{m=1}^{M} \gamma_m Control_t^m + \mu_{t+k} \tag{11}$$

$$Initial\ abnormal\ return_t = \beta_0 + \beta_1 H - L\ Range + \sum_{m=1}^{M} \gamma_m Control_t^m + \mu_{t+k} \tag{12}$$

$$Initial\ abnormal\ return_t = \beta_0 + \beta_1 NOK\ Volume + \sum_{m=1}^{M} \gamma_m Control_t^m + \mu_{t+k} \tag{13}$$

If $\beta_1$ is significant in the models, liquidity, expressed through the different liquidity measures, correlates with the initial abnormal returns. We estimate the model with different sets of control

[34] See all regressions in Appendix 3 and 4.

variables as shown in Appendix 3, to find the most solid fit between initial abnormal returns and the liquidity measure in each model.

Further, we estimate the following models for long-run abnormal returns with the four liquidity measures.

$$Long - run\ abnormal\ return_t = \beta_0 + \beta_1 Amihud + \sum_{m=1}^{M} \gamma_m Control_t^m + \mu_{t+k} \tag{14}$$

$$Long - run\ abnormal\ return_t = \beta_0 + \beta_1 Share\ Turnover + \sum_{m=1}^{M} \gamma_m Control_t^m + \mu_{t+k} \tag{15}$$

$$Long - run\ abnormal\ return = \beta_0 + \beta_1 H - L\ Range + \sum_{m=1}^{M} \gamma_m Control_t^m + \mu_{t+k} \tag{16}$$

$$Long - run\ abnormal\ return_t = \beta_0 + \beta_1 NOK\ Volume + \sum_{m=1}^{M} \gamma_m Control_t^m + \mu_{t+k} \tag{17}$$

$\beta_1$ can be interpreted similarly in these regression estimations. Multiple models for regressions with long-run abnormal returns as the dependent variable are shown in Appendix 4.

We run several models and report the best fitting ones in the results, while the alternative models are presented in the appendix. Intuitively, we expect liquidity to be negatively correlated to abnormal returns as the well-known liquidity premium states that illiquid stocks should require higher expected returns.

Then, sentiment-based models are constructed as an alternative to hot and cold issue markets. Hot markets are known to cause high levels of underpricing and high liquidity. This approach lets us examine the differences between strong and weak sentiment periods. We choose to split the dataset rather than applying an interaction dummy, because we are more interested in the relationships – rather than the differences – between liquidity and underpricing. Furthermore, we know that 'a split sample is analogous to a fully interacted regression'.

We then proceed to the investigation of the marketplace diverged sample to look for differences in liquidity between OSE and Oslo Axess, as our descriptive indications in Figure 9 in Subchapter 3.6.3 visualise substantial differences between big and small companies. We choose to split the dataset by marketplace instead of market value or liquidity, because in general, OSE consists of bigger and more liquid companies compared to Oslo Axess. Furthermore, the marketplaces differ with respect to company characteristics.

The regressions for the sentiment- and marketplace-based approaches are identical to the originals, except for the sorting of observations. This should give more power to the understanding of the relationship between initial and long-run IPO abnormal returns and liquidity in the Norwegian market.

## 3.8 Econometric Concerns

We log-transform every variable except the three dummy variables and share turnover, as described in this chapter. This way we obtain as normally distributed variables as possible, increasing the efficiency of the models. There are yet several possible problems to account for.

We find some evidence of heteroskedasticity in some of our models, using both the White`s test and Breusch-Pagan`s test and account for this through estimation of heteroskedastic robust standard errors in the models.

Endogeneity problems can occur as results of omitted variable bias, functional form misspecification, measurement errors and simultaneity. We address some concerns for possible bias and measurement errors in Subchapter 3.2. Furthermore, functional form misspecification is tested for through inclusion of variables in different functional forms. For example, offer size is tested as a level variable, log variable, squared variable and as a dummy variable before concluding on the functional form.

Recall the correlation matrix and accompanied observations, correlating variables is a validity concern. Hence, all models are controlled for multicollinearity by using the VIF-test, consistently avoiding VIF values above 2.50. The yearly VIX is colinear with the year 2014. Therefore, the yearly VIX variable is excluded from all models where yearly dummies are applied.

# 4. Results and Analysis

In the following chapter, the results of our analysis are presented. Until now, descriptive and inferential statistics concerning IPO underpricing and long-run performance have been examined. In this chapter, we focus on identifying relationships of significance between liquidity and abnormal returns, connecting the two together. First, we present results for underpricing and long-run performance before finally attempting to differentiate between IPO behaviour on Oslo Stock Exchange and Oslo Axess. The results are presented in Subchapters 4.1, 4.2 and 4.3 respectively. Finally, we will address some limitations of our work and suggestions for further research.

## 4.1 Underpricing and Liquidity

| | (4) Log(Initial returns) | (8) Log(Initial returns) | (12) Log(Initial returns) | (16) Log(Initial returns) |
|---|---|---|---|---|
| Log(Amihud) | -0.0057 | | | |
| | (-1.14) | | | |
| Share turnover | | -0.0324 | | |
| | | (-0.90) | | |
| H-L range | | | -0.0162 | |
| | | | (-1.21) | |
| Log(NOK volume) | | | | 0.0140** |
| | | | | (2.09) |
| Log(Company age) | 0.0132** | 0.0144** | 0.0136** | 0.0116** |
| | (2.06) | (2.25) | (2.19) | (2.00) |
| Log(Offer size) | -0.0078 | -0.0004 | -0.0064 | -0.0114 |
| | (-1.00) | (-0.06) | (-0.77) | (-1.44) |
| Log(Brent) | 0.3210 | 0.3340 | 0.3730 | 0.2930 |
| | (0.71) | (0.73) | (0.82) | (0.67) |
| Log(VIX) | -0.0455 | -0.0500 | -0.0405 | -0.0286 |
| | (-1.10) | (-1.14) | (-0.96) | (-0.69) |
| Energy sector dummy | 0.0168 | 0.0188 | 0.0131 | |
| | (0.58) | (0.69) | (0.45) | |
| Yearly dummy | Yes | Yes | Yes | Yes |
| _cons | 0.178 | 0.149 | 0.194 | 0.106 |
| | (1.01) | (0.81) | (1.05) | (0.62) |
| *N* | 125 | 125 | 125 | 125 |
| $R^2$ | 0.088 | 0.087 | 0.090 | 0.108 |
| adj. $R^2$ | -0.057 | -0.059 | -0.055 | -0.024 |

*Table 8: The accompanying table presents the results of linear regressions assessing the effect of liquidity on initial abnormal returns in IPOs. Each of the four regressions attempts to explain the underpricing phenomenon, using (4) the Amihud illiquidity ratio, (8) share turnover, (12) H-L range measure and (16) NOK volume. The included regressions for each of the four measures are the ones deemed optimal, hence why they do not include entirely similar control variables. The control variables include logarithmic transformations of company age, offer size, change Brent Spot oil price, and daily value on the CBOE volatility index (VIX), as well as an energy sector dummy variable and a yearly dummy variable. The sample runs from January 2007 through December 2018. A VIF-test is run to control for multicollinearity. Heteroscedastic robust standard errors are reported in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

As expected, liquidity seems to affect the underpricing of IPOs. However, the four selected measures exhibit varying significance. It is of importance to notify that liquidity, being an elusive concept per definition, might not be directly interpretable in a numerical manner. Thus, the interpretation of the results requires a main focus on the interaction between variables as relationships and tendencies, not numerical magnitudes. The best-fitted regression model for each liquidity measure is presented above. The alternative regressions which were conducted with each liquidity measure can be found in Appendix 3.

The Amihud illiquidity ratio, a volume-based measure, and the constructed high-low range, which attempts to capture movements of the bid-ask spread, both reveal the same relationship tendency between liquidity and underpricing – the more underpriced the stock during the initial offerings, the less illiquid the stock in the aftermarket. The simple NOK volume measure further confirms this relationship, the variable being significant at a 5% level. The coefficient implies a 1% increase in NOK volume resulting in a 0.014% increase in initial return, ceteris paribus. Albeit not significant at the benchmark 10% level, each and all three measures indicate a positive relationship between initial abnormal returns and secondary market liquidity. The fourth measure however, the share turnover, weakly, but noteworthily, indicates the opposite relationship.

NOK volume is based solely on sheer volume, while share turnover determines trading volume relative to shares outstanding, thus measuring liquidity per size. Larger firms are traded in higher NOK volumes, and were observed as more underpriced, recall Subchapter 3.5.3. Though, when controlling for shares outstanding, the liquidity increase per share is lower in larger firms. Hence, a negative share turnover coefficient reflects smaller firms being recognised as more liquid given size. This explains the difference between the NOK volume and share turnover coefficients.

Other noteworthy observations include the 5% level significance of company age. Inconsistent with Loughran and Ritter (2004), we find underpricing positively related to the age of the IPO issuer, implying the older the issuing firm, the more underpriced the stock. The company age variable is consistently significant in all models.

Busaba and Chang (2010) examine the book-building (and fixed price) approach, focusing on the influence of the presence of informed investors on underpricing, based on aftermarket liquidity. They propose that high magnitudes of expected noise trading in the aftermarket catches the attention of informed investors, since it generates opportunities of easily liquidating the stocks. Based on the model developed by Benveniste and Spindt (1989), they prove that as a result of informational asymmetry, underwriters are incentivised to increase underpricing, to attract informed investors to surrender private information and forgo the aftermarket profit potential. Hence, book-building becomes costly, due to this profit potential adversely affecting premarket bidding behaviour. Thus, their models predict a positive relationship, and are supportive of the theory of expected aftermarket liquidity boosting underpricing.

The general indication revealing itself in the regression models, that the relationship between underpricing and aftermarket liquidity is positive, is furthermore consistent with the findings of Booth and Chua (1996) and Hahn et al. (2013). Noteworthily, the data used by both Booth and Chua, and Hahn et al. contain, as confirmed by themselves, *an overwhelming majority of U.S. firms*. Concluding their research, Hahn et al. attempt to determine the driver of the contradictory results between their own findings and those of Ellul and Pagano (2006). A closer inspection reveals that the data of Ellul and Pagano is from London Stock Exchange from 1998-2000, an exchange where a fixed price approach to IPOs is utilised and a time-period of less general suitability. Moreover, liquidity is estimated over four weeks after the IPO.

In contrast, Norwegian IPOs are predominantly carried out using the book-building approach, whereas U.S. markets use it exclusively. Engelen and van Essen (2010) showed that underpricing is affected by the form of offering.[35] Furthermore, Hahn et al. are analysing a significantly longer (1988-2009) period, and consistent with our methodology, they estimate liquidity over the first year following the IPO. Although, Hahn et al. show that this difference is not the driver of the contradicting results. Moreover, Ellul and Pagano's data coincide with the height of the dotcom bubble, which might affect results. In our data, we have attempted to take care of highly abnormal years. Finally, our variables slightly differ both from those of Hahn et al. and Ellul and Pagano.

### 4.1.1 Underpricing, Liquidity and Hot Markets

We try several ways to construct a sample of IPOs in hot periods in contrast to cold periods. Recall, hot periods are characterised as periods where IPO volume and trading volume are high. Few yearly IPOs limit the ability to differentiate between hot and cold periods based on IPO volume, see Figure 6.[36] The fluctuations in IPO volume are also severe within each year, so listings per year do not provide a precise picture of market conditions. Thus, in a study by Ibbotson and Jaffe (1975), market conditions are measured on a monthly basis. Here, hot markets are characterised as the average return on listings in a month being above the median of the same month`s observations. Rajan and Servaes (1997) argue that an increase in investor sentiment positively affects the number of new issues. The positive sentiment, a bull market,

[35] Different approaches include book-building, fixed price, auction and hybrid.
[36] We conduct regressions based on the three highest IPO volume years, defined as hot markets, without any substantial effects of hot and cold markets.

can relate to hot issue periods. Furthermore, bull markets are by Gonzalez, Hoang, Powell and Jing (2006) identified as periods of higher than usual returns. We create hot markets as a positive sentiment indicator by using 2-month market returns prior to each listing. The issue is hot when the market return is positive and cold if the market return is negative. Hence, we attempt to identify isolated effects from IPOs issued in different market conditions.

| | (33) Initial AR HOT | (34) Initial AR HOT | (35) Initial AR HOT | (36) Initial AR HOT | (37) Initial AR COLD | (38) Initial AR COLD | (39) Initial AR COLD | (40) Initial AR COLD |
|---|---|---|---|---|---|---|---|---|
| Log(Amihud) | -0.0120* (-1.92) | | | | 0.0131 (0.80) | | | |
| Share turnover | | -0.00311 (-0.09) | | | | -0.133* (-1.72) | | |
| H-L range | | | -0.0232* (-1.75) | | | | -0.0008 (-0.02) | |
| Log(NOK volume) | | | | 0.0194** (2.23) | | | | 0.0028 (0.14) |
| Log(Company age) | 0.00525 (0.77) | 0.00742 (1.06) | 0.00605 (0.85) | 0.00573 (0.90) | 0.0341* (1.92) | 0.0321* (1.86) | 0.0332* (1.85) | 0.0278 (1.51) |
| Log(Offer size) | -0.00567 (-0.65) | 0.00590 (0.65) | -0.000731 (-0.07) | -0.00754 (-0.83) | 0.00187 (0.09) | -0.00943 (-0.78) | -0.0133 (-0.72) | -0.0128 (-0.63) |
| Log(Brent) | 0.187 (0.33) | 0.121 (0.20) | 0.250 (0.44) | 0.264 (0.48) | 0.535 (0.53) | 0.746 (0.75) | 0.425 (0.39) | 0.255 (0.22) |
| Log(VIX) | -0.0231 (-0.43) | -0.0239 (-0.42) | -0.0283 (-0.51) | -0.0130 (-0.25) | -0.141 (-1.33) | -0.177 (-1.68) | -0.145 (-1.33) | -0.141 (-1.26) |
| Energy sector dummy | 0.0211 (0.70) | 0.0192 (0.64) | 0.0150 (0.47) | | 0.0307 (0.52) | 0.0579 (1.15) | 0.0392 (0.66) | |
| Yearly dummy | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| _cons | -0.00441 (-0.02) | -0.0361 (-0.17) | 0.0549 (0.25) | -0.0743 (-0.39) | 0.517 (1.35) | 0.656* (1.79) | 0.613 (1.48) | 0.581 (1.44) |
| *N* | 82 | 82 | 82 | 82 | 43 | 43 | 43 | 43 |
| $R^2$ | 0.226 | 0.177 | 0.203 | 0.232 | 0.239 | 0.298 | 0.210 | 0.197 |
| adj. $R^2$ | 0.021 | -0.041 | -0.008 | 0.043 | -0.184 | -0.092 | -0.229 | -0.205 |

*Table 9: The accompanying table presents the results of linear regressions assessing the effect of different liquidity measures on initial abnormal returns in IPOs on a diverged sample characterised as hot and cold sentiment markets. Each of the eight regressions attempts to explain the liquidity on underpricing, using (33) and (37) the Amihud illiquidity ratio, (34) and (38) share turnover, (35) and (39) H-L range measure and (36) and (40) NOK volume. The control variables include logarithmic transformations of company age, offer size, change Brent Spot oil price, and daily value on the CBOE volatility index (VIX), as well as an energy sector dummy variable and a yearly dummy variable. The sample runs from January 2007 through December 2018. A VIF-test is run to control for multicollinearity. Heteroscedastic robust standard errors are reported in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

The regressions in Table 9 show the effect of aftermarket liquidity on underpricing when sorting by hot and cold sentiment markets. We see that the underpricing has significant relationships with aftermarket liquidity when issuing in hot periods. Three of the liquidity measures are significantly showing higher underpricing followed by higher aftermarket liquidity.

We perform a Chow-test to acquire statistical foundation for whether the coefficients differ in magnitude, the null hypothesis being that the slopes are equal. The dataset suffers from a small sample size, which causes the standard errors to be larger, due to the implied uncertainty regarding the 'true population'. In turn, models and tests are affected by these large standard errors, resulting in conservativeness when producing p-values. Howbeit, the results from the performed Chow-test shows an indication of difference between the coefficients of hot and cold periods. The p-values we receive for the respective liquidity measures are 0.071, 0.183, 0.324 and 0.199.

Zheng and Li (2008) find that trading volume is higher, and spread is lower in issues characterised as hot. Consistent with consensus, we find that the volume measures, Amihud and NOK volume, are positively related to higher underpricing. The volume measures are statistically significant at the 10% and 5% significance level respectively. Further, the high-low range coefficient indicates a lower relative spread leading to higher underpricing, significant at the 10% level. Again, the share turnover is insignificant, with a t-value close to zero. The discussion in Subchapter 4.1 treated the underlying cause of share turnover contradicting the three other measures.

In line with the investor attention hypothesis, higher underpricing causes investors to gravitate towards the stock. Hence; price-rise-induced increase in investor attention leads to higher trading volumes.

The findings in hot markets are consistent with Busaba and Chang (2010) explaining that higher underpricing is a result of the ability of the informed investors to profit in the aftermarket, recall their previously discussed study. The intuitive explanation for the strong indications in hot markets can further be explained by Bakke, Leite and Thorburn (2017). They develop a model proposing a rational explanation for the puzzling predictability that market returns prior to issue are correlated with underpricing. Based on Benveniste and Spindt`s (1989) model they add a public signal. Their incentive effect suggests that the underwriter must increase underpricing when public signal is negative to induce investors to truthfully reveal their signals.

Our finding, that aftermarket liquidity is positively related to underpricing, is supported by Bakke et al. elucidating the intuition of demand and incentive effects as a rational cause. However, the positive relationship between higher liquidity and underpricing evaporates when markets are characterised as cold. In fact, the share turnover significantly points in the opposite direction, higher share turnover in the aftermarket leading to lower underpricing in cold periods.

Issues with higher turnover rates are less underpriced, implying that firms with lower float relative to volume seem to be less underpriced.

Furthermore, in the cold issues, the three other measures are insignificant, indicating that there is no relationship between aftermarket liquidity and underpricing. Share turnover, as a relative trading volume measure, shows that the relative trading volume is significantly lower for more underpriced issues in cold periods. Intuitively, the Norwegian market might not behave in line with theory in cold periods due to irrational behaviour. A large fraction of the issues characterised as cold coincide with the financial crisis and the oil downturn arising in 2014, clearly differing from “normal” market conditions, both in investor rationality and market behaviour. Hence, we believe the relationship may subside due to turbulent markets.

## 4.2 Long-run Returns and Liquidity

| | (20)<br>Long-run returns | (24)<br>Long-run returns | (28)<br>Long-run returns | (32)<br>Long-run returns |
|---|---|---|---|---|
| Log(Amihud) | -0.0386* (-1.76) | | | |
| Share turnover | | 0.2170 (1.52) | | |
| H-L range | | | -0.0838 (-1.44) | |
| Log(NOK volume) | | | | 0.0946*** (3.11) |
| Log(Company age) | 0.0066 (0.18) | 0.0040 (0.11) | 0.0084 (0.23) | -0.0025 (-0.08) |
| Log(Offer size) | -0.0587* (-1.70) | -0.0341 (-1.21) | -0.0438 (-1.39) | -0.0870** (-2.31) |
| Log(Initial returns) | 1.0820*** (2.65) | 1.2010*** (2.94) | 1.0880*** (2.65) | 0.9060** (2.45) |
| Log(Brent) | -0.4780*** (-3.40) | -0.4820*** (-3.42) | -0.4980*** (-3.51) | -0.5260*** (-4.21) |
| Log(Std. dev.) | -0.4470*** (-4.73) | -0.5190*** (-5.16) | -0.4690*** (-4.97) | -0.4730*** (-4.67) |
| Energy sector dummy | -0.1100 (-1.06) | -0.1440 (-1.38) | -0.1280 (-1.24) | -0.1840* (-1.69) |
| Yearly dummy | Yes | Yes | Yes | Yes |
| _cons | 0.1440 (0.31) | 0.1750 (0.37) | 0.2810 (0.56) | 0.0157 (0.03) |
| $N$ | 125 | 125 | 125 | 125 |
| $R^2$ | 0.389 | 0.385 | 0.383 | 0.425 |
| adj. $R^2$ | 0.286 | 0.280 | 0.279 | 0.328 |

*Table 10: This table shows the results of regressing long-run IPO stock abnormal returns on liquidity measures, assessing the individual effects of (20) the Amihud illiquidity ratio, (24) share turnover, (28) H-L range measure and (32) NOK volume. Additional variables used include logarithmic transformations of company age, offer size, initial returns, yearly change in Brent Spot oil price, and the standard deviation of returns, as well as an energy sector dummy variable and a yearly dummy variable. Each control variable is used for all the four models. A VIF-test is run to control for multicollinearity. Heteroscedasticity is controlled for in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

The regressions modelling aftermarket performance are conducted using the equivalent four liquidity measures, which were used in the modelling of initial abnormal returns. In addition, the models include a set of supplementary proxy and control variables, selected due to their deemed significance in explaining the dependent variable, the long-run performance. In Table 10, the best-fitted regression models and their respective results are presented. The alternative regressions with each liquidity measure can be found in Appendix 4, exhibiting similar results and showing the robustness of the results.

Without exception, the liquidity measures point in the same direction. The Amihud illiquidity ratio and the high-low range both exhibit negative coefficients indicating higher illiquidity yielding lower long-run abnormal returns. The model (20) considering the effect of the Amihud illiquidity ratio deems the ratio statistically significant at a 10% level, rather strongly indicating a negative relationship.[37] The second model (24) uses high-low range as liquidity measure. The coefficient is not quite statistically significant, depicting a p-value of 0.15, but supports the general assumption that higher spreads indicate less liquidity in stocks.

The share turnover and NOK volume further indicate an equivalent relationship. Both measures exhibit positive coefficients indicating higher liquidity yielding higher long-run abnormal returns. The NOK volume variable is significant at a 1% level, while share turnover, like the high-low range, is not significant. Even though the coefficient is not statistically significant, the result regardless points in the direction of a positive relationship.

Our observed results contrast the results of Eckbo and Norli (2005), discovering a relationship where higher share turnover in IPO stocks is a sign of lower volatility, in turn explaining why IPO stocks underperform in the long-run compared to size-matched firms. However, their research is based on the liquidity difference between IPOs and matched firms, a deviation which is found significant, while our research investigates the liquidity differences within our sample of IPOs. Worthy of note is also the fact that their results are based on American stocks, and that they analyse a longer and different time-period as compared to our data. Nevertheless, the relationship detected, that IPOs with greater liquidity yield higher long-run returns, opposes the findings of Eckbo and Norli, that higher liquidity yield lower returns.

Furthermore, on a general note, Amihud and Mendelson (1986) argue in favour of higher expected return justifying larger spreads, and Datar et al. (1998) find strong negative relationships between long-run returns and share turnover, confirming a premium for illiquidity. Hence, both works establishing the opposite relationship of our finding. Amihud, Hameed, Kang and Zhang (2015) investigate the stock illiquidity in international equity markets, including Norway, finding a significant positive liquidity premium. Admittedly, their research is not confined to IPOs, but rather investigates the entirety of the market. Still, large sections of literature find illiquidity to affect long-run returns positively. The fact that each and all our four

[37] See results for the variation in Amihud ratio coefficient values in the regressions in Appendix 4: A.

models indicate the opposite relationship is interesting, showing a more robust tendency of our results. In Subchapter 4.3, we will attempt to detect possible drivers for this currently counterintuitive result.

Our result can be interpreted as consistent with Næs, Skjeltorp and Ødegaard (2008), stating that trading activity and trading costs often become positively connected during periods of distress. This indicates that lower liquidity leads to lower trading costs in periods of distress. A likewise relationship can be observed in our data and models, where the correlation between liquidity and abnormal returns is positive. A large proportion of our IPOs are listed prior to periods of distress,[38] which could legitimate our finding. Noteworthily, Næs, Skjeltorp and Ødegaard's investigation occurs in the Norwegian market between 1980 and 2007, while we investigate aftermarket liquidity in IPOs from 2007-2018.

Other noteworthy findings include indications of offer size being negatively related to the long-run performance of IPOs. Thus, smaller offerings are expected to perform better than large offerings. This indication is consistent with prior studies.[39] Although implying the same tendency, not all the models provide significant results on offer size and the findings should be interpreted with such concerns in mind.

The standard deviation of returns is highly significant, exhibiting a significance level of 1% throughout the models. The variable coefficients imply a 1% increase in standard deviation indicating a decrease between 0.45% and 0.52% in long-run performance in all models, ceteris paribus. This conflict fundamental theories of finance, such as risk-return trade-off, drawing a positive relationship between risk, volatility, and return. Our result, however, supports the findings of Carter, Dark and Singh (1998), who reported highly significant results, indicating a negative relationship between standard deviation and market-adjusted three-year post-IPO returns in the U.S. market.

Initial abnormal returns are used as a variable in our long-run models. We find significant evidence proving underpricing to be positively correlated with long-run abnormal returns. Krishnan, Ivanov, Masulis and Singh (2011) also use underpricing as a variable to explain post-IPO performance, but do not find any significant relationships. Ritter (1991) on the other hand, uncovers indicative results of underpricing being negatively related to three-year raw returns

[38] Exemplified; 35 IPOs listed in 2007 and 15 in 2014.
[39] See for example Carter, Dark and Singh (2002) and Krishnan, Ivanov, Masulis and Singh (2011).

for a sample of 1526 IPOs from 1975-84. The finding states that the larger the underpricing, the worse the long-run abnormal return, the opposite of our results.

## 4.3 Long-run Returns and Liquidity on OSE vs. Oslo Axess

Since the liquidity differences in our dataset are plentiful, and our long-run findings depict an opposite relationship of anticipated, non-intuitive based on theory, we wish to investigate whether size can be utilised as a driver to track differences. There are several ways to split the data. A natural way is separating OSE listed IPOs from those listed on Oslo Axess. Recall, the IPOs listed on OSE are larger and more liquid than the ones on Oslo Axess. Additionally, the listing requirements are slightly different, causing the listings to differ with respect to additional characteristics as well.

We also conduct a similar regression for initial abnormal returns, split into OSE and Oslo Axess. The effect on the different marketplaces seems to be less reliant on and more random for the liquidity measures. We report the model in Appendix 5, however we focus on the findings in the long-run regressions.

| | (41) Long-run Amihud OSE | (42) Long-run Amihud Axess | (43) Long-run Share turnover OSE | (44) Long-run Share turnover Axess | (45) Long-run H-L-Range OSE | (46) Long-run H-L-Range Axess | (47) Long-run NOK Volume OSE | (48) Long-run NOK Volume Axess |
|---|---|---|---|---|---|---|---|---|
| Log(Amihud) | -0.0055 | -0.0772 | | | | | | |
| | (-0.21) | (-1.46) | | | | | | |
| Share turnover | | | -0.0486 | 0.315 | | | | |
| | | | (-0.26) | (1.17) | | | | |
| H-L range | | | | | -0.0856 | -0.159 | | |
| | | | | | (-1.01) | (-1.68) | | |
| Log(NOK volume) | | | | | | | 0.0512 | 0.0978** |
| | | | | | | | (1.12) | (2.23) |
| Log(Company age) | 0.0169 | -0.0251 | 0.0179 | -0.0306 | 0.0195 | -0.0317 | 0.0179 | -0.0244 |
| | (0.37) | (-0.36) | (0.39) | (-0.44) | (0.43) | (-0.46) | (0.42) | (-0.37) |
| Log(Offer size) | 0.00308 | -0.150** | 0.0145 | -0.109** | -0.0110 | -0.153** | -0.0306 | -0.138*** |
| | (0.06) | (-2.53) | (0.37) | (-2.08) | (-0.27) | (-2.64) | (-0.68) | (-3.13) |
| Log(Initial returns) | 1.081* | 1.418** | 1.087* | 1.546** | 1.069* | 1.336** | 0.945* | 1.204 |
| | (1.88) | (2.24) | (1.89) | (2.36) | (1.88) | (2.13) | (1.82) | (1.55) |
| Log(Brent) | -0.549** | -0.324 | -0.544** | -0.353* | -0.571*** | -0.342* | -0.583*** | -0.389** |
| | (-2.57) | (-1.60) | (-2.58) | (-1.69) | (-2.71) | (-1.69) | (-2.88) | (-2.63) |
| Log(Std. dev.) | -0.397*** | -0.575*** | -0.385*** | -0.665*** | -0.392*** | -0.680*** | -0.401*** | -0.646*** |
| | (-2.96) | (-4.04) | (-2.71) | (-4.45) | (-2.95) | (-4.69) | (-3.07) | (-4.29) |
| Energy dummy | -0.192 | 0.148 | -0.187 | 0.0606 | -0.204 | 0.140 | -0.212 | -0.00759 |
| | (-1.48) | (0.84) | (-1.42) | (0.34) | (-1.58) | (0.81) | (-1.52) | (-0.05) |
| Yearly dummy | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| _cons | -0.492 | 1.131 | -0.598 | 1.446 | -0.330 | 2.014** | -0.486 | 0.826 |
| | (-0.69) | (1.21) | (-0.84) | (1.59) | (-0.47) | (2.14) | (-0.73) | (1.22) |
| *N* | 73 | 52 | 73 | 52 | 73 | 52 | 73 | 52 |
| $R^2$ | 0.351 | 0.616 | 0.351 | 0.607 | 0.362 | 0.623 | 0.362 | 0.637 |
| adj. $R^2$ | 0.150 | 0.440 | 0.150 | 0.428 | 0.164 | 0.450 | 0.165 | 0.471 |

*Table 11: This table shows the results of regressing long-run IPO stock returns with all four liquidity measures on the two samples, assessing the individual effects of (41) and (42) the Amihud illiquidity measure, (43) and (44) share turnover, (45) and (46) H-L range measure and (47) and (48) NOK volume. Additional variables used include logarithmic transformations of company age, offer size, initial returns, yearly change in Brent Spot oil price, and the standard deviation of returns, as well as an energy sector dummy variable and a yearly dummy variable. Each control variable is used for all the eight models. Heteroscedasticity is controlled for in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

Table 11 shows eight different regression models, the four liquidity measures applied to the two samples representing the two marketplaces. The liquidity measure coefficients reveal that the positive correlation between liquidity and abnormal returns found in Subchapter 4.2 is driven by the listings on Oslo Axess. However, only one of the liquidity measures is statistically significant for Axess listings. The simple NOK volume measure is significant at a 5% significance level, confirming the same strong positive relationship found in the previous regressions. The three other liquidity measures are not significantly convincing but depict a strong indication, strengthened by all four measures pointing in the same direction. All four liquidity measures are pointing towards higher liquidity leading to higher long-run abnormal returns on Oslo Axess.

When sorting by marketplace, the OSE-listed firms' performance seems unaffected by liquidity. From the sorted models, we observe OSE liquidity coefficients closer to zero, the relations being both weaker and aberrated. The Amihud ratio and share turnover show coefficients with t-values increasingly close to zero, while high-low range and NOK volume indicate the same results as previously but fail to depict significant relationships.

The stock volatility is consistently significant in all models, amongst both markets. The volatility of Oslo Axess stocks is greater and the negative relationship between volatility and long-run abnormal returns in Axess is stronger, indicating that higher volatility on Oslo Axess leads to even higher negative abnormal returns. The offer size is only significant in the models with Oslo Axess and highlights the same relationships found earlier, bigger offer size leads to lower abnormal returns. The relationship is non-existing in the OSE regressions.

OSE and Oslo Axess have, as previously mentioned, different requirements for listing and thereby attract firms with different characteristics. A large proportion of the Oslo Axess sample clearly fits the characteristics from the definitions of what literature describes as penny stocks.[40] Locke and Gupta (2008) examine a situation similar to our OSE vs. Oslo Axess, analysing New Zealand's junior market opening, the Alternative Exchange (AX) at the New Zealand Stock Exchange (NZX), comparable with Oslo Axess. They found that small firms listed on the junior exchange perform worse than those listed on the main exchange, and that small entrepreneurial companies perform worse than other small firms and the overall market. This is suggestive of the same relative underperformance which we find for Oslo Axess. Our models clearly depict that the listings on OSE, in general, do better than those on Oslo Axess. Hence, the negative liquidity premium experienced on Oslo Axess is consistent with the literature on penny stocks and junior markets.

Furthermore, having included IPOs of all sizes leads to a dataset with great variation, including everything from large international companies to small entrepreneurial companies. Carpentier and Suret (2011) investigate Canadian penny stocks from 1986 to 2003. They point out that firms entering the stock market on a pre-revenue stage is a strategy involving considerable risk and find significant relations between listing requirements and survival of the IPOs. The least liquid stocks are often the ones in most immense distress, hence it is reasonable to assume that

[40] No concrete definition of penny stocks but suggested as IPOs with stock prices below $5 per share or market value below $10 million (Carpentier and Suret, 2009).

the liquid stocks on Oslo Axess are doing better, an assumption which is confirmed by the models.

Consequently, some of the most acknowledged IPO researchers omit all IPOs with low offer prices. Ritter (1991) excludes all IPOs with offer prices below $1 and Ibbotson (1975) all IPOs with offer prices below $3. Furthermore, Seguin and Smoller (1997) research price per share’s correlation with returns for newly listed U.S. stocks on Nasdaq. They find evidence that a portfolio of low-priced penny stocks underperforms compared to all other stock price categories the first year. The low-priced Nasdaq stocks have significantly negative risk-adjusted returns even before adjusting for risk. This is relevant to our research, showing that smaller, riskier stocks yield negative returns, contradicting the risk-return trade-off theory. Assessing this to liquidity, we believe that the illiquid smaller stocks of newly issued companies do not follow liquidity factor premium theory; thus, there is no apparent risk-return trade-off.

The smaller and more illiquid IPOs in the Norwegian market, mainly found in the speculative Oslo Axess market, are not sufficiently compensated for the underlying risk they imply. This is consistent with the literature on penny stocks, other junior markets and the relationship found with liquidity in periods of distress.

## 4.4 Limitations and Further Research

In the following subchapter, we highlight the statistical shortcomings of our study and discuss trade-offs and biases which potentially influence our results. Lastly, we propose suggestions for further research.

The implications of the nature of IPOs and IPO markets, and specifically the Norwegian IPO market, required us to make cost-benefit trade-off decisions. Firstly, the data sample is relatively small, and extracted from a narrow timeframe. Secondly, our long-run performance measure is based on one-year development in stock prices. Furthermore, our models might suffer from omitted variable bias, and are most certainly affected by survivorship bias.

As discussed, the IPO market exhibits cyclical patterns consisting of hot- and cold issue periods. Research proves that IPO stocks seem to behave differently during bullish and bearish market trends. Hence, a wide enough timeframe is essential to ensure both trends are included and considered in the sample. Simultaneously, we are aware of the ever-decreasing underpricing level, which implies too wide a timeframe would bias our results as well. Consequently, the timeframe of the study is relatively short from a macroeconomic perspective. Furthermore, our sample size suffers from being small, due to few yearly offerings in the Norwegian market, especially after the financial crisis. Hence, we increasingly rely on each observation being representative of the population.

While most IPO related studies track long-run returns on a three-year basis, we choose a one-year basis. Whilst a three-year basis can be argued to be more representative of true 'long-run' performance, a one-year basis is also defended by researchers as adequate and sufficient as a long-run performance measure.

The extracting of data was another process that demanded trade-offs to be made. Two factors that have been proven to affect returns are whether the IPO is venture-capital-backed and the underwriter characteristics, including quality and quantity of underwriter(s). We were unable to track these factors for approximately 60 observations, mostly missing data on early listed, smaller firms. Consequently, including these variables would imply omitting a substantial number of observations from our already 'size-fragile' data. Therefore, we made the decision to omit them. Moreover, there might be other important unobservable variables that are not included in our models.

Furthermore, there were qualities we were not able to track down for a few more firms. These were typically firms, which performed badly or suffered from bankruptcy shortly after the initial public offerings. The exclusion of these firms might cause bias in our dataset.

Based on our own experiences and findings, several suggestions for future research arise. Firstly, like Eckbo and Norli (2005), a size-matched study based on the Norwegian IPO market can be conducted, where IPOs are size matched with the rest of the market. Thence, liquidity differences can be examined, attempting to explain the underperformance of IPOs by identifying the liquidity factor premium. The hypothesis being that IPOs are more liquid than other stocks, implying less risk, and less return.

Secondly, we found Oslo Axess traded IPOs to perform significantly worse than OSE traded IPOs. A study regarding whether this finding is limited to IPOs can be conducted, analysing the entirety of the market. In general, small stocks are expected to yield higher returns, but SMB-portfolios normally have requirements for size and liquidity, which many listings on Oslo Axess may not meet. Hence, it would be intriguing to investigate the existence of a small-stock premium on Oslo Axess. Furthermore, it would be interesting assessing whether the liquidity factor premium exists in the Norwegian market.

# 5. Conclusions

This thesis has aimed to investigate whether aftermarket liquidity is related to initial public offering (IPO) underpricing and long-run performance, by analysing the Norwegian IPO market between 2007 and 2018. Through identifying and accounting for relevant factors, we are able to produce models specifically constructed to signify the relationship between liquidity and abnormal returns. We design models that include all sampled IPOs, in addition to models that separate the firms based on marketplace or sentiment during the time of listing.

We find evidence of underpricing in the Norwegian IPO market, albeit small when sizeably compared to other country averages. We observe an average abnormal underpricing of 1.857%, calculated as the first-day return. Furthermore, Norwegian IPOs are underperforming significantly in the long run, calculated as the abnormal return the first year of listing. The underperformance is 9.183% lower than the benchmark index performance.

Consistent with the findings of Booth and Chua (1996) and Hahn et al. (2013), our underpricing models determine liquidity to be positively related to initial abnormal returns, NOK volume being significant at the 5% level. When arranged by sentiment during the time of issue, based on the previous two-months' market return, the results increase in significance. Hot market periods depict a strong positive relation between underpricing and liquidity, while cold market issue returns not seem to be connected to the aftermarket stock liquidity.

In the long run, contradictive to the findings of Eckbo and Norli (2005), all four liquidity measures indicate liquid stocks performing better. Although only the NOK volume measure is significant, each and all measures express this relationship. Næs, Skjeltorp and Ødegaard (2008) find the relationship to be reversing in periods of distress, which we suggest might be one of the causes for our counter-intuitive results, encouraged by the presence of the financial crisis in 2008 and the oil downturn in 2014-2015.

Thereafter, we investigate marketplace deviations, by splitting OSE and Axess listed firms, motivated by substantial differences in long-run returns measured by company size. Smaller firms were observed to yield lower returns. The resulting models indicate that Oslo Axess is the driver of liquidity and long-run performance being positively correlated, while for OSE, the main exchange, the relationship subsides. The discovered relationship with respect to Oslo Axess can be explained by theory on penny stocks and junior markets. Consistent with our findings, Carpentier and Suret (2011) investigate penny stocks in Canada, pointing to the least liquid stocks often being in largest distress, leading to the illiquid penny stocks performing worst. Furthermore, Locke and Gupta (2008) found that junior exchange-listed firms performed worse, relatively. Hence, smaller, riskier stocks do not compensate for liquidity risk.

Generally, IPO underpricing and long-run performance are highly dependent on over-time variations, prior evidence suggesting large deviations depending on timeframe and country. Hence, the timeframe is decisive for results, and being aware of cycle movements within the selected timeframe is of necessity. This is also the case for our thesis. Our timeframe is limited, and the sample size is relatively small, including small stocks, causing the models to be extra sensitive to cyclical patterns.

With this thesis, we extend the literature on liquidity and IPOs, laying forth evidence from the Norwegian market. Simultaneously, we confirm the notion of hot sentiment market issue behaviour and junior market distress tendencies, both in accordance with prior literature. We propose for future research to investigate the liquidity risk in IPOs, possibly by size-matching and conducting comparisons with the market as a whole.

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# 6. Appendices

## 6.1 Appendix 1: Distribution of Dependent Variables

### A: Initial Return

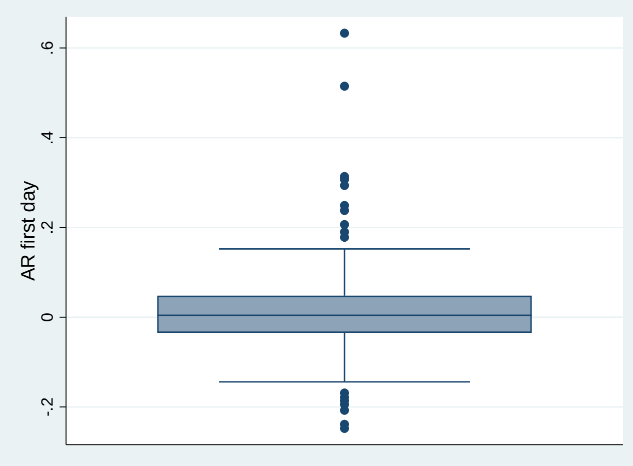


*Figure 11: Box plot of first-day abnormal return.*

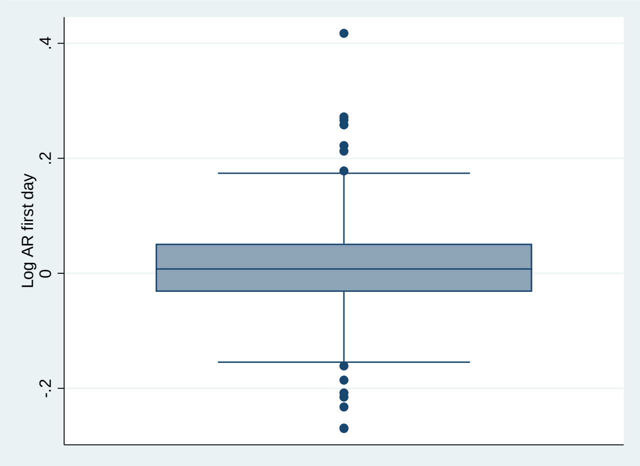


*Figure 12: Box plot of first-day log-transformed abnormal return.*

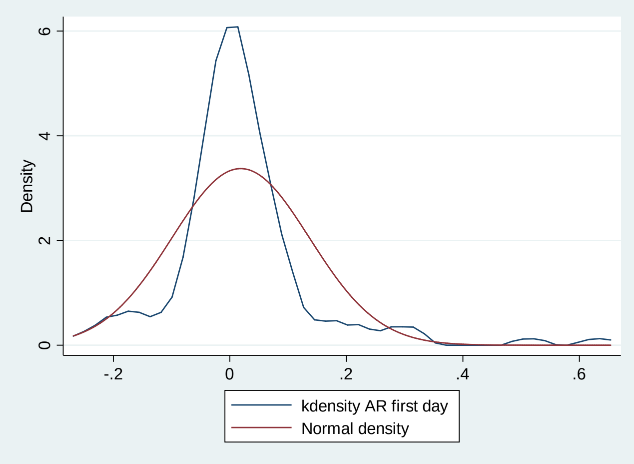


*Figure 13: Kernel density and normal distribution for first-day abnormal return. Bandwidth for the Kernel distribution: 0.0209.*

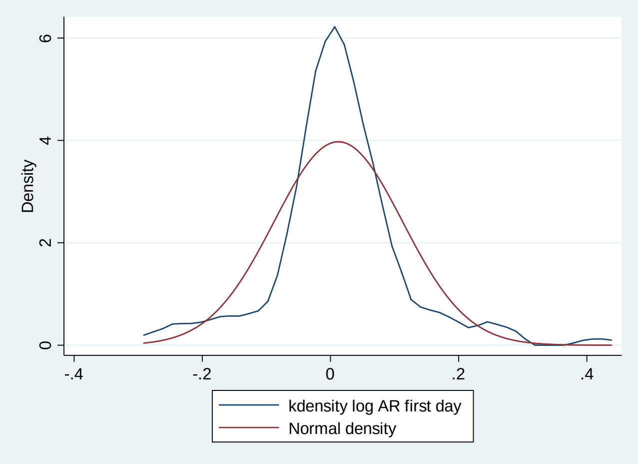


*Figure 14: Kernel density and normal distribution for first-day abnormal return. Bandwidth for the Kernel distribution: 0.0212.*

## B: Long-run Return

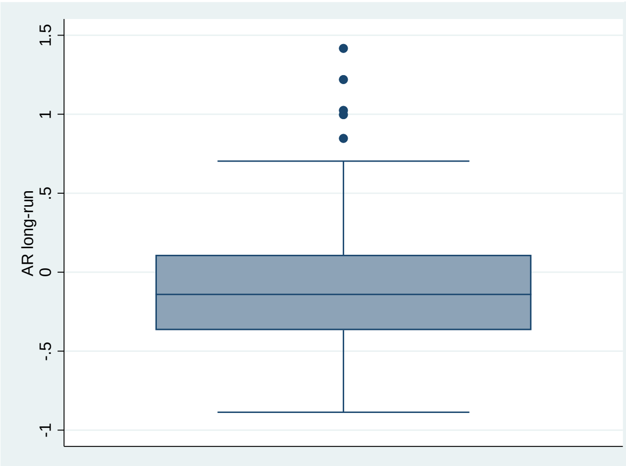


*Figure 15: Box plot of long-run abnormal return.*

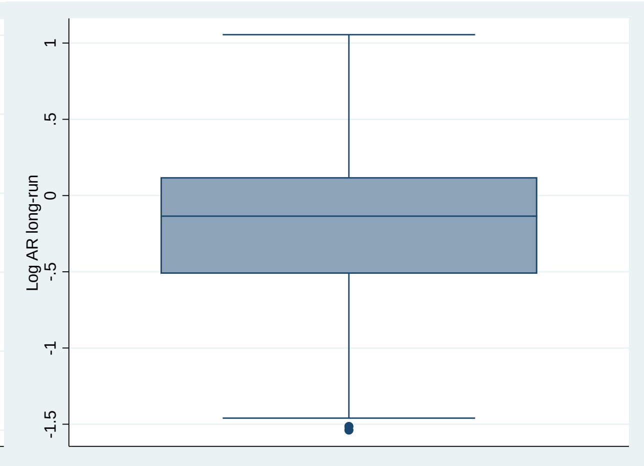


*Figure 16: Box plot of long-run log-transformed abnormal return.*

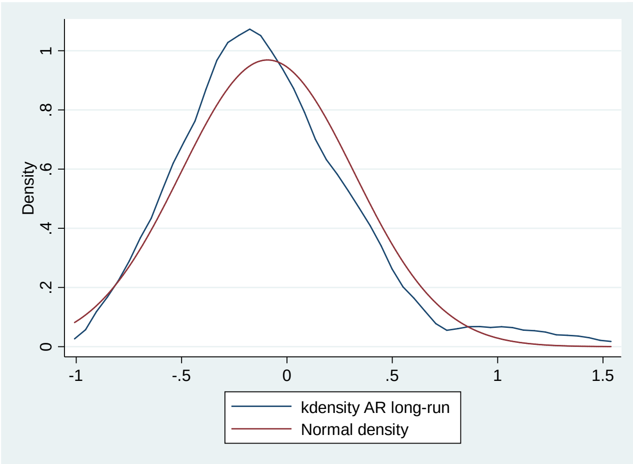


*Figure 17: Kernel density and normal distribution for long-run abnormal return. Bandwidth for the Kernel distribution: 0.1212.*

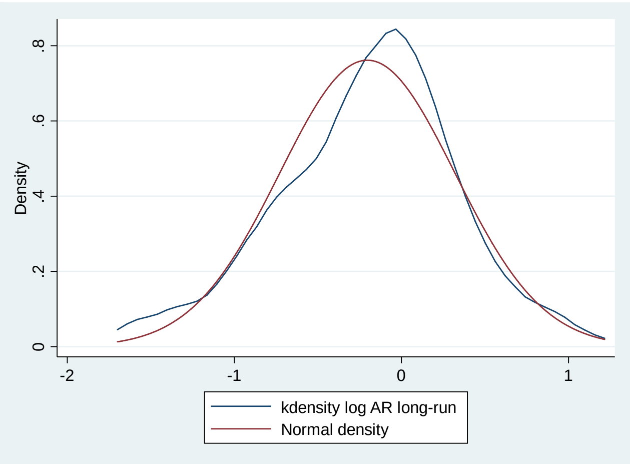


*Figure 18: Kernel density and normal distribution for long-run abnormal return Bandwidth for the Kernel distribution: 0.1610.*

## 6.2 Appendix 2: Characteristic Differences Between the Three Marketplaces at OSE

| | Oslo Stock Exchange | Oslo Axess | Merkur Market |
|---|---|---|---|
| **Marketplace status** | Stock exchange listing in accordance with EU requirements and Norwegian Securities Trading Act. | Authorised and fully regulated marketplace | Multilateral trading facility. |
| **Financial advisor** | No, but common in practice | No, but common in practice | Yes, a Merkur Advisor is required |
| **Type of company** | Public limited companies, equity certificate issuers, and equivalent types of foreign company | Public limited companies and equivalent types of foreign company | Private limited companies, public limited companies, equity certificate issuers, and equivalent types of foreign company |
| **Admission process duration** | 4-8 weeks | 4-8 weeks | 1-2 weeks |
| **Admission decision** | Oslo Børs ASA | Oslo Børs ASA | Oslo Børs ASA |
| **Market capitalisation** | NOK 300 million | NOK 8 million | No requirement |
| **Minimum price per share** | NOK 10 | NOK 1 | NOK 1 |
| **Minimum number of shareholders** | 500 | 100 | 30 |
| **Minimum proportion of share capital distributed among general public** | 25% | 25% | 15% |
| **Due diligence** | Full financial and legal due diligence; advisors must be independent | Full financial and legal due diligence; advisors must be independent | Limited-scope financial and legal due diligence. No requirement for advisors to be independent |
| **Admission document/prospectus** | EEA prospectus subject to inspection and approval by Finanstilsynet | EEA prospectus subject to inspection and approval by Finanstilsynet | Admission document which is less comprehensive than an EEA prospectus |
| **Accounting standards** | IFRS | IFRS | Norwegian GAAP, IFRS or other recognised standard |
| **History and activity** | At least three years' history and activity. An exemption may be applied for | At least one audited interim or annual report. Must have commenced main activities | At least one audited interim or annual report. Not required to have fully commenced activities |
| **Financial reporting** | Half-yearly starting from 01/01/2017, but quarterly recommended | Half-yearly starting from 01/01/2017, but quarterly recommended | Half-yearly; deadline for publication one month later than for Oslo Børs and Oslo Axess |
| **Duty of disclosure** | From submission of application | From submission of application | From admission |
| **Publication of inside information without delay and on own initiative** | Yes | Yes | Yes |
| **Able to delay public disclosure of information** | Yes | Yes | Yes |
| **Temporary admission of shares belonging to a class of shares already listed on Oslo Axess or Oslo Børs** | No | No | Yes |
| **Temporary admission of a new class of shares for companies listed on Oslo Axess or Oslo Børs** | - | - | Yes |
| **Corporate governance** | Report required | Report required | No requirements |

## 6.3 Appendix 3: Regressions for Initial Abnormal Returns

### A: Amihud

| | (1) Log(Initial return) | (2) Log(Initial return) | (3) Log(Initial return) | (4) Log(Initial return) |
|---|---|---|---|---|
| Log(Amihud) | -0.00460 | -0.00367 | -0.00345 | -0.00569 |
| | (-1.06) | (-0.77) | (-0.65) | (-1.14) |
| Log(Company age) | 0.0124 | 0.0126 | 0.0123* | 0.0132** |
| | (1.65) | (1.63) | (1.93) | (2.06) |
| Log(Offer size) | -0.00720 | -0.00818 | 0.00104 | -0.00776 |
| | (-1.13) | (-1.19) | (0.11) | (-1.00) |
| Market value dummy | | 0.0171 | | |
| | | (0.72) | | |
| Log(Brent) | | 0.461 | 0.324 | 0.321 |
| | | (0.92) | (0.68) | (0.71) |
| Log(VIX) | | -0.00906 | -0.0415 | -0.0455 |
| | | (-0.32) | (-1.03) | (-1.10) |
| Log(Std. dev.) | | 0.00768 | 0.00231 | |
| | | (0.38) | (0.10) | |
| Log(Float rate)[41] | | | -0.0108 | |
| | | | (-1.06) | |
| Energy sector dummy | | | | 0.0168 |
| | | | | (0.58) |
| Yearly dummy | | | Yes | Yes |
| _cons | 0.0508 | 0.106 | 0.0242 | 0.178 |
| | (0.55) | (0.76) | (0.12) | (1.01) |
| *N* | 125 | 125 | 125 | 125 |
| $R^2$ | 0.033 | 0.046 | 0.090 | 0.088 |
| adj. $R^2$ | 0.009 | -0.011 | -0.064 | -0.057 |

*This table shows the results of regressing log-transformed initial returns with the Amihud ratio as the independent liquidity measure. Additional variables used include logarithmic transformations of company age, offer size, IPO date change in Brent Spot oil price, the VIX value at IPO date and the standard deviation of returns, as well as an energy sector dummy variable and a yearly dummy variable. In addition, a market value dummy variable and the log-transformed float rate are also tested in the regressions. Heteroscedastic robust standard errors are reported in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

[41] Float rate is simply the percentage of shares issued in the IPOs relative to total shares outstanding.

## B: Share Turnover

| | (5) Log(Initial return) | (6) Log(Initial return) | (7) Log(Initial return) | (8) Log(Initial return) |
|---|---|---|---|---|
| Share turnover | -0.0254 | -0.0236 | -0.0304 | -0.0324 |
| | (-0.77) | (-0.69) | (-0.82) | (-0.90) |
| Log(Company age) | 0.0128** | 0.0132** | 0.0128** | 0.0144** |
| | (2.20) | (2.12) | (2.16) | (2.25) |
| Log(Offer size) | -0.00140 | -0.00259 | 0.00939 | -0.000444 |
| | (-0.23) | (-0.36) | (0.84) | (-0.06) |
| Market value dummy | | 0.0166 | -0.00544 | |
| | | (0.90) | (-0.22) | |
| Yearly dummy | | Yes | Yes | Yes |
| Log(Brent) | | | 0.319 | 0.334 |
| | | | (0.70) | (0.73) |
| Log(VIX) | | | -0.0461 | -0.0500 |
| | | | (-1.09) | (-1.14) |
| Log(Float rate) | | | -0.0164 | |
| | | | (-1.31) | |
| Energy sector dummy | | | | 0.0188 |
| | | | | (0.69) |
| _cons | 0.0173 | 0.0455 | -0.0676 | 0.149 |
| | (0.16) | (0.37) | (-0.25) | (0.81) |
| *N* | 125 | 125 | 125 | 125 |
| $R^2$ | 0.031 | 0.071 | 0.096 | 0.087 |
| adj. $R^2$ | 0.007 | -0.056 | -0.058 | -0.059 |

*This table shows the results of regressing log-transformed initial returns with Share turnover as the independent liquidity measure. Additional variables used include logarithmic transformations of company age, offer size, IPO date change in Brent Spot oil price and the VIX value at IPO date, as well as an energy sector dummy variable and a yearly dummy variable. In addition, a market value dummy variable and the log-transformed float rate are also tested in the regressions. Heteroscedastic robust standard errors are reported in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

## C: High-Low Range

| | (9)<br>**Log(Initial return)** | (10)<br>**Log(Initial return)** | (11)<br>**Log(Initial return)** | (12)<br>**Log(Initial return)** |
|---|---|---|---|---|
| H-L range | -0.00587 | -0.0160 | -0.0132 | -0.0162 |
| | (-0.51) | (-1.03) | (-0.79) | (-1.21) |
| Log(Company age) | 0.0127* | 0.0132 | 0.0137 | 0.0136** |
| | (1.68) | (1.64) | (1.62) | (2.19) |
| Log(Offer size) | -0.00510 | -0.00599 | 0.00168 | -0.00640 |
| | (-0.79) | (-0.85) | (0.12) | (-0.77) |
| Market value dummy | | 0.000959 | -0.0127 | |
| | | (0.03) | (-0.39) | |
| Yearly dummies | | Yes | Yes | Yes |
| Log(Brent) | | | 0.335 | 0.373 |
| | | | (0.59) | (0.82) |
| Log(VIX) | | | -0.0401 | -0.0405 |
| | | | (-0.87) | (-0.96) |
| Log(Float rate) | | | -0.0106 | |
| | | | (-0.65) | |
| Energy sector dummy | | | 0.00951 | 0.0131 |
| | | | (0.38) | (0.45) |
| _cons | 0.0647 | 0.0785 | 0.0340 | 0.194 |
| | (0.61) | (0.66) | (0.11) | (1.05) |
| *N* | 125 | 125 | 125 | 125 |
| $R^2$ | 0.026 | 0.075 | 0.094 | 0.090 |
| adj. $R^2$ | 0.002 | -0.052 | -0.070 | -0.055 |

*This table shows the results of regressing log-transformed initial returns with high-low range as the independent liquidity measure. Additional variables used include logarithmic transformations of company age, offer size, IPO date change in Brent Spot oil price and the VIX value at IPO date, as well as an energy sector dummy variable and a yearly dummy variable. In addition, a market value dummy variable and the log-transformed float rate are also tested in the regressions. Heteroscedastic robust standard errors are reported in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

## D: NOK Volume

| | (13) | (14) | (15) | (16) |
|---|---|---|---|---|
| | Log(Initial return) | Log(Initial return) | Log(Initial return) | Log(Initial return) |
| Log(NOK volume) | 0.0126** | 0.0169** | 0.0137* | 0.0140** |
| | (2.08) | (2.05) | (1.93) | (2.09) |
| Log(Company age) | 0.0119 | 0.0113 | 0.0120 | 0.0116** |
| | (1.62) | (1.38) | (1.44) | (2.00) |
| Log(Offer size) | -0.0132* | -0.0115 | -0.0116 | -0.0114 |
| | (-1.91) | (-1.44) | (-1.50) | (-1.44) |
| Market value dummy | | -0.0177 | | |
| | | (-0.63) | | |
| Log(VIX) | | -0.0309 | -0.0289 | -0.0286 |
| | | (-0.68) | (-0.63) | (-0.69) |
| Log(Std. dev.) | | -0.00533 | | |
| | | (-0.25) | | |
| Yearly dummy | | Yes | Yes | Yes |
| Log(Brent) | | | 0.293 | 0.293 |
| | | | (0.53) | (0.67) |
| Energy sector dummy | | | 0.00476 | |
| | | | (0.20) | |
| _cons | 0.0628 | 0.0804 | 0.110 | 0.106 |
| | (0.69) | (0.47) | (0.68) | (0.62) |
| *N* | 125 | 125 | 125 | 125 |
| $R^2$ | 0.058 | 0.110 | 0.109 | 0.108 |
| adj. $R^2$ | 0.035 | -0.032 | -0.033 | -0.024 |

*This table shows the results of regressing log-transformed initial returns with NOK volume as the independent liquidity measure. Additional variables used include logarithmic transformations of company age, offer size, IPO date change in Brent Spot oil price, the VIX value at IPO date and the standard deviation of returns, as well as an energy sector dummy variable and a yearly dummy variable. In addition, a market value dummy variable and the log-transformed float rate are also tested in the regressions. Heteroscedastic robust standard errors are reported in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

## 6.4 Appendix 4: Regressions for Long-run Abnormal Returns

### A: Amihud

| | (17)<br>Long-run AR | (18)<br>Long-run AR | (19)<br>Long-run AR | (20)<br>Long-run AR |
|---|---|---|---|---|
| Log(Amihud) | -0.0464* | -0.0277 | -0.0254 | -0.0386* |
| | (-1.98) | (-1.21) | (-1.10) | (-1.76) |
| Log(Company age) | 0.0620** | 0.0470 | 0.0119 | 0.00664 |
| | (2.01) | (1.26) | (0.34) | (0.18) |
| Log(Offer size) | -0.0322 | -0.0395 | -0.0857** | -0.0587* |
| | (-0.91) | (-1.20) | (-2.56) | (-1.70) |
| Log(Initial return) | | 1.096** | 1.035** | 1.082*** |
| | | (2.43) | (2.57) | (2.65) |
| Market value dummy | | 0.201* | 0.202* | |
| | | (1.71) | (1.86) | |
| Log(Brent) | | -0.0387 | -0.519*** | -0.478*** |
| | | (-0.38) | (-3.71) | (-3.40) |
| Log(Std. dev.) | | | -0.473*** | -0.447*** |
| | | | (-5.17) | (-4.73) |
| Yearly dummy | | | Yes | Yes |
| Energy sector dummy | | | | -0.110 |
| | | | | (-1.06) |
| _cons | -0.440 | -0.101 | 0.653 | 0.144 |
| | (-0.86) | (-0.20) | (1.31) | (0.31) |
| *N* | 125 | 125 | 125 | 125 |
| $R^2$ | 0.067 | 0.135 | 0.402 | 0.389 |
| adj. $R^2$ | 0.043 | 0.091 | 0.301 | 0.286 |

*This table shows the results of regressing long-run IPO stock returns with the Amihud ratio as the independent liquidity measure. Additional variables used include logarithmic transformations of company age, offer size, initial returns, yearly change in Brent Spot oil price, and the standard deviation of returns, as well as an energy sector dummy variable and a yearly dummy variable. In addition, a market value dummy variable is tested. Yearly VIX average was omitted because of collinearity with the yearly dummy 2014. Heteroscedasticity is controlled for in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

## B: Share Turnover

| | (21) Long-run AR | (22) Long-run AR | (23) Long-run AR | (24) Long-run AR |
|---|---|---|---|---|
| Share turnover | 0.140 | 0.159 | 0.162 | 0.217 |
| | (0.75) | (1.13) | (1.14) | (1.52) |
| Log(Company age) | 0.0308 | 0.0108 | 0.00969 | 0.00402 |
| | (1.03) | (0.31) | (0.28) | (0.11) |
| Log(Offer size) | -0.0481 | -0.0771** | -0.0921* | -0.0341 |
| | (-1.57) | (-2.55) | (-1.73) | (-1.21) |
| Log(Std. dev.) | -0.457*** | -0.529*** | -0.532*** | -0.519*** |
| | (-4.92) | (-5.39) | (-5.38) | (-5.16) |
| Log(Initial return) | | 1.104*** | 1.121*** | 1.201*** |
| | | (2.75) | (2.76) | (2.94) |
| Market value dummy | | 0.231** | 0.260* | |
| | | (2.26) | (1.97) | |
| Log(Brent year) | | -0.529*** | -0.531*** | -0.482*** |
| | | (-3.79) | (-3.78) | (-3.42) |
| Yearly dummy | | Yes | Yes | Yes |
| Log(Float rate) | | | 0.0217 | |
| | | | (0.34) | |
| Energy sector dummy | | | | -0.144 |
| | | | | (-1.38) |
| _cons | 0.238 | 0.774 | 1.083 | 0.175 |
| | (0.44) | (1.52) | (1.04) | (0.37) |
| *N* | 125 | 125 | 125 | 125 |
| $R^2$ | 0.186 | 0.403 | 0.403 | 0.385 |
| adj. $R^2$ | 0.159 | 0.301 | 0.295 | 0.280 |

*This table shows the results of regressing long-run IPO stock returns with share turnover as the independent liquidity measure. Additional variables used include logarithmic transformations of company age, offer size, initial returns, yearly change in Brent Spot oil price, and the standard deviation of returns, as well as an energy sector dummy variable and a yearly dummy variable. In addition, a market value dummy variable and the log-transformed float rate are tested. Yearly VIX average was omitted because of collinearity with the yearly dummy 2014. Heteroscedasticity is controlled for in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

## C: High-Low Range

| | (25)<br>Long-run AR | (26)<br>Long-run AR | (27)<br>Long-run AR | (28)<br>Long-run AR |
|---|---|---|---|---|
| H-L range | -0.0494 | -0.0196 | -0.0278 | -0.0838 |
| | (-0.77) | (-0.30) | (-0.40) | (-1.44) |
| Log(Company age) | 0.0654** | 0.0140 | 0.0128 | 0.00844 |
| | (2.24) | (0.40) | (0.36) | (0.23) |
| Log(Offer size) | -0.00746 | -0.0705** | -0.0885 | -0.0438 |
| | (-0.21) | (-2.27) | (-1.52) | (-1.39) |
| Log(Initial return) | | 1.058** | 1.071** | 1.088*** |
| | | (2.61) | (2.62) | (2.65) |
| Market value dummy | | 0.227* | 0.252* | |
| | | (1.94) | (1.85) | |
| Log(Brent year) | | -0.528*** | -0.531*** | -0.498*** |
| | | (-3.75) | (-3.75) | (-3.51) |
| Log(Std. dev.) | | -0.488*** | -0.491*** | -0.469*** |
| | | (-5.34) | (-5.33) | (-4.97) |
| Yearly dummy | | Yes | Yes | Yes |
| Log(Float rate) | | | 0.0245 | |
| | | | (0.37) | |
| Energy sector dummy | | | | -0.128 |
| | | | | (-1.24) |
| _cons | -0.344 | 0.690 | 1.048 | 0.281 |
| | (-0.58) | (1.35) | (0.95) | (0.56) |
| *N* | 125 | 125 | 125 | 125 |
| $R^2$ | 0.038 | 0.396 | 0.397 | 0.383 |
| adj. $R^2$ | 0.014 | 0.293 | 0.288 | 0.279 |

*This table shows the results of regressing long-run IPO stock returns with high-low range as the independent liquidity measure. Additional variables used include logarithmic transformations of company age, offer size, initial returns, yearly change in Brent Spot oil price, and the standard deviation of returns, as well as an energy sector dummy variable and a yearly dummy variable. In addition, a market value dummy variable and the log-transformed float rate are tested. Yearly VIX average was omitted because of collinearity with the yearly dummy 2014. Heteroscedasticity is controlled for in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

## D: NOK Volume

| | (29) Long-run AR | (30) Long-run AR | (31) Long-run AR | (32) Long-run AR |
|---|---|---|---|---|
| Log(NOK volume) | 0.0792** | 0.0646* | 0.102** | 0.0946*** |
| | (2.57) | (1.84) | (2.42) | (3.11) |
| Log(Company age) | 0.0615 | 0.0113 | -0.00853 | -0.00249 |
| | (1.64) | (0.33) | (-0.24) | (-0.08) |
| Log(Offer size) | -0.0537 | -0.0994*** | -0.172** | -0.0870** |
| | (-1.53) | (-2.96) | (-2.35) | (-2.31) |
| Log(Initial return) | | 0.918** | 0.931** | 0.906** |
| | | (2.26) | (2.33) | (2.45) |
| Market value dummy | | 0.127 | 0.213 | |
| | | (1.07) | (1.65) | |
| Log(Brent year) | | -0.543*** | -0.556*** | -0.526*** |
| | | (-3.91) | (-4.04) | (-4.21) |
| Log(Std. dev.) | | -0.501*** | -0.487*** | -0.473*** |
| | | (-5.56) | (-5.25) | (-4.67) |
| Yearly dummy | | Yes | Yes | Yes |
| Log(Float rate) | | | 0.0951 | |
| | | | (1.25) | |
| Energy sector dummy | | | -0.168 | -0.184* |
| | | | (-1.61) | (-1.69) |
| _cons | -0.415 | 0.447 | 1.577 | 0.0157 |
| | (-0.90) | (0.88) | (1.40) | (0.03) |
| *N* | 125 | 125 | 125 | 125 |
| $R^2$ | 0.082 | 0.414 | 0.442 | 0.425 |
| adj. $R^2$ | 0.060 | 0.315 | 0.335 | 0.328 |

*This table shows the results of regressing long-run IPO stock returns with NOK volume as the independent liquidity measure. Additional variables used include logarithmic transformations of company age, offer size, initial returns, yearly change in Brent Spot oil price, and the standard deviation of returns, as well as an energy sector dummy variable and a yearly dummy variable. In addition, a market value dummy variable and the log-transformed float rate are tested. Yearly VIX average was omitted because of collinearity with the yearly dummy 2014. Heteroscedasticity is controlled for in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*

## 6.5 Appendix 5: Underpricing and Liquidity on OSE vs. Oslo Axess

| | (49) Initial returns Amihud OSE | (50) Initial returns Amihud Axess | (51) Initial returns Share turnover OSE | (52) Initial returns Share turnover Axess | (53) Initial returns H-L Range OSE | (54) Initial returns H-L Range Axess | (55) Initial returns NOK Volume OSE | (56) Initial returns NOK Volume Axess |
|---|---|---|---|---|---|---|---|---|
| Log(Amihud) | -0.00392 | 0.00519 | | | | | | |
| | (-0.69) | (0.43) | | | | | | |
| Share turnover | | | -0.0143 | -0.0841 | | | | |
| | | | (-0.33) | (-1.67) | | | | |
| H-L range | | | | | -0.00950 | -0.00977 | | |
| | | | | | (-0.55) | (-0.29) | | |
| Log(NOK volume) | | | | | | | 0.0219*** | 0.00834 |
| | | | | | | | (2.91) | (0.61) |
| Log(Company age) | 0.0159** | 0.0105 | 0.0163** | 0.0120 | 0.0167** | 0.0101 | 0.0140* | 0.0112 |
| | (2.10) | (0.65) | (2.33) | (0.75) | (2.27) | (0.64) | (1.92) | (0.72) |
| Log(Offer size) | -0.00795 | 0.00116 | -0.00195 | -0.00277 | -0.00545 | -0.00385 | -0.0193* | -0.00736 |
| | (-0.65) | (0.10) | (-0.17) | (-0.22) | (-0.47) | (-0.27) | (-1.95) | (-0.53) |
| Log(Brent) | 0.621 | -0.0253 | 0.615 | 0.0488 | 0.645 | 0.117 | 0.724 | 0.104 |
| | (1.20) | (-0.03) | (1.12) | (0.05) | (1.29) | (0.11) | (1.49) | (0.11) |
| Log(VIX) | -0.0949 | -0.0416 | -0.0948 | -0.0689 | -0.0941 | -0.0320 | -0.0901 | -0.0188 |
| | (-1.61) | (-0.52) | (-1.52) | (-0.86) | (-1.62) | (-0.41) | (-1.62) | (-0.22) |
| Energy sector dummy | 0.0321 | -0.0232 | 0.0349 | -0.00277 | 0.0314 | -0.0170 | | |
| | (0.87) | (-0.63) | (0.92) | (-0.07) | (0.81) | (-0.48) | | |
| Yearly dummy | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| _cons | 0.328 | 0.186 | 0.279 | 0.266 | 0.316 | 0.158 | 0.299 | 0.0840 |
| | (1.48) | (0.45) | (1.24) | (0.73) | (1.38) | (0.46) | (1.56) | (0.22) |
| *N* | 73 | 52 | 73 | 52 | 73 | 52 | 73 | 52 |
| $R^2$ | 0.171 | 0.259 | 0.166 | 0.287 | 0.168 | 0.259 | 0.206 | 0.261 |
| adj. $R^2$ | -0.066 | -0.050 | -0.072 | -0.011 | -0.070 | -0.050 | -0.003 | -0.019 |

*This table shows the results of regressing initial abnormal IPO stock returns with all four liquidity measures on the two samples, assessing the individual effects of (49) and (50) the Amihud illiquidity measure, (51) and (52) share turnover, (53) and (54) high-low range measure and (55) and (56) NOK volume. Additional variables used include logarithmic transformations of company age, offer size, change in Brent Spot oil price the day of listing, and daily value on the CBOE volatility index (VIX), as well as an energy sector dummy variable and a yearly dummy variable. Each control variable is used for all the eight models. Heteroscedastic robust standard errors are reported in all models. The t-statistics are reported in parenthesis, and *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.*