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Initial Public Offerings

An empirical study of the significance of relative pricing and initial demand for the aftermarket performance

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Master thesis in Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

1. Abstract

This thesis investigates initial public offerings (IPOs) on the Oslo Stock Exchange in the years 2009-2014. The analysis focuses on the short-term aftermarket performance, and how this may be affected by the initial demand for the issue and the pricing of the IPO relative to a set of comparable companies.

I found the average abnormal returns for the IPOs in the years 2009-2014 to be negative for first day, week and month. The returns aggravated with the time horizon, indicating that the markets require more than one day to eliminate mispricing of IPOs. These results stand out compared to prior research, as fundamental underpricing of IPOs has been considered an established fact on theoretical ground. Assuming the same theories to hold, the apparent persistent overpricing of Norwegian IPOs may entail challenges for companies considering going public.

To reflect the initial demand I examined two proxies, namely the placement of the final offer price relative to the indicative price range and the level of oversubscription at the final offer price. The Norwegian IPOs appeared to have strong skewness towards the left of the price range midpoint, and the oversubscription levels came out lower than for international studies. However, both proxies proved strong indicators of aftermarket performance, as the IPOs with high initial demand outperformed the IPOs with low initial demand.

The relative peer pricing aspect was reflected through the valuation multiples P/E and EV/EBITDA. For both multiples I found significant underpricing of the IPO companies relative to listed peers. Once again, this contradicts prior research, which has justified higher valuation of IPO companies on the basis of higher growth rates than their mature peers. In accordance with the asymmetric information theory regarding IPO pricing, the IPO companies which were priced cheap relative to peers significantly outperformed the IPO companies which were priced rich relative to peers. It is interesting to observe that although the IPO companies on average were underpriced relative to peers, they underperformed the general market in the time after listing.

2. Preface

This thesis concludes my Master of Science in Financial Economics at the Norwegian School of Economics. The writing process has been challenging, although above all it has been interesting and considerably increased my insight into the Norwegian IPO market.

Several persons have contributed academically and with support during the writing process. Firstly, I would like to thank my supervisor, Thore Johnsen, for prolific discussions and essential input during the writing process. His academic advices have significantly improved the quality of the analysis. Further, I would like to thank ABG Sundal Collier, a leading Nordic investment bank, which has provided data that is not publicly attainable, and thus enabled an analysis that would otherwise not be possible. In addition, I would like to thank Ragnhild Balsvik for valuable guidance regarding the econometric analysis. Other than this, I would like to thank the finance department of the Norwegian School of Economics for the motivational and inspiring Master programme during the two past years. The theoretical framework for my analysis is based on knowledge I have attained through the corporate finance courses at this school, and this has truly been decisive for my interest in finance and choice of career path after I finalize my education.

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3. Introduction

3.1 Background

During the past decade, a large number of initial public offerings have taken place on the Oslo Stock Exchange. From the year 2005 and up to the financial crisis in 2008, 96 new companies were listed on either Oslo Børs or Oslo Axess. The crisis reminded investors that risk capital was, indeed, risky, and capital fled the markets. The IPO activity recovered slowly after the financial turbulence, and only 2 listings were successfully executed in Norway in 2009. However, as the markets shook off the fear and new risk capital was ready to enter the markets, we have seen 49 new listings in the years 2009 and up to today.

In international finance literature extensive research has been done on the nature of initial public offerings and their market adjusted performance after listing. Historically one has observed great abnormal initial returns of subscribing to IPOs. As this appears to be “money left on the table”, numerous attempts have been made to explain and rationalise this fundamental underpricing. However, there are few empirical studies on this topic regarding the Norwegian IPO market, which has been the motivation behind my thesis.

3.2 Research questions

I will analyse the aftermarket performance of the initial public offerings that have been executed on the Oslo Stock Exchange from 2009 and up to October 2014. This will include listings both on the main list, Oslo Børs, and the alternative listing option, Oslo Axess. Through econometric modelling I will examine the relationship between certain predicators and the aftermarket performance.

The thesis can be seen as a two-part analysis. The first part addresses how the initial demand for the issue may affect the pricing of the IPO and the aftermarket performance. To investigate the significance of the initial demand I will consider two potential independent variables. The first variable relates to where the final offer price is set relative to the indicative price range disclosed in the prospectus. A high demand of issue shares during the bookbuilding period is assumed to result in an upward revision of the final offer price. As high initial demand is expected to positively correlate with aftermarket performance, offerings going public above the midpoint of the price range should outperform the ones going public with an offer price below midpoint. The second variable relates to the oversubscription to the issue and how this may affect the aftermarket performance. A high demand of issue shares relative to the shares available will result in investors receiving insufficient allocations. This may in turn lead investors with insufficient allocations to acquire shares in the aftermarket. Thus, a higher level of oversubscription should imply a better aftermarket performance.

The second part of the thesis addresses the pricing of the IPO relative to comparable companies, and how this in turn may affect the aftermarket performance. The relative pricing will be determined through financial multiples, and compared to the average multiples of a relevant peer group. The average valuation of the peer group will define the “fair value” of the IPO company. The asymmetric information theory of IPO pricing suggests that the efficient markets will eliminate any mispricing immediately. Hence, IPO companies which are priced cheap relative to peers should outperform those who are priced rich relative to peers.

While there are numerous studies separately examining the two abovementioned factors’ impact on the aftermarket performance, I have not been able to obtain any studies examining both factors collectively. Hence, I am of the opinion that an analysis including both factors may provide a more comprehensive overview of the aftermarket performance of IPOs.

The hypotheses I will examine are therefore:

1) The higher the initial demand for the issue, the higher are the abnormal returns in the aftermarket

2) The lower the IPO company is priced relative to peers, the higher are the abnormal returns in the aftermarket

4. Theory

4.1 Initial public offering

An initial public offering (IPO) is the first time a company sells shares to the public. The company will hire an investment bank to determine the offer price and perform the marketing towards potential investors and execute the sale of the new shares. As the company goes from having exclusively private shareholders to trade their shares over the stock exchange, the IPO is commonly referred to as “going public”. Now the company must comply with a new set of rules and regulations regarding disclosure of information, financial reporting and the like. The company’s behaviour will be overseen by governing agencies, and any actions (or lack of actions) contrary to the regulations will be reported and potentially prosecuted.

A company considering an IPO should weigh the benefits against the disadvantages. One significant, and probably the most compelling benefit of going public, is the access to a large and liquid capital market. Young growth companies in need of funding to further expand its business can entice the investors with shares on a highly liquid market place in return for fresh capital for the firm. In addition, the listing of the company’s shares might raise awareness of the firm, making it more attractive for potential customers and investors. On the negative side, the company will experience direct costs of being a public company, related to financial documentation, accounting fees, investor relations departments and so on. In addition, many would argue that the public investors are more short-sighted than private investors, forcing the management to focus on short-term profitability. This may negatively affect the long-term performance. (James & Fawcett, 2006)

4.2 Book building vs. fixed price

Companies that seek to list their shares will generally either choose the strategy of fixed price or book building. In the fixed price strategy, the advisors of the company establish the final offer price without first formally examining external perceptions of the company value. Naturally, the advisors may in advance conduct noncommittal valuation surveys among investors, however, this process is not formalized through a bidding process. Establishing an offer price in this situation, where investors are not forced to reveal their price perception, will be a process of weighing the benefits of raising the price against the increased likelihood that the issue will not sell. (Benveniste & Busaba, 1997)

The other, and in later years more common strategy for pricing an issue, is the book building method. The advisor conducts a pre-offer marketing effort, which provides non-binding indications of interest from the investor community. Together with the advisor's internal valuation of the company, these indications help to set the indicative price range, which faces the investors during the book building period. Throughout this period the underwriter receive bids which are used to "build the book" (Jenkinson & Jones, 2002). The underwriters decide allocations based on a tiering-system with different levels of preferential interest, based on the quality of the investor, the trustworthiness of the information they reveal and to what extent the investor is a "repeat bidder" in numerous offerings. The benefit of the formalization of the information process vis-á-vis fixed price surveys is that investors are forced to reveal their identity, making it possible for the book runner to make allocations on a discretionary basis (Jenkinson & Jones, 2002). However, the potential downside is the risk of investors providing untruthful indications, as they know their input may affect the setup of the price range. The underwriters address this issue by giving truthful and trustworthy investors better "tiering" and hence potentially a more comprehensive allocation, in both the current and future issues. Cornelli and Goldreich (2001) found that repeat bidders generally were favoured in the allocation process, and that the final price often was set close to the limit orders provided by large and high-quality investors. Hanley (1993) also found that truthful revelation of credible information is rewarded by an increase in share allocation.

4.3 Abnormal rate of return

In order to investigate how the aftermarket performance is affected by the factors mentioned in the abstract, it is important to define the measurement of performance. Abnormal rate of return, also known as *alpha*, *excess return* or *market adjusted return,* is a common measure in this regard. The abnormal return reflects the return of the stock or asset that is not explained by general movements in the market portfolio. This way the returns can be compared regardless of point in time. In financial theory the abnormal return is often estimated based on the CAPM model as:

$$Abnormal\ return = r_i - [r_f + \beta_i(r_m - r_f)]$$

where r_i is the return of the stock of interest, r_m is the return of the market portfolio, r_f is the risk-free rate and β_i is the beta of the stock of interest. However, for empirical studies one will apply the actual observed differences between the performance of the stock of interest and the market portfolio. The calculation of the abnormal return will be calculated as:

$$Abnormal\ return = \frac{p_1 - p_0}{p_0} - \frac{m - m_0}{m_0}$$

where p_1 is the price of the relevant stock at close of the first day (or 1st week/1st month), while p_0 is the final offer price. $m_1$is the value of the market index at close of the first day (or 1st week/1st month) the stock has been listed, and m_0 is the value of the index at closing the day before listing. As the CAPM model is a theoretical approximation to reality, the use of actual observed differences in performance eliminates the potential source of error related to estimating the CAPM based abnormal returns.

A benchmark or reference index is necessary in order to calculate the abnormal returns. The purpose of this index is to reflect the alternative investment opportunities the investors face. One could argue that a narrow sector index or the returns for a group of comparable companies could function as a reference index. However, the investment universe for the investors is not limited to one single sector, and hence the alternative investment universe should not be either. Thus, one should apply the same reference index for all companies. The IPO companies will come in all shapes and sizes, with different risk profiles and maturity. To catch this great variety in characteristics, a broad index will be ideal. I will return to the selection of the appropriate reference index in the methodology section.

4.4 Relevant listing indeces

When companies apply for listing in Norway, this can be done either on Oslo Børs or Oslo Axess. While an Oslo Børs-listing will be a full stock exchange listing, complying with all EU requirements, an Oslo Axess listing will be a listing to a fully regulated and authorised market place, although with fewer regulative demands. The requirements for Oslo Børs are more detailed and extensive than for Oslo Axess, e.g. with regards to the number of shareholders, disclosure of sensitive information and the like. While Oslo Børs is the most relevant alternative for mature companies with a long history, Oslo Axess is suitable for companies in a pre-commercial phase seeking the benefits of being listed on a regulated market place (Børs, n.d.). This thesis will include the listings on both of these two market places.

4.5 Relative pricing based on financial multiples

In the process of explaining a mismatch between a company's performance and those of its competitors, a multiple comparison within the relevant sector can be a helpful tool. Koller et al. (2010) point out that one should be careful to apply an average multiple for a peer group as comparative basis, as this might ignore important differences in return on invested capital (ROIC). However, the application of peer group averages is a recognized and common procedure among practitioners. As this is the type of analysis the investor community are presented with and relies on, it also becomes the most relevant method for practical considerations. Technical limitations with regards to the regression analysis also make the peer group average comparison the only feasible approximation.

One should apply forward-looking multiples in a peer group analysis. This is consistent with general principle of valuation, as the company's net worth equals the present value of future cash flows, rather than sunk costs. In addition, forward-looking projections are usually normalized, ignoring large one-offs that can have substantial effect on prior performance (Koller, et al., 2010). Companies going through an IPO process often have negative earnings due to high costs of growth and expansion. This makes it increasingly important to focus on future, rather than historical, profitability.

When investigating the relative pricing, it is all about choosing the right multiples. One alternative would be to average several multiples in order to obtain one measurement of the relative pricing. However, Damodaran (2003) argues that averaging more than one multiple is "… completely inappropriate since it averages good estimates with poor ones equally". He argues that if one or few multiples are chosen based on a thorough consideration, these will separately facilitate the best analysis.

For the regression analysis the EV/EBITDA multiple (enterprise value divided by earnings before interest taxes, depreciation and amortization) and P/E (share price divided by earnings per share) will represent the relative pricing aspect. The EV/EBITDA multiple is ideal for companies in early stage, with high growth and negligible or negative net income, where earnings can depend heavily on the depreciation method (Damodaran, 2003). The remaining economic lifetime of operational assets may also be a source of difference in profitability. Old assets often appear highly profitable as aggressive depreciation profiles lead to low depreciation in late years. However, as this difference is also connected to the depreciation, one will avoid the issue by applying an EBITDA based multiple. The rationale behind applying a multiple based on enterprise value is that such a multiple measures the unlevered value of the company, thus making the multiple unaffected by differences in capital structure among the peers. (Suozzo, et al., 2001). The EV/EBITDA is the most popular enterprise value multiple among practitioners, as it ignores both differences in depreciation policy and capital structure. In other words, it gives the "cleanest" perspective on the core operational profitability of the firm (Suozzo, et al., 2001). One could argue that the EV/EBIT multiple would be closer to a free cash flow multiple, as it takes into account the capital expenditures related to depreciation and amortization. However, for these early-stage companies, we might observe positive EBITDA at the same time as the EBIT is negative. As negative multiples are meaningless, choosing the EV/EBITDA multiple may increase the number of data points.

I will also apply the P/E multiple in my analysis. This is simply because of the broad acceptance and reliance on this multiple among investors. The P/E multiple is, due to both historical and practical reasons, by far the most popular valuation multiple, and the relevance of this multiple is therefore hard to ignore. There are many reasons to argue why the P/E multiple is not necessarily theoretically the most appropriate multiple for valuation purposes, and some of these reasons are listed as benefits of the EV/EBITDA multiple in the paragraph above. Despite this, it has its clear benefits. As the new listings on OSE have a wide spectre of characteristics, it would be hard to find "the one right" multiple for all of them. For example, one could argue that the P/NAV (market value of equity divided by the net asset value) would be appropriate for shipping companies, but not at all be appropriate for companies that heavily rely on human capital. Therefore, my objective will be to find the multiples that will have the broadest catchment. In this "competition" the P/E multiple has a large utility value.

4.6 IPO underpricing

Fundamental underpricing of IPOs is an area of extensive research and clearly related to what I try to investigate in this thesis. Theoretically, the underpricing is most often calculated as the difference between the first day closing price and the offer price divided by the offer price (also referred to as initial return) (Georgieva, 2011). IPOs have a history of high positive abnormal initial returns, and in order to explain this (what appears to be) easy money, a number of explanations have been suggested. One popular explanation is the winner's curse caused by asymmetric information between informed and uninformed investors. As informed investors are assumed to have access to all necessary information to determine the fair value of the firm, they will only subscribe to the underpriced IPOs. Due to asymmetric information, one further assumes the uninformed investors to subscribe to all issues indiscriminately, both overpriced and underpriced. Consequently, uninformed investors will only receive full allocation in the overpriced IPOs. If the uninformed investors on average lose money of subscribing to IPOs, they will shy away from the issue market. However, as informed investors alone not are able to absorb the issues, uninformed investors are needed in order to attain full subscription. Thus, the issues on average need to be underpriced (Georgieva, 2011). The second explanation suggests that because of asymmetric information high quality firms will underprice their IPO in order to signal their strength. This explanation suggests that the high quality companies signal that they can bear the costs of underpricing in order to be able to attract more investors in the future and consequently raise capital on better terms later. A third explanation suggests that the issuing company underprices their IPO simply to avoid lawsuits from unsatisfied investors, as these lawsuits will be less likely if the IPO turns out to be underpriced (Yong & Isa, 2003). A fourth explanation focuses on the underwriters' role in the process. While the underwriter will receive goodwill from regular trading clients if the IPO is underpriced, the underwriter will also lose reputation as a reliable counterpart for the issuing company if the IPO is too heavily underpriced. Hence, the underwriter will choose a level of underpricing that satisfies the traders, at the same time not so significantly underpriced that they run the risk of losing reputation and possibly market share in the IPO market (Georgieva, 2011). As Georgieva also points out, the underpricing phenomenon differs substantially between different countries. Table 10-1 in Appendix 10.1 illustrates that the Norwegian IPO market historically has had low abnormal returns compared to other countries. One may argue that this may be due to differences in the characteristics and growth expectations of the companies being listed in Norway relative to other countries, however, I have found no research to back up that assertion.

4.7 Econometric analysis

4.7.1 Characteristics of the data sample

To analyse the aspects described in the introduction I will have to apply an econometric model. Intuitively, our data sample might appear to be cross-sectional data, as we have a random collection of different companies going through the IPO process. However, an assumption for cross-sectional data is that the data is collected at the same point of time. The IPOs in our sample happened over a period of five years, and hence we have a modified version of cross-sectional data, called *pooled* cross-sectional data. For practical purposes, the pooled cross-sectional data will be analysed much in the same way as regular cross-sectional data, although it is important to be aware of secular differences that might occur across time for the variables in interest. Basing an econometric analysis on a pooled cross-sectional data sample often leads to problems of heteroscedasticity in the residuals. To address this issue I will apply the adjusted White's heteroscedasticity consistent estimates for all regressions.

4.7.2 The Ordinary Least Squares-model (OLS)

The econometric analysis will apply an OLS multiple regression model. This allows us to investigate how our dependent variable varies with a set of independent variables. The model can be stated as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_n x_n + u$$

where each x_i represents a new independent variable, and the corresponding β_i is the associated population slope parameter. If u is fixed, the change in y will solely depend on the changes in the independent variables. Many factors may potentially be captured in the error term u. If there is correlation between an independent variable and an omitted variable, the estimates from the model are likely to be biased. For the OLS-model to provide unbiased estimators for the population parameters, there are a few key assumptions that need to be fulfilled. These assumptions are described in Appendix 10.2, and given that these hold, the OLS model will provide the best linear unbiased estimators (BLUE) of the population parameters, and the model we will be suitable for inference. To implement qualitative information into the econometric model, a quantitative independent variable might not be sufficient. In order to represent specific characteristics of the unity of interest one may apply binary variables, often referred to as dummy variables. (Balsvik, 2013)

5. Prior research

In this section I will present prior research related to the two topics I wish to examine. The impact of initial demand on the aftermarket performance is covered by both international and Norwegian studies, and these differ in both methodology and results. However, there are no Norwegian studies on the significance of pricing relative to peers. That was also my main motivation to perform this study on the Norwegian IPO market.

5.1 Part1: Initial demand for the issue

As a proxy for initial demand I will look into two alternative variables: one regarding where the final offer price is set relative to the price range, and one regarding how many times the book is oversubscribed. The topic of initial demand and its effect on aftermarket performance is covered in an extensive amount of prior research.

5.1.1 Part 1a: Final price relative to indicative price range

Jay. R. Ritter (2009) investigated the price setting relative to the indicative price range disclosed in the preliminary prospectus. In the period 1980-2008 49 % of all US IPOs were listed with a final price within the range, while 28 % and 23 % of the IPOs were priced below and above the range, respectively. Further, he investigated the differences in returns for the different pricing levels (Table 5-1). IPOs priced below the range had an average first day return of 3 %, while the issues priced within the range had an average first day return of 11 %. The IPOs priced above the range had an average first day return of 39 %. (Ritter, 2009)

Table 5-1: Abnormal returns with respect to pricing relative to range, Ritter (2009)

Percentage of IPOs relative to indicative price range			
	Below	Within	Above
1980-1989	30%	57%	13%
1990-1998	27%	49%	24%
1999-2000	18%	38%	44%
2001-2008	34%	44%	22%
1980-2008	**28%**	**49%**	**23%**
Average first-day returns relative to indicative price range			
	Below	Within	Above
1980-1989	0%	6%	20%
1990-1998	4%	11%	32%
1999-2000	8%	26%	121%
2001-2008	3%	10%	30%
1980-2008	**3%**	**11%**	**39%**

Almost two decades earlier, Hanley (1993) performed a similar study. He examined US IPOs in the period 1983-1987, and found lower initial returns than Ritter (2009). Hanley found 63 % of the IPOs to go public with an offer price within the price range, and 27 % and 10 % below and above the range, respectively. In Hanley's sample, offerings going public below the indicative price range on average had an initial return of 0.6 %, while offerings going public within the range had an initial return of 10 %. The offerings going public above the range had an average initial return of 20.7 %. He found the differences in returns between the pricing levels to be significantly different from zero on 99 % level. Hanley also found that although the short-run returns are related to the relationship between the final offer price and the indicative price range, the long-run performance cannot be explained by revisions in the offer price. (Hanley, 1993)

Bakke, et al. (2011) investigated more than 5,000 US IPOs in the time frame 1981-2008. The authors define the offerings going public below the price range as Low Demand State (LDS), the offerings going above the range as High Demand State (HDS), and the offerings going public within the range as Medium Demands State (MDS). They confirm Ritter's and Hanley's findings, observing that average initial returns for LDS is low, while it is higher for MDS and highest for HDS. In addition, they investigated how the distribution across the pricing levels was affected by the general market conditions. In bear markets 48 % of the offerings were LDS, while in bull markets 42 % of the offerings were HDS. Regardless of market situation Ritter found 28 % and 23 % of the IPOs to be LDS and HDS, respectively.

As Bakke, et al. examined the same IPO market in the same period as Ritter, these findings therefore indicate that market conditions may affect where the final price is set relative to the range. Thus, it will be important for me to control for the market conditions in the regression model. (Bakke, et al., 2011)

Similar studies have been done for the Norwegian IPO market. Samuelsen and Tveter (2006) primarily focused on oil related IPOs in Norway in the period 2001-2005. Their data sample consists of 38 IPOs, of whom only 12 were oil related. Due to the limited sample size, the findings should be interpreted with caution. For the whole sample they found an abnormal initial return of 2.21 %. The oil related stocks had a higher abnormal initial return of 4.84 %, compared to the non-oil related stocks with an abnormal initial return of 1.12 %. These numbers are considerably lower than for international studies. The authors argue that this can be attributed to the increased share of book building IPOs in Norway, which is believed to give a more accurate IPO pricing, and hence less fluctuations in the aftermarket. Samuelsen and Tveter also argue that business leaders may no longer be willing to “leave money on the table”, as researchers have shed light upon the aspect of underpricing and immense abnormal initial returns. Consistent with Ritter (2009) and Hanley (1993) they further investigate the difference in performance with respect to the pricing relative to the range. As they observed few IPOs priced outside the range, Samuelsen and Tveter instead distinguished between IPOs priced above and below the price range *midpoint*. In their sample, 61 % of the IPOs were priced below midpoint. For all companies (regardless of sector), the companies priced below midpoint had an average abnormal return of -1.31 %, while the IPOs priced above midpoint had an abnormal return of 5.5 %. However, neither the abnormal returns, nor the difference between the two groupings proved significantly different from zero. (Samuelsen & Tveter, 2006)

Ellingsen (2012) examined Norwegian IPOs in the period 2006-2011. As stated in Table 5-2, the average abnormal initial return for the whole sample was 2.41 %, in line with the returns for the period 2001-2005 (Samuelsen & Tveter, 2006). In the years before the financial crisis in 2008, the average first day abnormal return was 3.68 %, while it was -0.97 % in the years after the crisis. For the whole sample, Ellingsen found a negative first week abnormal return of -1.06 %, with particularly poor performance in the years after the financial crisis, when the first week abnormal returns were -4.6 %.

Table 5-2: Average abnormal returns for the different time horizons, Ellingsen (2012)

	2006 - Aug 2008	Sept 2008 - 2011	**Total**
First day	3.68%	-0.97%	**2.41%**
First week	1.07%	-4.60%	**-1.06%**

Ellingsen made the same distinction as Samuelsen and Tveter with regards to the pricing relative to the price range midpoint. She points to Derrien (2005), who found European IPOs to be less frequently priced outside the range compared to US IPOs. In the years 2006-2011 65 % of the Norwegian IPOs were priced below midpoint, a slightly higher share than the 61 % Samuelsen and Tveter found for the years 2001-2005. The tendency of low pricing was particularly true for the years 2008-2011, where 80 % were priced below midpoint.

The IPOs in Ellingsen's sample priced above midpoint had an average initial return of 5.5 %, compared to the IPOs priced below midpoint with 2.2 %. The difference proved to be small in the years prior to the crisis. However, as Table 5-3 illustrates, the differences were magnified in the years after the crisis.

Table 5-3: Abnormal returns with respect to pricing relative to range, Ellingsen (2012)

Total	**First day**	**First week**
Offer price ≥ Midpoint	5.51%	2.10%
Offer price < Midpoint	2.22%	-1.55%
2006 - Aug 2008	First day	First week
Offer price ≥ Midpoint	5.54%	1.18%
Offer price < Midpoint	3.43%	0.83%
Sept 2008 - 2011	First day	First week
Offer price ≥ Midpoint	5.36%	6.37%
Offer price < Midpoint	0.26%	-5.31%

Ellingsen included a dummy variable to take into account that some IPOs made available a stabilization mechanism through a green-shoe option. She found this variable to be far from significant, which is in line with Hanley (1993), who also found the green shoe option to be insignificant on initial returns. Hence, I will not control for this in my analysis. Ellingsen further controlled for the market returns prior to listing. However, she does not control for the general volatility of the markets. Practitioners often refer to the volatility when determining whether investors are receptive to IPOs or not. I will most likely choose to control for both market returns and market volatility. Consistent with Ellingsen, I will also control for the size of the IPO company, to avoid a potential size effect to be captured by any other unrelated independent variable. However, the assessments regarding the control variables will be described later. (Ellingsen, 2012)

5.1.2 Part 1b: Level of oversubscription

The relationship between the level of oversubscription and aftermarket performance is in research context a relatively unchartered territory, as it requires information that is not publicly disclosed. Kenourgios, et al. (2007) are some of the few researchers that have touched upon this relationship. The authors examined this relationship for the Greek IPO market in the period 1997-2002, for the first day, first week and first month after listing. They found a correlation between oversubscription and the abnormal returns the first day of 0.799, implying a very strong relationship. In their sample, the average oversubscription level was found to be 89.96 times the number of shares to be issued. These levels of oversubscription were related to abnormal returns of 54.3 %, 45.3 % and 43.8 % for first day, week and month, respectively. Not surprisingly, the authors found the level of oversubscription to be significant for the initial returns. (Kenourgios, et al., 2007)

Wai Wai (2013) performed a similar study for the Malaysian IPO market in the period 2006-2011, and found an average oversubscription rate of 26.7 times the shares to be issued. He further found the correlation between the oversubscription ratio and the initial return to be 0.364, which is less than half of what Kenourgios, et al. (2007) found. We should note that both Wai Wai and Kenourgios, et al. rely on fixed-price offerings only. As the price is held fixed in their samples, the pricing dynamics with regards to over subscription may behave differently than what we will observe in our sample, as our sample primarily consists of book building IPOs.

Although it seems to be a strong relationship between the level of oversubscription and initial return, the level of oversubscription is not necessarily a strong indicator whether the IPO is “hot” or “cold” (high or low initial demand for the issue). At the very basic level, the level of oversubscription should be an indicator of the demand of issue shares relative to the number of available shares. However, as Cowan (2012) points out, investors often inflate their indications of interest, as they anticipate only receiving a fraction of the allocation they demand. He therefore argues that if an IPO is oversubscribed and still does not provide abnormal initial returns, this may imply that the price is too high, and that the oversubscription (i.e. demand) in some degree is artificial (Cowan, 2012).

5.2 Part 2: Pricing relative to listed comparable companies

As discussed in the paragraphs above, prior research has found the placement of the final offer price relative to the range to be a solid predictor for the aftermarket performance. I want to test if this still holds if we control for another aspect of relative pricing, namely the pricing of the IPO company relative to a set of comparable companies. This is a less explored area within the IPO pricing literature.

Ritter and Kim (1999) investigated the possibilities of pricing IPOs based on valuation multiples of comparable companies. They examined US IPOs in the period 1992-1993, and justify the short time horizon with the proposition that one would observe secular differences in valuation multiples over longer time horizons. The authors attempt to identify the usefulness of numerous multiples, such as P/E (share price divided by earnings per share), P/S (share price divided by sales per share), P/B (share price divided by book value per share) and EV/EBITDA (enterprise value divided by operating earnings). They define the “fair value” of the company as the closing price after the first day, as they assume the efficient markets to eliminate any potential mispricing immediately. Consequently, as they found an average abnormal return of 12 % for the first day, they argue that the valuation multiples of the IPO companies in their sample should be 12 % lower than for listed peers. Using trailing earnings and sales data to calculate the multiples gave poor results, while using estimates for the next twelve months significantly improved the predictions. They stress the importance of choosing comparable companies based on a discretionary assessment, rather than an algorithm looking for similarities in sales, profit margins and other numeric measures. They further test the idea about the difficulties of pricing young companies with high growth rates, and found a higher pricing error for young companies than for mature companies. One weakness of their analysis, as they point out, is to use the same set of multiples for all industries, while in practice analysts may apply certain multiples for certain industries. However, this is a necessity of practical reasons, and a weakness that will be present in my analysis as well. They also point to the incentives of investment bankers as a potential source of error. As the universe of listed companies is very large, they argue that the investment bankers have the opportunity to make a “hot” IPO look fairly priced at high multiples by choosing peers with high multiples, and correspondingly make a "cold" IPO look attractive by using peers with low multiples. (Ritter & Kim, 1999)

Based on the same framework as Ritter and Kim, I will test whether the mispricing on valuation multiples corresponds to the abnormal returns. However, unlike Ritter and Kim, I suspect that the markets will require more than one day to eliminate the mispricing, and hence I will also examine this relationship for first week and first month. In addition, as I will control for other aspects than the peer pricing in my model, I will have to compare the mispricing on the valuation multiples to the coefficient associated with the peer pricing variable rather than the initial returns, as it is the ceteris paribus effect that is of interest. Further, the authors do not examine how the relative peer pricing affects the aftermarket performance, which is what I seek to do in my analysis.

Purnanandam and Swaminathan (2003) recognise that most research on underpricing of IPOs relates to whether the stock skyrockets the first day or not. As one historically has observed large initial returns, researchers have concluded that IPOs are indeed underpriced. Purnanandam and Swaminathan, who examined more than 2,000 US IPOs in the years 1980-1997, argue that likely inefficiencies in the securities markets invalidate the assumption regarding the immediate elimination of mispricing. They therefore apply another approach, similar to what I seek to do in this thesis. Instead the authors define the "fair value" of the IPO company to be based on relative pricing compared to a group of listed peers. To determine this fair value the authors apply the multiples P/EBITDA (share price divided by operational earnings per share), P/E (share price divided by earnings per share) and P/S (share price divided by sales per share). As rationalised in section 4.5, I will base my analysis on the P/E and EV/EBITDA multiples. Purnanandam and Swaminathan define 48 industry groupings based on Fama and French (1997), and choose the peer groups by their similarity to the IPO company in terms of their operating characteristics. These groupings should reflect similar operational risk, profitability and growth.

I am of the opinion that industry averages may provide poor comparative basis due to large intra-industry variations in company characteristics. Hence, I will create a unique peer group for each IPO company in my sample. However, while earlier research generally found IPOs to be systematically underpriced, Purnanandam and Swaminathan surprisingly found the IPOs in their sample to be systematically overpriced relative to peers. The overpricing ranges from 14 % to 50 %, depending on which control variables that are included in the model.

The lowest overpricing of 14 % was obtained when controlling for analyst earnings forecasts. They suggest that this might indicate that investors rely too heavily on optimistic earnings forecasts, rather than current profitability. To investigate whether the relative pricing affects the returns in the aftermarket, they divided the stocks into three groups: High, medium and low priced IPOs. The authors observed that overvalued stocks outperformed undervalued stocks the first day, and underperformed in the long run. They acknowledge that the high performance of overvalued IPOs the first day is inconsistent with asymmetric information theory, which would suggest underperformance of such stocks. However, they argue that the underperformance in the long run proves the relative peer valuation of IPOs to be a solid method to determine fair value of IPOs. (Purnanandam & Swaminathan , 2003)

6. Method

In this section I will describe where and how I have gathered the necessary data, and the conduction of the analysis. A couple of challenges had to be overcome along the way, which required certain assumptions and approximations. These will be thoroughly outlined and rationalised.

6.1 Identifying relevant listings

Oslo Stock Exchange (hereafter referred to as OSE) discloses all new listings on their website with date, price, number of shares and total issue size. A large number of listings have successfully been executed in the past 10 years, however, the financial crisis in 2008 completely disrupted the possibility for companies to go public. Henry and Gregoriou (2013) argue that there has been a significant increase in the level of scrutiny of new issues by both investors and regulators, which in turn have made the IPO processes more difficult and lengthy. They also argue that companies going public after the crisis are significantly larger in terms of sales volume than the IPOs prior to the crisis (Henry & Gregoriou, 2013). The difference in the IPO climate is supported by Fauzi, et al. (2012), who found the financial crisis to significantly and negatively affect the short-term initial returns for IPOs. Ellingsen (2012) could confirm this tendency for the Norwegian market as well, as she found higher abnormal returns for IPOs before than after the crisis. As the main goal of this thesis is to analyse the relationship between aftermarket performance and the two factors initial demand and relative peer pricing, fundamental secular differences in the dependent variable (i.e. aftermarket performance) may result in biased and misleading estimates. This, in turn, may deteriorate the inference of the model. In addition, Ritter and Kim (1999) recommend restricting the time span when conducting analysis based on valuation multiples, as these have proven to fundamentally change over larger time periods. Obvious practical limitations also impose restrictions on the ability to prolong the time period further back than the financial crisis. The availability of peer companies for the oldest IPOs may be limited, as a large number of today's relevant peers may have been listed in later years, and relevant peers at the date of listing may have been delisted. After an overall assessment of the arguments above, I will base my analysis on the Norwegian IPOs in the years 2009 and up to October 2014, in total 49 listings.

6.2 Abnormal returns

The abnormal returns of the newly listed stock will function as the dependent variable in the regression model. As described earlier, prior research base their analysis on the proposition that the efficient markets eliminate mispricing the first day. As I suspect the markets to require more time to eliminate this mispricing, I will also investigate the returns after the first week and first month.

To obtain the returns after the first day, week and month I will need the historical closing prices for the IPO companies, which I extract from Bloomberg and Factset. I compare the prices from the two databases to check for any irregularities or errors. Further, if a company executes a split in the time frame we analyse, the returns will come out wrong if the non-adjusted share prices are applied. However, as none of the companies in the sample executed splits within the first month after listing, the non-adjusted share prices can be applied directly together with the offer price from the prospectus. As the offer price by default is non-adjusted, this will provide the correct returns.

To calculate the abnormal returns, I also need the daily closing prices for a reference index in the same period. Based on the arguments presented in the theory section and discussions with practitioners, I chose the OSEBX index (Oslo Stock Exchange Benchmark Index) as reference index, which is supposed to contain a representative sample of the companies listed on OSE. When comparing the returns of IPO companies with alternative investments, this broad index will be appropriate, especially since the characteristics, size and maturity of the companies in our sample differs substantially. As companies going through the IPO process often are small, with a different risk profile than large and mature companies, a narrower index as OBX, which consist of the 25 largest companies on OSE, will not in adequate extent reflect the risk profile of subscribing to IPOs.

6.3 Part 1: Initial demand for the issue

6.3.1 Part 1a: Final price relative to indicative price range

In book building IPOs the underwriters will disclose an indicative price range in the prospectus. This is the price range investors must adhere to during the book building period. During this period the underwriters will get a sense of where they can set the final offer price with sufficient coverage of high quality investor bids. Occasionally, the underwriters update the price range during the book building period based on feedback from the investor community. This was done for a couple of the IPOs in our sample. However, the updates were only crimping of the initial price ranges, and it was done only a day or two before the books closed. Although this may be taken as an indicator of the demand for the issue, this aspect will sufficiently be revealed through the placement of the final offer price relative to the initial price range, and hence not reveal any new information. Thus, I will not include a control variable for these few instances, as it will sequester degrees of freedom in my model.

Only five out of the 49 IPOs in our sample were executed with a fixed price. As our data sample already is rather small for an econometric analysis, all data points will be very important. The fixed price issues should therefore ideally be included. For the book building issues, the number of shares is held fixed, while the final offer price is set somewhere relative to the price range. On the other hand, for the fixed price issues, a range is set for the number of shares to be issued and the price is held fixed. Common for both instances is that the range defines the upper and lower limit of the proceeds the company is believed to be able to raise. The purpose of the price range variable is to capture the demand effect on the aftermarket performance. Therefore it becomes less relevant whether you hold the offer price or quantity of shares fixed. Following from this, for the IPOs executed with fixed price, a proxy will be to investigate where the final number of shares is set relative to the range, as this will equally reflect the supply and demand dynamics as for the book building issues. Consequently, we do not need to exclude the fixed price issues. One might argue that the offer price, regardless of method, is more important than the number of shares to be issued, as the price will determine the market value of the entire equity in the company. However, I believe the relative peer pricing variable will capture the valuation aspect in sufficient degree, and hence justify the proxy for the fixed price issues.

Three of the companies going public in the period are clean demergers from their respective parent company. In these instances the offer price is based on a proportion of the value of the parent company at a certain date. Naturally, it will not be possible to capture the demand dynamics in these instances. Thus, the three demergers are excluded from the sample.

As described in the prior research section, international studies often rely on dummy variables to distinguish between issues going public with an offer price below, within or above the price range. However, it becomes evident that few of the IPOs in my sample went public with an offer price outside the range, and hence it will be more meaningful to divide the issues into two categories: the companies going public below the price range *midpoint* and the companies going public at or above the *midpoint*. This approach is consistent with both Samuelsen and Tveter (2006) and Ellingsen (2012). This distinction only requires one dummy variable, and consequently increases the degrees of freedom in our model relative to the more traditional threefold distinction. As our sample is on the small side for an econometric analysis, this argument is compelling.

6.3.2 Part 1b: Level of oversubscription

In prior research, the initial demand aspect has often been reflected through where the final offer price is set relative to the indicative price range, similar to the methodology just presented. However, it should also be possible to capture the demand effect by observing how many times the book is oversubscribed.

The data on book coverage in IPOs is not publicly disclosed. I have gained access to oversubscription data in the offerings where ABG Sundal Collier has been involved. ABG has for the relevant time period executed a large share of the Norwegian IPOs, and hence the data points may be sufficient in numbers to conduct a statistical analysis. I will return to the potential implications of few observations (relative to the other variables), and how this may affect the inference, in the analysis section.

For the level of oversubscription I have data on how many times the books are covered at the final offer price. Due to selection bias it can be deceptive to assume a linear relationship for this variable. We will obviously not observe any IPOs with book coverage below 1, and it is also reasonable to assume the effect of oversubscription on the aftermarket performance to diminish above a certain level of oversubscription. However, these potential implications will be further discussed in the analysis section.

6.4 Part 2: Pricing relative to listed comparable companies

This part of the thesis will address the pricing of the IPO companies relative to listed comparable companies, and how this may affect the aftermarket performance of the newly listed stock. As described in the prior research section, Purnanandam and Swaminathan (2003) relied on Fama and French-based industry groupings as comparative basis for the IPO companies. However, I am of the opinion that this approach may provide inaccurate estimates and hence constitute a potential source of error. Thus, I will construct a unique peer group for each IPO company, where the operating characteristics of the IPO company should be better reflected than through an industry grouping.

Ritter (1999) recommends choosing peer groups based on a discretionary assessment, rather than a standardized algorithm focusing on certain parameters, e.g. sales numbers, size, growth rate and so on so forth. Six weeks after the IPO, brokerage firms are allowed to release their initiating coverage analysis of the newly listed company. This is a thorough analysis, including company description, earnings forecasts and their perception of the value of the company. Most of these analyses include a multiple valuation section, based on current valuation of comparable companies. I have extracted the lists of peers from these analyses, and supplemented with peer suggestions from Bloomberg and Factset. Then, I conducted an assessment of the operational similarities with the IPO company, in order to create the final peer group.

For all peers I gathered EPS and EBITDA estimates for the next twelve months from the listing date of their associated IPO company. I applied the forecast multiples as this proved more suitable than trailing multiples (Ritter & Kim, 1999). This is also the most common practice by analysts. I further gathered the historical share prices and enterprise values for the same companies to be able to calculate the P/E and EV/EBITDA multiples. I had to exclude the comparable companies with negative earnings estimates, as this would provide meaningless multiples. On the other hand, one might also observe very high multiples. Such instances are most likely due to company specific factors and hence not useful as comparable basis. I therefore excluded the extreme multiples by setting upper limits for both P/E and EV/EBITDA. After adjusting for these instances, the peer groups ranged from 4 to 12 peers for each IPO company, and the final data set consisted of approximately 400 comparable companies. The collection and adjustment of the estimates for each company was obviously a time consuming exercise, however, I felt it to be more accurate to create specific peer groups for each IPO company, as estimated industry averages may provide poor comparative basis.

For the IPO companies the EPS and EBITDA consensus estimates will be available in Factset and Bloomberg after the initiating coverage analyses are released six weeks after listing. As earnings estimates are updated relatively infrequently, an approximation will be to use the estimates that come with the initiating coverage analyses, and assume that these would have been the same at the date of listing. I did spot checks and went through the stock exchange releases in the period in-between, to check for any potential earnings indications that might affect these estimates. No such releases appeared, and hence this approximation should be satisfying. The multiples for the IPO companies will be:

$$\frac{P}{E} = \frac{Final\ offer\ price}{Consensus\ EPS\ NTM}$$

$$\frac{EV}{EBITDA} = \frac{Final\ offer\ price * outstanding\ shares + net\ debt}{Consensus\ EBITDA\ NTM}$$

where outstanding shares will include the newly issued shares and the net debt is total debt less cash and cash equivalents at the time of listing. The consensus estimates for EPS and EBITDA are for the next twelve months from listing date.

As discussed in the theory section, companies are often in a state of high and costly growth at the time of listing. Consequently, the EPS and EBITDA estimates might be negative for the next twelve months. Again, as our data sample is relatively limited, approximations would be necessary for these companies. All initiating coverage analyses contain full year estimates for EPS and EBITDA for at least three years ahead. As we are interested in the relative pricing aspect we can simply raise our sights and look for the first full year of positive earnings for the IPO company. If we compare the valuation for this year with the peer group averages for the same year we will still maintain the relative pricing aspect. It is reasonable to assume that the investors will look for the first year of positive earnings when evaluating the relative pricing of the company.

The quantitative variable for relative peer pricing is calculated by dividing the multiple of the IPO company by the average multiple of the peer group. Hence, a "fairly priced" IPO company will have the value 1. A 10 % overpricing will give the value 1.1 and correspondingly an underpricing of 10 % the value 0.9. To avoid poor comparable basis, outliers caused by company specific factors will be excluded from the statistical calculations, as these will adversely affect the inference of the model.

Instead of applying a quantitative variable, Purnanandam and Swaminathan (2003) constructed dummy variables to distinguish between low, medium and high priced IPOs. In the analysis section I will examine the potential benefits of including the peer pricing aspect as dummy variables rather than a quantitative variable. Purnanandam and Swaminathan further found the distribution of the relative pricing to be skewed, and hence a standard t-test assuming normal distribution proved insufficient. Depending on the distribution of the pricing in my sample, I will have to choose between the standard t-test and a distribution-free test. The mathematical equations and description of both methods can found in Appendix 10.4 and Appendix 10.5, respectively.

6.5 Control variables

If certain factors that are not accounted for in the model affect the abnormal returns and also correlate with the independent variables, we might experience problems with omitted variable bias. As the coefficients of the independent variables may capture the effect of the unrelated factors, the estimation of the independent variables' associated coefficients may be misleading and invalid for inference. In order to avoid omitted variable bias, I will therefore include certain control variables in the regression model. Although many factors may potentially affect the returns, I would have to limit the number of control variables in order to remain an acceptable number of degrees of freedom. Below I will present the few variables I intend to include.

6.5.1 Market returns

As discussed in the prior research section, the general market conditions may affect the success of the listing, with regards to both pricing and aftermarket performance, and ultimately also for the probability that the issue will sell. To control for this potential impact, I will create a variable to represent the market development in the time up to listing. In line with all presented research (e.g. Bakke, et al. (2011)), this aspect will be included as a dummy variable. As the OSEBX index functions as reference index for the abnormal return calculations, this index will also represent the general market returns for this control variable. I distinguish between bull and bear markets, and define bull markets as positive returns of the OSEBX index for the three months prior to the listing. Hence, this variable will have the value 1 if the IPO goes public in bull markets, and 0 otherwise.

6.5.2 Volatility of the market

In addition to the distinction between bull and bear markets, I will take into account the general volatility of the markets. Practitioners often talk about the “IPO window”, and whether this is “open” or “closed”. What they refer to is whether or not the investors are receptive to IPOs to the extent that the underwriters will be able to cover the book on acceptable terms. Practitioners often use the volatility of the markets as an indicator of how receptive the investors are to new issues. For this purpose, the VIX index, a put-option based index connected to the S&P500, will function as a reference point. When insecurity rise in the markets, investors will acquire insurance to protect for losses related to declining markets. When investors increase their level of insurance through put-options, this index will rise. Based on input from practitioners, the VIX index value of 20 is perceived to be the distinction between an open and closed IPO window. One could also apply a corresponding volatility index based on the OBX. Oil related companies constitute a large share of the companies included in the OBX, which also applies for the companies in my sample. Hence, one may argue that the OBX volatility index would better reflect the volatility related to the Norwegian IPOs. However, I was not able to obtain data on this index. In addition, practitioners most frequently referred to the VIX, and had no clear perception of what index value that would define an open or closed window with the OBX volatility index. Hence, I will base my control variable for volatility on the VIX index.

6.5.3 Size of the IPO company

In discussions with practitioners within the Norwegian issue market, the first thing they point out attempting to explain the large deviations in abnormal returns is the size of the companies going public. In addition, prior research has proven that the size of the IPO company may have an impact on the aftermarket performance. Yong (2011) found a negative size effect, i.e. that small IPO companies significantly outperformed large IPO companies. It may be reasonable to assume that the size of the company may also affect the relative pricing of the company. Thus, if size is not controlled for, the model may provide biased estimates. To further strengthen this argument, Ritter and Kim (1999) pointed out that the pricing error based on peer valuation was larger for young companies. As age and size are believed to be closely correlated, a control variable on size may limit the potential pricing error for these companies. In addition, many institutional investors face restrictions regarding the size of the companies they are allowed to invest in. The ceteris paribus effect of this will be that the investors that are allocated shares in the large companies on average are of higher quality than for the small companies. IPOs with a large share of high quality investors have, historically, been associated with better aftermarket performance than IPOs with a large share of low quality investors. This aspect may alone make size a determining factor for the aftermarket performance.

To define the size of the company one may apply both equity value and enterprise value. In my analysis I will base the control variable on enterprise value. As discussed in the theory section, I am of the opinion that this is the most objective assessment of the size, as this metric will encompass the entire business and ignore potential differences in capital structure. This will limit the potential sources of error in the estimation process.

The size may be included both as a quantitative variable and a dummy variable. The quantitative variable would simply be the NOK based enterprise value of the companies. However, prior research, (e.g. Ellingsen (2012)) argued that a dummy variable distinguishing between large and small companies proved the most efficient solution. The choice of implementation of the size variable in the regression model will be described in the introductory analysis in later sections.

7. Analysis

In this section I will first determine and discuss the characteristics of the dependent variable, i.e. the abnormal returns of the newly listed stocks. Then I will perform a stepwise high-level analysis of the independent variables, and very briefly discuss the relevance of the control variables. In the end I will present the regression analysis, enabling isolation of the individual impacts of the independent variables on the aftermarket performance.

7.1 Abnormal returns

Figure 7-1 illustrates the distribution of the IPOs with respect to the abnormal returns for the different time horizons. We observe a longer tail for the negative returns, however, normal distribution appears to be a fair approximation for estimation purposes. As a result, the standard t-test will be sufficient to determine whether the returns are significantly different from zero or not. Due to the limited number of observations, I will allow myself to check the significance down to an 85 % level in some instances.

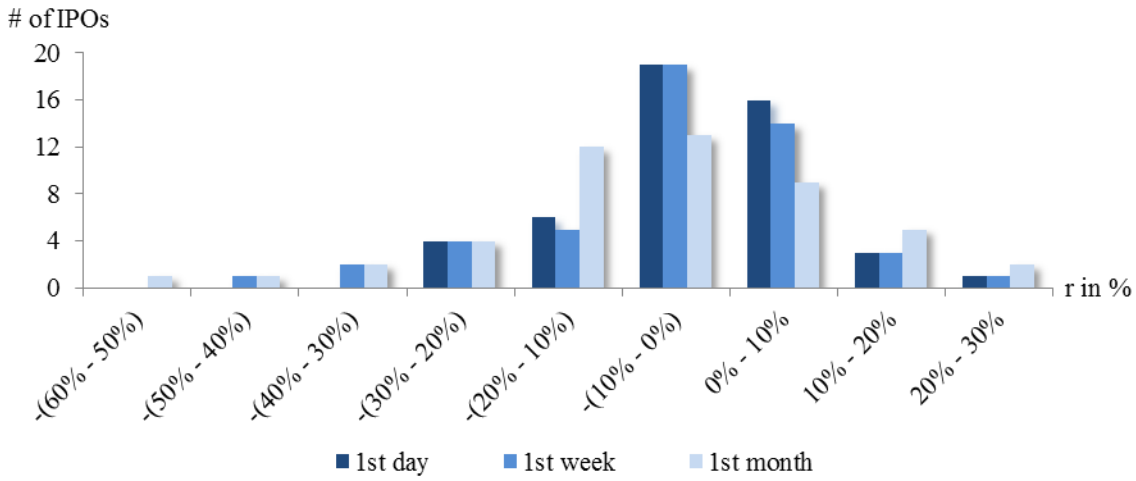

Figure 7-1: Distribution of IPOs with respect to abnormal returns

Considering all years under one, we observe negative average abnormal returns for all time horizons. The abnormal returns deteriorate with the time horizon, indicating that not all mispricing is realised the first day. In line with my proposition, this points in the direction of partial inefficiency in the markets. However, this will be further investigated when we are able to examine the ceteris paribus effect in the regression analysis. The average abnormal return for the first day was -2.1 %, significantly different from zero on a 90 % confidence level. For first week and first month the abnormal returns were -4.1 % and -7.0 % respectively, significantly different from zero on a 95 % and 99 % confidence level, respectively. The negative average abnormal returns for the whole sample contradict all prior research I have obtained, as these papers generally have found fundamental underpricing of IPOs. Although Norway historically has had lower abnormal returns than many other countries, no studies have so far found negative returns over a longer period of time (Ritter, et al., 2014). Ellingsen (2012), with a sample reaching from 2006-2011, pointed out that Norwegian IPOs in 2009 and 2010 on average actually had negative abnormal returns, although not statistically significant. She argued that the average negative returns in these years may have occurred due to coincidences and relatively few observations. However, I now have 49 data points prolonging her time period, and the tendency does not seem to alter.

Table 7-1: Abnormal returns for all time horizons

	1st day	1st week	1st month	# of IPOs
All years	**-2.1%***	**-4.1%*****	**-7.0%******	49
2009	-2.1%	-4.9%	-10.4%	2
2010	-4.2%	-6.9%	-9.8%*	14
2011	7.1%	1.9%	2.4%	7
2012	-3.2%	-6.8%	-9.6%*	2
2013	-2.7%*	-5.6%	-6.6%**	11
2014	-4.1%*	-2.6%	-8.7%**	13

****Significant on a 99 % level; *** 95 % level; **90 % level; *85 % level

Table 7-1 shows that all years, besides 2011, have negative average abnormal returns of subscribing to IPOs. One might expect the positive returns in 2011 to be due to particular high-performers, however, this is only partially true. 2011 had a higher share of IPOs with positive returns on all horizons than the other years in the sample. Due to large standard deviations and few observations within each year, few of the yearly averages prove significantly different from zero.

Intuitively, it would be reasonable to believe that the climate for IPOs would become more favourable the further away we move from the financial crisis. However, this does not seem to be true, as the abnormal returns are just as bad for the latter years as for the first years after the crisis. This points in the direction of long-lasting effects of the crisis on the performance of IPOs in Norway. Although international research has confirmed the negative short-term impact of the crisis on the IPO market (e.g. (Fauzi, et al., 2012)), I have not been able to obtain any research investigating the endurance of this effect. Thus, I am not able to determine whether the persistent poor performance of Norwegian IPOs after the crisis is a country-specific phenomenon or not.

The negative abnormal returns may have implications beyond the wealth of the investors involved in the Norwegian IPOs the past five years. If one takes the stand of the winner's curse explanation of underpricing, this phenomenon of what appears to be persistent overpricing might endanger the Norwegian issue market. As described earlier, the winner's curse-explanation suggests that all uninformed investors will subscribe equally and indiscriminately to all issues, as long as they on average profit. If the tendency of negative initial returns in the Norwegian issue market proceeds, we may observe uninformed investors refraining new issues. Thus, the underwriters may struggle to obtain full subscription, making it difficult for companies to raise capital by going public. In addition, Ellul and Pagano (2003) and Pritsker (2006) suggest that IPOs need to be underpriced to compensate investor for the fact that newly listed companies are less liquid than comparable companies for some time after listing. Ellul and Pagano argue that aftermarket illiquidity stem from asymmetric information that persists after the IPO. Hence, higher stock returns need to compensate investors for the losses they can expect from trading with better informed investors and for the affiliated risk. If this liquidity premium proceeds to be absent this may hamper the book buildings in the future.

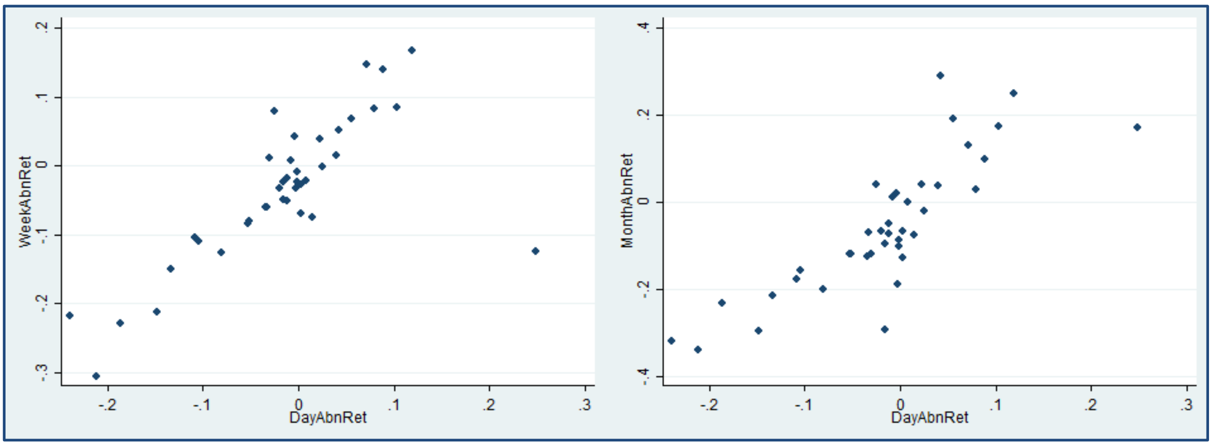

Figure 7-2: First week and first month returns scattered with respect to first day returns

One interesting finding regarding the abnormal returns is the predictability of the returns for the first week and first month based on the returns the first day. In Figure 7-2 the first week abnormal returns (left plot) and first month abnormal returns (right plot) are scattered with respect to the first day abnormal returns. The first day performance turns out to be a strong indicator of the returns for the longer time horizons. For example, observing the 29 companies with negative abnormal returns the first day, 25 of these had negative abnormal returns also after the first month. In 24 of these 25 instances the stock continued to decline after first day. A correlation matrix (Table 7-2) further strengthens the evidence of this strong relationship, revealing a correlation between the first day and first month returns of 0.8279. Ritter (1991) found the initial returns to be insignificant for long-term aftermarket performance. However, as he examined a three-year horizon, his results are naturally not comparable to mine. I have not succeeded in obtaining any research examining this relationship for the relatively short time horizons I investigate.

Table 7-2: Correlation matrix between the dependent variables

	1stday	1st week	1st month
1st day	1		
1 week	0.6892	1	
1st month	0.8279	0.8166	1

It would be interesting to see if the tendency of high predictability is present for a larger sample of IPOs, as this stands possible to monetize as a trading strategy. For the fun of it: if one had shorted all stocks with negative first day abnormal returns on the second day of listing, and realised the position after the first month, one would have an accumulated abnormal return of 237.6 % from the end of 2009 and up to present, with a very low level of average capital employed. For the IPOs with marginal positive returns the first day the returns for the first month tend to be more ambiguous, and my hypothesis is that this may be due to the green-shoe option included in some IPOs. To include long positions in the trading strategy one should therefore control for the potential disruptions of the green shoe option.

7.2 Part 1: Initial demand for the issue

7.2.1 Part 1a: Final price relative to indicative price range

Out of the 49 IPOs in the sample, 41 applied the book building method. Five IPOs set a fixed price in the prospectus, with a range for the number of shares to be issued. Using the proxy described earlier, I therefore have data points for 46 out of the 49 companies going public regarding where the final offer price is set relative to the indicative price range. The remaining three plain demergers had to be excluded from this part of the analysis. Table 7-3 summarizes the distribution with regards to the pricing relative to the range.

Table 7-3: Distribution of IPOs with respect to pricing relative to range

	Below midpoint	Above midpoint	Below range	@ lower limit	@ upper limit	Above range
# of IPOs	36	10	9	17	1	0
% of IPOs	78%	22%	20%	37%	2%	0%

Out of the 46 IPOs, only 10 went public with an offer price at or above (hereinafter referred to as above) the price range midpoint, corresponding to 22 % of the IPOs. The remaining 78 % landed on an offer price below the price range midpoint. Ellingsen (2012), who analysed Norwegian IPOs between 2006 and 2010, found 65 % of the IPOs to be priced in this manner. Ellingsen further found the financial crisis to increase the share of low-priced IPOs from 57 % to 80 %. In the years 2009-2012 86 % of the IPOs in my sample were priced below midpoint, while this share decreased to 72 % for the years 2013-2014. The decreasing share in the later years indicates that the demand of issues in some degree has recovered after the financial crisis, although not entirely.

In international research papers, we often observe about half of the IPOs priced within the price range and one quarter above and one quarter below the price range (see e.g. Ritter, 2009). In our sample 80 % of the IPOs were priced within the range, and out of these 73% were priced in the lower half. The Norwegian IPO market therefore appears more bound by the indicative price range, and in addition having a stronger skewness towards the left of the midpoint than the international IPO market. The findings are consistent with Derrien (2005), who found European IPOs to be less frequently priced outside the range. We found 20 % of the IPOs to be priced below the range, compared to Ritter’s (2009) 28 % and Hanley’s (1993) 27 %. None of the IPOs in our sample were priced above the range, compared to 10 % in Hanley’s sample, and 28 % for Ritter. Despite the discrepancy between Ritter’s and Hanley’s findings, our results clearly differ from both. Only one company in the sample was priced *at* the upper limit of the range, which stands out compared to Ellingsen (2012), who found 23 % of the Norwegian IPOs in the years 2006-2008 to be priced at the upper limit. The lower share of IPOs priced at the upper limit may indicate long-term negative pricing effects of the financial crisis, however, I have not been able to confirm similar alterations for international IPO markets.

Although the average abnormal returns are negative for the whole sample, the placement of the final offer price relative to the price range can prove to be a solid indicator of the aftermarket performance. As Table 7-4 illustrates, the IPOs going public above the midpoint had a first day average abnormal return of 1.9 %, and the IPOs going public below midpoint had a negative first day abnormal return of -3.1 %. This difference is extrapolated with the time horizon, e.g. after one month the IPOs priced above midpoint have an average abnormal return of 3.5 %, compared to -9.2 % for the IPOs priced below the midpoint. The returns for the IPOs going public with an offer price below midpoint are significantly different from zero, while the returns for the IPOs priced above midpoint are not. The difference in significance should not be puzzling, as the mean returns are slightly below zero. However, in this section, whether or not the returns are significantly different from zero is not the subject of interest. As we examine the impact of where the price is set relative to the range, we should determine if there is a significant difference between the returns for the IPOs priced above and below midpoint.

Table 7-4: Abnormal returns with respect to the final price relative to the price range

2009-2014	**1st day**	**1st week**	**1st month**	**# of IPOS**
All	**-2.0%**	**-3.9%*** **	**-6.6%**** **	**46**
Offer price ≥ Midpoint	1.9%	-0.4%	3.5%	10
Offer price < Midpoint	-3.1%**	-4.9%****	-9.3%****	36
Difference	*5.0%**	*4.5%*	*12.8%***	
2009-2012	**1st day**	**1st week**	**1st month**	**# of IPOS**
All	**-0.4%**	**-3.9%****	**-5.3%**	**22**
Offer price ≥ Midpoint	5.5%	6.4%	15.7%	3
Offer price < Midpoint	-1.3%	-5.5%***	-8.6%***	19
Difference	*6.8%**	*11.9%***	*24.2%***	
2013-2014	**1st day**	**1st week**	**1st month**	**# of IPOS**
All	**-3.5%****	**-4.0%***	**-7.7%*** **	**24**
Offer price ≥ Midpoint	0.3%	-3.3%	-1.8%	**7**
Offer price < Midpoint	-5.0%***	-4.3%**	-10.2%****	17
Difference	*5.4%*	*0.9%*	*8.4%*	

(Returns based on the 46 IPOs with data on price range)
****Significant on a 99 % level; ***95 % level; **90 % level; *85 % level

Examining the whole sample, the differences in returns for the IPOs priced above and below midpoint are of considerable size for all time horizons, with a difference of 5.0 % for the first day and as much as 12.8 % for the first month. The differences are significant on an 85 % level for first day and 90 % level for first month. Samuelsen and Tveter (2006) found the first day difference to be 6.8 % for the Norwegian IPOs in the years 2001-2005, while Ellingsen (2012) found it to be 3.3 % for the Norwegian IPOs between 2006 and 2011.

Ellingsen further found the difference to be 3.7 % for the first week, compared to my result of 4.5 %. For the first month horizon I have no comparative basis.

When splitting the dataset into the two time periods 2009-2012 and 2013-2014, with 22 and 24 IPOs in each period respectively, we observe large alterations in both average abnormal returns and the differences in abnormal returns between the two pricing levels (Table 7-4). Reviewing the years 2009-2012, the differences more than double for the first week and the first month, and are significant on an 85 % level for the first day and a 90 % level for both the first week and the first month. For the period 2013-2014, the differences are substantially lower than prior years and insignificant for all time horizons. This may indicate that where the final offer price is set relative to the price range no longer have the same prediction value for the aftermarket performance as for earlier years. At the same time, the average abnormal returns have deteriorated from the first to second time period. In short; the returns of subscribing to IPOs have worsened, and it has also become harder to distinguish between the "good" and "bad" IPOs based on the final pricing relative to the price range.

The apparent breakup of the relationship between the price setting relative to the range and the aftermarket performance is remarkable. There are many potential explanations for this break up. However, I believe the answer may lie in the underlying pricing dynamics. The distribution with regards to size shows a large number of very small companies going public the last two years. As discussed earlier, restrictions regarding size for institutional investors justify the assumption that small companies on average have a set of lower quality investors than large companies. Thus, the average IPO in the last period may contain an investor base of lower quality, relative to the first period. As investor quality historically has proved to correlate positively with aftermarket performance, this may explain the lower abnormal returns in the last period. In addition, as I will return to later, the smaller companies tended to be overpriced in my sample, and hence underperformed the larger companies. This may also help explaining the deteriorating returns.

However, these arguments cannot explain the decreased predictability with regards to where the price is set in the range. We know that the placement of the offer price relative to the range is a proxy for the level of demand for the issue, assuming the "quality level" of the investors to be *equal* at all final offer prices. However, it may be reasonable to assume that, ceteris paribus, the investor quality decreases somewhat the higher you move in the range. If this is true, you will have offsetting effects in both ends of the range with regards to the aftermarket performance: In the higher end, the relatively lower investor quality indicates poor aftermarket performance, while, at the same time, a high price relative to the range indicates high demand and strong aftermarket performance. Reversely, in the low end, a relatively higher investor quality indicates strong performance, while the low price relative to the range indicates poor demand and weak performance. It is reasonable to assume that the intra-range variation in investor quality is higher for the smallest companies. Thus, as the average size of the companies is significantly smaller in the last two years, the offsetting effect should be stronger. This may explain the reduced predictability in the last period.

Table 7-5: IPOs priced at the price range limits

	1st day	1st week	1st month	# of IPOS
All	**-2.0%**	**-3.9%**	**-6.6%**	**46**
Priced below range	-0.1%	-1.4%	-5.8%	9
Priced at lower limit	-4.7%	-7.2%	-11.1%	17
Difference (@ lower vs below)	*4.6%*	*5.8%*	*5.3%*	
Priced at upper limit	11.9%	16.7%	24.8%	1

Another striking aspect is the high share of IPOs that are priced exactly at the lower limit of the range (Table7-5). Out of the 34 companies priced below midpoint, as many as 17 were priced *at* the lower limit of the interval, corresponding to 37 % of the sample. As Ellingsen (2012) found 37 % of the IPOs in the period 2006-2011 to be priced at the lower limit as well, this phenomenon proves not to be peculiar for later years. There is no theoretical reason for why the lower limit price should be more frequently observed than others, assuming equilibrium is determined by traditional supply and demand of the issue. Intuitively, an IPO being priced below the range should indicate lower demand for the issue, and hence one would expect poorer performance in the aftermarket relative to the IPOs priced at the lower limit. However, we observe the opposite effect, as the IPOs priced at the lower limit significantly underperform the IPOs priced below the range. One possible explanation may be found through the incentives for the investment bank acting as advisor. Pricing the IPO below the range may indicate that the advisors misinterpreted the investor appetite for the issue and failed to determine the correct company valuation. The investment bankers may look less competent than if they are be able to set the final price within the range they themselves determined prior to the book building. The reluctance of further lowering the offer price may cause the underwriter to accept bids from investors of lower quality than what they might attain at a lower price. As investors of lower quality in greater extent “flip” the stock and sell their share right after listing, the lower-limit IPOs significantly underperforms the IPOs priced below the range. Based on this, one may simply suggest that the IPOs priced at the lower limit are not worthy their price, and should ideally been priced below the range. The significant underperformance also strengthens the proposition that investor quality has a considerable impact on the aftermarket performance.

Although we only have one IPO priced at the upper limit of the range, the returns for this stock coincides with the hypothesis, namely that IPOs priced high in the range performs well in the aftermarket. This IPO had an abnormal return of 11.9 % the first day, and 24.8 % the first month. However, one would obviously need additional observations to ascertain anything about the significance of being priced at the upper limit.

7.2.2 Part 1b: Level of oversubscription

In Figure 7-3 the first month abnormal returns are scattered with respect to how many times the book is covered at the final offer price. It appears to be a linear relationship between the two variables, which indicates that the book coverage might be a suitable independent variable to represent the initial demand aspect in the regression analysis. However, as discussed in the methodology section, the selection bias may be looming for the interpretation of the coefficient associated with the book coverage variable. Obviously, there will not be any observations with book coverage below 1. In addition, for the IPOs where the book is barely covered, the outcome with regards to returns appears highly ambiguous.

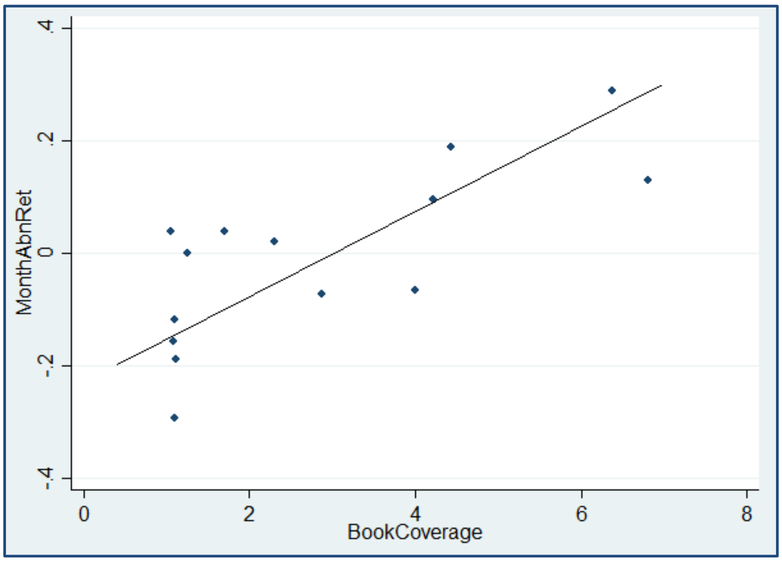

Figure 7-3: First month abnormal returns scattered with respect to book coverage

A regression with the book coverage as the only independent variable indicates that the abnormal returns increase with the level of oversubscription (Table 7-6). The explanatory power of this one-variable model is strikingly high, with an adjusted R-squared of 52.12 % for the first month. As an example, the interpretation of the coefficient for the first month implies that for each time the book is covered, the abnormal return the first month will increase by 5.78 %. As the regression output illustrates, the coefficients are highly significant for all horizons, which supports the proposition regarding the positive relationship between oversubscription and aftermarket performance.

Table 7-6: Regression with book coverage as independent variable

	1st day	1st week	1st month
Coefficient	0.0176**	0.0245*	0.0578***
Standard error	0.0052	0.0086	0.0148
Adjusted R-squared	0.4902	0.3559	0.5212
# of observations	14	14	14

***significant on 99 % confidence level; **95 % level; *90 % level

As presented in the prior research section, Kenourgios, et al. (2007) tested the correlation between the book coverage and first day abnormal returns, and obtained a correlation of 0.799. The corresponding correlation in my sample of 0.7001 confirms the strong relationship between first day returns and the book coverage (Table 7-7). The average oversubscription to the IPOs in my sample is 2.8 times the issued shares, compared to 89.9 for Kenourgios et al. and 26.8 for Wai Wai (2013). As these studies cover fixed price IPOs, I suggest these numbers to not be directly comparable. In book building IPOs, which constitute the vast majority of my sample, the final price will be adjusted with regards to the level of demand that becomes evident during the book building period. Consequently, the final offer price will be revised upwards if the demand for the issue is high. Naturally, the oversubscription rate at the final offer price will therefore be lower. However, the correlation and impact on the initial returns seem to be aligned with the international studies.

Table 7-7: Correlation between book coverage and first day abnormal return

	Book coverage	1st day abn. ret.
Book coverage	1.0000	
1st day abn. ret.	0.7001	1.0000

As we read from the regression output in Table 7-6, we unfortunately only have 14 observations on book coverage. As the regression tool requires data on all variables for each

IPO, the IPOs without book coverage data would have to be excluded from the final sample. Hence, when including the other independent variables in the regression, the estimation of the coefficients would sequester degrees of freedom to the extent that the inference of the model would be invalid.

Although we do not have an adequate number of data points on book coverage to perform an econometric analysis, we do not necessarily lose the purpose of this variable, namely to investigate the initial demand effect on the aftermarket performance. The variable related to where the final price is set relative to the price range may be sufficient in this regard. It is reasonable to assume the oversubscription to correlate positively with the price setting relative to the range, i.e. an IPO with a high level of oversubscription should end up with a price high in the range, and vice versa. A correlation analysis for the two variables provides a comfortably high correlation of 0.8554. This inferes that if one of the variables is already included in the model, implementing the other will not bring any "new information to the table". The high correlation also indicates that including both variables most likely will lead to problems of collinearity, which in turn may result in biased estimators and invalidate the inference of the model. Since we have 46 data points on the pricing relative to the price range, compared to only 14 data points on the book coverage, it is an easy decision to choose the price range variable to represent the initial demand aspect in the final regression.

7.3 Part 2: Pricing relative to listed comparable companies

Figure 7-4 illustrates the distribution of the IPOs with respect to the relative peer pricing. The P/E and EV/EBITDA multiples illustrate the same pricing image, namely that the majority of the IPOs are priced cheaper than peers.

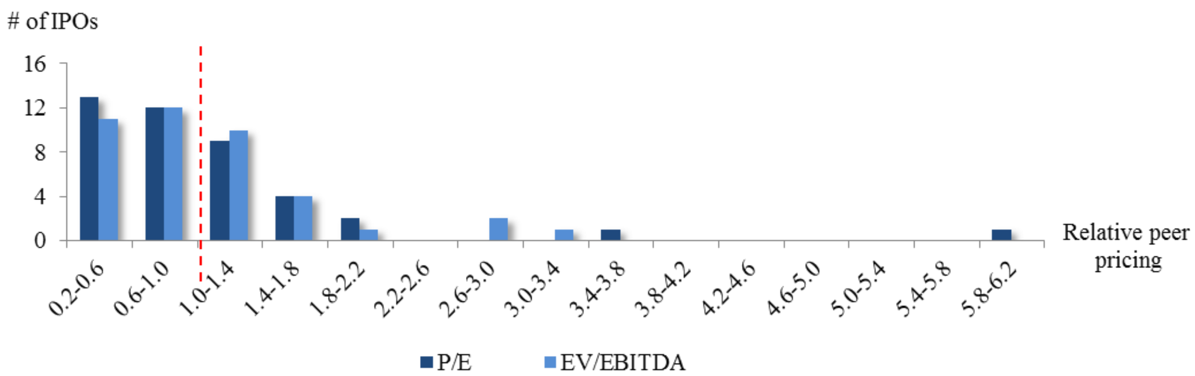

Figure 7-4: Relative pricing compared to listed peers

We observe a few outliers priced substantially higher than peers. When calculating the relative peer pricing variable, it can be expedient to exclude the extreme values, as these will affect the test observator in an inappropriate large extent. As these valuations must be assumed to be related to company specific characteristics or estimation errors, they are not directly of interest when attempting to infere the pricing of a large sample of IPOs. This argument is also strenghtened by the fact that none of these extreme values on one multiple were confirmed by an extreme value on the other multiple, indicating that either estimation errors or accounting specific conditions are the reasons for the extreme values. When these values are excluded, we obtain an underpricing of 9 % and 11 % based on P/E and EV/EBITDA, respectively (Table 7-8). As discussed in the prior research section, the mispricing on the valuation multiples will be compared to the coefficient of the peer pricing variable in the regression analysis in later sections.

Table 7-8: Relative pricing based on P/E and EV/EBITDA

	P/E	EV/EBITDA
Relative pricing	0.91*	0.89*
Standard deviation	0.43	0.40
# of observation	40	39

*Significantly different from 1 on a 90 % confidence level (Based on Wilcoxon (Mann-Whitney) Rank Sum Test)

In line with Purnanandam and Swaminathan’s (2003) findings, our observations are heavliy skewed to the left (Figure 7-4), and a distribution-free test statistic will be needed in order to determine the significance of the results. Thus, I apply the distribution-free two-sided Wilcoxon (Mann-Whitney) Rank Sum Test to determine whether the pricing is significantly different from 1, i.e. a significant difference in pricing relative to peers. This test is more efficient than a standard t-test for samples that prove to be non-normal. The test confirms the underpricing to be significant on a 90 % level for both multiples.

On one hand the underpricing of the IPOs relative to peers seems strange, having in mind that companies going through the IPO process often are young and successful companies with high current and future estimated growth rates. Mature peers may have lower growth rates, which will justify higher valuation multiples for the IPO companies. On the other hand, there is high uncertainty regarding the future operations connected with a company with a relatively short track record. Thus, one may argue that investors have to be compensated for investing in such high risk companies, and hence require a lower pricing relative to peers.

The underpricing of IPOs in my sample contradicts Purnanandam and Swaminathan (2003), who found overpricing of IPOs relative to peers. Since there are no prior research on peer pricing of Norwegian IPOs, it is hard to determine how my results stand compared to historical pricing of IPOs in Norway. A possibe explanation of the underpricing of Norwegian IPOs relative to US IPOs may be found in the characteristics of the companies going public. IPOs in the US have often been related to high-tech and software related companies, while Norwegian IPOs often have been related to asset-heavy oil-related companies. Consequently, one may assume that the US IPO companies on average have a higher current and estimated growth rate than the Norwegian IPO companies, which may explain some of the differences in pricing. However, I have not found any research to back up that proposition. In addition, it is important to note that the small sample size makes it difficult to draw any conclusions regarding the potential underpricing of Norwegian IPOs.

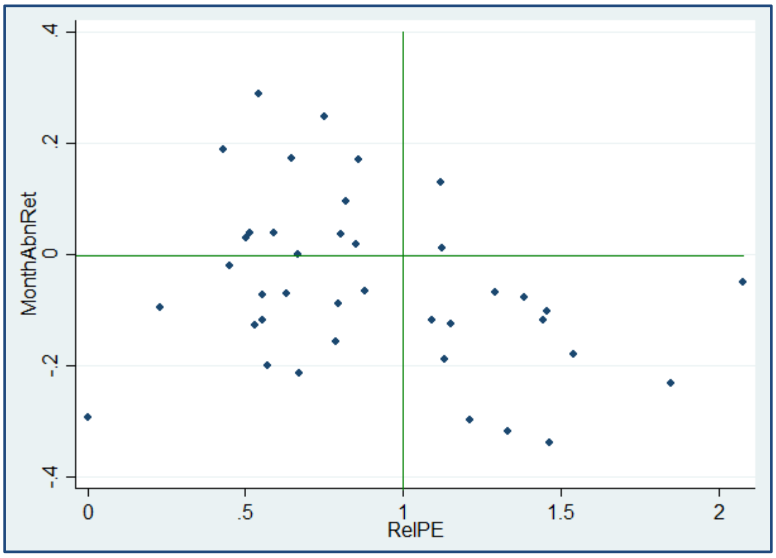

Figure 7-5: First month abnormal returns scattered with respect to the quantitative P/E variable

In Figure 7-5 the first month abnormal returns are scattered with respect to the quantitative P/E variable. It is hard to determine any clear linear relationship between the two variables, and hence a quantitative variable may not be appropriate for the final regression model. Despite the apparent absence of a linear relationship, there is a tendency of IPOs priced above peers to have negative abnormal returns (bottom right quadrant). For the IPOs priced below peers, the outcome is more ambiguous, with nearly the same number of IPOs with postive and negative abnormal returns (top and bottom left quadrants). This tendency proved to be similar for the two other time horizons, as well as for the EV/EBITDA multiple. The apparent difference in performance indicates that the distinction between overpriced and underpriced IPOs may serve properly as a predicator for aftermarket performance. Purnanandam and Swaminathan (2003) made the same observation and created dummy variables for the relative peer pricing. Although they chose to distinguish between low, medium and high priced IPOs, I will only distinguish between underpriced and overpriced IPOs, in order to spare degrees of freedom. This variable will have the value 1 if the IPO is priced higher than peers, and the value 0 otherwise.

Investigating the correlation between the first month abnormal returns and the dummy variables, we observe a noteworthy relationship, both for P/E and EV/EBITDA. There is strong negative correlation between the first month abnormal returns and both valuation multiples, with -0.491 for the P/E multiple and -0.413 for the EV/EBITDA multiple. This indicates that IPOs priced above its peers should have poorer abnormal returns than the IPOs priced below its peers.

Table 7-9: Pricing distribution based on P/E and EV/EBITDA

	On P/E multiple	On EV/EBITDA multiple
Higher priced than peers	40%	43%
Lower priced than peers	60%	57%

From Table 7-9 one can see that the dummy variables entail the same the distribution with regards to relative peer pricing as the quantitative variables, namely that the majority of the IPOs are priced below peers. In addition, the table confirms the coinciding pricing distributions for the P/E variable and the EV/EBITDA variable.

Table 7-10: Abnormal returns with respect to the relative pricing

Abnormal returns	**1st day**	**1st week**	**1st month**	***# of IPOS***
Overpriced on P/E	-5.6%***	-7.2%***	-14.1%****	*17*
Underpriced on P/E	1.0%	-1.4%	-1.2%	*25*
Difference	*6.6%***	*5.8%**	*12.9%****	
Overpriced on EV/EBITDA	-4.3%***	-6.3%***	-12.4%****	*18*
Underpriced on EV/EBITDA	0.3%	-1.8%	-2.0%	*24*
Difference	*4.5%**	*4.5%*	*10.4%***	

****Significant on a 99 % level; ***95 % level; **90 % level; *85 % level

In Table 7-10 the abnormal returns for the three horizons are illustrated with respect to the relative peer pricing, which appears to have significant impact on the aftermarket performance. The negative returns for overpriced IPOs are significantly different from zero on 95 % level for first day and week, and 99 % level for first month with both the P/E and EV/EBITDA multiple. We observe large differences between the overpriced and underpriced IPOs across all time horizons, and the differences tend to increase with the horizon. For the P/E multiple the differences are significant on a 90 % level for first day, 85 % level for first week and 95 % level for first month. For the EV/EBITDA multiple the differences are significant on an 85% level for first day, insignificant for week and significant on a 90 % level for the first month.

In this type of analysis it is important to evaluate the relationship between the different independent variables. Our model will include a variable regarding the pricing relative to the price range, and it is natural to think that an IPO priced high in the range might also be priced high relative to peers, simply because the final valuation ends up richer. We can check for collinearity between the two variables, i.e. a linear relationship. For this purpose we may conduct a Variance Inflation Factor test (VIF test) (Wooldridge, 2012). This test is generally performed to quantify the severity of multicollinearity, and works by calculating how much the variance of the coefficients in interest increase due to collinearity. A test observator of 10 or more is reason for concern. Running the VIF test on the peer pricing variable and the interval pricing variable, we obtain a test observator of 1.001. Hence, it will be safe to include both variables in the regression model.

As discussed in the methodology section, the relative peer pricing aspect may be implemented both as quantitative variables and dummy variables. From the cursory analysis above it appeared to be no linear relationship between the abnormal returns and the peer pricing. Consequently, a quantitative variable may result in poor estimates. On the other hand, we observe highly significant differences in returns when distinguishing between relatively overpriced and underpriced IPOs, which favors the dummy variable approach. This is also most common approach by researchers, among others Purnanandam and Swaminathan (2003). Thus, I choose to apply dummy variables to implement the peer pricing aspect into the regression model.

7.4 Control variables

As described in the methodology section, the control variables will be absolutely necessary in order to avoid omitted variable bias. In this section I will briefly provide insight into the relationship between the dependent variables and the control variables I have chosen to include.

7.4.1 Market returns

Prior research has indicated that general market conditions may affect where the final price ends up relative to the indicative price range. We found 78 % of the IPOs in my sample to be priced below midpoint regardless of market conditions. In bear markets this number increased to 85 %. In bull markets 24 % of the IPOs were price above midpoint, compared to 21 % regardless of market conditions. If one observes the share of IPOs priced exactly at the lower limit, the distinction between bull and bear markets become more evident. Regardless of marked condition, 37 % of the IPOs were priced exactly at the lower limit, while this number was 30 % and 54 % for bull and bear markets, respectively.

Bakke, et al. (2011) define bull markets as positive market returns for the 45 trading days before listing. Although this slightly differs from my period of three months (corresponding to 60 trading days), their results should work as comparative basis. Bakke, et al. found 42 % of the IPOs to be priced above the range in bull markets, while Ritter (2009), who examined the same sample of IPOs, found 23 % of the IPOs to be priced above range regardless of market conditions. In our sample, no IPOs were priced above the range. In bear markets Bakke, et al. found 48 % to be priced below the range, compared to Ritter's 28 % regardless of market conditions. In our sample 20 % were priced below the range regardless of market conditions, while the percentage share just slightly increased to 23 % in bear markets. Thus, the fluctuations in pricing due to changes in market conditions appear more modest for the Norwegian IPOs than for the US IPOs. Bakke, et al. (2011) stated that "the probability of positive first-day returns is higher when public markets are doing well". We can support their statement, as we find the probability of positive the first day to be 42.3 % in bull markets, compared to 30.8 % in bear markets.

7.4.2 Volatility of the market

Based on the discussion in the methodology section we want to control for the general volatility of the market. In Figure 7-6, the first month abnormal returns are scattered with respect to the VIX index values. It is hard to observe any linear relationship between the abnormal returns and the index values, and a similar tendency is revealed for the other horizons as well. Consequently, this variable will most likely not provide useful information in a regression analysis as a quantitative variable. Thus, I will test if implementation as a dummy variable may provide better results. Based on input from practitioners, the natural dividing line will be the VIX index value of 20, which is believed to be the limit determining whether investors are receptive for IPOs or not. Based on interpretation of the scatter plot, it is hard to argue that the VIX has any significant impact on the returns for the IPOs going public when the VIX is below 20 (top and bottom left quadrants). However, for the VIX above 20, we see that most IPOs have negative returns (bottom right quadrant).

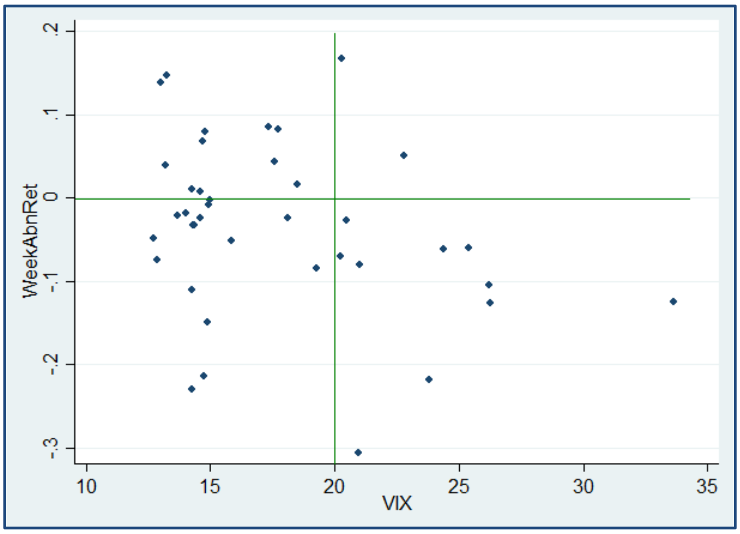

Figure 7-6: First week abnormal returns scattered with respect to VIX index values

This observation is confirmed by the two correlation matrices below (Table 7-11), illustrating the correlation between the VIX and first month abnormal returns for IPOs where the VIX was below 20 (left matrix) and above 20 (right matrix). The correlation is negligibly positive for IPOs in low volatility markets. However, for IPOs going public in high volatility markets, there is a negative correlation -0.222. Hence, a dummy variable may provide useful input. However, the selection bias will be a serious concern associated with this variable. For VIX index values above 20 there are very few data points, simply because the probability of observing IPOs in high volatility markets is much smaller than for low volatility markets. As the coefficient may be calculated on uncertain grounds, we must interpret the estimates with great caution.

Table 7-11: First week abnormal returns with respect to the VIX in high- and low volatility markets

	VIX>20	WeekAbnRet
VIX>20	1	
WeekAbnRet	-0.222	1

	VIX<20	WeekAbnRet
VIX<20	1	
WeekAbnRet	0.041	1

If we investigate the returns for the IPOs with respect to the volatility at the time of listing, it is hard to spot any clear relationship (Table 7-12). Only for the first week abnormal returns, there seem to be any considerable difference. However, due to large deviations, the difference is not significantly different from zero. Even though this single control variable may not prove significant by itself, it might stand out as joint significant with the other control variables. This will be further investigated in the section regarding the regression analysis.

Table 7-12: Returns with respect to volatility

	1st day	1st week	1st month
High volatility	-1.5%	-6.1%**	-6.2%
Low volatility	-2.2%*	-2.9%*	-6.7%***
Difference	*0.7%*	*-3.3%*	*0.5%*

***Significant on a 95 % level; **90 % level; *85 % level

7.4.3 Size of the IPO company

During my analysis I tested control variables for size based on both equity value and enterprise value. Both seemed to correlate considerably with the abnormal returns, however, based on the rationalisation in the methodology section, I believe the enterprise value variable is easiest to defend on economic ground. When the abnormal returns are scattered with respect to the size, no linear relationship becomes evident. Hence, I constructed a dummy variable distinguishing between small and large companies. This is consistent with Ellingsen (2012) who also found the dummy variable approach to be the most efficient solution. The enterprise value of NOK 1,000 million is a natural breaking point, as passing this value stands as a milestone for many companies. In addition, this limit also provides approximately the same number of IPOs in both categories, which is preferable with regards to statistical comparison.

Table 7-13: Abnormal returns with respect to company size

	1st day	1st week	1st month	# of IPOS
EV > NOK 1000m	-1.2%	-1.1%	-3.5%	27
EV < NOK 1000m	-3.2%	-7.9%***	-11.4%****	22
Difference	*2.0%*	*6.8%***	*7.9%***	

****Significant on a 99 % level; ***95 % level; **90 % level; *85 % level

From Table 7-13 it becomes clear that small IPO companies underperform the large IPO companies, and the differences are significantly different from zero on a 90 % confidence level for first week and first month. This contradicts Yong's (2011) findings, who found small companies to outperform the large companies. To determine whether size is the determining factor with regards to the outperformance by large companies, we should check if there is a relationship between the size and the relative peer pricing. On the P/E multiple the large companies appear underpriced relative to the small companies (Table 7-14). On the EV/EBITDA we do not observe this difference. However, if we for this sake base our analysis on the P/E multiple, it is consistent with the asymmetric information theory regarding IPO pricing that the large companies outperform the small companies, as they appear underpriced relative to the small companies. The reason behind the higher valuation of small companies may be found in the characteristics of the companies. It is reasonable to assume the small companies on average are younger than the large companies. Ritter and Kim (1999) found higher growth rates in young companies, and as higher growth rates justify higher valuation, this may explain some of the pricing differences in our sample.

Table 7-14: Relative peer pricing of large vs. small companies

	P/E	EV/EBITDA
Large	0.78	0.90
Small	1.09	0.89

Although the size appears significant for the aftermarket performance, the relationship with the peer pricing variable may turn the size insignificant in a regression were both variables are included. However, as we discussed in the methodology section, some institutional investors face restrictions regarding the size of the companies they are allowed to invest in. This may result in a larger share of high quality investors in large companies, which may explain the better performance of large companies in our sample. As this aspect may cause the size effect to be significant, the size should be controlled for in order to avoid potential omitted variable bias.

7.5 Regression analysis

7.5.1 Presentation of the variables

The regression analysis will start off with a brief presentation of the relevant variables and their characteristics, which are summarized in Table 7-15. As all IPOs with missing values on any variable have been excluded from the final sample, we now only have 39 observations. Note that this may result in means slightly differing from the introductory analysis in previous sections. As we can read from the minimum and maximum values in the summary table, all independent variables are dummy variables.

Table 7-15: Summary statistics of the relevant variables

	Mean	Standard dev.	Min.	Max.	# of obs.
DayAbnRet	-0.0155	0.0918	-0.2387	0.2490	39
WeekAbnRet	-0.0349	0.1038	-0.3052	0.1670	39
MonthAbnRet	-0.0583	0.1534	-0.3394	0.2893	39
HigherPE	0.4103	0.4983	0	1	39
HigherEvEbitda	0.4359	0.5024	0	1	39
AboveMidpoint	0.2308	0.4268	0	1	39
mBull	0.6667	0.4776	0	1	39
HighVol20	0.3077	0.4676	0	1	39
EVsize1000	0.6154	0.4929	0	1	39

A more detailed description of the variables may also be found in Appendix 10.6

The correlations in Table 7-16 give the reader a quick idea whether the hypotheses may hold or not. The relationships between the independent variables and the abnormal returns will thoroughly be discussed later, and hence I will only briefly comment on this in the introductory presentation. In addition, a matrix illustrating the correlations between the independent variables may be found in Appendix 10.8.1.

Table 7-16: Correlations between the dependent and independent variables

	DayAbnRet	WeekAbnRet	MonthAbnRet
HigherPE	-0.4093	-0.3517	-0.4938
HigherEvEbitda	-0.2933	-0.2876	-0.4118
AboveMidpoint	0.2226	0.3557	0.3976
mBull	0.1402	0.0708	0.1659
HighVol20	-0.0949	-0.2918	-0.0519
EVsize1000	0.3042	0.4792	0.3744

Abnormal returns

The abnormal returns will function as the dependent variable in the regressions. The abnormal returns are calculated for first day, week and month with OSEBX as reference index. The mean returns are negative for all horizons, although we observe great variation in the sample, e.g. for first day of trading the best performer had a positive abnormal return of 24.9 % while the worst performer had a negative abnormal return of -23.9 %.

Pricing relative to listed comparable companies

To determine the effect of relative peer pricing on the aftermarket performance, I have the two dummy variables *HigherPE* and *HigherEvEbitda*. The variables will have the value 1 if the IPO is overpriced relative to peers and 0 otherwise. Slightly more than 40 % of the IPOs are overpriced relative to peers according to both variables, with a mean of 0.410 and 0.436 for P/E and EV/EBITDA, respectively. In line with the hypothesis, the correlation table clearly illustrates the negative relationship between overpricing relative to peers and aftermarket performance.

Final price relative to indicative price range

The dummy variable *AboveMidpoint* will represent the aspect of where the final offer price is set relative to the price range. This variable will have the value 1 if the IPO goes public with an offer price above the price range midpoint and 0 otherwise. From Table 7-15 we observe that 23 % of the IPOs are priced above midpoint. Consistent with the hypothesis, the positive correlation between *AboveMidpoint* and the abnormal returns indicates that high initial demand for the issue positively affects the aftermarket performance.

Control variables

To control for general market returns I have included the dummy variable *mBull*, which will have the value 1 if the market returns are positive for the three months prior to listing. We observe that 67 % of the IPOs were executed in bull markets, and positive market returns prior to listing appear to positively affect the aftermarket performance of the newly listed stock.

Further, we control for the market volatility through the dummy variable *HighVol20*. This variable will have the value 1 if the IPO is executed with an average VIX index value above 20 in the three months prior to listing. Only 31 % of the IPOs went public during high-volatility markets and high volatility appears to negatively affect the abnormal returns.

The potential size effect is controlled for through the dummy *EVsize1000*, which will have the value 1 if the IPO company has an enterprise value above NOK 1,000 million. 61 % of the companies going public are defined as large companies, and the size correlates positively with the abnormal returns.

7.5.2 Rationalisation of the final model

As described earlier in the analysis section, the final regression model will consist of a considerable number of independent variables and control variables in order to avoid omitted variable bias. At the same time, the number of variables will be limited to the absolute necessary to avoid seizure of unnecessary degrees of freedom. All models will be level-level models, assuming that the variables may be incorporated in their ordinary form. See Appendix 10.3 for more information regarding the interpretation of the estimated slope parameters. Based on the rationalisation in previous sections, all independent variables will be included as dummy variables. This is line with prior research, and has proved to be the most efficient implementation of the relevant aspects. Still, as I have two potential variables regarding the peer pricing, there are a few different possibilities regarding the implementation of this aspect. The following discussion will address this.

First, I run a regression including both variables on relative peer pricing, *HigherPE* and *HigherEvEbitda*. This gives the following regression equation:

$$DayAbnRet = \beta_0 + \beta_1 * HigherPE + \beta_2 * HigherEvEbitda + \ \beta_3 * AboveMidpoint + \beta_4 * mBull + \beta_5 * HighVol20 + \beta_6 * EVsize1000 + \varepsilon$$

The output from this regression may be found in Appendix 10.8.2. Both variables on peer pricing basically reflect the same characteristic of the company, however, the variables prove different with regards to both magnitude and significance. The coefficient of the P/E variable appears more significant with a larger magnitude than the coefficient of the EV/EBITDA variable. However, the coefficients are consistent for all time horizons for both variables, and the negative coefficients make economic sense, namely that overpriced IPO companies will underperform the underpriced IPO companies. Still, one may argue that including two variables reflecting the relative peer pricing aspect should make one of them redundant. Ideally, one of these variables should alone be able to capture the entire impact of peer pricing. This will also increase the degrees of freedom in the model. I therefore run the following two regressions, including either *HigherPE* or *HigherEvEbitda:*

1) $DayAbnRet = \beta_0 + \beta_1 * HigherPE + \beta_2 * AboveMidpoint + \beta_3 * mBull + \beta_4 * HighVol20 + \beta_5 * EVsize1000 + \varepsilon$
2) $DayAbnRet = \beta_0 + \beta_1 * HigherEvEbitda + \beta_2 * AboveMidpoint + \beta_3 * mBull + \beta_4 * HighVol20 + \beta_5 * EVsize1000 + \varepsilon$

The output from these regressions may be found in Appendix 10.8.3 and 10.8.4, respectively. Naturally, the two models are not very different. However, the independent variables come out more significant in the P/E model than for the EV/EBITDA model. If we compare the coefficients of the peer pricing variables for the two regressions we observe differences in the magnitudes. Ideally, the total effect of peer pricing should remain unchanged regardless of the choice of variables to reflect this aspect in the model. In other words, the magnitude of the P/E and EV/EBITDA coefficients should in the last two models individually equal the sum of the two coefficients in the model including both. This is very close to true for the P/E model, while we observe significant differences for the EV/EBITDA model. In addition, the coefficients of the unrelated variables should not be affected by how the peer pricing is implemented. These coefficients remain relatively unchanged in the P/E model, while changing considerably for the EV/EBITDA model. This is a compelling argument for choosing the P/E model. Also, the explanatory power of the P/E model is higher than for the EV/EBITDA model, and actually the highest among the models presented. Hence, I choose to base my regression analysis on the P/E model.

7.5.3 The final regression model

In this section I will thoroughly discuss the final model and interpret the coefficients. I will discuss the economic sense of the findings, and further compare these with prior research. The stepwise interpretation of the isolated effects will be a continuation of the cursory analysis from previous sections. The final regression model is (in this case stated with the *daily* abnormal returns as dependent variable):

$$DayAbnRet = \beta_0 + \beta_1 * HigherPE + \beta_2 * AboveMidpoint + \beta_3 * mBull + \beta_4 * HighVol20 + \beta_5 * EVsize1000 + \varepsilon$$

The right hand side of the equation will be identical for all time horizons. Table 7-17 summarizes the regression, with the coefficients and the associated t-values for each variable for all time horizons. The interpretation of the variables in the following section should be seen together with this table.

Table 7-17: Regression summary

	1st day	1st week	1st month
HigherPE	-0.0612**	-0.0436*	-0.1315****
	-1.84	*-1.55*	*-2.82*
AboveMidpoint	0.0402	0.0683*	0.1318***
	1.33	*1.55*	*2.39*
mBull	0.0221	0.0283	0.0307
	0.82	*0.97*	*0.68*
HighVol20	-0.0246	-0.0762****	-0.0279
	-0.66	*-2.84*	*-0.61*
EVsize1000	0.0378	0.0879****	0.0636
	0.95	*2.81*	*1.38*
Intercept	-0.0301	-0.0824***	-0.0858
	-0.65	*-2.22*	*-1.39*
# of observations	*39*	*39*	*39*
R-squared	*0.268*	*0.483*	*0.451*
Adjusted R-squared	*0.156*	*0.404*	*0.371*

****Significant on a 99 % level; ***95 % level; **90 % level; *85 % level (Extensive regression output can be found in Appendix 10.8.3)

HigherPE

We observe the effect of overpricing being highly negative for abnormal returns for all time horizons. The coefficient of *HigherPE* for the first day is -0.0612, indicating that an IPO company overpriced on P/E relative to peers ceteris paribus will underperform an IPO company underpriced relative to peers by 6.12 % the first day. The coefficient is significantly different from zero on a 90 % level for first day and 99 % for first month. From earlier we know that the average abnormal returns deteriorate with the time horizon in our sample. However, the magnitude of the coefficient for the first week is lower than for first day, as well as less significant, although significant on an 85 % level. I will return to this phenomenon later, when discussing the increased significance of the control variables for the first week horizon.

All known prior research regarding IPO peer pricing focus on the first day abnormal returns. Purnanandam and Swaminathan (2003) found overpriced IPOs to outperform underpriced IPOs. As they themselves point out, this is inconsistent with traditional financial theory, more specifically the asymmetric information theory of IPO pricing. This theory suggests that an undervalued stock would outperform the first day, as the efficient markets bids up the price to fair value immediately. Our findings contradict Purnanandam and Swaminathan, but are consistent with the asymmetric information theory, as the underpriced IPOs in our sample outperform the overpriced IPOs. In section 7.3 we found the underpricing on the P/E multiple to be 9 % and significantly different from zero on a 90 % level. As earlier mentioned, Kim & Ritter (1999) suggest that the coefficients for the first day should "approximately equal" the mispricing on the valuation multiple with the opposite sign. Our coefficient for the first day of -6.1 % is smaller in magnitude than the mispricing, indicating that not all mispricing is eliminated the first day, i.e. some degree of inefficiency in the markets. This result is in line with Ellul & Pagano (2003) who suggests that some asymmetric information persists after listing, and hence the market requires more than one day to the eliminate mispricing. This proposition is further strengthened by the fact that the magnitude of the coefficient increases to -13.2 % for the first month horizon. As this coefficient, on the other hand, is larger than the mispricing, it would be interesting to see if the coefficient with time converges towards the mispricing in the multiple, however, such a study will not be feasible with my data.

The general findings regarding the peer pricing coefficient are consistent with the hypothesis, namely that the IPO companies priced low relative to peers will outperform the IPO companies priced high relative to peers. This was also indicated in Section 7.3, where we found the difference in performance of the two groupings to be significantly different from zero. In the regression analysis we were able to determine the ceteris paribus effect of peer pricing, which proved significant as well.

AboveMidpoint

We observe the effect of being priced high relative to the price range midpoint to be highly positive. The *AboveMidpoint* variable has a coefficient of 0.04 for the first day, indicating that an IPO company priced above midpoint ceteris paribus will outperform an IPO company priced below midpoint by 4.0 % the first day. The magnitude of the coefficient increases with the time horizon, in line with the overall deteriorating returns, with the coefficients 6.8 % and 13.2 % for first week and first month, respectively. The coefficient is not significant for the first day, although significant on an 85 % and 95 % level for first week and first month, respectively.

As discussed earlier, both Kim & Ritter (1999) and Bakke, et al. (2011) split the IPOs differently than I do. Consequently, their numbers are not directly comparable with mine. However, my findings are in line with their general results, namely that the IPOs priced high relative to the price range performs better in the aftermarket than the IPOs priced low relative to the range. Ellingsen (2012) and Samuelsen & Tveter (2006) use the same distinction as I do, and are therefore more comparable. Ellingsen found the coefficient for the *AboveMidpoint* variable to be 1.4 % and 1.5 % for first day and first week, respectively, compared to my results of 4.0 % on day 6.8 % for first day and first week. As her model does not include the same control variables as my model, her coefficients are not directly comparable either. Samuelsen & Tveter (2006) did not perform a regression analysis, and were therefore not able to determine the ceteris paribus effect. However, they performed an examination of the mean returns for IPOs priced above and below midpoint, similar to the introductory analysis I presented in section 7.2.1, and our results match. In general, the findings regarding the effect of where the price is set relative to the price range are consistent with the hypothesis, namely that the IPO companies priced high relative to the range outperform those priced low relative to the range.

Control variables

The dummy variable *mBull*, which controls for the market returns prior to the IPO, appears insignificant on all horizons. However, as the general market performance is frequently referred to when discussing the performance of IPOs, a control variable taking this aspect into account should be included. The coefficients make economic sense, as we observe market returns contributing positively, although insignificant. We observe only minor fluctuations in the magnitude of the coefficients across the different time horizons, with 2.2 % for the first day and 3.1 % for the first month. This seems logical, as the market performance prior to listing should affect the initial returns positively, however, it should not have any additional impact on the longer horizons. It is more likely that the current market conditions after listing will affect the returns for the longer horizons.

The dummy variable *HighVol20*, which controls for the market volatility prior to the IPO, has a coefficient of -0.025 for the first day, which indicates that IPOs going public in high-volatility markets ceteris paribus will underperform IPOs going public in low-volatility markets by 2.5 % the first day. The coefficient is approximately the same for the first month, and in accordance with the flat coefficients for *mBull* across the horizons, this makes intuitive sense. The volatility before listing should not affect the returns beyond the initial returns. For first day and first month the coefficients are not significant. However, for the first week we observe a substantially increased magnitude and significance. I will return to this puzzling finding shortly, when I interpret the coefficient of the size control variable.

The dummy variable *EVsize1000*, which controls for the size of the IPO company, has a positive coefficient for the first day of 0.0378. This indicates that IPOs of large companies outperform IPOs of small companies by 3.78 % the first day, ceteris paribus, although the effect came out insignificant. This contradicts the findings of Yong (2011), who found small companies to significantly outperform the larger companies. In the analysis in section 7.4.3, we found a negative correlation between size and peer pricing. As Yong does not include peer pricing in his model, his findings regarding the size effect will not be directly comparable. The size effect is insignificant for the first month horizon as well, while the coefficient for the first week horizon appears highly significant with a large magnitude. This resembles the findings for *HighVol20*, which also increase in significance and magnitude for the first week horizon. This seems odd, as the coefficients for this horizon run counter to the logical linkage between first day and first month. The spiking significance and magnitude of the control variables occurs simultaneously as the P/E variable turns insignificant and is reduced in magnitude. My hypothesis is that coincidences make the internal correlations between the variables change, and hence the size and volatility control variables extract magnitude and significance out of the P/E coefficient. This effect illustrates the danger of running econometric analysis based on a small sample, and becomes evident by examining the correlation table presented earlier in Table 7-16. We observe the positive correlation between size and abnormal returns spiking for week, at the same time as the correlation for volatility with regards to abnormal returns triples. Although we see some fluctuations in the correlations for all variables, these stand out as particularly significant. Hence, the results for the first week should be interpreted with caution, and we should not put too much emphasis into the findings for this time horizon.

Although the *EVsize1000* variable does not prove significant on all horizons, the control variable on size has a very important function in the model. We found the larger companies to be priced relatively lower on P/E, and the P/E variable to correlate negatively with the returns. Thus, omitting the control variable on size would make the P/E variable look substantially more significant and larger in magnitude. This becomes very evident when we run the regressions while excluding *EVsize1000* (regression output can be found in Appendix 10.8.5). The coefficients associated with the P/E variable substantially increase in both significance and magnitude for all time horizons. In addition, the explanatory power of the model is reduced. The control variable on size is therefore absolutely necessary to avoid omitted variable bias.

It is important to note that the significance figures from the regression output are regarding the *individual* significance. Particularly for the control variables in a regression like this, the *joint* significance should be in focus. This can be tested through an F-test, which tests the probability that all coefficients of the control variables would equal zero. A description of the technicalities of the test can be found in Appendix 10.7. Hence, it is no longer relevant which variables that prove significant, but rather the broad set of variables. If we run the F-test for the control variables in the first week regression we obtain a test observator of 5.44, corresponding to a probability that all coefficients will equal zero of 0.4 %, i.e. the test proves a high joint significance (test output can be found in Appendix 10.8.6). Although the F-test reveals high joint significance for first week, it proves insignificance for first day and first month. However, we know that including an additional variable will not cause any bias (for day and month), but excluding it may cause omitted variable bias (for week). Since we need common comparable ground for all horizons, the full set needs to be included on all horizons.

Intercept

The intercept is the expected abnormal returns for the IPOs with all dummy variables equalling zero, i.e. a small, underpriced (relative to peers) company, priced below midpoint in the price range, going public in low-volatility, although, bear markets. We have a coefficient for first day of -0.03, indicating that a company with these characteristics may expect negative abnormal returns of -3 % the first day. The coefficients for first week and first month are -0.082 and -0.086, respectively. The coefficients are significantly different from zero only for the week horizon. However, these characteristics only apply for one company in our sample. Hence, we know that the intercept is calculated with great uncertainty, and should therefore not be emphasized.

8. Limitations and further analysis

The most obvious limitation of this analysis is the limited number of data points. The final data set for the regression analysis consists of 39 IPOs, which is on the small side to conduct an econometric analysis. Although most of the independent variables proved significant in the regression analysis, a low number of observations will make it challenging to draw any conclusions for a population. The downside of few observations became evident for the first week horizon, where deviations in the data resulted in somewhat inconsistent estimates relative to the first day and first month horizons.

In addition, the limited number of observations put restrictions on the number of control variables I could include in the model. Regarding the relative peer pricing analysis there are some aspects that should be further investigated. Differences in profitability and growth can justify differences in relative peer pricing, and should hence be controlled for. In addition, institutional investors often invest for the long-run. Consequently, it could be helpful to include relative peer pricing multiples further ahead than twelve months. In addition, we apply the same valuation multiples for all industries, while we know that practitioners apply certain multiples for certain industries. In order to correctly reflect the relative valuation perception of investors, we should ideally apply the same multiples as practitioners. It could be possible, although very time consuming, to test which multiples give the best predictability and significance within each industry, and thus apply different multiples for different industries.

Through the discussion in section 7.2.1 regarding the IPOs which were priced exactly at the lower limit, it became evident that variation in investor quality could affect both the aftermarket performance and the predictability of the variable related to where the final offer price was set relative to the price range. If one could control for the investor quality directly, it would help eliminate potential bias in the *AboveMidpoint* variable. This could only be achievable through access to the book data from the investment bank taking the companies public. As described in the theory section, investment banks differentiate the investors into different tiering levels with regards to preferential interest in the allocation process. If one could obtain the average tiering level for the investors who received allocation in the IPOs, one could investigate the direct effect of variations in investor quality.

The only control variable regarding size in this analysis is linked to the enterprise value of the company. One additional size aspect that could be of interest is the size of the issue relative to the pre-issue equity value. A large issue causes a large supply of shares, which further would require high initial demand to achieve a high price in the offering. Also, the IPO is often utilized by current shareholders to sell shares. A large amount of sale shares will increase the supply of shares, which in the same way as for the issue size would require increased demand to maintain a high final price. In addition, large divestments by insiders may signal lower future earnings expectations, and may therefore possibly lead to a reduced demand.

Regarding the market conditions, it could be interesting to investigate the effect of long-term market conditions in addition to the short period of three months. It is reasonable to assume that if bearish markets persist over the long term, the investment bankers may revise down the indicative price range to make the issue sell. As a result, the final price may not end up low relative to the range, even though the IPO is priced low on other measures.

As becomes evident from this discussion, there are several aspects of this analysis that have room for improvement. Limitations with regards to time and available data have prevented me from performing a more thorough analysis for now. The main obstacle to be able to improve the analysis will be to obtain a larger data set, eliminating the restrictions with regards to the number of control variables one can include in the model.

9. Conclusion

In this thesis I have examined the Norwegian IPO market for the period after the financial crisis. I found the average abnormal returns for the IPOs in the years 2009-2014 to be negative for first day, week and month, and the returns aggravated with the time horizon. This apparent overpricing in the Norwegian issue market contradicts all prior research on IPO pricing, as fundamental underpricing of IPOs has been a well established phenomenon and rationalised on theoretical grounds. Based on the same rationalisation of underpricing, the poor performance of Norwegian IPOs may impose severe challenges for companies seeking to go public in the years to come. If the investors feel they are not sufficiently compensated for bearing the risk of subscribing to IPOs, the advisors of companies going through the IPO process may struggle to obtain full subscription at acceptable terms.

Although the average abnormal returns came out negative, the performance of the newly listed stocks proved to be surprisingly predictable. Related to the first hypothesis, I investigated how the initial demand for the issue affected the aftermarket performance. I proposed that offerings with high initial demand should outperform the offerings with low initial demand. The first proxy for demand was the placement of the final offer price relative to the indicative price range. The second proxy was the book coverage, i.e. how many times the issued shares were oversubscribed. In general the Norwegian IPOs appear heavily skewed towards the left of the price range midpoint, which stands out relative to international studies. The absolute level of oversubscription at the final offer price also came out lower than for other countries. Consistent with the hypothesis, both proxies confirmed a strong and positive relationship between the initial demand and the aftermarket performance.

Related to the second hypothesis, I examined the pricing of IPOs relative to peers, and its impact on the aftermarket performance. I suggested that the cheaper the IPO is priced relative to listed comparable companies, the higher are the abnormal returns. Consistent with the hypothesis, IPOs which were underpriced relative to peers significantly outperformed the IPOs which were overpriced relative to peers. Based on the valuation multiples P/E and EV/EBITDA I found a significant underpricing of IPO companies relative to listed comparable companies. This contradicts prior research, which has found overpricing of IPO companies relative to listed peers. The coefficient related to the peer pricing variable for the first day did not fully reflect the underpricing on the valuation multiple. This indicates that the markets require more than one day to eliminate mispricing, i.e. partial inefficiency in the equity markets.

A remarkably large share of the IPOs was priced exactly at the lower limit of the range, although there is no theoretical reason for why this price should be more frequently observed than others. Contrary to the assumption regarding initial demand and pricing relative to the range, the IPOs priced at the lower limit significantly underperformed the IPOs priced below the range. The high share of IPOs priced at the lower limit may indicate that the investment bankers are reluctant of lowering the price below the range, and hence may accept bids from investors of lower quality than what they could have attained at a lower price. As low investor quality is assumed to negatively affect the aftermarket performance, one may suggest that the IPOs priced at the lower limit simply are not worthy their price, and ideally should have been priced lower.

The first day returns proved to be a solid indicator of the performance for the two longer time horizons first week and first month. Out of the 29 IPOs with negative returns the first day, 24 continued declining the first month. The predictability was somewhat more ambiguous for the IPOs with positive returns the first day, most likely due to stabilization measures through the green shoe option included in some of the IPOs.

I controlled for general market returns, market volatility and the size of the IPO company in my model. Large size and positive market returns positively affected the aftermarket performance, while high volatility negatively affected the aftermarket performance. Common for both market returns and volatility is that their effect beyond the first day returns was neglectable. The complete set of control variables proved highly joint significant, hence limiting the potential omitted variable bias in the model and enhancing the inference of the model.

Although the sample size is on the small side for an econometric analysis, we obtain significant results for the variables of interest. However, in order to draw any conclusions for a population regarding the subjects investigated in this thesis, one should conduct a similar analysis on a larger sample. Nevertheless, this analysis should provide the reader insight into the general characteristics of the Norwegian IPO market and the relationship between initial demand, relative pricing and aftermarket performance.

10. Appendix

10.1 Abnormal returns - Differences between countries

Table 10-1: Equally weighted average initial returns for 52 countries

Country	Source	Sample Size	Time Period	Avg. Initial Return
Argentina	Eijgenhuijsen & van der Valk; Dealogic	26	1991-2013	4.2%
Australia	Lee, Taylor & Walter; Woo; Pham; Ritter	1,562	1976-2011	21.8%
Austria	Aussenegg	103	1971-2013	6.4%
Belgium	Rogiers, Manigart & Ooghe; Manigart DuMortier; Ritter	114	1984-2006	13.5%
Brazil	Aggarwal, Leal & Hernandez; Saito; Ushisima	275	1979-2011	33.1%
Bulgaria	Nikolov	9	2004-2007	36.5%
Canada	Jog & Riding; Jog & Srivastava; Kryzanowski, Lazrak & Rakita; Ritter	720	1971-2013	6.5%
Chile	Aggarwal, Leal & Hernandez; Celis & Maturana; Dealogic	81	1982-2013	7.4%
China	Chen, Choi, & Jiang; Jia, Xie & Zhang	2,512	1990-2013	118.4%
Cyprus	Gounopoulos, Nounis, and Stylianides; Chandriotis	73	1997-2012	20.3%
Denmark	Jakobsen & Sorensen; Ritter	164	1984-2011	7.4%
Egypt	Omran; Hearn	62	1990-2010	10.4%
Finland	Keloharju	168	1971-2013	16.9%
France	Husson & Jacquillat; Leleux & Muzyka; Paliard & Belletante; Derrien & Womack; Chahine; Ritter; Vismara	697	1983-2010	10.5%
Germany	Ljungqvist; Rocholl: Ritter; Vismara	736	1978-2011	24.2%
Greece	Nounis, Kazantzis & Thomas; Thomadakis, Gounopoulos & Nounis	373	1976-2013	50.8%
Hong Kong	McGuinness; Zhao & Wu; Ljungqvist & Yu; Fung, Gul, and Radhakrishnan; Dealogic	1,486	1980-2013	15.8%
India	Marisetty and Subrahmanyam; Ritter	2,964	1990-2011	88.5%
Indonesia	Suherman	441	1990-2013	25.0%
Iran	Bagherzadeh	279	1991-2004	22.4%
Ireland	Dealogic	38	1991-2013	21.6%
Israel	Kandel, Sarig & Wohl; Amihud & Hauser; Ritter	348	1990-2006	13.8%
Italy	Arosio, Giudici & Paleari; Cassia, Paleari & Redondi; Vismara	312	1985-2013	15.2%
Japan	Fukuda; Dawson & Hiraki; Hebner & Hiraki; Pettway & Kaneko; Hamao, Packer, & Ritter; Kaneko & Pettway	3,236	1970-2013	41.7%
Jordan	Al-Ali and Braik	53	1999-2008	149.0%
Korea	Dhatt, Kim & Lim; Ihm; Choi & Heo; Mosharian & Ng; Cho; Joh; Dealogic	1,720	1980-2013	59.3%
Malaysia	Isa; Isa & Yong; Yong; Ma; Dealogic	474	1980-2013	56.2%

Country	Source	Sample Size	Time Period	Avg. Initial Return
Mauritius	Bundoo	40	1989-2005	15.2%
Mexico	Aggarwal, Leal & Hernandez; Eijgenhuijsen & van der Valk; Villarreal	123	1987-2012	11.6%
Morocco	Alami Talbi; Hearn	33	2000-2011	33.3%
Netherlands	Wessels; Eijgenhuijsen & Buijs; Jenkinson, Ljungqvist, & Wilhelm; Ritter	181	1982-2006	10.2%
New Zealand	Vos & Cheung; Camp & Munro; Alqahtani; Dealogic	242	1979-2013	18.6%
Nigeria	Ikoku; Achua; Dealogic	122	1989-2013	13.1%
Norway	Emilsen, Pedersen & Saettem; Liden; Dealogic	209	1984-2013	8.1%
Pakistan	Mumtaz	80	2000-2013	22.1%
Philippines	Sullivan & Unite; Dealogic	155	1987-2013	18.1%
Poland	Jelic & Briston; Woloszyn	309	1991-2012	13.3%
Portugal	Almeida & Duque; Dealogic	32	1992-2013	11.9%
Russia	Dealogic	64	1999-2013	3.3%
Saudi Arabia	Al-Anazi, Forster, & Liu; Alqahtani	80	2003-2011	239.8%
Singapore	Lee, Taylor & Walter; Dawson; Dealogic	609	1973-2013	25.8%
South Africa	Page & Reyneke; Ali, Subrahmanyam & Gleason; Dealogic	316	1980-2013	17.4%
Spain	Ansotegui & Fabregat; Alvarez Otera; Dealogic	143	1986-2013	10.3%
Sri Lanka	Samarakoon	105	1987-2008	33.5%
Sweden	Rydqvist; Schuster; de Ridder	374	1980-2011	27.2%
Switzerland	Kunz, Drobetz, Kammermann & Walchli; Dealogic	164	1983-2013	27.3%
Taiwan	Chen; Chiang	1,620	1980-2013	38.1%
Thailand	Wethyavivorn & Koo-smith; Lonkani & Tirapat; Ekkayokkaya and Pengniti; Vithessonthi	500	1987-2012	35.1%
Tunisia	Hearn	32	2001-2013	24.3%
Turkey	Kiymaz; Durukan; Ince; Kucukkocaoglu	355	1990-2011	10.3%
United Kingdom	Dimson; Vismara; Levis	4,932	1959-2012	16.0%
United States	Ibbotson, Sindelar & Ritter; Ritter	12,496	1960-2013	16.9%

Sources: See references listed in the published 1994 article and updates listed below. Where more than one set of authors is listed as a source of information, combined sample sizes have been constructed. Average initial returns are constructed in different manners from study to study. In general, in countries where market prices are available immediately after offerings, the one-day raw return is reported. In countries where there is a delay before unconstrained market prices are reported, market-adjusted returns over an interval of several weeks are reported. All of the averages weight each IPO equally.

10.2 Assumptions for the OLS model

As described in section 4.7.2, there are a few key assumptions that need to be fulfilled for the OLS-model to provide unbiased estimators for the population parameters. The first five assumptions constitute the Gauss-Markov theorem, and given that these assumptions hold, the OLS estimators will be the best linear unbiased estimators (BLUE) of the population parameters.

Assumption 1: The population is linear in parameters

The population has to be linear in parameters, meaning that each independent variable has a linear variation with the dependent variable (the ceteris paribus effect).

Assumption 2: The sample size must be random

The sample must be randomly selected, with n $[(x_i, y_i): i = 1,2 \dots n]$, where each unity of the population has the same probability of being in the sample. For cross-sectional data, this is often reasonable to assume.

Assumption 3: The outcomes of the independent variables are not all the same value

None of the independent variables can be constant, as this would incapacitate to determine how the changes in the independent variable would affect the dependent variable. There can be no exact linear relationships among the independent variables (i.e. no perfect collinearity).

Assumption 4: Zero conditional mean

The expected value of the error term has to be zero given any values of the independent variables, i.e. $E(u|x) = 0$. This means that the error term is independent of the x, which is crucial to be able to determine the ceteris paribus of a change in the independent variable.

Assumption 5: Homoscedasticity

The variance of the error term u has to the same regardless of the value of the independent variable. Mathematically, this may be stated as:

$$Var(u|x_i) = \sigma^2, which\ implies\ Var(y|x_i) = \sigma^2$$

Although the five assumptions above are sufficient in order to obtain the best linear unbiased estimators (BLUE) of the population parameters, one additional assumption is required in order to be able to draw inference of the model.

Assumption 6: The error term is independently and identically distributed

The error term of the population must be independent of the explanatory variables and normally distributed with mean zero and variance σ^2.

$$u \sim Normal(0, \sigma^2)$$

$$u \sim Normal(0, \sigma^2)\ implies\ that\ \hat{\hat{\beta}}_j \sim Normal(\beta_j, Var\left(\hat{\hat{\beta}}_j\right))$$

In other words, the error term must be independently and identically distributed (often referred to as i.i.d.). This last assumption is stronger than the fourth and fifth assumption combined, because it also requires normal distribution. (Wooldridge, 2012)

10.3 Interpretation of estimated slope parametres

As earlier described, the first assumption requires the population model to be linear in parameters. However, assuming a linear relationship between the dependent variable and the independent variables is not as restrictive as it might seem. Many non-linearities can be incorporated into the model by redefining the variables. Combinations of logarithmic and level variables can deal with nonlinearities that otherwise would make the estimation of the model useless for predication. The redefinitions of the variables will not affect the mechanics in the estimation, however, it will affect the size and interpretation of the estimated coefficients.

The level-level model:

$$y = \beta_0 + \beta_1 x + u,$$

where a ceteris paribus change in *x* (keeping all other constant) gives:

$$\Delta y = \beta_1 \Delta x,$$

i.e. a one unit change in the independent variable gives a $\beta_1$change in the dependent variable *y*. The level-level model will be sufficient if the relationship between the dependent variable and the independent variable initially is linear and hence no modification will be necessary to fulfil the first assumption.

The log-level model:

$$\ln(y) = \beta_0 + \beta_1 x + u,$$

where a ceteris paribus change in *x* gives:

$$\%\Delta y = 100\beta_1 \Delta x$$

i.e. a one unit change in *x* gives a $(100\beta_1)$ % change in *y*.

The log-log model:

$$\ln(y) = \beta_0 + \beta_1 \ln(x) + u$$

where a ceteris paribus change in *x* gives:

$$\%\Delta y = \beta_1 \ \%\Delta x$$

i.e. a one % change in *x* gives a β_1 % change in *y*. This means that β_1 is the elasticity of *y* with respect to *x*.

The level-log model:

$$y = \beta_0 + \beta_1 \ln(x) + u$$

where a ceteris paribus change in *x* gives:

$$\Delta y = \frac{\beta_1}{100} \ \%\Delta x$$

i.e. a one % change in *x* increases *y* with $\frac{\beta_1}{100}$. (Balsvik, 2013)

10.4 T-test for two populations with different variance

I concluded that the normal distribution was a fair assumption for the returns in my sample. Hence I can apply a t-test two determine whether there is a significant difference between the two populations. The test statistic

$$T = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$$

is approximately t-distributed with

$$v = \frac{(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2})^2}{\frac{(S_1^2/n_1)^2}{n_1 - 1} + \frac{(S_2^2/n_2)^2}{n_2 - 1}}$$

degrees of freedom. If *T* exceeds the critical value with *v* degrees of freedom, one can reject the null hypothesis. The critical value will depend on both the significance level applied, and the degrees of freedom. The critical values may be found in a distribution table (not attached in this document). (Møen, 2012)

10.5 Wilcoxon (Mann-Whitney) Sum Rank Test

To test whether the relative peer pricing significantly differs from 1, I use the distribution-free two-sided Wilcoxon Mann-Whitney Rank Sum Test. Then I can test the null hypothesis that to samples are the same against the alternative hypothesis that they differ. The test is more efficient than the standard t-test for distributions that prove non-normal. This is the case for the relative pricing in my sample, which proved to be heavily skewed towards the left. The test ranks the observations in the two samples, and the test statistic *W* is the smallest rank sum of the two samples. For sufficiently large samples the test-statistic is approximately normal N(μ, σ), with

$$\mu = \frac{n_1(n_1 + n_2 + 1)}{2}$$

and

$$\sigma^2 = \frac{n_1 * n_2(n_1 + n_2 + 1)}{12}$$

With a large sample (assumed to be larger than 20), we can perform a standard z-test with

$$z = \frac{W - \mu}{\sigma}$$

where we can reject the null hypothesis if the test statistic exceeds the critical value. In the case of a large *n* (assumed to be more than 20) it is indifferent whether we use the smallest or largest rank sum when calculating the test statistic. As the Wilcoxon Mann-Whitney Rank Sum Test is created to test difference between two samples I simply create a sample of *n* observations with the pricing value 1. Then I further test whether the relative pricing based on P/E and EV/EBITDA significantly differs from this constructed sample. (Møen, 2012)

10.6 List of variables

Name	Description
DayAbnRet/WeekAbnRet/MonthAbnRet	Dependent variables. Abnormal return of the newly listed stock after first day/week/month. Calculated with OSEBX as reference index
HigherPE & HigherEvEbitda	Dummy variables regarding the the relative peer pricing, with P/E and EV/EBITDA. The variables will have the value 1 if the company is overpriced relative to peers, and correspondingly have the value 0 if the company is underpriced relative to peers
AboveMidpoint	Dummy variable regarding the pricing relative to the price range midpoint. The variable will have the value 1 if the company has a final offer price at or above the price range midpoint, correspondingly the value 0 if the company has a final offer price below the price range midpoint
mBull	Dummy variable regarding the general market performance. The variable will have the value 1 if the reference index OSEBX has a positive return the three months prior to listing, correspondingly the value 0 if negative returns
HighVol20	Dummy variable regarding the volatility in the market. The variable will have the value 1 if the reference volatility index VIX has an average value above 20 the three months prior to listing, correspondingly the value 0 if the average volatility index value is below 20
EVsize1000	Dummy variable regarding the company size. The variable will have the value 1 if the company has an enterprise value above NOK 1,000 million, correspondingly the value 0 if the company has an enterprise value below NOK 1,000 million

10.7 F-test of joint significance

If we want to test a hypothesis involving more than one coefficient it requires a different test statistic and null distribution. For this purpose we may apply the F-test, which simply tests if all slopes of the coefficients of interest are zero. The null hypothesis will then be:

$$H_{0:}\, \beta_1 = 0$$

and $\beta_2 = 0$

and $\beta_3 = 0$

The test statistic *F* would be calculated as

$$F_0 = \frac{(SSR_r - SSR_{ur})/q}{SSR_{ur}/(n - (k+1))}$$

where SSR_r is the sum of the squared residuals of the restricted model and SSR_{ur} is the sum of squared residuals of the unrestricted model. *n* is the number of observations, *k* is the number of independent variables in the unrestricted model and *q* is the number of restrictions (i.e. the number of coefficients being tested). The critical value of an F-test is disproportionally complex to state mathematically and should be obtained through statistical software. (Blackwell, 2008)

10.8 Regression output

10.8.1 Correlation overview

```
. corr HigherPE AboveMidpoint mBull EVsize1000 HighVol20
(obs=39)

             | HigherPE AboveM~t    mBull EVs~1000 HighV~20
-------------+---------------------------------------------
    HigherPE |   1.0000
AboveMidpo~t |   0.0381   1.0000
       mBull |  -0.1843   0.1291   1.0000
  EVsize1000 |  -0.3050   0.1828  -0.2236   1.0000
   HighVol20 |   0.0087   0.0304   0.1179   0.0703   1.0000
```

10.8.2 Regression with both peer pricing variables

	1st day	1st week	1t month
HigherPE	-0.0530	-0.0290	-0.0949**
	(0.0390)	(0.0262)	(0.0512)
HigherEvEbitda	-0.0120	-0.0211	-0.0536
	(0.0351)	(0.0238)	(0.0449)
AboveMidpoint	0.0396	0.0672*	0.129***
	(0.0312)	(0.0446)	(0.0554)
mBull	0.0234	0.0306	0.0366
	(0.0282)	(0.0298)	(0.0463)
HighVol20	-0.0238	-0.0748***	-0.0242
	(0.0391)	(0.0276)	(0.0469)
EVsize1000	0.0388	0.0896****	0.0679*
	(0.0395)	(0.0319)	(0.0449)
_cons	-0.0298	-0.0819***	-0.0845
	(0.0471)	(0.0370)	(0.0612)
adj. R^2	0.133	0.393	0.372
N	39	39	39

Standard errors in parentheses
* $p < 0.15$, ** $p < 0.1$, *** $p < 0.05$, **** $p < 0.01$

10.8.3 Final regression with P/E variable

	1st day	1st week	1t month
HigherPE	-0.0612**	-0.0434*	-0.132****
	(0.0332)	(0.0280)	(0.0466)
AboveMidpoint	0.0402	0.0683*	0.132***
	(0.0301)	(0.0441)	(0.0552)
mBull	0.0221	0.0283	0.0307
	(0.0269)	(0.0291)	(0.0452)
HighVol20	-0.0246	-0.0762****	-0.0279
	(0.0372)	(0.0269)	(0.0457)
EVsize1000	0.0378	0.0879****	0.0636
	(0.0399)	(0.0313)	(0.0462)
_cons	-0.0301	-0.0824***	-0.0858
	(0.0466)	(0.0371)	(0.0617)
adj. R^2	0.156	0.404	0.371
N	39	39	39

Standard errors in parentheses
* $p < 0.15$, ** $p < 0.1$, *** $p < 0.05$, **** $p < 0.01$

10.8.4 Regression with EV/EBITDA variable

	1st day	1st week	1t month
HigherEvEbitda	-0.0423	-0.0377	-0.108***
	(0.0310)	(0.0259)	(0.0433)
AboveMidpoint	0.0323	0.0632	0.116***
	(0.0310)	(0.0440)	(0.0536)
mBull	0.0369*	0.0379	0.0608*
	(0.0223)	(0.0260)	(0.0387)
HighVol20	-0.0241	-0.0749***	-0.0247
	(0.0412)	(0.0279)	(0.0509)
EVsize1000	0.0544	0.0982****	0.0959***
	(0.0379)	(0.0306)	(0.0443)
_cons	-0.0552	-0.0958****	-0.130***
	(0.0385)	(0.0303)	(0.0503)
adj. R^2	0.112	0.400	0.337
N	39	39	39

Standard errors in parentheses
* $p < 0.15$, ** $p < 0.1$, *** $p < 0.05$, **** $p < 0.01$

10.8.5 Final regression without control variable on size

	1st day	1st week	1t month
HigherPE	-0.0753***	-0.0761***	-0.155****
	(0.0287)	(0.0315)	(0.0419)
AboveMidpoint	0.0506*	0.0924***	0.149***
	(0.0310)	(0.0417)	(0.0556)
mBull	0.00897	-0.00226	0.00862
	(0.0286)	(0.0337)	(0.0470)
HighVol20	-0.0204	-0.0664***	-0.0208
	(0.0337)	(0.0298)	(0.0427)
_cons	0.00398	-0.00309	-0.0284
	(0.0291)	(0.0331)	(0.0487)
adj. R^2	0.146	0.274	0.354
N	39	39	39

Standard errors in parentheses
* $p < 0.15$, ** $p < 0.1$, *** $p < 0.05$, **** $p < 0.01$

10.8.6 F-test of joint significance of control variables (first week)

```
. test mBull HighVol20 EVsize1000

 ( 1)  mBull = 0
 ( 2)  HighVol20 = 0
 ( 3)  EVsize1000 = 0

       F(  3,    33) =    5.35
            Prob > F =    0.0041
```

11. Bibliography

Bakke, E., Leite, T. E. & Thorburn, K. S., 2011. Public Information and IPO Underpricing. *The Norwegian School of Economics.*

Balsvik, R., 2013. *The Simple Regression Model - Assumptions and Derivation of the OLS Estimator.* s.l.: The Norwegian School of Economics.

Benveniste, L. M. & Busaba, W. Y., 1997. Bookbuilding vs. Fixed Price: An Analysis of Competing Strategies for Marketing IPOs. *Journal of Financial and Quantitative Analysis,* December, 32(4), pp. 383-403.

Blackwell, M., 2008. *Multiple Hypothesis Testing: The F-test,* s.l.: s.n.

Børs, O., n.d. *The Difference between Oslo Børs and Oslo Axess.* [Online]
Available at: http://www.oslobors.no/ob_eng/Oslo-Boers/Listing/Shares-equity-certificates-and-rights-to-shares/The-difference-between-Oslo-Boers-and-Oslo-Axess
[Accessed 17 09 2014].

Cornello, F. & Goldreich, D., 2001. Bookbuilding and Strategic Allocation. *Journal of Finance,* Volume 56, pp. 2337-2369.

Cowan, L., 2012. *"Oversubscribed" is a Weak IPO Signal.* [Online]
Available at:
http://online.wsj.com/news/articles/SB10001424052702303822204577468931105122266
[Accessed 25 September 2014].

Damodaran, A., 2003. *Averaging Across Multiples.* [Online]
Available at: http://people.stern.nyu.edu/adamodar/pdfiles/eqnotes/relchoic.pdf
[Accessed 23 09 2014].

Damodaran, A., n.d. *Averaging Across Multiples.* [Online]
Available at: http://people.stern.nyu.edu/adamodar/pdfiles/eqnotes/relchoic.pdf
[Accessed 23 09 2014].

Derrien, F., 2005. IPO Pricing in "Hot" Market Condition: Who Leaves Money on the Table. *The Journal of Finance,* 9(1), pp. 487-522.

Ellingsen, B. H., 2012. Initial Public Offerings - An Empirical Study of How the IPOs on Oslo Stock Exchange are priced relative to the Indicative Price Range. *The Norwegian School of Economics.*

Ellul, A. & Pagano, M., 2003. IPO Underpricing and After-Market Liquidity. *CSEF Working Papers.*

Fauzi, F., Wellalage, N. H. & Locke, S., 2012. The Global Financial Crisis' Impact on Short-term Performance of IPO: The Case Study of New Zealand Firms' IPOs. *Asian Journal of Finance & Accounting,* 22 May, 4(2), pp. 180-198.

Georgieva, K., 2011. The Issue of Underpricing in Initial Public Offerings. *University of Essex,* April.

Hanley, K. W., 1993. The Pricing of Initial Public Offerings and the Partial Adjustment Phenomenon. *Journal of Financial Economics,* 2(34), pp. 231-250.

Henry, S. C. & Gregoriou, G. N., 2013. IPO Firm Characteristics pre- and post- Financial Crisis. *SUNY College at Pittsburgh,* 9 July.

James, B. C. & Fawcett, S. E., 2006. Initial Public Offerings: An Analysis of Theory and Prcatice. *The Journal of Finance,* February.pp. 399-435.

Jenkinson, T. & Jones, H., 2002. Bids and Allocations in European IPO Bookbuilding. *Oxford University.*

Kenourgios, D. F., Papathanasiou, S. & Melas, E. R., 2007. Initial performance of Greek IPOs, Underwriter's Reputation and Oversubscription. *Managerial Finance,* 33(5), pp. 332-343.

Kim, M. & Ritter, J., 1999. Valuing IPOs. *Journal of Financial Economics,* 53(3), pp. 409-437.

Koller, T., Goedhart, M. & Wessels, D., 2010. *Valuation - Measuring and Managing the Value of Companies.* Fifth Edition ed. s.l.:McKinsey & Company.

Møen, J., 2012. *Lecture notes,* Bergen: Norwegian School of Economics.

Pritsker, M., 2006. A Fully-Rationl Liquidity-Based Theory of IPO Underpricing and Underperformance. *Federal Reserve Board, Washington, D.C.*

Purnanandam, A. K. & Swaminathan , B., 2003. Are IPOs Really Underpriced?. *Cornell University.*

Ritter, J. R., 1991. The Long-Run Performance of Initial Public Offerings. *Journal of Finance,* 46(1), pp. 3-27.

Ritter, J. R., 2009. Some Factoids About the 2008 IPO Market. *University of Florida.*

Ritter, J. R. & Kim, M., 1999. Valuing IPOs. *Journal of Financial Economics,* September, 53(3), pp. 409-437.

Ritter, J. R., Loughran, T. & Rydqvist, K., 2014. Initial Public Offerings: International Insights. *Pacific-Basin Finance Journal,* Volume 2, pp. 165-199.

Samuelsen, A. & Tveter, L. K., 2006. Børsintroduksjoner - Prising av Norske Børsintroduksjoner Med Vekt På Oljerelaterte Selskaper. *The Norwegian School of Economics.*

Suozzo, P., Cooper, S., Sutherland, G. & Deng, Z., 2001. *Valuation Multiples: A Primer,* s.l.: s.n.

Wai Wai, F., 2013. The Initial Performance of Malaysian IPOs During the Financial Crisis: Evidence From Global Financial Crisis of 2008. *Universiti Tunku Abdul Rahman.*

Wooldridge, J. M., 2012. *Inroductory Econometrics: A Modern Approach.* 5th ed. Mason, OH: Thomson/South-Western.

Yong, O., 2011. Investor Demand, Size Effect and the Immediate Post-Listing Behaviour of Malaysian IPOs. *Universiti Tun Abdul Razak E-Journal* , June, 7(2), pp. 23-32.

Yong, O. & Isa, Z., 2003. Initial Performance of New Issues of Shares in Malaysia. *Applied Economics,* Issue 35, pp. 919-930.

Zheng, S. X., 2006. Are IPOs Really Overpriced?. *Journal of Empirical Finance,* June.