Norwegian School of Economics
Bergen, Fall 2016

Initial Public Offerings

An Empirical Assessment of IPO Performance in the Energy Sector

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Master Thesis in Financial Economics & Business Analysis and Performance Management

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

This thesis investigates Initial Public Offerings (IPOs) on the Oslo Stock Exchange the last ten years (2006-2015). The analysis focuses on short- and long-term aftermarket performance between companies in the energy sector and other sectors. The energy sector is dominating the Norwegian IPO market, but few papers examine their performance. In the short run, we find an average underpricing of 3.08% for the energy sector, which is higher than the other sectors. The difference in underpricing between them is, however, insignificant. Moreover, when controlling for other variables, underpricing in the energy sector decreases. In the long run, energy companies are more overpriced compared to other companies (excluding high-tech). If the company listed is an energy company, abnormal returns decreases by 10.90%, ceteris paribus. This means that energy companies perform worse than other companies after six months of trading. Furthermore, underpricing after first-day of trading is decreasing over the sample period, and average abnormal returns are negative for most years after the financial crisis. Long-run overpricing is increasing over the period, which means that IPOs perform worse today than in previous years. However, we examine a relatively "cold" period, which may affect our results. As the IPO market is cyclical, IPOs may perform better in the future.

Preface

This thesis represents the completion of our Master of Science in Financial Economics and Business Analysis and Performance Management at the Norwegian School of Economics (NHH). Even though writing our thesis has been challenging and time-consuming, it has above all been very interesting and educational. Writing this thesis has increased our interest and fascination of the equity markets, and especially increased our insight in the Norwegian IPO market. We would like to thank our supervisor, Maximilian Rohrer, for great discussions and indispensable input and feedback. Furthermore, we would like to thank the department of Finance and the department of Business and Management Science at the Norwegian School of Economics for the inspiring and academically excellent Master programs during the two past years.

Norwegian School of Economics

Bergen, 19.12.2016

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1. Introduction

Norway is highly exposed to natural resources, and one third of total market capitalization on Oslo Stock Exchange is allocated in the energy sector (Oslo Stock Exchange, 2016). Energy companies have a major impact on the Norwegian IPO market as 40% of the listings the last ten years are in the energy sector, see Figure 1.1. As energy companies are highly dependent on commodity prices, their future is uncertain. Sectors with high levels of uncertainty perform better in the short run, and worse in the long run, than less uncertain sectors when going public (Beatty & Ritter (1986), Bakke, et al., (2010)). An interesting question is therefore whether the performance of IPOs in the energy sector differs from other sectors. Moreover, there are few energy companies going public during the oil price downturn (2014-2015), and IPO volume is low during the financial crisis (2008-2009), see Figure 1.1. Consequently, it is interesting to examine the changing market conditions' effect on IPO performance.

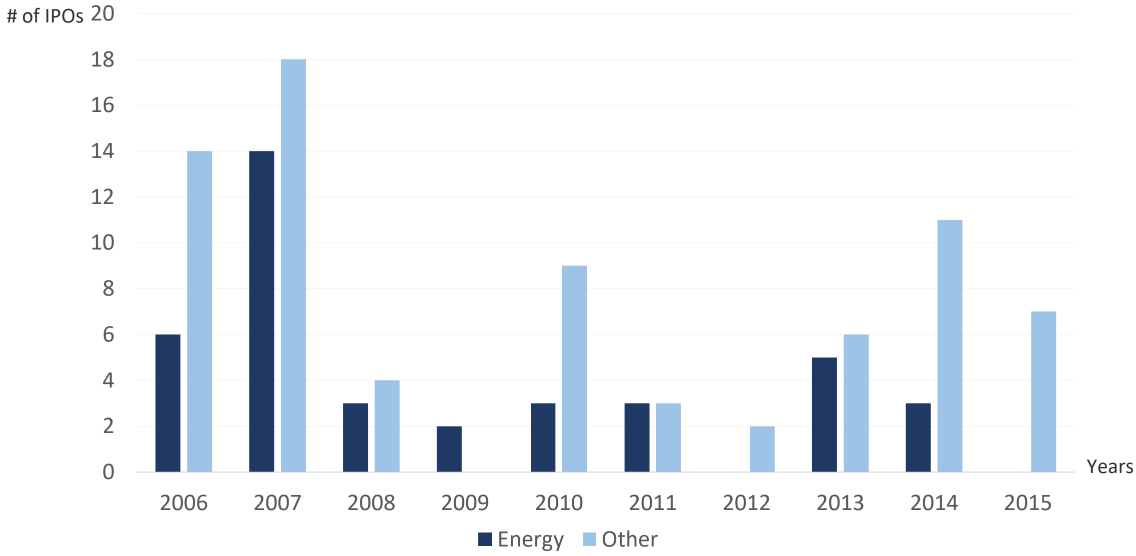

Figure 1.1: Number of IPOs in the Energy Sector vs. Other Sectors 2006-2015

In our analysis, we examine the short-term and long-term performance for companies in the energy sector compared to other sectors between January 2006 and December 2015. Commodity prices impact the energy sector, and thus we take different time periods into account where the price varies, see Appendix 8.4. Furthermore, we control for offer size as scholars find larger offerings post the financial crisis, and these are less underpriced than small issues (Gregoriou & Henry, 2013).

There are few papers examining IPO performance of energy companies in Norway, even though they are dominating the Norwegian IPO market. We therefore find it relevant to compare IPO performance in the energy sector to the remaining sectors. This paper contributes to existing literature on IPO performance in the Norwegian market. More specifically, we answer the following hypothesis:

H1: IPOs within the energy sector in Norway are more underpriced in the short run and more overpriced in the long run compared to IPOs within other sectors.

H2: IPOs during the financial crisis and the oil price downturn are less underpriced in the short run and more overpriced in the long run.

After first day of trading, average underpricing in the energy sector amounts to 3.08% which is 2.41% more than in other sectors. This higher underpricing applies to all periods except post-financial crisis. There is, however, no significant difference in underpricing between energy companies and other companies. When controlling for more variables in the multivariate regressions, the abnormal returns in the energy sector decreases. Consequently, energy companies are not more underpriced than companies in other sectors (excluding high-tech). This indicates that the energy companies are not relatively higher priced in the secondary market the first day compared to other companies. Hence, investors subscribing to IPOs in the energy sector do not receive higher returns after one day of trading than IPOs in other sectors.

After six months of trading, average abnormal return is -9.93% for the energy sector, while it is -7.25% for the other sectors. During the financial crisis and the oil price downturn, IPOs in the energy sectors perform worse. On the contrary, they perform better during the other two periods (2006-2007 and 2010-2013). The difference in abnormal returns is, however, insignificant in our univariate analysis. In our regression analysis, we find energy companies to be more overpriced when controlling for the size of the issue. By controlling for the size of the issues, abnormal returns in the energy sector decreases by 5.32% and becomes significant at 15% significance level. If the company listed is in the energy sector, abnormal returns decreases by 10.90% in the long run. Hence, IPOs within the energy sector perform worse in the aftermarket. Consequently, investors subscribing to issues in the energy sector will have lower abnormal returns after six months of trading than if they subscribe to issues in other sectors (excluding high-tech). Higher ex-ante uncertainty for commodity dependent companies and a higher need of correcting the valuations when new information is revealed, may explain the underperformance in the aftermarket.

Average first-day returns decrease over the sample period. After the financial crisis there are more years with negative first-day returns than positive. If the probability of average negative returns is greater than positive returns, it may harm future IPOs in Norway. Uninformed investors may refrain of subscribing to new offerings if the expected returns are negative (Rock, 1986). As most IPOs are dependent on these investors to get full subscription, it makes it more difficult for companies to raise new capital by going public. However, we do not find IPOs to be significantly less underpriced during the financial crisis and oil price downturn. Furthermore, long-run abnormal returns are more negative during the financial crisis compared to the other periods. None of these differences in abnormal returns are significant.

Several scholars analyze short-term underpricing and long-term overpricing (Ritter (1991), Emilsen et al., (1997), Hahn et al., (2013)). The research on differences in abnormal returns between different sectors in Norway is, however, limited. Falck and Hagatun (2009) study underpricing in different sectors in the Norwegian market between 1982-2008. They find lower average abnormal returns for the energy sector (10.6%) than industrials and information technology (11.6% and 22.6% respectively). Samuelsen and Tveter (2006) examine underpricing in oil related companies in the Norwegian market between 2004-2005. They find an average initial return of 4.84% for oil related companies, while it is 1.12% for other companies. In the long run, Samuelsen and Tveter (2006) find an average six-month return of 11.75% for oil-related companies, while it is 5.23% for other companies. This contradicts long-term overpricing. However, they argue that the high returns are due to a period of strong growth in oil prices. Ellingsen (2012) examines aftermarket performance in the Norwegian market between 2006 and 2011, and find abnormal returns of -0.02% in the long run. Her research does, however, not examine different sectors' performance. This paper contributes to the literature because we analyze the performance of IPOs in the energy sector both on short-term and long-term. Additionally, we examine a period where there are great variations in the oil price.

2. Theory

2.1 Initial Public Offering

An initial public offering is the first time a private company offers stocks to the public (Ibbotson et al., 1994). The company goes from having exclusively private shareholders to trade their shares over a stock exchange, and is therefore referred to as "going public". The shares are normally a combination of newly issued shares, primary shares and secondary shares (Jenkinson & Ljungqvist, 2001).

2.1.1 Why go Public?

There are several explanations why firms go public. IPOs allow the issuing firm to raise capital on more favorable terms due to access to larger number of investors (Ibbotson et al., 1994). Capital is crucial in order to grow as it can fund capital expenditure, pay off debt and fund research and development. Public offerings also increase the company's publicity, which is vital in reaching new groups of potential customers and investors. As a result, this may increase the company's market share. An IPO can also serve as an exit strategy for the founders of the firm since it allows them to sell their shares to the public market.

Nevertheless, there are some disadvantages of going public. IPOs involve additional costs, both in terms of going public and being a public company (PwC, 2012). The issuer is burdened with the direct costs of an IPO, and these costs will to some extent continue as ongoing after the offering. Additionally, the issuer must disclose proprietary information in IPOs, which may weaken its competitiveness (Draho, 2004). Brau & Fawcett (2006) argue that public investors are more shortsighted, and thus focus on short-term profitability at the expense of long-term profitability. Lastly, increasing number of owners dilutes management's control (Draho, 2004).

2.1.2 How to go Public

The process of an initial public offering is extensive and involves several steps (Jenkinson & Ljungqvist, 2001). It starts with choosing a suitable marketplace. In Norway issuers can choose between two different marketplaces: Oslo Børs and Oslo Axess (Oslo Stock Exchange, 2016). The requirements for listing at Oslo Børs are stricter than the requirements at Oslo Axess. As a result, many small and young companies list at Oslo Axess. Furthermore, the issuing firms have to produce the information required for an initial prospectus, and hire underwriters, auditors and lawyers. Finally, they need to price and allocate the shares of the issue.

Pricing Mechanisms

IPO pricing mechanisms define the rules and procedures issuers and underwriters must follow to sell the offering to investors (Draho, 2004). In Norway, IPOs are either priced through bookbuilding or fixed price, see Table 5.6 Section 5.15. The difference mainly revolves around when and how the offer price is set, when and which investors that can submit orders, and allocation rules for distributing shares. Bookbuilding is the predominant mechanism worldwide, and is by far the most common method in Norway (Jenkinson & Ljungqvist, 2001).

Bookbuilding is the most accurate pricing mechanism and involves using investor bids to determine the final offer price (Draho (2004), Loughran & Ritter (2004)). The first step involves setting an indicative price range per share. Thereafter, the bookbuilding period starts, which involves a "road show" where investors submit their indications of demand. Investors specify the number of shares they want to buy and how much they are willing to pay. Thus, investors reveal whether demand for the issue is weak or strong. Consequently, the underwriter is able to set a suitable offer price.

The *fixed price* mechanism is less comprehensive than bookbuilding (Ritter, 2003). The offer price is set relatively early in the IPO process, often when demand and external perception of the company value is unknown. Therefore, the preliminary prospectus includes the offer price. Moreover, the underwriter does not actively sell the fixed price IPOs. In this case the underwriters task is to distribute the prospectus to potential investors, collect order applications and allocate the shares (Draho, 2004). Today, fixed price IPOs are rather uncommon (Ritter, 2003).

2.2 Short-term Performance: Underpricing

Underpricing of initial public offerings is a well-known phenomenon (Rock (1986), Hanley (1993), Loughran & Ritter (2002), Bakke et al. (2010)). Underpricing occurs when the offer price of a stock is below its true market value. Thus, the stock yields a positive initial return.

The fact that a firm's shares are sold at a higher price in the secondary market means that the issuing firm can gain more equity by pricing the shares higher. Consequently, they "leave money on the table".

Many scholars examine underpricing of IPOs, see table 2.1. However, few investigate underpricing in the energy sector. Falck and Hagatun (2009) study underpricing in different sectors in the Norwegian market between 1982-2008. They find an average initial return of 10.2% for all sectors, while the average underpricing is 10.6% for the energy sector. The average underpricing in the energy sector is lower compared to industrials and information technology (11.6% and 22.6% respectively). Samuelsen and Tveter (2006) study underpricing in oil related companies in the Norwegian market between 2004-2005 and find an average initial return of 4.84% in oil related companies, while it is 1.12% for other companies.

Table 2.1 – Previous Research Underpricing

Authors	Market (Period)	# of IPOs	Average Underpricing
Emilsen, Pedersen & Sættem (1997)	Norway (1984-1996)	68	12.50 %
Ljungqvist & Wilhelm (2003)	US (1996-2000)	2178	35.70 %
Loughran & Ritter (2004)	US (1980-2003)	6391	18.70 %
Samuelsen & Tveter (2006)	Norway (2004-2005)	38	2.21 % Oil related: 4.84%
Falck & Hagatun (2009)	Norway (1982-2008)	268	10.2 % Energy: 10.6%
Bakke, Leite and Thorburn (2010)	US (1981-2008)	5093	19.20 %
Ellingsen (2012)	Norway (2006-2011)	69	2.41 %
Hahn, Ligon, & Rhodes (2013)	Global (1988-2009)	2693	27.80 %
Pukthuanthong, Shi, & Walker (2013)	Global (1995-2002)	6025	29.30 %
Berg (2014)	Norway (2009-2014)	46	-2.00 %

2.2.1 What Explains Underpricing?

In explaining underpricing, theories pull in different directions. Consequently, there is no final explanation. However, we choose to only discuss the relevant theories for this thesis.

Institutional Explanations

Draho (2004) argues that there are informational asymmetries between issuers and investors, as well as among investors. In these cases, intentional underpricing may be the best response to the imperfections as it actually maximizes expected profits. *Informational rent* builds on asymmetric information between the underwriter and the investors. Some investors hold positive information regarding the value of the stock being issued (Benveniste & Spindt, 1989). In order to compensate these investors to reveal truthfully information when demand is strong, the underwriter must underprice the offerings.

The winner's curse builds on asymmetric information between investors (Rock, 1986). The main assumption is that only some investors have perfect information regarding the fair value of the shares, while others are unaware of this information. Rock (1986) argues that uninformed investors bid without regard to the quality of the IPO. Informed investors, on the other hand, bid only on the IPOs they think will gain superior returns. This leads to what Rock (1986) calls the winner's curse. As a result, only the uninformed investors ends up bidding on the weak IPOs, and thereby lose money. Because of great losses, they will eventually withdraw from the IPO market. Since the informed investors do not exist in sufficient numbers, the underwriters also need the uninformed investors to bid. To ensure that both the informed and the uninformed investors bid, underwriters choose to underprice the IPO. In this way, underpricing serves as compensation to the uninformed investors to make them participate in the IPO market.

Issuer Objectives

Some companies underprice their issues on purpose. Welch (1989) suggests that some high quality companies use underpricing as a *signal of strength*. Issuers can intentionally price the stocks in the lower part of the indicative price range to prove to investors that they can bear the cost of underpricing, and hence signal their quality and strength. The aim is to attract large numbers of investors in order to raise capital on better terms in the future.

Today, issuing firms tend to care more about hiring an underwriter with a lead analyst than whether or not the underwriter is known for underpricing (Loughran & Ritter, 2004). The value of growth opportunities have become more important in valuing firms, and thus *analyst coverage* post-IPO. If the underwriter's analyst is leading within the industry of the issuing firm, it leads to higher underpricing (Cliff & Denis, 2004). Thus, issuing firms purchase post-

IPO analyst coverage through underpricing. Only a few underwriters have lead analysts, which results in oligopoly in the market. The more market power the underwriters have, the more underpricing there are in equilibrium (Hoberg, 2003).

Behavioral Explanations

Underpricing can occur unintentional and therefore not be part of the issuer and underwriter's strategic plan (Draho, 2004). Behavioral explanations focus on why the offer price is too low, or why the price in the secondary market is too high. According to Kahneman and Tversky's (1979) prospect theory, individuals tend to care more about their level of wealth than they do about the absolute amount. When the offer price is too low, it will attract investors and thus increase the price (Loughran & Ritter, 2002). As a result, issuers focus on the positive unexpected wealth instead of the money left on the table. This deviates from rationality as rational issuers want less underpricing. Furthermore, speculation among investor may be a reason why prices increase to irrational level after a public issue. The price after the issue should be an unbiased estimate of the shares intrinsic value. Nevertheless, these prices are often optimistically biased.

2.2.2 Cross-sectional Variation of IPO Underpricing

There exist cross-sectional variations in underpricing among IPOs. The certification hypothesis, ex-ante uncertainty, hot issue markets and the partial adjustment phenomenon can explain these cross-sectional variations.

Certification Hypothesis

Minimizing information asymmetries through certification can reduce underpricing. IPOs managed by more reputable underwriters leads to less short-run underpricing, and less negative underpricing in the long run (Carter et al., 1998). Underwriters certify that the issue price is consistent with inside information regarding the firm's future (Booth & Smith, 1986). Thus, underwriter reputation signals the underlying risk of the offering as prestigious underwriter want to remain their reputation by reflecting relevant information. Booth & Smith (1986) further argue that prestigious underwriters often market larger offerings by more established firms, which are less risky. Others argue that the use of prestigious underwriter's leads to higher underpricing of the stocks (Loughran & Ritter, 2004). Underwriters may intentionally leave money on the table in order to induce investors to participate in additional issues in the future.

Ex-ante Uncertainty Hypothesis

Future performance of firms going public is uncertain (Beatty & Ritter, 1986). In order to decrease this uncertainty, investors have the desire to obtain information about their investment. The less information the issuing firm discloses, the higher the costs for the investors. The winner's curse problem enhances with uncertainty, and hence the level of underpricing increases with the level of ex-ante uncertainty. Consequently, issuers have incentives to reveal information in order to decrease the level of ex-ante uncertainty of the issue. If the proportion of IPOs that represent risky stocks increases, and thus higher ex-ante uncertainty, it should result in greater average underpricing.

"Hot Issues" Market

The IPO market is cyclical, and IPO activity increases when market returns are high (Ibbotson & Jaffe, 1975). "Hot" issues markets are periods with high IPO activity, while "cold" markets are periods with low activity. Thus, "hot" issue markets yield higher abnormal returns than "cold" issue markets. The Internet-bubble of 1999-2000 is an example of a "hot" issue market. Loughran and Ritter (2004) find in their study that the average underpricing during this period is 71.2%, while the average is 8.9% in the "cold" period in 2002.

There are several explanations why "hot" markets tend to yield higher abnormal returns. Loughran and Ritter (2002) argue that issuing companies bargain the price less aggressively when stock returns are high as they care more about their wealth than about leaving money on the table. Leite (2007) shows that positive public information (a proxy for market returns) reduces adverse selection and thus the cost of going public. There is also a positive relationship between the expected return to uninformed investors and positive public information, which reduces the winner's curse problem. According to Derrien (2005), the behavior of the investors is correlated with market conditions. In bull markets it derives their demand, which leads to higher underpricing of the public offerings.

Partial Adjustment Phenomenon

The partial adjustment phenomenon refers to underwriters only partially revising the offer price when investors reveal positive new information (Hanley, 1993). By only partially adjusting the offer price upwards, they compensate the investors with higher initial returns. Consequently, revising the offer price upwards leads to positive first-day returns. On the contrary, negative information regarding the issue is fully incorporated into the offer price as both investors and underwriters want to avoid overpricing of issues.

2.3 Long-term Performance: Overpricing

The positive average short-run return is often followed by a poor long-run performance (Ritter, 1991). IPOs within oil and gas in the US between 1975-1984 perform worse compared to other sectors. Their average unadjusted return after three years of trading is -43.86%. Samuelsen and Tveter (2006) find an average six-month return of 11.75% for oil-related companies in Norway between 2004-2005, while it is 5.23% for other companies. This contradicts long-term overpricing. However, they argue that the high returns are due to a period of strong growth in oil prices. The table below shows a selection of previous studies of long-run performance.

Table 2.2 – Previous Research Aftermarket Performance

Authors	Market (Period)	# of IPOs	Window (Years)	Average Abnormal Return
Ritter (1991)	US (1975-1984)	1526	3	-29.10 % Oil-related: - 43.86%
Loughran, Ritter & Rydqvist (1994)	Sweden (1980-1990)	162	3	1.20 %
Loughran & Ritter (1995)	US (1970-1990)	4753	5	-20.00 %
Samuelsen & Tveter (2006)	Norway (2004-2005)	38	0.5	Oil-related: 11.75% Other: 5.23%
Ellingsen (2012)	Norway (2006-2011)	66	0.5	-0.02 %
Ritter (2016)	US (1980-1989)	2043	0.5	3.60 %
Ritter (2016)	US (1990-1999)	4090	0.5	12.90 %
Ritter (2016)	US (2000-2014)	1927	0.5	-2.90 %

Several theories explain why initial public offerings are overpriced in the long run (Jenkinson & Ljungqvist, 2001). Three explanations of this poor long-run performance is; the divergence of opinion hypothesis, impresario hypothesis and windows of opportunity. It is worth noticing that these are not exclusive, and may occur simultaneously.

2.3.1 The Divergence of Opinion Hypothesis

Different investors have deviating opinions regarding an issues value (Miller, 1977). This divergence of opinions among investors may lead to short-term overpricing and long-term underperformance. Many companies face restriction regarding short sale, and optimistic investors determines the price of these firms. The optimistic investors overvalue the price of the stocks, which leads to high abnormal returns on short-term. This overvaluation by optimistic investors corrects itself as more information becomes available. Thus, the divergence of the value of the company between optimistic and pessimistic investors becomes smaller. Consequently, short-term returns are high while expected return decreases in the long run. This is known as the Miller effect.

2.3.2 Impresario Hypothesis

According to the impresario hypothesis, the companies with the highest short-term abnormal returns have the lowest returns in the long run (Shiller, 1990). Higher underpricing increases interest and publicity for the issues. The secondary market adjusts this positive abnormal return, which leads to negative abnormal returns in the long run.

2.3.3 Windows of Opportunity

According to the windows of opportunity hypothesis, companies are more likely to experience overvaluation if they go public in high volume periods with high volumes (Ritter, 1991). High volume periods typically occur when investors are particularly optimistic about future growth potentials. To take advantage of the investor’s optimism, issuers seek to successfully time their IPOs to these windows of opportunities. As a result, the companies going public in these high volume periods experience poor long-run performance as the overvaluation is corrected for. Thus, high volume periods have the lowest long-run returns.

3. Methodology

3.1 Calculation of Abnormal Returns

Scholars use different methods to calculate IPO underpricing and aftermarket performance. Some adjusts the initial returns for market returns (based on a benchmark) to take account for alternate investments (Pukthuanthong et al., 2013). Others argue that adjusting market returns is unnecessary as average market returns are usually small compared to average initial returns (Beatty & Ritter, 1986). Thus, it will only result in minor changes. However, as the majority of previous research uses market adjusted returns, we adjust for market returns in our calculations of underpricing and aftermarket performance.

Researchers also apply different methodologies in terms of which closing price to use in the calculation of short-term abnormal returns. Some argue that the efficient markets eliminate mispricing the first day, and use the closing price after the first day of trading (McGuinness, 1992). Others argue that underwriter price stabilization activities influence the stock prices in the days following the offer, and use prices a week or month after the first trading day (Lowry et al., 2010). The majority of recent empirical literature uses the closing price after first-day of trading in the calculation of short-term abnormal returns (Bakke et al., 2010). The reason why, is that markets have become more efficient. Thus, we use the closing price after first-day of trading in our calculations of short-term abnormal returns.

In the calculation of long-run performance, we use the closing price after six months (120 trading days). Scholars often use larger windows when examining long-run performance (Ritter, 1991). However, six months allows us to examine the IPOs in the recent years when oil prices are declining. As markets are more efficient today, the closing prices after 120 days of trading serve as a good proxy for long-term performance.

Abnormal returns are stock or assets returns that cannot be explained by the movements in the market portfolio (Bodie et al., 2014). The abnormal return is often calculated based on the Capital Asset Pricing Model (CAPM). As this is an empirical study, we use the actual observed differences between the performance of the stock and the market portfolio. Further, the returns are log adjusted to make them less skewed, see Appendix 8.1.1 & 8.1.2. Accordingly, we use the following formula in the calculation of the abnormal returns:

$$Abnormal\ Return = \log\left(\frac{p_1}{p_0}\right) - \log\left(\frac{m_1}{m_0}\right)$$

P_1 is the given stock's closing price the first day of trading (or six months after listing), while p_0 is the offer price. M_1 is the market index's closing value the first day of trading (or six months after listing), while m_0 is the index's closing value the day before listing.

The Oslo Stock Exchange Index (OSEBX) serves as a reference index in the calculation of abnormal returns. A broad index like the OSEBX is appropriate as it captures the different characteristics of the companies in the sample. The benchmark, or reference index, reflect alternate investments when calculating abnormal returns.

3.2 Independent Variables

We use the Global Industry Classification Standard (GICS) to divide the companies into different sectors. The GICS divide the companies into ten different sectors based on their main business activities. Furthermore, we use dummy variables in the regression model to take the different periodical trends into account. There are four different periods in the model; pre-financial crisis (2006-2007), financial crisis (2008-2009), post-financial crisis (2010-2013) and "oil downturn" (2014-2015).

Issue size serves as a proxy for ex-ante uncertainty in the regressions (Ritter, 1987). To calculate the size of the companies going public, we use market value of equity. Issue size is in different forms to analyze its effect on abnormal returns, as a dummy and in logs. The dummy is equal to one if the issue is small (less than 1 000 MNOK). Using enterprise value instead of equity value may be more accurate as it takes into account potential differences in capital structure. However, we do not think the use of enterprise value instead of equity value is crucial for our analysis.

3.3 Univariate Analysis

To test the level of abnormal returns for the different variables we apply both parametric and nonparametric tests. Parametric tests require several assumptions for the sample distribution in order to hold (Dunning, 1993). One assumption is that the variables are normally distributed. The central limit theorem and law of large numbers do, however, state that the distribution of the average is approximately normal if the sample is large enough (Smith & Wells, 2006). We deem the t-tests valid as our final sample contains 113 observations.

The Student t-test is a one-sample test which tests if the mean abnormal returns are different from zero, see Table 3.1. Welch's t-test testes differences between two means that are assumed to have unequal variances and population size (Welch B. , 1938). The Welch's t-test is an adaption of the Student t-test, see Table 3.1.

Table 3.1 – Parametric and Nonparametric Tests

	Student t-test ($H_0: \bar{X} = 0, H_a: \bar{X} > 0 \text{ or } H_a: \bar{X} < 0$)	**Welch's t-test** ($H_0: \bar{X}_1 - \bar{X}_2 = 0, H_a: \bar{X}_1 - \bar{X}_2 \neq 0$)	**Wilcoxon Rank Sum Test** (H_0: No difference in means)
Test-statistics	$t = \frac{\bar{X}_i}{s_i \cdot \sqrt{\frac{1}{n_i}}}$	$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)}}$	$z = \frac{T - E(T)}{\sigma_T}$
Mean and st.dev.	$\bar{X}_i$ = mean AR for sample i s_i = st.dev. of AR for sample i n_i = number of observations in sample i	$\bar{X}_i$ = mean AR for sample i s_i = st.dev. of AR for sample i n_i = number of observations in sample i	$E(T) = \frac{n_1(n_1 + n_2 + 1)}{2}$ $\sigma_T = \sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}$ T= rank sum of sample 1

Nonparametric tests require no or very few assumptions about the data (Whitley & Ball, 2002). The tests are distribution-free tests since they do not require specific probability distributions. The cost of having fewer assumptions compared to the parametric tests is that they are less powerful. The nonparametric tests complement our t-tests by checking the robustness of our results. To compare the means between two independent groups, we use the Wilcoxon signed rank test, or Mann-Whitney test, see Table 3.1.

3.4 Multivariate Analysis

The multivariate analysis isolates the effect of one variable from the other variables affecting abnormal returns, which the univariate tests are not able to. We apply the ordinary least square (OLS) model in our analysis of abnormal returns. By applying the OLS-model, it enables us to determine how the different independent variables impact the dependent variables, ceteris paribus (Wooldridge, 2013). The population model is:

$$y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + u_i$$

where x_i is the independent variables, $\beta_0, \ldots, \beta_k$ are $k + 1$ unknown population parameters, and u is an unobserved random error term. Several assumptions have to be fulfilled for the OLS-model to provide unbiased estimators, see Appendix 8.3.1. If the assumptions of the multiple regression model hold, it provides the best linear unbiased estimators (BLUEs) of the population parameters, and statistical inference can be made (Wooldridge, 2013).

3.4.1 Endogenity Problems

Specification problems can occur by applying the OLS-model. We have a specification problem when the econometric model is specified in such a way that there is correlation between one or more of the independent variables and the error term (Wooldridge, 2013). Thus, we have an endogeneity problem. This implies that assumption 4 does not hold, see Appendix 8.3.1, and we know that the OLS estimator is biased. Omitted variable bias, functional form misspecification, measurement errors and simultaneity cause endogeneity. As our data are not likely to suffer from simultaneity problems, we will not go further into this source of endogeneity.

Omitted Variable Bias

We include proxy and control variables in our regressions in order to try to avoid omitted variable bias. Omitted variable bias occurs when a relevant variable is omitted from the regression and correlates with one or more of the independent variables in the regression (Wooldridge, 2013). When omitted variable bias is present, the estimation of the independent variables' coefficients may be misleading and thus harm statistical inference. There are numerous variables that may affect short- and long-term abnormal returns. However, we limit the number of proxy and control variables in order to remain an acceptable number of degrees of freedom.

Proxy and Control Variables

Market Return

The public information available affects the abnormal return first day of trading (Bakke et al., 2010). When the public signal is positive, the probability of an issue being underpriced is higher. We therefore control for public information in the time before listing. The market development in the time before listing serves as a proxy for the public information. We use the OSEBX index to control for the general market conditions 60 trading days (3 months) preceding the offer. 60 days is likely to represent the time from filing for an IPO to the actually IPO itself.

Volatility of the Market

We use market volatility as a proxy of how open investors are to new share issues. The IPO window is open when investors are receptive to new issues, while it is closed when investors are not receptive to new issues. The CBOE Volatility Index (VIX Index) is a forward-looking index of the expected volatility over the next 30 days implied by S&P 500 stock index option prices. Investors mainly use the index to insure the value of stock portfolios (Whaley, 2008). An increase in expected market volatility results in investors demanding higher rates of return on stocks, which further leads to a drop in stock prices. Consequently, investors acquire insurance to protect for potential losses related to declining prices, which leads to an increase in the VIX index.

Higher market volatility hurt IPOs as swings in valuation can make it difficult to set a pricing range (Patel, 2013). Lower volatility, on the other hand, increases financial activity, which normally leads to a lower VIX and IPO conditions improve. A low index is associated with low market uncertainty, and offerings can benefit from high investor sentiment and thus higher valuation of their issue. VIX levels above 30 indicate high volatility, while levels below 20 indicates low volatility. To distinguish between whether or not the IPO window is open, we include a dummy variable equal to one if the VIX index is above 20. To calculate the level of the index at the time of the listings, we use the average index one month before listing since the VIX index is a forward-looking index over expected volatility the next 30 days. The OBX volatility index is likely to reflect the Norwegian IPO window better, but we are not able to collect data for this index.

Underwriter Reputation

We include underwriter reputation in our regressions to capture potential certification effects, and to control for the potential correlation between issue size and the use of prestigious underwriters. See Appendix 8.2 whether an underwriter is prestigious or not.

Age of Firm at Listing

The age of the firm at listing affects the share price, and thus the abnormal return (Loughran & Ritter, 2004). Younger firms are riskier than older firms, and investors expect compensation for this risk. It is also easier to value older companies as more information is available. We therefore include age at listing as a proxy for risk. Since smaller issues are often younger firms, we also control for this correlation by including age at listing. The dummy is equal to one if the company is three years or younger.

Bookbuilding vs. Fixed Price

The pricing mechanism in the offering impacts underpricing (Ritter, 2003). Fixed price IPOs are more underpriced than offers done by bookbuilding. Larger issues normally use bookbuilding, while smaller firms more often use fixed price. To control for the correlation between issue size and pricing mechanism (see Appendix 8.3.8), a dummy variable is equal to one in the regressions if the offer is done by bookbuilding.

Functional Form Misspecification

We test the different regressions for specification problems through the RESET test and Davidson-Mackinnon test, see Appendix 8.3.3. Functional form misspecification occurs when we include the correct variables in the model, but not in the correct functional form (Wooldridge, 2013). We test for functional from misspecification by including some of the variables in levels and logarithmic forms in different regressions, or as a dummy.

Measurement Errors

There is a possibility of differences between the observed value and actual value in our data. This measurement error can cause endogeneity problems. If the measurement error is correlated with the unobserved explanatory variable, it leads to a biased and inconsistent estimator.

3.4.2 Detecting Multicollinearity

Our regressions are likely to suffer from some multicollinearity as the variables explain the same phenomena. Multicollinearity occurs when there is a high degree of correlation between several of the independent variables (Wooldridge, 2013). The existence of multicollinearity is not a violation of the OLS assumption as long as it is not perfect multicollinearity. If multicollinearity (not perfect) is present in the model, the OLS will still be *BLUE*, but inference is not reliable. To detect whether or not our regressions suffers from multicollinearity, we use the Variance Inflation Factor, see Appendix 8.3.5. Furthermore, if the overall F-statistic is significant while none of the individual t-statistics are, it is a warning of multicollinearity.

3.4.3 Detecting Heteroscedasticity

Basing an econometric analysis on a sample of cross-sectional data often leads to problems of heteroscedasticity in the residuals (Wooldridge, 2013). To test if our residuals exhibit heteroscedasticity, we use White's test as it is more generic than Breuch-Pagan's test, see Appendix 8.3.6. Furthermore, we plot the fitted values of y against the residuals to check for heteroscedasticity, see Appendix 8.3.6 Figures 8.5.1 and 8.5.2. If the variance of the unobserved factors changes across different segments of the population, where the different values of the explanatory variables determine the segments, heteroscedasticity is present (See Appendix 8.3.1, assumption 5). Heteroscedasticity does not cause biased estimators, but the OLS is no longer the *best linear unbiased estimator (BLUE)*, thus it is inefficient.

3.4.4 Normality of Residuals

To check for normality, we calculate the Kernel density estimate of the residuals together with the Shapiro-Wilk test. According to assumption six, see Appendix 8.3.1, the distribution of the residuals must be normal. If the residuals are not normal, it leads to less accurate inference (Wooldridge, 2013). The OLS will, however, still provide unbiased estimates.

4. Data

4.1 Sample Selection

The overall sample for the analysis consists of IPOs on the Oslo Stock Exchange between January 2006 and December 2015. The sample period includes both the financial crisis and the oil price downturn. From OSE's website we find an overview over listings during the sample period, and our initial sample consists of 181 IPOs. To make our sample more consistent, we exclude 64 of the companies as they are already priced in the market. Our final sample includes only those companies introduced on an exchange for the first time, and simultaneously offering a public sale of shares or increase in share capital. Consequently, we exclude five of the offerings as they are secondary listings, and 25 due to mergers or demergers of already listed companies. Additionally, we remove two relisting's of stocks and eight companies already listed on other exchanges. Finally, due to missing data, we exclude 24 companies from the sample. As a result, our finale sample consists of 117 IPOs.

4.2 Data Collection

Primarily, we collect our data from the OSE website, Bloomberg and the respective IPO prospectus. The offer price for the IPOs and the closing price after first-day of trading are from statistics on the OSE's website, and checked with data from Bloomberg. The closing prices after 120 trading days are from Bloomberg. Total offer sizes are from OSE's website which provide statistics of both number of shares issued and total offer size for each IPO. Information regarding underwriter and pricing mechanism is mainly from prospectus, but in cases where the prospectus is not available, it is from OSE's Newsweb site. The historical prices of the OSEBX and VIX index are from Yahoo! Finance. The age of the companies at listing is either from the firm's home page or the IPO prospectus. To make the data more consistent, we assume the companies are established the year they start their ongoing activities.

4.3 Potential Biases

4.3.1 Outliers

To make the means more informative and the statistical inference more accurate, we remove outliers from our sample. We remove the 1% most extreme observations in each direction, see Box-plot Appendices 8.1.1 & 8.1.2. Outliers can have great impact on the sample mean and influence the variables of interest. By removing the most severe outliers, we minimize the error variance and the probability of making Type I or Type II errors (Osborne & Overbay, 2004).

4.3.2 Selection Bias

Selection bias arises because data are missing on the variables in an analysis (Heckman, 1977). The ones being analyzed or the actions of the analysts can cause selection bias. Self-selection leads to deviation between the sample characteristics and the actual population, and thus distorts the validity of the inference. Due to strict rules of going public, selection-bias by the companies themselves are minimized in our sample. However, our analysis may contain two potential selection biases due to our own self-selection. Closing prices, underwriters and pricing mechanism are for some companies challenging to find. Consequently, our sample may be distorted towards larger and more profiled IPOs as these often exhibit greater transparency than smaller IPOs. We also find it hard to obtain data and prospectus of listings in the beginning of the sample period. This may distort our sample towards listings taking place at the end of the sample's time period. Regardless of our hard work trying to find all relevant data, we acknowledge the risk of exclusion of relevant observations.

4.3.3 Source Inconsistency

We crosscheck our data between different sources, for example between OSE and Bloomberg. For some of the data, inconsistency exists between the different sources. Our data, and consequently our analysis, may therefore exhibit minor errors.

4.4 Descriptive Statistics

Figure 4.1 shows the frequency of IPOs in the Norwegian market between 2006 and 2015. The IPO activity is highest in 2006 and 2007, while there is a huge drop in IPOs during the financial crisis. IPO activity is increasing after the financial crisis, but activity is still low compared to the levels pre-financial crisis.

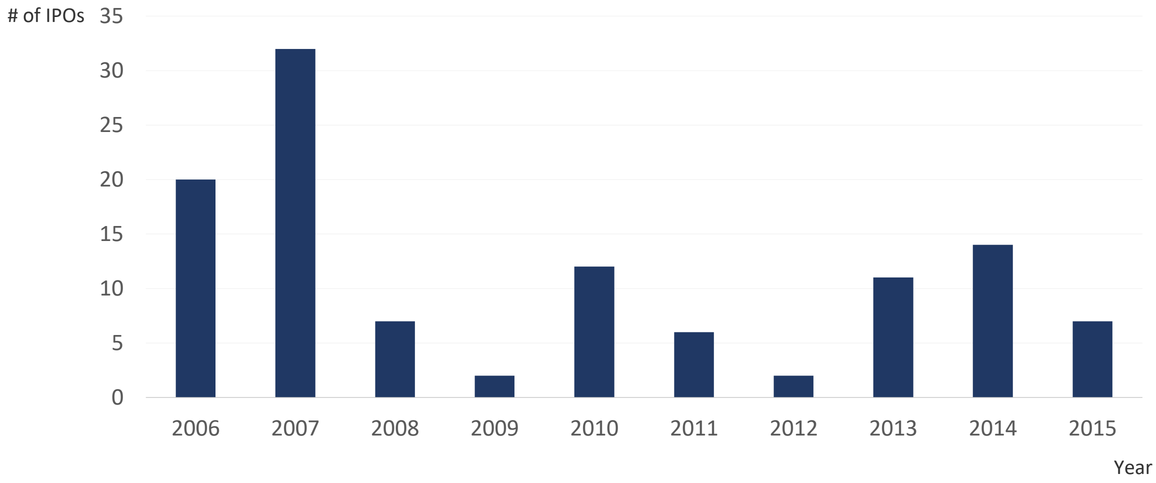

Figure 4.1: Number of IPOs Each Year (2006-2015)

Figure 4.2 presents the number of IPOs in the different sectors from 2006 until 2015. 39 out of the 113 IPOs in our sample appear in the energy sector. The frequency of IPOs in the other sectors, except utilities and telecommunications, are more alike with IPOs ranging from 6 to 14. We expect higher frequency of energy IPOs due to Norway's great exposure to natural resources. However, the number of IPOs in the energy sector in relation to the other sectors are declining, see Figure 1.1 Section 1. There are none IPOs within the energy sector in Norway in 2015, and the fraction of IPOs in the energy sector in 2014 is less than in previous years.

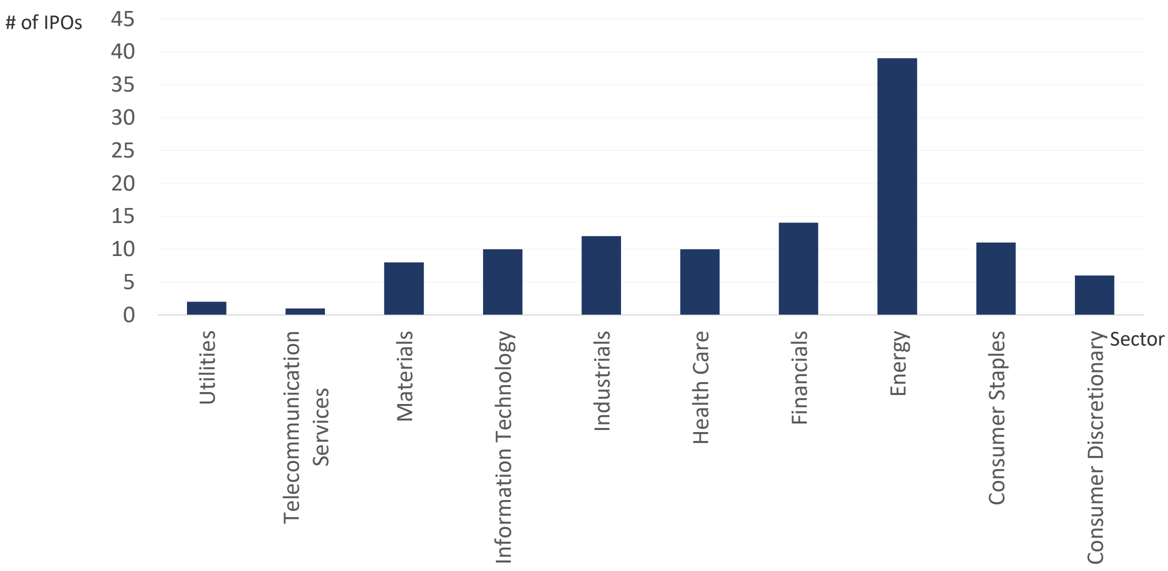

Figure 4.2: Number of IPOs by Sector (2006-2015)

Table 4.1 summarizes key descriptive statistics for the energy sector and other sectors. We find average offer size to be greater for IPOs in the energy sector. Furthermore, the fraction of energy companies using more prestigious underwriters is higher. Energy companies are also younger at listing compared to the other companies. On the contrary, there are no major differences in the fraction of companies using bookbuilding between energy companies and other companies.

Table 4.1 – Key Descriptive Statistics

The table shows key descriptive characteristics for the energy sector compared to other sectors for some of the proxy and control variables. Offer size and age are the means within the samples, while use of prestigious underwriters and bookbuilding is the percentage of IPOs using this within the samples.

	Offer size	Use of prestigious underwriter	Age	Bookbuilding
Energy	2 603 197	51.28 %	11.62	79.49 %
Other	1 953 328	45.95 %	21.46	77.03 %
Difference	**649 869**	**5.34 %**	**-9.85**	**2.46 %**

Figure 4.3 illustrates the average offer size of the sample in the given time period. Average offer sizes are remarkably higher in 2006 and 2010 than the other years, while average offer size is low during the financial crisis. The average offer sizes are almost the same the last five years, and only increasing some.

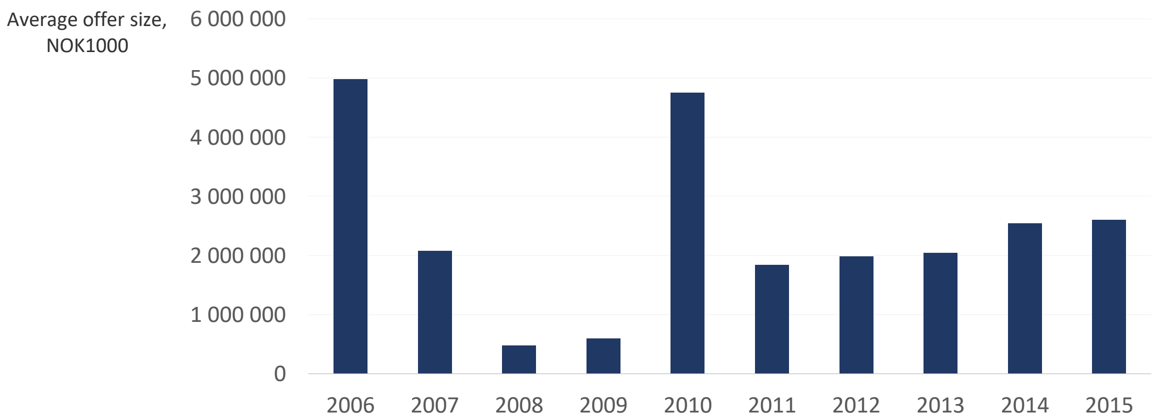

Figure 4.3: Average Offer Size Each Year (2006-2015)

The frequency of larger issues is higher than smaller issues over the sample period. 62 of the offerings is over 1 000 MNOK, while 51 offerings are below 1 000 MNOK. There are more large offerings than small offerings before the financial crisis, see Figure 4.4. After the financial crisis, from 2010, there is no clear trend of whether or not there are more large than small issues. This contradicts previous research that finds a trend of larger issues post-financial crisis.

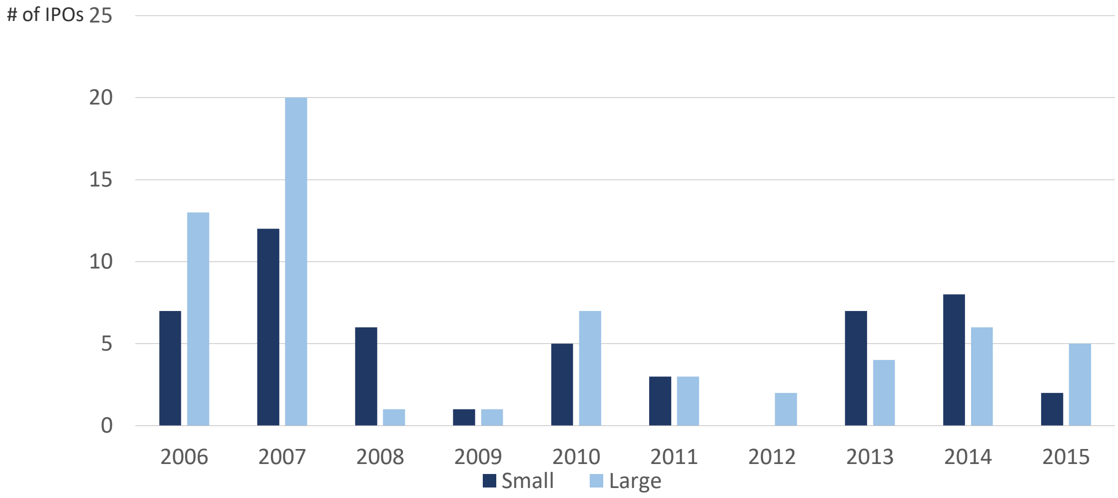

Figure 4.4: Number of Small vs. Large Offer Each Year (2006-2015)

5. Results and Analysis

5.1 Univariate Analysis

5.1.1 Abnormal Returns

Figure 5.1 shows the distribution of the IPOs first-day abnormal log-returns. The majority of log-returns are between -5% and 5%. For the entire sample, the average first-day abnormal return is 1.50%, and significantly different from zero at a 5% significance level, see Table 5.1. This positive average first-day return is in accordance with previous research (Emilsen et al. (1997), Loughran & Ritter (2004), Falck & Hagatun (2009), Hahn et al. (2013)). The average underpricing is, however, lower than what we find in previous studies, see Table 2.1 Section 2.

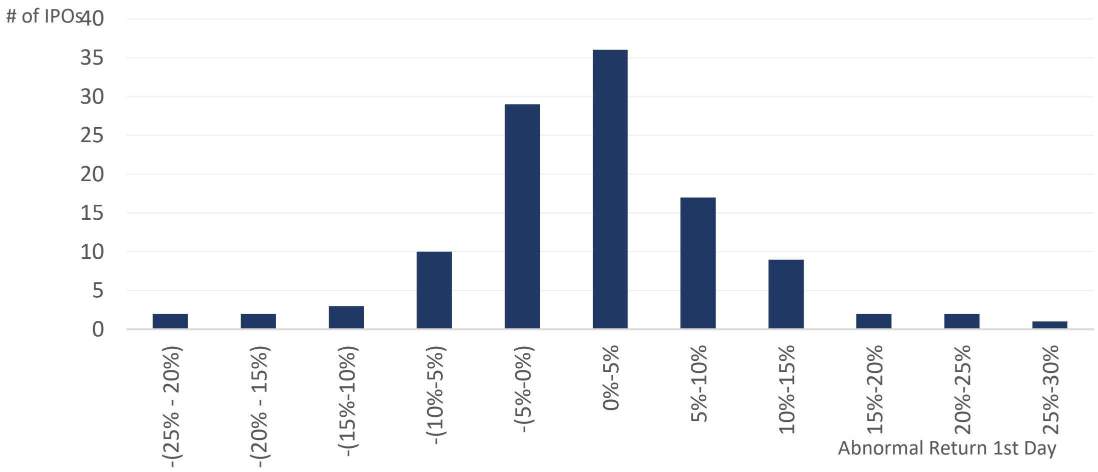

Figure 5.1: Distribution of First-day Abnormal Returns

Table 5.1 – Abnormal Returns and Key Distribution Characteristics

The table depicts the average abnormal returns for the entire sample, both short-term and long-term. The Student t-test tests if the average returns differ significantly from zero. The standard deviation of the average returns is used in the calculation of the t-statistic. Additionally, the table depicts key distribution characteristics of the samples average returns. Skewness measures whether the returns are symmetrically distributed to left and right of the mean. If the skewness is between -0.5 and 0.5, the distribution is approximately symmetric. Kurtosis measures the thickness of the tails of the distribution, and the kurtosis of the normal distribution is 3.

	# of IPOs	Mean	Median	Min	Max	Std.	Skewness	Kurtosis
Underpricing	113	1.50%**	1.05 %	-21.53 %	26.64 %	8.17 %	0.152	4.451
Aftermarket Performance	113	-8.17%***	-7.49 %	-97.76 %	68.56 %	32.82 %	-0.163	3.439

Figure 2.1 illustrates the distribution of the IPOs six-month abnormal returns. The positive first-day return decline in the long run, and the frequency of negative returns is higher than positive returns after six months of trading. For the entire sample, the average six-month abnormal return is -8.17%. This average is significantly different from zero at a 1% significance level. The median of the distribution of the average abnormal return after six

months is -7.49%, which means that the return for 50% of the sample is below -7.49%. Negative return after six months of trading is in accordance with previous research (Ritter, 2016). After a positive initial return, a period of poor long-run performance often follows, which indicates overpricing relative to the true value in the long run (Ritter, 1991).

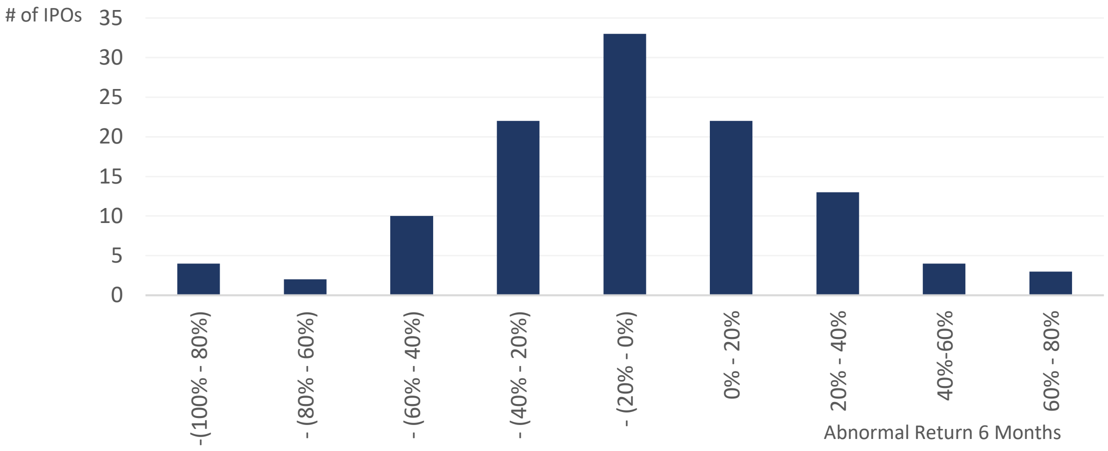

Figure 5.2: Distribution of Six-Months Abnormal Returns

The correlation between abnormal returns after one day and six months of trading is 0.274. This positive correlation can be seen by scattering the two variables against each other, see Figure 5.3. 46 companies in the sample have negative abnormal returns after the first day of trading. After six months, the return is still negative for 32 out of these 46 companies. On the contrary, the relationship is not as strong for the companies with positive returns after first day of trading. 39 out of the 67 companies with positive short-run returns experience negative long-run returns. Average returns are negative in the time after listing, and it is therefore likely that the underpriced companies are overpriced in the long run (Ritter, 1991).

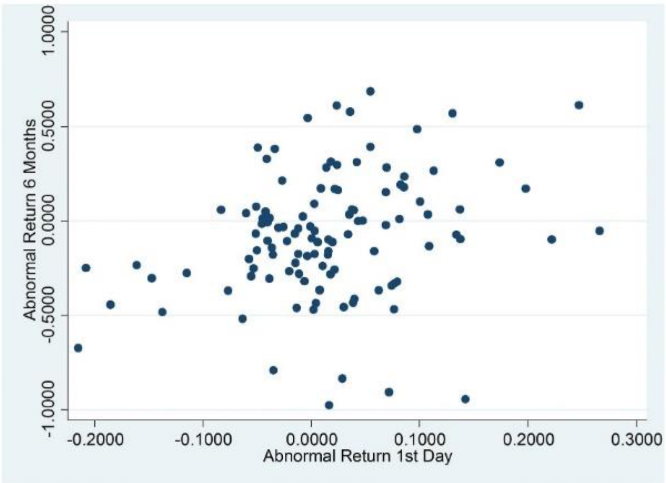

Figure 5.3: First-day Returns Scattered Against Six-months Returns

5.1.2 Abnormal Returns by Sector

For companies listed within the energy sector, average abnormal return after first day of trading is 3.08% and significantly different from zero, see Table 5.2. These companies experience average positive first-day returns in every period, except in the years after the financial crisis. Additionally, energy companies are more underpriced than companies in other sectors, except after the financial crisis. The difference in underpricing between them is increasing. However, the difference is insignificant due to few observations and high standard deviations.

Table 5.2 – Comparison of Abnormal Returns Between Sectors

The table depicts the average abnormal returns for the energy sectors and other sectors separately, and the difference in abnormal returns between them. The one-sided null hypothesis is that the mean is different from zero, while the two-sided null hypothesis is that the means do not differ.

	2006-2015		2006-2007		2008-2009		2010-2013		2014-2015	
	# of IPOs	Mean	# of IPOs	Mean	# of IPOs	Mean	# of IPOs	Mean	# of IPOs	Mean
Underpricing										
Energy	39	3.08%***	20	4.06%***	5	2.83 %	11	-0.09 %	3	8.61 %
Other	74	0.67 %	32	2.18%**	4	0.04 %	20	0.33 %	18	-1.50 %
Diff	**113**	**2.41 %**	**52**	**1.87 %**	**9**	**2.80 %**	**31**	**0.42 %**	**21**	**10.11 %**
Aftermarket Performance										
Energy	39	-9.93%*	20	-0.01 %	5	-52.78%**	11	-7.69 %	3	-12.88 %
Other	74	-7.25%**	32	-6.40%*	4	8.06 %	20	-8.52 %	18	-10.74 %
Diff	113	**2.68 %**	**52**	**6.39 %**	**9**	**60.84%***	**31**	**0.83 %**	**21**	**2.15 %**

In the long run, average abnormal return is -9.93% for energy companies and statistically significant at a 10% significance level. It is also negative (-7.25%) for companies in other sectors. From table 5.2, we see that other companies outperform energy companies during the financial crisis and the last two years. Thus, worsened market conditions impact the energy sector more. This may be due to lower oil-prices during these periods, and hence higher risk regarding the energy companies' future. The difference in means is only significant during the financial crisis.

5.1.3 Time Periods

Average abnormal returns after first day of trading varies from year to year, see Table 5.3. Five of the years experiences average negative returns after listing, and average returns are declining over the sample's time period, see Table 5.4. Pre-financial crisis is, however, the only period with significant returns due to few observation and large standard deviation in the other periods, see Appendix 8.1.2 Table 8.2. This negative abnormal return contradicts previous research (Emilsen et al. (1997), Loughran & Ritter (2004), Falck & Hagatun (2009) Hahn et al. (2013)). According to previous research, periods with negative returns are normal due to "cold" periods (Ibbotson & Jaffe, 1975). Normally, these cold periods only last for a short time and not over longer periods. Scholars find a negative short-term impact on the IPO market after the financial crisis (Fauzi et al., 2012). We are not able to find research on the financial crisis' impact on the IPO market over longer periods. Berg (2014) do, however, find average overpricing of -2.00% after first-day of trading for the Norwegian market between 2009-2014, and the negative returns aggravate with the time horizon. Thus, these negative abnormal returns over several years might be country specific for the Norwegian IPO market.

Table 5.3 – Abnormal Returns for the Different Years

The table depicts the average abnormal returns for the different years separately. The one-sided null hypothesis is that the mean is different from zero.

Year	# of IPOs	Underpricing	Aftermarket Performance
2006	20	3.82%**	5.04 %
2007	32	2.34%***	-9.56%**
2008	7	2.70 %	-34.78%*
2009	2	-2.30 %	5.90 %
2010	12	-0.30 %	-5.61 %
2011	6	6.26%*	-0.58 %
2012	2	-3.28 %	-14.57 %
2013	11	-1.98 %	-14.09%**
2014	14	-1.61 %	-9.65 %
2015	7	3.05 %	-13.84 %
Total	**113**	**1.50%****	**-8.17%*****

Table 5.4 – Abnormal Returns for the Different Periods

The table depicts the average abnormal returns for the different periods separately. The one-sided null hypothesis is that the mean is different from zero.

Period	# of IPOs	Underpricing	Aftermarket Performance
2006-2007	52	2.91%***	-3.95 %
2008-2009	9	1.59 %	-25.74 %
2010-2013	31	0.18 %	-8.22%*
2014-2015	21	-0.05 %	-11.04%*
Total	**113**	**1.50%****	**-8.17%*****

If abnormal returns in the Norwegian market continue to be negative for most years, it may hurt future IPOs. According to the winner's curse, uninformed investors will subscribe to all issues, even the ones with high ex-ante uncertainty, as long as they experience positive average returns (Rock, 1986). If the likelihood of average negative returns is higher than positive returns in Norwegian IPO market, it may result in uninformed investors not subscribing to new issues. Most initial public offerings are dependent on uninformed investors in order to get full subscription. Consequently, if they are not able to get full subscription, it makes it difficult for companies to raise new capital by going public. Moreover, there is a risk that the stocks of newly listed companies are less liquid in the secondary market than comparable companies due to asymmetric information (Ellul & Pegano, 2006). Investors expect to be compensated for this potential illiquidity through higher stock returns. If this liquidity premium continues its absent in Norway, it may hamper future bookbuilding processes.

After six months of trading, average abnormal returns are negative for all years except two, see Table 5.3. This overvaluation in the long run is consistent with previous research (Ritter, 2016). The average negative six-month returns are higher for the financial crisis and the oil price downturn, see Table 5.4. Hence, the IPOs during these two periods are performing worse in the long run compared to the two other periods. The last two periods are, however, the only two periods significantly different from zero due to large standard deviations pre-financial crisis, and few observations during the financial crisis.

5.1.4 Size

In the short run, the small issues are less underpriced than the large issues, see Table 5.5. Outperformance by the large issues contradicts previous research (Young (2011), Helwege & Liang (2004)). The large offer’s average abnormal return after first day of trading is significant different from zero at 1% significance level, while the small offers average abnormal return is insignificant. The outperformance by the large issues is present in all periods except during the financial crisis. After the financial crisis, the small issues experience average negative returns, which exhibit overpricing. The difference in underpricing between small and large issues is, however, insignificant.

Table 5.5 – Comparison of Abnormal Returns Between Issue Size

The table depicts the average abnormal returns for issue size separately, and the difference in abnormal returns between them. The one-sided null hypothesis is that the mean is different from zero, while the two-sided null hypothesis is that the means do not differ.

	2006-2015		2006-2007		2008-2009		2010-2013		2014-2015	
	# of IPOs	Mean	# of IPOs	Mean	# of IPOs	Mean	# of IPOs	Mean	# of IPOs	Mean
Underpricing										
Small	51	0.35 %	19	1.21 %	7	2.83 %	15	-0.54 %	10	-1.71 %
Large	62	2.46%***	33	3.88%***	2	-2.74 %	16	0.86 %	11	1.45 %
Diff	**113**	**2.11 %**	**52**	**2.66 %**	**9**	**5.57 %**	**31**	**1.40 %**	**21**	**3.17 %**
Aftermarket Performance										
Small	51	-19.44%***	19	-7.31%*	7	-22.00 %	15	-29.98%***	10	-24.85%**
Large	62	1.09 %	33	-2.00 %	2	-38.81 %	16	12.17 %	11	1.51 %
Diff	**113**	**20.53%*** **	**52**	**5.31 %**	**9**	**16.80 %**	**31**	**42.16%*** **	**21**	**26.37%***

Large issues outperform small issues in the long run. Average abnormal return is 1.09% for large issues, while it is -19.44% for small issues, see Table 5.5. The difference in average abnormal return is statistically significant at a 1% level. Positive abnormal returns for the large issues after six months of trading contradicts previous research, which find that IPOs are overpriced in the long run (Ritter, 1991). While the small issues long-term performance worsens during the sample period, the average returns for the large issues increase. The difference in long-term performance is statistically significant after the financial crisis.

5.1.5 Proxy and Control Variables

Table 5.6 – Comparison of Abnormal Returns Proxy and Control Variables

The table depicts the average abnormal returns for the different proxy ad control variables separately, and the difference in abnormal returns between them. The one-sided null hypothesis is that the mean is different from zero, while the two-sided null hypothesis is that the means do not differ.

Variable	# of IPOs	Underpricing	Aftermarket Performance
Market Return			
Bull	82	1.75%**	-10.94%***
Bear	31	0.85 %	-0.87 %
Diff	**113**	**0.90 %**	**10.06 %**
VIX			
VIX>20	36	1.24 %	-10.72%*
VIX<20	77	1.62%**	-6.98%**
Diff	**113**	**0.38 %**	**3.74 %**
Prestigious Underwriter			
Yes	55	2.92%**	-1.48 %
No	58	0.16 %	-14.52%***
Diff	**113**	**2.75%***	**13.03%****
Age			
Young	25	3.65%***	-6.55 %

Old	88	0.89 %	-8.64%***
Diff	**113**	**2.76 %**	**2.09 %**
Strategy			
Book Building	88	1.14%*	-7.50%***
Fixed Price	25	2.78%*	-10.55 %
Diff	**113**	**1.64 %**	**3.06 %**

Market Return

82 of the companies go public during bull markets, see Table 5.6. Due to less adverse selection, it is less costly to go public in bull markets (Leite, 2007). Thus, most companies go public when market returns are positive. The probability of short-term underpricing is higher when going public in bull markets, which is in accordance with previous research (Bakke et. al., 2010). Average underpricing is 1.75% for the companies going public in bull markets, while it is 0.85% for the companies going public in bear markets, see Table 5.6. The difference in underpricing is, however, insignificant. After six months of trading, average abnormal returns are negative for companies going public in both bull and bear markets. The average return is -10.94% for public offerings in bull market and statistically significant at a 1% level. Offerings in bull markets are more overpriced than offerings in bear markets. The difference in average returns is, however, insignificant.

Volatility

Most companies go public in low volatility markets, when investors are more open to new issues. IPOs are more underpriced in low volatility markets than in high volatility markets, see Table 5.6. When the VIX index is below 20, the average abnormal return after one-day of trading is 1.62%, while it is 1.24% when the index is above 20. The difference in average return is insignificant when expected volatility is low and high. After six months of trading, the average abnormal return is negative in both low and high volatility markets. Average returns are lower for the companies going public when the VIX index is above 20.

Underwriter Reputation

Companies listed by prestigious underwriters outperform the companies listed with less reputable underwriters in the short run, see Table 5.6. The difference in average underpricing between them is 2.75%. This difference is significant at a 10% significance level. Thus, using a more reputable underwriter leads to higher underpricing. In the long run, companies using more reputable underwriters also outperform the companies using less reputable underwriters, see Table 5.6. The average returns are negative regardless of the underwriters' prestige. However, the difference in average long-run returns is 13.03% and statistically significant at a 5% level.

Age of Firm at Listing

The difference in underpricing between young and old companies is 2.76%, see Table 5.6. Higher underpricing of younger companies is in accordance with previous research as younger companies are riskier and harder to value (Dietrich, 2012). Young companies also outperform older companies in the long run. The difference in six-month performance is 2.09%, and contradicts previous research (Ritter, 1991). None of the differences in average returns are significant. Only 25 of the companies are young, and this low number of young companies makes the difference in average returns insignificant.

Pricing Mechanism

After one day of trading, the average abnormal return is higher for fixed price offerings than bookbuilt, see Table 5.6. This is consistent with previous research; bookbuilding leads to more accurate pricing of offerings and hence less underpricing (Ritter, 2003). In the long run, the bookbuilt offerings outperform the fixed price offerings. The differences in average returns are 1.64% in the short run and 3.06% in the long run. Both are, however, insignificant.

5.1.6 Robustness

We use the Wilcoxon Rank Sum test to evaluate the robustness of the results. The nonparametric test for the difference between averages in the energy sector and the other sectors, are all insignificant, see Table 5.7. This is almost consistent with our results applying Welch's t-test. According to Welch's t-test, there is a difference in long-term performance during the financial crisis between the energy sector and other sectors. The number of IPOs during the financial crisis is, however, only 9. Accordingly, this number is too low to deem the t-test valid.

Table 5.7 – Robustness Assessment Sectors Using Wilcoxon Rank Sum Test

The table compares abnormal returns of the energy sector and other sectors using the nonparametric Wilcoxon Rank Sum Test.

	2006-2015		2006-2007		2008-2009		2010-2013		2014-2015	
Energy vs. Other	**z-stat**	**P-value**	**z-stat**	**P-value**	**z-stat**	**P-value**	**z-stat**	**P-value**	**z-stat**	**P-value**
Underpricing	1.455	14.55 %	1.147	25.12 %	0.49	62.42 %	0.206	83.65 %	1.206	22.78 %
Aftermarket Performance	0.145	88.48 %	0.715	47.48 %	1.47	14.16 %	0.495	62.03 %	0.201	84.07 %

According to the Wilcoxon Rank Sum test, there is a difference in underpricing between young and old companies. This contradicts Welch's t-test, which only claims a difference in underpricing between companies using prestigious and non-prestigious underwriters. There are significant differences in the long run between small and large offers, and companies using prestigious underwriters and not, see Table 5.8. This difference is consistent with the results using Welch's t-test. The nonparametric test also verifies the difference in average return between small and large issues in the long run.

Table 5.8 – Robustness Assessment Proxy and Control Variables Using Wilcoxon Rank Sum Test

The table compares abnormal returns of the different proxy and control variables using the nonparametric Wilcoxon Rank Sum Test.

	Underpricing		**Aftermarket Performance**	
	z-stat	**P-value**	**z-stat**	**P-value**
Small = Large	0.952	34.11 %	3.121***	0.18 %
Bull = Bear	0.618	53.67 %	1.133	25.74 %
VIX>20 = VIX<20	0.092	92.64 %	0.105	91.66 %
Prestigious = Nonprestigious	1.201	22.99 %	2.217**	2.66 %
Young = Old	1.958*	5.03 %	0.367	71.39 %
Bookbuilding = Fixed Price	0.367	71.39 %	0.000	100.00 %

5.2 Multivariate Analysis – OLS

The multivariate analysis isolates the different variables' effect on underpricing and aftermarket performance. The regression models consist of proxy and control variables to avoid omitted variables. We also test them for functional form misspecification, heteroscedasticity, multicollinearity and normality of residuals, see Appendices 8.3.3, 8.3.5 & 8.3.6. Based on these tests, the two final regressions are the most fitted ones. The final regression models have the same independent, proxy and control variables, but different dependent variables. Due to the limited number of observations, we allow ourselves to check the significance down to an 85% level for our regressions.

5.2.1 Presentation of Variables

Variable	
2006-2007, 2008-2009, 2014-2015	Represent period dummy variables. Hence, 2010-2013 represents the reference category
Energy	Dummy variable, equal to one if the company is within the energy sector, zero otherwise
High-tech	Dummy variable, equal to one if the company belongs to GICS sectors `Information technology` or `Telecommunication Services`
Offer size	Log offer size
Market return	Log market returns 60 trading days prior to listing
Highvol	Dummy variable; equal to one if the VIX index prior to listing is above 20, zero otherwise
Prestu	Dummy variable; equal to one if a "prestigious" underwriter is used, zero otherwise
Bookb	Dummy variable; equal to one if the offer is priced using bookbuilding, zero otherwise
Young	Dummy variable; equal to one if the company listed is three years or younger, zero otherwise

5.2.2 Regressions

Table 5.9 – Multivariate Regressions Underpricing

The table below reports the coefficients and corresponding standard error (in parenthesis) from the regressions. The regressions are run with log returns (adjusted for market returns) after first-day of trading as the dependent variable, and variables assumed to affect abnormal returns as independent variables. The regressions do not suffer from heteroscedasticity.

VARIABLES	**Regression 1** Underpricing	**Regression 2** Underpricing	**Regression 3** Underpricing	**Regression 4** Underpricing	**Regression 9** Underpricing
Energy	0.0244* (0.0166)	0.0223 (0.0170)	0.0186 (0.0175)	0.0162 (0.0175)	0.0147 (0.0175)
High-tech	0.0023 (0.0267)	0.0050 (0.0269)	0.0126 (0.0280)	0.0116 (0.0272)	0.0107 (0.0273)
2006-2007		0.0268 (0.0186)	0.0254 (0.0187)	0.0253 (0.0186)	0.0156 (0.0194)
2008-2009		0.0103 (0.0313)	0.0169 (0.0320)	0.0212 (0.0321)	-0.0140 (0.0352)
2014-2015		0.0023 (0.0234)	0.0013 (0.0234)	-0.001 (0.0234)	0.0038 (0.0243)
Osize			0.0167 (0.0172)		

Lnsize				0.0087 (0.0063)	0.0106* (0.007)
Lnmreturn					0.231*** (0.110)
Highvol					0.0096 (0.0206)
Prestu					0.0135 (0.0175)
Young					0.0250 (0.0197)
Bookb					-0.0307* (0.0204)
Constant	0.0064 (0.0103)	-0.0068 (0.0165)	-0.0150 (0.0186)	-0.126 (0.0883)	-0.147* (0.0928)
F-value	F(2,110) = 1.12 Prob>F = 0.33	F(5,107) = 0.96 Prob>F = 0.44	F(6,106) = 0.96 Prob>F = 0.46	F(6,106) = 1.13 Prob>F = 0.35	F(11,101) = 1.54 Prob>F = 0.13
Observations	113	113	113	113	113
R-squared	0.020	0.043	0.052	0.060	0.144
Adj. R^2	0.0021	-0.0016	-0.0021	0.0068	0.0504

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

Table 5.10 – Multivariate Regressions Aftermarket Performance

The table below reports the coefficients and corresponding standard error (in parenthesis) from the regressions. The regressions are run with log returns (adjusted for market returns) after six month of trading as the dependent variable, and variables assumed to affect abnormal returns as independent variables. The regressions do not suffer from heteroscedasticity.

VARIABLES	**Regression 10** Aftermarket Performance	**Regression 11** Aftermarket Performance	**Regression 12** Aftermarket Performance	**Regression 13** Aftermarket Performance	**Regression 18** Aftermarket Performance	**Regression 19** Aftermarket Performance
Energy	-0.0581 (0.0662)	-0.0538 (0.0675)	-0.0958 (0.0670)	-0.107* (0.0671)	-0.109* (0.0692)	-0.109* (0.0681)
High-tech	-0.210** (0.106)	-0.219*** (0.106)	-0.134 (0.107)	-0.162* (0.104)	-0.160* (0.108)	-0.159* (0.107)
2006-2007		0.0330 (0.0737)	0.0164 (0.0716)	0.0198 (0.0710)	-0.00742 (0.0768)	-0.00684 (0.0748)
2008-2009		-0.193* (0.124)	-0.118 (0.123)	-0.0984 (0.123)	-0.154 (0.140)	-0.155 (0.131)
2014-2015		-0.0366 (0.0926)	-0.0481 (0.0897)	-0.0647 (0.0895)	-0.0696 (0.0963)	-0.0686 (0.0919)
Osize			0.188**** (0.0658)			
Lnsize				0.0752**** (0.0242)	0.0758**** (0.0279)	0.0758**** (0.0277)
Lnmreturn					0.229 (0.436)	0.234 (0.418)
Highvol					-0.00300	

					(0.0819)	
Prestu					0.0488 (0.0695)	0.0492 (0.0683)
Young					0.0541 (0.0780)	0.0534 (0.0753)
Bookb					-0.0653 (0.0810)	-0.0652 (0.0805)
Constant	-0.0412 (0.0410)	-0.0349 (0.0655)	-0.128** (0.0713)	-1.067**** (0.338)	-1.051**** (0.368)	-1.052**** (0.365)
F-value	F(2,110) = 2.05 Prob>F = 0.134	F(5,107) = 1.61 Prob>F = 0.163	F(6,106) = 2.79 Prob>F = 0.015	F(6,106) = 3.07 Prob>F = 0.008	F(11,101)=1.82 Prob>F = 0.060	F(10,102)=2.02 Prob>F= 0.039
Observations	113	113	113	113	113	113
R-squared	0.036	0.070	0.136	0.148	0.165	0.165
Adjusted R^2	0.0184	0.0265	0.0876	0.0996	0.0745	0.0835

5.2.3 Sector Specific Conditions

Underpricing

Underpricing increases by 2.44% if the company listed is within the energy sector, see regression 1 Table 5.9. The relatively high level of ex-ante uncertainty in the energy sector may explain this higher underpricing. Activities in many of these companies relate to oil and gas, and they are therefore highly dependent on the price of oil and gas. Since we cannot predict future commodity prices, these companies are hard to value. Consequently, commodity companies are associated with great uncertainty and investors require greater abnormal returns for subscribing to them. The increase in underpricing for energy companies is significant at a 15% significance level.

We include a dummy variable for companies within “high-tech” to control for their high level of ex-ante uncertainty and asymmetric information (Bakke et al., 2010). The variable is equal to one if a company belongs to the GICS sectors information technology or telecommunication services. Underpricing increases by 0.22% if a company is high-tech. This increase in underpricing is lower than the increase for energy and other companies (the intercept). The lower coefficient contradicts previous research, which finds high-tech companies more underpriced than companies within other sectors. The coefficient is, however, insignificant.

By including dummies for the samples’ different time periods, the coefficient for the energy sector decreases to 2.23% and becomes insignificant, see regression 2 Table 5.9. The period of listing can explain some of the difference in underpricing. However, none of the time dummies have significant impact on underpricing.

Controlling for offer size decreases the coefficient of the energy dummy to 1.62%, see regression 4 table 5.9. Consequently, the size of the offer can explain some of the underpricing in regression 1 for the energy dummy. Underpricing increases in the size of the issue, but does not have a significant impact on underpricing in regression 4.

Underpricing within the energy sector decreases further when controlling for market return prior to listing, see regression 5 Appendix 8.3.9. In the final regression (regression 9, Table 5.9), underpricing increases by 1.47% if the company is within the energy sector, ceteris paribus. The coefficient is insignificant. Consequently, energy companies are not more underpriced than companies in other sectors (excluding high-tech). This indicates that the energy companies are not relatively higher priced in the secondary market the first day compared to other companies. Hence, investors subscribing to IPOs in the energy sector do not receive significantly higher returns after one day of trading than IPOs in other sectors. On the contrary, Samuelsen and Tveter (2006) find oil-related companies to be more underpriced than other companies in Norway between 2004-2005. Since there is no difference in underpricing between energy companies and other companies from 2006-2015, investors might be less optimistic about the future and value of energy companies during this period compared to 2004-2005.

Aftermarket Performance

Returns after six months of trading decrease by 5.81% if the company listed is within the energy sector, see regression 10 Table 5.10. High-tech companies perform worse than energy companies, and returns decrease by 21% for high-tech firms. The dummy for high-tech companies is significant at a 10% level. Other companies (the intercept) are less overpriced in the long run compared to energy companies and high-tech companies. This is consistent with previous research (Ritter, 1991).

The coefficient of the energy dummy does not change considerably when including time dummies in the regression. Thus, the different time periods do not explain much of the overpricing in the energy sector. However, there are only 5 energy companies going public during the financial crisis and 3 companies going public during the oil price downturn the last two years. Since the number of energy IPOs is low during these two periods, we are likely to not have any statistical impact on long-run abnormal returns in the energy sector.

By controlling for offer size, the coefficient of the energy dummy decreases by almost 5%, see regression 13 Table 5.10. The coefficient decreases to -10.7% for the energy dummy, and it becomes significant at a 15% level. Hence, offerings in the energy sector tend to be large as abnormal returns drop when controlling for size. Larger issues are less overpriced in the long run. Thus, the size of the offer can explain the less negative coefficient for the energy sector in regression 10. A 1% increase in offer size increases six-months returns by 7.56%, ceteris paribus.

The energy dummy does not change much when controlling for other variables. If the company listed is an energy company, it decreases abnormal returns by 10.90% in the final regression, see regression 19 Table 5.10. In the long run, energy companies are more overpriced than companies in other sectors (excluding high-tech), however, only at 15% significance level. Consequently, investors subscribing to issues in the energy sector will have lower abnormal returns after six months of trading than if they subscribe to issues in other sectors. There is higher ex-ante uncertainty for commodity dependent companies. Lower oil prices may therefore explain the difference in abnormal returns in the long run, and thus worsen future prospects for the energy companies compared to other companies, see Appendix 8.4. Consequently, there might be a higher need of correcting the valuations when new information is revealed for the energy companies, which leads to lower abnormal returns. We do, however, not include a variable capturing the oil price in our regression. Thus, we cannot say with certainty that lower oil prices explain the difference in abnormal returns in the long run.

5.2.4 Time Specific Market Conditions

Underpricing decreases by 1.4% for IPOs during the financial crisis, see regression 5 Table 5.10. The cyclicality in IPO activities, and the hot and cold markets, may explain the decrease in underpricing (Ibbotson & Jaffe, 1975). If the IPO is between 2014 and 2015, it increases underpricing less than if the company is listed pre-financial crisis. Low investor sentiment during the financial crisis and the oil price downturn the last two years may explain this. If the general market conditions are worsening, investors may refrain from subscribing to new issues, and thus lowering underpricing. In the long run, abnormal returns decrease more if the IPO is during the financial crisis than in other periods. Nevertheless, none of the time specific dummies are significant.

5.2.5 Size

Underpricing is increasing in the size of the issue, ceteris paribus. A 1% increase in the size of the issue increases underpricing by 1.06%, see regression 9 Table 5.9. Hence, the larger the issues are, the higher the underpricing. The fact that large issues outperform small issues contradicts previous research (Yong, 2011). According to the winner's curse hypothesis, informed investors do not participate in less solid issues, thus only uninformed optimistic investors tend to subscribe to small issues. These optimistic investors overvalue the price of the stock, which leads to higher positive abnormal returns for small issues. On the contrary, larger companies signaling their strength can explain increasing underpricing in issue size. The large companies may intentionally price their stock in the lower price range in order to prove their quality and strength, and thus raise capital on better terms later.

Abnormal returns are also increasing in the size of the issue after six months of trading. A 1% increase in the offer size increases returns by 7.58%, see regression 19 Table 5.10. It is easier to value large companies, and thus there is less ex-ante uncertainty related to these companies. The offer price of large issues is therefore likely to represent almost all information available regarding the company. Hence, the need of correcting the valuation of the offer decreases when more information is revealed in the aftermarket. Furthermore, institutional investors often face restrictions regarding the size of the companies to invest in (Ngao, 2012). These restrictions lead to a greater share of informed investors in large companies, which may explain some of the large companies' outperformance of the small.

5.2.6 Proxy and Control Variables

Market Return

Market return prior to listing is significant at a 5% significance level. A 1% increase in average market return prior to listing, increases underpricing by 23.1%, see regression 9 Table 5.9. The coefficient makes sense economically; higher market returns lead to higher underpricing. Underwriters do not fully adjust the offer price to public information, which leads to higher underpricing when markets return are positive (Hanley, 1993). Furthermore, the demand among investors is likely to increase when market returns are high due to investor sentiment.

Market return prior to listing increases abnormal return after six months of trading. This increase in abnormal returns somehow contradicts the window of opportunities hypothesis (Ritter, 1991). When market returns are high, investors are optimistic and overvalue the companies' going public. During periods with high market returns, IPO volumes are normally high. According to Ritter (1991), periods with high IPO volume experience poorer long-run performance as the optimistic overvaluation is corrected for. The coefficient is insignificant, which makes sense as positive public information prior to listing may have less impact on long-run performance.

Volatility

IPOs in high volatility market outperform offerings in low volatility markets by 0.96%, ceteris paribus, see regression 9 Table 5.9. This contradicts our findings in the univariate analysis, where companies going public in low volatility markets are more underpriced. In high volatility markets, investors are less receptive to new issues. Issues may therefore be priced lower in order to attract investors, which lead to higher underpricing. The coefficient is, however, insignificant. As market volatility is a proxy for how open investors are to new issues and does not impact abnormal returns in the long run, we do not control for it in the final regression, see Regressions 18 and 19 Table 5.10. The F-test of joint significance confirms this, see Appendix 8.3.4. It makes sense that expected volatility before listing do not impact returns after six months of trading.

Certification by Prestigious Underwriter

Companies taken public by prestigious underwriters are more underpriced than those taken public by less reputable underwriters, see regression 9 Table 5.10. Underpricing increases by 1.35% if using prestigious underwriters. This difference in underpricing contradicts previous research, which find a negative relationship between the use of prestigious underwriters and underpricing (Carter et al., 1998). These results may be due to self-selection by the issuing companies. Companies that expect their stock to be underpriced might choose more reputable underwriters as they anticipate them to reduce expected underpricing. If the underwriters are only able to improve pricing and demand partly, it still leads to positive abnormal returns.

In the long run, a more reputable underwriter leads to higher abnormal returns. Offerings by prestigious underwriters increases return by 4.92%, see regression 19 Table 5.10. This is consistent with previous research (Carter et al., 1998). Prestigious underwriters are incentivized to reflect relevant information regarding the issuing firm, thus there is less adverse information in the time after the issue.

Furthermore, analyst coverage can explain some of the difference in abnormal returns by more reputable underwriters (Loughran & Ritter, 2004). Many issuers care more about analyst coverage than underpricing, and they often "purchase analyst coverage" when choosing underwriters. Thus, higher average abnormal returns can be due to high coverage by well-known analysts. Both coefficients are, however, insignificant.

Age of Firm at Listing

Younger companies outperform older companies after first-day of trading. Underpricing increases by 2.5% if the company listed is younger than 4 years old, see regression 5 Table 8.8. This is in line with previous research (Dietrich, 2012). Younger companies are more risky and harder to value than older companies, and hence underpricing is higher. Moreover, younger companies outperform older companies after six months of trading. Abnormal returns increases by 5.34% if the company listed is young. This result contradicts previous research, which argues that young growth firms tend to underperform in the long run as investors adjust to overoptimistic initial valuation as information is revealed (Miller, 1977).

IPO Pricing Mechanism

IPOs priced through bookbuilding are less underpriced than fixed price IPOs. If the company is bookbuilt, it decreases underpricing by 3.07%, see regression 9 Table 5.9. Bookbuilding leads to more accurate pricing of the offer, and hence less underpricing (Jenkinson & Ljungqvist, 2001). The coefficient is significant at a 15% level. By controlling for pricing mechanism, the coefficient of the offer size increases and becomes significant at a 15% level. Larger issues normally use bookbuilding, and there is a correlation between the two variables, see Appendix 8.3.8. The variable is therefore necessary to avoid omitted variable bias.

Bookbuilt IPOs also underperform fixed price IPOs in the long run. If the IPO is bookbuilt, six-months return decreases by 6.52%. It makes more sense if bookbuilt offerings outperform fixed price offerings in the long run as bookbuilding leads to more accurate pricing (Draho, 2004). The coefficient of the bookbuilding dummy is insignificant in the long run.

5.2.7 Intercept

The intercept in regression 9 is the expected underpricing for IPOs when all dummy variables are equal to zero. This involves old companies in all sectors, except high-tech and energy, offered through fixed price between 2010-2013 by less reputable underwriters and in low volatility markets. The intercept is -0.147, which means that companies with these characteristics are less underpriced. The coefficient is significant at a 15% level. There are only two companies with these characteristics. Hence, there is great uncertainty in calculation of the intercept, and thus it should not be emphasized. In the long run, we exclude volatility from the intercept. The intercept after six-months of trading is -1.052, and significant at a 1% significance level.

6. Limitations and Further Analysis

The main problem is the limited number of data points. The final sample after trimming includes 113 initial public offerings, which is only seen as an adequate number when doing multiple regressions (Morgan & Van Voorhis, 2007). We do not get many significant results in our regression analysis. To improve the analysis, we are in need of a larger dataset. Using a greater time period can solve this.

Another limitation of our analysis is the measure of long-run performance. We measure long-run performance over a window of 120 days. In contrast, other studies focus on performance over a window of three years (Ritter (1991), Loughran et al., (1994)). Using similar windows will decrease the sample size as this information is not available for IPOs in 2014 and 2015. Furthermore, we only adjust for the OSEBX index. A more accurate method is to compare the long-run aftermarket performance with a control group of non-issuing firms (matched by market capitalization).

For a more accurate and in-depth analysis, more variables can be included to control for their impact on IPO performance. It can be interesting to see how differences in profitability and growth impact abnormal returns in public offerings. Moreover, previous studies investigate how the final offer price relative to the indicative price range, and its impact on abnormal returns. Furthermore, a comparison of the development in abnormal returns between different countries can be interesting in order to check if the declining returns in Norway are country specific or not. For instance, to examine countries where the frequency of energy IPOs is as high as in Norway.

7. Conclusion

This thesis focuses on short- and long-term aftermarket performance of energy companies listed on the Oslo Stock Exchange between 2006-2015. Few of our variables of interest are significant in our econometric analysis, and thus we are not able to draw any clear conclusions. This is likely due to our limited sample size. However, our analysis provides following insight into the characteristics of the Norwegian IPO market the last ten years.

After one day of trading, the average market adjusted is positive. However, average first-day returns are decreasing over the sample period. After the financial crisis, there are more years with negative first-day returns than positive. If the probability of average negative returns is greater than positive returns, it may harm future IPOs in Norway. Uninformed investors may refrain of subscribing to new offerings if the expected returns are negative (Rock, 1986). As most IPOs are dependent on these investors to get full subscription, it makes it more difficult for companies to raise new capital by going public. However, we examine a relatively “cold” period, which may affect our results. As the IPO market is cyclical, IPOs may perform better in the future.

After six months of trading, average abnormal returns are negative. The negative returns are higher during the financial crisis compared to the other periods. Average abnormal returns in the long run decreases by -15.5% for IPOs during the financial crisis. Moreover, there is an increase in negative long-run returns post-financial crisis compared to the returns pre financial crisis. Long-run returns decreases by -0.68% for IPOs pre the financial crisis, while it decreases by -6.86% for IPOs in 2014 and 2015. The multivariate analysis does, however, not produce any significant results between abnormal returns for the different periods.

The average underpricing for IPOs in the energy sector is higher compared to the other sectors. Underpricing is 3.08% for energy companies, while it is only 0.67% for other companies. However, when testing for differences among companies listed in the energy sector and other sector (using both univariate and multivariate testing), we find no significant results. When controlling for more variables in the multivariate regressions, the abnormal returns in the energy sector decreases. Consequently, energy companies are not more underpriced than companies in other sectors (excluding high-tech). This indicates that energy companies are not relatively higher priced in the secondary market the first day compared to other companies.

Hence, investors subscribing to IPOs in the energy sector will not receive higher returns after one day of trading than IPOs in other sectors.

Energy companies are more overpriced after six months of trading than other companies in our sample. Average abnormal returns are -9.93% for energy companies, while it is -7.25% for other companies. During the financial crisis and the declining oil prices the last two years, energy companies perform worse. On the contrary, they perform better than other companies pre- and post- financial crisis. The differences in average returns are only significant during the financial crisis. However, due to few observations we cannot deem Welch's t-test valid. In our regression analysis, we find energy companies to be more overpriced when controlling for the size of the issue. By controlling for the size of the issues, abnormal returns in the energy sector decreases by 5.32% and becomes significant at 15% significance level. Hence, IPOs within the energy sector perform worse in the aftermarket. Consequently, investors subscribing to issues in the energy sector will have lower abnormal returns after six months of trading than if they subscribe to issues in other sectors (excluding high-tech). Higher ex-ante uncertainty for commodity dependent companies and a higher need of correcting the valuations when new information is revealed, may explain the underperformance in the aftermarket.

In addition, some of our control variables produce significant results. Increasing market returns prior to listing increases abnormal returns in the short run. Underpricing also increases in the size of the issue, whereas bookbuilt IPOs decreases underpricing. Offer size and bookbuilding are, however, only significant at a 15% level. In the long run, abnormal returns are increasing in offer size, while high-tech companies are more overpriced.

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8. Appendix

8.1 Distribution Characteristics

8.1.1 Untrimmed Sample

The figures below show the density distribution together with the normal distribution for the untrimmed sample, not using log returns. Both distributions indicate non-normality. The abnormal returns after first-day of trading are approximately symmetric, while abnormal returns after six-months are left-skewed. Furthermore, both distributions have a high degree of "peakedness".

Exhibit A: Underpricing

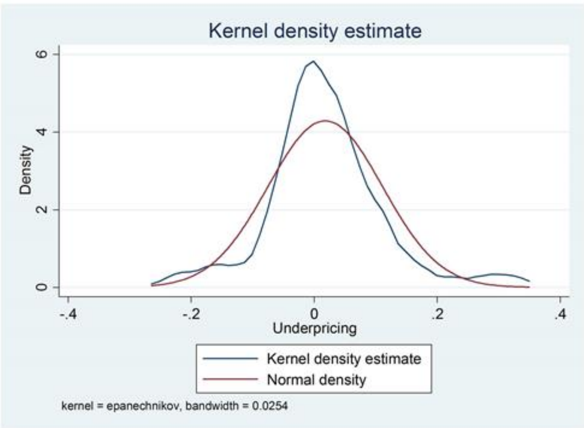
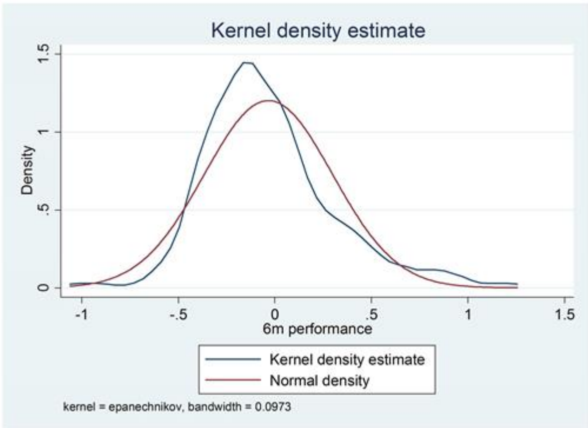


Exhibit B: Aftermarket Performance



Figures 8.1.1 & 8.1.2: Kernel Density Distribution & Normal Density Distribution Untrimmed Sample

Figures 8.2.1 and 8.2.2 depicts the box-plots of the untrimmed sample. The sample includes outliers for both abnormal returns after first-day and six-months of trading. However, abnormal returns after six-months of trading have more severe outliers than after one-day of trading.

Exhibit A: Underpricing

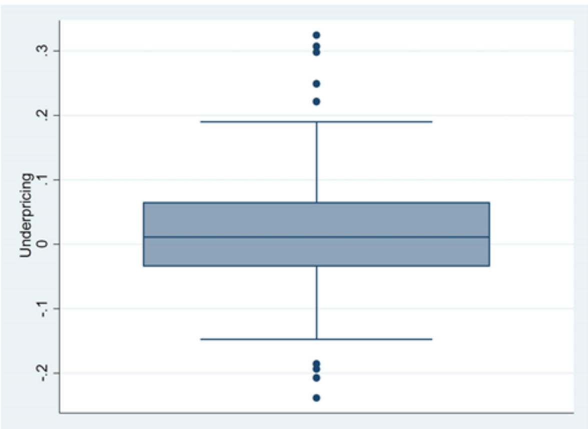
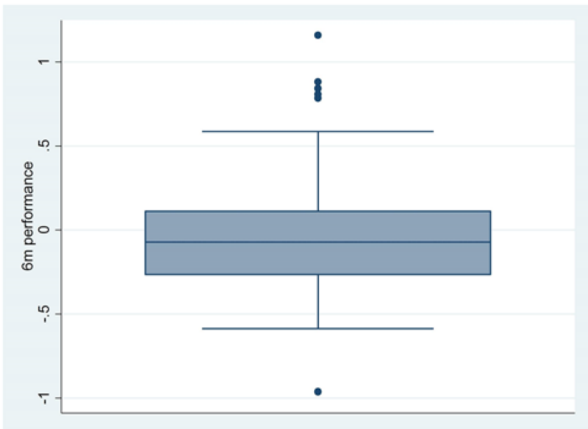


Exhibit B: Aftermarket Performance

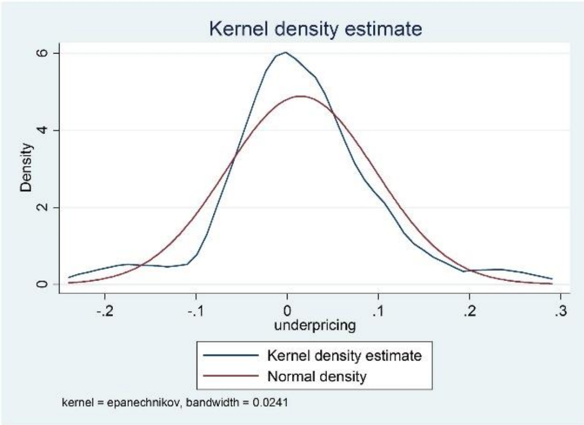


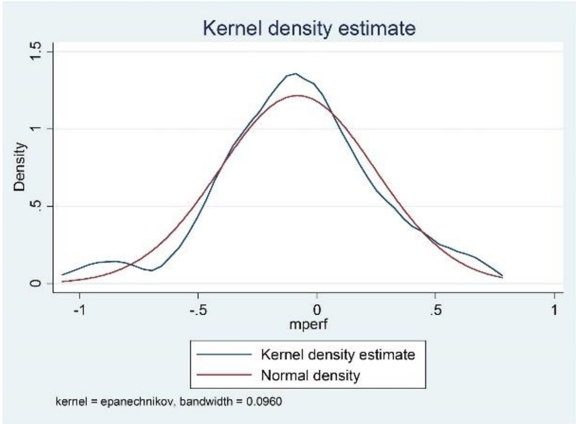
Figures 8.2.1 & 8.2.2: Box-plots Untrimmed Sample

8.1.2 Trimmed Sample

The figures below depict the Kernel Density distribution together with the normal distribution for the trimmed sample. Figure 8.3.1 indicates non-normality of the abnormal returns (log returns) after first-first day of trading, while figure 8.3.2 indicates normality of the abnormal returns (log returns) after six-months of trading. By using log return, the skewness of the six-month abnormal returns reduces. Furthermore, the peakedness of both distributions decreases.

Exhibit A: Underpricing **Exhibit B: Aftermarket Performance**





Figures 8.3.1 & 8.3.2: Kernel Density Distribution & Normal Density Distribution Trimmed Sample (Log Returns)

The Shapiro-Wilk test for the trimmed sample confirms that the abnormal returns after first-day of trading is normally distributed, while the abnormal returns after six-months of trading is normally distributed, see Table 8.1.

Table 8.1 – Shapiro-Wilk Test for Normal Data Trimmed Sample

The table depicts the Shapiro-Wilk test for normal data for the trimmed sample. The null hypothesis of the test is that the data is normally distributed. The values reported under W are the test statistics, which is tested using a z-test. V is another index for detecting normality, and V equal to 1 indicates normality, while large values indicate non-normality.

Variable	# of IPOs	W	V	z	Prob>z
Underpricing	113	0.9634	3.344	2.696	0.35 %
Aftermarket Performance	113	0.9822	1.632	1.093	13.71 %

The box-plots below, Figures 8.4.1 & 8.4.2, illustrates that by trimming the sample and using log returns, we have gotten rid of the most severe outliers which may have great impacts on the result.

Exhibit A: Underpricing

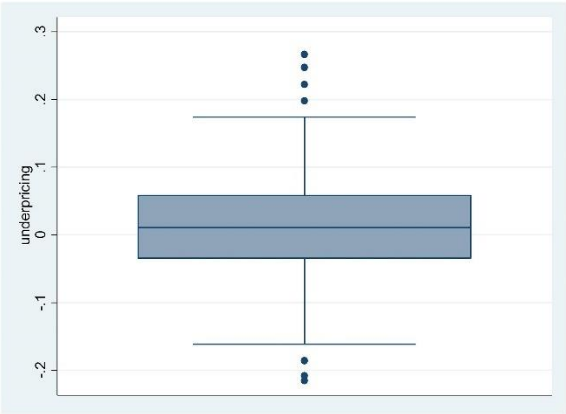
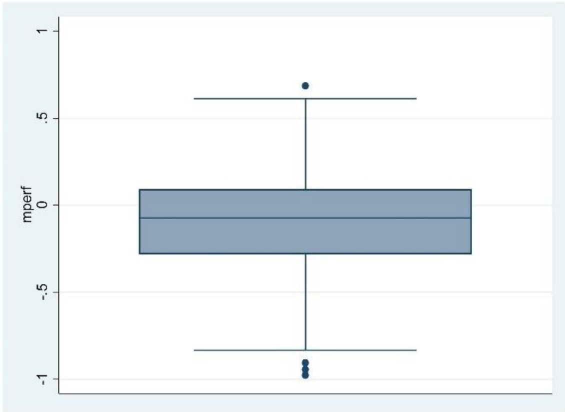


Exhibit B: Aftermarket Performance



Figures 8.4.1 & 8.4.2: Box-plots Trimmed Sample (Log Returns)

Table 8.2 summarizes key distribution characteristics for the independent variables.

Table 8.2 – Distribution Characteristics of Abnormal Returns Independent Variables

The table summarizes key characteristics of the distribution of abnormal returns. Skewness measures whether the returns are symmetrically distributed to left and right of the mean. If the skewness is between -0.5 and 0.5, the distribution is approximately symmetric. Kurtosis measures the thickness of the tails of the distribution, and the kurtosis of the normal distribution is 3.

		Mean	Median	Min	Max	Std.	Skewness	Kurtosis
Energy	UP	3.08 %	1.79 %	-13.76 %	26.64 %	7.63 %	1.04	5.32
	AP	-9.93%	-5.32 %	-97.76 %	61.23 %	37.74 %	-0.36	2.98
Other	UP	0.67 %	0.36 %	-21.53 %	22.21 %	8.38 %	-0.14	3.82
	AP	-7.25%	-8.39 %	-90.70 %	68.56 %	30.14 %	0.09	3.57
Small	UP	0.35 %	0.89 %	-21.53 %	26.64 %	9.38 %	0.00	4.12
	AP	-19.44 %	-16.09 %	-97.76 %	57.88 %	31.43 %	-0.49	3.65
Large	UP	2.46 %	1.31 %	-11.48 %	24.72 %	6.97 %	0.79	2.80
	AP	1.09 %	1.16 %	-83.40 %	68.56 %	31.22 %	0.08	2.80
Bull	UP	1.75 %	1.14 %	-21.53 %	24.72 %	7.98 %	0.03	4.53
	AP	-10.94 %	-9.59 %	-97.76 %	61.23 %	31.98 %	-0.37	3.56
Bear	UP	0.85 %	1.05 %	-18.58 %	26.64 %	8.76 %	0.44	4.36
	AP	-0.87 %	-5.25 %	-79.29 %	68.56 %	34.41 %	0.18	2.78
VIX>20	UP	1.24 %	1.72 %	-18.58 %	22.21 %	7.98 %	0.04	3.82
	AP	-10.72 %	-8.41 %	-97.76 %	68.56 %	40.98 %	-0.28	2.76
VIX<20	UP	1.62 %	0.42 %	-21.53 %	26.64 %	8.31 %	0.19	4.67
	AP	-6.98 %	-7.49 %	-90.70 %	61.23 %	28.45 %	0.15	3.40
Prestigious	UP	2.92 %	1.95 %	-11.48 %	26.64 %	7.84 %	0.94	4.00
	AP	-1.48 %	-0.82 %	-97.76 %	68.56 %	32.09 %	-0.32	3.87
Non-prestigious	UP	0.16 %	0.53 %	-21.53 %	22.21 %	8.32 %	-0.41	4.14
	AP	-14.52 %	-13.01 %	-94.52 %	57.88 %	32.50 %	-0.03	3.34
Young	UP	3.65 %	2.97 %	-8.35 %	22.21 %	6.26 %	0.98	4.85
	AP	-6.55 %	-9.89 %	-94.52 %	68.56 %	37.50 %	-0.24	3.27
Old	UP	0.89 %	0.31 %	-21.53 %	26.64 %	8.57 %	0.16	4.23
	AP	-8.64 %	-6.79 %	-97.76 %	61.23 %	31.58 %	-0.14	3.44
Bookbuilding	UP	1.14 %	0.82 %	-21.53 %	22.21 %	7.77 %	-0.21	4.09

	AP	-7.50 %	-7.17 %	-94.52 %	68.56 %	28.96 %	0.13	3.34
Fixed Price	UP	2.78 %	1.59 %	-18.58 %	26.64 %	9.54 %	0.73	4.27
	AP	-10.55 %	-9.73 %	-97.76 %	61.23 %	44.48 %	-0.35	2.56

8.2 Ranking of Underwriters

We distinguish between "prestigious" underwriters and not, by we developing a ranking procedure based on the Norwegian underwriter ranking by TNS Sifo and the international underwriter ranking by Dealogic and the Wall Street Journal. If an underwriter's ranking is among top three in Norway, or top 10 internationally in the year of the given IPO, we label the underwriter as prestigious.

8.3 Multivariate Testing

8.3.1 The Assumptions of the OLS-model

For the OLS-model to provide unbiased estimates, several assumptions need to be fulfilled. The first five assumptions constitute the Gauss-Markow theorem. The first four establish the unbiasedness of the OLS, whereas the fifth is added to derive the usual variance formulas and to conclude that the OLS is the best linear unbiased estimator (BLUE).

Assumption 1: Linear in Parameters

The population is linear in parameters, which means that the dependent variable is related to the independent variables and the error term

$$y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} + u_i$$

where x_i is the independent variables, $\beta_0, \dots, \beta_k$ are $k + 1$ unknown population parameters, and u is an unobserved random error term.

Assumption 2: Random Sampling

The sample is random with observation, $\{(x_{i1}, x_{i2} \dots, x_{ik,} y_i): i = 1, 2, \dots, n\}$, and each unit from the underlying population has equal probability of being in the sample. This can often be assumed with cross-sectional data.

Assumption 3: No Perfect Collinearity

In the sample (and therefore in the population), none of the independent variables are constant, $\{x_i,\ i = 1, 2, \ldots, n\}$, and there is no exact linear relationship among the independent variables (no perfect collinearity). It is hard to figure out how a change in the independent variable may affect the dependent variable without any variation in the independent variable. This does however not require all values of the independent variables to be different.

Assumption 4: Zero Conditional Mean

The expected value of the error term is the same for all possible values of the independent variables, which means that the error term is mean independent of the independent variables, $E(u|x_1, x_2, \ldots, x_k) = 0$. Assumption 4 is crucial for a causal interpretation of the OLS-model.

Assumption 5: Homoscedasticity

The variance of the error term is the same given any value of the explanatory variable, which can be stated as:

$$Var\big(u|x_{1,}x_2, \ldots, x_k\big) = \sigma^2, which\ implies: Var(y|x_1, x_2, \ldots, x_k) = \sigma^2$$

If assumption 5 does not hold, and $Var\big(u|x_{1,}x_2, \ldots, x_k\big)$ depends on x, the error term is said to exhibit heteroscedasticity.

The Gauss-Markov theorem, assumptions 1-5, states that the population parameters are the best linear unbiased estimators (BLUE). However, one additional assumption is required to be able to draw statistical inference.

Assumption 6: Normality

The population error term is independent of the explanatory variables $x_{1,}x_2, \ldots, x_k$, and normally distributed with mean zero and variance σ^2. The error term is "i.i.d", which means that it is independently and identically distributed.

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

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

Assumption 6 is stronger than assumption 4 and 5 combined as it also requires normal distribution. The assumption can however be dropped if the sample size is reasonably large as the central limit theorem holds.

8.3.2 Interpretation of Coefficients

Interpretation of the Constant Term

The constant term β_0 equals the value of the dependent variable y when the independent variables x_i equals zero. If the independent variables never take the value of zero in the population, the constant term is of no interest. The constant term is usually of no interest, but if an independent variable is a dummy variable, the interpretation of the constant term is clear.

Interpretation of Slope Parameters

Assumption 1 of the OLS model requires the population to be linear in parameters. However, it is easy to incorporate nonlinearities regression analysis by redefining the dependent and independent variables. By redefining the variables into a logarithmic form, one is able to deal with nonlinearities that would otherwise make the estimation of the model useless for predication. The mechanics of the regression does not depend on how the dependent variable and independent variables are defined. The interpretation of the coefficients does however depend on their definitions.

The level-level model

$$y = \beta_0 + \beta_1 x_1 + u$$

a change in x_1 holding all other constant (ceteris paribus) gives:

$$\Delta y = \beta_1 \Delta x_1$$

In other words: a one-unit change in the independent variable x_1 gives rise to a $\beta_1$units change in the dependent variable y, ceteris paribus. The model is only sufficient if the dependent and independent variable has a linear relationship.

The log-level model

$$ln(y) = \beta_0 + \beta_1 x_1 + u$$

a ceteris paribus change in x_1 gives:

$$\%\Delta y = (100\beta_1)\Delta x_1$$

In other words: a one-unit change in x_1 gives rise to a $(100\beta_1)\%$ change in y.

The level-log model

$$y = \beta_0 + \beta_1 \ln(x_1) + u$$

a ceteris paribus change in x_1, everything else constant, gives:

$$\Delta y = \left(\frac{\beta_1}{100}\right) \%\Delta x_1$$

In other words: a one percent change in x_1 increases y with $\left(\frac{\beta_1}{100}\right)$ units.

The log-log model

$$\ln(y) = \beta_0 + \beta_1 \ln(x_1) + u$$

a change in x_1, everything else constant, gives:

$$\%\Delta y = \beta_1 \%\Delta x_1$$

In other words: a one percent change in x_1 gives rise to a β_1% change in y. This means that β_1 is the elasticity of y with respect to x_1.

8.3.3 Detecting Functional Form Misspecification

The table below shows the Davidson-Mackinnon test for the regressions where issue size is included as a dummy or in logarithmic form. None of the models are rejected. Thus, R^2 is used to choose between the two models. R^2 is highest for the regressions where issue size is in a logarithmic form, see Table 8.3. Consequently, issue size is in a logarithmic in the rest of the regressions.

Table 8.3 – Davidson Mackinnon Test (Regressions 4, 5, 12 and 13)

The table below shows the Davidson-Mackinnon test used to test two non-nested models with the same dependent variables against each other. For example, testing whether an explanatory variable should be in level or a logarithmic form. If the first model is the correct one, then the fitted value $\hat{y}$ from the second model should not be significant in model one.

Regression	F-value	P-value
4	0.94	33.32 %
5	0.01	91.29 %
12	2.02	15.87 %
13	0.6	43.85 %

8.3.4 The F-test of Joint Significance

The control variables' joint significance is tested by applying the F-test, see Table 8.4. Volatility is dropped in the final regression model for long-term performance as it does not impact abnormal returns in the long run. By dropping volatility, the control variables go from being jointly insignificant to jointly significant (regression 18 and 19 below).

Table 8.4 – F-test of Joint Significance Control Variables (Regressions 9, 18 and 19)

The table below shows the F-test for the final regressions. The f-test involves the hypothesis that more than one population parameter is zero at the same time. It tests whether or not the independent variables have an effect on the dependent variable. If F is large, we want to reject the null hypothesis and we can say that the independent variables are jointly statistically significant at the appropriate level. If we cannot reject the null hypothesis, the variables jointly insignificant, which often justifies dropping them from the model.

Regression	F-value	P-value
9	1.98	7.58 %
18	1.92	8.41 %
19	2.33	4.77 %

8.3.5 Variance Inflation Factor

The Variance Inflation Factor (VIF) detect if the variables suffer from multicollinearity. The VIF-value is not a test, but an indicator of multicollinearity. It measures the degree of multicollinearity between the independent variables in a regression (O'Brien, 2007). According to several scholars, VIF-values above 10 indicate severe multicollinearity. None of the VIF-values exceeds 10, thus multicollinearity is not a problem in the regressions, see Table 8.5.

Table 8.5 – Variance Inflation Factor Independent Variables

The table shows the VIF index for the two final regressions, both regressions share the same VIF-values as they have the same independent variables.

Variable	VIF
2006-2007	1.66
2008-2009	1.62
2014-2015	1.59
Energy	1.23
High-tech	1.17
Lnsize	1.56
Lnmreturn	1.18
Highvol	1.65
Prestu	1.37
Young	1.19
Bookb	1.28
Mean VIF	**1.41**

8.3.6 Evaluating Homoscedasticity of the Residuals

Figures 8.5.1 & 8.5.2 shows the residuals plotted against the predicted values of y for the two regressions final regressions. There is no clear trend of the variance of the error terms against the predicted values of y, and therefore no indication of heteroscedasticity. The White's test confirms this, see Table 8.6. Hence, our OLS regressions are BLUE.

Exhibit A: Underpricing (Regression 9)

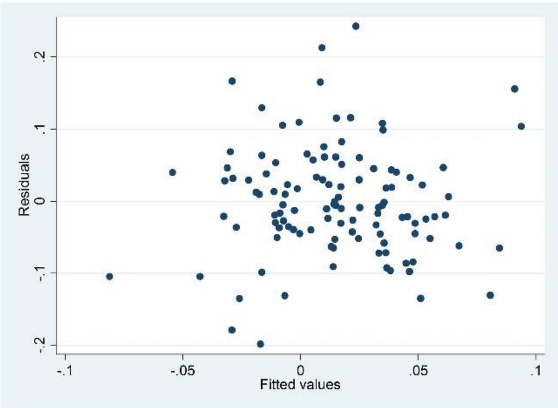
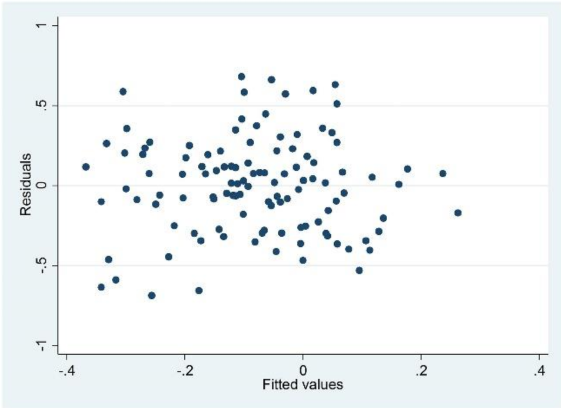


Exhibit B: Aftermarket Performance (Regression 19)



Figures 8.5.1 & 8.5.2: Residuals Plotted Against Fitted Values

Table 8.6 – White's Test of Homoscedasticity (Regression 9 and 19)

The table shows White's test of homoscedasticity for the two final regression models. To save degrees of freedom, we use the simplified White test to test for homoscedasticity in the residuals. The null hypothesis null hypothesis is that the error term in the regressions has a constant variance conditional on the independent variables, thus homoscedasticity is present. The alternative hypothesis is that the error term does not have a constant variance conditional on the independent variables, and thus exhibit heteroscedasticity. To test the null hypothesis, we can use a F-statistic.

Regression	F-value	P-value
9	1.25	29.19 %
19	0.57	56.60 %

8.3.7 Evaluating Normality of Residuals

Figures 8.6.1 & 8.6.2 shows the Kernel density estimates of the residuals together with the normal distribution. The residuals seem are normally distributed, which is confirmed by the Shapiro-Wilk test. Consequently, assumption 6 holds.

Exhibit A: Underpricing (Regression 9)

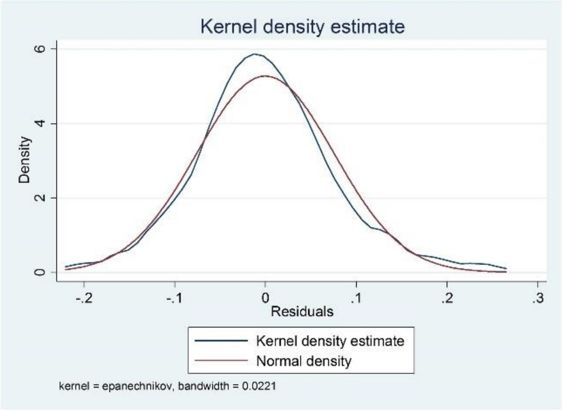
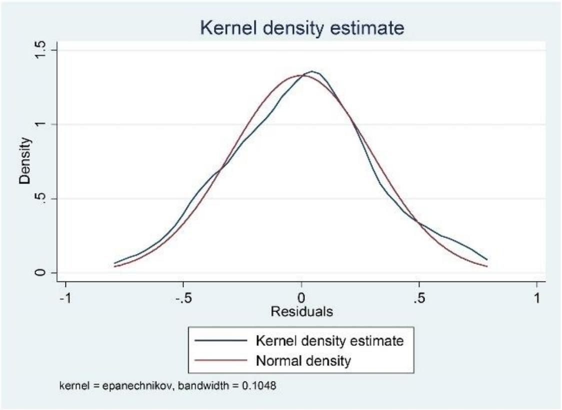


Exhibit B: Aftermarket Performance (Regression 19)



Figures 8.6.1 & 8.6.2: Kernel Density Distribution & Normal Distribution Residuals

8.3.8 Correlation Matrix

Table 8.7 – Correlation Matrix Independent Variables & Control Variables

The table depicts the correlation between the explanatory variables. Correlation of -1.00 is a perfectly negative relationship, while correlation of 1.00 is a perfectly positive relationship.

	Energy	High-tech	Offer Size	Mreturn	Prestu	Highvol	Young	Bookb
Energy	1.000							
High-tech	-0.238	1.000						
Offer Size	0.241	-0.199	1.000					
Mreturn	0.082	0.114	-0.062	1.000				
Prestu	0.075	-0.081	0.393	0.057	1.000			
Highvol	-0.017	-0.161	-0.145	-0.170	-0.248	1.000		
Young	0.106	-0.103	-0.097	0.145	-0.135	0.276	1.000	
Bookb	0.073	0.031	0.329	-0.009	-0.036	-0.139	0.027	1.000

8.3.9 Regression Output

Table 8.8 – Multivariate Regressions Underpricing

The table below reports the coefficients and corresponding standard error (in parenthesis) from the regressions. The regressions are run with log returns (adjusted for market returns) after first-day of trading as the dependent variable, and variables assumed to affect abnormal returns as independent variables. The regressions do not suffer from heteroscedasticity.

VARIABLES	**Reg. 1** UP	**Reg. 2** UP	**Reg. 3** UP	**Reg. 4** UP	**Reg. 5** UP	**Reg. 6** UP	**Reg. 7** UP	**Reg. 8** UP	**Reg. 9** UP
Energy	0.0244 (0.0166)	0.0223 (0.0170)	0.0186 (0.0175)	0.0162 (0.0175)	0.0130 (0.0173)	0.0145 (0.0175)	0.0153 (0.0175)	0.0137 (0.0176)	0.0147 (0.0175)
High-tech	0.00228 (0.0267)	0.00502 (0.0269)	0.0126 (0.0280)	0.0116 (0.0272)	0.00248 (0.0270)	0.00514 (0.0273)	0.00587 (0.0274)	0.00794 (0.0274)	0.0107 (0.0273)
2006-2007		0.0268 (0.0186)	0.0254 (0.0187)	0.0253 (0.0186)	0.0208 (0.0183)	0.0237 (0.0189)	0.0198 (0.0194)	0.0178 (0.0194)	0.0156 (0.0194)
2008-2009		0.0103 (0.0313)	0.0169 (0.0320)	0.0212 (0.0321)	0.0114 (0.0319)	0.00359 (0.0340)	-0.00128 (0.0344)	-0.00125 (0.0344)	-0.0140 (0.0352)
2014-2015		0.00229 (0.0234)	0.00127 (0.0234)	-0.000964 (0.0234)	0.00106 (0.0230)	0.00622 (0.0243)	0.00424 (0.0244)	0.00511 (0.0244)	0.00376 (0.0243)
Osized			0.0167						

			(0.0172)						
Lnsize				0.00871 (0.00632)	0.00908 (0.00621)	0.00921 (0.00623)	0.00688 (0.00670)	0.00726 (0.00670)	0.0106 (0.00703)
Mreturn					0.234** (0.105)	0.252** (0.109)	0.249** (0.109)	0.227** (0.111)	0.231** (0.110)
Highvol						0.0132 (0.0199)	0.0166 (0.0202)	0.0110 (0.0208)	0.00960 (0.0206)
Prestu							0.0164 (0.0173)	0.0180 (0.0174)	0.0135 (0.0175)
Young								0.0222 (0.0197)	0.0250 (0.0197)
Bookb									-0.0307 (0.0204)
Constant	0.00638 (0.0103)	-0.00675 (0.0165)	-0.0150 (0.0186)	-0.126 (0.0883)	-0.137 (0.0868)	-0.146 (0.0882)	-0.120 (0.0923)	-0.127 (0.0924)	-0.147 (0.0928)
Observations	113	113	113	113	113	113	113	113	113
R-squared	0.020	0.043	0.052	0.060	0.102	0.106	0.114	0.125	0.144
Adj. R^2	0.0021	-0.0016	-0.0021	0.0068	0.0424	0.0373	0.0362	0.0387	0.0504

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

Table 8.9 – Multivariate Regressions Aftermarket Performance

The table below reports the coefficients and corresponding standard error (in parenthesis) from the regressions. The regressions are run with log returns (adjusted for market returns) after six-month of trading as the dependent variable, and variables assumed to affect abnormal returns as independent variables. The regressions do not suffer from heteroscedasticity.

VARIABLES	Reg. 10 AP	Reg. 11 AP	Reg. 12 AP	Reg. 13 AP	Reg. 14 AP	Reg. 15 AP	Reg. 16 AP	Reg. 17 AP	Reg. 18 AP	Reg. 19 AP
Energy	-0.0581 (0.0662)	-0.0538 (0.0675)	-0.0958 (0.0670)	-0.107 (0.0671)	-0.110 (0.0675)	-0.110 (0.0684)	-0.107 (0.0686)	-0.111 (0.0690)	-0.109 (0.0692)	-0.109 (0.0681)
High-tech	-0.210* (0.106)	-0.219** (0.106)	-0.134 (0.107)	-0.162 (0.104)	-0.173 (0.105)	-0.173 (0.107)	-0.170 (0.107)	-0.166 (0.108)	-0.160 (0.108)	-0.159 (0.107)
2006-2007		0.0330 (0.0737)	0.0164 (0.0716)	0.0198 (0.0710)	0.0145 (0.0716)	0.0147 (0.0740)	0.00161 (0.0759)	-0.00263 (0.0764)	-0.00742 (0.0768)	-0.00684 (0.0748)
2008-2009		-0.193 (0.124)	-0.118 (0.123)	-0.0984 (0.123)	-0.110 (0.124)	-0.110 (0.133)	-0.127 (0.135)	-0.127 (0.135)	-0.154 (0.140)	-0.155 (0.131)
2014-2015		-0.0366 (0.0926)	-0.0481 (0.0897)	-0.0647 (0.0895)	-0.0623 (0.0898)	-0.0619 (0.0952)	-0.0686 (0.0957)	-0.0667 (0.0960)	-0.0696 (0.0963)	-0.0686 (0.0919)
Osized			0.188*** (0.0658)							
Lnsize				0.0752*** (0.0242)	0.0756*** (0.0242)	0.0756*** (0.0244)	0.0678** (0.0263)	0.0686** (0.0264)	0.0758*** (0.0279)	0.0758*** (0.0277)
Mreturn					0.275 (0.411)	0.276 (0.426)	0.268 (0.426)	0.219 (0.435)	0.229 (0.436)	0.234 (0.418)
Highvol						0.000877 (0.0777)	0.0121 (0.0790)	4.46e-05 (0.0816)	-0.00300 (0.0819)	
Prestu							0.0548 (0.0679)	0.0584 (0.0684)	0.0488 (0.0695)	0.0492 (0.0683)
Young								0.0481 (0.0775)	0.0541 (0.0780)	0.0534 (0.0753)
Bookb									-0.0653 (0.0810)	-0.0652 (0.0805)
Constant	-0.0412 (0.0410)	-0.0349 (0.0655)	-0.128* (0.0713)	-1.067*** (0.338)	-1.079*** (0.339)	-1.080*** (0.345)	-0.994*** (0.362)	-1.009*** (0.364)	-1.051*** (0.368)	-1.052*** (0.365)
Observations	113	113	113	113	113	113	113	113	113	113
R-squared	0.036	0.070	0.136	0.148	0.151	0.151	0.157	0.160	0.165	0.165
Adj. R^2	0.0184	0.0265	0.0876	0.0996	0.0949	0.0862	0.0831	0.0776	0.0745	0.0835

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

8.4 Oil Price

Figure 8.7: Oil Price 1.1.2006 – 31.12.2015