Aftermarket Performance of Norwegian Initial Public Offerings

Olav Leren Moen & Danuka Madduma Hewage

Advisor: Professor Knut Kristian Aase

Master Thesis in Financial Economics

NORGES HANDELSHØYSKOLE

Bergen, spring 2012

Abstract

The objective of this thesis is to examine whether the aftermarket performance of Norwegian initial public offerings (IPOs) is consistent with market efficiency. Previous studies state that market efficiency can be disrupted by market anomalies. This study focuses on short-term underpricing and long-term underperformance of IPOs. The initial returns are measured by benchmarking IPOs against market indexes. Our results reveal that initial average abnormal returns fluctuate from 0.5% to 1.5%. The long-term underperformance anomaly is also present in the Norwegian stock market. Based on different benchmarks, we have found an average of three-year abnormal returns varying from -10% to -30%. We have found little empirical evidence as to why IPOs underperform in the long run, but our results indicate that aftermarket returns varies among sectors. Despite finding evidence of underpricing and long-term underperformance, it is unlikely whether investors can exploit these anomalies. This study concludes that these anomalies are difficult to exploit, which means that we have found few, if any, departures from market efficiency in the market for Norwegian IPOs.

Preface

This thesis is the final step to completing our Masters of Science in Financial Economics from the Norwegian School of Economics (NHH).

IPO performance was first brought to our attention during the "Corporate Finance", course that both authors attended at NHH. Much has been written lately about the performance of IPOs, especially in regards to firms such as LinkedIn, Groupon and Facebook. This makes the topic both interesting and relevant to study.

The writing process has been both educational and challenging. While writing this thesis, we have utilized the knowledge and analytical skills obtained during our five years at NHH. We have developed a good understanding of the IPO process; from listing to the aftermarket performance, as well as a better understanding of econometrics.

We hope this thesis is of interest to the reader and will provide valuable information on IPO performance in Norway.

Acknowledgement

Throughout the process of writing this thesis, we have been in contact with several individuals who have provided us with valuable insight and information on the subject. First of all, we would like to express our gratitude to our advisor, Professor Knut Kristian Aase. We are grateful for all the help and guidance we have received during this process. A special appreciation to our friends; Jørgen Flatmo Opsahl at Credit Suisse and Pål Hegseth at DNB Markets for valuable help with collecting data. We would also like to thank Julia Bishop for proof reading of our work. Finally, we would like to thank Kenneth Steen for motivational support.

Bergen, June 18th 2012

Olav Leren Moen   Danuka Madduma Hewage

Contents

1 Introduction

1.1 Description of topic

The aftermarket performance of initial public offerings (IPOs) has puzzled investors for many years. The two main IPO puzzles are the positive abnormal first-day returns, referred to as underpricing, and the long-run underperformance. Several studies indicate that these anomalies are breaches of market efficiency (Ibbotson, 1975). In an inefficient market, one can exploit market anomalies in order to make a profit.

It is well documented that IPOs tend to be underpriced[1] and we have seen instances of extreme underpricing in recent years. For example, LinkedIn went public in 2011 and achieved an initial return of 106.87% (Baldwin & Selyukh, 2011). Since this market anomaly has been extensively studied, initial returns will not be the main focus in this thesis.

Another IPO anomaly is the long-run underperformance of IPOs. It has been proven that IPOs consistently underperform during the first three years of listing (Ritter, 1991). A recent example is Groupon, which advanced 31% in its trading debut in November 2011. At the time of writing[2], the share price is down by -61% from the close price on its initial trading day. This may indicate long-term underperformance. Since this anomaly is less studied than the underpricing phenomenon, particularly in Norway, we will focus on this market anomaly in our thesis.

The fundamentals of equity trading have changed significantly since researchers first found proof of these anomalies in the 1960s and 1970s. The implementation of computerized trading services and robot trading has changed the dynamics of the stock market. Since most of the previous studies on this subject are based on relatively old data, especially in Norway, we wanted to examine these phenomena under prevailing market conditions.

IPOs involve the sale of private companies where some of the firm owners may possess superior information relative to potential investors. This can be crucial to determine the

[1] High return from offer price to close price the first day
[2] May 10th 2012

true value of a company. This information asymmetry results in different opinions about the valuation of companies going public. The uncertainty about the true value of the companies, as well as other features, makes initial public offerings especially interesting to study.

1.2 Research question

Empirical studies document the existence of anomalies in IPOs such as underpricing (short-term performance) and long-term underperformance. It can be inferred that the stock market is subject to market inefficiencies due to the existence of these anomalies. In order to examine if these anomalies are present in the Norwegian stock market, our study is founded on three objectives.

The objectives of the study are: (1) to measure the initial price performance of Norwegian IPOs, from the offering price to the close price on the first day of trading; (2) to measure the three-year aftermarket performance subsequent to listing; (3) to study if external factors or firm characteristics can explain the aftermarket performance.

By studying these objectives, we will be able to answer our research question;

"Is the aftermarket performance of Norwegian IPOs consistent with market efficiency?"

1.3 Approach

We begin this thesis with a presentation of relevant theory around IPOs in chapter 3. Here, we describe what an IPO is and how a company goes public. Thereafter, results from empirical studies for the main IPO anomalies are presented in chapters 4, 5 and 6.

In chapter 4, we present the analysis for the long-term performance of IPOs. We have chosen to study Norwegian IPOs listed in the period 2000 to 2008, and we have analyzed their three-year abnormal returns compared to three different benchmarks. The benchmarks chosen are: market indexes, peer companies, and sector indexes.

After the long-term analysis, we have performed cross-sectional regressions in order to determine if aftermarket performance is related to specific firm characteristics or external factors. This analysis is presented in chapter 5.

In chapter 6, we have analyzed the short-term performance of Norwegian IPOs from 2000 to 2011. We have examined the short-term performance by calculating abnormal returns in excess of market indexes from the offer price to the close price the first day of trading.

Our findings are then compared to other empirical studies and discussed in light of economic theories. We will only present the key findings from our analysis - the complete results are enclosed in the appendix in chapter 9.

1.4 Scope limitations

We have limited our analysis to the Norwegian market. Our background from a Norwegian business school has provided us with a better understanding of the Norwegian market than other markets and it was therefore natural for us to choose the Norwegian stock market as area of study. The majority of the empirical studies on this subject are based on data that is older to our study. Therefore, one must be cautious when comparing results, since the market dynamics might have changed over time.

This thesis focuses more on the long-term IPO performance than on the short-term performance. As aforementioned, the anomaly of short-term underpricing is well documented. We have therefore chosen to study the long-term underperformance anomaly more thoroughly.

The choice of a three-year aftermarket period limits us to study whether the IPO long-term underperformance lasts for more than three years. Empirical studies reveal that the duration of IPO underperformance varies from three to five years (Ibbotson, 1975), (Ritter, 1991). Since we have chosen to study IPOs issued from 2000 to 2008, some of the IPOs have not yet been listed for five years. We have therefore limited our aftermarket period to three years. The fact that Rao (1991) and Ritter (1991) found that underperformance is isolated to the first three years post listing gives support to our choice of aftermarket period.

2 Market efficiency and anomalies

Market efficiency suggests that prices on traded assets fully reflect all available information at any given time. Eugene Fama (1970) expressed this idea through the Efficient Market Hypothesis (EMH). The idea is that if the EMH holds, no investor can beat the market by predicting a return on a stock because all investors will have the same information (Fama, 1970).

Investors and researchers have questioned the validity of the EMH. Empirical support for the theory is mixed, but the strong form of market efficiency[3] has generally not been supported. Some have found market anomalies with specific characteristics of stocks - for instance that low P/E stocks produce greater returns than high P/E stocks (Dreman & Berry, 1995). "Anomalies are empirical results that seem to be inconsistent with maintained theories of asset-pricing behavior. They indicate either market inefficiency (profit opportunities) or inadequacies in the underlying asset-pricing model" (Schwert, 2002, p.939). Academics have found anomalies related to IPOs. According to Berk & DeMarzo (2007), there are four characteristics that puzzle financial economists:

1. Underpricing: The closing price the first day of trading is often substantially higher than the offer price.
2. Cyclicality: Both the number of IPOs and the average initial returns tend to follow market cycles.
3. Long-run underperformance: The returns of an IPO investment with a three to five year holding period is on average negative.
4. High costs: It is unclear why firms willingly incur the high costs associated with an IPO.

[3] The "strong form" of market efficiency assumes that all information, public and private, is available to all investors. This implies that no one can consistently produce excess return. This form of market efficiency is impossible if there are legal barriers preventing information for being made public. An example of a legal barrier is laws preventing insider trading (Jensen, 1978).

Puzzle number one, two and three can be viewed as anomalies and are signs of market inefficiency. Each puzzle will be discussed and/or studied in this thesis, but we will focus on the long-run underperformance anomaly.

Ibbotson (1975) argued that an IPO is market-efficient if the IPO's long-run performance is not significantly different from zero. He also claim that a market anomaly is only market inefficient if an investor is able to make profit from it after transaction costs are incurred.

By transaction costs, Ibbotson referred to the bid-ask spread and the brokerage commission. Bid-ask spread is the difference in price between the highest price a buyer is willing to pay for a stock and the lowest price a seller is willing to sell for. Brokerage commission is the fee rendered to a broker for stock trading. Even if market anomalies exist, investors have to be able to exploit them in order for the market to be inefficient - a transaction cost is one obstacle which might hinder this.

3 Initial Public Offering theory

An Initial Public Offering (IPO) is the process of going public for the first time by selling stocks listed on a stock exchange to a large number of diversified investors (Ibbotson & Ritter, 1995).

3.1 Reasons for going public

Most startup companies finance their initial investments by raising capital from a small number of investors that are often private sources. If the investors or the entrepreneurs wish to sell their stock, they have no liquid market in which to sell them. This source of equity capital is therefore usually quite expensive because the investors need to be compensated for the lack of liquidity in their investment. The amount of money a startup company can get from private sources is often limited to the existing stockholders' ability or willingness to inject more equity into the company. Without another source of financing, a startup company will therefore be hindered in their growth plans. To finance future expansions, many companies find it more attractive to go public and raise capital at more favorable terms rather than financing through private sources.

The key motivation for going public is to raise equity for the company and/or to work as an (partial) exit for current stockholders (Ritter & Welch, 2002). An IPO can be the best way to get funds for a strategic expansion or it can be a part of a financial strategy. Strategic expansion can be achieved through internal or external growth, where a hostile takeover is the most extreme form of expansion. When a company goes public, the liquidity in the stock will increase, which might lead to a lower weighted average cost of capital (WACC) required by investors. Pagano et al. (1998) claim that the decision to go public is a result of value maximization for the original owners who are willing to sell down. When a company is (partly) sold to the public, more potential investors are involved than in an alternative trade sale[4], where a company is sold to one or just a few investors. The price reached through an IPO is normally better than in a trade sale, and this is therefore another motivating factor for going through with an IPO.

[4] "A trade sale is a sale to shops or businesses, rather than to members of the public" (Financial Times Lexicon, 2012).

Based on the Italian stock market, Pagano et al. (1998) found that the probability for going through with an IPO is correlated with the company and the industry's price-to-book ratio and its size. Ritter & Welch (2002) concluded that companies decide to go public when market conditions are good, but only after a certain stage in their life cycle. Figure 3.1 is showing that the most common stage to go public in a company's life cycle is in the growth phase (Johnsen, 2011).

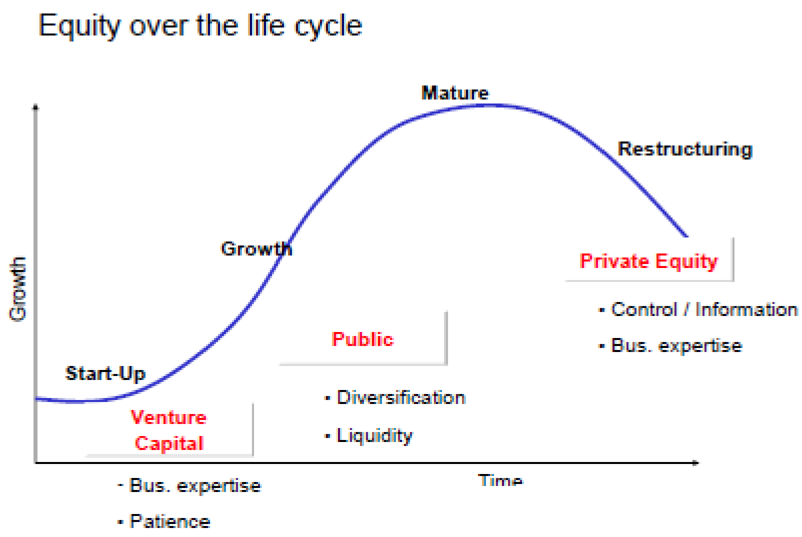


Figure 3.1: **(Johnsen, 2011)**.

3.2 Issues associated with an IPO

Many companies have not started to generate a significant amount of income in their first years of existence, and most of the value of their company is therefore represented by their present value of future growth opportunities (PVGO). The PVGO is highly dependent upon the future decisions the managers choose to make, which are unknown, and it is hence difficult for investors to value startup companies before they go public. It is not only the potential investors who have trouble to determine the correct valuation, but the parties who determine the offer price may also be unsure. We will explain that this valuation problem can amount to a substantial cost for the company going public. There are many other one-time costs associated with an IPO. These costs can be categorized as direct and indirect costs.

The direct costs include auditing, legal, and underwriting fees. An underwriter is an investment bank, or often a syndicate of several investment banks, who manages the security issuance and designs its structure. The fee[5] often charged by the underwriter is called the underwriting spread. This is the discount below the issue price at which the underwriter purchases the stocks from the issuing firm. A typical spread is 7% of the issue price (Berk & DeMarzo, 2007), which means that this cost could constitute a large amount. For instance, the underwriting spread of an issue of NOK 300 million amounts to NOK 21 million.

The indirect costs are split into the costs associated with the time and the effort the management devotes to the preparation of the offer, and the indirect cost of underpricing. Underpricing is the anomaly associated with the dilution[6] that occurs when stocks are sold at an offer price which is lower than the close price at the initial day of trading (Ibbotson & Ritter, 1995). Underpricing costs may be substantial, and combined with the underwriting spread, the total one-time costs associated with going public can often end up with being over 10%. In addition to the one-time costs, there are regular costs for publicly traded firms associated with the need to supply regular information to investors and regulators.

There are also other issues one has to have in mind before deciding to go public. Firstly, a firm runs the risk of being subjected to a hostile takeover, since regulations allow for increased insight into the company's accounts and sources of revenues. Secondly, the owners will lose control of parts of the company. This is due to regulations on the Oslo Stock Exchange (OSE), which requires companies going public to sell minimum 25% of the stocks to new stockholders (Oslo Børs, 2012).

3.3 The IPO process

The IPO process on OSE is a formal stepwise process which is similar to the processes in most Nordic countries. The regulations comprise rules that have to be met prior to

[5]This fee is used in a «Firm commitment» structure which is the most common structure. Different structures are described further down.

[6]The stock dilution is a consequence of a firm needing to issue additional stocks, in order to raise the same amount of equity as indicated by the market capitalization at the close of the initial day of trading.

listing[7]. The rules include criteria for market capitalization, business maturity, and number of stockholders et cetera. The underwriters have the responsibility for the legal and financial due diligence of the company. They control the budgets, accounts, compliance of accounting rules and are responsible for the development of a prospectus to potential investors. The purpose of this process is to learn about the company in order to give an accurate presentation of the company to the potential investors on the road show. Most importantly, the underwriter works closely with the company to determine a fair valuation of the company. The road show, where the underwriter and senior management travels around to promote the issue, can start once this is done.

When the road show is finished, investors inform the underwriter how many stocks they intend to purchase. Although these commitments are not binding, they give a good indication of the demand and are therefore used to determine the final offer price. This process is called the book-building process.

Thereafter, a transaction structure has to be chosen. The three most common structures are:

- Auctions: Investors are allocated stocks according to the highest bids. In recent years, these have taken the form of online auctions where the offer price is determined by the market. This structure is not regularly used.

- Best-Effort: The offer price is fixed before the book-building is initiated. The underwriter does not guarantee that the issue will be sold out, but tries to achieve the best possible price for the seller. This model is recommended in small transactions with few institutional investors.

- Firm Commitment: This is the most commonly used transaction structure. The underwriter provides an indicative price interval before the book-building starts. Institutional investors are picked to participate in the offering, which allows for price adjustment according to the market demand. Based on the result from the book-building, the final subscription

[7]Listing criteria found on Oslo Børs website (Oslo Børs, 2012)

price is determined before listing. The underwriter purchases the whole issue at a discount/spread, and is then responsible for selling out the stocks. This is therefore a large commitment for the underwriter and constitutes a huge risk for the underwriter.

The last two transaction structures allow for over-subscription. Over-subscription occurs when the demand is higher than the supply, and implies that investors want to buy more stocks than the planned issue. The most common way of allocating stocks, in the case of over-subscription, is to allocate according to interest. In other words, the investors who signed up for the most stocks get the most.

The underwriter has another option when there is excess demand; they may have the possibility of distributing 115% of the stocks offered. If this option is included and used, the underwriter normally borrows these stocks from the main stockholders of the company. This creates a short position for the underwriter, which can be covered in two ways. If the stock price increases above the offer price, the underwriter can use a Green Shoe Option (Berk & DeMarzo, 2007). A Green Shoe Option is an option for the underwriter to buy back the shorted stocks through the issuance of new stocks. In the opposite scenario, when the stock price falls below the offer price, the underwriter may buy back the stocks in the open market. Normally, the short position has to be covered within 30 days after listing[8]. For further information on this topic, "Going Public: What the CFO Needs to Know" (Zeune, 1994) presents an in-depth description on this subject.

3.4 The underpricing phenomenon

Underpricing refers to when the stock price for IPOs increases, on average, from the offer price to the closing price on the first day of trading.

3.4.1 Empirical findings of underpricing

The first study on this topic was done by the U.S Securities and Exchange Commission (SEC) in 1963, which found that the average initial return for IPOs was positive (Ibbotson & Ritter, 1995). Later, this phenomenon has been studied by many people in various countries. Although the size of the underpricing varies, the underpricing

[8] Regulations described by The Committee of European Securities Regulators (CESR, 2002)

phenomenon exists in every country with a stock market (Ibbotson & Ritter, 1995). A summary of some of these studies can be viewed in table 3.2 below. The large variations in underpricing between the different countries in table 3.2 can be partly explained by differences between the countries in terms of rules, regulations, national and regional factors for listing, as well as random differences in data samples. The average return is also measured in different ways depending on the country, where some are adjusted for market movements and some are not. The chief reason for large variations in underpricing is probably because the studies are done in different time perspectives. We will later show that the degree of underpricing can change drastically from year to year[9].

[9] See figure 3.5 and 3.6.

Country	Source	Size number	Time period	Average return
Australia	Lee, Taylor & Walter; Woo	381	1976-1995	12.1%
Austria	Aussenegg	83	1984-2002	6.3%
Belgium	Rogiers, Manigart & Ooghe; Manigart	86	1984-1999	14.6%
Brazil	Aggarwal, Leal & Hernandez	62	1979-1990	78.5%
Canada	Jog & Riding; Jog & Srivastava;Kryzanowski & Rakita	500	1971-1999	6.3%
Chile	Aggarwal, Leal & Hernandez; Celis & Maturana	55	1982-1997	8.8%
China	Datar & Mao; Gu & Quin (A-shares)	432	1990-2000	256.9%
Denmark	Jakobsen & Sørensen	117	1984-1998	5.4%
Finland	Keloharju; Westerholm	99	1984-1997	10.1%
France	Husson & Jacquillat; Leleux & Muzyka; Paliard & Belletante;Muzyka; Paliard & Belletante;	571	1983-2000	11.6%
Germany	Ljungqvist	407	1978-1999	27.7%
Greece	Kazantis & Thomas; Nounis	338	1987-2002	49,0 %
Hong Kong	McGuinnes; Zao & Wu; Ljungqvist & Yu	857	1980-2001	17.3%
India	Krishnamurti & Kumar	98	1992-1993	35.3%
Indonesia	Hanafi; Ljungqvist & Yu	237	1989-2001	19.7%
Israel	Kandel, Sarig & Wohl;Amihud & Hauser	285	1990-1994	12.1%
Italy	Arosio, Giudici & Paleari; Cassia, Paleari & Redondi	181	1985-2001	21.7%
Japan	Fukuda; Dawson & Hiraki; Hebner & Hiraki; Hamao, Packer & Ritter; Kaneko & Petteway	1 689	1970-2001	28.4%
Korea	Dhatt, Kim & Lim; Ihm; Choi & Heo	477	1980-1996	74.3%
Malaysia	Isa; Isa & Young	401	1980-1998	104.1%
Mexico	Aggarwal, Leal & Hernandez	37	1987-1990	33,0 %
Netherlands	Wessels; Eijgenhuijsen & Buijis; Ljungqvist, Jenkinson & Wilhelm	143	1982-1999	10.2%
New Zealand	Vos & Cheung; Camp & Munro	201	1979-1999	23,0 %
Nigeria	Ikoku	63	1989-1993	19.1%
Norway	Emilsen, Pedersen & Sættem	68	1984-1996	12.5%
Philippines	Sullivan & Unite	104	1987-1997	22.7%
Polen	Jelic & Briston	140	1991-1998	27.4%
Portugal	Almeida & Duque	21	1992-1998	10.6%
Singapore	Lee, Taylor & Walter; Dawson	441	1973-2001	29.6%
South Africa	Page & Reynecke	118	1980-1991	32.7%
Spain	Ansotegui & Fabergat	99	1986-1998	10.7%
Sweden	Rydqvist; Schuster	332	1980-1998	30.5%
Switzerland	Drobertz, Kammermann & Walchli	120	1983-2000	34.9%
Taiwan	Lin & Sheu; Liaw, Liu & Wei	293	1986-1998	31.1%
Thailand	Wethyavivorn & Koo-Smith; Lokani & Tirapat	292	1987-1997	46.7%
Turkey	Kiymaz	163	1990-1996	13.1%
UK	Dimson; Levis; Ljungqvist	3 122	1959-2001	17.4%
USA	Ibbotson, Sindelar & Ritter	14 978	1960-2003	18.3%

Table 3.2: Average initial returns for 36 countries - **(Loughran, et al., 1994)** (updated 2003).

Despite the large variations in underpricing, there is evidence that the underpricing is substantial and consistent in the long run. Figure 3.3 below illustrates the abnormal short-run returns on IPOs in contrast to the pure market returns for companies in the U.S. from 1960 to 2001. With a strategy of investing $1000 in 1960 in a random sample of IPOs and then reinvesting in a new set of IPOs each month, the portfolio from this strategy would have been worth $533x10^{33}. By comparison, a similar strategy with investments in the market portfolio would have been worth $74000 (Schwert, 2002). We have not found evidence of any investor who has been able to follow this strategy. We will present a few theories that try to explain why in the following.

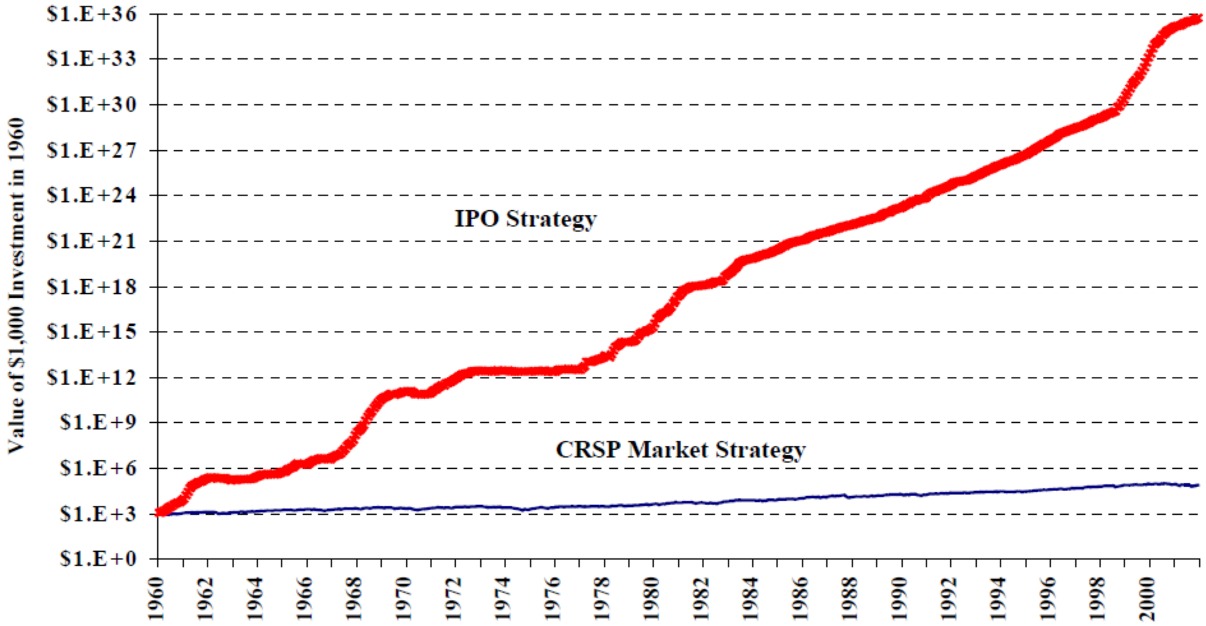


Figure 3.3: The value of a portfolio from 1960 to 2001 after investments in IPOs or the market portfolio **(Schwert, 2002)**.

3.4.2 Explanations of underpricing

There are many theories that try to explain underpricing. Most of the theories are linked to the information asymmetry problem as explained in the introduction. Rock (1986) assumes that some investors are better informed about the true value of the company going public than others. He claims that better informed investors only bid for the IPOs that are favorably priced and that less informed investors bid for all IPOs. This theory is referred to as "The winner's curse", where the less informed investors are allocated relatively more stocks in IPOs with unfavorable pricing than in favorably priced IPOs. This happens because the informed investors bid more heavily on the good IPOs and thus overbid the less informed investors during the auction process. In order to attract the less informed investors, IPOs have to be priced at a discount. This gives an explanation for the underpricing phenomena.

Another example of information asymmetry is that the entrepreneurs are better informed than the potential investors. Only issuers with lower than average quality are willing to sell their stocks at the average price. The result is that high quality companies do not find it beneficial to go public and only low quality firms decide to go public. This problem is referred to as "The Lemons problem" (Akerlof, 1970). High quality companies may have recognized that this problem could be present in the current market, as fewer companies decide to go public in the U.S. (Social Science Research Network, 2012).

High quality companies can bypass the lemons problem by "leaving money on the table" in an IPO. Leaving money on the table is the same as selling a stock at a discount, and can be viewed as a form of signaling of a company's quality. This is lost capital for the entrepreneurs that could have been raised if the stock had been offered at a higher price. Welch (1989) claims that it can be rational to leave money on the table for high quality companies because they can regain the money in a subsequent directed stock issue. Low quality companies will reveal their true quality in the market before the directed stock issue is done and they will therefore not be able to recuperate the money left on the table. In other words; only high quality firms issuing equity will decide to sell their stocks at a discount in order to prove superior quality, compared to other new listings, since the true value of the company will be revealed in the aftermarket. Therefore, only high quality companies will achieve a beneficial price in a subsequent directed stock issue.

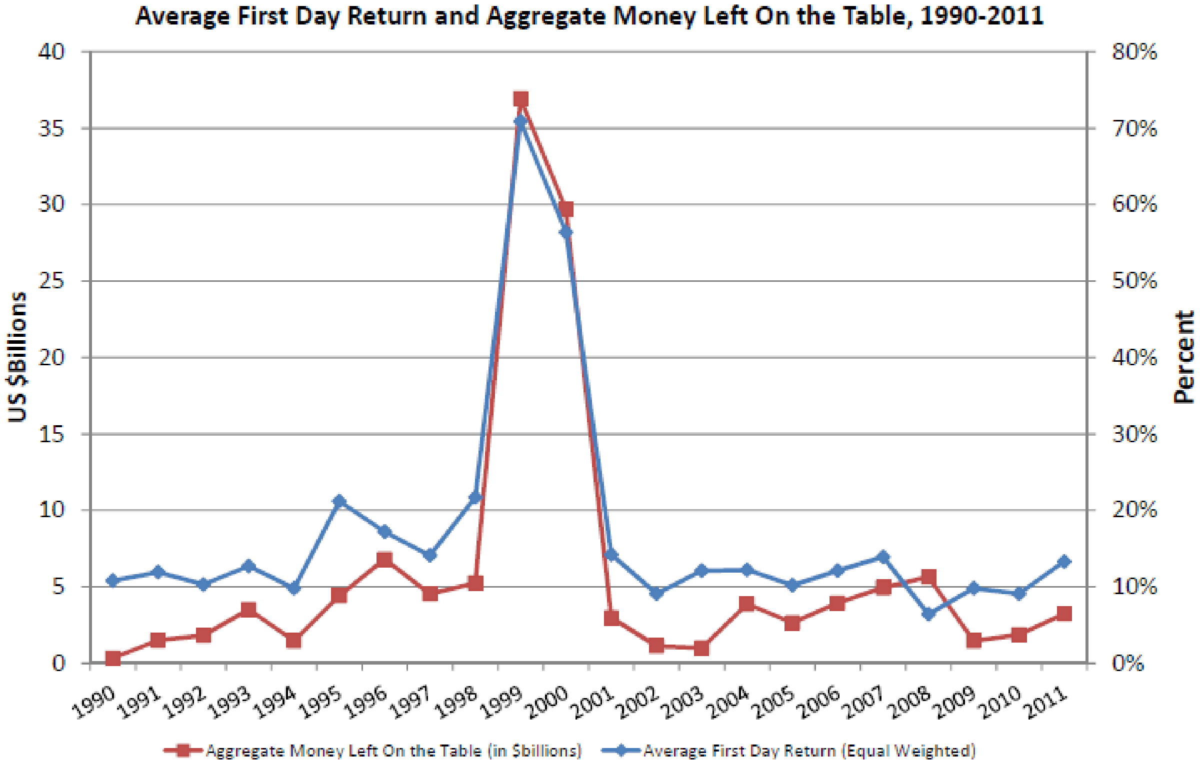


Figure 3.4: **(Ritter, 2011)**

Figure 3.4 illustrates that average first day returns and the aggregate money left on the table for American IPOs are highly correlated. This proves that a lot of the "money left on the table" can be regained in a subsequent directed stock issue.

Another explanation of the underpricing phenomena is that underwriters purposefully set the issue price low. They do that to control their own risk as the underwriter. The main risk for an underwriter, that has chosen a firm commitment structure, is to set a price which is too high to sell out the entire issue. The underwriter may also risk their reputation if they are not able to sell out the issue and may thereby potentially lose future customers. This is another example of problems with information asymmetry, where the underwriter is better informed than the issuer.

Since the issuer cannot monitor the underwriter without costs, the underwriter has full control of the pricing of the issue. The entrepreneurs want the offer price to be set as high as possible, but they have little power to assure that the underwriter is setting the best price (Baron, 1982). Despite Baron's argument, Muscarella & Vetsupiens (1989) found that IPOs are equally underpriced when issuers go public on their own, as opposed to when they use underwriters. Beneviste et al. (1996) explain the underpricing phenomenon with the rationale that underwriters who have agreed to provide price support[10] will underprice the issue on purpose in order to avoid losses.

An example of the classical principal-agent problem is that underwriters may not always serve their clients' best interests when they have the power to allocate stocks at their own discretion (Ritter & Welch, 2002). Underwriters may unnecessarily underprice IPOs and then allocate stocks to hand-picked investors or clients in order to make them rich. This will also benefit the underwriter as an investment bank because a part of the profit will be passed on to the brokers who charge for the use of their services. Stoughton & Zechner (1989) claim institutional investors are more valuable for underwriters than retail investors. This is due to the existence of the agency problem which occurs because only institutional investors are able to monitor the firm's management, while retail investors are often not capable of these activities. Booth & Chua (1996) are on the other hand claiming that retail investors are more valuable (for an underwriter) because they consist of a broader investor base which creates higher liquidity in the stock. Either way, an underwriter may choose to underprice the issue to additionally serve their most valuable customers. Randall & McGee (2000) wrote that underwriters allocate stocks in an IPO first to large institutional investors. If these large institutional investors are able to distinguish between favorably and unfavorably priced IPOs, stocks available to retail investors are likely to produce lower returns compared to those available to institutional investors (Schwert, 2002).

As explained earlier, the underwriter is using the book-building process to determine the final offer price. If the underwriter, for a fully subscribed issue, organizes the book-building process such that investors are allocated stocks according to their bids, the bidders have to place realistic bids. The investors that are bidding aggressively are thus revealing that they think the IPO is underpriced. Beneviste & Spindt (1989) argues that the offer price has to be set low in order to compensate investors to reveal their information - underpricing is thus a consequence of asymmetric information. Hanley (1993) demonstrates that IPOs, which end up with a final offer price in the upper range

[10] To buy stocks if the stock price falls below offer price.

of the pricing interval from the book-building process, will have a higher initial return than IPOs from the lower range. This phenomenon is called “partial adjustment”.

Welch (1992) presents an explanation for the underpricing phenomenon based on behavioral factors. He argues that there is a “sheep mentality” amongst investors that he calls the “cascade effect”. He claims that investors may disregard their own information, even if they have superior information, and instead pay attention to whether other investors are buying or not. If no one else is buying, an investor may not decide to buy, and vice versa. To make sure that some investors are buying and to initiate the cascade effect, underwriters set the offer price low in order to attract buyers.

3.5 Cyclicality

Another anomaly with IPOs is that both the issuing volume and the average initial return tend to follow market cycles. Figure 3.5 illustrates that there are large fluctuations in first-day return and number of IPOs in the U.S.

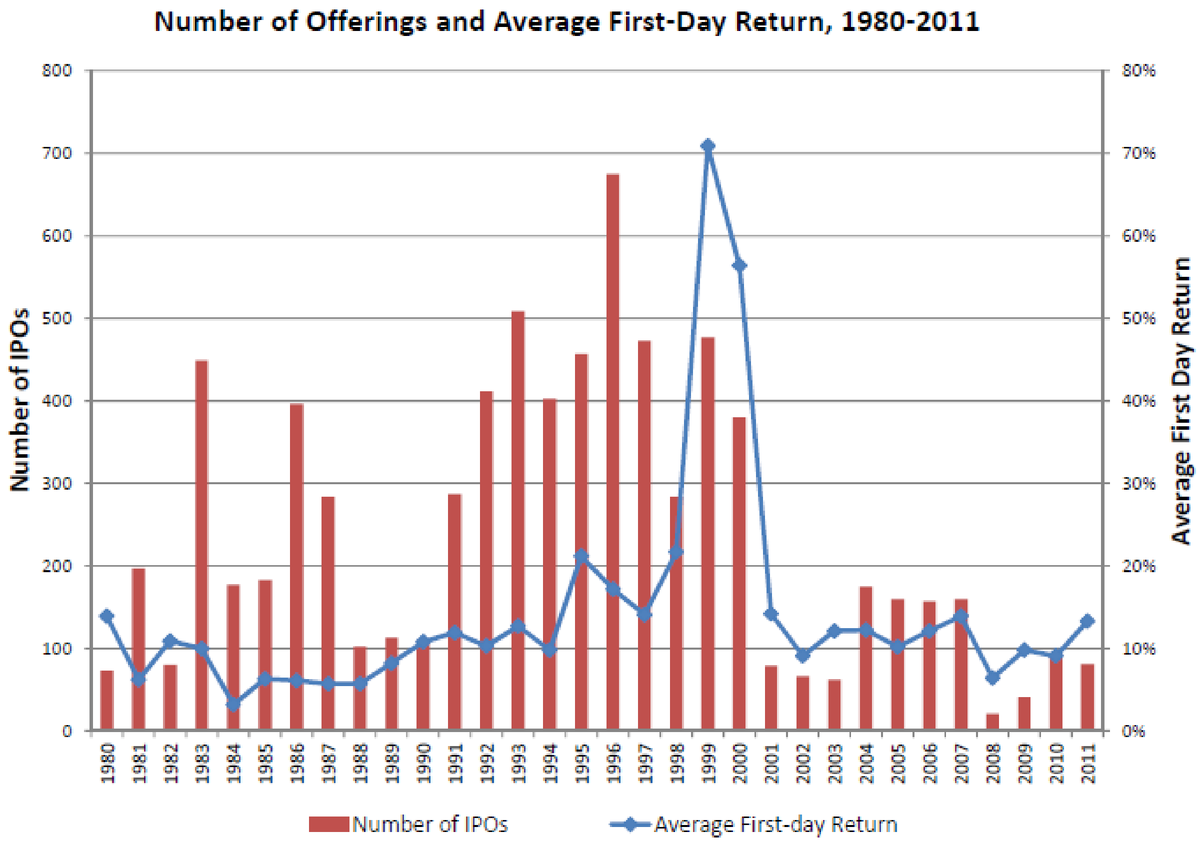


Figure 3.5: **(Ritter, 2011)**

It is not surprising that there are variations in the number of companies that go public. We would expect that companies, in general, will have greater need for capital in times characterized by more growth opportunities than in times with fewer growth opportunities. What is surprising about the cyclicality is how large the variations are. From the years 2000 to 2003, the dollar volume of new issues declined by 75%. Even though the growth opportunities declined over that period, this cannot wholly explain the change.

Loughran et al. (1994) found that the IPO volume in both the U.S. and other countries tends to be high following periods of high stock market returns. Lerner (1994) concluded that venture capitalists tend to take companies public when equity valuations are high, and that private financing is the most common practice when equity values are low.

lbbotson & Jaffe (1975) were the first to document cyclicality of high initial returns, which they called "hot issue" markets. Academics have difficulty in finding rational explanations for this phenomenon. Rajan & Servaes (1993) assumes that there is positive autocorrelation for the initial return in IPOs and argues that some investors follow "positive feedback" strategies. They claim that investors may be especially tempted to invest in IPOs if other recent issues have risen in price. Ritter (1984) hypothesizes that the large fluctuations in initial returns could be explained by the riskiness of the issue. He has found some evidence that hot issue periods are dominated by risky issues, but the evidence is not strong enough to explain the whole phenomenon. The rationale behind this hypothesis is that riskier issues tend to be underpriced to a greater extent than issues with lower risk. Despite the absence of evidence with good explanations for the cyclicality anomaly, we can observe that there are large fluctuations in both the initial IPO returns and issuing volume. Figure 3.6 shows monthly IPO returns - we can observe that the initial return is even more volatile than the yearly returns.

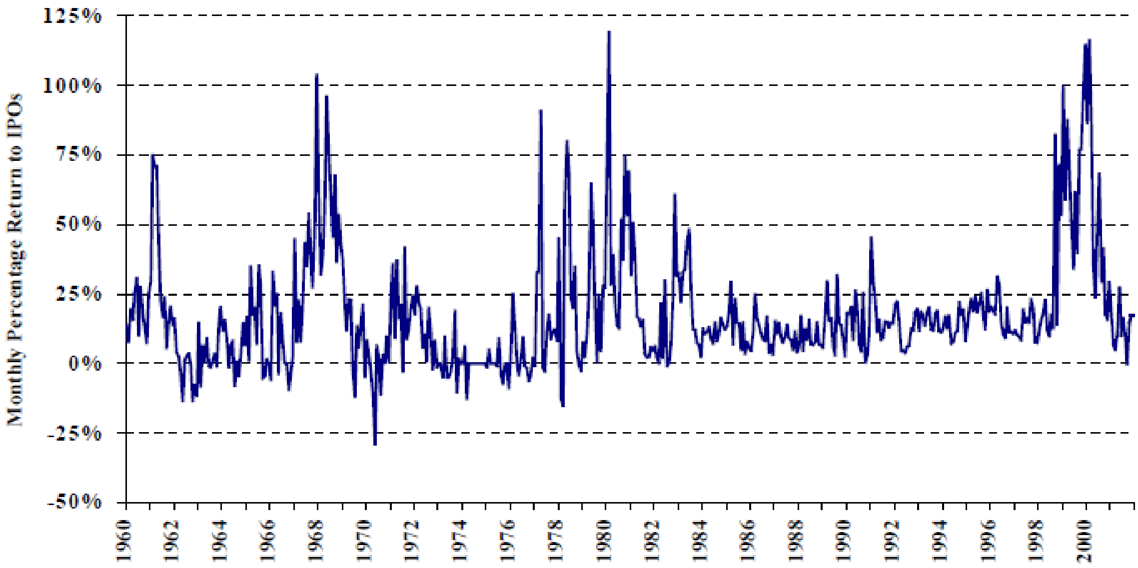


Figure 3.6: Monthly data on the average initial returns to IPO investors, U.S. data from January 1960 to December 2001 Source: **(Ibbotson, et al., 1994)**

Lowry & Schwert (2002) claim that there are noticeable cycles in the returns from figure 3.6, with high initial returns followed by high returns. They argue that companies are not able to use this information to time their IPO in order to minimize the initial return.

The same argument goes for investors; they are not able to time their purchases in IPOs in order to maximize their return. Although IPOs potentially can offer large abnormal returns to investors who are able to obtain stocks in IPO allocations, it is not clear that the cyclicality anomaly can be exploited by most investors.

3.6 Long-term performance of IPOs

Long-term underperformance is referred to as the market anomaly that IPOs tend to underperform in their first three years of listing, relative to other benchmarks. Ritter studied this phenomenon first in 1991, and his article; "The long-run performance of initial public offerings" became the reference for most articles on this subject (Ritter, 1991).

3.6.1 Empirical findings of long-term IPO performance

Prior to the 1990s, Stoll & Curley (1970), Ibbotson (1975) and Stern & Bornstein (1985) presented evidence of long-term IPO underperformance in the U.S., while Buser & Chan (1987) found no evidence of underperformance in a two year study of the NASDAQ Composite Index. Ritter (1991) explained that this result was due to the use of NASDAQ Composite Index as benchmark, which underperformed other markets during the observation period. In addition, they did not include the most speculative IPOs.

Long-term IPO performance attracted more interest during the 1990s, after Ritter's study. Despite prior studies, Ritter claim to be the first to confirm long-term underperformance of IPOs. Based on a study of 1526 U.S. IPOs between 1975 and 1984, Ritter found statistically significant results supporting the theory of underperformance. Ritter used two event-time approaches: cumulative abnormal return (CAR) and buy-and-hold abnormal return (BHAR). He then calculated abnormal return by matching IPOs against peer companies. Ritter found an average three-year abnormal return on -29.13% (CAR) and -27.39% (BHAR).

To prove that IPO underperformance is not a characteristic solely of the American market, Loughran et al. (1994) examined long-term IPO performance in nine different countries in Asia, South America and Europe. Based on this report, they found statistical evidence that IPOs tend to offer relatively low return in a three-year perspective. The three-year aftermarket performance for IPOs issued in Germany, between 1974 and 1989, had an average adjusted return of -12.8% (Ljungqvist, 1993). Aftermarket performance in the U.K, for IPOs issued from 1980-88, had a three-year average adjusted return of -8.1% (Levis, 1990). However, a study performed on the Swedish stock market show a positive three-year average return of 1.2% based on IPOs issued in 1980-90

(Loughran et al., 1994). The returns for the abovementioned studies have been adjusted against the GSC100 index for actively traded small stocks. Unfortunately, Loughran et al. (1994) did not study long-term performance of Norwegian IPOs. However, the authors question the robustness of the studies of the Swedish and German markets. This is because the German and Swedish market analysis was based on a relatively small sample (119 and 162, respectively[11]). Regardless of the robustness of the different studies, Loughran et al.'s study shows that IPO underperformance is a global phenomenon.

In terms of duration of the underperformance, Ritter (1991) argued that underperformance is confined to the initial three years after going public. This is supported by research conducted by Rao (1991). Ibbotson (1975) found underperformance up to the fourth year of going public, but no signs of underperformance in year five. Lerner (1993) reported that IPOs underperform in the five first years of listing. Based on Lerner's study, Speiss & Affleck-Graves (1995) examined how seasoned equity offerings (SEO) performed five years after the equity offering. Their study found significant negative abnormal returns at the end of the fifth year. Based on this, they concluded that negative long-term returns are not specific for initial offerings, "but are a more pervasive feature found in all common stock offerings" (Speiss & Affleck-Graves, 1995). Hence, literature on SEOs can provide valuable insight into IPOs' long-term performance as well.

3.6.2 Empirical explanations of long-term underperformance

By using cross-sectional regressions, Ritter (1991) explains that underperformance is a result of investor's over-optimism in certain sectors of the market which he called "fads". Despite high initial return of IPOs (the underpricing phenomenon), Ritter claims that long-term return will be lower than the return of comparable firms due to market adjustments of the initial over-optimism.

Ritter also connects long-term underperformance and fads to market timing. He claim that companies use "windows of opportunity", where issuers "time" their IPO issues to market peaks or industry fads. During market peaks, stock prices increase beyond their

[11] In comparison, Levis' (1990) study on the UK market is based on 712 observations.

fundamental values and managers and issuers take advantage of this overpricing by issuing equity. Over time, the market peaks or the industry fads will subside and the market adjusts for the initial overpricing, which in turn results in long-term underperformance of IPOs. Ritter (1991) found that IPOs issued during booms tend to yield lower long-term returns compared to average IPOs. The theory of "window of opportunity" is supported by several other studies, such as Loughran & Ritter (1995, 1998), Baker & Wurgler (2000) and Hirshleifer (2001).

Schultz (2002) provides an alternative theory to market timing. Schultz acknowledges the underperformance tendency of equity offerings, but he concludes that this is not due to issuers using "windows of opportunity". The paper questions how managers can correctly predict future earnings to evaluate whether their stock is overvalued. Instead, Schultz claims that firms decide to go public when they can receive a higher price of their company. As a result, there will be more issues during booms, when valuations generally are higher. This is referred to as "pseudo market timing". Schultz (2002) explains underperformance by managers deciding to take their firms public during peaks. As stock valuations increase, more firms decide to issue equity. Issuers can get a higher stock price for equity offerings during peaks – consequently, the cost and risk of raising equity is reduced. Since the risk is reduced, more IPOs will follow suit. The latter group of IPOs is comprised of companies with lower risk, and they are therefore yielding lower expected return. Schultz claims that the second group of IPOs consists of more listings than the initial group of IPOs and that the average return for all IPOs will be lower or in some cases negative as a result.

IPO performance explained by firm characteristics

Another interesting facet of IPOs is whether underperformance is linked to certain firm characteristics. Ritter (1991) found that young companies tend to yield lower long-term returns compared to average IPOs.

Studies on seasoned equity offerings can also provide valuable information for IPO underperformance. Based on returns adjusted against specific benchmarks, Speiss & Affleck-Graves (1995) found evidence of long-term IPO underperformance. They calculated abnormal return against size, industry-and-size and book-to-market-and-size.

They proved long-term negative abnormal returns across all three benchmarks. The findings discussed are supported by Brav et al. (2000), who also found IPO and SEO underperformance in excess of market benchmarks. Speiss & Affleck-Graves (1995) conclude that underperformance is most severe among small issuing firms with low book-to-market ratios. However, Brav et al. (2000) did not find IPO or SEO underperformance when matched against size and book-to-market portfolios. Brav et al. (2000) explain the different findings by claiming to have used a superior matching technique to Speiss & Affleck-Graves (1995).

IPO performance explained through risk

An alternative explanation to the long-term underperformance of equity offerings is provided by Eckbo et al. (2000), who claim that IPO underperformance is related to differences in risk between IPOs and their matches. They claim that issuing firms (IPOs & SEOs) have lower systematic risk compared to non-issuing firms (matching firms) and that issuing firms therefore yield lower return than their non-issuing counterparts.

Eckbo et al. (2000) argue that the matched firm technique used by Ritter (1991) and Speiss & Affleck-Graves (1995) does not account for differences in risk. Eckbo et al. use a different technique to expose risk difference by constructing zero investment portfolios; going short in stocks of equity issuers and long in stocks of similar firms matched on size and book-to-market ratio. Based on the portfolios, the issuing firms had a higher exposure towards macro-economic risks like unanticipated inflation, default spread and changes in the term structure compared to matched firms. Eckbo et al. (2000) suggest that the lower exposure to micro-economic risks exceed the higher exposure to macro-economic risks and that IPOs thus have less systematic risk. This is because when a firm issues equity, with everything else constant, the total leverage of the firm is reduced. Therefore, the unanticipated inflation and default risks of the issuing firm are reduced. Due to the reduction in systematic risk, the issuing firm will yield a lower return relative to the non-issuer.

Another study conducted by Eckbo & Norli (2000) discusses that IPO underperformance can be related to stock turnover. This is based on the negative relationship between average return and trading volume that Brennan et al. found in 1997. Eckbo & Norli

(2000) found that new listings are more traded, compared to peers, and they use this link to explain two to five year IPO underperformance. In the same study, they found that IPOs with a high stock turnover and less leverage[12] tend to underperform. IPOs with these two characteristics have less systematic risk than the non-issuing counterparts. Eckbo & Norli confirm that long-term underperformance is due to lower systematic risk of new listings.

In extension to the previous studies that explain equity performance through risk, Carlson et al. (2006) conducted a study on SEO underperformance. The framework used for this study is different from previous studies; they viewed SEOs as real options, rather than focusing on leverage and exposure to macro-economic risks. The principle behind the study is that firms issue equity in order to expand or invest. The expansions are viewed as growth options converted to assets in place. The authors argue that these assets are less risky than the growth options, which reduces the total risk of the firm. Lower company risk contributes to a reduction in expected return for the issuing firm. In other words: SEO underperformance is explained by the risk reduction which occurs when growth opportunities are converted to assets by raising equity.

Carlson et al. (2006) argue that matching abnormal returns based on firm characteristics like size and book-to-market ratio does not account for the risk adjustments following an equity issue. They therefore claim that the real option framework provides a better explanation of the aftermarket performance. The intuition behind risk reduction for SEO can also be applied to IPO studies. The argument is that the reduction in risk after an equity issue is largest for firms with huge growth options - a characteristic which is often found for IPO firms.

Summary of empirical explanations of long-term underperformance

We have seen that there are several different empirical explanations of the long-term underperformance of IPOs. The most prominent explanations are related to market conditions, firm characteristics and differences in risk between IPOs and their matches.

[12] Leverage of IPOs are measured against the leverage of peers (non- issuing firms), matched against size and book-to-market ratio.

We have used SEO literature to prove that underperformance is related to all equity offerings and that studies on SEO underperformance are transferable to IPOs.

4 Analysis of long-term performance

4.1 Sample selection

We have collected data on IPOs issued on Oslo Børs from 2000 to 2008. We have chosen this observation period because we wanted to test IPO performance under prevailing market conditions. The implementation of internet trading and robot trading has changed the dynamics of the equity markets considerably in recent years. Many famous studies on this subject, such as Ritter (1991) and Ibbotson (1975), are done before the computerization of equity markets. A possible weakness with our chosen time horizon is that it is relatively short. External events, such as booms and recessions, may therefore have another impact on our sample data than with a longer time perspective. Despite this, the merit of examining the market under prevailing market conditions weighs heaviest. In addition, the chosen observation period of three year is commonly used for similar studies.

We have used several sources for data collection. We have gathered data from Bloomberg and Factset[13] terminal servers. In addition, we have used resources at NHH, namely Thompson Reuters Datastream and Amadeus[14]. Our initial dataset from this sample period consisted of 179 IPOs, but after extensive filtering (explained below) our final dataset comprises of 99 IPOs.

During the filtering process, we cleaned all data which did not fit the interpretation of an IPO "as a company selling stocks to the general public for the first time" (Høiseth, 2004). Thus, we removed all IPOs that were a result of a merger or acquisition where one of the entities was previously listed on Oslo Børs. We have also removed relisted companies. We removed IPOs with these characteristics because they have previously been fully or partially valued by the market and are thus less subject to possible market anomalies.

[13] Factset and Bloomberg were accessed from friends in DNB Markets and Credit Suisse.
[14] Amadeus is a database with historical prices from Oslo Børs.

Listings of large privatized companies were also removed. Large privatized public companies, such as Statoil ASA, Telenor ASA and Yara ASA, have already been subject to thorough valuations by many analysts before they go public. Hence, investors have better indices of their true value relative to other IPOs. A recent example of this is the Facebook IPO. Damodaran claim that this was "the most pre-priced IPO in history, with transactions in the private share market providing information on what investors would be willing to pay for the stock" (Damodaran, 2012). This prophecy came true, and the stock price remained virtually unchanged from the offer price to the close price on the first day of trading. We have also removed spin offs from listed companies. These are not included because the value of the new entity is already valued in the holding company.

4.1.1 Length of aftermarket period

We have chosen a three-year aftermarket period to evaluate long-term IPO performance. The return is calculated from the close price on the initial trading day to close price three years post-listing. The aftermarket period for the long-term analysis was chosen after reading similar studies performed on IPOs in the American market. Studies show that the underperformance trend lasts for the first three years post-listing (Ritter, 1991) & (Rao, 1991). Based on the observation period chosen (2000 to 2008), we had to end the sample period in 2008, since we needed a three-year aftermarket period to study long-term return. The decision to study IPO performance in recent time restricts us from expanding the observation period from three to five years, as done in Rao (1991).

4.2 Methodology

To analyze if there is a long-term trend in our data, we have used descriptive statistics. Descriptive statistics is the discipline of quantitatively describing the main features of a dataset (Mann, 1995). Descriptive statistics aim to summarize a dataset, and are not developed on the basis of probability theory (Dodge, 2003).

When analyzing descriptive data, we have used statistical definitions like mean and median. The mean is referred to as the arithmetic average of the dataset. The mean is found by summing the number of variables, divided by the number of values. When a dataset is analyzed, the median is considered to be less efficient than the mean. However, the median is less sensitive to outliers (Weisstein, 2012). Outliers are defined as observations that lie outside the overall pattern of a distribution (Moore & McCabe, 1999). Therefore we will use both the median and the mean in our analysis.

In order to measure long-term IPO performance, we have calculated abnormal returns in excess of three benchmarks (Index, Peer companies and Sector industries). Before we present the results of our analysis, we will explain the calculation methods used.

In order to evaluate IPO returns, we have used monthly adjusted close prices and daily returns for the initial trading day. Mitchell & Stafford (2000) claim that monthly returns provide a better estimate when abnormal returns are calculated, because daily prices introduce too much noise to reliably measure abnormal returns .

Adjusted close prices[15] are used, as these are adjusted for stock splits and dividends payments. Adjusted close prices provide a better foundation for comparing different IPOs than pure close prices. This is because dividends and stock splits are also components to the total return of a stock, which is not accounted for when unadjusted stock prices are used. In the instances where a price on the last trading day of a month was missing, we have used the daily price closest to the end of the month in order to calculate monthly returns.

For IPOs delisted prior to their three year anniversary, we have truncated the observation period accordingly. Consequently, the long-term performance for the respective IPO ends after delisting. In order to calculate the return for the initial month of trading, we have truncated the monthly return from the first day of listing to the last trading day of the respective month.

4.2.1 Abnormal Return

Abnormal return is defined as return to a portfolio/stock in excess of the return of a market portfolio (Brav et al., 2000). We have calculated abnormal returns relative to three benchmarks, which will be explained in depth later. Abnormal returns are calculated based on this formula:

$$ar_{it} = r_{it} - r_{mt}$$

[15] Adjusted close prices were generated from Amadeus and Thompson Reuters Datastream.

Let r_{it} denote the return for a sample IPO for time $_t$ and let r_{mt} denote the benchmark return for time $_t$. Thus ar_{it} is the abnormal return for $IPO_{i,}$ in excess of market return r_{mt}.

The reason for using abnormal return rather than simple return is because abnormal return measures return relative to a benchmark which accounts for external factors such as market cycles, and is therefore a better indicator of pure IPO aftermarket performance. When simple returns are used, one might find negative return during a period where the stock market is in recession because their stock prices are affected by general market movements rather than factors connected to the IPOs. Thus, if only simple returns are studied, one might conclude that underperformance exists irrespective of how the rest of the market fared in the same period.

To measure the long-term performance of IPOs, we have calculated abnormal returns based on two event-time approaches: Buy and Hold Abnormal Return (BHAR) and Cumulative Abnormal Return (CAR) (Ritter, 1991).

BHAR is calculated as the percentage change of an IPO from the initial day of trading until three years post listing. The abnormal return is then calculated by subtracting the return for the benchmark used with the same time horizon.

$$BAHR_{i,T-t} = \prod_{t=1}^{T}(1 + R_{i,t}) - \prod_{t=1}^{T}(1 + R_{Benchmark,t})$$

$R_{i,t}$ is defined as the raw return for a sample IPO_i in month *t*. The benchmark is defined as $R_{Benchmark,t}$ which indicates the corresponding return of the respective benchmark in month *t*.

The mean BHAR is the arithmetic average of the individual BHARs, where N defines months, (36 months is equivalent to a three-year aftermarket period):

$$\overline{BHAR} = \left(\frac{1}{N}\right)\sum_{i=1}^{N} BHAR_i$$

Cumulative Abnormal Return (CAR) is the average benchmark adjusted return on an IPO. In order to calculate the CAR for each IPO, we first calculated the monthly abnormal return for each IPO based on the different benchmarks used. The calculation is based on the formula below:

$$ar_t = \left({(r_{i,t} - r_{i,t-1})}\big/{r_{i,t-1}} \right) - \left({(r_{Benchmark,t} - r_{Benchmark,t-1})}\big/{r_{Benchmark,t-1}} \right)$$

Let $r_{i,t}$ denote the monthly return for a sample IPO in month t, while $r_{i,t-1}$ denotes the monthly return for the previous month (t -1). We calculated the percentage change in return for the sample IPO based on the change from the previous months return. The same percentage change is found for the benchmark, denoted by $r_{Benchmark,t}$, for month t. The abnormal return (ar_t) for a sample firm in month t is found by subtracting the percentage change of the benchmark return from the IPO return.

$$CAR_i = \sum_{i=1}^{T} ar_{i,t}$$

$ar_{i,t}$ is the abnormal return for a sample IPO_i in month t.

The cumulative abnormal return for the whole data sample is the arithmetic average of the CAR_i for all IPOs:

$$CAR_{1,36} = \left(\frac{1}{N}\right) \sum_{i=1}^{N} CAR_i$$

Let N denote the total number of IPOs in or sample.

4.2.2 Measurement biases with BHAR and CAR

Existing studies show differences in preferred methodology for abnormal return calculations. Lyon et al. (1999) and Mitchell & Stafford (2000) conclude that CAR generates less skewed abnormal returns and is preferred over BHAR, which they claim has more statistical problems. The statistical problems with BHAR are related to the assumption of independence for multiple event-firm abnormal returns. In other words, the BHAR calculation assumes that the abnormal return calculation for two firms within the same calendar period will not be affected by each other. Mitchell & Stafford (2000) argue that this is very rarely the case, and that "major corporate events cluster through time by industry" (Mitchell & Stafford, 2000, p.290). This may lead to cross-correlation of abnormal returns, and they therefore argue that CAR is the preferred calculation method. Conrad & Kaul (1993) documented, on the other hand, that CAR tends to yield negatively biased abnormal returns over long periods.

Other studies prefer the BHAR calculation. For instance, Barber & Lyon (1997) argue that CAR is a biased predictor of the BHAR calculation. Based on a study of the U.S. equity market, they document that a sample of firms which all have zero annual return calculated with BHAR, would on average have a corresponding 12 month mean CAR of +5%. In this case, one would reach an incorrect conclusion of positive abnormal returns by only reading the CAR results. The same study emphasizes that the bias stems from differences in calculation method. The study further argues that the BHAR gives a more precise return for a given time horizon than CAR, since BHAR measures the return from day one to the end of the holding period, and not from month to month.

Barber & Lyon (1997) conclude that there are possibilities for biases with both BHAR and CAR calculations of abnormal return. They argue that this stems from the new listing bias, the rebalancing bias and skewness biases which affect the calculation methods differently. These biases will be described below.

The new listing bias is defined as the positive abnormal return bias which occurs when the BHAR calculation is used (Barber & Lyon, 1997). Ritter (1991) argues that new listings are overrepresented by young and high growth firms. The difference between the two calculation methods can be illustrated by an example: consider an IPO with a ten percent return in month one and two, while the benchmark has a zero percent return in the same months. CAR will then show a 20 percent return (10%+10%), while BHAR will show a 21 percent return (110%*110%-1). Hence, the BHAR calculation can be positively skewed (Barber & Lyon, 1997).

The rebalancing bias is defined as the inflated market return which occurs when equally weighted indices are constantly rebalanced in order to hold their constraints of equal weights of the stocks in the portfolio (Barber & Lyon, 1997). Jegadeesh & Titman (1993) document the momentum effect whereby past winners empirically outperform past losers in the intermediate term. This leads to an inflated long-run return of the benchmark portfolios relative to the matched IPOs, and the result is a positive bias in the measurement of the long-run BHAR. The effect of rebalancing bias is severe when daily prices are used, but less of a problem when monthly returns are used. The rebalancing effect is stifled when CAR is used, since this calculation is based on monthly summed returns, rather than compounded returns (Cania et al., 1998).

Skewness bias occurs because statistical tests assume normally distributed variables. Abnormal returns are often not normally distributed, but rather represent skewed distributions. With a positively skewed BHAR, we will get a negatively skewed test statistic because it is calculated by dividing the mean BHAR by the cross-sectional standard deviation of the sample IPOs. This bias is less severe in the CAR approach.

As is made apparent in the discussion above, there is no infallible method to calculate abnormal return. We have therefore chosen to use both BHAR and CAR in our study. We have seen from the previous studies that there are possible biases with both methods, and one should be cautious of these when reading the statistics derived.

4.2.3 Benchmark matching

In order to calculate abnormal returns, we have compared the IPO returns to three benchmarks. The three benchmarks used are:

- Market indexes: “Index”
- Peer companies “Peers”
- Sector indexes “Sector”

Index

The index benchmark is used to measure abnormal return for an IPO. Based on market capitalization, a sample IPO is matched against one of Oslo Børs' market indexes. BHAR and CAR is then calculated for each IPO based on its matching index.

We have classified the IPOs into three categories based on their market capitalization; large capitalized firms (large cap), medium capitalized firms (mid cap) and small capitalized firms (small cap). This classification is based on a similar classification done by the internet stockbroker Nordnet (Nordnet, 2012). We classified each IPO after this classification, based on the market capitalization at the end of the first trading month, for each respective firm. Thus, our dataset was classified into two large cap, 33 mid cap and 67 small cap IPOs[16]. The classification system we have used is based on market capitalization in 2012. Unfortunately, Nordnet does not provide similar classifications for previous years. This means that all our IPOs (from 2000 to 2008) have been classified based on market capitalization sizes today. An obvious weakness with our classification method is that there is a possibility that the average market sizes have changed over the past decade, and that as a consequence our classifications can be incorrect. However, during our classification process, we noted that in most cases, the relative value differences between our IPOs (based on companies listed in the same year), coincided with the classification given by Nordnet. Despite the possibility of changes in the relative size differences, our size classification should be an adequate approach.

For IPOs defined as large capitalized firms, we have used the OBX index as the benchmark. The OBX index is made up of the 25 most liquid equities on Oslo Børs. OBX is a total return index, meaning the index is adjusted for dividends and stock splits (Oslo Børs, 2003). While the index comprise the 25 most liquid stocks on OSE, the index is capital weighted, meaning that companies with large market capitalization is given a

[16] Market capitalization are defined based on market capitalization; MNOK 1400< Small cap < MNOK 40. MNOK 1400< Mid cap<MNOK 40 000. Large cap >MNOK 40 000.

higher weight in the index. Although the weightings have some restrictions[17], large capitalized companies as Statoil have larger weights than the smaller companies[18]. The OBX index is therefore highly sensitive to Statoil's stock price development. One might argue that benchmarking large capitalized companies against the OBX index may cause a measurement bias, as the OBX index is mainly based on liquidity and not market capitalization. Nevertheless, the weighting of the index makes it highly correlated to the performance of large capitalized companies and the OBX index can therefore be used as a proxy for the price development of large capitalized companies on OSE.

For IPOs defined as medium capitalized firms, abnormal returns are measured against the Oslo Stock Exchange Benchmark Index (OSEBX). The OSEBX index consists of the 65 most-traded companies listed on OSE. The OSEBX index contains a representative selection of the companies listed on the stock exchange and will thus reflect the overall price development of the stocks on OSE. This index is also a total return index and is computed in the same way as the OBX index. Since OSEBX is computed in the same way as OBX, we have the same weighting bias problem as for the OBX index. Despite this, the index is mainly made up by companies which are comparable to our medium capitalized IPOs.

For IPOs defined as small market capitalized companies, abnormal returns are measured against the Oslo Stock Exchange Small Cap Index (OSESX). The OSESX index is based on market capitalization and is made up by the small capitalized companies listed on OSE. This index should therefore be a good matching benchmark for small capitalized companies.

An issue with liquidity weighted indexes is the constant revision of the indexes. This makes our results prone to the rebalancing bias discussed earlier, which can result in biased abnormal results. A weakness with market capitalization weighted indexes is the possibility of a high variance. This is because the index variance can be biased towards

[17] "The capping rules restrict the weighting of the largest company in the index to a maximum of 30%, no other company can have a weighting of more than 15%, and the total weighting of non-EEA companies is limited to a maximum of 10%" (Oslo Børs, 2012).

[18] Statoil accounted for 23.27% of the OSEBX index a last revision of the index May 14th 2012. (Oslo Børs Newsweb, 2012)

the risk of the single firm (Ritter & Loughran, 2000). This is the case with both the OBX and the OSEBX index, due to the high weighting of Statoil. Despite these weaknesses and due to a lack of a better alternative, we proceeded using the chosen indexes as benchmarks for abnormal returns.

Another concern is that some companies, like Statoil, are included in both the OBX and the OSEBX index. This may cause an estimation bias. However, since we only have two IPOs classified as large cap, the effect of this should be marginal and is therefore ignored. The same concern goes for small capitalized companies such as Algeta, which is included in both the OSESX and the OBX index. This is because Algeta meets the requirements for both the OBX and the OSESX indices, as the firm is a heavily traded equity and a small capitalized company, respectively. However, this problem is only present for a few stocks, so this not a major concern. We simply acknowledge the weakness described and proceed with the index matching methods described above. Since only 35 of 99 IPOs are matched against liquidity based indexes and the rest (64 IPOs) are matched against a market capitalization based index, the problem with liquidity based indexes is subdued.

Peers

The second benchmark used is peer companies, where abnormal returns are calculated by subtracting the return of a peer company from an IPO. This technique is adopted from similar studies on American IPOs by Ritter (1991) and Speiss & Affleck-Graves (1995).

The selection criteria for each peer company are based on sector and size. Firstly, we found matching firms within the same industry[19]. Secondly, we chose a peer company with the closest market size, based on market capitalization of the IPO, at the end of the issue month.

The chosen matching firms are firms which were listed no less than three years prior to the IPO because we did not want to match two IPOs. We matched firms by market

[19]The sector classifications for sample IPOs and matching firms are from the Thompson Reuters Datastream terminal.

capitalization based on three benchmark dates; 31.12.1999, 31.12.2003 and 31.12.2007. We have used these three dates as intervals, and found the peer with firm value closest to the issue date. For instance, an IPO issued 01.03.2000 is matched against the peer with the closest market capitalization on 31.12.1999. We matched peers which fell between 70%-130% of the market capitalization value of the sample firm.

During the matching process, we wanted to use unique peers for each IPO. However, due to few matching peers in some sectors, some peers are used for multiple IPOs. In the case where there was not a comparable company within the same sector, we chose a matching firm from a similar sector. To measure their comparability, we analyzed the historical price development of both stocks to make sure that a correlation existed. Matching by peers effectively eliminates the rebalancing bias, mentioned as a risk when matching by index, since a sample IPO is matched with one peer for the entire observation period (Barber & Lyon, 1997).

After finding peers for the IPOs in the dataset, we have measured abnormal returns for each IPO based on monthly adjusted close prices of the matching firm. For IPOs delisted before three years, we truncated the observation period and used the prior time period to calculate the abnormal returns for the long-term analysis.

Sector

The third benchmark, Global Industry Classification Standard (GICS) industry sectors (Sector), calculates abnormal return for each IPO based on its respective GICS index[20]. If an IPO is delisted before its three-year anniversary, we have truncated the observation period based on the period prior to delisting.

GICS is a classification system introduced by MSCI and Standard & Poors. The system is a universally used system for classification of equities based on sectors, industries and sub-industries (MSCI, 2012). We have used the broad sector indices to classify our dataset. Our dataset consists of seven GICS sector indexes. The seven GICS sectors used and the number of IPOs matched are given in the table below:

[20] The GSCI sector indexes returns were collected from the Amadeus data terminal.

GSCI Sector	Matched IPOs
Industry	15
Health Care	11
Finance	9
Consumer Staples	9
Consumer Discretionary	9
IT	6
Energy	16

Table 4.1[21]

The reason for using broad sectors for matching instead of narrower categories, such as sub-industries, is because certain sub-industry categories would have contained only one or two companies. In some instances, the relevant IPO was also included in the sub-industry. To avoid a measurement bias, we have therefore used the broader sector indexes for matching.

The use of sectors for matching is not based on earlier studies. The reason for measuring abnormal returns based on sectors is because we wanted to compare IPOs to a broader segment of similar companies. By doing this, we wanted to capture the effects on abnormal returns for an IPO, from changes in micro- and macro-factors which affects the entire sector and not random events of a single firm. On the other hand, effects from events that only affect a few firms in a sector, as well as the sample IPO, are then reduced.

Despite the fact that sector matching is a similar technique to peer matching, we believe that matching IPOs against sectors will provide a better measure of the effects of micro- and macro-incidents which affect an industry as a whole, compared to just matching against a single firm. The weakness of measuring excessive returns against broader sectors, rather than narrower industries categories, is a weakness. Due to the lack of matches on firm level, we have no option but to use the broad sectors.

[21] A full description of the sectors used can be found in Appendix 9.1.

Another issue with sector matching is the rebalancing bias that follows. Many IPOs are included in the GSCI sector indexes, meaning that we match the abnormal returns against an index which includes the sample firm. However, the price effect from the sample IPO is somewhat reduced because the broad indexes consist of many companies. The overall rebalancing effect of a particular IPO on the index is therefore subdued. We view the effects of this problem to be small, but it is nevertheless a weakness with sector matching.

Despite the weaknesses described above, we chose to proceed with sector matching, as we wanted to add some originality to our analysis. We acknowledge the weaknesses, but still hope sector matching will provide insightful results.

4.2.4 Risk adjustment

When abnormal return is calculated, one needs to account for differences in risk between the sample IPO and its benchmarks since risk and return are positively correlated (Brav et al., 2000).

In order to adjust for risk between a sample IPO and its benchmarks, Ritter (1991) and Loughran & Ritter (1995) use size matching to control the systematic risk of IPO firms. Since both index and peer benchmarks are matched based on size[22], the sample IPOs are matched against benchmarks with approximately similar systematic risk. This is not the case for sector matching, since size is not a criterion. The technique used accounts for sector-specific risks between the IPOs and their sector. Nevertheless, we acknowledge that this is not a solid risk adjustment, since it does not adjust for systematic risk.

Adjusting for risk by size matching also has weaknesses. Eckbo et al. (2000) state that size matching does not effectively account for differences in risk. They argue that constructing zero investment portfolios, with short positions in IPOs and long positions in size-matched peers, is a better risk adjustment. Due to difficulties with constructing these portfolios, we have used Ritter (1991) and Loughran & Ritter's (1995) method to account for risk.

[22] Size is accounted for by matching index and peers based on market capitalization of the sample firms.

We have not adjusted the IPOs for beta values in our index matching procedure. Berk & DeMarzo (2007) define beta as "a measure of systematic risk, of a security or a portfolio in comparison to the market as a whole". The reason for not adjusting for differences in beta values is firstly because IPOs do not have historical market prices which are needed to calculate a beta value. Secondly, it would be incorrect to use a company's beta after the listing as a proxy. This is due to the fact that a beta value will be adjusted for abnormal returns. Consequently, we would not be able to identify abnormal returns for the respective IPOs. Ibbotson (1975), Chan & Lakonishok (1990) and Clarkson & Thompson (1990) all conclude that the average beta of IPOs fall significantly in the aftermarket period. To calculate a beta straight after listing is therefore not an option either.

4.2.5 Data trimming

A few observations, which may not be representative of the underlying area of study, can be highly influential in datasets with a small sample size. To avoid a wrongfully influenced dataset, a dataset can be trimmed. To trim a dataset is simply to remove a certain percentage of the most extreme data in each direction. It is usual to trim a dataset by 5% or 10%, but the most important aspect of data trimming is to remove unusual observations. If a dataset is trimmed by 10%, it means that the dataset is reduced by the 10% highest and 10% lowest observations (from the full sample). The mean values derived after the trimming of the data are called the trimmed mean (or the truncated mean).

The trimming of data is a useful tool when median values are calculated based on datasets with outliers. Bloch (1966) argues that the truncated mean is a robust estimator, since it is less sensitive to outliers compared to the full sample mean. Bloch further states that despite removing observations, the trimmed mean still provides useful insight on the central tendency of a dataset.

Another advantage of using a trimmed mean is evident in the case of a Cauchy distribution - a bell shaped distribution with fatter tails than the normal distribution (Rothenberg et al., 1966). In the case of a Cauchy distribution, the trimmed mean produces a better estimate for the population location parameter[23] than the full sample mean. This result is based on a study with 38% trimming performed by Ferguson (1978). He points out that the use of a trimmed mean is not completely robust and suggests that a maximum likelihood estimator is a better option. However, a maximum likelihood estimator is difficult to compute and a trimmed mean can therefore be considered a useful substitute. We will not discuss the maximum likelihood estimator further, but for further references please see Ferguson (1978). In the extension of the Central Limit Theorem, Rosenblatt (1955) argues that a sample size greater than 40 and without outliers is large enough to approximate a normal distribution.

The aim of trimming the data is to fit our datasets to a normal distribution, located around a center-value with even tails both left and right from the center-value. Hence, the observations should somewhat be grouped together.

4.3 Results of the long-term performance analysis

Based on the abnormal return calculation methods described above, we have calculated BHAR and CAR to identify abnormal returns for IPOs based on a three-year aftermarket period. In order to get a graphical overview of our dataset, we have run a boxplot diagram in Minitab (figure 4.2). The diagram plots abnormal return for each dataset in descending order. We will only present the most relevant results in the narrative of this thesis – the complete results are enclosed in appendix 9.2.

[23] A location parameter test compares the location parameter of a statistical population to a constant. A location parameter test can also be used to compare location parameters of two statistical populations. Most commonly, location parameters are used to compare against expected values, but location tests can also be based on median (Gosh, 1973).

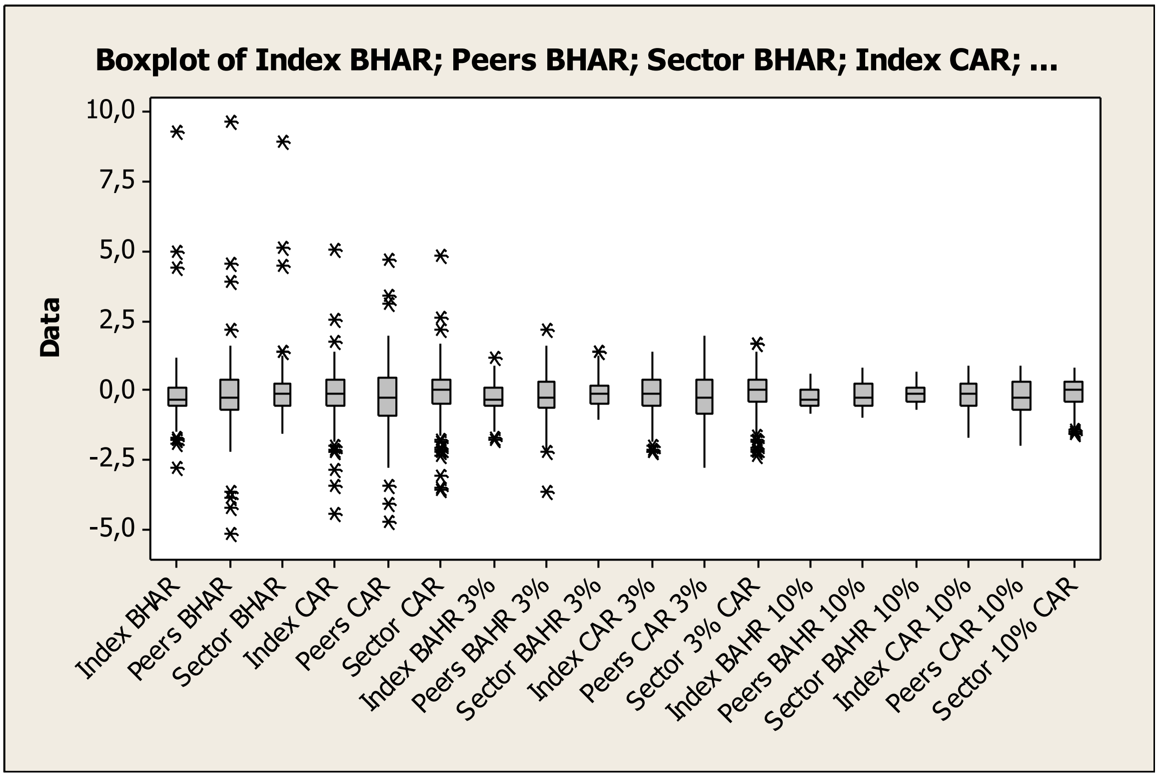


Figure 4.2

In the boxplot diagram, the boxes indicate multiple observations with a similar value. The asterisks are single observations, whilst the lines are multiple observations, indicating a tail. Based on the boxplots for the raw data, we note that all six plots (full sample data) have extreme values. The problem with outliers is that these extreme values can adversely affect the analysis and can lead to misinterpretation of the statistics derived. For this reason, we decided to trim our data to remove outliers.

Both the index and peer adjusted returns have three outliers on both sides of zero. Based on these observations we decided to trim our data, by removing the three highest and lowest returns (3% trim, $\frac{3}{99} \approx 3\%$). Note that sector BHAR does not have extreme negative values, yet we chose to trim both positive and negative outliers in order to be consistent. The 3% trimmed datasets consist of 93 observations.

The results of the 3% trimming are given in the same figure (figure 4.2). Despite the 3% trimming, the data still contains a few outliers. Following the same rationale as above, we trimmed further, trimming the ten highest and lowest observations from the raw data. The 10% trimmed data gives a dataset without outliers, and all our data are centered on zero, with small tails. The 10% trimmed dataset contains of 79 observations.

One might argue that trimming what was a small dataset (99 observations) as extensively as we have done, might reduce the possibility of reaching a conclusive result. For this reason, we chose to proceed with all three datasets in our statistical analysis. Consequently, we performed statistical analysis for the raw data, the 3% trimmed and the 10% trimmed data. Since a trimmed dataset gives a better estimate of the mean and the median (Bloch, 1966), we will focus more on the results from the trimmed data than for the results from the full dataset. Since the full samples do not meet the full requirements of a Cauchy distribution, particularly when we take into account that the full samples do not have even and fat tails, we proceeded with the trimmed data, because the observations are located around a center-value.

In general in this thesis, we will not label a result as statistically significant if the P-value is larger than 10%, in order to not make Type 1 errors (rejecting a true null hypothesis). We will be more confident in our results for lower P-values, since the possibility of making type II errors (failing to reject a false null hypothesis) is less.

4.3.1 Results from market index matching

Figure 4.3 presents statistics on IPO returns in excess of the index benchmark. The mean values for all datasets indicate negative abnormal returns, but statistically significant mean values are only present in the trimmed datasets. Both BHAR and CAR show that the long-run underperformance is severe, but the robustness of the observed means is reduced by the large standard deviation. The negative median values also support underperformance based on index matching. However, the median values are only statistically significant for the BHAR datasets.

Skewness measures asymmetry in the distribution. A distribution with skewness means that one of the tails is longer than the other. The distribution will consequently have a majority of values on one of the sides of the center-value. Heavily skewed data can generate biased results, due to the nature of the distribution and existence of outliers. Figure 4.3 show that the trimmed data reduces this problem.

In light of the data presented, we have found evidence of IPO underperformance in excess of market indexes. According to the discussions of skewness and statistically significant results, we rely mostly on the 10% trimmed dataset, which indicates a buy and hold average abnormal return of -26.3%. A negative median value gives further evidence of underperformance. The CAR calculated returns yield higher returns (-16.6%[24]), but is also supporting underperformance in excess of index.

	BHAR – Index matched			CAR – Index matched		
	Raw data	3% trimmed	10% trimmed	Raw data	3% trimmed	10% trimmed
Mean	-0.132	-0.27*	-0.263*	-0.217	-0.216*	-0.166*
Standard Deviation	1.340*	0.555*	0.363*	1.168*	0.804*	0.572*
Skewness	4.29	-0.0827	0.4787	0.073	-0.695	-0.57
Median	-0.326*	-0.326*	-0.326*	-0.126	-0.126	-0.126
N	99	93	79	99	93	79

Figure 4.3: Descriptive statistics for index adjusted returns. *Statistically significant on a 95% confidence interval. **Statistically significant on a 90% confidence interval.

4.3.2 Results from peer company matching

Statistics for IPO return benchmarked against peer companies are shown in figure 4.4. They prove that IPOs underperform when matched against peers. This is evident through negative mean values for both the full data sample and the trimmed data. The mean values are statistically significant for all data samples, except for the BHAR raw dataset. The CAR yield a lower excess return compared to BHAR. This is in contrast to the index adjusted return calculated, which gave the opposite result. Despite high standard deviation for the average returns, statistically significant median and most mean values support the case of negative peer adjusted returns.

The skewness of the distributions is less severe for these datasets compared to the index matched datasets. The skewness for the raw BHAR dataset is high, but is significantly reduced in the trimmed datasets. Note that trimming from 3% to 10% trimmed data

[24] Based on the 10% trimmed mean from CAR-Index matched return.

gives a higher trimmed mean. This argues the case of how outliers can adversely affect a statistical result. Since the 10% trimmed dataset gives the lowest skewness, we will again rely on this result in our analysis.

The BHAR is on average higher for the peer adjusted dataset compared to the index matched set, but the result is the opposite for the CAR calculations. The difference in results between that the two calculation methods, provides evidence of the calculation biases we have discussed earlier and is an example of why one calculation method is not preferred over the other.

Based on the discussed results, we can conclude that IPOs yield negative returns when benchmarked against peers. The 10% trimmed BHAR datasets state that the average BHAR for IPOs is -21.5% lower than their peers. For the CAR calculated return, IPO underperformance is more severe; with an average adjusted return on -29.2% based on the 10% trimmed dataset. Despite statistically significant result, the standard deviations are still high which means that the IPO returns are very volatile.

	BHAR – Peers matched			**CAR – Peers matched**		
	Raw data	**3% trimmed**	**10% trimmed**	**Raw data**	**3% trimmed**	**10% trimmed**
Mean	-0.16	-0.22*	-0.215*	-0.312*	-0.318*	-0.292*
Standard Deviation	1.6*	0.82*	0.49*	1.374*	0.996*	0.694*
Skewness	2.08	-0.452	0.429	0.037	-0.291	-0.276
Median	-0.3*	-0.3*	-0.3*	-0.311*	-0.311*	-0.311*
N	99	93	79	99	93	79

Figure 4.4 - Descriptive statistics for peer company adjusted returns. *Statistically significant on a 95% confidence interval. **Statistically significant on a 90% confidence interval.

4.3.3 Results from sector matching

The statistics for sector-adjusted IPO returns are shown in figure 4.5. Apart from the BHAR raw data, negative mean values are evident in both calculation methods. However, statistically significantly means are only evident for the trimmed datasets for BHAR and the 3% trimmed CAR dataset. The mean values yield average abnormal return of -14.6% for 10% trimmed BHAR and -15.4% for 3% trimmed CAR. The median for the 10% trimmed BHAR is -14.7%. The CAR medians are substantially higher, though still negative, but none of them are statistically significant. Consequently, sector adjusted returns yield the highest long-term return, compared to the other benchmarks.

The few statistically significant median and mean values casts doubt over the robustness of this analysis. This argument is strengthened by the large standard deviations. We have previously explained several weaknesses with the sector matching technique, such as the rebalancing bias problem and the use of broad sectors, rather than narrow industry indexes. We have also discussed that this matching technique may not be adequate, because each sample IPO is most likely also included in the sector index which the IPO is matched against. This is possibly an explanation for why the results from sector matching are less statistically significant. Despite the weak robustness of the results, this matching technique also proves that long-term underperformance exists, but the analysis indicates that the underperformance is less severe than depicted from the other benchmark analyses.

	BHAR – Sector matched			**CAR – Sector matched**		
	Raw data	**3% trimmed**	**10% trimmed**	**Raw data**	**3% trimmed**	**10% trimmed**
Mean	0.048	-0.106**	-0.146*	-0.132	-0.154**	-0.096
Standard Deviation	1.27*	0.526*	0.37*	1.17*	0.82*	0.55*
Skewness	4.64	0.797	0.326	0.093	-0.73	-0.796
Median	-0.147*	-0.147*	-0.147*	-0.025	-0.038	-0.025
N	99	93	79	99	93	79

Figure 4.5: Descriptive statistics for sector adjusted returns. *Statistically significant on 95% confidence interval. **Statistically significant on 90% confidence interval.

4.3.4 Key findings of the descriptive statistics

In general, the 10% trimmed datasets produce the results that are the least affected by outliers, have the least skewness and the lowest standard deviation. We have therefore chosen to focus on the results from these datasets. Based on statistically significant negative mean and median values, we can conclude that IPOs yield negative long-term returns across all benchmarks. However, the robustness of our analysis is mitigated by high standard deviation, and we cannot therefore conclude that IPOs underperform with a definite percentage number. We can instead infer that IPOs are most likely to yield an abnormal return within the interval; -10% to -30% on average. We can thus conclude that the IPO anomaly of long-term underperformance is present in the Norwegian stock market.

Our results concur with most other foreign studies, as for instance Ritter's (1991) findings of long-term underperformance from -27.4% to -29.1% and Barber & Lyon's (1997) finding of -5.27% return. We have seen that the calculation method is decisive for the results, and that the choice of observation period is also playing a big role in the results observed.

The effect of using CAR and BHAR to measure aftermarket performance demonstrates the calculation biases discussed in other studies. The CAR is on average lower than the BHAR for all three benchmarks[25], indicating that CAR is a negatively biased predictor of BHAR. This result coincides with the results found by Conrad & Kaul (1993). Nevertheless, this conclusion does not explain the index-adjusted returns, where the average CAR trimmed mean is higher than the BHAR return. Despite the differences in calculation methods, both CAR and BHAR supports the conclusion of long-term underperformance.

The fact that the IPOs in our dataset underperform relative to their benchmarks can prove that the lemons problem (Akerlof, 1970) exists in the Norwegian stock market. The rationale is that low quality firms yield lower long-term returns than high quality firms. In most cases, investors have an information disadvantage as compared to the firm owners. This supports the notion that investors could be unaware of the true quality of the firm, and that IPO underperformance is a sign of low quality for a firm. The

[25]For the peer and sector adjusted return, CAR yields a lower average return than buy-and-hold return. The peer adjusted return is -8.75% lower using CAR compared to BHAR, and for sector the CAR yields -4.8% lower return. The differences in average return are based on the average of the statistically significant trimmed means found for Peer and Sector adjusted returns from the 10% trimmed dataset. In the case of sector matching, this is based on the 3% trimmed datasets.

underperformance of IPOs can be related to other factors than the quality of a firm. For instance, differences in risk (Schultz, 2003), over-optimism and fads (Ritter, 2001) or other factors can explain the negative aftermarket returns.

4.3.5 Monthly development of abnormal returns

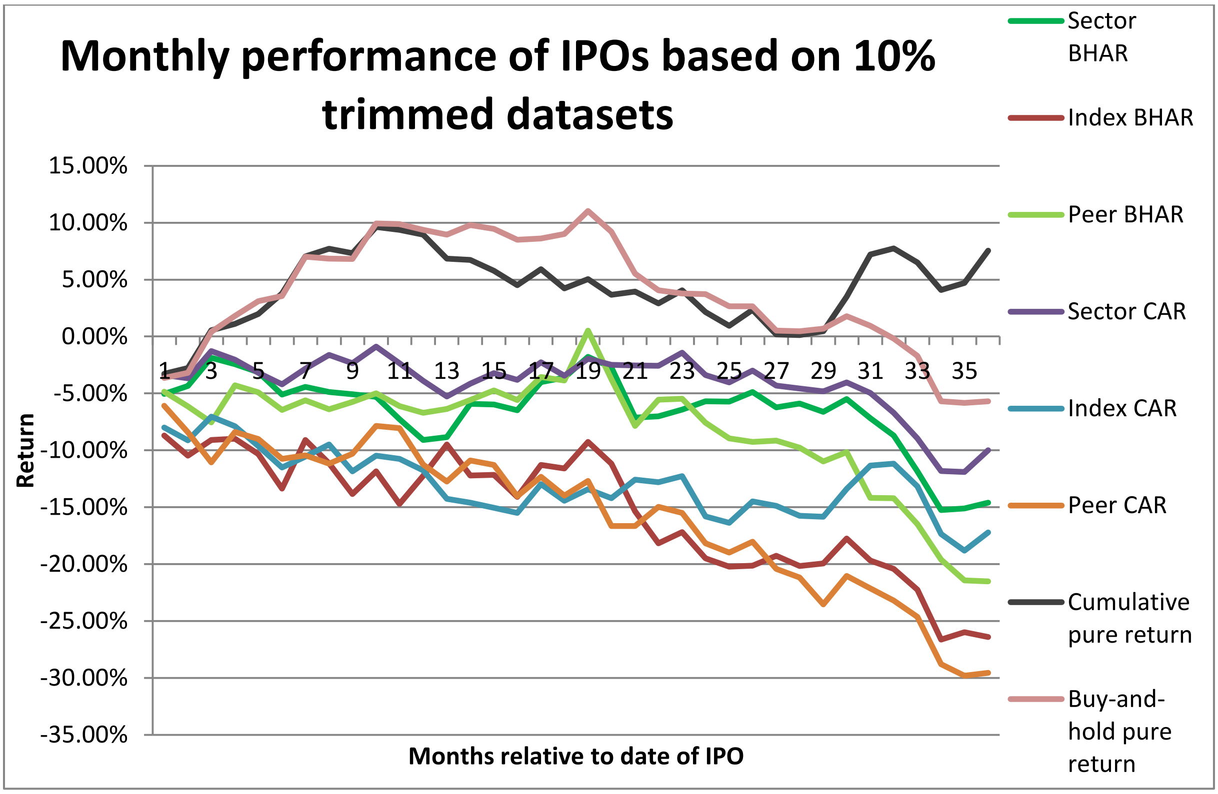


Figure 4.6

Figure 4.6 illustrates average monthly abnormal returns compared to all benchmarks, based on the 10% trimmed dataset. Underperformance is evident since all the abnormal returns are located below the pure IPO returns. The 10% trimmed datasets indicate that IPOs yield a three-year abnormal return between -10% to -30%, depending on the benchmark used and the calculation method.

The graph indicates that underperformance begins in the first month and declines until the 34th month. Although the overall three-year trend shows a negative price development, there are signs of a recovery. In the 34th month the negative abnormal returns trend ends, and returns seem to rise or stabilize at the current level. This is evident across all abnormal return calculations. The recovery in the 34th month can be an indication that IPO underperformance is isolated to the three-year aftermarket period. This result would be in line with studies by Ritter (1991) and Rao (1991), who reached the same conclusion. The fact that we have used a three-year aftermarket period does not permit us to examine the price development further. Hence, there is not enough evidence to conclude whether this recovery is a temporary market correction or a long-term price development. Nevertheless, there is an indication that IPO underperformance is isolated to a three-year aftermarket period.

4.3.6 IPO listing cyclicality

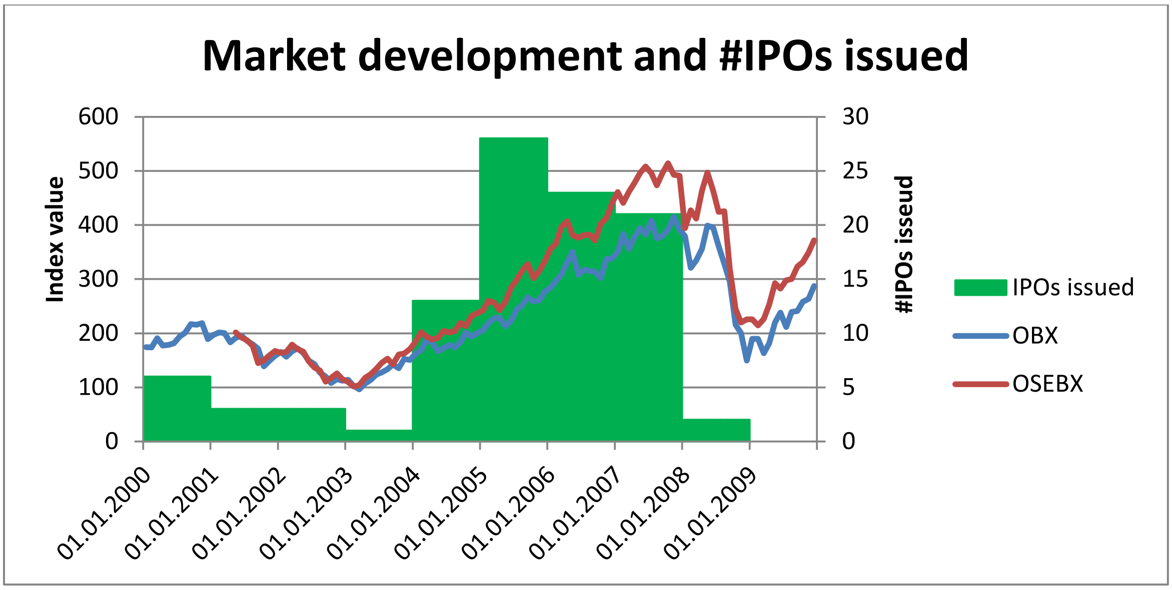


Figure 4.7

Berk & DeMarzo (2007) assert that the number of IPO listings tends to follow market cycles. Listing cyclicality is explained by Ritter (1991), who argued that managers and issuers "time" equity listings to periods when the stock prices are rising. We have tried to illustrate this market anomaly in figure 4.7, which shows the price development of the OSEBX index and the OBX index for the period January 2000 to December 2009 together with the number of new listings each year. The figure illustrates that there is a correlation between the market price development and the number of new issues.

The majority of the IPOs in our study were issued before 2008. In fact, 98 of the 99 IPOs in the full sample were listed before the financial crises in 2008. The "golden years" for new listings were 2005 (28 IPOs), 2006 (23 IPOs) and 2007 (21 IPOs). This coincides with a period where Oslo Børs rallied. This result corresponds with the market anomaly of IPO listing cyclicality discussed by Berk & DeMarzo (2007) which states that IPO listings tend to follow a cyclical pattern. Schultz (2003) explained that most issuers will raise equity during good market conditions, which coincides with this result.

Although we have found evidence of the cyclicality in a number of new issues, this is not an anomaly that an investor can exploit in order to earn extraordinary profits. This is therefore not a departure from market efficiency. In chapter 5, we will try to examine if there is any connection between the long-term IPO return and market cycles.

4.4 Obstacles for exploiting the long-run underperformance anomaly

Ibbotson (1975) claim that a market anomaly is only market inefficient if an investor is able to make profit from it after transaction costs are incurred. He argued that the aftermarket of IPOs is market efficient if long-run performance of IPOs is not significantly different from zero. Although he found evidence of positive performance the first year and negative performance the next three-years for IPOs, he concluded that his results indicate few, if any, departures form market efficiency. The reason for not discarding market efficiency, despite finding significant results, is that there were substantial transaction costs associated with stock trading at the time Ibbotson studied IPOs. He claimed that it was it was impossible to exploit the aftermarket trends in IPOs, due to high transaction costs, included bid-ask spreads from 6%-7%.

Today, the transaction costs for trading in stocks are remarkably lower than they were in the 1970s. After the introduction of stock trading through the internet, the bid-ask spreads have decreased and are now down to 0.01% for the most liquid stocks, and 1%-2% for more illiquid stocks. Along with brokerage commission, which currently typically stands at about 0.05%, it is evident that the transaction costs are, in total, much lower than for forty years ago.

The long-run degree of underperformance is, on the other hand, larger; -10% to -30% as we have found. At first sight, it seems easy to make a profit on the long-term underpricing anomaly, but a stock has to be shorted in order to exploit this anomaly. Shorting a stock means that you sell a stock you do not own, and thereafter buy it back for delivery at a later point in time. This way, an investor will make a profit if the stock price falls because he is able to buy back the stock at a lower price than he borrowed it for.

Taking short positions in stocks has been increasingly restricted since the financial crisis began in 2008. There have been periods in later years where short selling has been forbidden and naked shorting[26] is now completely forbidden in Norway. Even though short selling is presently legal in Norway, most stock brokers only allow for a limited standardized list[27] of companies to be shorted. The stocks that are normally allowed to be shorted are typically the most liquid stocks at Oslo Børs. IPOs are usually not among these stocks during their first years of listing. If an investor wants to short a stock outside the standardized list, this has to be done through customized trades.

In order to be able to short most IPOs, the stock broker usually has to borrow the stock you wish to short from one of the current stockholders. This arrangement is possible to accomplish, but it will most likely imply very high transaction costs and may not be easy to complete. First of all, the current stockholders may not be willing to lend you the stocks, because they will then lose their voting rights and dividend payments during the period you borrow the stocks. If you are allowed to borrow the stocks you want, most shorting agreements contain a clause that the owner has a call provision in the borrowing period. The borrower can, in other words, call back the stock at any point in time, and this makes this strategy highly uncertain. It is possible to borrow a stock without a call provision, but it comes at a cost.

This leads us to the second problem with the shorting of IPOs – the transaction costs will most likely exceed the possible gains. There are several reasons for why the costs connected with a short position in an IPO may be high. One cost is the interest you have to pay to the stock lender. Pareto Securities operates with a yearly interest on securities loans from 4.5% per year[28]. The interest you will have to pay will most likely exceed regular securities loans. This is because IPOs are highly volatile, and are therefore a

[26] A form of short selling; where the stock is not borrowed in advance or ensured that the stock can be borrowed.
[27] Nordnet stock broker allow 13 stocks to be shorted, while Pareto Securities allow 31 stocks to be shorted (as of May 2012).
[28] Information found on Pareto Securities' website (Pareto Securities, 2012).

risky investment. In addition, you will most likely have to pay a premium on the interest rate to convince a stockholder to lend you the stocks.

In a short sale, there is also a margin requirement because you potentially have an unlimited loss. The margin requirement is usually the inverse of the leverage degree, with a minimum requirement. The minimum requirement is 20% in Pareto Securities[29], but we have reason to believe that this will be higher for most IPOs as we have found such a high standard deviation in their aftermarket performance. Since the margin requirement will be inaccessible for the investor, the funds tied up cannot be invested. In contrast, since it is common with high leverage in short positions, there is an advantage of tying up less funds compared to a regular long position in stocks.

The brokerage commission is usually the same for short sales as regular purchases. We will later show that most companies go public when they are young, and that they have a relatively low market capitalization compared to the most traded firms at Oslo Børs. This means that most Norwegian IPOs are less liquid than the companies at OBX, and the bid-ask spread is therefore usually higher for IPOs than the most liquid stocks.

4.5 Conclusion long-term performance

In sum, the costs associated with shorting an IPO the first three years are: brokerage commission, bid-ask spread, margin requirement, a premium to avoid call provision and yearly interests for borrowing the stock. Despite lower bid-ask spreads and lower brokerage commission in later years, the costs that will occur by this strategy will most likely exceed the possible gains from shorting an IPO. In addition to the high costs associated with shorting an IPO, we have described that it may be difficult to borrow IPO stocks and to hold them for three consecutive years. Professor Thore Johnsen and Tore Leite at NHH both concur that it is impossible to exploit this anomaly in order to make a profit[30].

Irrespective of the mentioned issues with shorting IPOs, it is still a risky strategy to do so. This is because we have found that Norwegian IPOs have an extremely volatile

[29] Information found on Pareto Securities' website (Pareto Securities, 2012).
[30] Based on conversations with the professors at NHH in May 2012.

aftermarket performance, measured in standard deviation. Since few companies are listed on Oslo Børs each year, "the law of large numbers" will most likely not occur after many years by this strategy. This law states that the average result obtained from a series of trials should be closer to the expected value as more trials are performed (Hsu & Robbins, 1947). The final result of following a strategy by shorting Norwegian IPOs is therefore highly uncertain.

The high costs, the difficulties with borrowing stocks and the uncertain outcome of shorting IPOs for three years subsequent listing, makes the long-term IPO performance anomaly very difficult to exploit. According to Ibbotson's definition of market efficiency, this anomaly is therefore not market inefficient.

5 Cross-sectional regression

5.1 Regression background

The analysis of long-term performance concluded that IPOs yield an abnormally low return the first three years after going public. Now we want to examine which factors can explain this abnormal return. Previous studies have examined the performance of IPOs and found that some variables can explain the phenomenon (Ritter, 1991). We have therefore chosen to study how these variables affect the abnormal returns. In addition, we have relied on economic theory and examined if these theories fit our data sample. The previous studies mainly stem from the American stock market. Since we will examine the Norwegian market, we have chosen to include Brent Crude oil as one of the explanatory variables in addition. Each variable will be explained in depth.

5.2 Methodology

In order to examine how these variables affect the return on IPO companies, we have chosen to run cross-sectional regressions. Regression analysis is used to predict the value of one variable, the abnormal IPO return in our case, on the basis of other variables. This type of analysis generate a mathematical equation with the variable to be forecasted on one side of the equation (the dependent variable) and other variables you think can explain the dependent variable (independent variables) on the other side of the equation (Keller, 2005). The generated equation is a so-called ordinary least squares (OLS) approximation. OLS approximations estimate a linear approximation that fits the data sample in such a way that the sum of squared vertical distances between the observations and the predicted linear approximation is minimized (Bretscher, 1995). The equation is in the following format:

$$Y_i = \beta_0 + \beta_j x_{ij} + \varepsilon_i$$

Y_i = Dependent variable, x_i = Independent variables, β_0 = y-intercept, β_j = Slope coefficients of the line and the ε_i's are independent statistical noise terms with a zero mean value and standard deviation σ. The subscription scheme is done so that X_{ij} is the value of the j^th^ independent variable X_j for data point *i*.

We will not explain the statistical methods used in depth, as we expect readers of this thesis to be general economists. For those who would like to investigate further, books on these topics are enclosed in the bibliography (see, for example, Keller (2005) and Woolridge (2009)).

In order to develop as strong a model as possible, we have applied the Gauss-Markov theorem for OLS models. In order to develop the best model as possible, the following assumptions must hold true for the OLS regression (Woolridge, 2009):

1. Linearity
   - The model must be linear in its parameters.
2. Sample Variation
   - The independent variables cannot all have the same value.
3. Random Sampling
   - The n observations in the sample must be random.
4. Zero Conditional Mean
   - The mean of the error terms of the independent variable x_i is zero.
5. No Multicollinearity
   - Multicollinearity refers to a situation in which two or more explanatory variables in a multiple regression model are highly linearly related.
6. No Heteroskedasticity
   - The variance of the error terms is constant. This means that the variance of the error term does not depend on the value of x_i. If this is the case, the error terms are called homoscedastic.
7. No Serial Correlation/auto correlation
   - The error terms are independently distributed so that their covariance is 0. Serial correlation occurs in time-series studies when the errors associated with a given time period carry over into future time periods.
8. Normally Distributed Errors
   - The error terms are normally distributed.

If the first five assumptions are satisfied, the OLS estimator is unbiased, meaning that the mean value of the estimator equals the true value of the underlying quantity it is estimating. If there is no additional heteroskedasticity, the OLS model has the minimum variance of all unbiased estimators. The theorem states that if all the assumptions for the OLS model hold, the OLS model is the Best Linear Unbiased Estimator (BLUE). This means that out of all possible linear unbiased estimators, OLS gives the most precise estimates of the regression. If the assumptions of no heteroskedasticity, no serial correlation and no multicollinearity are not satisfied, then the OLS is still unbiased, but is no longer BLUE. Because we have cross-sectional data, and not time-series data, we do not have to concern ourselves with serial correlation in this thesis.

We have used the same dataset in our calculations as the one used to examine abnormal long-term performance of IPOs. Thus, we started with 99 companies, but ended up with 94 companies in our final dataset due to problems with finding data for all our companies. The five excluded companies were excluded mainly because of missing data for the market-to-book values from Thomson Reuters Datastream (although we managed to calculate some of the missing data manually based on public information). We have chosen to only analyze the BHAR and not the CAR, because we expect that the two analyses will produce approximately the same results, and it would require too much space in this thesis to do both. Initially, we had three BHAR dependent variables to examine; the abnormal IPO return matched against market indexes, peer companies and GSCI sectors. We have included seven sectors as explanatory independent variables in our regression - therefore it would be meaningless to run a regression with sector as dependent variable while sectors are included as independent variables. We have thus chosen to only analyze what can explain BHAR with index and peer matching.

5.3 Explanation of the chosen independent variables

5.3.1 Age

Ritter (1991) claims that there is a strong relationship between how old a company is before going public and its aftermarket performance. We have therefore chosen to include the variable “ageyears” in our cross-sectional regressions. This variable measures how old a company is before going public, and is computed by subtracting the year when the company was founded from the year when the company went public. We found the date each company was founded by using Brønnøysundregistrene (Brreg.no, 2012) and the companies' respective webpages. Age can be an approximation of risk because young startup firms usually have an uncertain destiny. Therefore investors usually require an initially higher return when such firms are going public compared to older firms with more certain prospects. Because age has an effect on the issue price of an IPO, we expect the independent variable to have an effect on the long run return as well as the initial return.

Ritter (1991) and Speiss & Affleck-Graves (1995) have found that younger firms underperform relative to older firms in the long run after an equity issue. Ritter (1991) explains this with the rationale that younger firms often have a higher market-to-book ratio than older firms because of the over-optimism and fads effect. This argument stems from Fama & French (1993), who found a relationship between return and book equity (B) over market capitalization (M). They found abnormally high returns for B/M ratio (value stocks) and abnormally low returns for low B/M ratio (growth stocks). The inverse ratio is equivalent to Ritter's argument about low return on high M/B ratio.

Young companies usually have a high risk premium at the IPO date and it is reasonable to assume that this risk premium will decrease as the company ages. As a young company grows older and its future prospects become more certain, investors are willing to pay more for their stocks (assuming that they believe the company will succeed). This is because the beta will be lower which ultimately results in a lower WACC and a higher valuation of the company (Ibbotson, 1975). If this happens, young companies will perform better than old companies in the long run (three-years). For instance, a pharmaceutical company with an uncertain idea is likely to be traded at a discount in the startup phase when they choose to go public to finance their idea. Investors are surely not willing to pay a stock price that implicitly infers that the idea is 100% likely to succeed, they will price the stock at a discount based on the uncertainty (and other factors). If the overall chance for a startup company to succeed increases as they mature, their stock price will increase over time. Thus, young companies will probably perform better than older companies.

Another theory about the performance of companies in relation to their firm age is the "value effect theory" (Basu, 1977). Proponents of this theory claims that low price/earnings (P/E) securities will tend to outperform high P/E stocks. Young companies tend to have a high P/E ratio, and this theory thus supports Fama & French and Ritter's arguments about underperformance of younger companies.

Young companies usually have lower market capitalization as compared to more established companies. Few young companies have truly reached their full market potential, and it is reasonable to say that most companies increase in value as they age (figure 3.1). Blume & Stambaugh (1983) have examined the effect on firm size and return. They concluded that risk-adjusted returns on small firms exceed the return on large firms. This reasoning implies that young companies are expected to have lower market capitalization than older companies; the stock return is thus expected to be lower for older companies than younger companies.

Theories about company age at the time of listing infer that this independent variable should have an effect on aftermarket performance, but the theories are inconsistent in terms of which direction they affect the abnormal IPO long-run return. Thus, it is difficult to determine the sign character[31] that the independent variable "ageyears" will have in our regression. The average company age at the IPO date in our data sample is 14.6 years, but from figure 5.1, we can see that most of the companies went public before that. Based on a median of 6 years, we can conclude that the companies in our data sample are relatively young.

[31] Positive or negative coefficient

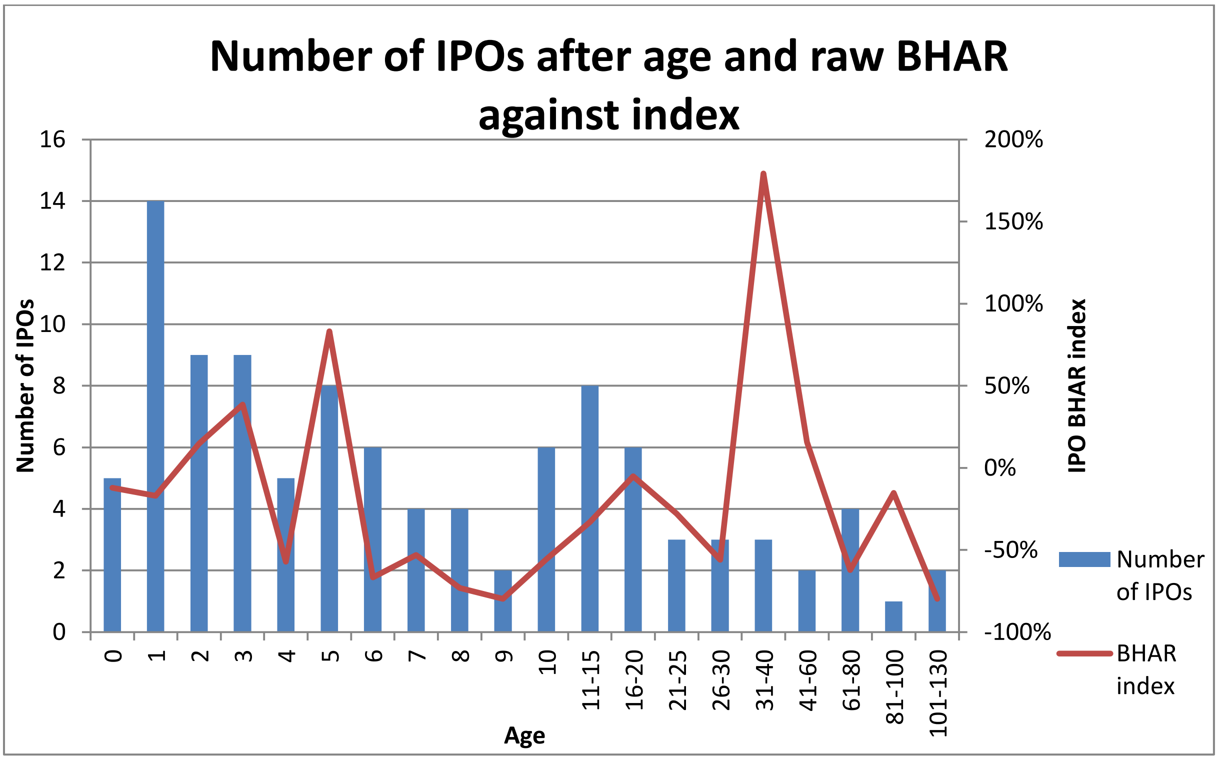


Figure 5.1

There are a lot of theories attached to firm age, and we are therefore expecting high multicollinearity between the variables "mbook", "age" and "mcap". We will examine this in chapter 5.4.

5.3.2 Brent

Oil production accounts for a large part of the Norwegian GDP. Hence, the Norwegian economy and Oslo Stock Exchange (OSE) are highly sensitive to fluctuations in the oil price (Brent Crude oil). Gjerde & Sættem (1997) found that the Norwegian stock market responds accurately to oil price changes. Since the Norwegian stock market is highly dependent on the oil price, we would like to examine if and how the oil price impacts the abnormal return on IPO companies. In order to study this phenomenon, we have found the prices[32] for the Brent Crude oil and its return for the three-year period for each company in our data sample. We believe that the oil price increases when the market conditions are favorable. Since the price of Brent Crude oil follows market cycles, we expect the "brent" variable to have the same sign coefficient as the market condition

[32] Prices are found on Thompson Reuters Datastream.

variable. Based on the discussion of the market condition variable in chapter 5.3.3, we expect both variables to have a negative sign coefficient.

5.3.3 Market conditions

The aftermarket performance of our sample firms varies considerably between years and market cycles. As explained in chapter 3, companies choose to go public when financing is needed, but they try to time the IPO to a so-called bull market (Maheu & McCurdy, 2000), when the market conditions are favorable. Companies try to seize "windows of opportunity", as explained in chapter 3. The timing of the listing is therefore an important factor. As seen in figure 5.2, there are large fluctuations in the number of IPOs per year. On average, 10.6 companies went public each year in our sample period. Based on figure 5.2, we find no clear link between the number of IPOs per year and the three-year BHAR. Even though the BHAR varies substantially, there is only one year (2005) where the average BHAR is higher than the general market.

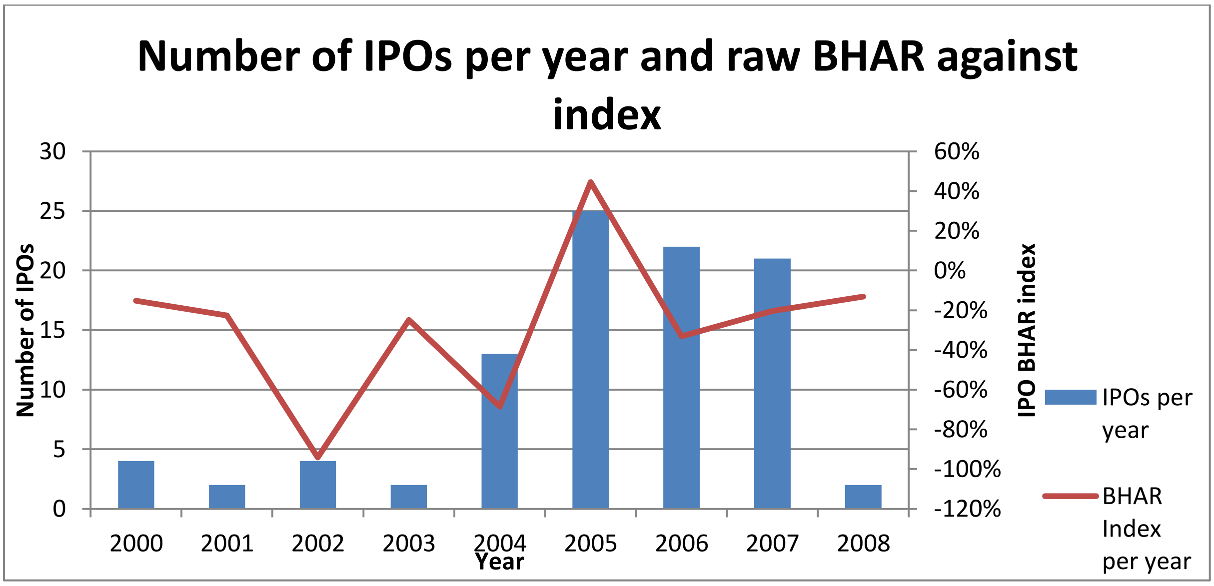


Figure 5.2

The number of listings per year does not necessarily give us a good picture of how the market conditions truly are because the market conditions can change dramatically within a year. For example, in 2008, we had a bull market in the spring, which turned into a severe recession in the fall. To better capture the market conditions, we have therefore chosen to measure the conditions based on months instead of years, as did

Helwege & Liang (2004). Although the market conditions may change drastically within a year, they are usually the same over several consecutive months. We have therefore chosen to measure how many IPOs there are within three months and have calculated a three months centered moving average for each month in the sample. We have measured market conditions in three categories; "hot", "neutral" and "cold", where hot periods are months with more than two IPOs, neutral periods are months with from one to two IPOs and cold periods are months with fewer than one IPO[33]. By using a centered moving average, we are avoiding to classify months as cold when they are followed by a hot month and will thus give a more accurate representation than a pure moving average. In our OLS cross-sectional regression, we have merged the hot and neutral groups together, which we then define as hot market conditions, because they are both probably issued during a favorable market cycle. We now have an independent dummy variable, where 1 is hot market conditions, and 0 is cold conditions. A dummy variable is an indicator variable that takes on the values 0 or 1, where the value of 1 represents that the observation is hot, and the value 0 represents that the observation is cold.

As discussed in chapter 4.3.6, there is a relationship between increasing stock prices and the number of new issues. Despite that, our way of measuring market conditions is not taking into account the valuation of the stocks. The independent variable "marcond" is therefore not exactly measuring "windows of opportunities" (Ritter, 1991) or "pseudo market timing" (Schultz, 2002), but it should be a fairly well approximation. It is important to note that this variable is not examining whether companies are trying to exploit windows of opportunities or not - it is measuring if market conditions have an impact on abnormal IPO return.

Ritter (1991) suggests that companies that went public in years with high IPO activity will suffer from greater underperformance than those listed in years with low IPO activity. Based on this result, we expect the sign character for the dummy variable "marcond" to be negative.

[33] This classification gives us 50 IPOs in hot periods, 23 in neutral periods and 21 in cold periods.

5.3.4 Market capitalization

Market capitalization is included in our analysis as an independent variable in order to analyze the effect of market size on long-term performance. Market capitalization is defined as the number of outstanding stocks multiplied with the stock price at the end of the first month of trading. Because the stock price is more volatile in the first period of trading (Ritter, 1991), especially during the first few days, we have chosen to measure market capitalization for each company at the end of the first month of trading instead of the first day of trading. The market capitalization[34] is measured by million Norwegian kroners, and the coefficient for the independent variable "mcap" will therefore show the change in abnormal IPO return for an increase in market capitalization of 1 million NOK.

Spiess & Affleck-Graves (1995) found that underperformance is concentrated among the smallest companies. On the other hand, Reinganum (1982) found that companies in the lowest market capitalization decile exceed the average return for companies in the highest decile. Blume & Stambaugh (1983) also found that the average risk-adjusted returns on small firms exceed those of larger sized firms. Some of the best-known research on this topic is the study by Fama & French (1993), where they suggest an alternative to the CAPM-model called the "three factor model". One of the explanatory variables for stock return is the "Small Minus Big" (SMB) variable, which indicates that small firms tend to outperform larger ones. Previous studies are, in other words, inconclusive about which sign character our independent variable "mcap" should have, and we therefore do not have any specific expectations about the sign character.

5.3.5 Market-to-book ratio

Fama & French (1993) found that book-to-market ratio (B/M) can explain much of the average returns. If the B/M ratio can explain average returns, it is fair to assume that there is a link between abnormal returns and market to book value as well. We have therefore included "mbook" as an independent explanatory variable. Since we could only find market-to-book (M/B) values[35], we chose not to invert the ratio[36], as it would not provide any further explanatory power. Using the M/B ratio is also consistent with

[34] Found on Thompson Reuters Datastream.
[35] From Thompson Reuters Datastream.
[36] Could have simply inverted the ratio by taking 1 divided by M/B.

Ritter's (1991) study. We have used the M/B ratio at the end of the first month of trading based on the same rationale as described for the market capitalization variable.

The results from Fama & French's (1993) study show that companies with high B/M-ratios perform better than companies with low B/M-ratios. With our interpretation of the inverted ratio, we should expect companies with low M/B-ratio to perform better than companies with high M/B-ratio. In other words; we expect the sign character for "mbook" to be negative.

5.3.6 Sector

The last set of independent variables we have included in our regression is GICS sectors. Ritter (1991) found that the long-run performance of IPOs in different industries varies widely, and we will therefore examine if this is true for our data sample. We have used the seven GICS sectors explained in chapter 4.2.3 and converted them to dummy variables. The seven sectors included are: Industry "Ind", Health Care "Health", Finance "Fin", Consumer Staples "Costap", Consumer Discretionary "Cos", "IT" and Energy "Nrg". In order to avoid a situation with perfect multicollinearity between the seven dummy variables (a situation with an exact linear relationship between the variables), we had to omit one sector and use this sector as the benchmark sector. Since approximately half of the total market capitalization on OSE is represented by companies within the energy sector[37] and our sample is dominated by companies within the energy sector (table 4.1), we found energy to be a natural candidate as a benchmark sector. The coefficients in the regression for the remaining dummy variables represent how much the mean value of the relevant sector differs from the mean value of the energy sector.

[37] Information found on Oslo Børs' website (Oslo Børs, 2012).

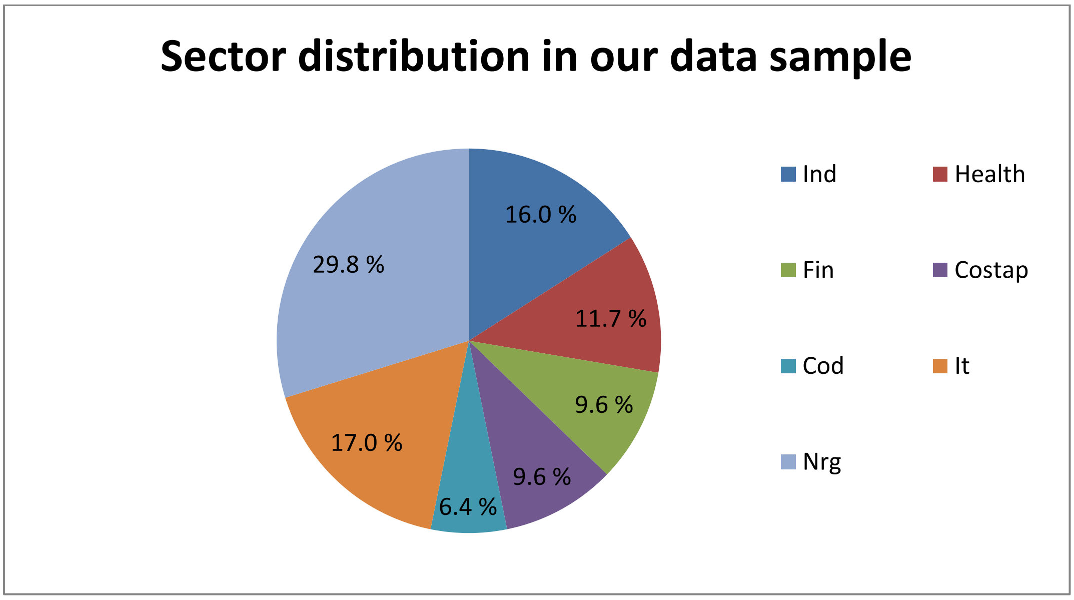


Figure 5.3

Ritter (1991) classified the sectors into 14 industry groups, and found that all but three industry groups underperformed in the market. Financial institutions had the best long-run performance, while oil and gas firms substantially underperformed the market. Most of the oil and gas companies in Ritter's study went public in 1981 to 1983 - this was a period with a large decline in the oil prices. In our sample period, the Brent Crude oil price rose by 457%, which indicates that we should expect the energy sector to have performed better than the other sectors. In other words, we expect the sign character for the sector dummy variables to be negative.

5.4 Regression analysis

In this section, we will run cross-sectional regressions to find out if the abnormal long-run IPO return can be explained by the independent variables we have described in chapter 5.3. As we will analyze the BHAR for IPOs matched against both indexes and peers, we will present a more thorough analysis for the index matching than for peers in order to not repeat ourselves. To analyze the data, we have mainly used a statistical software program called Eviews, supplemented with another program named Minitab because of different features of the various packages. We will present a thorough analysis of the underlying assumptions of an OLS regression (discussed in chapter 5.2) for the first presented regression, but for the rest, we will only comment on the most interesting findings. Complete results for all our analyses are enclosed in appendix 9.3.

5.4.1 Regression diagnostics for BHAR index raw, included all independent variables

The first analysis we did was a cross-sectional regression on the BHAR, matched against market indexes with the entire dataset (named "raw"), which included all the independent variables (see appendix 9.3.1). To find out if it is appropriate to apply an OLS regression, we have to investigate if the underlying assumptions hold.

The first assumption is that the model has to be linear in the parameters. This means that the coefficients for the independent variables, like $\alpha, \beta\ and\ \varepsilon$ in the equation described in chapter 5.2, are linear (β) and not exponential (β^2), for example. This would violate the assumption, but this is not the case in our model.

The second assumption about sample variation, that the independent variables cannot all have the same value, is not an issue here because the variables all have different values.

The third assumption about random sampling, that the data can be used to estimate the independent variables and that the data have been chosen from a representative sample of the population, should not prove problematic either. We have used the data material available to us, and we have no reason to believe that the sample should be biased in any direction from a representative sample. The only objection to random sampling is that our sample period could be biased by market cycles. Our last observation is *exempli gratia* just before the recession in 2008, and we have no observations from that period or after. This could bias our analysis from future projections, but we have no reason to believe that the data from our sample period is non-random. Assumptions number one, two and three are fulfilled in all our regressions and will therefore not be mentioned again in this thesis.

The fourth assumption about zero conditional mean states that the standard error of estimate (sε) should be a random variable with a mean of zero. The standard error of estimate is defined as:

$$s_\varepsilon = \sqrt{\frac{\text{SSE}}{n-2}}$$

SSE is the sum of squared errors which is: $\text{SSE} = \sum(y_i - \hat{y})^2$ (Keller, 2005). When SSE equals zero, all the points in the data sample fall on the regression line, and the model fits perfectly. We do not expect the s_ε to be zero, but the s_ε should not be too large. When the s_ε is very large, it is an indication that the model has a poor fit, and should either be rejected or improved (Keller, 2005). Our regression output from the first regression gives us a s_ε on 1.29 while the mean of dependent variable is -0.15. The s_ε is in other words large compared to the sample mean for the dependent variable, and is an indication that the model is somewhat poor. Despite the fact that we have a relatively large standard error, we have no reason to believe that the mean should be anything else than zero, so we treat this assumption as satisfied.

Assumption number five states that we should have no correlation between two independent variables. There will always be some correlation, so the question is rather how much correlation we can accept. As discussed in the previous chapter, we expect the variables to correlate to a certain extent. Whilst moderate multicollinearity is not a problem, severe multicollinearity can increase the variance of the regression coefficients and make them unstable and difficult to interpret. In the case of severe multicollinearity, the solution is to remove one of the highly correlated variables. Correlations of close to 1 or -1 are considered highly correlated. We have made a correlation matrix to examine whether we have severe correlation (appendix 9.3.1), in order to determine whether we have to remove some of the independent variables. With correlation coefficients no higher than 0.30, we see no sign of severe multicollinearity.

A more formal way of testing for multicollinearity, is to use the Variance Inflation Factor (VIF)[38]. The VIF ranks how correlated variables are, where values of 5 to 10 indicates high correlation. Values greater than 10 may indicate that multicollinearity is influencing the regression, and that unimportant variables should be removed. With the

[38] Produced by Minitab

highest VIF of 1.4 (appendix 9.3.1), there is no sign of multicollinearity, and we are therefore keeping all the variables in the regression.

As the most crucial assumptions for an OLS regression seem to be satisfied, we know that we can make an unbiased OLS regression, but it remains to be seen if we have a BLUE model.

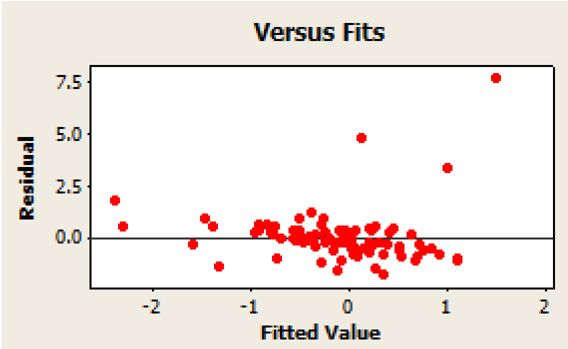


Figure 5.4: Residual plot versus fits

To examine the efficiency of the OLS model, the next step is to check for heteroskedasticity. To check for heteroskedasticity, the basic test is to examine the residuals versus the fitted values, and to determine if they form any kind of a pattern. A normal sign of heteroskedasticity is when the variance for the residuals is increasing with increasing values for the dependent and the independent variables. From the residual plot in figure 5.4, we can see that there is a sign of increasing variance, but this is mainly because of three outliers in the top right corner.

A more formal test to check for heteroskedasticity is the White test (White, 1980). The White test for this data sample gives a P-value of 0.0014 (appendix 9.3.1), which means that we have to reject the null hypothesis about no heteroskedasticity. This means that the OLS no longer gives the "best" estimator and that inference[39] is not valid, but the estimates are still unbiased. There is actually no way to remove heteroskedasticity; we simply have to accept that it is present. Despite not being able to remove heteroskedasticity, Eviews has an attribute when estimating a regression; it can include a White Heteroskedasticity-Consistent Standard Errors & Covariance-term, which takes the heteroskedasticity into consideration when calculating the regression output. This does not mean that heteroskedasticity is removed - the model does not provide further explanatory power, but it does provide a better model with respect to the coefficients.

[39] That we can draw absolute conclusions from our dataset

We will therefore include the White-term in our other regressions where heteroskedasticity is present.

The seventh step is to check for serial/auto-correlation. Since we have cross-sectional data and not time-series data, we can ignore this step in all our regressions.

The last step in the examination of the efficiency of the OLS regression is to check if the error terms are normally distributed. The first diagnostic is to look at the residual plots and see if they follow the normal distribution. For the errors to be normally distributed, the plots in figure 5.5 should follow the red straight line. We have at least three influential observations which make the line more elastic than it would have been without them, which leads to that the blue plots do not follow the red line very accurately. This is the first sign of non-normally distributed errors. Figure 5.6 shows a histogram of the residuals, and this is intended to be bell-shaped in order for the residuals to be normally distributed. The histogram does not appear to be perfectly bell-shaped with its relatively fat tails, and this is therefore another sign that the assumption of normally distributed errors is violated.

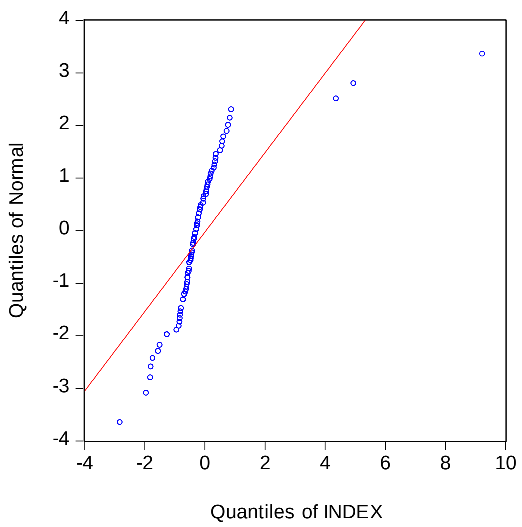


Figure 5.5: Normal probability plot

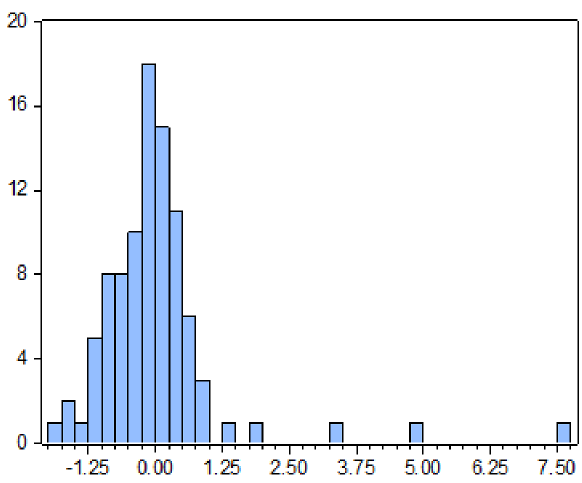


Figure 5.6: Histogram of residuals

The assumption of normally distributed errors can be tested more formally with a Jarque-Bera test (Bera & Jarque, 1981). The test is a goodness-of-fit measure of normality, based on the sample kurtosis and skewness. With a P-value of 0.0000 (appendix 9.3.1), we can, with confidence, reject the null hypothesis about normally distributed errors.

In small samples, statistical inference is not valid when this assumption is not satisfied, but in large samples, if the deviation from a normal distribution is not too large, statistical inference may be valid (Kelley & Maxwell, 2003). The "Central Limit Theorem" states that the sum of independent variables, with the same probability distribution, will reach a normal distribution if the sample is large enough (Rosenblatt, 1955). With our sample consisting of 94 observations, we have a relatively small sample size compared to some of the American studies[40], but since the sample is well above 40 observations, it should be large enough to approximate a normal distribution, despite the existence of few outliers (as discussed in chapter 4.2.5). Since we cannot formally conclude that the error terms are normally distributed, we have to treat our results from this regression with some skepticism. Even if the error terms are not normally distributed, the OLS is still unbiased and can be used as an efficient estimator (Møen, 2009).

Since it does not appear that the normal distribution fits perfectly, we have checked if another distribution could fit better. Student's t-distribution (Gosset, 1908), can be a natural alternative to the normal distribution. This distribution is very similar to the normal distribution, it is symmetric and bell-shaped, but it has heavier tails. Because it has heavier tails, the distribution fits better to a dataset with observations that fall far from its mean.

Figure 5.7 shows how our data fit the Student's t-distribution. As for the normal distribution, the blue dots should be located close to the red straight line for a good fit. We still have a lot deviation from the straight line, so we cannot positively say that the model has a better fit than the normal distribution. In our data sample, we have some observations at some

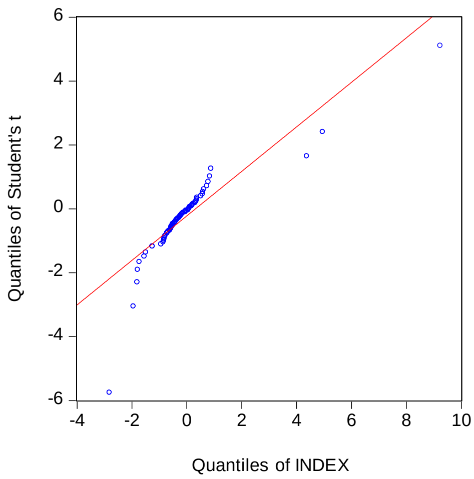


Figure 5.7: Probability plot of Student's t-distribution

[40] Ritter 1991 had 1526 observations.

distance from the mean, but mostly to the right of the mean. This implies that we have positive skewness and the distribution is not symmetric around the mean. Since we do not have symmetry in the tails, the Student's t-distribution will not produce a significantly better model, so we will proceed with the normal distribution. The difference of fit between the Student's t-distribution and the normal distribution is even smaller for most of our other regressions (see printouts in appendix 9.3), which further supports our choice of using the normal distribution.

To summarize the assumptions of the first analyzed OLS regression, the first five assumptions are reasonably satisfied, and we therefore have an unbiased estimator. Unfortunately we have heteroskedasticity, and we cannot therefore formally say that the error terms are normally distributed, so the model is not BLUE. This means that the OLS makes unbiased estimates, but statistical inference is not valid and we have to be cautious when making any strongly held conclusions based on the results.

The F-statistic shows that the model is about twice as good as no model, and it is statistically significant at a 5 % significance level. The adjusted R-squared value of 0.1315 indicates that our model can explain approximately 13% of the abnormal long-run return for Norwegian IPOs in our sample period. As 13% is not a high value, this implies that our model is not providing much explanatory power on abnormal IPO return.

The estimated regression from abnormal IPO returns matched against indexes, with all observations included, are as follows (the other regression outputs are presented in table 5.8):

$$\begin{aligned} y = 0.994 - 0.0145\, ageyears - 0.3656\, brent - 0.5472\, cod + 0.4197\, costap \\ + 0.5243\, fin - 0.3170\, ind + 0.3295\, it - 0.9089\, marcond \\ - 0.0172\, mbook - 0.00005\, mcap - 0.0034\, health \end{aligned}$$

Since the criterion of a BLUE model is not met, inference is not valid. We can however investigate if the regression is giving us reasonable outputs (sign coefficients), as well as determining whether the results are statistically significant.

The first independent variable, “ageyears”, is significant at a 10 % significance level (see table 5.8), meaning that we can reject the null hypothesis about age having no influence on abnormal long-run IPO return. The coefficient is -0.015, meaning that our regression suggests that an increase in age by one year results in a decrease in three-year abnormal IPO return by 1.5 percentage points. It is important to note that the change is not just a pure percentage change, but a change in percentage points. A change in IPO return from 0.01 to 0.02 is a 100% change, but only one percentage point change.

The next variable, Brent Crude oil, is not statistically significant. Therefore, we cannot say that that it has influence on the abnormal IPO return. A coefficient of -0.36 means that an increase in the three-year Brent return on 100 percentage point gives a decrease in abnormal IPO return on 36 percentage points.

The independent variables that are dummy variables, like the “cod” (Consumer Discretionary), are interpreted as if an IPO observation is in the Consumer Discretionary sector, the IPO will have a 55 percentage point lower long-term return relative to the base category (energy). It is statistically significant that this variable explains some of the abnormal IPO return. In order to not take up too much of the reader’s time, we will not interpret the rest variables, and the reader can instead study the regression output (table 5.8) for further investigation on this regression.

5.4.2 Influential observations

Minitab produces a list of influential observations for each regression. This can be leverage points (extreme in the x-direction), outliers (extreme in the y-direction relative to the predicted regression line) or both. We have investigated these points because they have potential to do great harm to the regression. If high leverage points are omitted, the regression coefficients could be very different compared to if they are included. We see that this is true in our case, because the coefficients are changing substantially from the raw data to the trimmed data. Influential observations are especially important to investigate with a small sample size, because they will have much more influence on the regression line than with a large sample size. Before one decide whether to remove influential observations or not, one should examine if the observations could be data entry or measurement errors. If they are not, removing influential observations is a trade-off between improvement of the regression model and data-manipulation. Simon (2003) recommends that high leverage points should be removed in general and that this is most important in data samples with below 400 observations, but that is a subjective decision.

From the regression outputs for both index and peer matching (appendix 9.3.1-9.3.6), we can see that almost all of the influential observations are within the three highest and three lowest observations for the abnormal three-year IPO return. We have therefore chosen to trim the data on a 3 % and a 10 % level[41]. When we trim our data, with a 3 % trim, most of the influential observations will therefore be removed. EMGS and REC are high leverage observations[42]. REC is removed after data trimming while EMGS remains. We have examined the values for EMGS particularly thoroughly, and cannot find anything incorrect with the data. The reason why the EMGS is a high leverage point is probably because of the high market-to-book ratio of 19, which is by far the highest in our sample. We have nevertheless chosen to keep the observation in our data samples because we see nothing wrong with the value[43].

We have run OLS regressions measuring abnormal return based on peers in the same way as for the market indexes. These findings are presented below in table 5.8 together with our key findings from all the regressions:

[41] The trimming is not exactly 3 % and 10 %, because we have removed three and ten observations out of 94 observations on each side, but we have chosen to use the same notation and technique as before. 3/94=3.2% and 10/94=10.6 %

[42] respectively observation 48 and 3 in the index raw regression, marked with an X in Minitab

[43] Such high values are not unusual, and the same company has had higher ratios later in the observation period.

Cross sectional regression summary included all independent variables

		Index raw	Peers raw	Index 3% trimmed	Peers 3% trimmed	Index 10% trimmed	Peers 10% trimmed
Assumptions 1-5 satisfied		yes	yes	yes	yes	yes	yes
Homoskedastic		no	yes	no	yes	no	yes
Normally distributed errors		no	no	no	no	no	yes
Adjusted R-squared		0,1315	0,0224	0,4304	0,1241	0,7675	0,1082
F-statistic		2,2667	1,1914	6,9070	2,1081	22,6017	1,7939
Probability F-statistic		0,0182	0,3063	0,0000	0,0297	0,0000	0,0747
	Expected coefficient						
C	-	0,993951	-0,089216	-0,118749	-0,380094	-0,372465	-0,560942
AGEYEARS	?	-0.014457 (0.0872)	-0.001508 (0.8502)	-0.002889 (0.3418)	0.003461 (0.3710)	0.000708 (0.2941)	0.000712 (0.7679)
BRENT	-	-0.365567 (0.3235)	0.717941 (0.0534)	-0.010683 (0.9029)	0.215339 (0.2774)	0.038785 (0.4836)	0.085576 (0.4954)
COD	-	-0.547177 (0.0582)	-1.632277 (0.0294)	-0.167006 (0.3588)	-0.315593 (0.4119)	-0.316317 (0.0000)	0.077711 (0.7510)
COSTAP	-	0.419725 (0.7062)	0.169998 (0.7995)	-0.707662 (0.0000)	0.486104 (0.1324)	-0.521019 (0.0000)	0.614491 (0.0043)
FIN	-	0.524344 (0.4457)	-0.80019 (0.2065)	0.088981 (0.6418)	-0.413246 (0.1746)	0.317169 (0.0006)	-0.185852 (0.3187)
IND	-	-0.316974 (0.2692)	-1.086373 (0.0478)	-0.103375 (0.6139)	-0.659132 (0.0175)	-0.294527 (0.0000)	-0.011945 (0.9466)
IT	-	0.329478 (0.1671)	-0.532698 (0.3105)	0.58152 (0.0000)	0.321131 (0.2253)	0.54238 (0.0000)	0.327577 (0.0592)
MARCOND	-	-0.908879 (0.0594)	0.204049 (0.6267)	-0.214513 (0.1529)	0.207536 (0.3073)	-0.019259 (0.6877)	0.245009 (0.0753)
MBOOK	-	-0.01719 (0.6547)	-0.012806 (0.8644)	-0.007838 (0.6087)	-0.043631 (0.2261)	0.006146 (0.4686)	-0.015075 (0.4796)
MCAP	?	-0.0000503 (0.0038)	-0.000000888 (0.9809)	0.000000148 (0.9943)	0.000000608 (0.9726)	-0.00000335 (0.7275)	-0.00000307 (0.7665)
HEALTH	-	-0.003406 (0.9888)	-0.396588 (0.5410)	0.313408 (0.0319)	0.106276 (0.7330)	0.135035 (0.1772)	0.289447 (0.1277)

Table 5.8 Statistically significant results are marked in red.

In general, the regressions with index matching are giving models that explain the abnormal long-run IPO return better than with peer-company matching. The adjusted R-squared for peers, ranging from 2% to 12%, indicates that the peer models are explaining very little of the abnormal IPO returns. F-statistics for peers ranging from 1.2 to 2.1 validate this finding. The P-value for "Peers raw" is not even significant, which means that the model is not better than any model. The regressions with index matching produce much higher adjusted R-squared and F-statistics and are therefore explaining the IPO return better. Despite higher explanatory power in the index regressions, they are not BLUE and we cannot make inferences from the output. The only model we have which is BLUE is the 10% trimmed regression with peers, but this model has a low adjusted R-squared and F-statistic. We can therefore not rely on this model in order to explain the abnormal IPO return either. The rest of the models are not BLUE, and we cannot therefore make statistical inferences from these models either. A consequence of our models not being BLUE is that the sign coefficients on the independent variables are not the same for all our regressions - they change from plus to minus from one regression to another for every independent variable except one. We can therefore not see a clear pattern. The same problem is present for the independent variables which shift from being significant to insignificant without any clear pattern.

5.5 Best subset regression

We started with a comprehensive regression model which included all conceivable independent variables that could have an influence on IPOs. Clearly, we have not found any good model for explaining abnormal IPO return - we have simply tested variables we believed would have an influence. Many of the tested independent variables do not have much influence on the abnormal IPO return (because they are insignificant), and we therefore need to find a model that can explain our dependent variable in a better way. A common way of finding a better model is to test less comprehensive sub-models and see if they adequately explain the dependent variable. The simplest of the adequate models is then chosen to be the "best" model (Hill & Lewiciki, 2007).

A useful way of finding the best sub-model is to use “stepwise regression” or “best subset regression”[44]. These tools, provided by Minitab, use an automated technique to identify the most significant variables and remove the least significant variables in order to reach the regression which produces the highest adjusted R-squared. These tools may also generate models with smaller variance than models with all conceivable variables, and are often easier to understand because they are less complex. The drawback to this technique is that there is often not a unique best subset. If there are two important independent variables that is highly correlated, one of the variables may end up with being removed from the best subset. Stepwise regression is an automated process, and will therefore not account for any special knowledge the analyst may have about the data. Because of these potential pitfalls, the best subset regressions may not actually be the best practical model. Despite this, we have reason to believe that we will find a model that explains the abnormal long-run IPO returns with a best subset regression. We have found best subset regressions for all our datasets, and presented a summary with our key findings in table 5.9 below:

[44] Both techniques end up with the same final set of independent variables, so we will therefore use both terms about the same result.

Best subset regressions

		Index raw	Peers raw	Index 3% trimmed	Peers 3% trimmed	Index 10% trimmed	Peers 10% trimmed
Assumptions 1-5 satisfied		yes	yes	yes	yes	yes	yes
Homoskedastic		yes	no	no	yes	no	yes
Normally distributed errors		no	no	no	no	no	yes
Adjusted R-squared		0,1607	0,0764	0,4573	0,1471	0,7786	0,1659
F-statistic		3,9677	2,9219	13,2175	2,8534	37,6837	3,9046
Probability F-statistic		0,0015	0,0254	0,0000	0,0078	0,0000	0,0036
	Expected coefficient						
C	-	1,126666	-0,143612	-0,203979	0,326093	-0,374845	-0,552602
AGEYEARS	?	-0.012675 (0.0115)		-0.002947 (0.2829)			
BRENT	-	-0.362507 (0.3363)	0.654744 (0.2287)		0.234705 (0.2199)	0.039662 (0.4519)	
COD	-	-0.710416 (0.0121)	-1.45694 (0.0928)		-0.368695 (0.3188)	-0.316481 (0.0000)	
COSTAP	-			-0.647896 (0.0000)	0.548953 (0.0620)	-0.487442 (0.0000)	0.622107 (0.0009)
FIN	-		-0.594639(0.0052)	0.150075 (0.4398)	-0.422458 (0.1481)	0.309519 (0.0003)	-0.182255 (0.2807)
IND	-	-0.5301 (0.0316)	-0.8959 (0.1122)		-0.643304 (0.0123)	-0.278742 (0.0000)	
IT	-			0.627816 (0.0000)	0.289435 (0.2389)	0.556422 (0.0000)	0.319979 (0.0371)
MARCOND	-	-0.918807 (0.0664)		-0.201324 (0.1708)	0.203238 (0.2389)		0.232693 (0.0740)
MBOOK	-				-0.041145 (0.2219)		
MCAP	?	-0.0000562(0.0025)					
HEALTH	-			0.338883 (0.0205)		0.161643 (0.0582)	0.205717 (0.1879)

Table 5.9 Statistically significant results are marked in red.

From table 5.9, we can state that we now generally have improved models that explain the dependent variable better than the models with all independent variables included. The problem with almost all of them not being BLUE is still present, but the adjusted R-squared and F-statistics have increased across all models.

The 10 % trimmed regression with index matching stands out. This is by far the model which explains the abnormal long-run IPO returns best, with respect to the adjusted R-squared and the F-statistic and it is also the model with the most significant independent variables. As this is the best model for explaining the abnormal long-run IPO return, we will rely mostly on the results from this model, but we still have to be cautious before drawing any absolute conclusions because of the non-BLUE regression.

What is interesting to note about this regression is that all the significant variables are sectors. There are three sectors which performed better than the Energy sector: the Finance sector, the Health Care and Equipment sector, and the IT sector. There are also three sectors that performed worse: the Consumer Discretionary sector, the Consumer Staples sector, and the Industry sector. We cannot explain why these sectors are performing better or worse than the energy sector, but that the finance sector is performing better than the energy sector is at least in line with the findings in Ritter (1991). All these results are significant at a 1% significance level (except Health which is significant at a 10 % level), which means that these independent variables can partly explain the abnormal long-run IPO return. When studying the sector results, we have to keep in mind that the energy sector performed especially well during our sample period. A possible explanation can be the huge increase in the Brent Crude oil price and the Norwegian stock market dependency on the oil price. Since the "brent" variable is included in this regression, the oil price has some explanatory power in regards to IPO returns, but the variable is not significant.

For the other independent variables, we cannot draw any absolute conclusions about the variables' effect on long-run IPO return. Since our data sample contains many relatively young companies, we may not have enough observations of old companies to make statistical inference from our data sample about the age variable. We can therefore not conclude if Ritter's findings (1991), that young companies underperform relative to older companies, are correct or not. We had a suspicion that companies which went public in periods with low IPO activity would perform better than those in high activity periods. From our regression results, we cannot confirm, nor can we discard, this hypothesis. Our suspicions that the market-to-book ratio and the firm size could explain the abnormal long-run IPO return is not statistically supported.

In general, we have few observations in our regressions and each independent variable can therefore lack observations across the whole specter to produce significant results. The companies in our data sample are for instance dominated by companies with relatively low market capitalization and we have few large capitalized companies. The median market capitalization is approximately 700 million NOK and we only have two companies with market capitalization over 10 000 million NOK. With few observations in some parts of the specter for a variable, just a few (or one) observation can make an independent variable insignificant. This problem is perhaps the explanation for why the sign coefficients and the significant level change for many of the independent variables when we trim the data. This may be the reason why we cannot draw more absolute conclusions on the influence of the independent variables and how they affect the long-run IPO return.

5.6 Summary cross-sectional regressions

In order discover what could affect the abnormal long-run IPO return, we started with cross-sectional regressions that included all conceivable independent variables from theory and own suspicions. These models did not give us any clear answers to our hypothesis with respect to sign coefficients and significance level. As mentioned, our data sample is relatively small, and single observations can therefore heavily influence our analysis. We observed that there were some outliers in our regression and decided to trim our data according to advice from Simon (2003). Even then, we were not able to draw any clear conclusions from the regression outputs.

The results from the regressions with all conceivable independent variables included did not show any clear pattern of how the independent variables affect the long-run performance of IPOs. The fact that the sign coefficients for the same variable changed between models and that the independent variables changed from being statistically significant to insignificant across different models, made us realize that the set of variables was not a good fit for explaining IPO underperformance. To find which variables were redundant, we ran best subset regressions.

From the best subset regressions, we found that the independent variables of age, market conditions, market-to-book and market capitalization were redundant in most of the regressions. This proves that the variables we have chosen to include based on empirical studies do not explain Norwegian IPO underperformance. The independent variables which were included still changed sign coefficient and changed from being statistically significant to statistically insignificant across the different models. Due to these problems and the fact that many models provide low explanatory power, we have used the results from the model with the highest adjusted R-squared and most significant independent variables as the basis for the cross-sectional regression, namely the 10% trimmed index adjusted model. This model explains 78% of the long-run IPO underperformance, but it is still not BLUE, which should be taken into consideration when reading the results.

The 10% index adjusted model included all the sector variables and the Brent oil variable, but only the five sector variables were statistically significant. This model shows that IPOs issued in Finance, Health Care and Equipment and IT sectors yield higher long-term return than the Energy sector, while IPOs issued in the Consumer Discretionary, Consumer Staples and the Industry sectors perform worse than Energy IPOs.

6 Analysis of the initial return

As shown in table 3.2, underpricing is a well-known phenomenon. Since underpricing is a thoroughly discussed subject, both internationally and in Norway, we will not focus extensively on this in our thesis. However, we have run descriptive statistics summaries to determine whether underpricing is present in Norwegian IPOs.

6.1 Methodology

In order to measure underpricing, we have collected information about IPOs issued on Oslo Børs from 2000 to 2011. To be consistent with our long-term performance analysis, we have used the same observation period to measure short term performance. However, since we do not need a three-year observation period in the short-term analysis, we extended the period from 2008 to 2011. This was done in order to include more observations and to produce analysis that is as up-to-date as possible.

Based on 192 IPOs, we cleaned our data according to the same criteria's as for the long-term analysis (chapter 4.1), where we removed spin offs, previously listed companies et cetera. Some of the offer prices were not publicly available through our accessible terminals[45] - these IPOs were therefore not included. Due to difficulties with obtaining offer prices for some companies and after extensive filtering of the data, our final data sample consists of 100 IPOs.

Based on the data sample, we have calculated return based on the percentage difference from the offer price to the close price on the initial day of trading. The formula is described below:

$$r_{i,t} = \left(\frac{P_{i,t} - P_{i,0}}{P_{i,0}}\right)$$

$P_{i,t}$ denotes the price of stock *i* at time *t* - the closing price on the first day of trading. $P_{i,0}$ denotes the offer price. Thus, $r_{i,t}$ is the percentage change for stock *i* at the end of day one. Note that in the case where $r_{i,t}$ is positive, a stock is underpriced. When a stock was

[45] Thompson Reuters Datastream, Amadeus, Factset and Bloomberg terminals

not traded on the listing day, we have used the closing price obtained on the first day of trading in order to calculate the return.

We have measured the initial return in excess of market indexes (abnormal return). Since we have chosen not to emphasize on the underpricing phenomenon in this thesis, we have chosen to only calculate abnormal returns against one benchmark. We have matched IPOs against market indexes based on market capitalization. We have used OBX, OSEBX and OSESX to adjust the initial returns for large cap, mid cap and small cap companies respectively. To find the abnormal return, we have calculated the relevant benchmark return[46] for each IPO and then subtracted it from each respective IPO return. We thereafter found the average abnormal return for the whole sample. This was done by the following formulas:

$$ar_{it} = r_{it} - r_{mt}$$

$$Average\ ar_{it} = \left(\frac{1}{N}\right)\sum_{i=1}^{N} ar_{it}$$

6.2 Descriptive statistics – short term analysis

We will only present the most relevant results from the analysis in the text – the complete results are enclosed in appendix 9.4.

6.2.1 Trimming of data

Before we performed the descriptive statistics analysis, we wanted to check the robustness of our data. Our prime concern was the existence of outliers, which could skew our data. We therefore chose to trim our data, and trimmed 3% and 10%, as we did for the long-term data. To get an overview of the data and to see if we have a normally bell shaped distributions, we generated boxplots through Minitab:

[46] With the same formula as for the initial IPO return

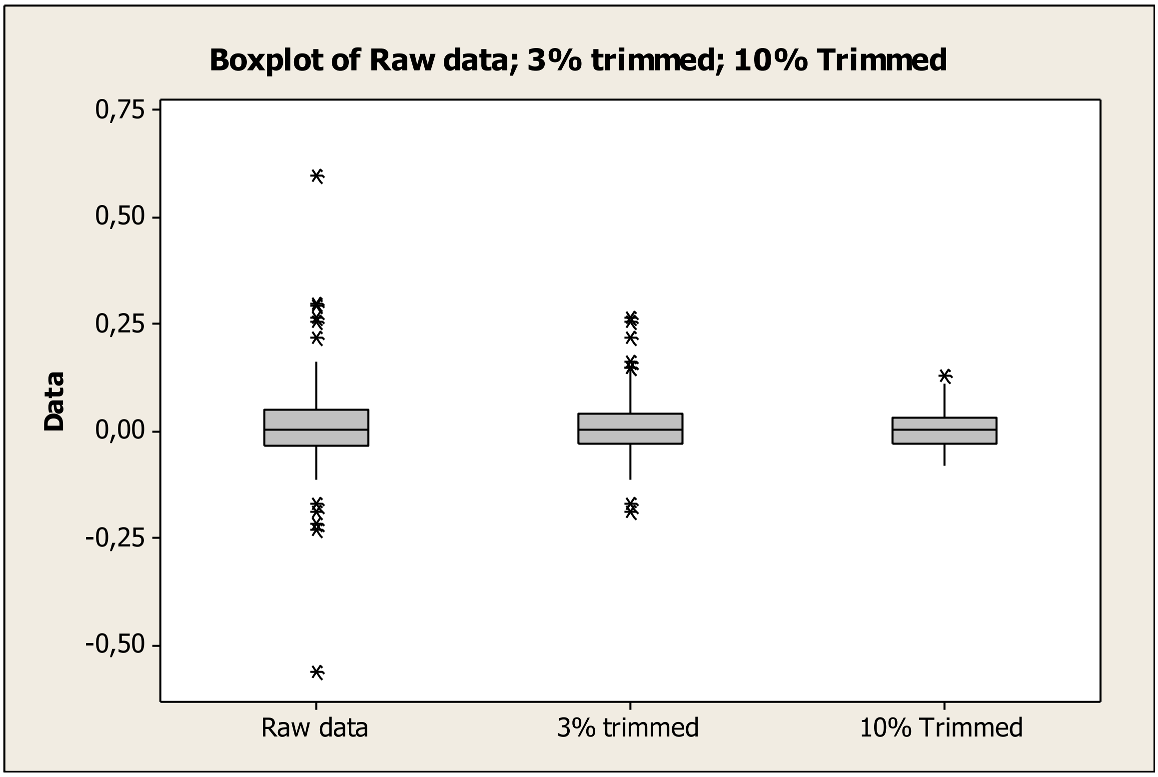


Figure 6.1

The boxplots[47] in figure 6.1 show the distributions for all our data samples. The diagram shows the distribution for raw data, 3% trimmed data and 10% trimmed data.

The raw data has the distribution with most observations centered together, indicated by the grey boxes. The tails indicate a slightly longer positive tail, compared to the corresponding negative tail. In terms of extreme observations, we see that we have four positive outliers and three negative outliers. To neutralize the effect of outliers, we chose to trim our dataset by 3%. This means that we removed the three highest and lowest observations from our sample. Thus, the 3% trimmed data sample consists of 94 observations. The result is that our 3% trimmed dataset is marginally positively skewed, shown by a longer positive tail. Despite trimming, the 3% data still had a few outliers. The outliers are mostly positive observations, so the distribution is positively skewed. We trimmed further, and trimmed the ten highest and lowest observations from the full sample. The 10% trimmed dataset seems to be normally distributed, with even tails. However, the dataset has one positive outlier, but since this is not an extreme

[47] For a detailed explanation of the makeup of the boxplot, see the descriptive statistics discussed under the long-term analysis in chapter 4.2.5.

observation we believe that it would not adversely affect the trimmed mean. The 10% trimmed dataset consists of 80 observations.

The effects and plausibility of using trimmed datasets is discussed earlier in chapter 4.2.5. The usage of a trimmed dataset, which is cleansed of extreme values, provides valuable information about the central tendencies of a dataset. Based on this, we will put more emphasis on the trimmed datasets, rather than the raw data.

6.2.2 Descriptive statistics results

Table 6.2 shows the output of the descriptive statistics for all three datasets. The mean abnormal initial return varied from 1% to 1.6% depending on the trimming. The results are all significant at a 5% significance level. We can therefore conclude that the underpricing anomaly is still present for Norwegian IPOs.

The data is positively skewed for all three datasets, but the degree of skewness is not large compared to Høiseth (2004) and the skewness we found on the raw data for our long-term return. Positive skewness is consistent with the conclusion reached from the boxplot analysis and is a result of a longer positive tail. Despite positive skewness, the median is still positive. This shows an initial return of approximately 0.5% for all three datasets. The effect of positively skewed data is that it tends to cause a measurement bias, indicating positive means. However, the existence of skewness is normal for most datasets, and since the skewness is not very high, we will not put too much emphasis on this. Our results are in line with Ibbotson's study (1975), where the author found that the distribution of initial returns were highly skewed with a positive mean and a median near zero.

	Raw data	**3% trimmed**	**10% trimmed**
Mean	0.0155	0.0144	0.0103
St.dev.	0.123	0.077	0.0472
Skewness	0.313	0.747	0.486
Median	0.0046	0.0046	0.0046
N	100	94	80
P-value	0.0244	0.0158	0.0105

Table 6.2 - Descriptive statistics for short term return. All results are significant at a 95% confidence level.

Despite finding statistically significant mean values, we see that the standard deviation is relatively high. This indicates that we cannot expect each IPO to perform in line with the means or the medians we have found, but that the returns are highly volatile. As Schwert (2002) asserted, no investor has been able to completely exploit the underpricing anomaly. With information asymmetry and underwriter's power of allocating stocks, it is not certain that most investors are able to exploit this anomaly.

6.3 Obstacles for exploiting the underpricing anomaly

Even though we can confirm that underpricing is present in Norway, the degree of underpricing is relatively low compared to most other countries[48]. It is also interesting to note that our results seem to be considerably lower than comparable studies performed on the Norwegian stock market. This may be an indication that underpricing is not as prominent as it was before. It would be interesting to examine if the trend of underpricing has declined over time. However, since the focus in this study is on the long-term return, we will not discuss this further.

A possible explanation for our finding of relatively low underpricing could be that most of the other studies performed on this area have measured pure return in a generally increasing stock market, while we have measured abnormal return. Another explanation can be that investors have been more aware of the underpricing phenomenon and thus try to exploit the market inefficiency.

In U.S. IPOs especially, we have seen some very extreme initial returns. For instance, the listing of LinkedIn in 2011 had an initial return on 106.87% (Baldwin & Selyukh, 2011). This might be an example of Welch' (1992) theory - that there is a sheep mentality among investors. Such events are contributing to the high standard deviation we have found in our data sample.

We have shown that there are several theories for why underpricing is present for IPOs. Theories like "leaving money on the table" and other underwriters' incentives will always be possible explanations. A newer phenomenon is that Exchange Traded Funds

[48] See table 3.2. Average initial returns for 36 countries (Ritter, 1991).

(ETFs) have been introduced to the public and have become popular amongst many retail investors. ETFs, like XACT Derivat BULL/BEAR[49], were introduced in 2008, and are compiled to mimic entire market indexes (OBX). In order for ETFs to meet their requirements, they need to be positioned in all the new companies that go public. This will put extra pressure on the new listings, which can boost their initial return. If these derivatives are becoming increasingly popular and the managers of these instruments are not able to buy into the IPOs during the subscription period, this will advocate that the underpricing will be more severe in the years to come. This argument is weakened because the owners of ETFs are institutional investors, who are more likely to be allocated stocks in the book-building process (Stoughton & Zechner, 1989). If all managers of ETFs are able to buy stocks at the offer price, this will lead to a lower degree of underpricing. The reason is that it is impossible to short stocks before they are listed on the exchange, and managers of ETFs who bet against an index (XACT Derivat BEAR) will thus be forced to short IPOs the first day of trading.

Since initial IPO returns are not the main focus of this thesis, we have not examined the cyclicality of the initial return; if the initial returns tend to follow market cycles. We can therefore not prove if this market anomaly is present for Norwegian IPOs.

No matter what the explanations are for the Norwegian underpricing, we can conclude that the underpricing anomaly is present in the Norwegian stock market. The abnormal initial return found is not higher than between 0.5% and 1.5%, so underpricing in Norway is therefore not severe. The extent of IPO underpricing is weakened by the high standard deviation found in this study. Since the average initial return is only marginally positive coupled with high standard deviation, it is highly uncertain that a sample IPO will generate initial positive return. This makes it difficult to exploit this anomaly. We must therefore be cautious of this fact, even though we have concluded that Norwegian IPOs are underpriced.

Since the average initial return is low, transaction costs might exceed the possible gains from this anomaly. We have found that most of the companies that go public are relatively young and small capitalized companies. IPOs are therefore not likely among

[49] Information found on Nordnet ETF website (Nordnet, 2012)

the most liquid stocks at the exchange in the initial period they are listed. This indicates that the bid-ask spread could be as high as 1%-2% for many companies the first trading day. The high bid-ask spread combined with brokerage commission, may result in higher transaction costs than the potential profit from the initial return for many IPOs.

6.4 Conclusion short-term performance

Despite finding evidence of IPO underpricing in Norway, the often relatively high transaction costs, accompanied with high standard deviation and the low average return, make it difficult for investors to exploit the underpricing anomaly. Since an investor has to be able to make a profit on an anomaly for a market to be inefficient, we cannot positively say that this anomaly is a departure from market efficiency.

7 Final summary

The purpose of this thesis is to investigate IPO anomalies and to find out whether Norwegian IPOs are traded in an efficient market or not. To determine this, we have studied the short- and long-term aftermarket performance of IPOs.

7.1 Long-term performance

We have found that Norwegian IPOs yield three-year abnormal returns between -10% and -30%, depending on benchmark and calculation method used. These results are based on the 10% trimmed datasets since it is less sensitive to outliers and produces a better estimate of the mean and the median than the entire dataset (Bloch, 1966). Based on our results, the negative trend of abnormal returns seems to be limited to 34 months post-listing. Since we limited the observation period to a three-year aftermarket horizon, we cannot prove that the negative trend ends after 34 months. However, Ritter (1991) and Rao (1991) found that the long-run underperformance of American IPOs is limited to three years, which is in line with our results. We have also found that the majority of IPOs are issued when share prices are increasing. We have thus proven that the market anomaly of IPO listing cyclicality is present in the Norwegian stock market. Ritter (1991) explains this phenomenon by companies using "windows of opportunity" to maximize the funds raised during a public offering (as explained in chapter 3.6.2).

In order to examine if the long-run underperformance is a result of specific firm characteristics or simply bad luck, we ran cross-sectional regressions. We found that most of the explanatory variables that we thought could have an impact on IPOs were not significant. Despite finding significant variables, some variables change sign coefficient in different regression models, which reduces the statistical robustness of the results derived. Therefore one must be cautious of making any strongly-held statistical or economical conclusions about which factors that influence the abnormal IPO returns. Based on our best regression model, we found differences in IPO performance among certain industry sectors. Relative to the energy sector, three sectors perform significantly better while the remaining three sectors yield lower abnormal returns in excess of market indexes.

Most empirical studies explain long-term IPO underperformance by specific firm characteristics, such as younger firms tending to underperform (Ritter, 1991) and through firm-specific risk. For instance, Schultz (2003) argued that the majority of new listings are low risk firms that yield low long-term returns. The results from the cross-sectional analysis reveal that few firm characteristics or external factors can explain the negative abnormal returns found. Although there are statistical weaknesses, we have found support for differences in long-term returns across different sectors. We have found that IPOs issued in Finance, Health Care and Equipment and IT sectors yield higher long-term return than the Energy sector, while IPOs issued in the Consumer Discretionary, Consumer Staples and the Industry sectors perform worse than Energy IPOs.

We have discussed the difficulties investors face when trying to exploit the underperformance anomaly. We conclude that the transaction costs of holding a short position for three years will exceed the potential returns. In addition, we have showed that it can be difficult to borrow an IPO stock for three consecutive years. Consequently, investors cannot make a profit by exploiting the long-term underperformance. This anomaly is therefore not in conflict with market efficiency (Ibbotson, 1975).

7.2 Short-term performance

We have found evidence of underpricing for IPOs in Norway during our sample period from 2000 to 2011. The magnitude of the underpricing is not severe, with abnormal returns ranging from 0.5% to 1.5%. Despite positive skewness and high standard deviation, the results are statistically significant.

Possible explanations for underpricing could relate to theories as “leaving money on the table” and other underwriter’s incentives, such as underwriters setting a lower price to sell out a listing. Since this thesis focuses more on the long-term performance, we have not studied reasons for the underpricing extensively. Regardless of the explanations, positive initial returns indicate that there is a market anomaly present in the Norwegian stock market.

The findings of this study support the well-documented IPO anomaly of underpricing. The results are lower than previous studies of underpricing done internationally and in Norway. For instance, the initial returns found in the U.S. are on average 18.3%[50]. In comparison, Emilsen et al. (1997) found average initial returns of 12.5% for Norwegian IPOs issued from 1989 to 1996. This indicates that the underpricing phenomenon is less pervasive in Norway than it is in the U.S. and that the magnitude of the Norwegian underpricing seems to have declined over time. We have not tested if the initial returns tend to follow market cycles and we can therefore not prove if this market anomaly is present for Norwegian IPOs.

Since the abnormal initial returns are low, with a median of only 0.5%, it is possible that transaction costs might be greater than the initial returns. Since an investor has to be able to make a profit on a market anomaly for a market to be inefficient (Ibbotson, 1975), we cannot positively say that this anomaly is a departure from market efficiency.

7.3 Conclusion on market efficiency in the Norwegian IPO market

To answer the research question, we have found evidence that the anomalies of short-term underpricing and long-term underperformance exist for Norwegian IPOs. Since there are obstacles to exploit these anomalies (for instance high transaction costs), we find it highly unlikely that investors are able to make a profit on IPO underpricing and long-term underperformance. Therefore, we have found few, if any, departures from market efficiency for Norwegian IPOs.

[50] From 1960 to 2003 (Loughran, et al., 1994)

8 Bibliography

Akerlof, G. A., 1970. The Market for "Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics* **84**(3), pp. 488-500.

Baldwin, C. & Selyukh, A., 2011. *Reuters.com.* [Online]
Available at: http://www.reuters.com/article/2011/05/19/us-linkedin-ipo-risks-idUSTRE74H0TL20110519
[Accessed 27 April 2012].

Barber, B. & Lyon, J., 1997. Detecting long-run abnormal stock return: The empirical power and specification of test statistics. *The Journal of Financial Economics **43**(3)*, pp. 341-372.

Baron, D. P., 1982. A model of the demand for investment banking advising and distribution services for new issues. *Journal of finance **37**(4*), pp. 955-976.

Basu, S., 1977. Investment performance of common stocks in relation to their Price-Earnings Ratios: A test of the Efficient Market Hypothesis. *The Journal of Finance **37**(3),* pp. 663-682.

Beneviste, L. M., Busaba, W. J. & Wilhelm, W. J. J., 1996. Price Stabilization As a Bonding Mechanism in New Equity Issues. *Journal of Financial Economics **42**(2),* pp. 223-255.

Beneviste, L. M. & Spindt, P. A., 1989. How investment bankers determine the offer price and allocation of new issues. *Journal of Financial Economics **24**(2) ,* pp. 343-362.

Bera, A. & Jarque, C., 1981. Efficient tests for normality, heteroskedasticity and serial independence of regression residuals: Monte Carlo evidence. *Economics Letter **7**(4),* pp. 313 – 318.

Berk, J. & DeMarzo, P., 2007. *Corporate Finance (Global Edition).* 2. ed: Pearson Education.Inc.

Bloch, D., 1966. A note on the estimation of the location parameter of the Cauchy Distribution. *Journal of the American Statistical Association **61**(315),* pp. 852-855.

Blume, M. E. & Stambaugh, R. F., 1983. Biases in computed returns, An application to the size effect. *Journal of Financial Economics **12**(3),* pp. 387-404.

Booth, J. R. & Chua, L., 1996. Ownership dispersion, costly information, and IPO underpricing. *Journal of Financial Economics **41***(2)*,* pp. 291-310.

Brav, A., Geczy, C. & Gompers, P. A., 2000. Is the abnormal return following equity issuances anomalous? *Journal of Financial Economics **56***(2), pp. 209-249.

Bretscher, O., 1995. *Linear Algebra With Applications.* 3rd ed. Upper Saddle River NJ: Prentice Hall.

Brønnøysundregistrene, *Brønnøysundregistrene.* [Online]
Available at: http://www.brreg.no/
[Accessed 20th February 2012].

Buser, S. & Chan, K., 1987. *NASDAQ/NMS* Qualification stand, Ohio registration experience and the price performance of initial public offerings, Columbus: Ohio Department of Commerce and national Association of Securities Dealers Inc.

Cania, L., Michaely, R., Thaler, R. & Womack, K., 1998. A warning about using the daily CRSP equally-weighted index to compute long run excess returns. *Journal of Finance* ***53***(1), pp. 403-416.

CESR, 2002. *Stabilsation and Allotment.* Paris, The Committee of European Securities Regulators.

Chan, L. & Lakonishok, J., 1990. Robust measurement of beta risk. University of Illinois (working paper).

Clarkson, P. & Thompson, R., 1990. Empiricial estimates of Beta when investors face estimation risk, *Journal of Finance* ***45****(2)*, pp. 431-453.

Conrad, J. & Kaul, G., 1993. Long-term market overreaction or biases in computed returns?. *Journal of Finance* ***48****(1),* pp. 39-63.

Damodaran, A., 2012. *Musings on Markets- Facebook: Sowing the wind, reaping the whirlwind.* [Online]
Available at: http://www.aswathdamodaran.blogspot.com/2012/05/facebook-sowing-wind-reaping-whirlwind.html
[Accessed 28 May 2012].

Dodge, Y., 2003. *The Oxford Dictionary of Statistical Terms.* 1. ed: OUP.

Dreman, D. N. & Berry, M. A., 1995. Overreaction, underreaction, and the low-P/E effect. *Financial Analysts Journal* ***51****(4),* pp. 21-30.

Economics, E. S. o., 2009. *Biases and errors in empirical methods.* [Online]
Available at: http://people.few.eur.nl/smant/m-economics/emh/biases.htm
[Accessed 28 March 2012].

Emilsen, N., Pedersen, K. & Sættem, F., 1997. Børsintroduksjoner. *Beta- Tidskrift for bedriftsøkonomi*, pp. 1-13.

Evans, J., 2009. *Basic Statistics Web Site For Nova Southeastern University Educational Leadership Students.* [Online]
Available at: http://www.fgse.nova.edu/edl/secure/stats/
[Accessed 15 March 2012].

Fama, E., 1970. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance* ***25****(2)*, pp. 383-417.

Fama, E. F. & French, K. R., 1992. The cross-section of expected stock returns. *Journal of Finance* **47**(2), pp. 427-465.

Fama, E. F. & French, K. R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics **33**(1),* pp. 3-56.

Fama, E. F. & French, K. R., 1995. Size and Book-to-Market factors in earnings and returns. *The Journal of Finance **50**(1),* pp. 131-155.

Fama, E. F. & French, K. R., 1996. Multifactor explanations of asset pricing anomalities. *The Journal of Finance **51**(1),* pp. 55-84.

Ferguson, T., 1978. Maximum Likelihood Estimates of the parameters of the Cauchy distribution for samples of size 3 and 4. *Journal of the American Statistical Association* ***73**(361)***,** p. 211-213.

Financial Times Lexicon, 2012. *Lexicon- Financial Times).* [Online]
Available at: http://lexicon.ft.com/Term?term=trade-sale
[Accessed 07 March 2012].

Gjerde, Ø. & Sættem, F., 1997. Causal relations among stock returns and macroeconomic. *Journal of International Financial Markets, Institutions and Money **9**(1),* pp. 61-74.

Gosh, M., 1973. Nonparametric selection procedures for symmetric location parameter populations. *The Annals of Statistics **1**(4,)* pp. 773-779.

Gosset, W. S., 1908. On the probable error of a mean. *Biometrika,* 6(Hill).
Handbook, E. S., 2006. *Measures of Skewness and Kurtosis.* [Online]
Available at: http://www.itl.nist.gov/div898/handbook/eda/section3/eda35b.htm
[Accessed 22 March 2012].

Hanley, K. W., 1993. The underpricing of initial public offerings and the partial adjustment phenomenon. *Journal of Finacial Economics **34**(2),* pp. 231-250.

Helwege, J. & Liang, N., 2004. Initial Public Offerings in hot and cold markets. *Journal of Financial and Quantitative Analysis **39**(3)*, pp. 541-569.

Hill, T. & Lewiciki, P., 2007. *Statistics: Methods and Applications.* Tulsa: Statsoft.

Hsu, P. L. & Robbins, H., 1947. Complete convergence and the law of large numbers. *National Academy of Sciences **33**(2),* pp. 25-31.

Høiseth, T., 2004. *Intital Public Offerings- An empirical study of the Oslo Stock Exchange,* Milano: SDA Bocconi .

Ibbotson, R., 1975. Price performance of common stock new issues. *Journal of Financial Economics* **2**(3), pp. 235-272.

Ibbotson, R. g. & Ritter, J. R., 1995. *Initial Public Offerings, Chapter 30.* Vol. 9 ed.:Elsevier Science B.V.

Ibbotson, R., Sinclear, J. & Ritter, J., 1994. The market's problems with the pricing of initial public offerings. *Journal of Apllied Corporate Finance **7(1)***, pp. 66-74.

Jegadeesh, N. & Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance **48(1)***, pp. 65-91.

Jensen, M. C., 1978. Some anomalous evidenceregarding market efficiency. *Journal of Financial Economics **6**(2),* pp. 95-101.

Johnsen, T., 2011. *FIE 402 Corporate Finance, lecture 9: Selling securities,* Bergen: Norwegian School of Economics.

Keller, J. G., 2005. *Statistics for management and economics.* 7th Edition ed. United Kingdom: Thomson Brooks/Cole.

Kelley, K. & Maxwell, S. E., 2003. Sample size for multiple regression: Obtaining regression coefficients that are accurate, not simply significant. *Psychological Methods **8*** (The American Psychological Association, Inc), pp. 305–321.

Kothari, S. & Warner, J., 1997. Measuring long-horizon security price performance. *Journal of Financial Economies **43**(301)***,** pp. 301-339.

lbbotson, R. & Jaffe, J., 1975. Hot issue markets. *Journal of finance,* Volume **30**(4), pp. 1027-1042.

Ledaal, T., 2009. *Masteroppgave: Analyse av kostnader ved børsintroduksjoner på Oslo Børs, 1998-2008,* Kristiansand: Universitet i Agder.

Lerner, J., 1993. NYSE vs NASDAQ returns: Market microstructure or the poor performance of intial public offerings. *Journal of Financial Economics **33**(2)*, pp. 241-260.

Lerner, J., 1994. Venture capitalists and the desicison to go public*. *Journal of Financial Economics **35**(3),* pp. 293-316.

Levis, M., 1990. The long-run performance of initial public offerings: The UK experience 1980-88. *Financial Management **22***, pp. 28-41.

Ljungqvist, A., 1993. *Underpricing and long term performance of German initial public offerings, 1978-92.* Nuffield College, Oxford.

Loughran, T., Ritter, J. R. & Rydqvist, K., 1994. Initial public offerings: International insights. *Pacific-Basin Finance Journal,* **2**(2), pp. 165-169.

Loughran, T. & Ritter, J., 1995. The new issue puzzle. *The Journal of Finance **50(1)*** , pp. 23-51.

Loughran, T. & Ritter, J., 2004. Why has IPO underpricing changed over time? *Financial Management* ***33****(3),* pp. 9-18.

Lowry, M. & Schwert, W. G., 2002. IPO market cycles: Bubbles or sequential learning? *The Journal of finance* ***57****(3),* pp. 1171-1200.

Lyon, J., Barber, B. & Tsai,C.L., 1999. Improved methods for tests of long-run abnormal stock returns. *Journal of Finance* ***54***(1), pp. 165-201.

Maheu, J. M. & McCurdy, T. H., 2000. Identifying bull and bear markets in stock returns. *Journal of Business & Economic Statistics* ***18****(1),* pp. 100-112.

Mann, P., 1995. *Introductory Statistics.* 2. ed: Cloth.

Mitchell, M. & Stafford, E., 2000. Managerial desicions and long term stock price performance. *Journal of Business* ***73****(1),* pp. 287-329.

Moore, D. & McCabe, G., 1999. *Introduction to the practice of statistics.* 1. ed. New York: W. H. Freeman.

MSCI, 2012. *MSCI Sector Indicies GICS Overview.* [Online]
Available at: http://www.msci.com/products/indices/sector/gics/
[Accessed 16 March 2012].

Muscarella, C. J. & Vetsupiens, M. R., 1989. A simple test of Baron's model of IPO underpricing. *Journal of Financial Economics* ***24****(1),* pp. 125-136.

Møen, J., 2009. *Compendium: INT010 - Anvent Metode,* Bergen: Norwegian School of Economics.

Nordnet, 2012. *Kurslister - Nordnet.* [Online]
Available at: https://www.nordnet.no/mux/web/marknaden/kurslista/aktier.html
[Accessed 15 February 2012].

Nordnet, 2012. *XACT Derivat Bull - Nordnet.* [Online]
Available at:
https://www.nordnet.no/mux/web/marknaden/aktiehemsidan/index.html?identifier=NO0010405848NOKNOOBFU&marketid=15&s_kwcid=TC|22998|xact%20bull|%7bplacement%7d|%7bifcontent:C%7d%7bifsearch:S%7d%7bifmobile:M%7d|%7bmatchtype%7d|10697410580
[Accessed 14 May 2012].

Oslo Børs, 2003. *Oslo Børs Minileksikon.* [Online]
Available at: http://www.oslobors.no/Oslo-Boers/Om-oss/Minileksikon#o
[Accessed 15 March 2012].

Oslo Børs, 2012. *Energy - Oslo Børs.* [Online]
Available at: http://www.oslobors.no/ob_eng/Oslo-Boers/Listing/Energy-shipping-and-seafood/Energy
[Accessed 10 April 2012].

Oslo Børs, 2012. *Listing criteria- Oslo Børs.* [Online]
Available at: http://www.oslobors.no/ob_eng/Oslo-Boers/Listing/Shares-equity-certificates-and-rights-to-shares/Listing-criteria
[Accessed 13 February 2012].

Oslo Børs, 2012. *Oslo Børs.* [Online]
Available at: http://www.oslobors.no/ob_eng/Oslo-Boers/Listing/Shares-equity-certificates-and-rights-to-shares/Listing-criteria
[Accessed 24 April 2012].

Oslo Børs, 2012. *Oslo Børs Aksjeindekser.* [Online]
Available at:
http://www.oslobors.no/markedsaktivitet/stockIndexIsinList?newt__menuCtx=1.6.1
[Accessed 21 March 2012].

Oslo Børs, 2012. *Oslo Børs Newsweb.* [Online]
Available at: http://www.newsweb.no/newsweb/search.do?messageId=300760
[Accessed 15 March 2012].

Oslo Børs, 2012. *Oslo Børs Newsweb MeldingsID: 305470.* [Online]
Available at: http://www.newsweb.no/newsweb/search.do?messageId=305470
[Accessed 28 May 2012].

Oslo Børs, 2012. *Oslo Børs-OBX Total Return Index (OBX).* [Online]
Available at:
http://www.oslobors.no/ob_eng/markedsaktivitet/stockIndexOverview?newt__ticker=OBX
[Accessed 15 March 2012].

Pagano, M., Panetta, F. & Zingales, L., 1998. Why do companies go public? An empirical analysis. *Journal of Finance,* Volume **53**(1), pp. 27-64.

Rajan, R. & Servaes, H., 1993. *The effect of market conditions on initial public offerings,*: Unpublished working paper, University of Chicago.

Randall, S. & McGee, S., 2000. Major Institutions, Led by Fidelity, Get Most of Hot IPOs, Lists Show," Heard on the Street, *The Wall Street Journal January 27, 2000*.

Rao, G., 1991. *The relation between stock returns and earnings:A study of newly-public firms,*: University of Illionois at Urbana-Champaign.

Reinganum, M. R., 1982. A direct test of Roll's conjecture on the firm size effect. *The Journal of Finance **37**(1),* pp. 27-35.

Ritter, J., 1984. The 'hot issue' market of 1980. *Journal of Business* ***57(2),*** pp. 215-240.

Ritter, J., 1991. The long-run perfomance of intital public offerings. *The Journal of Finance Vol* ***36***(1), pp. 3-27.

Ritter, J., 1998. Initial Public Offerings. *Contemporary Finance Digest* ***2***, pp. 5-30.

Ritter, J., 2011. *Initial Public Offerings: Underpricing statistics through 2011,* Gainesville: University of Florida.

Ritter, J. & Loughran, T., 2000. Uniformly least powerful tests of market effeciency, *Journal of Financial Economics* ***55(3),*** pp.361-389.

Ritter, J. & Welch, I., 2002. A review of IPO activity, pricing and allocations. *Journal of Finance,* Volume ***57(4)*****,** pp. 1795-1828.

Rock, K., 1986. Why new issues are underpriced. *Journal of Financial Economics* ***15(1),*** pp. 187-212.

Rosenblatt, M., 1955. A Central Limit Theorem and a strong mixing condition. *Proc Natl Acad Sci U S A* ***42,*** pp. 43–47.

Rothenberg, J., Fisher, F. & Tilanus, C., 1966. A note on the estimation of the location parameters of the Cauchy distribution. *Journal of the American Statistical Association* ***61****(315)*, pp. 460-463.

Schwert, G. W., 2002. Anomalies and market efficency, Cambridge: National Bereau of Economic Reserch

Securities, P., 2012. *Shorthandel (Shortselling) - Pareto Securties.* [Online]
Available at: http://www.pareto.no/no/Pareto-Securities/Mottak/Shorthandel.aspx
[Accessed 15 May 2012].

Simon, G., 2003. *Multiple Regression Diagnistics, course B01.1305.* New York, Stern School of Business, New York University.

Speiss, D. & Affleck-Graves, J., 1995. Underperformance in Long-Run Stock Returns Following
Seasoned Equity Offerings. *Journal of Financial Economics* ***38(3)*****,** pp. 243-267.

ssrn.com, 2012. *Social Science Research Network.* [Online]
Available at: http://www.ssrn.com/update/fen/fenann/ann12114.html
[Accessed 24 April 2012].

Stattrek, 2012. *Sampling Distributions.* [Online]
Available at: http://stattrek.com/sampling/sampling-distribution.aspx
[Accessed 15 March 2012].

Stern, R. & Bornstein, P., 1985. Why new issues are lousy investments. *Forbes* ***136***, pp. 152-190.

Stoll, H. & Curley, A., 1970. *Small Business and the New Issues Market for Equities, Journal of Financial and Quantitative Analysis* ***5****(3)*, pp. 309-322.

Stoughton, N. M. & Zechner, J., 1989. IPO-mechanisms, monitoring and ownership structure. *Journal of Financial Economics* ***49****(1),* pp. 45-77.

Weisstein, E., 2012. *Mathworld.* [Online]
Available at: http://mathworld.wolfram.com/StatisticalMedian.html
[Accessed 14 March 2012].

Welch, I., 1989. Seasoned offerings, imitation costs, and the underpricing of initial public offerings. *Journal of Finance* ***44****(2),* pp. 421-450.

Welch, I., 1992. Sequential sales, learning, and cascades. *Journal of Finance* ***47****(2),* pp. 695-732.

White, H., 1980. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica (The Econometric Society*) ***48****(4)*, pp. 817-838.

Woolridge, J. M., 2009. *Introductoury Econometrics.* Fourth edition. Mason, OH: South-Western Cengage Learning.

Zeune, G., 1994. *Going Public: What the CFO Needs to Know*:AICPA.

9 Appendix

9.1 Appendix A: GICS sector description

This appendix includes descriptions of the seven Global Industry Classification Standard (GICS) used in this study:

-**Industry**: The GICS Industrials Sector includes companies whose businesses are dominated by one of the following activities: The manufacture and distribution of capital goods, including aerospace & defense, construction, engineering & building products, electrical equipment and industrial machinery. The provision of commercial services and supplies, include printing, data processing, employment, environmental and office services. The provision of transportation services, include airlines, couriers, marine, road & rail and transportation infrastructure.

-**Health Care**: The GICS Health Care Sector encompasses two main industry groups. The first includes companies who manufacture health care equipment and supplies or provide health care related services, including distributors of health care products, providers of basic health-care services, and owners and operators of health care facilities and organizations. The second regroups companies primarily involved in the research, development, production and marketing of pharmaceuticals and biotechnology products.

-**Finance**: The GICS Financial Sector contains companies involved in activities such as banking, consumer finance, investment banking and brokerage, asset management, insurance and investment, and real estate, including REITs.

-**Consumer Staples**: The GICS Consumer Staples Sector comprises companies whose businesses are less sensitive to economic cycles. It includes manufacturers and distributors of food, beverages and tobacco and producers of nondurable household goods and personal products. It also includes food & drug retailing companies.

-**Consumer Discretionary:** The GICS Consumer Discretionary Sector encompasses those industries that tend to be the most sensitive to economic cycles. Its manufacturing segment includes automotive, household durable goods, textiles & apparel and leisure equipment. The services segment includes hotels, restaurants and other leisure facilities, media production and services and consumer retailing.

-IT: The GICS Information Technology Sector covers the following general areas: firstly, Technology Software & Services, including companies that primarily develop software in various fields such as the Internet, applications, systems and/or databases management and companies that provide information technology consulting and services; secondly Technology Hardware & Equipment, including manufacturers and distributors of communications equipment, computers & peripherals, electronic equipment & related instruments, semiconductor equipment and products.

-Energy: The GICS Energy Sector comprises companies whose businesses are dominated by either of the following activities: The construction or provision of oil rigs, drilling equipment and other Energy related service and equipment, including seismic data collection. Companies engaged in the exploration, production, marketing, refining and/or transportation of oil and gas products.

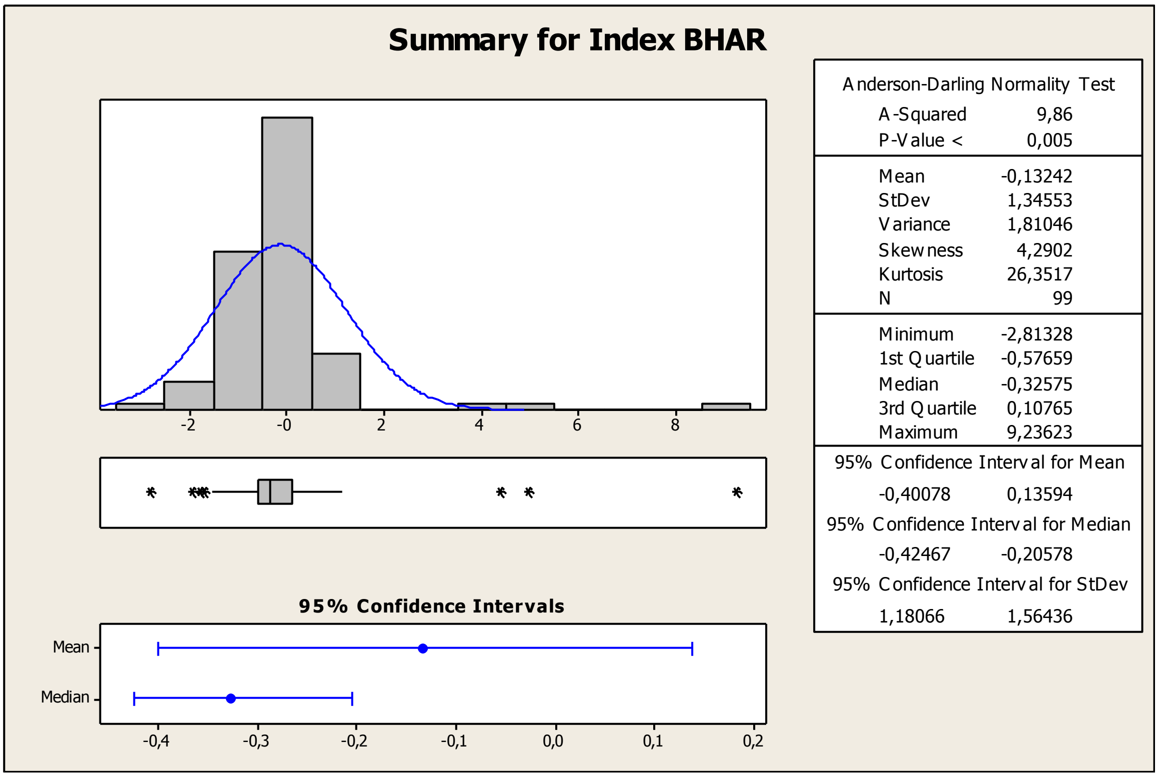
Source: **(Oslo Børs, 2012)**

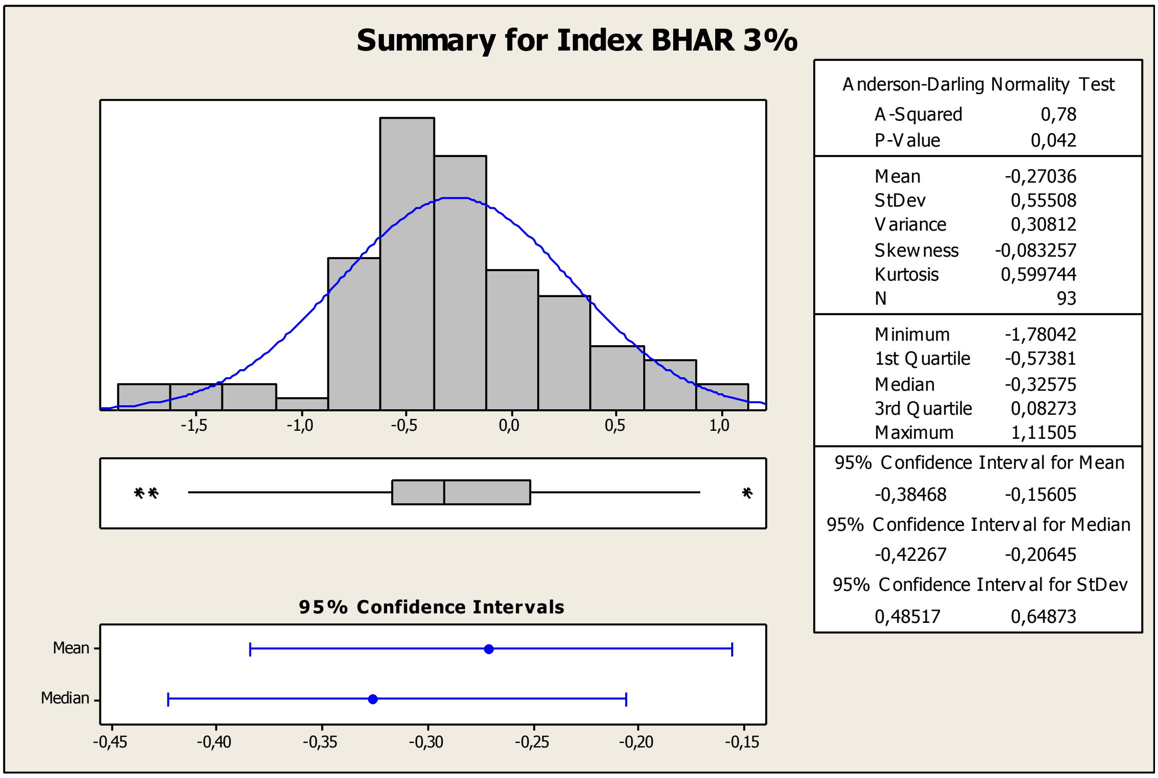
9.2 Appendix B: Long-term abnormal return analysis

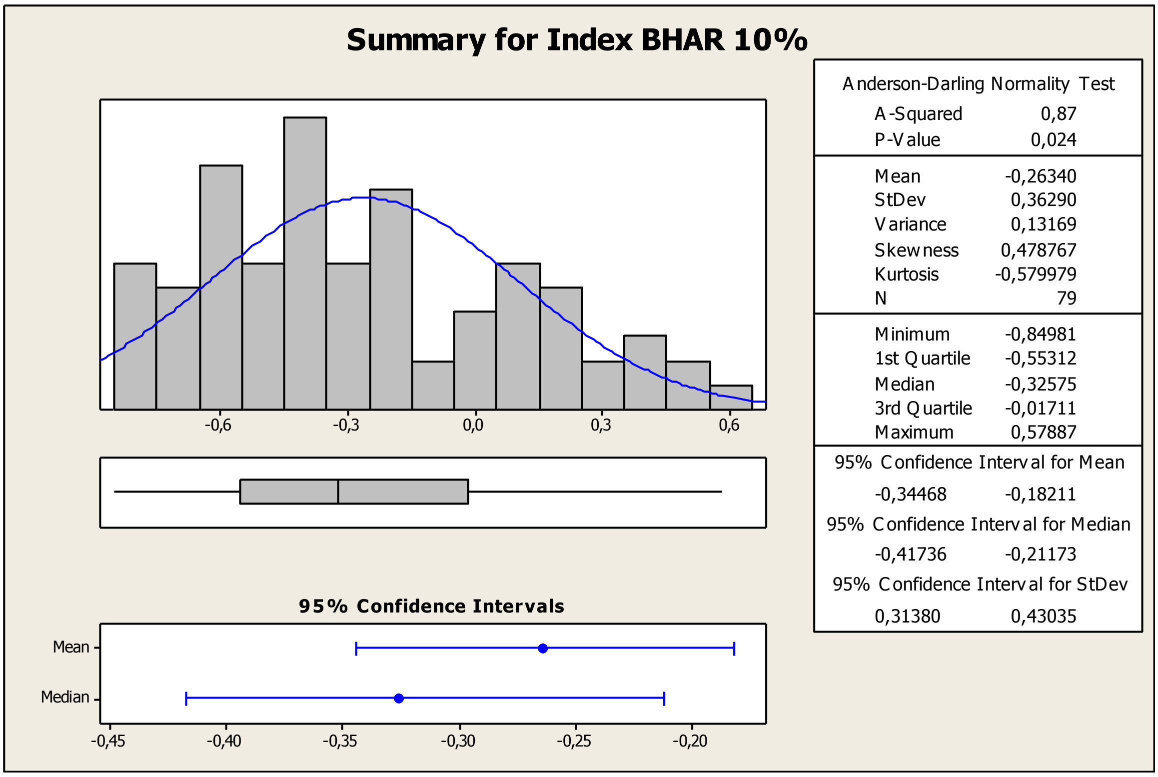
This appendix includes summaries of descriptive statistics for three-year abnormal return in excess of benchmark (index, peers and sector).

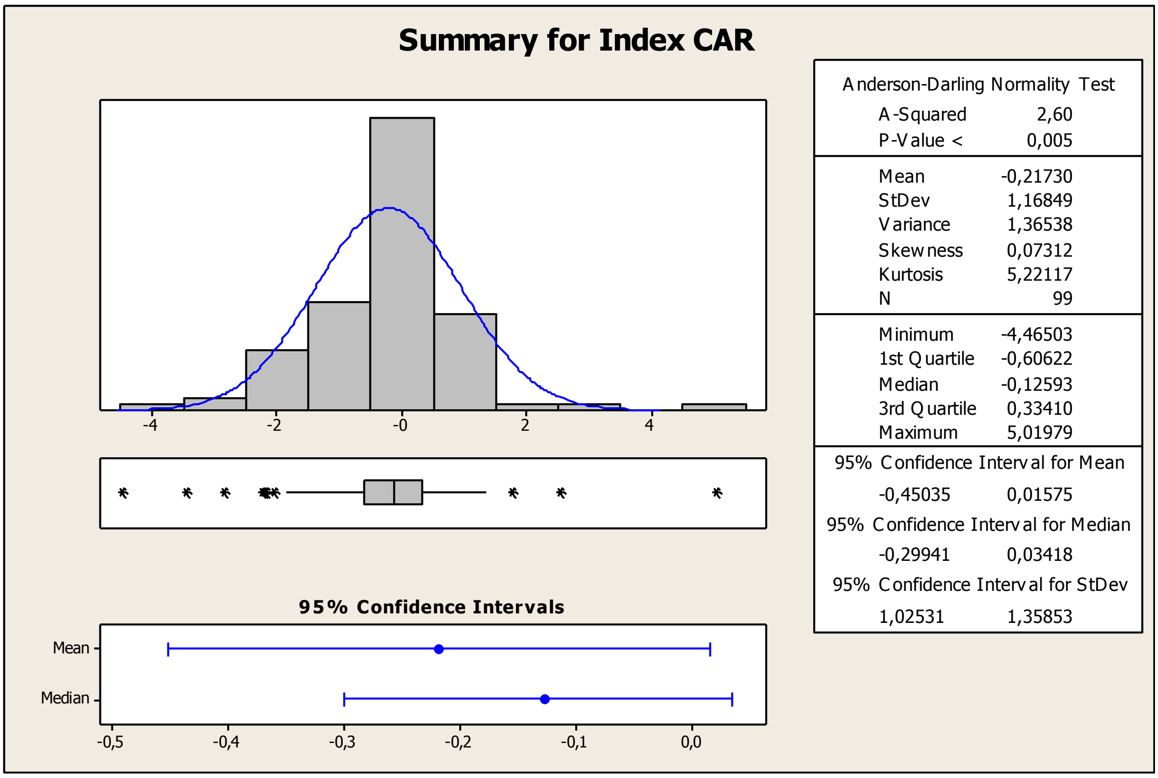
9.2.1 Long-term abnormal return in excess of index

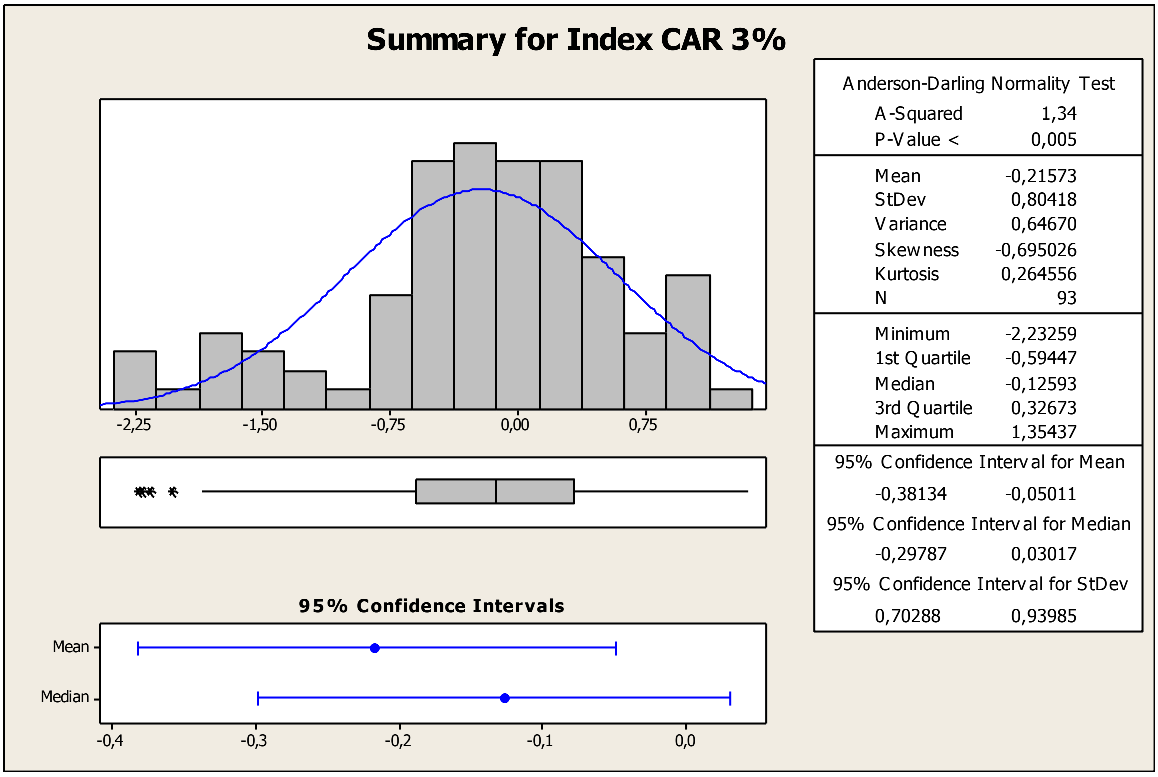
Minitab printouts of descriptive statistics summaries for abnormal return, using Buy-and-hold abnormal return (BHAR) and Cumulative abnormal return (CAR) for full sample, 3%-trimmed and 10% trimmed datasets.

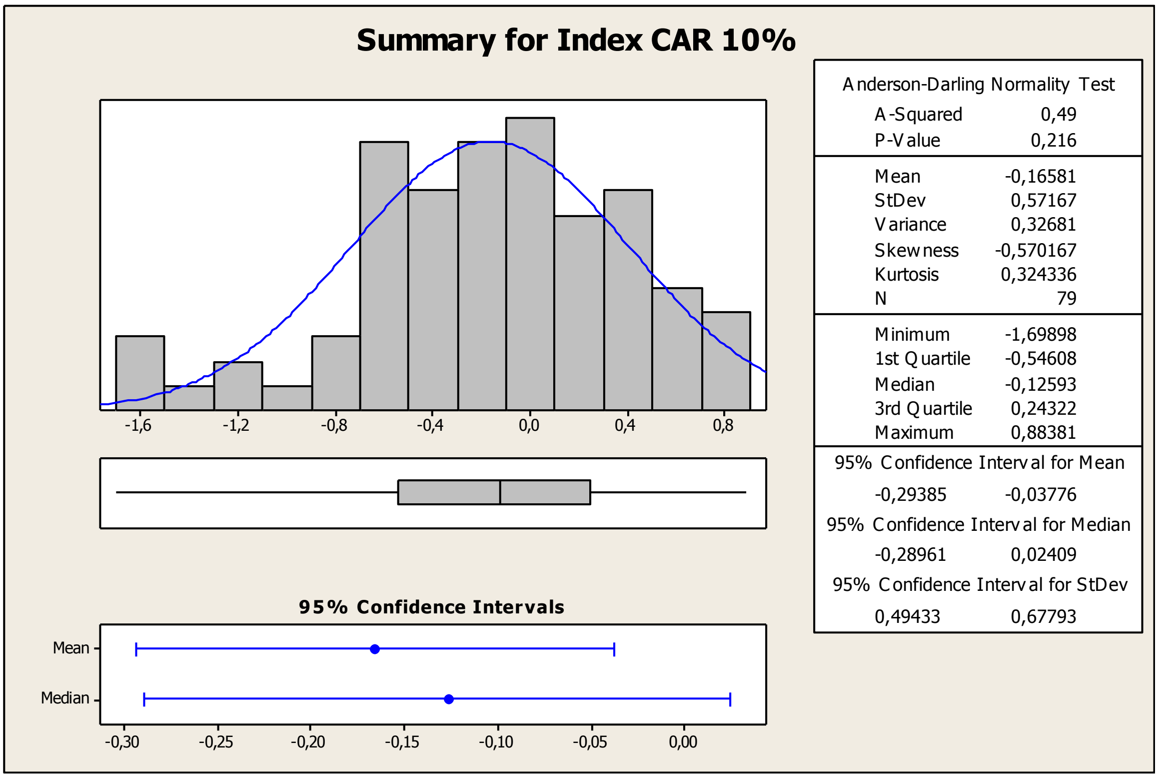



Summary for Index BHAR 3%
Anderson-Darling Normality Test
A-Squared 0,78
P-Value 0,042
Mean -0,27036
StDev 0,55508
Variance 0,30812
Skewness -0,083257
Kurtosis 0,599744
N 93
Minimum -1,78042
1st Quartile -0,57381
Median -0,32575
3rd Quartile 0,08273
Maximum 1,11505
95% Confidence Interval for Mean
-0,38468 -0,15605
95% Confidence Interval for Median
-0,42267 -0,20645
95% Confidence Interval for StDev
0,48517 0,64873
-1,5 -1,0 -0,5 0,0 0,5 1,0
95% Confidence Intervals
Mean
Median
-0,45 -0,40 -0,35 -0,30 -0,25 -0,20 -0,15


Summary for Index BHAR 10%
Anderson-Darling Normality Test
A-Squared 0,87
P-Value 0,024
Mean -0,26340
StDev 0,36290
Variance 0,13169
Skewness 0,478767
Kurtosis -0,579979
N 79
Minimum -0,84981
1st Quartile -0,55312
Median -0,32575
3rd Quartile -0,01711
Maximum 0,57887
95% Confidence Interval for Mean
-0,34468 -0,18211
95% Confidence Interval for Median
-0,41736 -0,21173
95% Confidence Interval for StDev
0,31380 0,43035
-0,6 -0,3 0,0 0,3 0,6
95% Confidence Intervals
Mean
Median
-0,45 -0,40 -0,35 -0,30 -0,25 -0,20

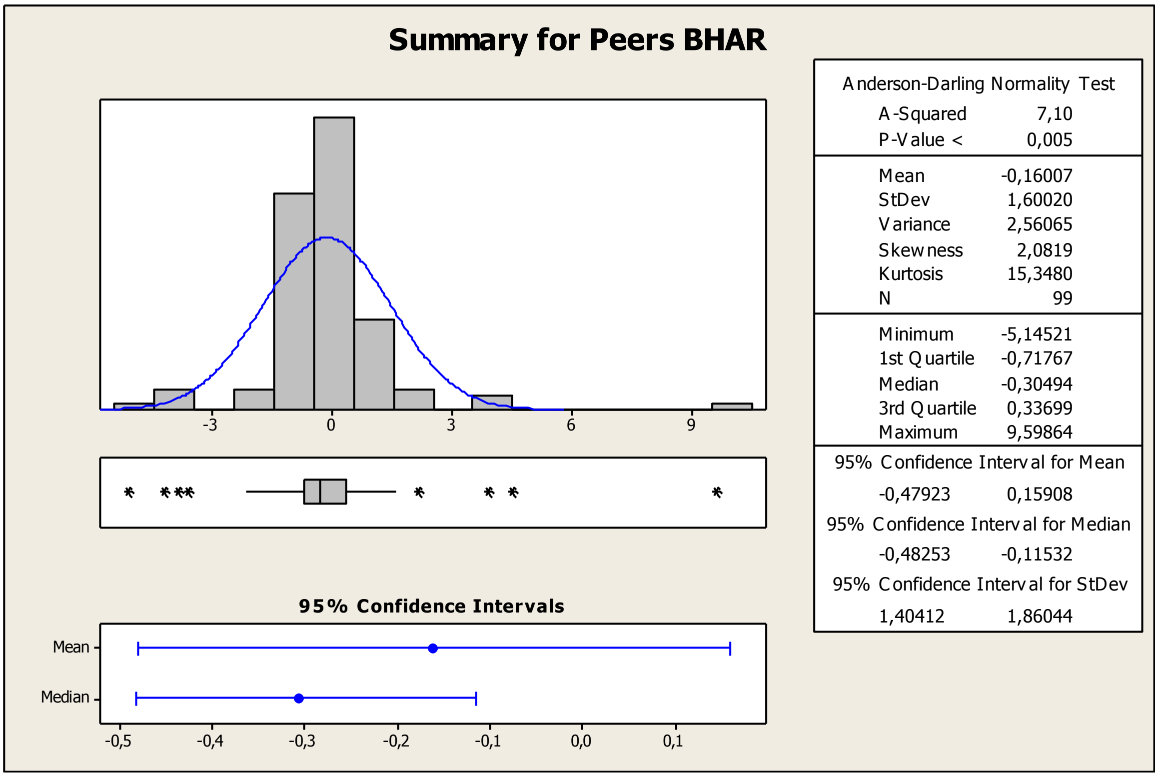

Summary for Index CAR
Anderson-Darling Normality Test
A-Squared 2,60
P-Value < 0,005
Mean -0,21730
StDev 1,16849
Variance 1,36538
Skewness 0,07312
Kurtosis 5,22117
N 99
Minimum -4,46503
1st Quartile -0,60622
Median -0,12593
3rd Quartile 0,33410
Maximum 5,01979
95% Confidence Interval for Mean
-0,45035 0,01575
95% Confidence Interval for Median
-0,29941 0,03418
95% Confidence Interval for StDev
1,02531 1,35853
-4 -2 -0 2 4
95% Confidence Intervals
Mean
Median
-0,5 -0,4 -0,3 -0,2 -0,1 0,0

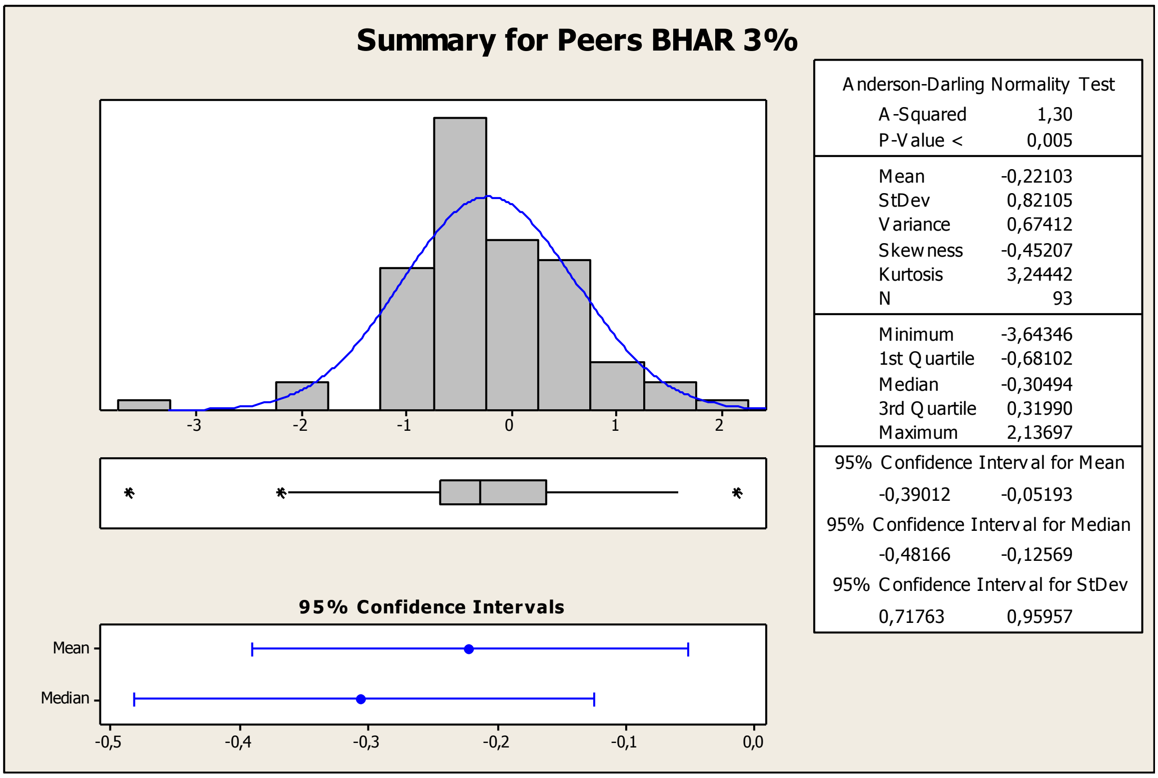

Summary for Index CAR 3%
Anderson-Darling Normality Test
A-Squared 1,34
P-Value < 0,005
Mean -0,21573
StDev 0,80418
Variance 0,64670
Skewness -0,695026
Kurtosis 0,264556
N 93
Minimum -2,23259
1st Quartile -0,59447
Median -0,12593
3rd Quartile 0,32673
Maximum 1,35437
95% Confidence Interval for Mean
-0,38134 -0,05011
95% Confidence Interval for Median
-0,29787 0,03017
95% Confidence Interval for StDev
0,70288 0,93985
-2,25 -1,50 -0,75 0,00 0,75
95% Confidence Intervals
Mean
Median
-0,4 -0,3 -0,2 -0,1 0,0

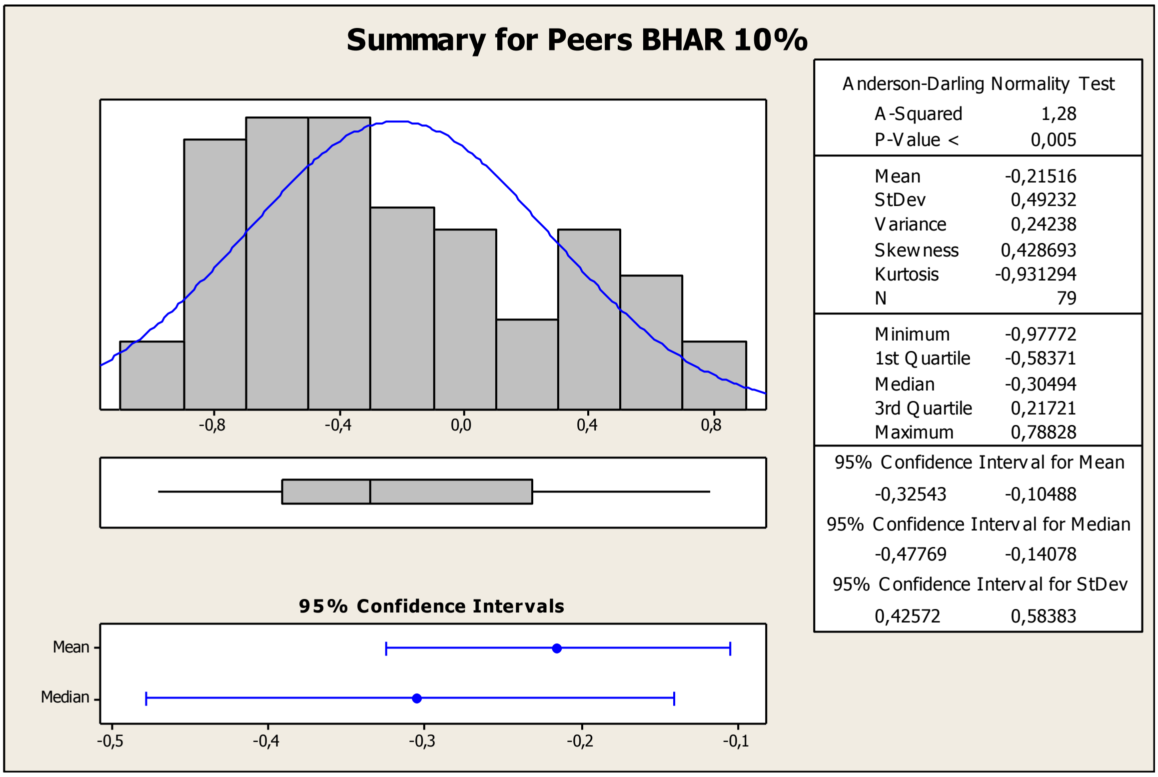


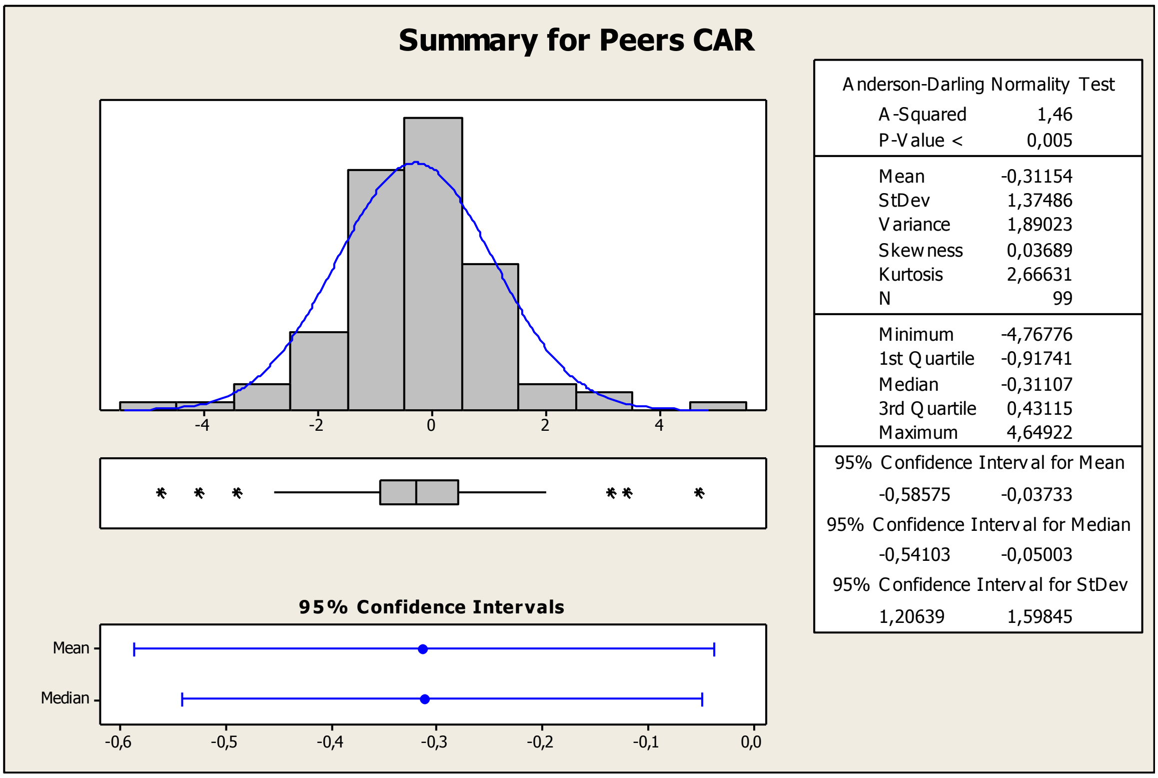
9.2.2 Long-term abnormal return in excess of peers

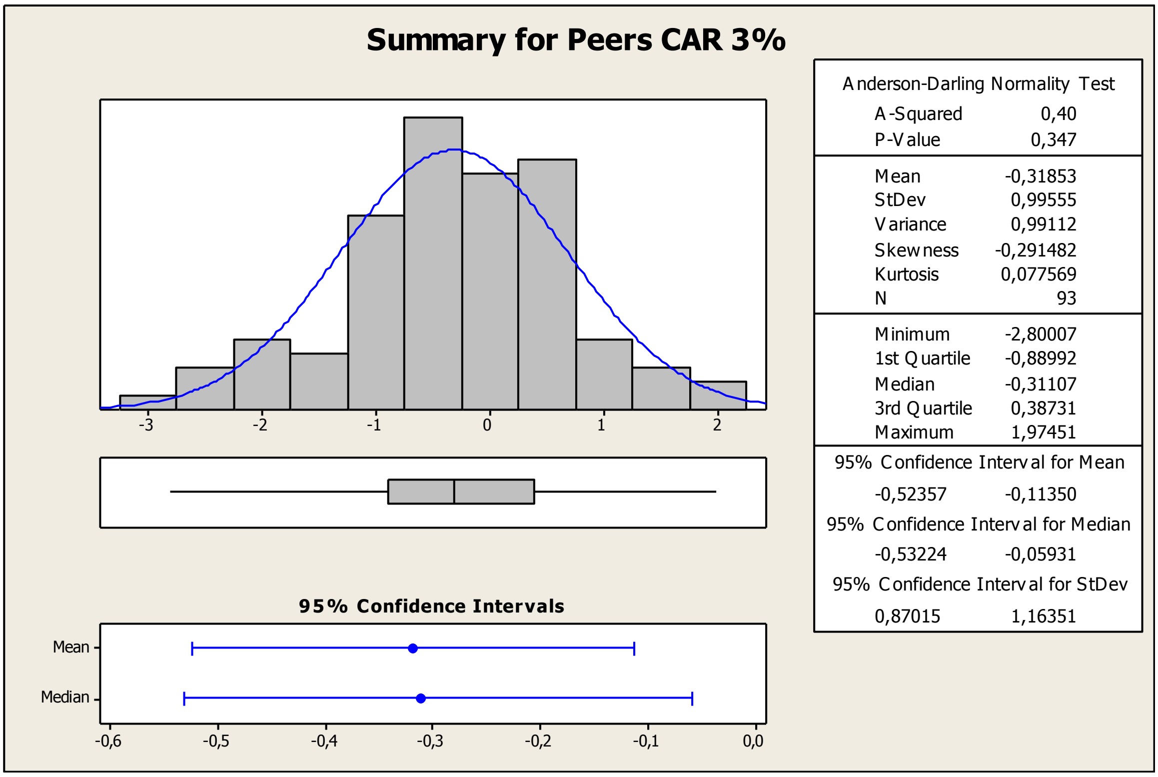
Minitab printouts of descriptive statistics summaries for abnormal return, using Buy-and-hold abnormal return (BHAR) and Cumulative abnormal return (CAR) for full sample, 3%-trimmed and 10% trimmed datasets.

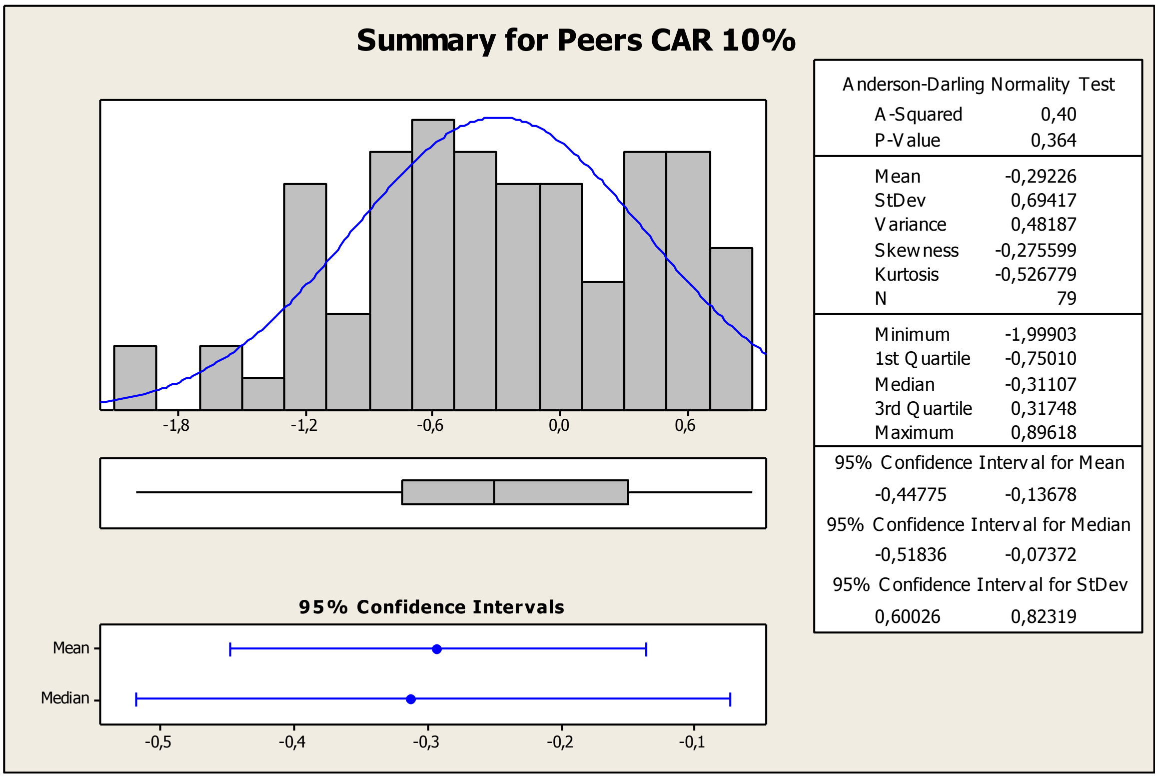



Summary for Peers BHAR 3%
Anderson-Darling Normality Test
A-Squared 1,30
P-Value < 0,005
Mean -0,22103
StDev 0,82105
Variance 0,67412
Skewness -0,45207
Kurtosis 3,24442
N 93
Minimum -3,64346
1st Quartile -0,68102
Median -0,30494
3rd Quartile 0,31990
Maximum 2,13697
95% Confidence Interval for Mean
-0,39012 -0,05193
95% Confidence Interval for Median
-0,48166 -0,12569
95% Confidence Interval for StDev
0,71763 0,95957
-3 -2 -1 0 1 2
95% Confidence Intervals
Mean
Median
-0,5 -0,4 -0,3 -0,2 -0,1 0,0


Summary for Peers BHAR 10%
Anderson-Darling Normality Test
A-Squared 1,28
P-Value < 0,005
Mean -0,21516
StDev 0,49232
Variance 0,24238
Skewness 0,428693
Kurtosis -0,931294
N 79
Minimum -0,97772
1st Quartile -0,58371
Median -0,30494
3rd Quartile 0,21721
Maximum 0,78828
95% Confidence Interval for Mean
-0,32543 -0,10488
95% Confidence Interval for Median
-0,47769 -0,14078
95% Confidence Interval for StDev
0,42572 0,58383
-0,8 -0,4 0,0 0,4 0,8
95% Confidence Intervals
Mean
Median
-0,5 -0,4 -0,3 -0,2 -0,1

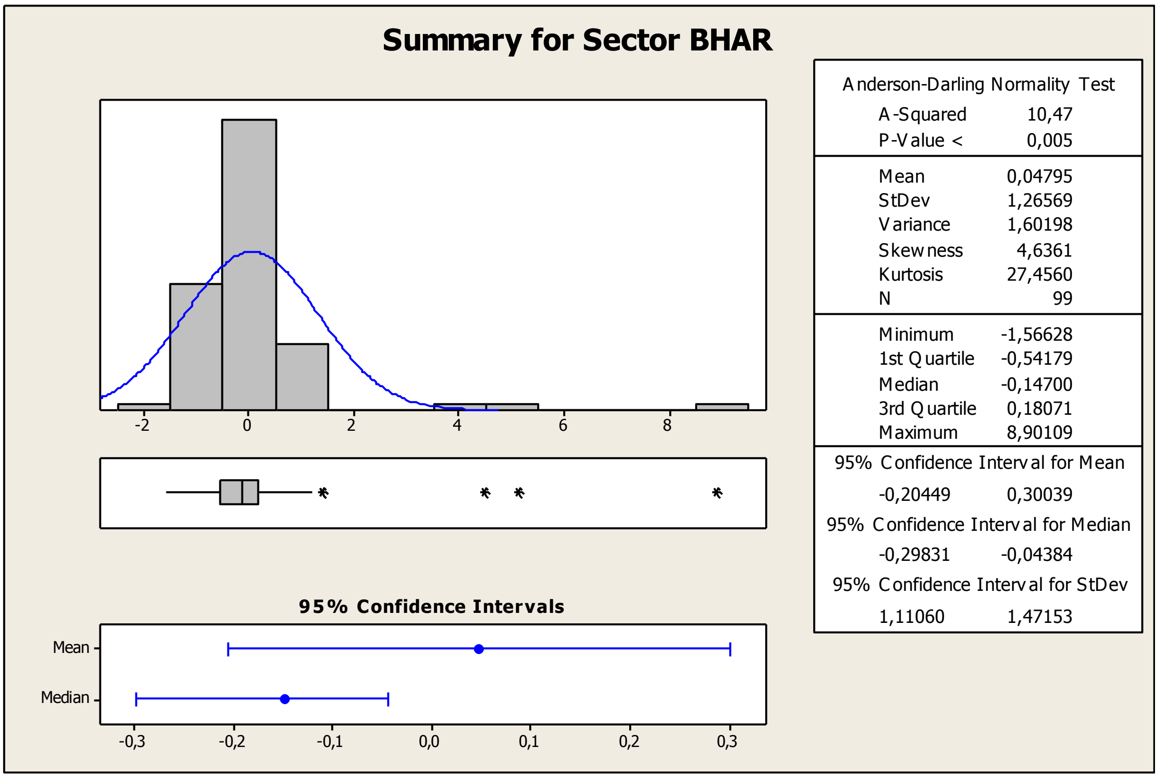

Summary for Peers CAR
Anderson-Darling Normality Test
A-Squared 1,46
P-Value < 0,005
Mean -0,31154
StDev 1,37486
Variance 1,89023
Skewness 0,03689
Kurtosis 2,66631
N 99
Minimum -4,76776
1st Quartile -0,91741
Median -0,31107
3rd Quartile 0,43115
Maximum 4,64922
95% Confidence Interval for Mean
-0,58575 -0,03733
95% Confidence Interval for Median
-0,54103 -0,05003
95% Confidence Interval for StDev
1,20639 1,59845
-4 -2 0 2 4
95% Confidence Intervals
Mean
Median
-0,6 -0,5 -0,4 -0,3 -0,2 -0,1 0,0

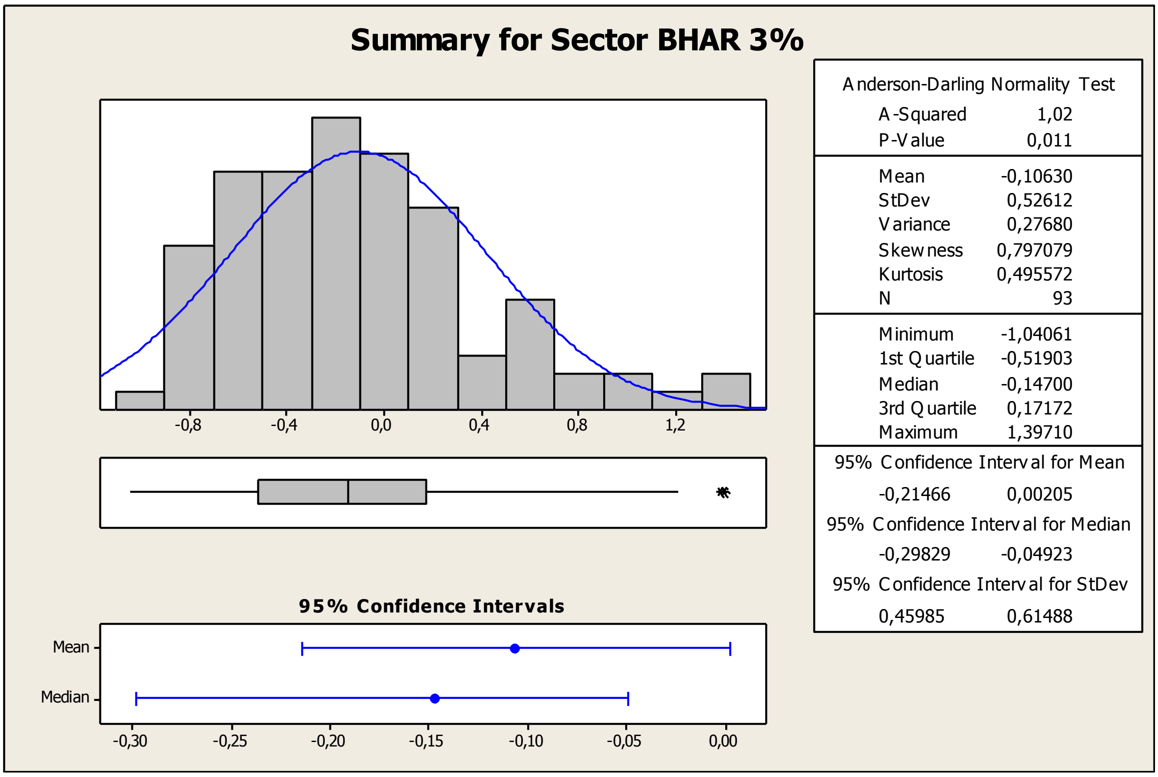

Summary for Peers CAR 3%
Anderson-Darling Normality Test
A-Squared 0,40
P-Value 0,347
Mean -0,31853
StDev 0,99555
Variance 0,99112
Skewness -0,291482
Kurtosis 0,077569
N 93
Minimum -2,80007
1st Quartile -0,88992
Median -0,31107
3rd Quartile 0,38731
Maximum 1,97451
95% Confidence Interval for Mean
-0,52357 -0,11350
95% Confidence Interval for Median
-0,53224 -0,05931
95% Confidence Interval for StDev
0,87015 1,16351
-3 -2 -1 0 1 2
95% Confidence Intervals
Mean
Median
-0,6 -0,5 -0,4 -0,3 -0,2 -0,1 0,0

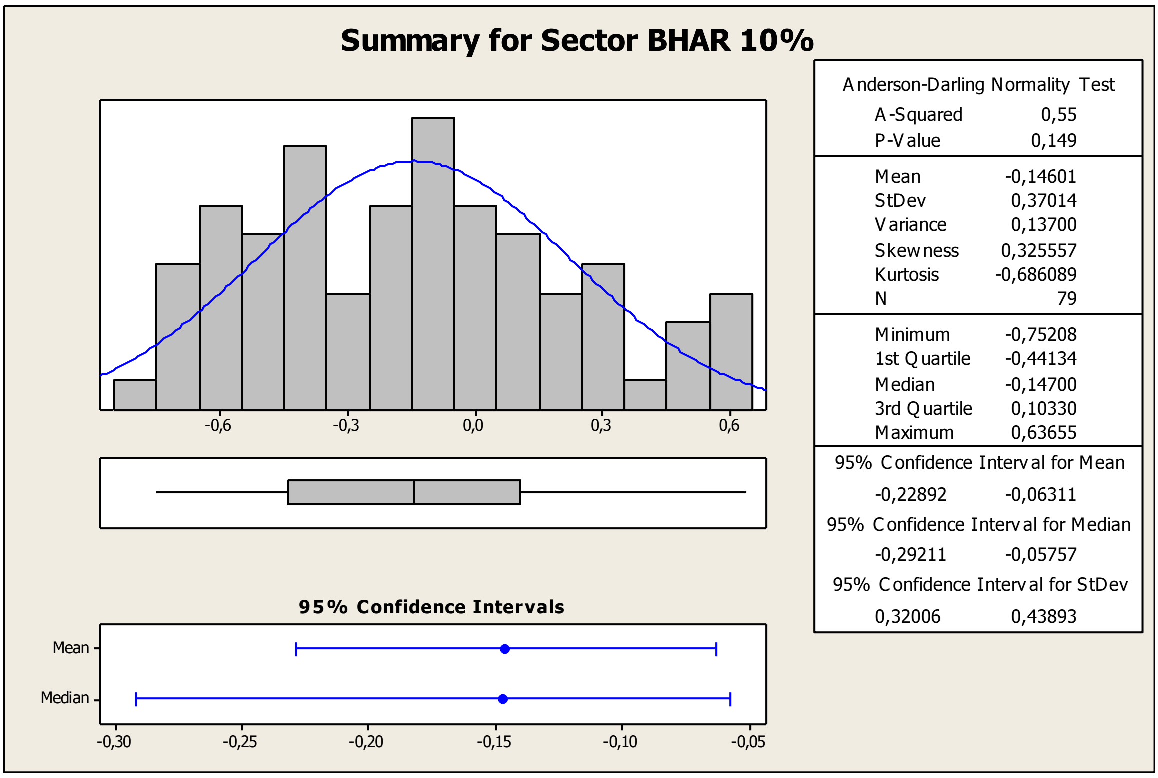

Summary for Peers CAR 10%
Anderson-Darling Normality Test
A-Squared 0,40
P-Value 0,364
Mean -0,29226
StDev 0,69417
Variance 0,48187
Skewness -0,275599
Kurtosis -0,526779
N 79
Minimum -1,99903
1st Quartile -0,75010
Median -0,31107
3rd Quartile 0,31748
Maximum 0,89618
95% Confidence Interval for Mean
-0,44775 -0,13678
95% Confidence Interval for Median
-0,51836 -0,07372
95% Confidence Interval for StDev
0,60026 0,82319
-1,8 -1,2 -0,6 0,0 0,6
95% Confidence Intervals
Mean
Median
-0,5 -0,4 -0,3 -0,2 -0,1

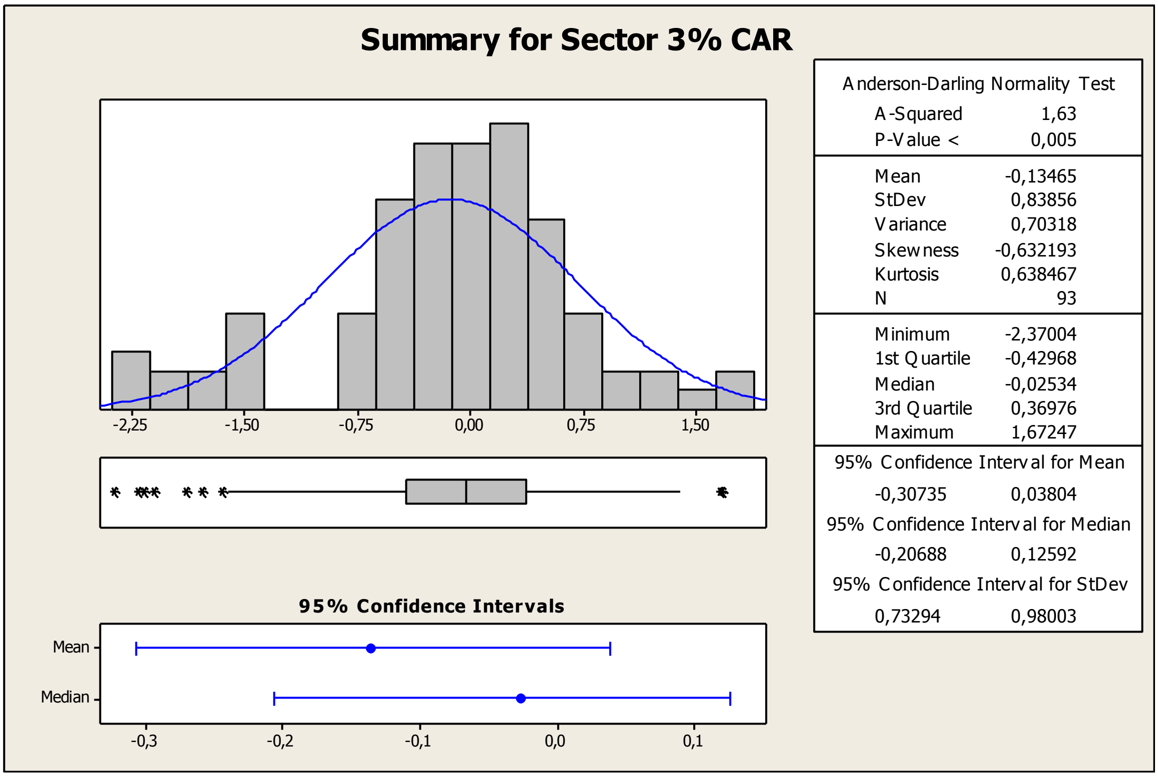
9.2.3 Long-term abnormal return in excess of sector

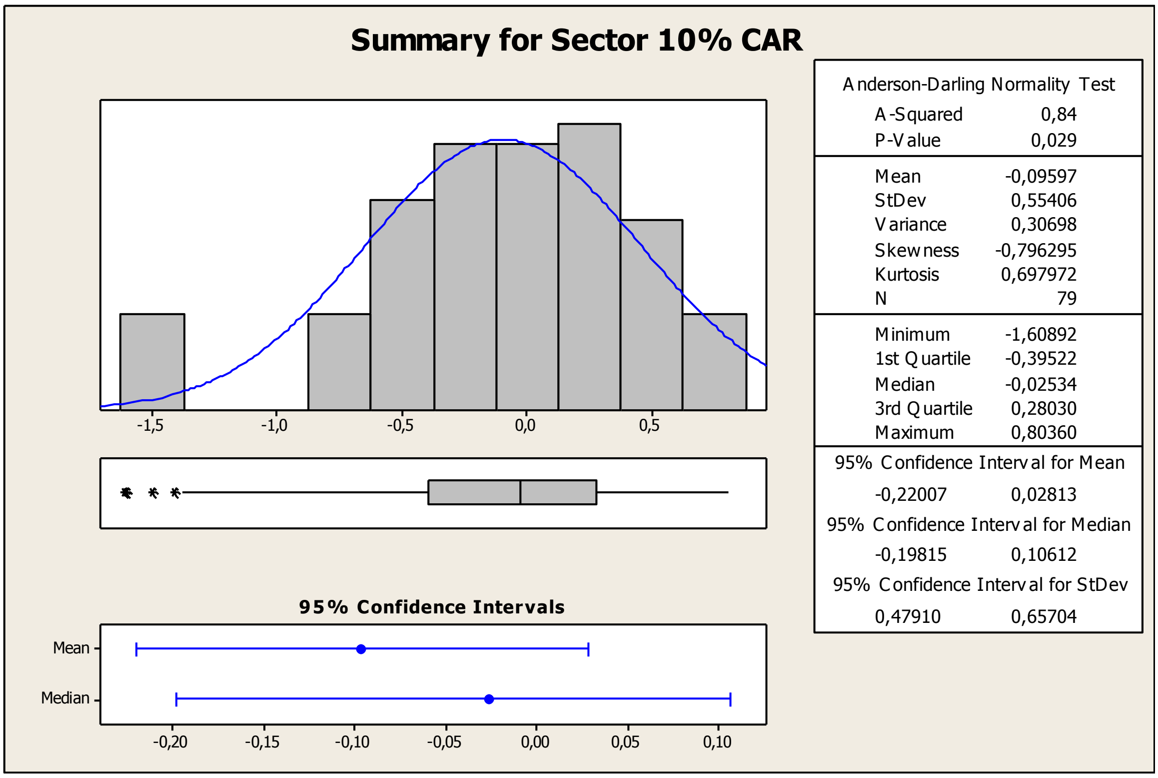
Minitab printouts of descriptive statistics summaries for abnormal return, using Buy-and-hold abnormal return (BHAR) and Cumulative abnormal return (CAR) for full sample, 3%-trimmed and 10% trimmed datasets.






Summary for Sector BHAR 10%
Anderson-Darling Normality Test
A-Squared 0,55
P-Value 0,149
Mean -0,14601
StDev 0,37014
Variance 0,13700
Skewness 0,325557
Kurtosis -0,686089
N 79
Minimum -0,75208
1st Quartile -0,44134
Median -0,14700
3rd Quartile 0,10330
Maximum 0,63655
95% Confidence Interval for Mean
-0,22892 -0,06311
95% Confidence Interval for Median
-0,29211 -0,05757
95% Confidence Interval for StDev
0,32006 0,43893
-0,6 -0,3 0,0 0,3 0,6
95% Confidence Intervals
Mean
Median
-0,30 -0,25 -0,20 -0,15 -0,10 -0,05


Summary for Sector 3% CAR
Anderson-Darling Normality Test
A-Squared 1,63
P-Value < 0,005
Mean -0,13465
StDev 0,83856
Variance 0,70318
Skewness -0,632193
Kurtosis 0,638467
N 93
Minimum -2,37004
1st Quartile -0,42968
Median -0,02534
3rd Quartile 0,36976
Maximum 1,67247
95% Confidence Interval for Mean
-0,30735 0,03804
95% Confidence Interval for Median
-0,20688 0,12592
95% Confidence Interval for StDev
0,73294 0,98003
-2,25 -1,50 -0,75 0,00 0,75 1,50
95% Confidence Intervals
Mean
Median
-0,3 -0,2 -0,1 0,0 0,1


Summary for Sector 10% CAR
Anderson-Darling Normality Test
A-Squared 0,84
P-Value 0,029
Mean -0,09597
StDev 0,55406
Variance 0,30698
Skewness -0,796295
Kurtosis 0,697972
N 79
Minimum -1,60892
1st Quartile -0,39522
Median -0,02534
3rd Quartile 0,28030
Maximum 0,80360
95% Confidence Interval for Mean
-0,22007 0,02813
95% Confidence Interval for Median
-0,19815 0,10612
95% Confidence Interval for StDev
0,47910 0,65704
-1,5 -1,0 -0,5 0,0 0,5
95% Confidence Intervals
Mean
Median
-0,20 -0,15 -0,10 -0,05 0,00 0,05 0,10

9.3 Appendix C: Cross-sectional regression output

All the outputs from the cross-sectional regressions are presented below together with tests of all the relevant OLS assumptions for a BLUE model.

9.3.1 Regression matched against index with raw data:

Regression Analysis: Index versus Mcap; mbook; ...

```
The regression equation is:
Index = 0.993 - 0.000050 Mcap - 0.0170 mbook - 0.0145 Ageyears - 0.909 marcond
        - 0.364 Brent - 0.316 Ind - 0.006 Health + 0.527 Fin + 0.419 Costap
        - 0.547 cod + 0.330 it

93 cases used, 1 cases contain missing values
```

Predictor	Coef	SE Coef	T	P	**VIF**
Constant	0.9927	0.4221	2.35	0.021	
Mcap	-0.00005003	0.00002923	-1.71	0.091	1.183
mbook	-0.01701	0.05920	-0.29	0.775	1.179
Ageyears	-0.014457	0.006303	-2.29	0.024	1.220
marcond	-0.9094	0.3309	-2.75	0.007	1.077
Brent	-0.3638	0.2900	-1.25	0.213	1.112
Ind	-0.3157	0.4281	-0.74	0.463	1.395
Health	-0.0059	0.5115	-0.01	0.991	1.412
Fin	0.5266	0.4975	1.06	0.293	1.217
Costap	0.4195	0.5281	0.79	0.429	1.371
cod	-0.5465	0.5828	-0.94	0.351	1.153
it	0.3300	0.4132	0.80	0.427	1.368

```
S = 1.28575   R-Sq = 23.5%   R-Sq(adj) = 13.1%

Analysis of Variance
```

Source	DF	SS	MS	F	P
Regression	11	41.152	3.741	2.26	0.018
Residual Error	81	133.905	1.653		
Total	92	175.057			

Source	DF	Seq SS
Mcap	1	3.960
mbook	1	0.005
Ageyears	1	11.637
marcond	1	13.734

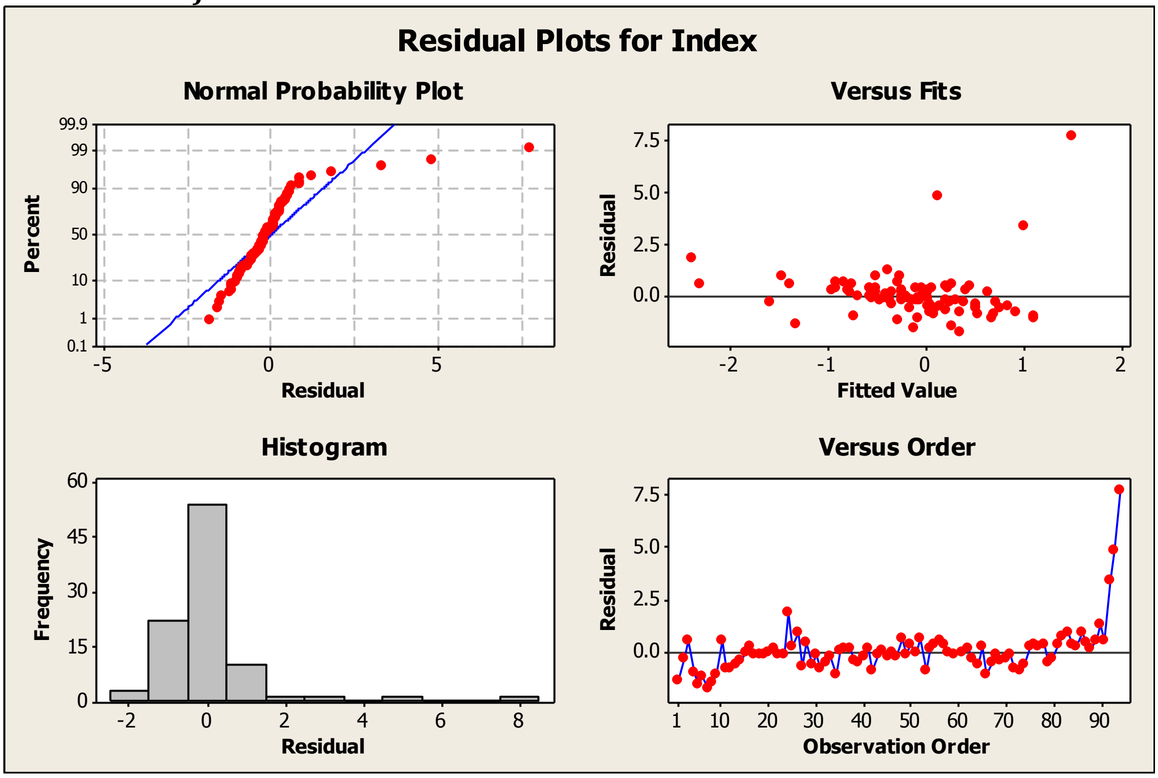
Brent	1	3.151
Ind	1	2.784
Health	1	0.155
Fin	1	1.432
Costap	1	0.932
cod	1	2.308
it	1	1.054

Unusual Observations

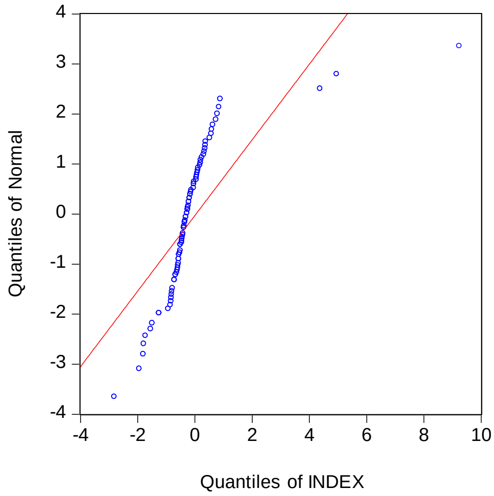
Obs	Mcap	Index	Fit	SE Fit	Residual	St Resid
3	46197	-1.796	-2.333	1.229	0.537	1.42 X
48	10687	-0.326	-0.919	1.016	0.593	0.75 X
92	1230	4.381	1.016	0.439	3.364	2.78R
93	573	4.963	0.126	0.487	4.837	4.06R
94	538	9.236	1.492	0.561	7.744	6.69R

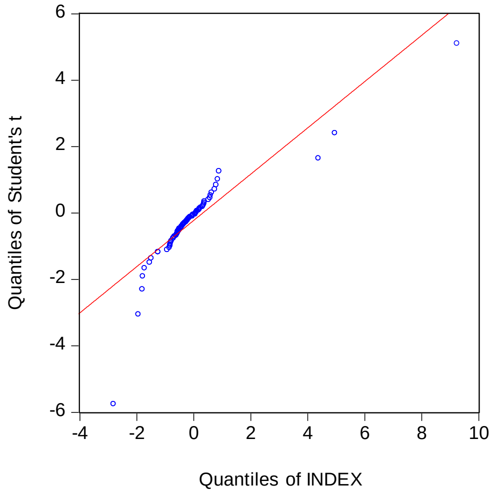
R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Residual Plots for Index

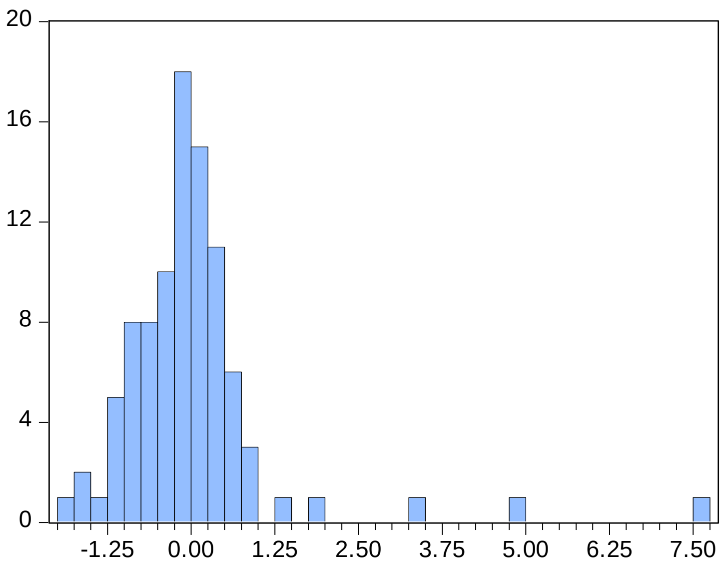


Probability plot of the normal- and Student's t-distribution:





Check for normality in the residuals:



Series: Residuals
Sample 1 94
Observations 93

Mean	1.91e-16
Median	-0.143579
Maximum	7.745268
Minimum	-1.832556
Std. Dev.	1.206360
Skewness	3.703377
Kurtosis	22.48393
Jarque-Bera	1683.624
Probability	0.000000

Multi-correlation matrix:

	AGEYEARS	BRENT	COD	COSTAP	FIN	IND	IT	MARCOND	MBOOK	MCAP	NRG	HEALTH
AGEYEARS	1.00	0.13	-0.13	0.29	-0.01	0.21	-0.08	0.04	-0.10	-0.05	-0.17	-0.07
BRENT	0.13	1.00	-0.02	-0.05	-0.10	0.10	0.15	-0.04	-0.01	-0.22	-0.03	-0.10
COD	-0.13	-0.02	1.00	-0.09	-0.09	-0.12	-0.12	-0.07	-0.03	-0.01	-0.17	-0.09
COSTAP	0.29	-0.05	-0.09	1.00	-0.11	-0.14	-0.15	-0.08	-0.14	0.03	-0.21	-0.11
FIN	-0.01	-0.10	-0.09	-0.11	1.00	-0.14	-0.15	0.09	-0.13	-0.02	-0.21	-0.11
IND	0.21	0.10	-0.12	-0.14	-0.14	1.00	-0.20	0.10	-0.03	-0.13	-0.29	-0.15
IT	-0.08	0.15	-0.12	-0.15	-0.15	-0.20	1.00	-0.09	0.08	-0.12	-0.30	-0.16
MARCOND	0.04	-0.04	-0.07	-0.08	0.09	0.10	-0.09	1.00	-0.07	0.02	0.13	-0.14
MBOOK	-0.10	-0.01	-0.03	-0.14	-0.13	-0.03	0.08	-0.07	1.00	0.21	-0.06	0.31
MCAP	-0.05	-0.22	-0.01	0.03	-0.02	-0.13	-0.12	0.02	0.21	1.00	0.01	0.29
NRG	-0.17	-0.03	-0.17	-0.21	-0.21	-0.29	-0.30	0.13	-0.06	0.01	1.00	-0.23
HEALTH	-0.07	-0.10	-0.09	-0.11	-0.11	-0.15	-0.16	-0.14	0.31	0.29	-0.23	1.00

White test for heteroskedasticity:

Heteroskedasticity Test: White

F-statistic	43.85860	Prob. F(55,37)	0.0000
Obs*R-squared	91.59506	Prob. Chi-Square(55)	0.0014
Scaled explained SS	746.3800	Prob. Chi-Square(55)	0.0000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/06/12 Time: 17:45

Sample: 1 94

Included observations: 93

Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	12.97152	1.641633	7.901599	0.0000
AGEYEARS	-0.697379	0.090629	-7.694889	0.0000
AGEYEARS^2	0.001040	0.000328	3.168325	0.0031
AGEYEARS*BRENT	-0.043485	0.032736	-1.328350	0.1922
AGEYEARS*COD	0.195812	3.313384	0.059097	0.9532
AGEYEARS*COSSNX	-0.171336	0.044269	-3.870327	0.0004
AGEYEARS*FIN	-0.136665	0.046320	-2.950438	0.0055
AGEYEARS*IND	-0.077599	0.045698	-1.698070	0.0979
AGEYEARS*IT	0.004791	0.047672	0.100502	0.9205
AGEYEARS*MARCOND	0.622679	0.063353	9.828776	0.0000
AGEYEARS*MBOOK	0.040174	0.018691	2.149348	0.0382
AGEYEARS*MCAP	5.93E-06	1.94E-05	0.306021	0.7613
AGEYEARS*HEALTH	0.025827	0.148657	0.173734	0.8630
BRENT	2.294779	2.353929	0.974872	0.3360
BRENT^2	0.780672	0.860096	0.907657	0.3699
BRENT*COD	-0.063678	13.79654	-0.004615	0.9963
BRENT*COSSNX	-8.899075	2.941345	-3.025512	0.0045
BRENT*FIN	37.19200	3.294203	11.29014	0.0000
BRENT*IND	4.590747	1.510635	3.038952	0.0043
BRENT*IT	-0.081857	1.079268	-0.075845	0.9400
BRENT*MARCOND	-2.006661	1.520847	-1.319436	0.1951
BRENT*MBOOK	-0.572208	0.328813	-1.740222	0.0901
BRENT*MCAP	0.000220	0.000409	0.536252	0.5950
BRENT*HEALTH	-0.072070	2.415809	-0.029832	0.9764
COD	-12.24222	2.600552	-4.707548	0.0000
COD*MARCOND	11.92232	3.751201	3.178267	0.0030

COD*MBOOK	-0.549527	6.657357	-0.082544	0.9347
COD*MCAP	0.000714	0.006217	0.114810	0.9092
COSSNX	45.31021	1.830707	24.75012	0.0000
COSSNX*MARCOND	-38.32146	2.595173	-14.76644	0.0000
COSSNX*MBOOK	-1.020027	0.937848	-1.087626	0.2838
COSSNX*MCAP	0.000508	0.000378	1.345431	0.1867
FIN	-17.09231	6.374513	-2.681352	0.0109
FIN*MARCOND	18.96896	5.246596	3.615479	0.0009
FIN*MBOOK	-3.745171	0.930111	-4.026587	0.0003
FIN*MCAP	0.001333	0.000980	1.360396	0.1819
IND	-8.808019	2.329054	-3.781801	0.0006
IND*MARCOND	7.006638	2.192334	3.195972	0.0028
IND*MBOOK	-0.091291	0.574543	-0.158893	0.8746
IND*MCAP	0.002254	0.001526	1.476945	0.1482
IT	-13.63153	2.663580	-5.117748	0.0000
IT*MARCOND	14.06807	2.576203	5.460776	0.0000
IT*MBOOK	-0.524108	0.633908	-0.826788	0.4137
IT*MCAP	0.002369	0.000787	3.009416	0.0047
MARCOND	-13.18242	1.681179	-7.841175	0.0000
MARCOND*MBOOK	-1.176702	0.474934	-2.477612	0.0179
MARCOND*MCAP	0.001905	0.000613	3.105675	0.0036
MARCOND*HEALTH	14.23296	3.946935	3.606079	0.0009
MBOOK	1.262864	0.613010	2.060105	0.0465
MBOOK^2	0.008461	0.068248	0.123973	0.9020
MBOOK*MCAP	-6.65E-06	0.000122	-0.054563	0.9568
MBOOK*HEALTH	-0.645596	0.882711	-0.731379	0.4692
MCAP	-0.001889	0.000559	-3.380976	0.0017
MCAP^2	-4.60E-08	2.38E-08	-1.935079	0.0607
MCAP*HEALTH	0.002158	0.001048	2.058354	0.0467
HEALTH	-13.99378	4.866078	-2.875782	0.0066

R-squared	0.984893	Mean dependent var	1.439657
Adjusted R-squared	0.962437	S.D. dependent var	6.709087
S.E. of regression	1.300299	Akaike info criterion	3.645685
Sum squared resid	62.55876	Schwarz criterion	5.170691
Log likelihood	-113.5243	Hannan-Quinn criter.	4.261439
F-statistic	43.85860	Durbin-Watson stat	2.615528
Prob(F-statistic)	0.000000		

Regression analysis included White heteroskedasticity term: Index versus Mcap; Mbook; …

Dependent Variable: INDEX

Method: Least Squares

Date: 03/07/12 Time: 10:40

Sample: 1 94

Included observations: 93

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.993951	0.713670	1.392732	0.1675
AGEYEARS	-0.014457	0.008350	-1.731454	0.0872
BRENT	-0.365567	0.368002	-0.993383	0.3235
COD	-0.547177	0.284737	-1.921696	0.0582
COSTAP	0.419725	1.109593	0.378270	0.7062
FIN	0.524344	0.684145	0.766422	0.4457
IND	-0.316974	0.284898	-1.112586	0.2692
IT	0.329478	0.236352	1.394016	0.1671
MARCOND	-0.908879	0.475341	-1.912056	0.0594
MBOOK	-0.017190	0.038290	-0.448937	0.6547
MCAP	-5.03E-05	1.68E-05	-2.982422	0.0038
HEALTH	-0.003406	0.242239	-0.014059	0.9888

R-squared	0.235369	Mean dependent var	-0.148817
Adjusted R-squared	0.131530	S.D. dependent var	1.379593
S.E. of regression	1.285667	Akaike info criterion	3.460346
Sum squared resid	133.8881	Schwarz criterion	3.787133
Log likelihood	-148.9061	Hannan-Quinn criter.	3.592294
F-statistic	2.266678	Durbin-Watson stat	0.469614
Prob(F-statistic)	0.018242		

Best subset regression index raw-data:

Summary over the adjusted R-squared effects from different regression models:

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	Mcap	mbook	Ageyears	marcond	Brent	Ind	Health	Fin	Costap	cod	it
1	8.3	7.3	8.1	1.3279				X							
1	6.2	5.1	10.4	1.3435			X								
2	14.0	12.1	4.0	1.2932			X	X							
2	11.0	9.0	7.3	1.3161				X		X					
3	16.5	13.7	3.4	1.2814	X		X	X							
3	15.8	12.9	4.2	1.2870			X	X				X			
4	18.4	14.7	3.4	1.2743	X		X	X	X						
4	18.3	14.6	3.5	1.2746	X		X	X		X					

5	20.0	15.4	3.7	1.2689	X		X	X	X	X					
5	19.9	15.3	3.8	1.2695	X		X	X		X				X	
6	**21.6**	**16.1**	**4.0**	**1.2634**	**X**		**X**	**X**	**X**	**X**				**X**	
6	20.9	15.4	4.7	1.2687	X		X	X	X	X		X			
7	22.3	15.9	5.3	1.2649	X		X	X	X	X		X		X	
7	22.3	15.9	5.3	1.2654	X		X	X	X			X	X		X
8	22.9	15.5	6.7	1.2677	X		X	X	X			X	X	X	X
8	22.8	15.4	6.8	1.2686	X		X	X	X	X		X	X	X	
9	23.4	15.1	8.1	1.2709	X		X	X	X	X		X	X	X	X
9	23.0	14.6	8.6	1.2747	X	X	X	X	X			X	X	X	X
10	23.5	14.2	10.0	1.2779	X	X	X	X	X	X		X	X	X	X
10	23.4	14.1	10.1	1.2785	X		X	X	X	X	X	X	X	X	X
11	23.5	13.1	12.0	1.2857	X	X	X	X	X	X	X	X	X	X	X

Regression Analysis included White Heteroskedasticity term: Best subset regression

Dependent Variable: INDEX

Method: Least Squares

Date: 03/13/12 Time: 17:37

Sample: 1 94

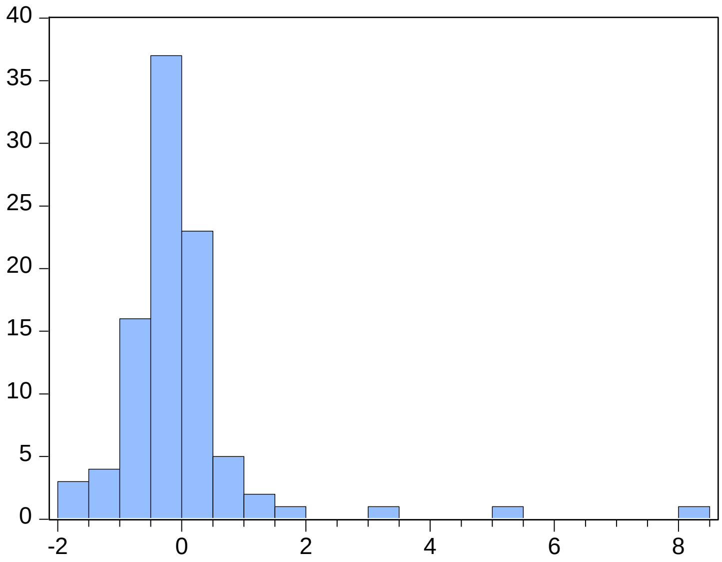
Included observations: 94

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.126666	0.660595	1.705533	0.0917
MCAP	-5.62E-05	1.80E-05	-3.116629	0.0025
AGEYEARS	-0.012675	0.004909	-2.581728	0.0115
MARCOND	-0.918807	0.494197	-1.859190	0.0664
BRENT	-0.362507	0.374951	-0.966812	0.3363
IND	-0.530100	0.242609	-2.184997	0.0316
COD	-0.710416	0.277233	-2.562520	0.0121

R-squared	0.214847	Mean dependent var	-0.149149
Adjusted R-squared	0.160698	S.D. dependent var	1.372160
S.E. of regression	1.257082	Akaike info criterion	3.367014
Sum squared resid	137.4823	Schwarz criterion	3.556408
Log likelihood	-151.2496	Hannan-Quinn criter.	3.443515
F-statistic	3.967734	Durbin-Watson stat	0.428638
Prob(F-statistic)	0.001483		

Check for normality in the residuals:



Series: RESID	
Sample 1 94	
Observations 94	
Mean	1.51e-16
Median	-0.138496
Maximum	8.022117
Minimum	-1.597380
Std. Dev.	1.215855
Skewness	4.043770
Kurtosis	24.93030
Jarque-Bera	2139.856
Probability	0.000000

White test for heteroskedasticity:

Heteroskedasticity Test: White

F-statistic	1.522293	Prob. F(23,70)	0.0922
Obs*R-squared	31.34093	Prob. Chi-Square(23)	0.1146
Scaled explained SS	321.2275	Prob. Chi-Square(23)	0.0000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/13/12 Time: 17:43

Sample: 1 94

Included observations: 94

White Heteroskedasticity-Consistent Standard Errors & Covariance

Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	18.23582	12.21464	1.492947	0.1399
MCAP	-0.003087	0.002256	-1.368007	0.1757
MCAP^2	1.80E-08	1.70E-08	1.058591	0.2934
MCAP*AGEYEARS	1.77E-05	2.02E-05	0.877730	0.3831
MCAP*MARCOND	0.002418	0.001868	1.294453	0.1998
MCAP*BRENT	0.001167	0.001359	0.858691	0.3934
MCAP*IND	0.002276	0.003385	0.672424	0.5035
MCAP*COD	2.40E-05	0.000536	0.044718	0.9645
AGEYEARS	-0.178113	0.152136	-1.170747	0.2457

AGEYEARS^2	0.000306	0.000434	0.704960	0.4832
AGEYEARS*MARCOND	0.110480	0.107196	1.030632	0.3063
AGEYEARS*BRENT	0.088708	0.108103	0.820588	0.4147
AGEYEARS*IND	-0.042397	0.086400	-0.490703	0.6252
AGEYEARS*COD	-0.227442	0.308120	-0.738159	0.4629
MARCOND	-16.66886	11.77804	-1.415249	0.1614
MARCOND*BRENT	14.88487	9.628902	1.545853	0.1266
MARCOND*IND	3.321173	7.197675	0.461423	0.6459
MARCOND*COD	7.017694	5.659786	1.239922	0.2191
BRENT	-19.58462	14.64735	-1.337076	0.1855
BRENT^2	3.258423	3.830084	0.850744	0.3978
BRENT*IND	2.048902	4.898748	0.418250	0.6770
BRENT*COD	2.367392	3.699678	0.639891	0.5243
IND	-4.968597	8.530471	-0.582453	0.5621
COD	-7.510645	4.991726	-1.504619	0.1369

R-squared	0.333414	Mean dependent var	1.462578
Adjusted R-squared	0.114393	S.D. dependent var	7.193089
S.E. of regression	6.769178	Akaike info criterion	6.878475
Sum squared resid	3207.524	Schwarz criterion	7.527827
Log likelihood	-299.2883	Hannan-Quinn criter.	7.140766
F-statistic	1.522293	Durbin-Watson stat	0.928549
Prob(F-statistic)	0.092198		

9.3.2 Regression matched against index with 3% trimmed data:

Regression Analysis: Index versus Mcap; mbook; ...

```
The regression equation is:
Index = - 0.121 + 0.000001 Mcap - 0.0077 mbook - 0.00288 Ageyears
        - 0.215 marcond - 0.0090 Brent - 0.101 Ind + 0.312 Health + 0.091 Fin
        - 0.708 Costap - 0.167 cod + 0.582 it

87 cases used, 1 cases contain missing values
```

Predictor	Coef	SE Coef	T	P	VIF
Constant	-0.1209	0.1596	-0.76	0.451	
Mcap	0.00000070	0.00003046	0.02	0.982	1.681
mbook	-0.00774	0.02186	-0.35	0.724	1.545
Ageyears	-0.002879	0.002106	-1.37	0.176	1.220
marcond	-0.2146	0.1134	-1.89	0.062	1.134
Brent	-0.00896	0.09976	-0.09	0.929	1.123
Ind	-0.1013	0.1479	-0.68	0.496	1.436

Health	0.3122	0.1749	1.78	0.078	1.465
Fin	0.0914	0.1687	0.54	0.590	1.227
Costap	-0.7082	0.1806	-3.92	0.000	1.407
cod	-0.1666	0.1880	-0.89	0.378	1.171
it	0.5821	0.1415	4.11	0.000	1.552

S = 0.410480   R-Sq = 50.3%   R-Sq(adj) = 43.0%

Analysis of Variance:

Source	DF	SS	MS	F	P
Regression	11	12.7738	1.1613	6.89	0.000
Residual Error	75	12.6371	0.1685		
Total	86	25.4109			

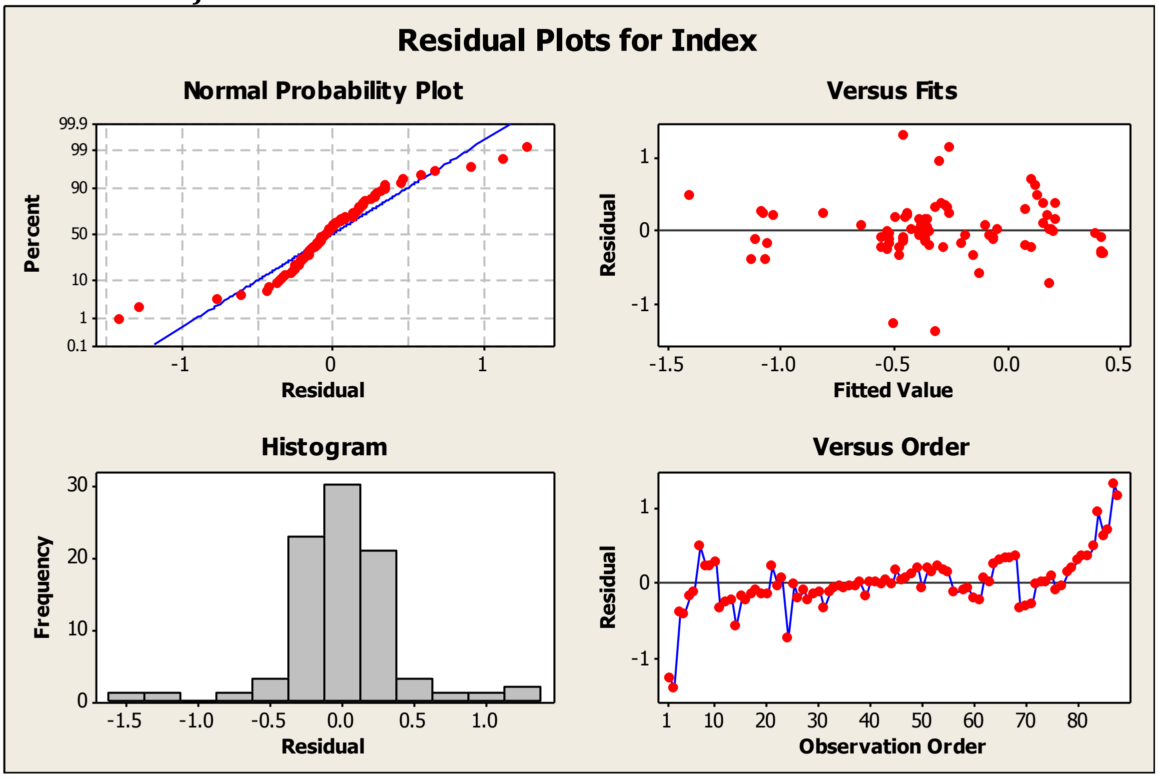
Source	DF	Seq SS
Mcap	1	0.4480
mbook	1	0.9772
Ageyears	1	2.0200
marcond	1	1.3391
Brent	1	0.0000
Ind	1	0.5865
Health	1	0.1040
Fin	1	0.0911
Costap	1	3.6234
cod	1	0.7343
it	1	2.8502

Unusual Observations:

Obs	Mcap	Index	Fit	SE Fit	Residual	St Resid
1	125	-1.7804	-0.4995	0.2079	-1.2809	-3.62R
2	643	-1.7157	-0.3108	0.1586	-1.4048	-3.71R
45	10687	-0.3257	-0.4932	0.3340	0.1674	0.70 X
84	1688	0.6297	-0.2970	0.1860	0.9266	2.53R
87	109	0.8459	-0.4536	0.1247	1.2995	3.32R
88	404	0.8948	-0.2485	0.1579	1.1433	3.02R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Residual Plots for Index



Regression Analysis included White Heteroskedasticity term: Index versus Mcap; mbook; ...

Dependent Variable: INDEX

Method: Least Squares

Date: 03/14/12 Time: 12:41

Sample (adjusted): 1 88

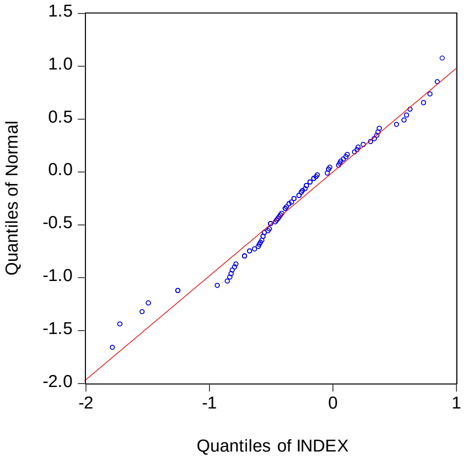
Included observations: 87 after adjustments

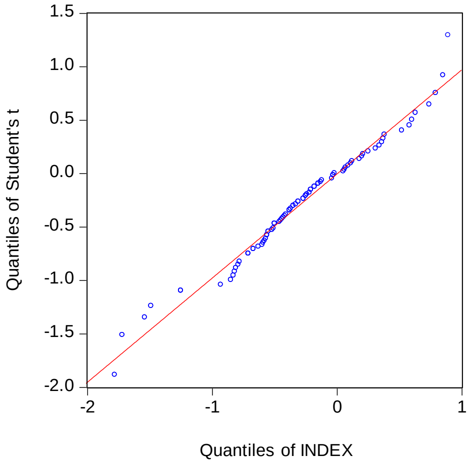
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.118749	0.159498	-0.744513	0.4589
AGEYEARS	-0.002889	0.002105	-1.372803	0.1739
BRENT	-0.010683	0.099800	-0.107046	0.9150
COD	-0.167006	0.187847	-0.889057	0.3768
COSTAP	-0.707662	0.180500	-3.920556	0.0002
FIN	0.088981	0.168563	0.527884	0.5991
IND	-0.103375	0.147824	-0.699316	0.4865
IT	0.581520	0.141430	4.111710	0.0001
MARCOND	-0.214513	0.113326	-1.892884	0.0622
MBOOK	-0.007838	0.021845	-0.358792	0.7208
MCAP	1.48E-07	3.04E-05	0.004862	0.9961
HEALTH	0.313408	0.174784	1.793115	0.0770

R-squared	0.503236	Mean dependent var	-0.297356
Adjusted R-squared	0.430378	S.D. dependent var	0.543517

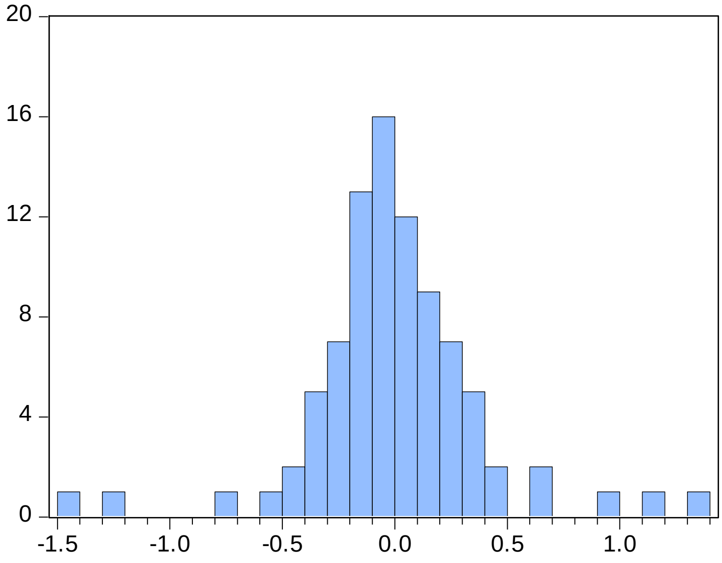
S.E. of regression	0.410210	Akaike info criterion	1.183148
Sum squared resid	12.62043	Schwarz criterion	1.523273
Log likelihood	-39.46692	Hannan-Quinn criter.	1.320106
F-statistic	6.907020	Durbin-Watson stat	0.457027
Prob(F-statistic)	0.000000		

Probability plot of the normal- and Student's t-distribution:





Check for normality in the residuals:



Series: RESID	
Sample 1 90	
Observations 87	
Mean	-4.59e-17
Median	-0.027944
Maximum	1.304272
Minimum	-1.406435
Std. Dev.	0.383079
Skewness	-0.079186
Kurtosis	7.132505
Jarque-Bera	61.99720
Probability	0.000000

Multi-correlation matrix:

	AGEYEARS	BRENT	COD	COSTAP	FIN	IND	IT	MARCOND	MBOOK	MCAP	NRG	HEALTH
AGEYEARS	1.00	0.08	-0.13	0.35	0.01	0.13	-0.07	-0.01	-0.11	-0.06	-0.15	-0.07
BRENT	0.08	1.00	-0.03	0.00	-0.17	0.04	0.16	-0.12	-0.02	-0.20	0.00	-0.06
COD	-0.13	-0.03	1.00	-0.09	-0.09	-0.11	-0.13	-0.08	-0.04	0.03	-0.18	-0.09
COSTAP	0.35	0.00	-0.09	1.00	-0.10	-0.13	-0.15	-0.02	-0.12	0.19	-0.21	-0.11
FIN	0.01	-0.17	-0.09	-0.10	1.00	-0.13	-0.15	0.07	-0.15	0.05	-0.21	-0.11
IND	0.13	0.04	-0.11	-0.13	-0.13	1.00	-0.20	0.07	-0.03	-0.23	-0.28	-0.14
IT	-0.07	0.16	-0.13	-0.15	-0.15	-0.20	1.00	-0.11	0.08	-0.22	-0.32	-0.16
MARCOND	-0.01	-0.12	-0.08	-0.02	0.07	0.07	-0.11	1.00	-0.11	-0.11	0.17	-0.19
MBOOK	-0.11	-0.02	-0.04	-0.12	-0.15	-0.03	0.08	-0.11	1.00	0.40	-0.05	0.30
MCAP	-0.06	-0.20	0.03	0.19	0.05	-0.23	-0.22	-0.11	0.40	1.00	0.18	0.02
NRG	-0.15	0.00	-0.18	-0.21	-0.21	-0.28	-0.32	0.17	-0.05	0.18	1.00	-0.23
HEALTH	-0.07	-0.06	-0.09	-0.11	-0.11	-0.14	-0.16	-0.19	0.30	0.02	-0.23	1.00

White test for heteroskedasticity:

Heteroskedasticity Test: White

F-statistic	3.857659	Prob. F(55,31)	0.0001
Obs*R-squared	75.90905	Prob. Chi-Square(55)	0.0324
Scaled explained SS	172.9758	Prob. Chi-Square(55)	0.0000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/14/12 Time: 12:41

Sample: 1 88

Included observations: 87

Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.909303	0.578763	-1.571116	0.1263
AGEYEARS	0.051901	0.031438	1.650905	0.1089
AGEYEARS^2	-6.35E-05	8.19E-05	-0.775890	0.4437
AGEYEARS*BRENT	0.005591	0.007460	0.749381	0.4593
AGEYEARS*COD	0.053931	0.549658	0.098118	0.9225
AGEYEARS*COSTAP	0.009208	0.010955	0.840526	0.4071
AGEYEARS*FIN	0.031954	0.010369	3.081756	0.0043
AGEYEARS*IND	-0.000894	0.008296	-0.107756	0.9149
AGEYEARS*IT	0.004665	0.008383	0.556433	0.5819
AGEYEARS*MARCOND	-0.049761	0.027540	-1.806863	0.0805
AGEYEARS*MBOOK	-0.002890	0.004228	-0.683430	0.4994
AGEYEARS*MCAP	8.81E-07	3.68E-06	0.239197	0.8125
AGEYEARS*HEALTH	0.023036	0.025231	0.913027	0.3683
BRENT	0.212283	0.470986	0.450720	0.6553

BRENT^2	0.069555	0.182009	0.382151	0.7050
BRENT*COD	-0.162533	2.300764	-0.070643	0.9441
BRENT*COSTAP	-0.144899	0.650458	-0.222765	0.8252
BRENT*FIN	-2.242440	1.876492	-1.195017	0.2411
BRENT*IND	0.020831	0.334480	0.062280	0.9507
BRENT*IT	-0.244991	0.181820	-1.347434	0.1876
BRENT*MARCOND	-0.342775	0.278395	-1.231252	0.2275
BRENT*MBOOK	-0.004165	0.060907	-0.068382	0.9459
BRENT*MCAP	2.83E-05	7.81E-05	0.362904	0.7191
BRENT*HEALTH	0.214114	0.407897	0.524922	0.6034
COD	1.589539	0.624115	2.546867	0.0161
COD*MARCOND	-1.224802	0.770602	-1.589408	0.1221
COD*MBOOK	-0.316838	1.105420	-0.286623	0.7763
COD*MCAP	0.000145	0.001031	0.140499	0.8892
COSTAP	-2.898058	1.714629	-1.690195	0.1010
COSTAP*MARCOND	3.103157	1.576110	1.968871	0.0580
COSTAP*MBOOK	-0.045966	0.182871	-0.251358	0.8032
COSTAP*MCAP	-3.22E-05	8.19E-05	-0.392513	0.6974
FIN	0.127055	1.372577	0.092567	0.9268
FIN*MARCOND	-0.494311	1.274375	-0.387885	0.7008
FIN*MBOOK	0.257606	0.238321	1.080922	0.2881
FIN*MCAP	4.02E-05	0.000179	0.224948	0.8235
IND	2.509742	0.530272	4.732928	0.0000
IND*MARCOND	-1.302944	0.478113	-2.725182	0.0105
IND*MBOOK	-0.074693	0.104092	-0.717569	0.4784
IND*MCAP	-0.001273	0.000293	-4.339600	0.0001
IT	0.717803	0.677715	1.059152	0.2977
IT*MARCOND	-0.702126	0.681517	-1.030240	0.3109
IT*MBOOK	0.115281	0.114390	1.007787	0.3214
IT*MCAP	-0.000207	0.000168	-1.234106	0.2264
MARCOND	1.004943	0.584919	1.718087	0.0958
MARCOND*MBOOK	0.085920	0.096379	0.891485	0.3795
MARCOND*MCAP	-0.000206	0.000140	-1.475451	0.1502
MARCOND*HEALTH	-1.833846	0.911182	-2.012601	0.0529
MBOOK	-0.078924	0.122786	-0.642778	0.5251
MBOOK^2	-0.011502	0.012656	-0.908809	0.3705
MBOOK*MCAP	2.28E-05	2.30E-05	0.988950	0.3303
MBOOK*HEALTH	-0.099574	0.172986	-0.575619	0.5690
MCAP	0.000134	0.000150	0.895029	0.3777
MCAP^2	2.99E-09	2.14E-08	0.139958	0.8896
MCAP*HEALTH	-0.000303	0.000217	-1.397675	0.1721
HEALTH	2.170813	1.062485	2.043147	0.0496

R-squared	0.872518	Mean dependent var	0.145062
Adjusted R-squared	0.646340	S.D. dependent var	0.361313

S.E. of regression	0.214871	Akaike info criterion	0.017875
Sum squared resid	1.431252	Schwarz criterion	1.605126
Log likelihood	55.22244	Hannan-Quinn criter.	0.657012
F-statistic	3.857659	Durbin-Watson stat	2.125790
Prob(F-statistic)	0.000062		

Regression Analysis included White Heteroskedasticity term: Index versus Mcap; mbook; ...

Dependent Variable: INDEX

Method: Least Squares

Date: 03/14/12 Time: 12:42

Sample (adjusted): 1 88

Included observations: 87 after adjustments

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.118749	0.155185	-0.765205	0.4466
AGEYEARS	-0.002889	0.003020	-0.956724	0.3418
BRENT	-0.010683	0.087285	-0.122395	0.9029
COD	-0.167006	0.180858	-0.923412	0.3588
COSTAP	-0.707662	0.143798	-4.921219	0.0000
FIN	0.088981	0.190496	0.467105	0.6418
IND	-0.103375	0.204024	-0.506683	0.6139
IT	0.581520	0.102967	5.647613	0.0000
MARCOND	-0.214513	0.148552	-1.444030	0.1529
MBOOK	-0.007838	0.015245	-0.514107	0.6087
MCAP	1.48E-07	2.06E-05	0.007170	0.9943
HEALTH	0.313408	0.143298	2.187110	0.0319

R-squared	0.503236	Mean dependent var	-0.297356
Adjusted R-squared	0.430378	S.D. dependent var	0.543517
S.E. of regression	0.410210	Akaike info criterion	1.183148
Sum squared resid	12.62043	Schwarz criterion	1.523273
Log likelihood	-39.46692	Hannan-Quinn criter.	1.320106
F-statistic	6.907020	Durbin-Watson stat	0.457027
Prob(F-statistic)	0.000000		

Best subset index 3% trimmed data:

Summary over the adjusted R-squared effects from different regression models:

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	Mcap	mbook	Ageyears	marcond	Brent	Ind	Health	Fin	Costap	cod	it
1	23.5	22.6	32.4	0.47829									X		
1	23.4	22.5	32.5	0.47846											X
2	40.7	39.3	8.4	0.42338									X		X
2	30.8	29.1	23.4	0.45764							X				X
3	45.4	43.5	3.3	0.40873							X		X		X
3	44.3	42.3	5.0	0.41300				X					X		X
4	47.5	45.0	2.1	0.40321				X			X		X		X
4	46.7	44.1	3.4	0.40637			X				X		X		X
5	48.8	45.7	2.2	0.40062			X	X			X		X		X
5	48.2	45.0	3.1	0.40306				X		X	X		X		X
6	**49.5**	**45.7**	**3.2**	**0.40070**			**X**	**X**			**X**	**X**	**X**		**X**
6	49.3	45.5	3.4	0.40119			X	X			X		X	X	X
7	49.9	45.5	4.5	0.40137			X	X		X	X		X	X	X
7	49.8	45.4	4.7	0.40181			X	X			X	X	X	X	X
8	50.2	45.0	6.2	0.40295			X	X		X	X	X	X	X	X
8	50.1	44.9	6.3	0.40338		X	X	X		X	X		X	X	X
9	50.3	44.4	8.0	0.40514		X	X	X		X	X	X	X	X	X
9	50.2	44.4	8.1	0.40549	X		X	X		X	X	X	X	X	X
10	50.3	43.7	10.0	0.40777		X	X	X	X	X	X	X	X	X	X
10	50.3	43.7	10.0	0.40779	X	X	X	X		X	X	X	X	X	X
11	50.3	43.0	12.0	0.41048	X	X	X	X	X	X	X	X	X	X	X

Regression analysis included White heteroskedasticity term: Best subset regression

Dependent Variable: INDEX

Method: Least Squares

Date: 03/14/12 Time: 12:45

Sample (adjusted): 1 88

Included observations: 88 after adjustments

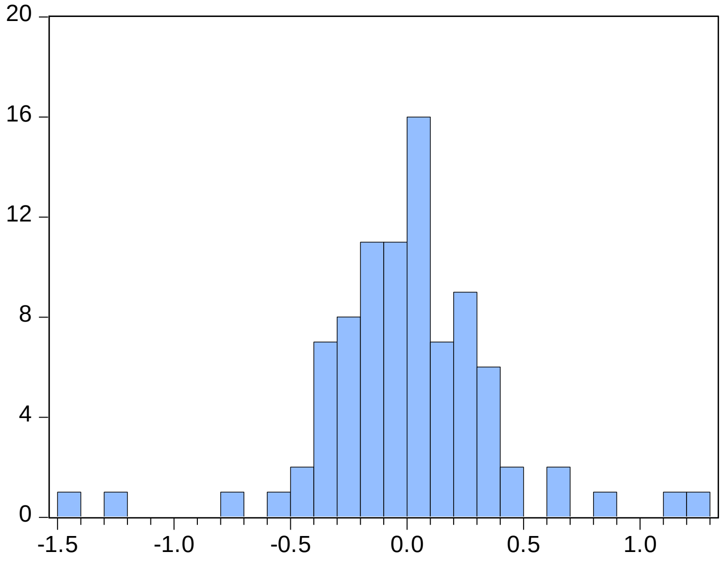
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.203979	0.172476	-1.182651	0.2404
IT	0.627816	0.111067	5.652569	0.0000
COSTAP	-0.647896	0.149013	-4.347919	0.0000
FIN	0.150075	0.193328	0.776271	0.4398
HEALTH	0.338883	0.143353	2.363975	0.0205

MARCOND	-0.201324	0.145668	-1.382069	0.1708
AGEYEARS	-0.002947	0.002726	-1.081107	0.2829

R-squared	0.494712	Mean dependent var	-0.296023
Adjusted R-squared	0.457283	S.D. dependent var	0.540529
S.E. of regression	0.398204	Akaike info criterion	1.072497
Sum squared resid	12.84386	Schwarz criterion	1.269558
Log likelihood	-40.18988	Hannan-Quinn criter.	1.151888
F-statistic	13.21745	Durbin-Watson stat	0.406269
Prob(F-statistic)	0.000000		

Check for normality in the residuals:



Series: RESID
Sample 1 90
Observations 88

Mean	-6.06e-17
Median	0.008460
Maximum	1.258250
Minimum	-1.454140
Std. Dev.	0.384227
Skewness	-0.261339
Kurtosis	6.855872
Jarque-Bera	55.51677
Probability	0.000000

White test for heteroskedasticity:

Heteroskedasticity Test: White

F-statistic	2.640646	Prob. F(16,71)	0.0027
Obs*R-squared	32.83018	Prob. Chi-Square(16)	0.0078
Scaled explained SS	81.44033	Prob. Chi-Square(16)	0.0000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/14/12 Time: 12:45

Sample: 1 88

Included observations: 88

White Heteroskedasticity-Consistent Standard Errors & Covariance

Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.549196	0.292040	1.880549	0.0641
IT	-0.524647	0.233126	-2.250490	0.0275
IT*MARCOND	0.523883	0.243614	2.150466	0.0349
IT*AGEYEARS	0.003171	0.002899	1.093680	0.2778
COSTAP	-1.019145	2.183949	-0.466652	0.6422
COSTAP*MARCOND	1.032903	2.188462	0.471977	0.6384
COSTAP*AGEYEARS	0.001390	0.000624	2.226209	0.0292
FIN	-0.548625	0.292040	-1.878592	0.0644
FIN*MARCOND	0.439702	0.296594	1.482503	0.1426
FIN*AGEYEARS	0.020157	0.001535	13.13129	0.0000
HEALTH	-0.427210	0.275811	-1.548925	0.1258
HEALTH*MARCOND	0.339872	0.295143	1.151551	0.2534
HEALTH*AGEYEARS	0.008469	0.013631	0.621318	0.5364
MARCOND	-0.455302	0.293567	-1.550931	0.1254
MARCOND*AGEYEARS	-0.007456	0.033653	-0.221562	0.8253
AGEYEARS	0.004611	0.034707	0.132852	0.8947
AGEYEARS^2	2.05E-05	2.63E-05	0.779685	0.4382

R-squared	0.373070	Mean dependent var	0.145953
Adjusted R-squared	0.231790	S.D. dependent var	0.355214
S.E. of regression	0.311337	Akaike info criterion	0.675823
Sum squared resid	6.882071	Schwarz criterion	1.154400
Log likelihood	-12.73623	Hannan-Quinn criter.	0.868630
F-statistic	2.640646	Durbin-Watson stat	1.366279
Prob(F-statistic)	0.002688		

9.3.3 Regression matched against index with 10% trimmed data:

Regression Analysis: Index versus Mcap; mbook; ...

```
The regression equation is:
Index = - 0.375 - 0.000003 Mcap + 0.00626 mbook + 0.00070 Ageyears
        - 0.0191 marcond + 0.0405 Brent - 0.292 Ind + 0.134 Health + 0.320 Fin
        - 0.521 Costap - 0.316 cod + 0.542 it

73 cases used, 1 cases contain missing values
```

Predictor	Coef	SE Coef	T	P	**VIF**
Constant	-0.37463	0.07125	-5.26	0.000	
Mcap	-0.00000287	0.00001340	-0.21	0.831	1.672
mbook	0.006259	0.009192	0.68	0.499	1.525
Ageyears	0.000705	0.001157	0.61	0.545	1.354
marcond	-0.01909	0.05472	-0.35	0.728	1.217

Brent	0.04049	0.04366	0.93	0.357	1.172
Ind	-0.29245	0.06800	-4.30	0.000	1.434
Health	0.13378	0.07640	1.75	0.085	1.327
Fin	0.31981	0.07227	4.43	0.000	1.187
Costap	-0.5214	0.1154	-4.52	0.000	1.375
cod	-0.31602	0.08182	-3.86	0.000	1.120
it	0.54245	0.06143	8.83	0.000	1.534

S = 0.166846   R-Sq = 80.2%   R-Sq(adj) = 76.6%

Analysis of Variance:

Source	DF	SS	MS	F	P
Regression	11	6.88134	0.62558	22.47	0.000
Residual Error	61	1.69809	0.02784		
Total	72	8.57943			

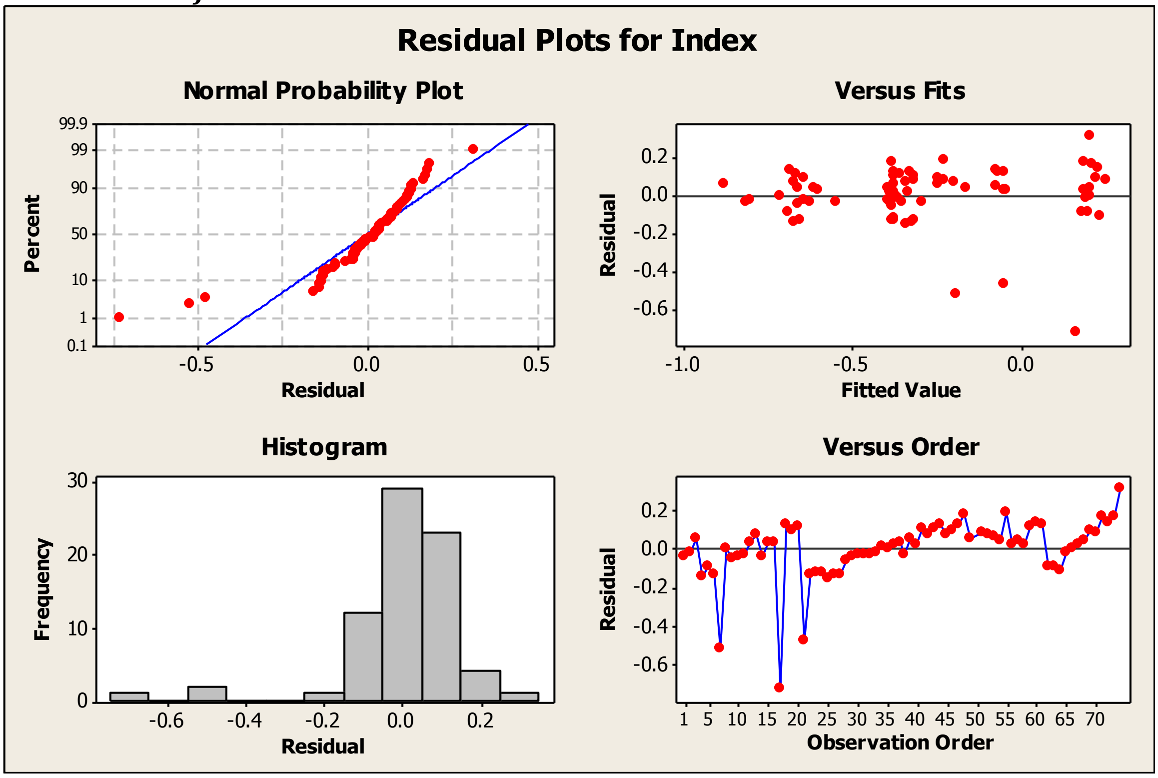
Source	DF	Seq SS
Mcap	1	0.06438
mbook	1	0.19085
Ageyears	1	0.30167
marcond	1	0.25269
Brent	1	0.07741
Ind	1	1.26033
Health	1	0.01262
Fin	1	0.45272
Costap	1	1.04656
cod	1	1.05136
it	1	2.17075

Unusual Observations:

Obs	Mcap	Index	Fit	SE Fit	Residual	St Resid
3	4570	-0.8232	-0.8832	0.1184	0.0600	0.51 X
7	200	-0.7132	-0.1918	0.0698	-0.5214	-3.44R
14	263	-0.5889	-0.5485	0.1233	-0.0404	-0.36 X
17	604	-0.5610	0.1668	0.0586	-0.7278	-4.66R
21	1540	-0.5230	-0.0482	0.0660	-0.4748	-3.10R
38	10687	-0.3257	-0.2928	0.1394	-0.0330	-0.36 X
74	479	0.5222	0.2064	0.0841	0.3159	2.19R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.

Residual Plots for Index:



Regression Analysis included White Heteroskedasticity term: Index versus Mcap; mbook; ...

Dependent Variable: INDEX

Method: Least Squares

Date: 03/07/12 Time: 11:17

Sample: 1 74

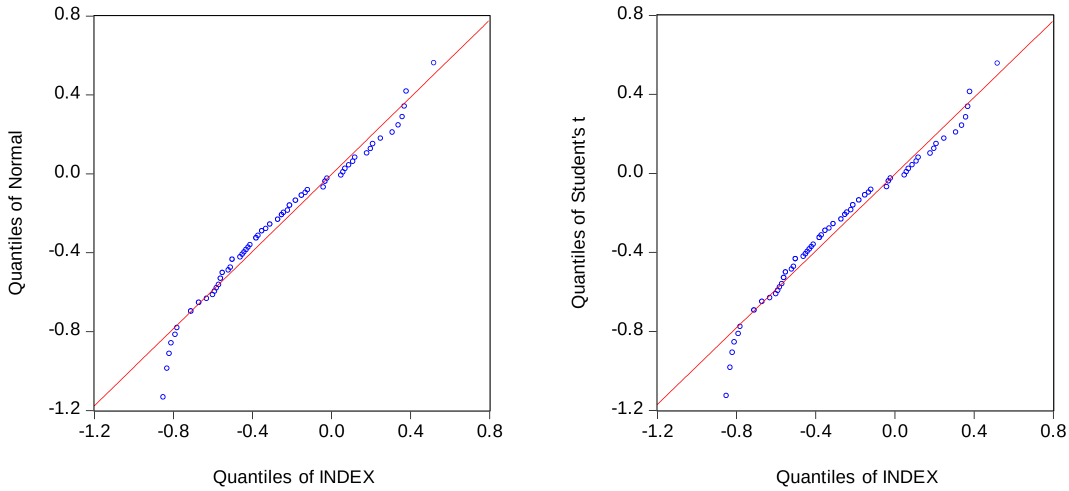
Included observations: 73

White Heteroskedasticity-Consistent Standard Errors & Covariance

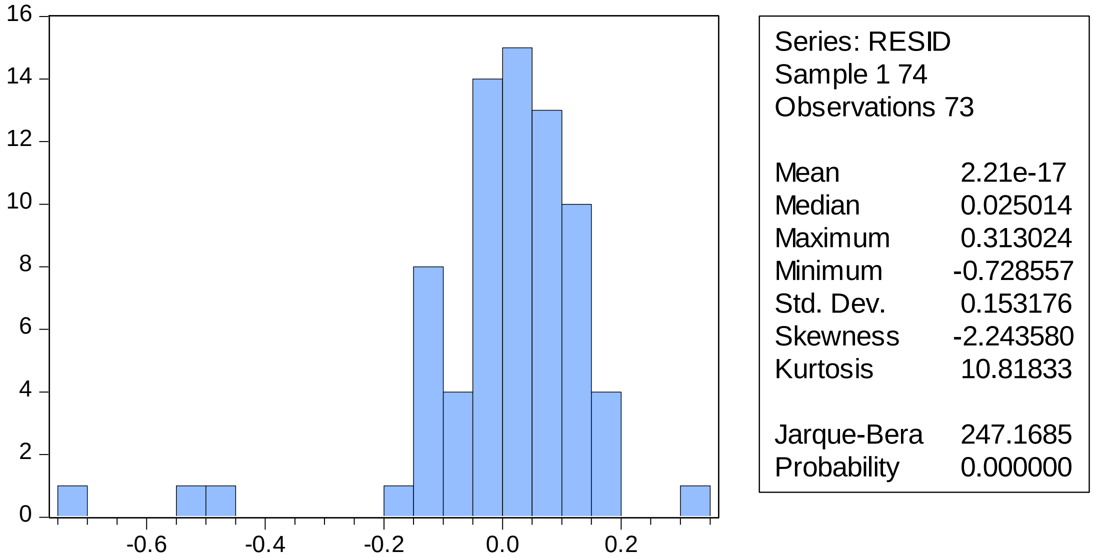
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.372465	0.048496	-7.680384	0.0000
AGEYEARS	0.000708	0.000669	1.058197	0.2941
BRENT	0.038785	0.055030	0.704789	0.4836
COD	-0.316317	0.053910	-5.867520	0.0000
COSTAP	-0.521019	0.053831	-9.678780	0.0000
FIN	0.317169	0.087551	3.622658	0.0006
IND	-0.294527	0.039882	-7.384900	0.0000
IT	0.542380	0.084085	6.450394	0.0000
MARCOND	-0.019259	0.047680	-0.403914	0.6877
MBOOK	0.006146	0.008428	0.729268	0.4686
MCAP	-3.35E-06	9.56E-06	-0.350103	0.7275
HEALTH	0.135035	0.098922	1.365071	0.1772
R-squared	0.802983	Mean dependent var		-0.287534

Adjusted R-squared	0.767456	S.D. dependent var	0.345096
S.E. of regression	0.166415	Akaike info criterion	-0.599484
Sum squared resid	1.689329	Schwarz criterion	-0.222970
Log likelihood	33.88116	Hannan-Quinn criter.	-0.449436
F-statistic	22.60170	Durbin-Watson stat	1.488264
Prob(F-statistic)	0.000000		

Probability plot of the normal- and Student's t-distribution:



Check for normality in the residuals:



Multi-correlation matrix:

	AGEYEARS	BRENT	COD	COSTAP	FIN	IND	IT	MARCOND	MBOOK	MCAP	NRG	HEALTH
AGEYEARS	1.00	0.17	-0.12	0.39	-0.12	0.25	-0.06	-0.11	-0.10	-0.09	-0.13	-0.03
BRENT	0.17	1.00	-0.04	0.14	-0.18	-0.01	0.21	-0.07	-0.07	-0.22	-0.02	-0.12
COD	-0.12	-0.04	1.00	-0.06	-0.09	-0.11	-0.13	-0.01	-0.01	0.04	-0.21	-0.09
COSTAP	0.39	0.14	-0.06	1.00	-0.07	-0.08	-0.10	-0.25	-0.08	0.08	-0.16	-0.07
FIN	-0.12	-0.18	-0.09	-0.07	1.00	-0.13	-0.16	0.04	-0.15	0.09	-0.25	-0.11
IND	0.25	-0.01	-0.11	-0.08	-0.13	1.00	-0.19	0.19	0.01	-0.20	-0.31	-0.13
IT	-0.06	0.21	-0.13	-0.10	-0.16	-0.19	1.00	-0.20	0.08	-0.21	-0.37	-0.16
MARCOND	-0.11	-0.07	-0.01	-0.25	0.04	0.19	-0.20	1.00	-0.08	-0.14	0.16	-0.08
MBOOK	-0.10	-0.07	-0.01	-0.08	-0.15	0.01	0.08	-0.08	1.00	0.43	-0.07	0.22
MCAP	-0.09	-0.22	0.04	0.08	0.09	-0.20	-0.21	-0.14	0.43	1.00	0.22	-0.02
NRG	-0.13	-0.02	-0.21	-0.16	-0.25	-0.31	-0.37	0.16	-0.07	0.22	1.00	-0.25
HEALTH	-0.03	-0.12	-0.09	-0.07	-0.11	-0.13	-0.16	-0.08	0.22	-0.02	-0.25	1.00

White test for heteroskedasticity:

Manually computed White test where not all independent variables are included. The test shows that we have several significant White variables, and that is therefore a sign of heteroskedasticity.

Dependent Variable: RESID2
Method: Least Squares
Date: 03/13/12 Time: 16:20
Sample: 1 74
Included observations: 73

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.040318	0.022395	1.800304	0.0790
AGEYEARS	0.001378	0.004141	0.332839	0.7409
AGE2	2.14E-05	2.51E-05	0.854341	0.3978
AGEBOOK	-0.000724	0.001063	-0.681060	0.4996
AGEBRENT	-0.000958	0.002467	-0.388337	0.6997
AGECAP	-4.54E-07	9.37E-07	-0.485026	0.6302
AGECOD	0.015457	0.141138	0.109514	0.9133
AGECOS	0.001745	0.003888	0.448829	0.6559
AGEFIN	0.010441	0.005713	1.827553	0.0747
AGEIT	0.006846	0.002361	2.899847	0.0059
AGEMAR	-0.000938	0.003219	-0.291261	0.7723
AGEHEAL	0.006993	0.006065	1.152992	0.2554
BOOK2	0.007814	0.001075	7.271000	0.0000
BOOKCAP	-1.74E-05	2.81E-06	-6.186304	0.0000
BOOKHEAL	-0.029183	0.017436	-1.673770	0.1016
BREBOOK	-0.031431	0.017249	-1.822227	0.0755
BRECAP	-7.24E-06	2.50E-05	-0.289480	0.7736
BRECOD	-0.068125	0.612795	-0.111172	0.9120

BRECOS	0.091386	0.151675	0.602509	0.5501
BREFIN	-0.164495	0.278390	-0.590880	0.5578
BREIND	-0.089487	0.095838	-0.933732	0.3558
BREIT	0.376663	0.058935	6.391127	0.0000
BREMAR	0.092325	0.064361	1.434483	0.1588
BRENT	0.051983	0.122686	0.423704	0.6739
BRENT2	-0.075345	0.059564	-1.264949	0.2129
BREHEAL	-0.003758	0.145775	-0.025782	0.9796
CAP2	7.47E-09	3.29E-09	2.274817	0.0281
CAPHEAL	5.55E-05	2.92E-05	1.900671	0.0642
COD	0.274990	0.249247	1.103281	0.2762
CODBOOK	-0.120957	0.220237	-0.549212	0.5858
CODCAP	4.36E-05	0.000237	0.184340	0.8546

R-squared	0.856467	Mean dependent var	0.125522
Adjusted R-squared	0.753944	S.D. dependent var	0.169909
S.E. of regression	0.084282	Akaike info criterion	-1.812775
Sum squared resid	0.298344	Schwarz criterion	-0.840115
Log likelihood	97.16630	Hannan-Quinn criter.	-1.425153
F-statistic	8.353875	Durbin-Watson stat	1.609675
Prob(F-statistic)	0.000000		

Best subset index 10% trimmed data:

Summary over the adjusted R-squared effects from different regression models:

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	Mcap	mbook	Ageyears	marcond	Brent	Ind	Health	Fin	Costap	cod	it
1	49.1	48.3	88.0	0.24810											X
1	16.5	15.3	188.4	0.31768						X					
2	60.2	59.0	55.8	0.22095								X			X
2	56.6	55.4	66.6	0.23053						X					X
3	65.6	64.1	41.0	0.20682								X	X		X
3	65.5	64.0	41.3	0.20712							X	X			X
4	73.2	71.6	19.6	0.18389						X			X	X	X
4	72.0	70.4	23.3	0.18794						X		X	X		X
5	78.2	76.5	6.3	0.16716						X		X	X	X	X
5	74.6	72.7	17.4	0.18045						X	X	X	X		X
6	79.6	77.7	4.0	0.16300						X	X	X	X	X	X
6	78.5	76.5	7.3	0.16718		X				X		X	X	X	X
7	**79.9**	**77.7**	**5.0**	**0.16290**					**X**	**X**	**X**	**X**	**X**	**X**	**X**

7	79.7	77.5	5.5	0.16362			X			X	X	X	X	X	X
8	80.0	77.5	6.5	0.16362		X			X	X	X	X	X	X	X
8	80.0	77.5	6.6	0.16372			X		X	X	X	X	X	X	X
9	80.2	77.3	8.1	0.16437		X	X		X	X	X	X	X	X	X
9	80.1	77.2	8.4	0.16474		X		X	X	X	X	X	X	X	X
10	80.2	77.0	10.0	0.16556		X	X	X	X	X	X	X	X	X	X
10	80.2	77.0	10.1	0.16566	X	X	X		X	X	X	X	X	X	X
11	80.2	76.6	12.0	0.16685	X	X	X	X	X	X	X	X	X	X	X

Regression analysis included White heteroskedasticity term: Best subset regression

Dependent Variable: INDEX

Method: Least Squares

Date: 03/13/12 Time: 18:05

Sample: 1 74

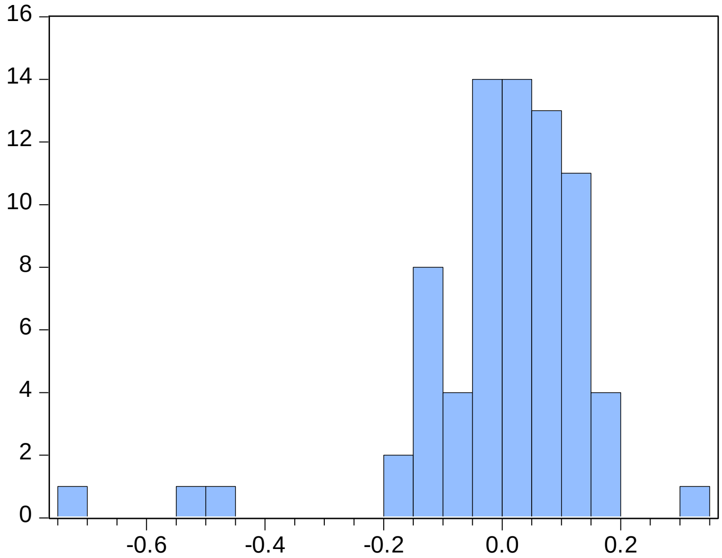
Included observations: 74

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.374845	0.026539	-14.12449	0.0000
BRENT	0.039662	0.052409	0.756774	0.4519
IND	-0.278742	0.029387	-9.485247	0.0000
HEALTH	0.161643	0.083855	1.927658	0.0582
FIN	0.309519	0.081224	3.810679	0.0003
COSTAP	-0.487442	0.027924	-17.45586	0.0000
COD	-0.316481	0.053784	-5.884355	0.0000
IT	0.556422	0.077803	7.151660	0.0000

R-squared	0.799870	Mean dependent var	-0.286081
Adjusted R-squared	0.778644	S.D. dependent var	0.342952
S.E. of regression	0.161353	Akaike info criterion	-0.708633
Sum squared resid	1.718306	Schwarz criterion	-0.459545
Log likelihood	34.21941	Hannan-Quinn criter.	-0.609268
F-statistic	37.68373	Durbin-Watson stat	1.412050
Prob(F-statistic)	0.000000		

Check for normality in the residuals:



Series: RESID	
Sample 1 74	
Observations 74	
Mean	1.20e-17
Median	0.019824
Maximum	0.342389
Minimum	-0.736421
Std. Dev.	0.153422
Skewness	-2.247689
Kurtosis	11.06058
Jarque-Bera	262.6426
Probability	0.000000

White test for heteroskedasticity:

Heteroskedasticity Test: White

F-statistic	2.583662	Prob. F(14,59)	0.0057
Obs*R-squared	28.12481	Prob. Chi-Square(14)	0.0137
Scaled explained SS	112.5400	Prob. Chi-Square(14)	0.0000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/13/12 Time: 18:05

Sample: 1 74

Included observations: 74

Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004035	0.015082	0.267540	0.7900
BRENT	-0.094570	0.051088	-1.851132	0.0692
BRENT^2	0.083311	0.039168	2.126990	0.0376
BRENT*IND	0.003087	0.062593	0.049324	0.9608
BRENT*HEALTH	0.190852	0.067421	2.830735	0.0063
BRENT*FIN	0.198171	0.191143	1.036768	0.3041
BRENT*COSTAP	-0.025734	0.157362	-0.163532	0.8707
BRENT*COD	0.060338	0.079564	0.758367	0.4513
BRENT*IT	-0.167636	0.044262	-3.787354	0.0004
IND	0.013172	0.034683	0.379778	0.7055
HEALTH	0.008367	0.028810	0.290415	0.7725

FIN	0.016724	0.038165	0.438207	0.6628
COSTAP	0.034638	0.122140	0.283595	0.7777
COD	-0.003995	0.040864	-0.097763	0.9225
IT	0.164268	0.033607	4.887916	0.0000

R-squared	0.380065	Mean dependent var	0.023220
Adjusted R-squared	0.232962	S.D. dependent var	0.074154
S.E. of regression	0.064945	Akaike info criterion	-2.451685
Sum squared resid	0.248851	Schwarz criterion	-1.984645
Log likelihood	105.7123	Hannan-Quinn criter.	-2.265377
F-statistic	2.583662	Durbin-Watson stat	1.801837
Prob(F-statistic)	0.005714		

9.3.4 Regression matched against peers with raw data:

Regression Analysis: Peers versus Mcap; mbook; ...

```
The regression equation is:
Peers = - 0.087 - 0.000001 Mcap - 0.0128 mbook - 0.00152 Ageyears
        + 0.203 marcond + 0.718 Brent - 1.09 Ind - 0.397 Health - 0.802 Fin
        + 0.170 Costap - 1.63 cod - 0.534 it

93 cases used, 1 cases contain missing values
```

Predictor	Coef	SE Coef	T	P	**VIF**
Constant	-0.0873	0.5331	-0.16	0.870	
Mcap	-0.00000097	0.00003692	-0.03	0.979	1.183
mbook	-0.01282	0.07478	-0.17	0.864	1.179
Ageyears	-0.001523	0.007961	-0.19	0.849	1.220
marcond	0.2033	0.4179	0.49	0.628	1.077
Brent	0.7175	0.3663	1.96	0.054	1.112
Ind	-1.0866	0.5407	-2.01	0.048	1.395
Health	-0.3969	0.6461	-0.61	0.541	1.412
Fin	-0.8016	0.6284	-1.28	0.206	1.217
Costap	0.1695	0.6671	0.25	0.800	1.371
cod	-1.6320	0.7361	-2.22	0.029	1.153
it	-0.5344	0.5219	-1.02	0.309	1.368

```
S = 1.62403   R-Sq = 13.9%   R-Sq(adj) = 2.2%
```

Analysis of Variance:

Source	DF	SS	MS	F	P
Regression	11	34.553	3.141	1.19	0.307
Residual Error	81	213.634	2.637		
Total	92	248.187			

Source	DF	Seq SS
Mcap	1	0.095
mbook	1	0.138
Ageyears	1	0.038
marcond	1	0.435
Brent	1	9.385
Ind	1	6.858
Health	1	0.011
Fin	1	2.258
Costap	1	1.785
cod	1	10.785
it	1	2.765

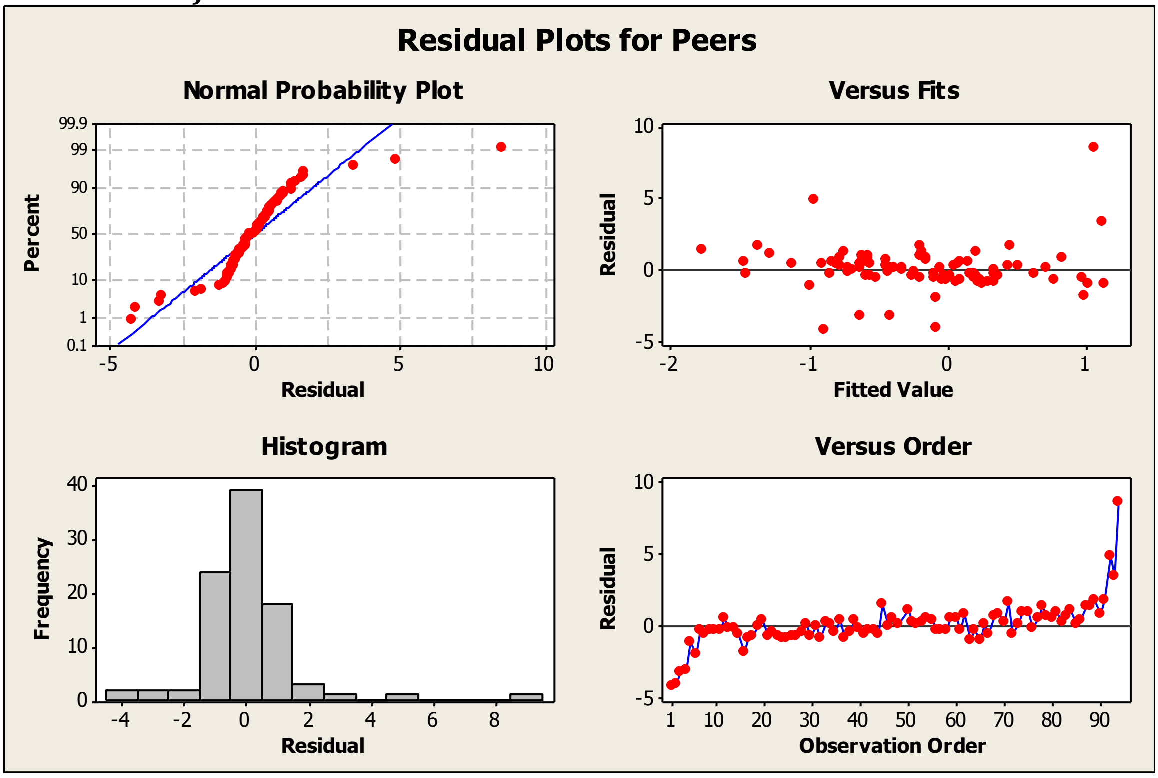
Unusual Observations:

Obs	Mcap	Peers	Fit	SE Fit	Residual	St Resid
1	320	-5.145	-0.894	0.710	-4.251	-2.91R
2	156	-4.224	-0.084	0.569	-4.140	-2.72R
3	169	-3.898	-0.635	0.520	-3.263	-2.12R
4	131	-3.643	-0.419	0.509	-3.225	-2.09R
23	10687	-0.741	-0.016	1.283	-0.725	-0.73 X
54	46197	-0.213	-0.632	1.552	0.419	0.88 X
92	376	3.883	-0.963	0.448	4.846	3.10R
93	609	4.494	1.110	0.514	3.385	2.20R
94	72	9.599	1.061	0.487	8.538	5.51R

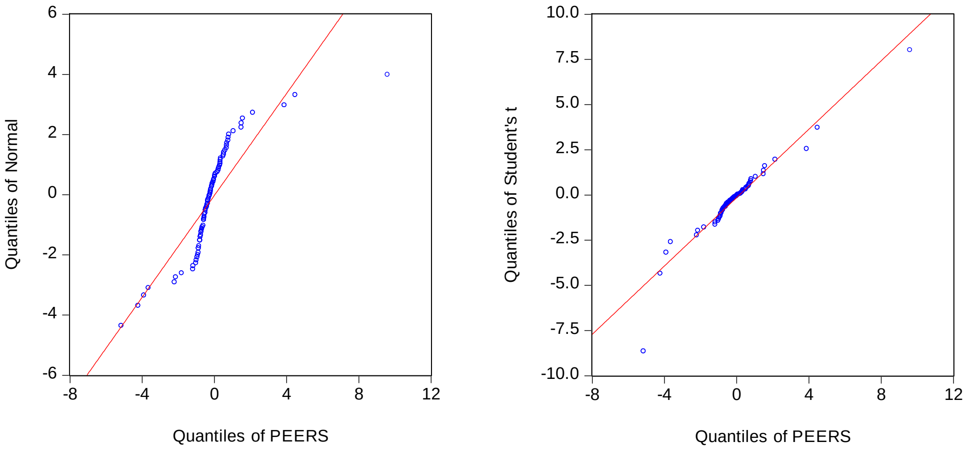
R denotes an observation with a large standardized residual.

X denotes an observation whose X value gives it large leverage.

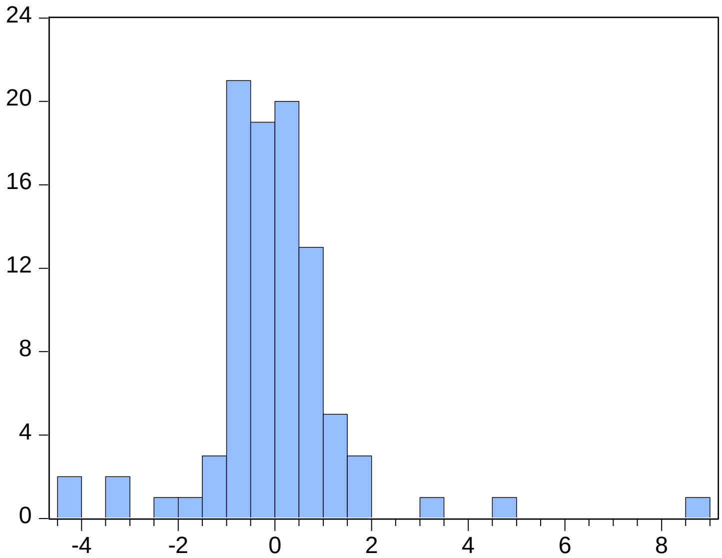
Residual Plots for Peers:



Probability plot of the normal- and Student's t-distribution:



Check for normality in the residuals:



Series: RESID
Sample 1 94
Observations 93

Mean	3.82e-17
Median	-0.105722
Maximum	8.539410
Minimum	-4.255070
Std. Dev.	1.523859
Skewness	1.732011
Kurtosis	14.10762
Jarque-Bera	524.5927
Probability	0.000000

Multi-correlation matrix:

	AGEYEARS	BRENT	COD	COSTAP	FIN	IND	IT	MARCOND	MBOOK	MCAP	NRG	HEALTH
AGEYEARS	1.00	0.13	-0.13	0.29	-0.01	0.21	-0.08	0.04	-0.10	-0.05	-0.17	-0.07
BRENT	0.13	1.00	-0.02	-0.05	-0.10	0.10	0.16	-0.04	-0.01	-0.22	-0.03	-0.10
COD	-0.13	-0.02	1.00	-0.09	-0.09	-0.12	-0.12	-0.07	-0.03	-0.01	-0.17	-0.09
COSTAP	0.29	-0.05	-0.09	1.00	-0.11	-0.14	-0.15	-0.08	-0.14	0.03	-0.21	-0.11
FIN	-0.01	-0.10	-0.09	-0.11	1.00	-0.14	-0.15	0.09	-0.13	-0.02	-0.21	-0.11
IND	0.21	0.10	-0.12	-0.14	-0.14	1.00	-0.20	0.10	-0.03	-0.13	-0.29	-0.15
IT	-0.08	0.16	-0.12	-0.15	-0.15	-0.20	1.00	-0.09	0.08	-0.12	-0.30	-0.16
MARCOND	0.04	-0.04	-0.07	-0.08	0.09	0.10	-0.09	1.00	-0.07	0.02	0.13	-0.14
MBOOK	-0.10	-0.01	-0.03	-0.14	-0.13	-0.03	0.08	-0.07	1.00	0.21	-0.06	0.31
MCAP	-0.05	-0.22	-0.01	0.03	-0.02	-0.13	-0.12	0.02	0.21	1.00	0.01	0.29
NRG	-0.17	-0.03	-0.17	-0.21	-0.21	-0.29	-0.30	0.13	-0.06	0.01	1.00	-0.23
HEALTH	-0.07	-0.10	-0.09	-0.11	-0.11	-0.15	-0.16	-0.14	0.31	0.29	-0.23	1.00

White test for heteroskedasticity:

Heteroskedasticity Test: White

F-statistic	0.529362	Prob. F(55,37)	0.9842
Obs*R-squared	40.95424	Prob. Chi-Square(55)	0.9206
Scaled explained SS	203.6090	Prob. Chi-Square(55)	0.0000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/14/12 Time: 11:14

Sample: 1 94

Included observations: 93

Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.294433	12.45358	-0.103941	0.9178
AGEYEARS	0.124691	0.686831	0.181545	0.8569
AGEYEARS^2	-0.001855	0.002491	-0.744795	0.4611
AGEYEARS*BRENT	-0.162969	0.247454	-0.658582	0.5142
AGEYEARS*COD	4.403420	24.69146	0.178338	0.8594
AGEYEARS*COSTAP	0.090693	0.335595	0.270247	0.7885
AGEYEARS*FIN	0.209377	0.351284	0.596035	0.5548
AGEYEARS*IND	0.300286	0.346293	0.867144	0.3915
AGEYEARS*IT	0.127290	0.361516	0.352099	0.7268
AGEYEARS*MARCOND	-0.043316	0.478406	-0.090542	0.9283
AGEYEARS*MBOOK	-0.040506	0.142204	-0.284844	0.7774
AGEYEARS*MCAP	5.99E-05	0.000147	0.407468	0.6860
AGEYEARS*HEALTH	0.004716	1.130109	0.004173	0.9967
BRENT	-1.622794	17.80863	-0.091124	0.9279
BRENT^2	6.871782	6.484263	1.059763	0.2961
BRENT*COD	-10.83400	103.0558	-0.105127	0.9168
BRENT*COSTAP	4.837471	22.32846	0.216650	0.8297
BRENT*FIN	-21.84785	24.97688	-0.874723	0.3874
BRENT*IND	-9.520576	11.44549	-0.831819	0.4108
BRENT*IT	-15.09169	8.155925	-1.850396	0.0723
BRENT*MARCOND	4.010557	11.55307	0.347142	0.7305
BRENT*MBOOK	2.841621	2.493233	1.139733	0.2617
BRENT*MCAP	-0.006178	0.003105	-1.989522	0.0541
BRENT*HEALTH	-8.723192	18.41275	-0.473758	0.6385
COD	-1.513020	19.50484	-0.077571	0.9386
COD*MARCOND	-1.580028	27.64511	-0.057154	0.9547
COD*MBOOK	-9.332405	49.55290	-0.188332	0.8516
COD*MCAP	0.010790	0.046350	0.232787	0.8172

COSTAP	0.568681	13.87654	0.040982	0.9675
COSTAP*MARCOND	-0.569002	19.59298	-0.029041	0.9770
COSTAP*MBOOK	-0.905831	7.101961	-0.127547	0.8992
COSTAP*MCAP	0.001334	0.002866	0.465340	0.6444
FIN	13.11806	48.23995	0.271933	0.7872
FIN*MARCOND	-16.73845	39.67517	-0.421887	0.6755
FIN*MBOOK	2.366936	7.037644	0.336325	0.7385
FIN*MCAP	0.000324	0.007408	0.043776	0.9653
IND	10.42459	17.69361	0.589173	0.5593
IND*MARCOND	0.363762	16.66021	0.021834	0.9827
IND*MBOOK	-3.271062	4.359050	-0.750407	0.4578
IND*MCAP	-0.006441	0.011584	-0.556069	0.5815
IT	13.20860	20.23530	0.652750	0.5180
IT*MARCOND	-5.275041	19.58048	-0.269403	0.7891
IT*MBOOK	-2.746704	4.811917	-0.570813	0.5716
IT*MCAP	0.000499	0.005983	0.083392	0.9340
MARCOND	1.503214	12.74424	0.117952	0.9067
MARCOND*MBOOK	1.102096	3.603173	0.305868	0.7614
MARCOND*MCAP	-0.001258	0.004654	-0.270316	0.7884
MARCOND*HEALTH	-4.041293	29.93724	-0.134992	0.8933
MBOOK	-0.990888	4.648536	-0.213161	0.8324
MBOOK^2	0.233585	0.517974	0.450958	0.6547
MBOOK*MCAP	-0.000362	0.000924	-0.391130	0.6979
MBOOK*HEALTH	-2.866623	6.698775	-0.427932	0.6712
MCAP	0.001086	0.004237	0.256189	0.7992
MCAP^2	-9.42E-08	1.80E-07	-0.522485	0.6044
MCAP*HEALTH	0.003554	0.007947	0.447248	0.6573
HEALTH	9.266673	36.91193	0.251048	0.8032

R-squared	0.440368	Mean dependent var	2.297177
Adjusted R-squared	-0.391517	S.D. dependent var	8.361881
S.E. of regression	9.863891	Akaike info criterion	7.698258
Sum squared resid	3599.965	Schwarz criterion	9.223264
Log likelihood	-301.9690	Hannan-Quinn criter.	8.314012
F-statistic	0.529362	Durbin-Watson stat	1.962922
Prob(F-statistic)	0.984218		

Best subset regression peers raw-data:

Summary over the adjusted R-squared effects from different regression models:

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	Mcap	mbook	Ageyears	marcond	Brent	Ind	Health	Fin	Costap	cod	it
1	3.7	2.6	1.7	1.6210					X						
1	3.6	2.6	1.7	1.6211										X	
2	7.1	5.1	0.4	1.6003					X					X	
2	6.3	4.2	1.2	1.6073						X				X	
3	10.5	7.5	-0.8	1.5798					X	X				X	
3	8.2	5.1	1.4	1.5998					X				X	X	
4	11.6	7.6	0.2	1.5790					X	X		X		X	
4	11.2	7.2	0.5	1.5823					X	X				X	X
5	12.8	7.7	1.1	1.5776					X	X		X		X	X
5	12.0	7.0	1.8	1.5840				X	X	X		X		X	
6	13.6	7.5	2.3	1.5792					X	X	X	X		X	X
6	13.1	7.1	2.8	1.5835				X	X	X		X		X	X
7	13.8	6.7	4.1	1.5865				X	X	X	X	X		X	X
7	13.6	6.5	4.3	1.5881		X			X	X	X	X		X	X
8	13.9	5.6	6.1	1.5954				X	X	X	X	X	X	X	X
8	13.8	5.6	6.1	1.5955		X		X	X	X	X	X		X	X
9	13.9	4.6	8.0	1.6047			X	X	X	X	X	X	X	X	X
9	13.9	4.5	8.0	1.6047		X		X	X	X	X	X	X	X	X
10	13.9	3.4	10.0	1.6141		X	X	X	X	X	X	X	X	X	X
10	13.9	3.4	10.0	1.6144	X		X	X	X	X	X	X	X	X	X
11	13.9	2.2	12.0	1.6240	X	X	X	X	X	X	X	X	X	X	X

Regression Analysis included White Heteroskedasticity term: Best subset regression

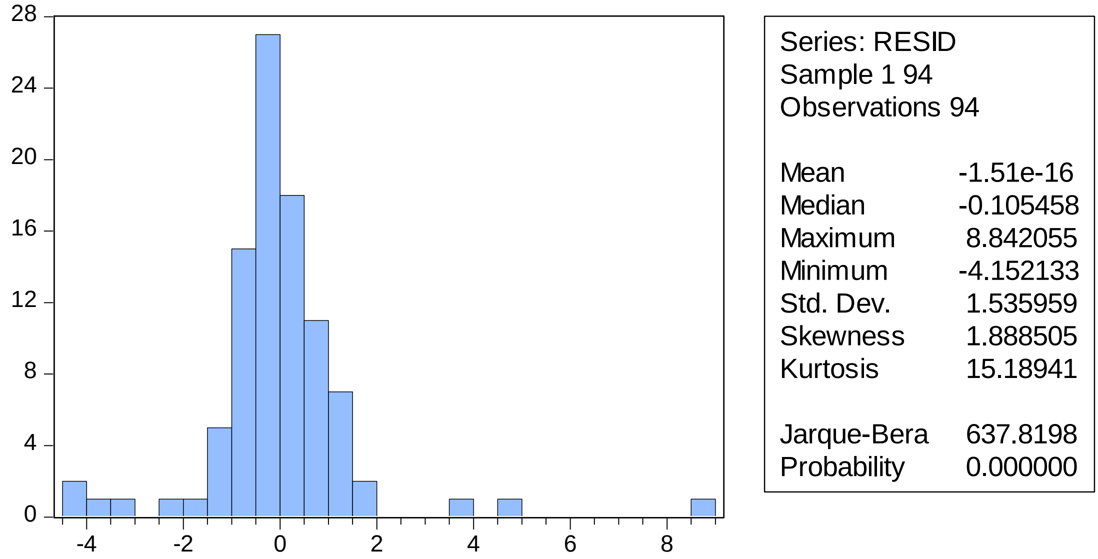
Dependent Variable: PEERS
Method: Least Squares
Date: 05/25/12 Time: 15:43
Sample: 1 94
Included observations: 94
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.043788	0.145037	-0.301908	0.7634
BRENT	0.719272	0.578993	1.242281	0.2174
COD	-1.578994	0.879592	-1.795142	0.0761
FIN	-0.709622	0.241514	-2.938224	0.0042
IT	-0.495702	0.478877	-1.035134	0.3034
IND	-1.028068	0.597402	-1.720899	0.0888

R-squared	0.127587	Mean dependent var	-0.188511
Adjusted R-squared	0.078018	S.D. dependent var	1.633702
S.E. of regression	1.568679	Akaike info criterion	3.800047

Sum squared resid	216.5464	Schwarz criterion	3.962384
Log likelihood	-172.6022	Hannan-Quinn criter.	3.865619
F-statistic	2.573929	Durbin-Watson stat	0.444057
Prob(F-statistic)	0.031991		

Check for normality in the residuals:



White test for heteroskedasticity:

Heteroskedasticity Test: White

F-statistic	2.319890	Prob. F(8,85)	0.0265
Obs*R-squared	16.84600	Prob. Chi-Square(8)	0.0318
Scaled explained SS	107.1410	Prob. Chi-Square(8)	0.0000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/14/12 Time: 11:18

Sample: 1 94

Included observations: 94

Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.191504	1.289469	-0.148513	0.8823
BRENT	-6.278701	4.235281	-1.482476	0.1419
BRENT^2	11.13174	3.692473	3.014710	0.0034
BRENT*IND	-4.668904	5.612579	-0.831864	0.4078
BRENT*COD	10.49544	9.754568	1.075951	0.2850
BRENT*FIN	-3.068983	10.73827	-0.285799	0.7757

IND	4.635697	3.733660	1.241596	0.2178
COD	-0.079282	4.882610	-0.016238	0.9871
FIN	1.165530	3.969664	0.293609	0.7698

R-squared	0.179213	Mean dependent var	2.334072
Adjusted R-squared	0.101962	S.D. dependent var	8.839323
S.E. of regression	8.376572	Akaike info criterion	7.179600
Sum squared resid	5964.191	Schwarz criterion	7.423107
Log likelihood	-328.4412	Hannan-Quinn criter.	7.277959
F-statistic	2.319890	Durbin-Watson stat	1.290470
Prob(F-statistic)	0.026535		

9.3.5 Regression matched against peers with 3% trimmed data:

Regression Analysis: Peers versus Mcap; mbook; ...

```
The regression equation is:
Peers = - 0.378 + 0.000001 Mcap - 0.0436 mbook + 0.00345 Ageyears
        + 0.207 marcond + 0.215 Brent - 0.659 Ind + 0.106 Health - 0.415 Fin
        + 0.486 Costap - 0.316 cod + 0.319 it

87 cases used, 1 cases contain missing values
```

Predictor	Coef	SE Coef	T	P	**VIF**
Constant	-0.3783	0.2567	-1.47	0.145	
Mcap	0.00000054	0.00001764	0.03	0.976	1.177
mbook	-0.04362	0.03575	-1.22	0.226	1.180
Ageyears	0.003449	0.003845	0.90	0.373	1.191
marcond	0.2066	0.2019	1.02	0.310	1.082
Brent	0.2150	0.1968	1.09	0.278	1.156
Ind	-0.6592	0.2713	-2.43	0.017	1.356
Health	0.1059	0.3103	0.34	0.734	1.420
Fin	-0.4145	0.3016	-1.37	0.173	1.223
Costap	0.4856	0.3196	1.52	0.133	1.373
cod	-0.3160	0.3825	-0.83	0.411	1.149
it	0.3192	0.2627	1.22	0.228	1.427

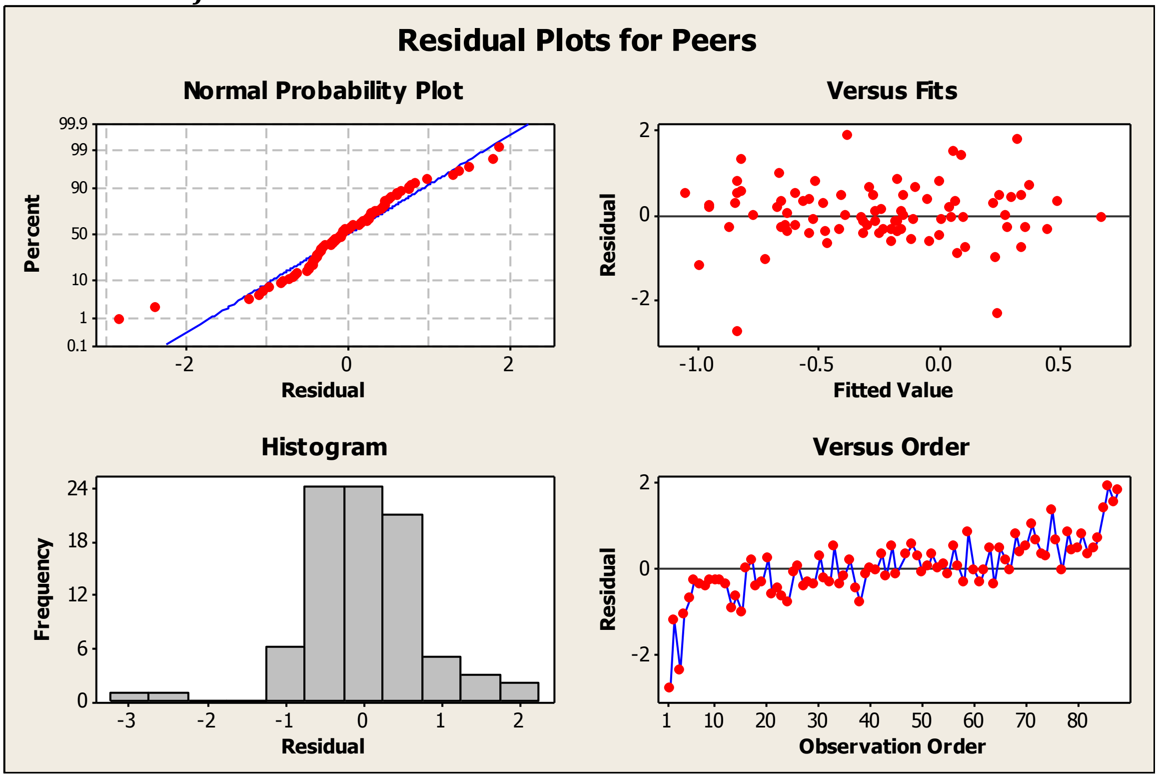
```
S = 0.774743   R-Sq = 23.6%   R-Sq(adj) = 12.4%
```

Analysis of Variance:

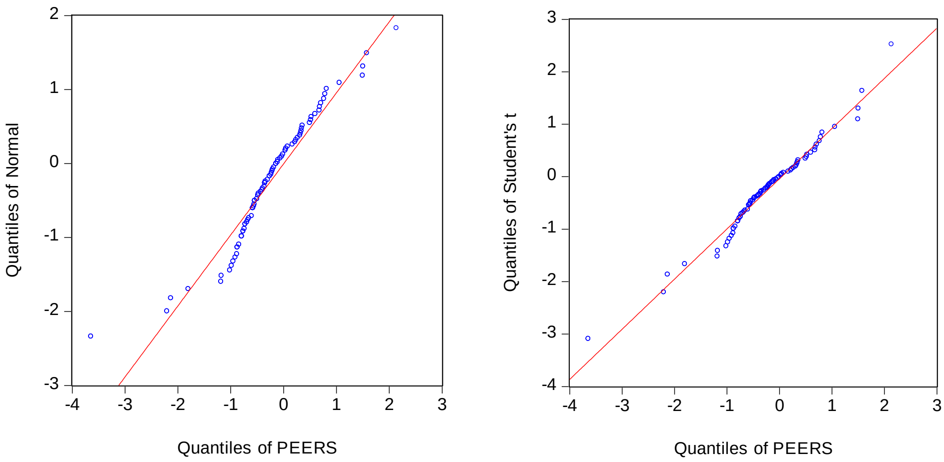
Source	DF	SS	MS	F	P
Regression	11	13.8893	1.2627	2.10	0.030
Residual Error	75	45.0170	0.6002		

```
Total           86  58.9063

Source    DF  Seq SS
Mcap       1  0.0104
mbook      1  0.8640
Ageyears   1  0.9727
marcond    1  0.0622
Brent      1  1.0802
Ind        1  5.8499
Health     1  0.0078
Fin        1  2.2197
Costap     1  1.1441
cod        1  0.7919
it         1  0.8865

Unusual Observations:
Obs   Mcap    Peers      Fit  SE Fit  Residual  St Resid
  1    131  -3.6435  -0.8340  0.2590   -2.8094     -3.85R
  3    382  -2.1297   0.2444  0.2204   -2.3740     -3.20R
 20  10687  -0.7409  -0.9489  0.6159    0.2080      0.44 X
 51  46197  -0.2131  -0.2665  0.7415    0.0534      0.24 X
 86    644   1.5128  -0.3800  0.2563    1.8927      2.59R
 87    337   1.5832   0.0643  0.2261    1.5189      2.05R
 88    360   2.1370   0.3270  0.2519    1.8099      2.47R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

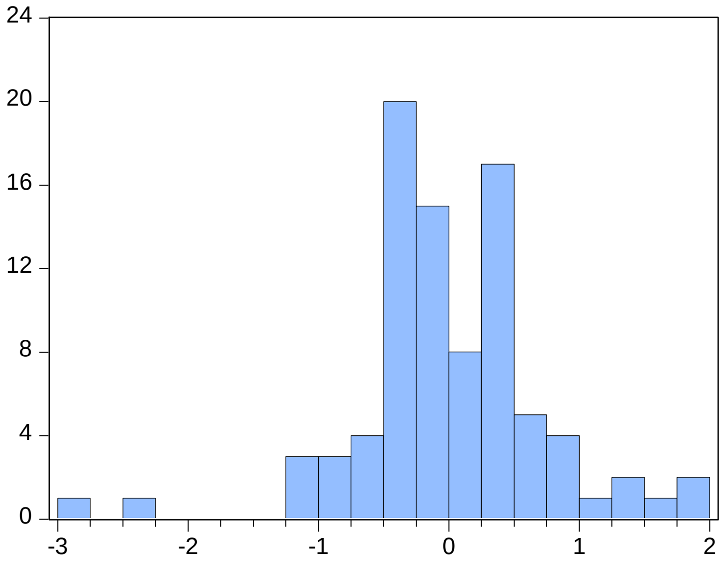
Residual Plots for Peers:



Probability plot of the normal- and Student's t-distribution:



Check for normality in the residuals:



Series: RESID
Sample 1 90
Observations 87

Mean	-6.13e-17
Median	-0.036828
Maximum	1.891575
Minimum	-2.805544
Std. Dev.	0.723443
Skewness	-0.528453
Kurtosis	6.052573
Jarque-Bera	37.82780
Probability	0.000000

Multi-correlation matrix:

	AGEYEARS	BRENT	COD	COSTAP	FIN	IND	IT	MARCOND	MBOOK	MCAP	NRG	HEALTH
AGEYEARS	1.00	0.13	-0.13	0.30	-0.01	0.16	-0.06	0.03	-0.10	-0.05	-0.15	-0.07
BRENT	0.13	1.00	-0.07	-0.04	-0.09	0.10	0.25	-0.08	-0.01	-0.22	-0.10	-0.09
COD	-0.13	-0.07	1.00	-0.08	-0.08	-0.10	-0.11	-0.09	-0.03	0.00	-0.16	-0.09
COSTAP	0.30	-0.04	-0.08	1.00	-0.12	-0.14	-0.16	-0.07	-0.14	0.02	-0.22	-0.12
FIN	-0.01	-0.09	-0.08	-0.12	1.00	-0.14	-0.16	0.10	-0.13	-0.03	-0.22	-0.12
IND	0.16	0.10	-0.10	-0.14	-0.14	1.00	-0.19	0.09	-0.03	-0.13	-0.27	-0.15
IT	-0.06	0.25	-0.11	-0.16	-0.16	-0.19	1.00	-0.10	0.09	-0.12	-0.30	-0.16
MARCOND	0.03	-0.08	-0.09	-0.07	0.10	0.09	-0.10	1.00	-0.07	0.03	0.13	-0.13
MBOOK	-0.10	-0.01	-0.03	-0.14	-0.13	-0.03	0.09	-0.07	1.00	0.21	-0.07	0.31
MCAP	-0.05	-0.22	0.00	0.02	-0.03	-0.13	-0.12	0.03	0.21	1.00	0.01	0.28
NRG	-0.15	-0.10	-0.16	-0.22	-0.22	-0.27	-0.30	0.13	-0.07	0.01	1.00	-0.24
HEALTH	-0.07	-0.09	-0.09	-0.12	-0.12	-0.15	-0.16	-0.13	0.31	0.28	-0.24	1.00

White test for heteroskedasticity:

Heteroskedasticity Test: White

F-statistic	1.082968	Prob. F(54,32)	0.4117
Obs*R-squared	56.23086	Prob. Chi-Square(54)	0.3914
Scaled explained SS	105.5702	Prob. Chi-Square(54)	0.0000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/14/12 Time: 11:29

Sample: 1 88

Included observations: 87

Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.337880	1.481058	0.903328	0.3731
AGEYEARS	0.098675	0.082230	1.199976	0.2390
AGEYEARS^2	-0.000317	0.000408	-0.775576	0.4437
AGEYEARS*BRENT	0.030138	0.035358	0.852354	0.4004
AGEYEARS*COD	0.239826	0.364668	0.657655	0.5155
AGEYEARS*COSTAP	-0.003006	0.050017	-0.060095	0.9525
AGEYEARS*FIN	-0.028809	0.041929	-0.687097	0.4970
AGEYEARS*IND	-0.094498	0.043008	-2.197208	0.0354
AGEYEARS*IT	0.003757	0.043095	0.087185	0.9311
AGEYEARS*MARCOND	-0.059448	0.055669	-1.067879	0.2936
AGEYEARS*MBOOK	0.012338	0.017004	0.725632	0.4733
AGEYEARS*MCAP	-1.31E-05	1.93E-05	-0.679542	0.5017
AGEYEARS*HEALTH	-0.158384	0.136239	-1.162546	0.2536
BRENT	-3.800146	2.285019	-1.663069	0.1061
BRENT^2	0.647482	0.878243	0.737247	0.4663
BRENT*COD	1.007485	2.716219	0.370915	0.7131
BRENT*COSTAP	-1.669218	2.813037	-0.593387	0.5571
BRENT*FIN	-2.107228	3.021740	-0.697356	0.4906
BRENT*IND	4.384643	1.592088	2.754021	0.0096
BRENT*IT	1.738638	1.225784	1.418389	0.1657
BRENT*MARCOND	2.537321	1.404851	1.806113	0.0803
BRENT*MBOOK	0.363005	0.338985	1.070857	0.2922
BRENT*MCAP	-0.000131	0.000405	-0.324360	0.7478
BRENT*HEALTH	0.144868	2.276905	0.063625	0.9497
COD	0.910865	2.187339	0.416426	0.6799
COD*MARCOND	-0.832446	2.322786	-0.358382	0.7224
COD*MBOOK	-0.096402	0.963225	-0.100082	0.9209
COSTAP	-1.770978	1.670834	-1.059937	0.2971
COSTAP*MARCOND	3.360788	2.492655	1.348276	0.1870
COSTAP*MBOOK	-0.727826	0.835901	-0.870709	0.3904
COSTAP*MCAP	0.000169	0.000339	0.499511	0.6208
FIN	1.709976	5.670499	0.301556	0.7649
FIN*MARCOND	-2.513678	4.685850	-0.536440	0.5954
FIN*MBOOK	0.656670	0.823313	0.797595	0.4310
FIN*MCAP	3.15E-05	0.000862	0.036600	0.9710
IND	0.467906	2.116933	0.221030	0.8265
IND*MARCOND	0.999130	1.948423	0.512789	0.6116
IND*MBOOK	-0.020476	0.565283	-0.036222	0.9713
IND*MCAP	-0.002380	0.001485	-1.602650	0.1188
IT	1.071904	2.583152	0.414960	0.6809

IT*MARCOND	-2.656220	2.290640	-1.159597	0.2548
IT*MBOOK	0.288124	0.607396	0.474360	0.6385
IT*MCAP	3.07E-05	0.000732	0.041976	0.9668
MARCOND	-1.197640	1.509048	-0.793640	0.4333
MARCOND*MBOOK	0.817627	0.429533	1.903526	0.0660
MARCOND*MCAP	0.000245	0.000554	0.442666	0.6610
MARCOND*HEALTH	-1.909990	3.562224	-0.536179	0.5955
MBOOK	-0.936168	0.549065	-1.705023	0.0979
MBOOK^2	-0.005062	0.065081	-0.077779	0.9385
MBOOK*MCAP	1.19E-05	0.000117	0.101746	0.9196
MBOOK*HEALTH	0.743238	0.799164	0.930020	0.3593
MCAP	-0.000160	0.000508	-0.315741	0.7542
MCAP^2	-7.38E-09	2.22E-08	-0.332710	0.7415
MCAP*HEALTH	0.000283	0.000986	0.286965	0.7760
HEALTH	0.452035	4.361805	0.103635	0.9181

R-squared	0.646332	Mean dependent var	0.517354
Adjusted R-squared	0.049517	S.D. dependent var	1.169645
S.E. of regression	1.140319	Akaike info criterion	3.364689
Sum squared resid	41.61048	Schwarz criterion	4.923596
Log likelihood	-91.36397	Hannan-Quinn criter.	3.992413
F-statistic	1.082968	Durbin-Watson stat	1.421515
Prob(F-statistic)	0.411670		

Best subset regression peers 3% trimmed data:

Summary over the adjusted R-squared effects from different regression models:

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	Mcap	mbook	Ageyears	marcond	Brent	Ind	Health	Fin	Costap	cod	it
1	7.6	6.5	7.7	0.80037						X					
1	6.5	5.4	8.8	0.80507									X		
2	12.4	10.3	5.0	0.78378									X		X
2	12.3	10.2	5.1	0.78424						X			X		
3	16.1	13.1	3.3	0.77157						X			X		X
3	15.3	12.3	4.1	0.77510					X	X			X		
4	17.7	13.7	3.8	0.76896					X	X			X		X
4	17.4	13.4	4.0	0.77018			X			X			X		X
5	18.9	13.9	4.6	0.76789		X				X		X	X		X

5	18.9	13.9	4.6	0.76795				X	X	X			X		X
6	20.3	14.4	5.2	0.76593		X			X	X		X	X	X	
6	20.3	14.3	5.2	0.76594		X			X	X		X	X		X
7	21.6	14.7	5.9	0.76454		X		X	X	X		X	X		X
7	21.6	14.6	6.0	0.76481		X			X	X		X	X	X	X
8	**22.6**	**14.7**	**7.0**	**0.76450**		**X**		**X**	**X**	**X**		**X**	**X**	**X**	**X**
8	22.6	14.6	7.0	0.76466		X	X	X	X	X		X	X		X
9	23.5	14.5	8.1	0.76525		X	X	X	X	X		X	X	X	X
9	22.9	13.9	8.7	0.76809		X	X	X	X	X	X	X	X		X
10	23.6	13.5	10.0	0.76963		X	X	X	X	X	X	X	X	X	X
10	23.5	13.4	10.1	0.77023	X	X	X	X	X	X		X	X	X	X
11	23.6	12.4	12.0	0.77474	X	X	X	X	X	X	X	X	X	X	X

Regression Analysis: Best subset regression

Dependent Variable: PEERS

Method: Least Squares

Date: 03/14/12 Time: 11:34

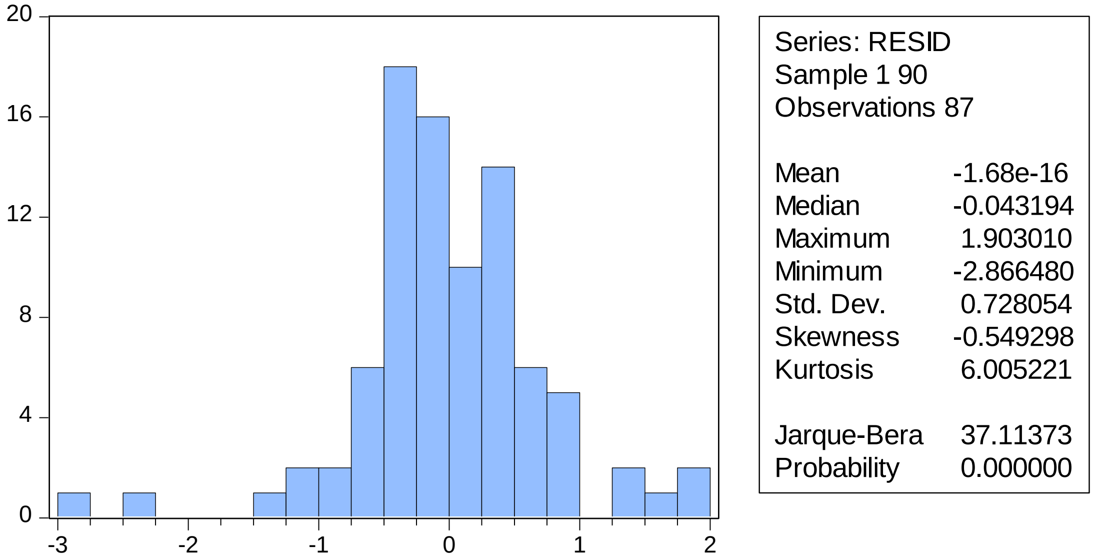
Sample (adjusted): 1 88

Included observations: 87 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.326093	0.238044	-1.369889	0.1747
IT	0.289435	0.243881	1.186786	0.2389
COD	-0.368695	0.367481	-1.003305	0.3188
COSTAP	0.548953	0.289949	1.893278	0.0620
FIN	-0.422458	0.289229	-1.460634	0.1481
IND	-0.643304	0.250888	-2.564107	0.0123
BRENT	0.234705	0.189774	1.236761	0.2199
MARCOND	0.203238	0.196129	1.036242	0.3033
MBOOK	-0.041145	0.033417	-1.231265	0.2219

R-squared	0.226401	Mean dependent var	-0.254253
Adjusted R-squared	0.147058	S.D. dependent var	0.827762
S.E. of regression	0.764479	Akaike info criterion	2.398452
Sum squared resid	45.58535	Schwarz criterion	2.653546
Log likelihood	-95.33265	Hannan-Quinn criter.	2.501170
F-statistic	2.853429	Durbin-Watson stat	0.558563
Prob(F-statistic)	0.007789		

Check for normality in the residuals:



White test for heteroskedasticity:

Heteroskedasticity Test: White

F-statistic	1.087984	Prob. F(28,58)	0.3833
Obs*R-squared	29.95956	Prob. Chi-Square(28)	0.3652
Scaled explained SS	60.26698	Prob. Chi-Square(28)	0.0004

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/14/12 Time: 11:34

Sample: 1 88

Included observations: 87

Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.173188	0.740182	1.584998	0.1184
IT	-0.565986	1.237677	-0.457297	0.6492
IT*BRENT	1.426775	0.904456	1.577495	0.1201
IT*MARCOND	0.354157	0.981826	0.360713	0.7196
IT*MBOOK	0.076420	0.184978	0.413130	0.6810
COD	0.015097	1.724488	0.008754	0.9930
COD*BRENT	-0.212021	2.516412	-0.084255	0.9331
COD*MARCOND	-0.628064	1.497275	-0.419471	0.6764
COD*MBOOK	0.227115	0.592861	0.383083	0.7031
COSTAP	-0.716311	1.315121	-0.544673	0.5881
COSTAP*BRENT	1.347214	1.355373	0.993981	0.3244

COSTAP*MARCOND	-0.033042	1.079632	-0.030605	0.9757
COSTAP*MBOOK	0.132208	0.581560	0.227333	0.8210
FIN	-0.332415	1.491276	-0.222906	0.8244
FIN*BRENT	-1.713494	2.326611	-0.736476	0.4644
FIN*MARCOND	-0.303492	1.648004	-0.184157	0.8545
FIN*MBOOK	0.461226	0.719764	0.640802	0.5242
IND	-0.903555	1.412822	-0.639539	0.5250
IND*BRENT	1.893786	1.026408	1.845063	0.0701
IND*MARCOND	-0.292556	1.323085	-0.221117	0.8258
IND*MBOOK	0.394651	0.253019	1.559766	0.1243
BRENT	-2.367823	1.476037	-1.604177	0.1141
BRENT^2	0.153338	0.726723	0.210999	0.8336
BRENT*MARCOND	1.682779	0.898576	1.872718	0.0662
BRENT*MBOOK	0.371177	0.195661	1.897046	0.0628
MARCOND	-0.793287	0.839089	-0.945415	0.3484
MARCOND*MBOOK	0.112327	0.201689	0.556934	0.5797
MBOOK	-0.172624	0.198419	-0.870001	0.3879
MBOOK^2	-0.000941	0.012253	-0.076806	0.9390

R-squared	0.344363	Mean dependent var	0.523970
Adjusted R-squared	0.027848	S.D. dependent var	1.179039
S.E. of regression	1.162506	Akaike info criterion	3.400234
Sum squared resid	78.38234	Schwarz criterion	4.222204
Log likelihood	-118.9102	Hannan-Quinn criter.	3.731216
F-statistic	1.087984	Durbin-Watson stat	1.179610
Prob(F-statistic)	0.383335		

9.3.6 Regression matched against peers with 10% trimmed data:

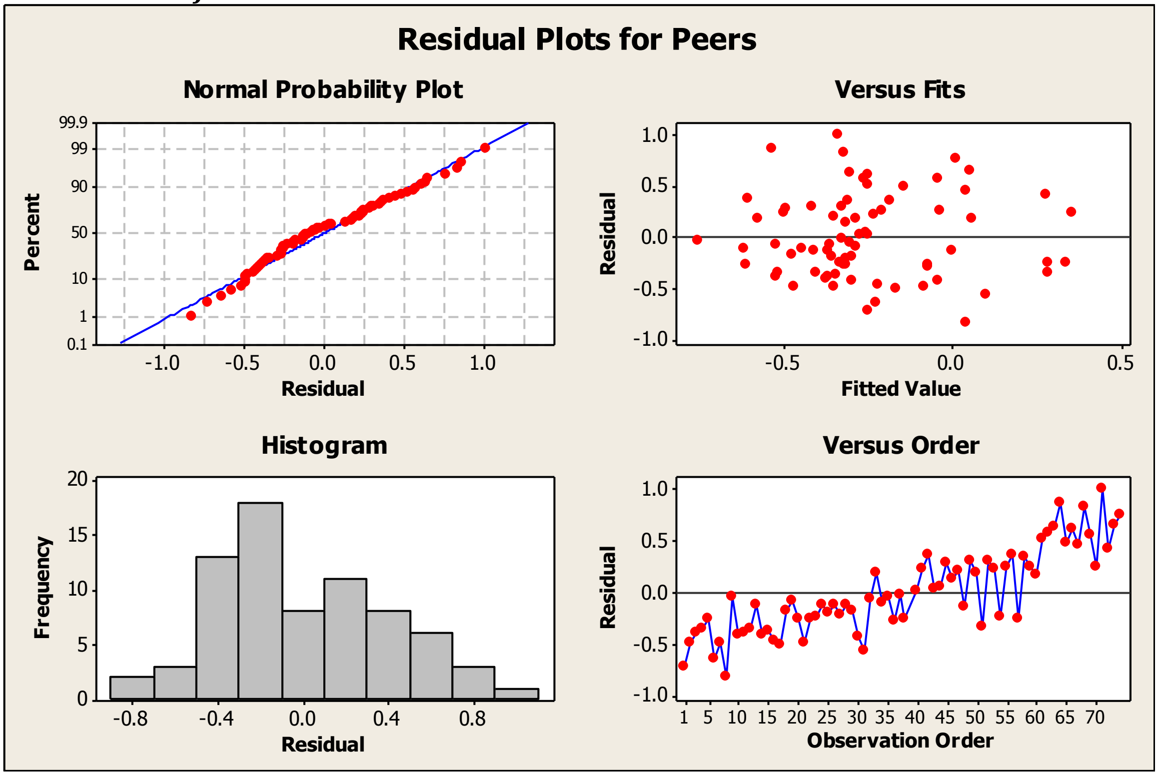
Regression Analysis: Peers versus Mcap; mbook; ...

```
The regression equation is:
Peers = - 0.559 - 0.000003 Mcap - 0.0150 mbook + 0.00069 Ageyears
        + 0.244 marcond + 0.085 Brent - 0.011 Ind + 0.289 Health - 0.186 Fin
        + 0.615 Costap + 0.077 cod + 0.325 it

73 cases used, 1 cases contain missing values
```

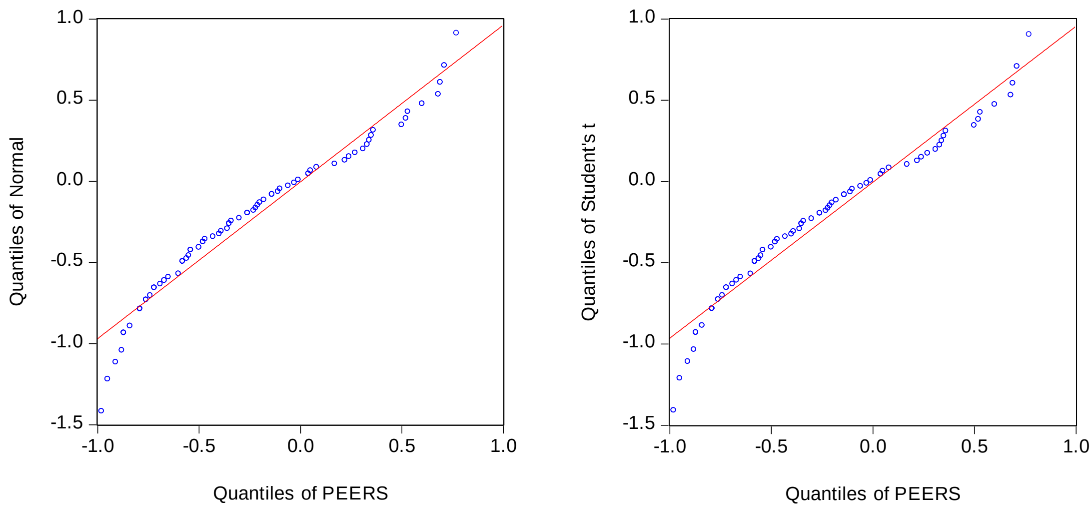
Predictor	Coef	SE Coef	T	P	**VIF**
Constant	-0.5593	0.1669	-3.35	0.001	
Mcap	-0.00000314	0.00001027	-0.31	0.761	1.173
mbook	-0.01502	0.02117	-0.71	0.481	1.172
Ageyears	0.000685	0.002399	0.29	0.776	1.247

```
marcond         0.2440      0.1352   1.80  0.076  1.086
Brent           0.0855      0.1246   0.69  0.495  1.123
Ind            -0.0111      0.1774  -0.06  0.950  1.353
Health          0.2893      0.1872   1.55  0.127  1.378
Fin            -0.1865      0.1847  -1.01  0.317  1.210
Costap          0.6154      0.2068   2.97  0.004  1.349
cod             0.0771      0.2435   0.32  0.753  1.117
it              0.3253      0.1702   1.91  0.061  1.347

S = 0.448072   R-Sq = 24.4%   R-Sq(adj) = 10.8%

Analysis of Variance:
Source          DF       SS      MS     F      P
Regression      11   3.9605  0.3600  1.79  0.075
Residual Error  61  12.2469  0.2008
Total           72  16.2074

Source    DF  Seq SS
Mcap       1  0.0104
mbook      1  0.0448
Ageyears   1  0.2425
marcond    1  0.1654
Brent      1  0.0975
Ind        1  0.2422
Health     1  0.1414
Fin        1  0.8925
Costap     1  1.3891
cod        1  0.0011
it         1  0.7337

Unusual Observations:
Obs   Mcap    Peers      Fit  SE Fit  Residual  St Resid
 13  10687  -0.7409  -0.6188  0.3638   -0.1221     -0.47 X
 44  46197  -0.2131  -0.2574  0.4309    0.0443      0.36 X
 64   1540   0.3370  -0.5323  0.1648    0.8693      2.09R
 71    938   0.6755  -0.3381  0.1377    1.0136      2.38R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large leverage.
```

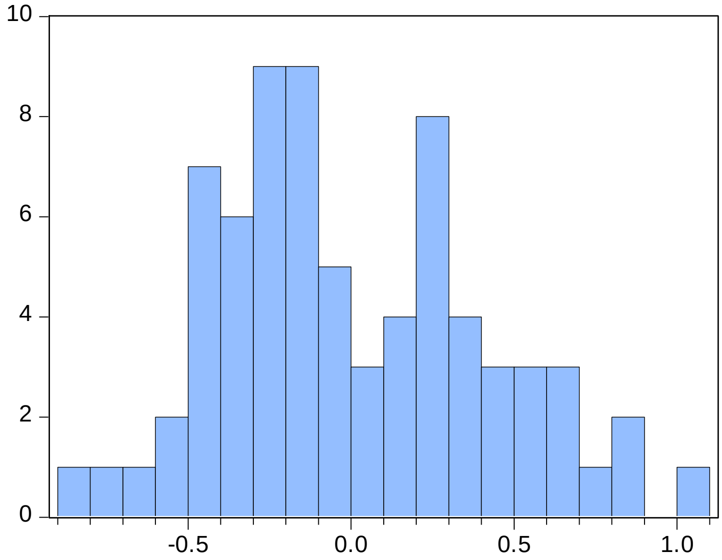
Residual Plots for Peers:



Probability plot of the normal- and Student's t-distribution:



Check for normality in the residuals:



Series: RESID
Sample 1 100
Observations 73

Mean	1.79e-16
Median	-0.079329
Maximum	1.017879
Minimum	-0.832647
Std. Dev.	0.412870
Skewness	0.380637
Kurtosis	2.458491
Jarque-Bera	2.654677
Probability	0.265182

Multi-correlation matrix:

	AGEYEARS	BRENT	COD	COSTAP	FIN	IND	IT	MARCOND	MBOOK	MCAP	NRG	HEALTH
AGEYEARS	1.00	0.10	-0.13	0.30	0.01	0.24	-0.12	0.05	-0.08	-0.04	-0.17	-0.06
BRENT	0.10	1.00	-0.08	-0.08	-0.06	0.13	0.18	-0.09	-0.02	-0.20	-0.07	-0.05
COD	-0.13	-0.08	1.00	-0.08	-0.08	-0.10	-0.10	-0.03	-0.05	0.01	-0.17	-0.09
COSTAP	0.30	-0.08	-0.08	1.00	-0.11	-0.13	-0.14	-0.06	-0.11	0.03	-0.23	-0.12
FIN	0.01	-0.06	-0.08	-0.11	1.00	-0.14	-0.15	0.07	-0.15	-0.04	-0.25	-0.13
IND	0.24	0.13	-0.10	-0.13	-0.14	1.00	-0.17	0.10	-0.04	-0.13	-0.28	-0.15
IT	-0.12	0.18	-0.10	-0.14	-0.15	-0.17	1.00	-0.16	0.12	-0.12	-0.29	-0.16
MARCOND	0.05	-0.09	-0.03	-0.06	0.07	0.10	-0.16	1.00	-0.09	0.01	0.14	-0.12
MBOOK	-0.08	-0.02	-0.05	-0.11	-0.15	-0.04	0.12	-0.09	1.00	0.21	-0.07	0.29
MCAP	-0.04	-0.20	0.01	0.03	-0.04	-0.13	-0.12	0.01	0.21	1.00	0.00	0.28
NRG	-0.17	-0.07	-0.17	-0.23	-0.25	-0.28	-0.29	0.14	-0.07	0.00	1.00	-0.26
HEALTH	-0.06	-0.05	-0.09	-0.12	-0.13	-0.15	-0.16	-0.12	0.29	0.28	-0.26	1.00

White test for heteroskedasticity without cross-check of variables:

Heteroskedasticity Test: White

F-statistic	0.306641	Prob. F(11,61)	0.9819
Obs*R-squared	3.825095	Prob. Chi-Square(11)	0.9748
Scaled explained SS	1.947735	Prob. Chi-Square(11)	0.9987

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/14/12 Time: 11:38

Sample: 1 74

Included observations: 73

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.135873	0.078164	1.738303	0.0872
AGEYEARS^2	-4.33E-06	1.05E-05	-0.413351	0.6808
BRENT^2	0.022992	0.055983	0.410703	0.6827
COD^2	-0.040074	0.118281	-0.338805	0.7359
COSTAP^2	0.043659	0.100485	0.434485	0.6655
FIN^2	-0.021396	0.090158	-0.237312	0.8132
IND^2	0.012160	0.084592	0.143746	0.8862
IT^2	0.053430	0.080265	0.665673	0.5081
MARCOND^2	0.041347	0.065778	0.628579	0.5320
MBOOK^2	-0.000479	0.000572	-0.836794	0.4060
MCAP^2	-6.91E-11	1.08E-10	-0.638076	0.5258
HEALTH^2	-0.030675	0.089827	-0.341492	0.7339

R-squared	0.052399	Mean dependent var	0.168126
Adjusted R-squared	-0.118480	S.D. dependent var	0.204448
S.E. of regression	0.216220	Akaike info criterion	-0.075856
Sum squared resid	2.851825	Schwarz criterion	0.300658
Log likelihood	14.76875	Hannan-Quinn criter.	0.074191
F-statistic	0.306641	Durbin-Watson stat	1.512069
Prob(F-statistic)	0.981916		

Best subset regression 10% trimmed data:

Summary over the adjusted R-squared effects from different regression models:

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	Mcap	mbook	Ageyears	marcond	Brent	Ind	Health	Fin	Costap	cod	it
1	11.4	10.1	2.5	0.44976									X		
1	4.3	3.0	8.2	0.46729								X			
2	15.2	12.8	1.4	0.44300									X		X
2	14.3	11.9	2.2	0.44544								X	X		
3	18.1	14.6	1.1	0.43850				X					X		X
3	17.3	13.7	1.8	0.44073							X		X		X
4	21.2	16.5	0.6	0.43348				X			X		X		X
4	20.3	15.6	1.4	0.43591				X				X	X		X

5	**22.5**	**16.8**	**1.5**	**0.43289**				**X**			**X**	**X**	**X**		**X**
5	22.1	16.3	1.9	0.43414				X	X		X		X		X
6	23.4	16.4	2.9	0.43381		X		X			X	X	X		X
6	23.4	16.4	2.9	0.43385				X	X		X	X	X		X
7	24.1	15.9	4.3	0.43500		X		X	X		X	X	X		X
7	23.6	15.4	4.7	0.43647	X	X		X			X	X	X		X
8	24.2	14.7	6.2	0.43806	X	X		X	X		X	X	X		X
8	24.2	14.7	6.2	0.43807		X		X	X		X	X	X	X	X
9	24.3	13.5	8.1	0.44120	X	X		X	X		X	X	X	X	X
9	24.3	13.5	8.1	0.44124		X	X	X	X		X	X	X	X	X
10	24.4	12.2	10.0	0.44446	X	X	X	X	X		X	X	X	X	X
10	24.3	12.1	10.1	0.44474	X	X		X	X	X	X	X	X	X	X
11	24.4	10.8	12.0	0.44807	X	X	X	X	X	X	X	X	X	X	X

Regression Analysis: Best subset regression

Dependent Variable: PEERS

Method: Least Squares

Date: 03/14/12 Time: 11:42

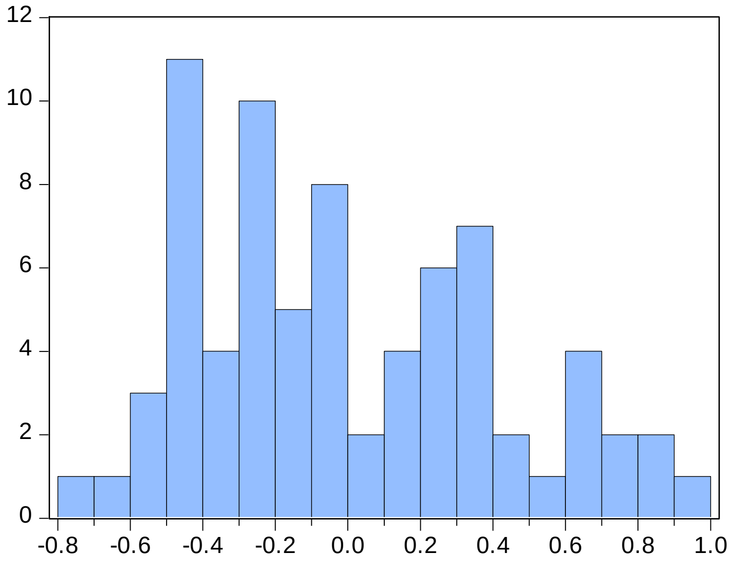
Sample (adjusted): 1 74

Included observations: 74 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.552602	0.131463	-4.203491	0.0001
IT	0.319979	0.150480	2.126387	0.0371
COSTAP	0.622107	0.178303	3.489039	0.0009
FIN	-0.182255	0.167593	-1.087480	0.2807
HEALTH	0.205717	0.154637	1.330316	0.1879
MARCOND	0.232693	0.128216	1.814856	0.0740

R-squared	0.223062	Mean dependent var	-0.252568
Adjusted R-squared	0.165934	S.D. dependent var	0.471747
S.E. of regression	0.430834	Akaike info criterion	1.231415
Sum squared resid	12.62199	Schwarz criterion	1.418231
Log likelihood	-39.56235	Hannan-Quinn criter.	1.305938
F-statistic	3.904610	Durbin-Watson stat	0.505420
Prob(F-statistic)	0.003597		

Check for normality in the residuals:



Series: RESID	
Sample 1 100	
Observations 74	
Mean	3.90e-17
Median	-0.076822
Maximum	0.999909
Minimum	-0.790070
Std. Dev.	0.415817
Skewness	0.447856
Kurtosis	2.300562
Jarque-Bera	3.982166
Probability	0.136547

Manually computed White test for heteroskedasticity:

Dependent Variable: RESID2

Method: Least Squares

Date: 03/14/12 Time: 14:30

Sample (adjusted): 1 74

Included observations: 73 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.127726	0.045123	2.830608	0.0068
AGE2	-7.51E-05	5.56E-05	-1.350235	0.1834
AGEBOOK	-0.003451	0.002261	-1.526451	0.1336
AGEBRE	-0.000715	0.006721	-0.106453	0.9157
AGECAP	-1.01E-06	1.06E-06	-0.950795	0.3466
AGECOD	0.039904	0.139707	0.285623	0.7764
AGECOSTA	-0.003306	0.006174	-0.535472	0.5948
AGEFIN	-0.008796	0.005704	-1.542077	0.1298
AGEIND	-0.003960	0.008060	-0.491274	0.6255
AGEIT	-0.001506	0.013751	-0.109521	0.9133
AGEMAR	-0.004690	0.006469	-0.725068	0.4720
AGEPHAR	-0.000207	0.012078	-0.017128	0.9864
AGEYEARS	0.023867	0.008741	2.730391	0.0089
BREBOOK	0.054431	0.044248	1.230137	0.2248
BRECAP	-1.69E-05	3.20E-05	-0.526655	0.6009
BRECOD	0.337215	0.435511	0.774296	0.4426
BRECOST	-0.150396	0.295321	-0.509263	0.6130
BREFIN	-0.040538	0.244756	-0.165624	0.8692

BREIND	0.087770	0.248687	0.352932	0.7257
BREIT	0.166919	0.194261	0.859255	0.3946
BREMAR	0.278007	0.168541	1.649495	0.1057
BRENT	-0.402280	0.274821	-1.463793	0.1499
BRENT2	0.066359	0.138299	0.479824	0.6336
BREPHAR	-0.137885	0.292552	-0.471319	0.6396
COD	0.240188	0.339315	0.707861	0.4825
CODBOOK	-0.139723	0.117674	-1.187381	0.2410

R-squared	0.303113	Mean dependent var	0.168126
Adjusted R-squared	-0.067572	S.D. dependent var	0.204448
S.E. of regression	0.211242	Akaike info criterion	0.000395
Sum squared resid	2.097295	Schwarz criterion	0.816175
Log likelihood	25.98559	Hannan-Quinn criter.	0.325497
F-statistic	0.817712	Durbin-Watson stat	1.463604
Prob(F-statistic)	0.701497		

9.4 Appendix D: Short-term abnormal return analysis

This appendix includes summaries of descriptive statistics for BHAR calculated, initial abnormal return measured by the price change from the offering price to close price at the first day of trading. Descriptive statistic summaries for full sample, 3% trimmed and 10% trimmed data sets.

9.4.1 Short-term abnormal return

RAW		***3% trimmed***		***10 % trimmed***	
Mean	0,015486799	**Mean**	0,014413	**Mean**	0,010313
Standard Error	0,012193545	**Standard Error**	0,007967	**Standard Error**	0,005281
Median	0,004777735	**Median**	0,004603	**Median**	0,004603
Mode	#I/T	**Mode**	#I/T	**Mode**	#I/T
Standard Deviation	0,122543608	**Standard Deviation**	0,077246	**Standard Deviation**	0,047238
Sample Variance	0,015016936	**Sample Variance**	0,005967	**Sample Variance**	0,002231
Kurtosis	9,246488489	**Kurtosis**	1,900559	**Kurtosis**	-0,1901
Skewness	0,314132152	**Skewness**	0,747203	**Skewness**	0,485907
Range	1,161433018	**Range**	0,453649	**Range**	0,21213
Minimum	-0,56106223	**Minimum**	-0,18553	**Minimum**	-0,07804
Maximum	0,600370791	**Maximum**	0,268121	**Maximum**	0,134094
Sum	1,564166666	**Sum**	1,354863	**Sum**	0,825078
Count	101	**Count**	94	**Count**	80
P-value with 95.0% confidence level	0,024191645	**P-value with 95.0% confidence level**	0,015822	**P-value with 95.0% confidence level**	0,010512