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Anomalies in the Norwegian Stock Market:

What is so Special About January?

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Abstract

In this thesis, we first look at the theory concerning efficient markets and anomalies. We then look at two effects in January in the Norwegian stock market, using data from the Oslo Stock Exchange (OSE) from the period 1980 – 2014. We first test for the existence of a January effect at the OSE in both an equally-weighted (EW) and a value-weighted (VW) portfolio. The January effect states that there exist abnormally high average returns in January compared to the average returns in all the other months of the year. In the testing procedure, we use both parametric and non-parametric tests and, find a statistically significant January effect in the EW portfolio, with a mean return that is at least 2.6% higher than the returns in the other months. Further, we test the EW size portfolios, and find a higher and more statistically significant January effect for small size firms, with a mean return that is at least 6.2% higher than the returns in the other months. Then, we test for the January effect for three sub-periods to see how the effect has changed over the years. For the EW portfolio the January effect has disappeared in resent years, whereas for the smallest size portfolio it still exists. Last, we test for the existence of the other January effect at the OSE. This effect states that the January return has the power to predict the market return for the rest of the year. If January returns are positive then the returns for the rest of the year are more likely to be positive and greater than if Januarys are negative. We use statistical tests and find a statistically significant other January effect for EW excess returns in the Norwegian stock market. We also check if the size of the firms has an impact on the other January effect, but we do not find such a connection.

Acknowledgements

This thesis is written as a part of our master's degree in finance at the University of Agder. During our master's degree, we gained interest for stock markets and the possibility to earn abnormal returns. We therefore thought that it would be interesting to look closer at the efficient market hypothesis, and to see if there exist some anomalies in the Norwegian stock market. After doing some research, it was especially the January effect that stood out, and we wanted to investigate this effect closer.

With the work of this thesis, we have received some valuable assistance. First, we would like to thank our supervisor, Professor Steen Koekebakker, for guidance during the writing process. We would also like to thank our Professor Jochen Jungeilges for help with the empirical work.

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1 Introduction

“Discovery commences with the awareness of anomaly, i.e. with the recognition that nature has somehow violated the paradigm-induced expectations that govern normal science.”

Thomas Kuhn (Allhoff, Alspector-Kelly, & McGrew, 2009, p. 497)

For decade’s researchers have been studying and speculated in different anomalies in the stock markets, trying to find evidence for or against the theory of efficient stock markets. A well-known anomaly in the world stock markets is the January effect. According to this effect, there exist an anomaly in the stock markets where the returns in January increase above its normal average in all the other months (Haugen, 2011). This means that the January returns exceed the returns for the remaining eleven months of the year. If this is true, it should be possible to exploit this anomaly and earn extra return on stocks without any additional risk.

In 1976, Michael S. Rozeff and William R. Kinney, wrote a paper about capital market seasonality. They found that large January returns contribute to significant differences in monthly mean returns (Rozeff, 1976). After their research, it has been done several similar studies about the January effect and other seasonalities in the market. The January effect has been a hot topic for several years, first in the early 80’s, and has now returned and become popular in resent years. Financial newspapers in Norway, such as “Dagens Næringsliv”, “Hegnar” and “e24” have written about the January effect the last years. Also, big banks in Norway such as “DNB” have been selling “Nyttårseffekten”-warrants to exploit this effect (DNB).

If the stock markets are efficient, and it is possible to exploit this anomaly, we would think that this opportunity of exploiting the market would have disappeared by now. Still, resent research show that this is not the case, and there still exists a January effect several places in the world (Anderson, Gerlach, & Ditraglia, 2007). Another effect in January, not as famous as the January effect, is the other January effect. According to this effect, the month January has a predictive power for the returns the rest of the year (Cooper, McConnell, & Ovtchinnikov, 2006). Because there have not been presented a lot of research about these January effects in Norway, it would be interesting to see if they exist in Norway as well.

In this thesis we want to see if the two January effects are present in the Norwegian stock market, and if the size of the firms has an impact. We also want to see how the January effect has changed over the years. We will test the effects for the aggregated monthly market returns, the decile size portfolios, and we will look closer on the daily returns at the turn of the year. We will test if there exists a systematically larger return in January than in the other months, and if January returns can predict the returns for the rest of the year.

In the next chapter of this thesis we will go through the efficient markets theories. We take a closer look at what anomalies are and mention some of them in chapter 3, we also look at possible explanations for the existence of a January effect and the other January effect. In chapter 4 we go through the testing procedures we will perform in Stata, and explain the statistical theory we use. In chapter 5 we will have a closer look at the data that we have used and at some descriptive statistics. We test if there exists a January effect in Norway in chapter 6, and in chapter 7 the other January effect will be tested. Finally, chapter 8 concludes the thesis.

2 Efficient Market Theories

"The more the theory of efficient markets is believed, the less efficient the markets become"

George Soros (Soros, 1987, p. 314)

Fama (1970) explains that there are three types of efficient markets: weak form, semi-strong form and strong form. The weak form consists only of information about historical prices. The semi-strong form consists of other information that is publicly available, this include announcements of annual earnings, stock splits, etc. The strong form consists of information that investors or groups have monopolistic access to, and that is relevant for the determination of prices (Fama, 1970). Now we want to look closer to some theories about the efficient markets.

2.1 The Efficient Market Hypothesis

The efficient market hypothesis discusses the behaviour of the financial markets, and if markets behave as economists expects it to. Do the prices in the market reflect the true underlying value? (Burton & Shah, 2013, p. 5). Kendall and Hill (1953) analyzed the stock market prices over a longer period. They found that there was a much smaller systematic pattern in the price series than what was generally believed. The random changes in the data where so large, they therefore concluded that it is not possible to predict future price movements without any extraneous information (Kendall & Hill, 1953).

If we imagine a situation where this is not the case, and that it is possible to predict future price movements, it would be naturally to assume that this would not last for long. If the price of a stock were expected to rise, then all investors would want to buy this stock, and if the price were expected to fall, then everyone would sell it. The competition in the market causes an immediate price increase when the future price is predicted to rise and vice versa. Thus, any information that could be used to predict future stock performance would already be reflected in current stock prices. Changes in stock prices should be random and unpredictable; they should follow a random walk. If it was possible to predict future prices, this would mean that there exists market inefficiency (Bodie, Kane, & Marcus, 2011, p. 372). When the stock price follows a random walk, it means that the future stock price has a fixed probability that is independent of all previous stock prices (Burton & Shah, 2013, p. 9). The idea that stock prices already reflect all available information is what is called the efficient market hypothesis (Bodie et al., 2011, p. 373). According to this hypothesis, prices will only change when the information changes (Burton & Shah, 2013, p. 6).

As mentioned, there are three types of efficient markets, depending on what information is available. This means that there are also three different definitions of the efficient market hypothesis. The most common is the semi-strong form, which says that prices precisely summarize all information that is publicly known. This means that it will not matter if an investor studies the companies he would like to invest in, because this information is already reflected in current stock prices. This price will always be the best estimate of the company's values. The weak form of the efficient market hypothesis says that historical stock prices are irrelevant when predicting future stock prices (Burton & Shah, 2013, p. 6). Some analysts try to beat the market by studying historical prices to try to find patterns, but the weak form says that this is not possible (Burton & Shah, 2013, p. 7). The strong form says that both private and public information is reflected in stock prices, thus it implies both the weak and semi-strong form of the efficient market hypothesis. This form may include illegally obtained information or information that is illegal to use. This means that the strong form is depending on that investors provide this information to researchers that are trying to confirm if they are beating the market, which may not be very likely (Burton & Shah, 2013, p. 8).

The idea of the efficient market hypothesis is that stock prices follow a random walk (Burton & Shah, 2013, p. 8). Expressed in formal terms, we can write:

$$P = E[P^*]$$

This equation says that the current price, P, of a security equals the expected value of all future cash flows from owning that security, $E[P^*]$. The efficient market hypothesis claims that when investors are given a set of information, then P equals the best possible estimate of P*. The market price is thus decided by supply and demand, where the supply and demand are functions of the security's current price, and the current market price is decided by the intersection between the two functions (Baker & Nofsinger, 2010, p. 334).

According to Baker and Nofsinger (2010), there are three situations where the market will be efficient. The first is when all the investors behave rationally. In this case, investors use all the information available to decide the expected value of future cash flows. If the current price is lower than this expected value, then they would want to buy more and vice versa (Baker & Nofsinger, 2010, p. 334). This means that the aggregate demand curve will be flat at $P = E[P^*]$. The second situation is when some of the investors behave irrationally, but that these irrationalities are uncorrelated so that they cancel each other out. Then, these investors can trade with each other without affecting the market price, and $P = E[P^*]$. In the third situation, arbitrage is unlimited. This means that even if there exist some systematically irrational investors, arbitrageurs can lead the market to efficiency. Knowing the real expected value of future cash flows, they make large trades when $P \neq E[P^*]$. If there are enough arbitrageurs in the market, then this will also lead to a flat demand curve at $P = E[P^*]$ (Baker & Nofsinger, 2010, p. 335).

2.2 Normal Returns

Normal returns are the returns that are expected in the market. The contrary to normal returns are abnormal returns, which occurs if the return of a stock or a portfolio differs from the expected normal return. To be able to examine if markets are efficient we need to have a benchmark of what normal returns are. The capital asset pricing model and the Farma French factor model are examples of two asset pricing models often used to estimate normal returns.

The Capital Asset Pricing Model

The capital asset pricing model (CAPM) shows the relationship between the risk of an asset and its expected return, and provides us with a benchmark rate of return (Bodie et al., 2011, p. 308). The model consists of many assumptions, including that individuals are equal, that they do not have initial wealth and that they are not risk averse. All these assumptions exclude many of the complexities in the real world. However, the model still gives some important insights to the security markets (Bodie et al., 2011, p. 309).

According to CAPM, the demand will equal the supply, this means that the prices in the market will adjust so that the efficient tangent portfolio and the market portfolio, M, will coincide. The market portfolio is thus equal to the tangent portfolio of risky securities (Berk & DeMarzo, 2014, p. 380). In this model, we will therefore obtain an equilibrium where all the investors want to hold the market portfolio. This portfolio consists of all traded stocks, where the proportions of these stocks are decided by the market value of the stock divided by the market value of all stocks (Bodie et al., 2011, p. 309).

The CAPM is given by:

$$E(r_i) = r_f + \beta_i[E(r_M) - r_f]$$

where $E(r_i)$ is the expected return of investment i, r_f is the risk-free rate of return, β_i is the security beta with respect to the market portfolio, $E(r_M)$ is the expected return of the market and $[E(r_M) - r_f]$ is the risk premium on the market portfolio (Bodie et al., 2011, p. 321). According to the Law of one price, investments with the same level of risk should also have the same expected return in a competitive market (Berk & DeMarzo, 2014, p. 382). The CAPM predicts that there is no abnormal excess return, α_i, on any security. This means that if the stock is fairly priced, the alpha must be zero (Bodie et al., 2011, p. 322).

Fama-French Factor Model

CAPM have to a large extent formed the way academics see the relationship between risk and return (Fama & French, 1992) but in tests the model perform poorly (Fama & French, 2004). Kenneth French and Eugine Fama (1992) proposed a model approach, based on research of historical data, called the three-factor model (FF3). This model was an alternative to the well-known CAPM and the arbitrage pricing model and included factors that had a significantly impact on the average return, like the size and price ratios, other than just the market.

The model is (Bodie et al., 2011, p. 363):

$$r_{it} = \alpha_i + \beta_{iM}R_{Mt} + \beta_{iSMB}SMB_t + \beta_{iHML}HML_t + e_{it}M$$

where r_{it} is the return of investment i, R_{Mt} is risk premium on the market portfolio and β_{iM} is the security beta with respect to the market. SMB_t (small minus big) is the size effect, showing the difference between the return on small and large cap stocks. HML_t (high minus low) is the difference between the return on high and low book-to-market stocks (Fama & French, 2004). The betas are often referred to as factor loadings, and according to this theory these factor loading's risk premiums should fully explain excess returns (Bodie et al., 2011, p. 447). In a regression these betas will show the slopes of the variables. The alpha value in this model is used as a measure of how fast the prices of stocks react to new information (Fama & French, 2004).

The choice of the factors, SMB and HML, are not obvious from an investor's point of view, but rather based on historical patterns that have been uncovered by research (Fama & French, 2004). The criticism of the model is based on the empirical approach. Researchers may look for factors to explain a phenomenon and find patterns that are there by luck. Although the additional factors in the Fama French three-factor model are not clearly relevant sources for risk, they may be a good proxy for variables that are still unknown sources of risk today (Bodie et al., 2011, p. 363).

2.3 The Joint Hypothesis Problem

According to the efficient market theory, stock prices reflect all information that is available. This means that it is not possible to earn abnormal returns and outperform the market. The CAPM and FF3 models also imply that there exists a close to linear relation between risk and expected return. This relationship is important when we use time-series data to test market efficiency (Kryzanowski & To, 1987). Testing for market inefficiency can be problematic, and this is what is called the joint hypothesis problem. According to this hypothesis, it is impossible to test if prices significantly differ from normal prices, unless we first formulate a "correct" model to determine this normal price (Borghesi, 2014). According to Campbell et al. (1996), all tests of market efficiency must assume a model that determines the normal stock returns. If one rejects market efficiency this could be because the market actually is inefficient, but it could also be because we have assumed a wrong equilibrium model from the beginning, or it could be a combination of both. This means that we cannot measure abnormal returns if we do not have a model that calculates the expected normal return correctly, and thus we cannot reject market efficiency (Campbell, Lo, & MacKinlay, 1996, p. 24).

Grossman and Stiglitz (1980) argues that because collecting information can be costly, markets will not always be in equilibrium (Grossman & Stiglitz, 1980). This means that there will occur abnormal returns, but that these returns are to compensate investors for the cost of collecting the information, and thus the returns are not abnormal after all (Campbell et al., 1996, p. 24). The essence of a joint test is that it tests efficiency in accordance to an equilibrium model. Still, the joint hypothesis problem argues that it is impossible to test for market efficiency due to the difficulty of finding a correct equilibrium model.

2.4 Behavioural Finance

In behavioural finance, it is assumed that individuals' investment decisions and the market outcomes are influenced by the information structure and the characteristics of the participants in the market. The human brain is affected by emotions and often processes information using different shortcuts or biases (Baker & Nofsinger, 2010, p. 3). This means that there exist irrationalities when investors make decisions. Investors do not always process information correctly and fails to make correct probability distributions about the returns in the future. Also, they often make inconsistent decisions even with a given probability distribution (Bodie et al., 2011, p. 410). This affects the efficiency of the market. The behavioural theory also argues that even if prices in the market are not correct, it can still be difficult to exploit this opportunity (Bodie et al., 2011, p. 409).

It has been argued that even if investors behave irrationally, then their biases are unlikely to be systematic, and that the different biases of the investors cancel each other out. If the investors' biases are systematic, then investors that are unbiased and rational should be able to take advantage of this and drive irrational investors out of the market (Baker & Nofsinger, 2010, p. 333). However, several studies have concluded that markets are not strong form efficient, and there has also been done research where weak and semi-strong forms of market efficiency have been violated (Baker & Nofsinger, 2010, p. 336). It is documented over the last decades that anomalies can be observed after different corporate events, and that returns after these events can be predicted. The question is then why rational investors do not take advantage of this, driving the returns down to zero (Baker & Nofsinger, 2010, p. 333).

2.5 Criticism of the Efficient Market Theory

The efficient market hypothesis is a theory with some controversy, and not all professionals agree with it. As explained in section 2.1, this hypothesis suggests that market prices will rapidly adjust after news or relevant information is known. Because of this, it is not possible for investors to predict price movements and make abnormal returns. The question now is how efficient the market really is and if abnormal returns can be the product of a risk premium? The empirical evidence for the efficient market hypothesis is also affected by selection bias. Only the investors that do not find an investment scheme that makes abnormal profit is sharing their experience. If an investor figured out how to invest to make money they would continue to do so and not share their investment scheme. Finding a way to make abnormal return can also be a lucky coincidence. If successful investors were to repeat their success in a different period, one would be able to test if it is skill or just lucky coincidence. This, however, rarely happens (Bodie et al., 2011, p. 384).

There has been done a lot of tests on market efficiency. The first tests of efficient markets were weak-form tests to find patterns in the stock returns. Measuring serial correlation is a method for testing if there is a pattern in stock returns. Serial correlation is when historical returns relate to present return. Although there is evidence of short-term relationship, it is not strong enough evidence to make a profit from buying stocks based on past performance. Later studies have shown a momentum effect in the intermediate-horizon. The momentum effect refers to resent performance that continues over time. If for example, a stock has performed well over the recent period, the stock will continue to perform well (Bodie et al., 2011, p. 386). There is also evidence that losing groups of stocks will outperform winning stocks after a 3-year period. This effect is referred to as the reversal effect, which states that stock markets have a tendency to overreact to news that are relevant (Bodie et al., 2011, p. 387).

Test of semi-strong form uses additional public information than just the historical data to improve the investment performance. Efficient market anomalies refer to the finding that measures like the price earnings ratio seems to predict abnormal risk-adjusted returns. In these semi-strong tests we have to adjust for risk, and often that is done by the use of CAPM. The CAPM may give us an inappropriate risk adjustment, which can lead to conclude that a portfolio performs better than what is the truth. The last test is of the strong form efficiency and deals with insider information. It is not expected that markets are strong form efficient, but there are still rules against insider trading (Bodie et al., 2011, p. 393). Although researchers test for market efficiency, there will always be a joint hypothesis problem.

3 Anomalies

Anomalies is the term used when patterns of returns seems to contradict the efficient market hypothesis (Bodie et al., 2011, p. 1023). Anomalies are of the semi-strong form where we find portfolios that have an abnormal return compared with their benchmark. One anomaly is the small-firm effect. This effect argues that a portfolio consisting of the smallest firms generate a higher average annual return than a portfolio consisting of bigger firms. According to the CAPM, the size should not matter when it comes to return. The neglected-firm effect is a further development of the small-firm effect. Because large institutions do not trade small firms as often, the information is not as accessible as for bigger firms. The lack of information makes small stocks a more risky investment, which should yield higher returns. Research have found, by dividing stocks into portfolios based on the information available, that the portfolios consisting of stocks with little information perform better than those with much available information (Bodie et al., 2011, p. 390). In efficient markets relevant news should be reflected in prices right after the news is reviled. Researchers have shown that the response in prices is not as rapid as theory predicts. There is a momentum effect after the news are available for all. This means that if good news is reviled about a company, the stock price will continue to grow even after the first day the news was available (Bodie et al., 2011, p. 392).

There are also other anomalies in the financial markets, both seasonal and not seasonal effects, all of them implicating that the efficient market hypothesis is not accurate. We will now look into some of them, before we continue with the January effect and the other January effect, which are the two anomalies that we will focus on in this thesis.

The December Effect

The December effect is the idea that when investors do not sell this years "winning stocks" in December, but instead wait to sell until January, then the price of the "winners" will increase in December. One explanation for this is tax-gain selling. When investors postpone their sale so that the capital gains do not get realized in the current fiscal year, they can defer payment of taxes on these gains by almost one year. This leads to an increase in the price of these winners (Chen & Singal, 2003).

The Weekend Effect

According to the weekend effect, returns are abnormally low early in the trading week, and abnormally high later in the trading week. U.S. stock data shows that Monday is the worst day of the week with the lowest returns, and that Friday is the best day with the highest returns (Burton & Shah, 2013, p. 181). One explanation of this is that, according to behavioural finance, mood tends to influence the behaviour of the investors in the market (Gama & Vieira, 2013). We could therefore assume that because the investors are in a happy mood when the weekend is close by, they also tend to buy more, pushing the prices up.

The Holiday Effect

It is shown that returns seems to be abnormally high on the last day before holidays, which is consistent with the explanation of Fridays having the highest returns before the weekend (Burton & Shah, 2013, p. 182). Lakonishok and Smidt (1988) studied seasonal anomalies and found evidence of persistently anomalous returns for several of these effects, including the weekend effect and the holiday effect (Lakonishok & Smidt, 1988, p. 403). Ariel (1990) also found statistically significant high mean returns on the trading day prior to holidays, with over one third of the total returns earned on the days that fall prior to holidays (Ariel, 1990).

The Halloween Effect

The Halloween effect is also called the Sell-in-May effect. This effect states that the stock returns has a tendency to be higher in the period November until April, than in the period May until October (Zhang & Jacobsen, 2012). According to this theory the month May is the beginning of a bear market, you should therefore sell your stocks in May and by them back again in October (Bouman & Jacobsen, 2002). Zhang and Jacobsen (2012) found significant evidence for a Halloween effect in the U.K. stock market for their full sample. Bouman and Jacobsen (2002) found significant evidence for a Halloween effect in most of the countries included in their study, for both developed and emerging markets.

The Presidential Cycle

Another much discussed anomaly in the stock market that is not seasonal, is the presidential cycle. According to this theory, the stock market has higher excess returns during Democratic than Republican presidencies in the US. Santa-Clara and Valkanov (2003) studied this effect and found that there was a stable, robust and significantly higher return when there was a Democratic presidency. They also found that across these presidencies, there was no difference in the riskiness of the stock market, meaning that these higher excess returns remained a mystery (Santa-Clara & Valkanov, 2003).

3.1 The January Effect

One of the most famous seasonal anomalies is called the January effect. The January effect states that average returns in January are higher than for all the other months of the year (Haugen, 2011, p. 606). This effect is sometimes referred to as the small-firm effect due to the fact that the January effect often is sighted in shares of small firms (Bodie et al., 2011, p. 390). Not only has there been evidence for an abnormal return in January, but there is also evidence stating that most of the abnormal return in January occurs within the first few trading days of January (Reinganum, 1983).

There has been done a lot of research during the last decades about the January effect, where most of them find evidence for its existence. Already in 1942, Sidney B. Wachtel discovered that there existed a January effect in the U.S. stock market (Wachtel, 1942), but it was not before the 80's that the topic became popular among researchers. Michael S. Rozeff and William R. Kinney revisited the January effect in 1976. They found evidence for significant differences in monthly mean returns, primarily due to high January returns (Rozeff, 1976).

Evidence for the hypothesis that the returns for small firms exceed the returns for large firms, and the relationship between this size effect and the January effect, was studied by Keim (1983). He found large abnormal returns in January, and a negative relationship between these abnormal returns and the size of the firms (Keim, 1983, p. 13). Banz (1981) and Reinganum (1981) also found significant evidence for the small-firm effect in the U.S. stock market. They found that smaller firms have higher risk-adjusted average returns than larger firms (Banz, 1981). Haug and Hirschey (2006) also found evidence for the existence of the January effect for small cap stocks in the U.S (Haug & Hirschey, 2006). Kohers and Kohli (1991) studied mean monthly returns for large firms, and found that these were highest in January compared to the rest of the year, thus it was independent of the small-firm effect (Kohers & Kohli, 1991).

There are several international studies about the January effect. Berges, McConnel and Schlarbaum (1984) found evidence of the January effect in Canada, and Kato and Schallheim (1985) found evidence for the existence of the January effect in Japan. Gultekin and Gultekin

(1983) studied seasonal effects in 18 major industrialized countries, and found evidence of strong seasonality's in most of them due to large January returns (Gultekin & Gultekin, 1983). Ho (1990) studied twelve markets and found that nine of them, where six were Asian Pacific emerging stock markets, had significantly higher January returns than any other months (Ho, 1990).

There are few studies about the January effect in the Norwegian stock market, but Gultekin and Gultekin (1983) included Norway in their study, and found evidence for the existence of the January effect in Norway. In a PhD Thesis from Norway, Dai (2004) studies the turn-of-the-year effect in Norway where she focuses on the tax-loss selling hypothesis as an explanation. She found significant evidences for this effect, and that it may be caused by tax-loss selling (Dai, 2004).

Because of the awareness of the January effect for so many years, we would assume that the effect might have disappeared by now. Still, resent studies in the last decade have found significant evidence for the January effect. Both Haug and Hirschey (2006) and Anderson, Gerlach and DiTraglia (2007) found statistically significant higher returns in January in the US. stock market. This means that there is evidence that the January effect still exists in the global stock markets.

3.2 The Other January Effect

Another anomaly that has been researched during the recent years is the other January effect. This effect says that the returns in January are positively related to the following next 11 months of the year (Burton & Shah, 2013, p. 181). If market returns in January are positive, then the returns in the next 11 months are more likely to be positive, and higher than if January returns are negative. This indicates that January returns have a predictive power for the returns during the rest of the year. (Cooper et al., 2006).

Yale Hirsch first discovered the other January effect in 1972, but at that time it was called the January Barometer (Bohl & Salm, 2010). Cooper, McConnell and Ovtchinnikov (2006) examined if the January returns had any predictive power in the period 1940-2003 for the US. stock market. They found evidence that January returns have the power to predict the market returns for the rest of the year (Cooper et al., 2006). They controlled their findings for presidential cycles, business cycles and other macroeconomic factors, and yet January had a predictive power. When the market return in January was positive, the return over the next 11 months was significantly much higher than if the return in January was negative. The other January effect was evident for both large and small cap stocks and for both value and growth stocks (Cooper et al., 2006).

Bohl and Salm (2010) searched for the other January effect in 19 different countries and found that only two of the 19 countries, Norway and Switzerland, exhibit the other January effect. This means that the other January effect is not a global phenomenon like the January effect. Marshall and Visaltanachoti (2010) found evidence of other January effect in the US stock market. They wanted to see if the other January effect could be used as a profitable strategy, but this effect did not provide significant excess return (Marshall & Visaltanachoti, 2010).

3.3 Possible Explanations for the January Effect

In earlier studies there are several possible explanations for the existence of a January effect in the stock markets, but there is no clear evidence of any of them. Some studies find evidence for a hypothesis, whereas others find evidence against the same one. The most logical answer is that there are more than one explanation for why we observe abnormal returns in January. Already in 1942, Sidney B. Wachtel presented some possible causes for a January effect, including tax selling, unusual demand for cash, a pre-holiday effect, and optimistic expectations (Wachtel, 1942). We will now look at some of the possible explanations for the January effect, that other studies has discussed.

Tax-Loss Selling

One of the most popular explanations for the existence of a January effect is the tax-loss selling hypothesis. This hypothesis is based on the fact that investors might want to realize capital losses against their taxable income by selling losing stocks at the end of the year. Because of this, there might be a decline in stock prices. In January the pressure of selling losing stocks will end, and the stock prices will return to their equilibrium prices. This will then lead to abnormally high January returns, due to the depressed levels in stock prices (Wachtel, 1942).

Whereas Haug & Hirschey (2006) does not find a relationship between tax-loss selling and the January effect, Starks, Yong, and Zheng (2006) finds evidence supporting the tax-loss selling hypothesis and that this hypothesis to a large extent can explain the January effect (Starks, Yong, & Zheng, 2006). Gultekin and Gultekin (1983) test the tax-loss selling hypothesis in thirteen countries, and find that there exists a close correlation between the large mean returns and the tax year in most countries. Eleven of the countries have January 1st as the beginning of the tax year, and they all experience higher returns in January than most of the other months. Also the U.K., which has its beginning of the tax year April 1st, show higher returns in April than most of the other months. The only country where this is not the case is Australia, which has its beginning of the tax year July 1st, but does not have higher July returns (Gultekin & Gultekin, 1983). Reinganum (1983) found a correlation with tax-loss selling and market capitalization, but it was not the case for all the firms that are categorized as small firms. Because the January effect might be a small-firm effect, this indicates that tax-loss selling is not the only explanation.

Canada is an interesting case that Berges, McConnell and Schlarbaum (1984) studied. They had data from before and after the tax-gain law was implemented. Their results show that there exist a January effect in Canada both before and after the tax gain was implemented, therefore they concluded that the tax-loss selling hypothesis was not the sole reason for the January effect (Berges, McConnell, & Schlarbaum, 1984). Another explanation to why countries without tax gain exhibits January effect may be because of foreign investors. To check if foreign investors had an impact Tong (1992) searched for a January effect in the Taiwanese and South Korean market. These markets have been closed off or hard to enter for foreign investors, in the sample period. The conclusion was that there is no significantly abnormal January effect in these Asian countries (Tong, 1992). This means that there might be a connection between the share of foreign investors and a January effect, both in countries with no tax-gain, and in countries with a tax year that does not end in December.

Window Dressing

There are few fund managers that want to show that they hold loser stocks when they send quarterly reports to their clients. Another popular explanation of the January effect is the window-dressing hypothesis. This hypothesis states that managers might want to impress investors at the end of the year. To do this they sell “embarrassing” losing stocks at the end of the year, before the revelation of their portfolio holding, only to buy them back again after the revelation (Zhang & Jacobsen, 2013).

Ng and Wang (2004) studied the window-dressing hypothesis, and found a relationship between this hypothesis and the trading behaviour at the turn of the year. They argued that institutional investors sell small losing stocks at the end of the year and buy back small loser and winner stocks at the beginning of the next year, making the January effect stronger. This means that their results suggests that it is not only the tax-loss selling hypothesis, but also institutional trading that drives the January effect. Even though institutions do not hold a lot of small stocks, the combined trading behaviour still affects the stock prices (Ng & Wang, 2004).

Haug and Hirschey (2006) argues that if it is the large institutional investors who perform window dressing, then this should mean that window dressing is a large-firm phenomenon. And if it is true that the January effect is a small-firm effect, then this contradicts this explanation (Haug & Hirschey, 2006). Lakonishok, Shleifer, Thaler and Vishny (1991) studied the window-dressing hypothesis among pension fund portfolio managers. Overall they found that these managers did perform some window dressing, and that it was stronger for small firms (Lakonishok, Shleifer, Thaler, & Vishny, 1991).

Information Availability

The information hypothesis is a possible cause for the January effect. This hypothesis explains that the January effect might be due to improper modeling of risk. Firms with a fiscal year that ends in December will release important information at the beginning of the subsequent year. The information hypothesis argues that the market fail to take into account this increased uncertainty in January, before this information is revealed (Zhang & Jacobsen, 2013). Another explanation may be the accessibility of information about the firm. This is because small firms may be considered more risky due to the lack of information available. If this risk is not considered then the return may seem abnormal, because investors will demand a higher risk premium. The January effect is not solely affected by the information difference, still if one finds another proxy for the information available about a security it might have an impact (Barry & Brown, 1984).

Increased Liquidity

The liquidity hypothesis is the theory that when investors get higher liquidity at the end of the year due to the end-of-the-year salaries, extra bonuses, dividend payments etc., the demand for stocks will increase at the beginning of the following year (Zhang & Jacobsen, 2013). This will lead to an increase in stock prices, and we will observe abnormally high January returns.

Ogden (1990) tests the turn-of-the-month liquidity hypothesis in the U.S. This hypothesis argues that the payment system in the U.S. is standardized in the way that most wages, dividends and other liabilities have a payoff date at the end of each month. This results in an increased demand for month-end securities, and thus also increases the security prices. Ogden (1990) also presents arguments for why the liquidity hypothesis is related to the January effect. He points out that in December there is an increase in business activity, especially in the retail industry, which means higher liquidity. This increased liquidity will lead to an increased demand for stocks and higher stock returns in the beginning of January. Another argument is related to January being a small-firm effect. Ogden argues that individual investors invests more in small-firm stocks than institutional investors, and that individual investors gets higher liquidity at the end of the year. Because of this, the returns in January will be larger for small-firm stocks than for large-firm stocks (Ogden, 1990).

Optimistic Expectations

People might make new-years resolutions because they have optimistic thoughts about the future, the same optimism might make investors invest in stocks at the beginning of the new year. Ciccone (2011) argues that the January effect can partly be explained by behavioral theory due to investors' optimistic expectations at the end of the year (Ciccone, 2011). The optimistic-expectation hypothesis suggests that stock prices in January will be bid up due to renewed optimism at the turn of the year (Zhang & Jacobsen, 2013). It is shown that investors' beliefs reach a peak in January, and this optimism will lead to an increase in stock prices for firms that have a higher uncertainty level in January. It is also argued that the optimistic expectation hypothesis is consistent with the January effect being a small-firm effect. This is because investors might feel extra optimistic about the performance of small-firm stocks as they have a higher uncertainty (Ciccone, 2011).

3.4 Possible Explanations for the Other January Effect

Because the other January effect is not as well known as the January effect, there is not as much research done with regard to possible explanations for the existence of this effect. According to Stivers, Sun and Sun (2009), there are three possible explanations for the other January effect. The first explanation is that the effect can exist due to a priced risk factor. If this is true, then the effect should be both international and persistent over time (Stivers, Sun, & Sun, 2009).

Cooper, McConnell and Ovtchinnikov (2006) investigated this possibility in their study, but they did not find evidence that risk can explain the other January effect. The second explanation is that the other January effect is connected with a behavioral bias, if so, this should also indicate that the effect is international and consistent over time. One behavioral bias can be the momentum phenomenon. If you use a momentum strategy then you by the stock when you see the price increase drastically, because then it is most likely to continue to increase. Then, when everyone has bought the stock, you sell it because then it is likely that the stock price will decrease in the future (Burton & Shah, 2013). The third explanation is that the other January effect might be just a temporarily effect, this in the way that it might be just a statistical irregularity without an economic explanation behind it. It could also be that the other January effect is related to a certain period of history, meaning that the returns are just a respond to economic factors at that time. If this is the case, then the effect is not expected to be international or consistent over time (Stivers et al., 2009). All of these possible explanations are quite general and can apply in all countries, also in Norway. They can also apply to other anomalies, like the January effect.

4 Testing Procedure

To test if there exists anomalies at the Oslo Stock Exchange (OSE), we use the statistical software Stata. Here we use the ordinary least square (OLS) method to estimate the parameters of the models. Given the estimates, we will perform parametric tests where we do a regular t-test and interpret the p-values of the test. These test procedures are only valid if the assumptions underlying the models hold. If it appears that our residuals are not normally distributed, we will perform some non-parametric tests. Another assumption is that the residuals should have a constant variance across all values of the predicted value of the dependent variable. We therefore need to test for heteroscedasticity as well. Because we use models with dummy variables, we will not have a problem with multicollinearity.

4.1 Parametric Tests

As mentioned above, parametric tests require the residuals we test to be normally distributed. This means that the values are symmetrically distributed around the mean, and that it has equal tails on each side. To test the significance of our parameters, we use a regular two-tail t-test. The formula for the test statistic is:

$$T = \frac{\hat{\alpha}_i - \alpha_i^*}{\sqrt{Var[\alpha_i]}}$$

We carry out the test:

$$H_0: \ \alpha_i = 0 \quad , \quad i = 2,3, \dots ,12$$
$$H_1: \ \alpha_i \neq 0 \quad , \quad i = 2,3, \dots ,12$$

Because $\alpha_i^* = 0$, the expression becomes:

$$T = \frac{\hat{\alpha}_i}{\sqrt{Var[\alpha_i]}}$$

This value tells us where in the t-distribution the t-ratio lies. It is possible to use different significance levels. When we use a significance level of 5%, the critical values are –1.96 and +1.96. If the t-value is less than –1.96 or larger than 1.96, this means that it lies in the rejection area. We then reject the null hypothesis, and the test statistics are significant, shown in figure 5.1:

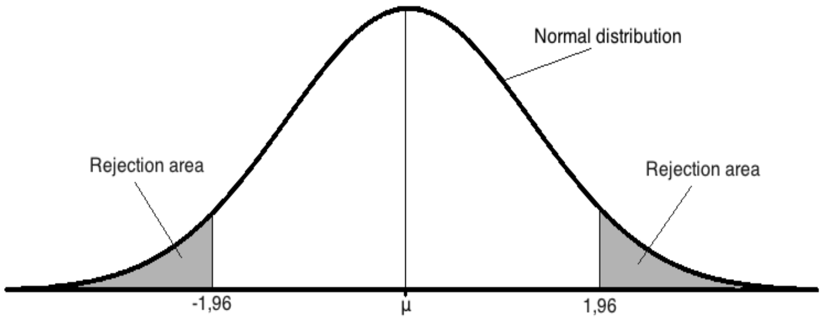


Figure 4.1: Shows at which t-values we can reject H_0 with a normal distribution

We can also interpret the p-values of the test. Given that H_0 is true, the p-value gives the probability of getting a test statistic that is as least as large as the one calculated (Thomas, 2005, p. 171). With a significance level of 5%, the critical value is 0.05. If the p-value is less than 0.05, we reject the null hypothesis and the test statistics are significant.

4.2 Test for Heteroscedasticity

If the assumption of homoscedasticity holds, a plot of the residuals against the fitted values should not reveal any pattern. This means that the variance of the residuals should be constant. If the errors do not have a constant variance, they are said to be heteroscedastic. To test if there exist this kind of a pattern in our dataset, we perform an IM-test. Due to White (1980) the IM-test tests the null hypothesis that the variance of the residuals is homogenous, and the alternative hypothesis that the variance of the residuals is not homogenous (White, 1980):

$$H_0: \quad Var[\varepsilon_{t,m}] = \sigma^2 \quad for\ all\ t, m$$
$$H_1: \quad Var[\varepsilon_{t.m}] \neq \sigma^2$$

This means that if we have a small p-value (less than 0.05), then we reject the null hypothesis, and conclude that the variance of the residuals is not constant, thus we have a problem with heteroscedasticity. If the p-value is larger than 0.05, we fail to reject the null hypothesis. In that case we consider the variance of the residuals to be constant and homoscedastic.

4.3 Test for Normality

One of the main assumptions for our models is that the residuals are normally distributed. To check if this is true with our dataset we can make a histogram with density lines, test for skewness and kurtosis and run a Shapiro-Wilks normality test.

Skewness measures if a distribution deviates in one direction or another, thus if there is an asymmetry in the data on the dependent variable and the residuals. When a distribution is normal it has a skewness equal to zero. If the distribution is positively skewed (skewness > 0), then we have a concentration of values to the left of the mean and more extreme values to the right. If the distribution is negatively skewed (skewness < 0), the concentration of the values is to the right of the mean with more extreme values on the left side (Acock, 2012, p. 259).

Kurtosis is a measure of the thickness of the tails in a distribution. When a distribution is normal it has a kurtosis equal to three (in Stata). If we have a kurtosis that is higher than three, then this means that the distribution is too peaked in the middle and the tails are too thin to be normally distributed. If we have a kurtosis that is lower than three, this means that the distribution is too flat in the middle and the tails are too thick for it to be normally distributed. (Acock, 2012, p. 259).

Another test we can perform is the Shapiro-Wilks normality test. The null hypothesis states that the data tested is normally distributed, whereas the alternative hypothesis say that the data is not normally distributed. A formal representation of the test statistic is:

$$H_0:\ x \sim \mathcal{N}(0, \sigma^2)$$
$$H_1:\ x \nsim \mathcal{N}(0, \sigma^2)$$

where the x, in our case, can be both the residuals and the returns. The significance level we will use in this test is 5%. This means that if the p-value from the test is higher than 0.05 we fail to reject H_0, and if the p-value is lower than 0.05 we reject H_0. If we reject H_0, we cannot assume that the estimates are normally distributed (Stata).

4.4 Correcting Tests

If we have a problem with heteroscedasticity we can run a regression with the robust option, and obtain the White-corrected standard errors. This method relies on the normality assumption, but gives more robust standard errors. This means that the standard errors takes into account that the assumption about heteroscedasticity may not hold.

If we do not have residuals that are normally distributed, we can use the bootstrapping method, that does not rely on normality. When we use the bootstrap method, Stata draws random samples, with the same number of observation as the original sample, from the dataset with replacement multiple times. Then Stata estimates the regression for each of the bootstrap samples that has been drawn. We use the solution in the bootstrap method to get the new t-values, called z, and standard errors (Acock, 2012, p. 260).

5 Data

In this thesis we have used data from the Oslo Stock Exchange (OSE) provided by Bernt Arne Ødegaard, professor of Finance at the University of Stavanger[1]. We use the monthly market returns, monthly risk free rates, the crossectional portfolios divided into size portfolios with monthly returns, and the daily market returns, all from the period January 1980 to December 2014.

We begin our analysis of the January effect in the Norwegian stock market by examining the aggregated monthly returns, both for the Value-Weighted (VW) index and the Equally-Weighted (EW) index. Further, we expand the analysis by examining the decile size portfolios for the EW portfolio. We also take a closer look at the daily returns for December and January, using the EW portfolio. Finally, we examine the other January effect using both EW, VW and the decile size portfolios.

Regardless of the firm's size, the EW portfolio puts equal weight to each security that is included in the portfolio. This means that the smallest firms at the stock exchange gets the same weight as large firms, such as Statoil. The VW portfolio, on the other hand, puts more weight on those firms with a large capitalization, and less weight on those firms with a small capitalization (Al-khalialeh & Al-Omari, 2004). In sum, this means that small firms get relatively more weight in the EW portfolio than in the VW portfolio, which places more weight on large firms.

According to Ødegaard, the market returns are constructed from most stocks at the OSE, only the smallest and least liquid stocks are omitted. The crossectional portfolios are sorted by similar criteria, where the size portfolios consist of 10 portfolios sorted by equity size. The risk free returns are given by the interest rate for borrowing the given month, and they are forward looking (Ødegaard). For a more detailed description of the data, see appendix A1.

[1]https://dl.dropboxusercontent.com/u/8078351/main/financial_data/ose_asset_pricing_data/index.html

5.1 History of the Oslo Stock Exchange

The Oslo Stock Exchange (OSE) has its origin in 1818, when the first Stock Exchange Act in Norway was sanctioned. Still, it was not before 1881 that OSE started with fund exchange, this in moderate terms with only 30 bonds and shares. Before 1880, stocks and bonds were not very common in Norway, but towards the end of the century the activity increased, and in 1919 there was 578 securities listed on the OSE. In the aftermath of World War 2, most activities on the stock market were characterized by the strict regulatory economy, but from the mid-80s the securities market showed an increasing vitality. It was in the 80s that foreigners also became interested in Norwegian securities, and in 1981 OSE became a member of the International Stock Exchange Federation (FIBV) (OsloBørs).

From the 1980s onwards, securities trading on the OSE increased considerably. Since then the stock prices have both decreased and increased in value. The first shock came in late 1987, when the all share index fell with 19%. In 1989, the stock prices started to increase, and they reached a new historic peak in 1990. This did not last long, until the end of the year in 1990 the all share index fell by 46%, this crisis lasted for the next two years. In 1992 there was a new upturn in the stock markets, and in 1994, the all share index passed the former peak. Later, the all share index has continued to increase and reach new highs, but the period also includes crisis, such as the financial crisis in 2008 (OsloBørs). The yearly average returns for the period 1980 to 2014 are shown in figure 5.1.

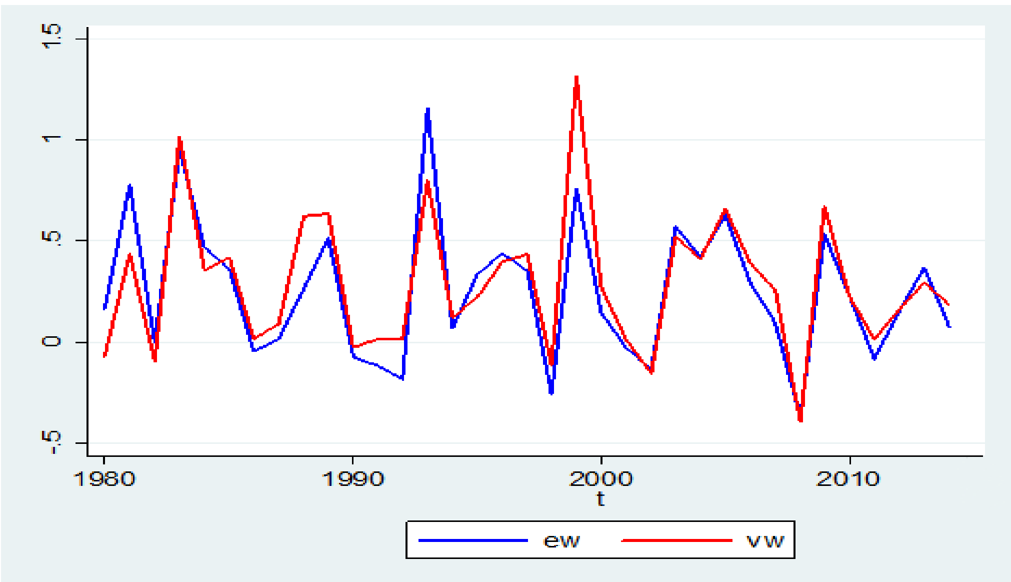


Figure 5.1: Yearly average returns for the EW and VW portfolios from 1980 to 2014

5.2 Return Characteristics at the Oslo Stock Exchange

Now we want to look closer at some descriptive characteristics at the OSE in the period 1980 to 2014. We have 420 observations in each portfolio. First, we look at monthly returns for the EW and the VW portfolios, and at the risk-free monthly returns.

	EW	VW	RF
MEAN	1,67 %	1,89 %	0,61 %
STD.	5,55 %	6,26 %	0,37 %
VAR.	0,31 %	0,39 %	0,001 %
MIN	-18,33 %	-23,79 %	0,12 %
MAX	19,06 %	19,72 %	2,07 %

Table 5.1: EW, VW and risk-free monthly return statistics from 1980 to 2014

From table 5.1 we have a monthly mean return of 1.67% for the EW portfolio and a monthly mean return of 1.89% for the VW portfolio. Over the same period, the risk-free monthly mean return was 0.61%. In yearly average returns this would equal a return of 20.04% for the EW portfolio, a return of 22.68 % for the VW portfolio and a risk-free rate of 7.32%. Even if the returns for our two portfolios are high, they also have a much higher volatility (std.). The EW and the VW portfolios have an average annually volatility of 19.23% and 21.67% respectively, whereas the risk-free average yearly volatility is only 1.28%. The spread between the highest and the lowest monthly return is 37.39% for the EW portfolio and 43.51% for the VW portfolio, whereas the risk free spread is only 1.95%. The returns vary widely for the EW and the VW portfolio over the whole period, this is shown in figure 5.2:

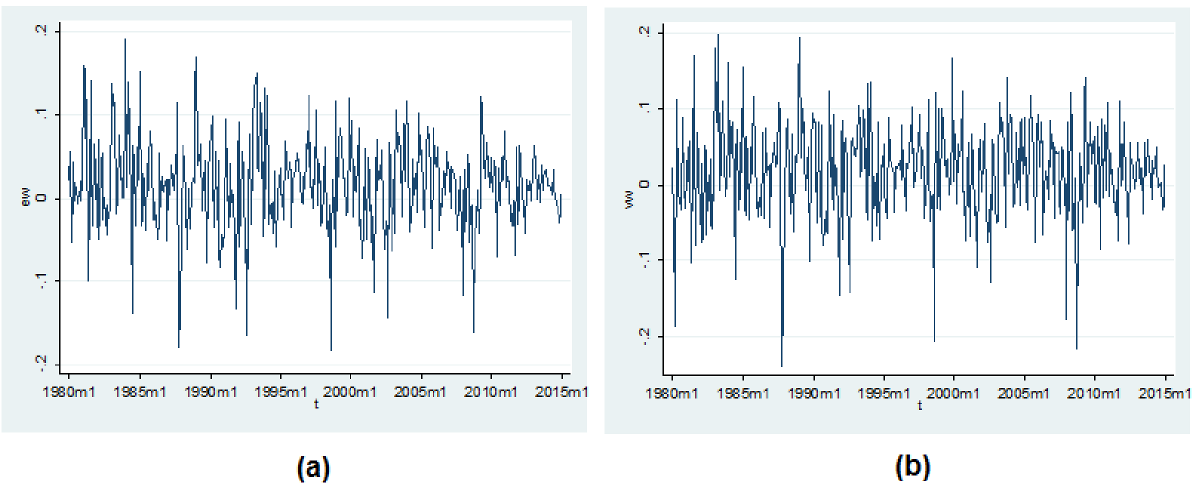


Figure 5.2: Monthly returns for the EW (a) and the VW (b) portfolios from 1980 to 2014

Now we will look at the monthly characteristics of the ten decile portfolios. Portfolio X1 represent the 10% smallest firms, X2 the 10% second smallest firms, etc. and portfolio X10 is the 10% biggest firms.

	X1	X2	X3	X4	X5
MEAN	2,87 %	2,16 %	1,57 %	1,50 %	1,95 %
STD.	7,14 %	6,78 %	6,65 %	6,81 %	6,88 %
VAR.	0,51 %	0,46 %	0,44 %	0,46 %	0,47 %
MIN	-18,12 %	-18,36 %	-24,10 %	-24,88 %	-19,16 %
MAX	46,71 %	31,94 %	32,27 %	29,06 %	53,34 %

	X6	X7	X8	X9	X10
MEAN	1,69 %	1,47 %	1,35 %	1,12 %	1,03 %
STD.	6,50 %	7,01 %	6,93 %	7,62 %	7,17 %
VAR.	0,42 %	0,49 %	0,48 %	0,58 %	0,51 %
MIN	-28,61 %	-24,20 %	-24,01 %	-28,50 %	-33,86 %
MAX	27,78 %	48,97 %	27,11 %	22,85 %	24,91 %

Table 5.2: EW decile portfolio’s monthly return statistics from 1980 to 2014

As we see from table 5.2, the monthly average return, with a few exceptions, decreases with the increasing size of the firms, ranging from 2.87% to 1.03%. The risk-free monthly average return is still much smaller than the average monthly return of all ten deciles. In yearly returns, the smallest decile has an average of 34.44%, whereas the largest decile has an average of 12.36%. We see that the volatility is high for all the portfolios, but it is higher for X10 than for X1. This means that one could get a higher return investing in the smallest firms without any additional risk. The spread between the highest and the lowest monthly return is large in each portfolio, and varies from around 50-75%. If we look at portfolio X5, for example, we see that the maximum monthly return is 53.34%, which is extreme. With a few exceptions, the minimum monthly return increases with the size of the firms, whereas the maximum value decreases with the size of the firms. The variations in the monthly returns for the smallest firms (X1) and the largest firms (X10) are shown in figure 5.3.

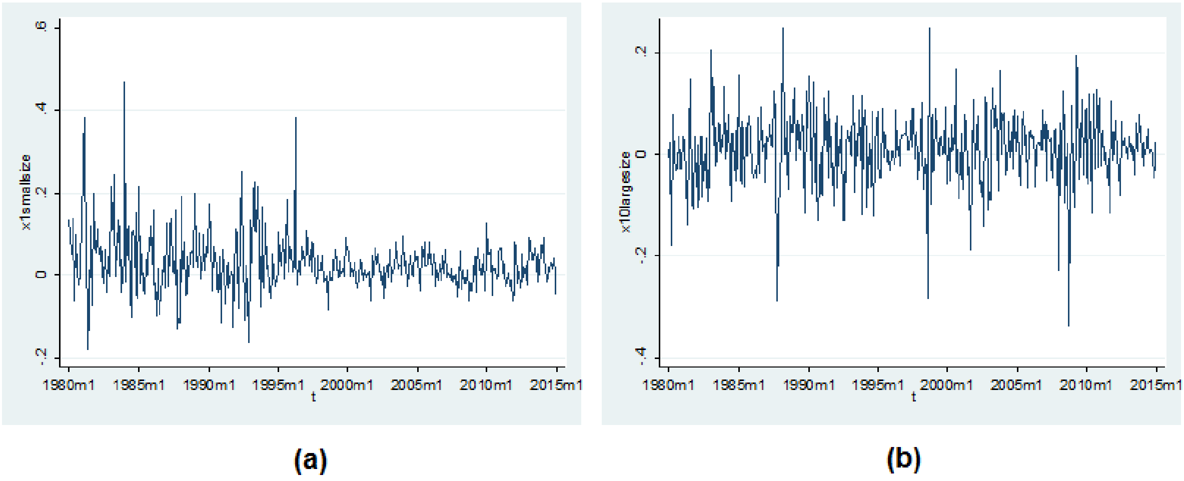


Figure 5.3: Monthly returns for the X1 (a) and the X10 (b) portfolios from 1980 to 2014

In figure 5.3 (a) we see that portfolio X1 has more positive returns than negative, and that some of the positive returns are very high. In the beginning of the period the returns vary widely, but this has smoothed out after around year 2000. In plot (b) there are larger and more negative returns, than in plot (a). For portfolio X10, the returns vary widely the whole period.

6 Testing for the January Effect

In this chapter, we will perform both parametric and non-parametric tests for the January effect on the EW and the VW portfolios, and on EW size portfolios. We analyze to see if there is statistically significant evidence for the existence of the January effect in the Norwegian stock market. We expect to find a statistical significant difference between January and at least one of the other 11 months. To support our theory about the January effect we expect that January returns are significantly higher than the returns for all the other months.

6.1 Methodology

We base our empirical work on the paper "Are Monthly Seasonals Real? A Three Century Perspective" by Zhang and Jacobsen (2013), and use the same model that they use.

To see if there exists a January effect at the OSE, we use a regression model with dummy variables. We test the joint significance of parameters α_2 to α_{12} using the following regression:

$$r_{t,m} = \alpha_1 + \alpha_2 D_{2t} + \alpha_3 D_{3t} + \cdots + \alpha_{12} D_{12t} + \varepsilon_{t,m} \qquad (1)$$

where $r_{t,m}$ is the monthly return, t = year and m = month, α_1 denotes the average return for January, α_2 to α_{12} are the differences between the January returns and the returns in the other months. D_{2t} to D_{12t} are the dummy variables for February to December, where D_{it} is equal to one for the i'th month and equal to zero otherwise. $\varepsilon_{t,m}$ is the error term that we assume is normally distributed. Taking the expectation of model (1):

$$E[r_{t,m}] = E[\alpha_1 + \alpha_2 D_{2t} + \alpha_3 D_{3t} + \cdots + \alpha_{12} D_{12t} + \varepsilon_{t,m}]$$

we get the expected regression model:

$$E[r_{t,m}] = \alpha_1 + \alpha_2 D_{2t} + \alpha_3 D_{3t} + \cdots + \alpha_{12} D_{12t} \qquad (2)$$

The model states that the expected return of month m is equal to the average return of January plus the sum of the difference between January and the other 11 months, times the dummy variable. If we for example want to find the expected return in February, model (2) would be:

$$E[r_{t,m}] = \alpha_1 + \alpha_2 1 + \alpha_3 0 + \cdots + \alpha_{12} 0$$
$$E[r_{t,m}] = \alpha_1 + \alpha_2$$

If $\alpha_1 = 5\%$ and $\alpha_2 = -2\%$ we would get an expected return in February of 3%.

The F-test's null hypothesis states that there is no January effect in the Norwegian stock market. This means that the differences in monthly returns are equal to zero. The alternative hypothesis states that there may exist a January effect in the Norwegian stock market. This means that at least one of the other month's returns is significantly different from the January return. Expressed in formal terms:

$$H_0: \quad \alpha_2 = \alpha_3 = \cdots = \alpha_{12} = 0$$
$$H_A: \quad \alpha_i \neq 0 \; for \; at \; least \; one \; i \in [2, 12]$$

If the returns for each month of the year are the same, then the parameters α_2 to α_{12} should be jointly insignificant (Zhang & Jacobsen, 2013). In that case we fail to reject the null hypothesis. We will also look at the t-values to see if January returns are significantly higher than the returns in all the other months. If that is the case, this indicates that there exists a January effect.

We use the OLS method to estimate the parameters of the model. Given the estimates, we will do a regular t-test and interpret the p-values of the test. Because these test procedures are only valid if the assumptions underlying model (1) hold, we therefore need to test for heteroscedasticity and normality.

6.2 Parametric Testing of Equally- and Value-Weighted Portfolios

We test the significance of the difference between January and the rest of the year. When doing the statistical tests we use three different significance levels, 1%, 5% and 10%, denoted by ***, ** and * respectively. Table 6.1 shows the result of the linear regression for both portfolios.

	Equally weighted					Value weighted				
	Coef.	Std. Err.	t	P>t	Sig. level	Coef.	Std. Err.	t	P>t	Sig. level
α_1	0.058	0.0089867	6.45	0.000	***	0.040	0.0103947	3.89	0.000	***
α_2	-0.029	0.0127092	-2.26	0.024	**	-0.020	0.0147004	-1.35	0.179	-
α_3	-0.035	0.0127092	-2.75	0.006	***	-0.021	0.0147004	-1.45	0.147	-
α_4	-0.026	0.0127092	-2.07	0.039	**	0.003	0.0147004	0.17	0.863	-
α_5	-0.043	0.0127092	-3.38	0.001	***	-0.019	0.0147004	-1.28	0.202	-
α_6	-0.063	0.0127092	-4.96	0.000	***	-0.041	0.0147004	-2.81	0.005	***
α_7	-0.031	0.0127092	-2.45	0.015	**	-0.009	0.0147004	-0.63	0.531	-
α_8	-0.057	0.0127092	-4.47	0.000	***	-0.032	0.0147004	-2.19	0.029	**
α_9	-0.069	0.0127092	-5.42	0.000	***	-0.047	0.0147004	-3.18	0.002	***
α_{10}	-0.050	0.0127092	-3.96	0.000	***	-0.025	0.0147004	-1.69	0.091	*
α_{11}	-0.055	0.0127092	-4.31	0.000	***	-0.039	0.0147004	-2.65	0.008	***
α_{12}	-0.037	0.0127092	-2.88	0.004	***	-0.007	0.0147004	-0.51	0.611	-
			F	P>F	Sig. level			F	P>F	Sig. level
			4.49	0.0000	***			2.40	0.0067	***

Table 6.1: Results from the OLS regression of the EW and VW portfolios, with significance levels

We see from table 6.1, that in the EW portfolio all the coefficients are statistically significant, this is not the case for the VW portfolio. Because January has the highest return in the EW portfolio, this could indicate that we have a January effect for the EW portfolio. To obtain heteroscedasticity consistent estimates of the standard errors, we follow the approach due to White (1980). This is achieved by running the robust option in connection with the standard regression procedure in Stata:

	Equally weighted					Value weighted				
	Coef.	Std. Err.	t	P>t	Sig. level	Coef.	Std. Err.	t	P>t	Sig. level
α_1	0.058	0.0109365	5.3	0.000	***	0.040	0.0126822	3.18	0.002	***
α_2	-0.029	0.0139397	-2.06	0.040	**	-0.020	0.0154455	-1.28	0.201	-
α_3	-0.035	0.0135627	-2.57	0.010	***	-0.021	0.0166255	-1.29	0.199	-
α_4	-0.026	0.0138832	-1.89	0.059	*	0.003	0.015639	0.16	0.871	-
α_5	-0.043	0.0133105	-3.22	0.001	***	-0.019	0.0156767	-1.20	0.231	-
α_6	-0.063	0.0133609	-4.72	0.000	***	-0.041	0.015737	-2.63	0.009	***
α_7	-0.031	0.0130065	-2.40	0.017	**	-0.009	0.0155555	-0.59	0.554	-
α_8	-0.057	0.0146673	-3.87	0.000	***	-0.032	0.0166654	-1.93	0.054	*
α_9	-0.069	0.0148094	-4.65	0.000	***	-0.047	0.0172161	-2.71	0.007	***
α_{10}	-0.050	0.0154656	-3.25	0.001	***	-0.025	0.0186333	-1.34	0.182	-
α_{11}	-0.055	0.0142611	-3.84	0.000	***	-0.039	0.0160036	-2.43	0.015	**
α_{12}	-0.037	0.0138684	-2.64	0.009	***	-0.007	0.0152517	-0.49	0.624	-
			F	P>F	Sig. level			F	P>F	Sig. level
			3.95	0.0000	***			2.53	0.0042	***

Table 6.2: Results from the regression with the robust option

The null hypothesis for the F-test states that there exist no difference between January and the other 11 months. From table 6.2 we reject the null hypothesis for both portfolios, and state that there is at least one of the months that are different from January. For the EW portfolio the significance levels for the p-values has not changed much, whereas for the VW portfolio we only have four statistical significantly coefficients, compared to the original linear regression that had five statistical significant coefficients. When comparing table 6.2 with table 6.1, we see that the coefficients are the same, but that there are changes in the standard errors. With the robust option we see an increase in the standard errors compared to the linear regression, both for the EW and the VW portfolios. This means that the dispersion from the regression line has increased, but the increase is only around 0.001, therefore it is hard to spot the difference in a graph. Because there are differences in the standard errors, this may indicate that we have a problem with heteroscedasticity, we will therefore test for this later.

Table 6.3 shows the percentage monthly mean returns for each month. The returns are calculated by taking the coefficient of January, plus the coefficients that states the difference between January and the other months. For example, the EW return in May is calculated by taking $\alpha_1 + \alpha_5 = 0.058 - 0.043 = 0.015 = 1.5\%$.

MONTHS	**EW**	**VW**
JANUARY	5,8 %	4,0 %
FEBRUARY	2,9 %	2,1 %
MARCH	2,3 %	1,9 %
APRIL	3,2 %	4,3 %
MAY	1,5 %	2,2 %
JUNE	-0,5 %	-0,1 %
JULY	2,7 %	3,1 %
AUGUST	0,1 %	0,8 %
SEPTEMBER	-1,1 %	-0,6 %
OCTOBER	0,8 %	1,5 %
NOVEMBER	0,3 %	0,1 %
DECEMBER	2,1 %	3,3 %

Table 6.3: Monthly mean returns for EW and VW portfolios

We see from table 6.3, that January has the highest average return for the EW portfolio, with a return that is 2.6% higher than the second highest return in April. For the VW portfolio, April has the highest mean return, with a return that is 0.3% higher than the return in January. We will now discuss our result from the regression in table 6.2, first for the EW portfolio, then for the VW portfolio.

Equally-Weighted Portfolio

The null hypothesis states that there is no difference between the average return in January and the other months. From table 6.2, we see that the F-test's p-value is equal to zero, we reject the null hypothesis and conclude that at least one of the months' average returns is significantly different from the average return of January. When performing the t-test, we see that all of the EW portfolio's test statistics are statistically significant with a minimum of 10% significance level. When looking at the coefficients, we see that the differences between January and all the other months are negative. This means that January has a higher expected average return than all the other months. Because the null hypothesis of the F-test and t-tests are rejected, this indicates that there exists a January effect. To see if these results are valid, we need to test for heteroscedasticity and normality. When testing for heteroscedasticity we first plot the residuals against the fitted values to see if there exists any pattern between them:

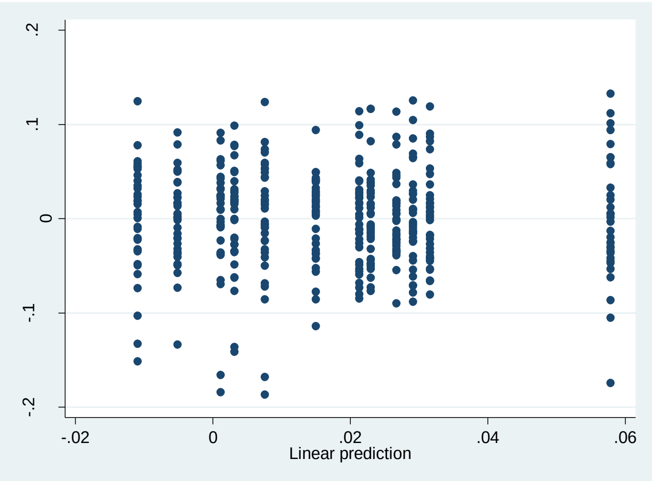


Figure 6.1: Plot of residuals vs. the fitted values for the EW portfolio

As we see in figure 6.1, there is no "visible" convincing systematic pattern with respect to the variance in the OLS residuals. To confirm this we also do the IM-test and get a p-value of 0.4492, because this number is larger than 0.05 we fail to reject the null hypothesis. This means that we do not have a problem with heteroscedasticity.

To proceed with the linear regression we also have to check if the data on the dependent variable and residuals are normally distributed. We do this by looking at a distribution plot, and by testing for skewness, kurtosis and running the Shapiro-Wilks normality test. In figure 6.2 we see the density of the EW portfolio and the residuals, the normal density line (solid line) and the kernel density line (dashed line), which gives the estimated density.

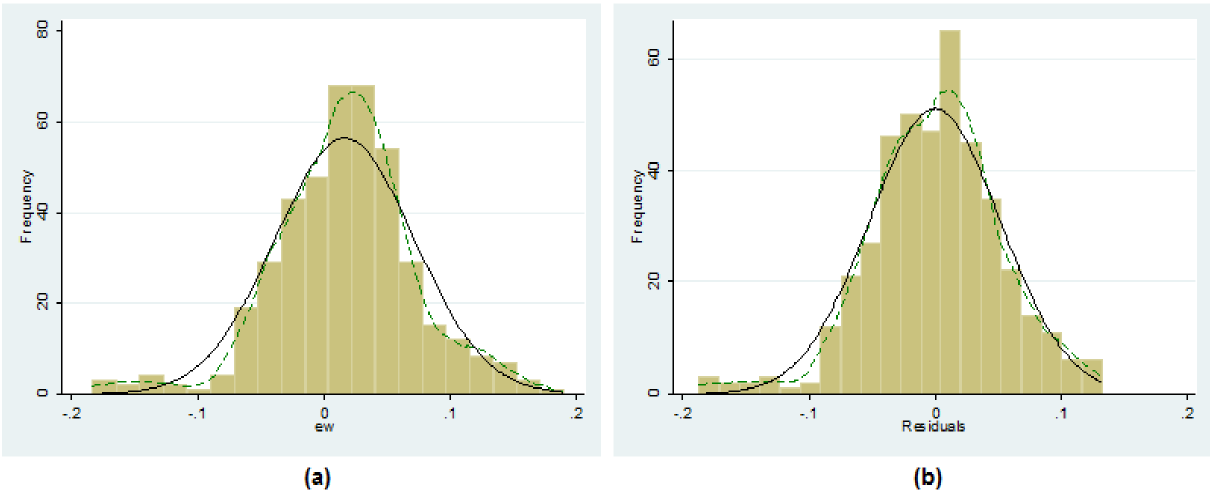


Figure 6.2: Distribution plots with a normal density line and a kernel density line, both for the data on the dependent variable (a) and for the residuals (b)

In figure 6.2, both of the plots show deviations from the normal distribution. In plot (a) we see the distribution of the returns in the EW portfolio. We see that the peak is higher than the normal density, and the concentration of the values is to the right of the mean. Because the distribution deviates from the normal density line, this could indicate that the residuals are not normally distributed. This gives us an idea of the distribution of the residuals shown in plot (b). Also here the peak is higher than the normal distribution, but not as high as in (a). This indicates that the residuals are not normally distributed either. We now test for skewness and kurtosis:

	EW	**RESIDUALS**
SKEWNESS	-0.253	-0.342
KURTOSIS	4.376	3.956

Table 6.4: Values for skewness and kurtosis

From table 6.4, we see that the data on the dependent variable and the residuals have a negatively skewed distribution (smaller than 0) and a high kurtosis (higher than 3). This is in accordance with figure 6.2 and indicates that our residuals and EW returns are not normally distributed. To confirm these results, we also do a Shapiro-Wilks normality test:

SHAPIRO – WILK NORMALITY TEST

	P-value
EW	0.00000
RESIDUALS	0.00011

Table 6.5: Shapiro-Wilk p-values

Because the p-values in table 6.5 are smaller than 0.05, the Shapiro-Wilks normality test tells us that we will reject the null hypothesis, and that there is not enough evidence to say that our residuals and EW returns are normally distributed. In sum, all our tests tell us that the data on the dependent variable and residuals are not normally distributed.

Value-Weighted Portfolio

When we look at the VW portfolio in table 6.2, we reject the null hypothesis in the F-test and conclude that at least one of the month's average returns is significantly different from January's average return. When we perform the t-test, we see that the test statistics for the VW portfolio only have five statistically significant coefficients. June, August, September, October and November are the only months significantly different from January, this means that we cannot state that there exists a January effect. To see if the results are statistically significant, we test for heteroscedasticity and normality. When testing for heteroscedasticity we first plot the residuals against the fitted values to see if there exists any pattern between them:

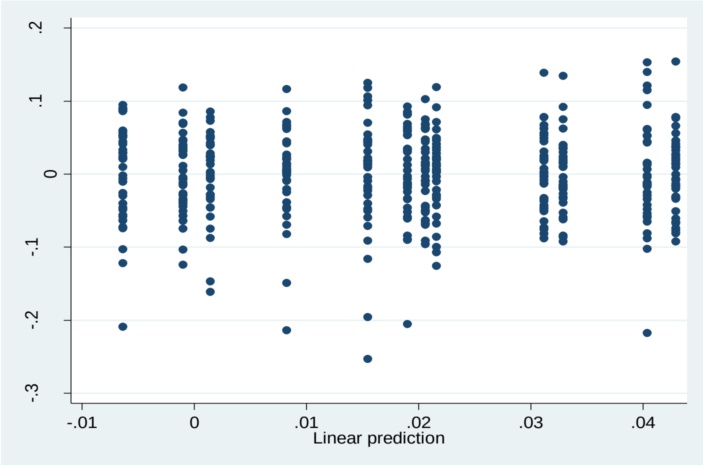


Figure 6.3: Plot of residuals vs. the fitted values for the VW portfolio

As we see in figure 6.3, there is no "visible" convincing systematic pattern with respect to the variance in the OLS residuals. To confirm this, we also do the IM-test and get a p-value of 0.2938, because this number is larger than 0.05 we fail to reject the null hypothesis. This means that we do not have a problem with heteroscedasticity.

Because the EW portfolio was not normally distributed, we suspect that the VW portfolio is not normally distributed either. We check for normality in the VW portfolio by looking at a distribution plot, and by testing for skewness, kurtosis and run the Shapiro-Wilks test. In figure 6.4 we see the density of the VW portfolio and the residuals, the normal density line (solid line) and the kernel density line (dashed line).

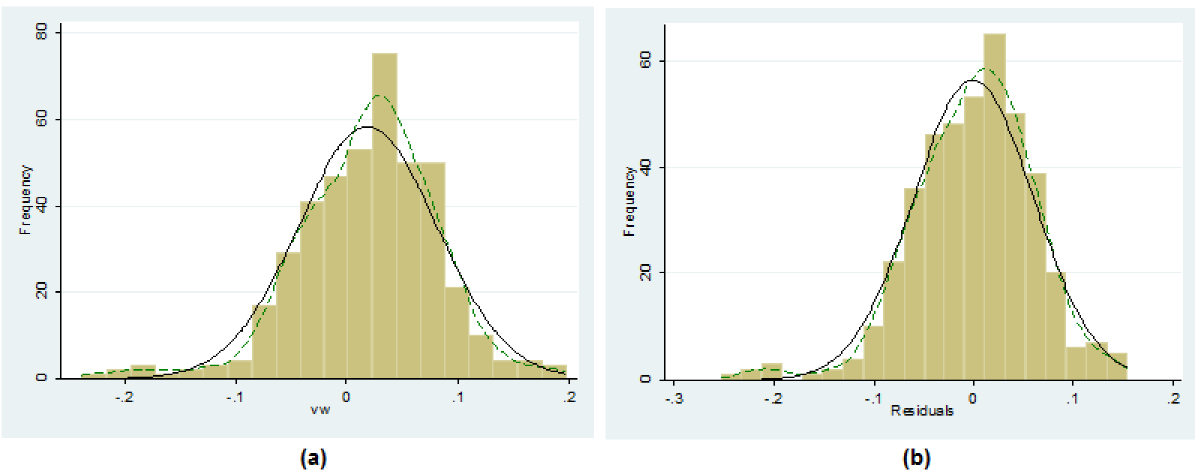


Figure 6.4: Distribution plots with a normal density line and a kernel density line, both for the data on the dependent variable (a) and for the residuals (b)

The plots show deviations from the normal distribution. Figure 6.4 plot (a) shows the distribution of the returns of the VW portfolio. We see that the peak is higher than the normal distribution and situated to the right of the mean. Plot (b) shows the estimated densities of the residuals, also here the peak is higher than the normal density. This means that both of the plots deviate from the normal density line, and indicates that the data on the dependent variable and the residuals are not normally distributed. To confirm this, we test for skewness and kurtosis.

	VW	**RESIDUALS**
SKEWNESS	-0.547	-0.570
KURTOSIS	4.543	4.348

Table 6.6: Values for skewness and kurtosis

From table 6.6, we see that the VW returns and the residuals have a negatively skewed distribution (smaller than 0) and a high kurtosis (higher than 3). This is in accordance with figure 6.4 and indicates that our residuals and VW returns are not normally distributed. To confirm these results, we also do a Shapiro-Wilks normality test:

SHAPIRO – WILK NORMALITY TEST

	P-value
VW	0.00000
RESIDUALS	0.00001

Table 6.7: Shapiro-Wilk p-values

The test statistics shown in table 6.7 tells us that we will reject the null hypothesis, and that there is not enough evidence to say that our residuals and the VW returns are normally distributed. All our tests, for both the EW and the VW portfolios, tell us that the data on the dependent variable and residuals are not normally distributed, and we have to perform non-parametric tests.

6.3 Bootstrapping the Equally- and Value-Weighted Portfolios

In order to increase the statistical validity for our results, we perform the bootstrap method. In our case the bootstrap sample contains 480 observations and we choose to draw 10 000 bootstrap samples. The results are shown in table 6.8:

	Equally weighted					Value weighted				
	Coef.	Std. Err.	t	P>t	Sig. level	Coef.	Std. Err.	t	P>t	Sig. level
α_1	0.058	.0109547	5.29	0.000	***	0.040	.0128384	3.15	0.002	***
α_2	-0.029	.0138389	-2.08	0.038	**	-0.020	.0155651	-1.27	0.204	-
α_3	-0.035	.013538	-2.58	0.010	***	-0.021	.0167193	-1.28	0.201	-
α_4	-0.026	.0136865	-1.92	0.055	*	0.003	.01575	0.16	0.872	-
α_5	-0.043	.0132865	-3.23	0.001	***	-0.019	.0158062	-1.19	0.234	-
α_6	-0.063	.0133788	-4.71	0.000	***	-0.041	.0159445	-2.59	0.009	***
α_7	-0.031	.0130186	-2.39	0.017	**	-0.009	.0156059	-0.59	0.555	-
α_8	-0.057	.014617	-3.89	0.000	***	-0.032	.0167495	-1.92	0.055	*
α_9	-0.069	.0147971	-4.65	0.000	***	-0.047	.0173364	-2.70	0.007	***
α_{10}	-0.050	.0155738	-3.23	0.001	***	-0.025	.0186942	-1.33	0.183	-
α_{11}	-0.055	.0141899	-3.86	0.000	***	-0.039	.016224	-2.40	0.016	**
α_{12}	-0.037	.0137285	-2.67	0.008	***	-0.007	.0152774	-0.49	0.624	-

Table 6.8: Results from the bootstrap regression

The coefficients in table 6.8 are the same as in the "robust" and the original regressions. The dispersions in the standard errors in the bootstrap method have changed compared to the "robust" regression. The changes are relatively small, and the deviations in the standard errors have both increased and decreased.

In the case of the EW portfolio, we see that most of the coefficients are statistically significant at a 1% level, except from α_2 and α_7 that are significant at a 5% level and α_4 that has a 10% significance level. With a 10% significance level, we can conclude that the EW January returns are significantly higher and different compared to all the other months. Because of these results we can conclude that there exists a January effect for the EW portfolio. This is not the case for the VW portfolio, only four of the coefficients are statistically significant, thus we cannot say that there exists a January effect for the VW portfolio.

The VW portfolio weights the firms according to size, while the EW portfolio weights the firms equally. Small firms will therefore have a relatively higher weight in the EW portfolio than in the VW portfolio. Because our results indicate a January effect in the EW portfolio, this supports the theory that the January effect is a small-firm effect. We will therefore examine the size effect closer by dividing the EW portfolio into ten size portfolios.

6.4 Testing Size Portfolios

We test the significance of the difference between January and the rest of the year for different size portfolios. The tests for normality and heteroscedatisiy can be found in Appendix A2. We found no problem with heteroscedatisity, but none of the ten portfolios were normally distributed. We therefore use the bootstrap regression in this section. X1 represents the 10% smallest firms, X2 the 10% second smallest firms etc., and X10 represents the 10% largest firms. Table 6.9 shows the results of the bootstrap regression for the ten portfolios, with 50 000 bootstrap samples.

	X1			X2			X3			X4			X5		
	Coef.	z	sig. level	Coef.	z	sig. level	Coef.	z	sig. level	Coef.	z	sig. level	Coef.	z	sig. level
α_1	0.110	6.89	***	0.068	6.38	***	0.058	4.48	***	0.059	4.53	***	0.065	4.95	***
α_2	-0.069	-3.47	***	-0.012	-0.64	-	-0.021	-1.18	-	-0.040	-2.27	**	-0.022	-0.98	-
α_3	-0.062	-2.77	***	-0.055	-3.45	***	-0.028	-1.51	-	-0.039	-2.23	**	-0.043	-2.69	***
α_4	-0.070	-3.68	***	-0.038	-2.31	**	-0.024	-1.45	-	-0.027	-1.61	-	-0.036	-2.17	**
α_5	-0.092	-4.57	***	-0.048	-3.38	***	-0.041	-2.68	***	-0.047	-3.06	***	-0.049	-3.05	***
α_6	-0.110	-6.22	***	-0.066	-4.85	***	-0.065	-3.83	***	-0.056	-3.26	***	-0.068	-4.12	***
α_7	-0.077	-4.16	***	-0.031	-2.11	**	-0.035	-2.43	**	-0.039	-2.58	***	-0.036	-2.4	**
α_8	-0.098	-5.43	***	-0.057	-3.87	***	-0.053	-3.31	***	-0.062	-3.56	***	-0.059	-3.43	***
α_9	-0.104	-5.68	***	-0.064	-4.34	***	-0.071	-4.45	***	-0.062	-3.68	***	-0.077	-4.37	***
α_{10}	-0.101	-5.3	***	-0.070	-5.09	***	-0.060	-3.23	***	-0.038	-2.18	**	-0.050	-2.77	***
α_{11}	-0.097	-4.96	***	-0.046	-3.05	***	-0.058	-3.5	***	-0.064	-3.38	**	-0.068	-3.92	***
α_{12}	-0.097	-5.38	***	-0.067	-4.11	***	-0.049	-2.91	***	-0.055	-3.07	**	-0.040	-2.58	***

	X6			X7			X8			X9			X10		
	Coef.	z	sig. level	Coef.	z	sig. level	Coef.	z	sig. level	Coef.	z	sig. level	Coef.	z	sig. level
α_1	0.062	4.61	***	0.059	4.8	***	0.032	2.28	**	0.041	3.09	***	0.021	1.49	-
α_2	-0.033	-1.89	*	-0.038	-2.4	**	-0.012	-0.69	-	-0.026	-1.7	*	-0.012	-0.73	-
α_3	-0.041	-2.7	***	-0.040	-2.68	***	-0.011	-0.66	-	-0.022	-1.21	-	-0.004	-0.22	-
α_4	-0.024	-1.32	-	-0.036	-2.28	**	-0.002	-0.1	-	-0.010	-0.56	-	0.009	0.49	-
α_5	-0.049	-3.16	***	-0.042	-2.7	***	-0.012	-0.64	-	-0.039	-2.37	**	-0.005	-0.29	-
α_6	-0.067	-3.87	***	-0.067	-4.23	***	-0.041	-2.4	**	-0.058	-3.35	***	-0.029	-1.76	*
α_7	-0.045	-2.89	***	-0.036	-2.37	**	-0.003	-0.17	-	-0.004	-0.27	-	0.008	0.47	-
α_8	-0.068	-3.72	***	-0.059	-3.31	***	-0.037	-1.93	*	-0.055	-2.79	***	-0.020	-1.04	-
α_9	-0.076	-4.22	***	-0.080	-4.63	***	-0.058	-3.03	***	-0.057	-2.74	***	-0.036	-1.84	**
α_{10}	-0.052	-3.03	***	-0.056	-3.07	***	-0.021	-1.14	-	-0.037	-1.73	*	-0.014	-0.63	-
α_{11}	-0.059	-3.54	***	-0.056	-3.24	***	-0.026	-1.44	-	-0.048	-2.71	***	-0.020	-1.09	-
α_{12}	-0.032	-1.89	**	-0.024	-1.21	-	0.005	0.26	-	-0.004	-0.21	-	-0.001	-0.04	-

Table 6.9: Results from the bootstrap regression for the decile portfolios

The null hypothesis states that there is no difference between the average return in January and each of the months. From table 6.9 we find that only portfolio X1 have significant coefficients for all the months. Portfolio X1 also has the highest coefficient in January, which supports our theory that the January effect is a small-firm effect. It is also evident from the coefficients that January has a positive return in every size portfolio.

In table 6.10, we present the monthly mean returns for the size portfolios. The returns are given in monthly percentage.

MONTHS	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
JANUARY	11,0 %	6,8 %	5,8 %	5,9 %	6,5 %	6,2 %	5,9 %	3,2 %	4,1 %	2,1 %
FEBRUARY	4,1 %	5,6 %	3,7 %	1,9 %	4,3 %	3,0 %	2,1 %	2,0 %	1,5 %	0,9 %
MARCH	4,8 %	1,3 %	3,0 %	2,0 %	2,2 %	2,1 %	2,0 %	2,1 %	1,9 %	1,7 %
APRIL	4,0 %	3,0 %	3,4 %	3,2 %	2,9 %	3,8 %	2,3 %	3,0 %	3,1 %	2,9 %
MAY	1,8 %	2,0 %	1,6 %	1,2 %	1,6 %	1,4 %	1,7 %	2,0 %	0,3 %	1,6 %
JUNE	0,0 %	0,2 %	-0,7 %	0,3 %	-0,3 %	-0,5 %	-0,8 %	-1,0 %	-1,7 %	-0,9 %
JULY	3,3 %	3,7 %	2,3 %	2,0 %	2,9 %	1,8 %	2,3 %	2,9 %	3,7 %	2,9 %
AUGUST	1,2 %	1,1 %	0,5 %	-0,3 %	0,6 %	-0,5 %	0,0 %	-0,5 %	-1,3 %	0,1 %
SEPTEMBER	0,6 %	0,4 %	-1,3 %	-0,3 %	-1,2 %	-1,3 %	-2,0 %	-2,7 %	-1,6 %	-1,6 %
OCTOBER	0,9 %	-0,2 %	-0,3 %	2,1 %	1,5 %	1,0 %	0,3 %	1,0 %	0,5 %	0,6 %
NOVEMBER	1,3 %	2,2 %	0,0 %	-0,5 %	-0,3 %	0,3 %	0,3 %	0,5 %	-0,7 %	0,1 %
DECEMBER	1,3 %	0,0 %	0,9 %	0,4 %	2,5 %	3,0 %	3,5 %	3,6 %	3,7 %	2,0 %

Table 6.10: Monthly mean returns for size portfolios (EW)

We see in table 6.10, that January has the highest return in each decile portfolio, except from portfolio X10 where April and July are the months with highest returns and portfolio X8 where December has the highest return. The January return for portfolio X1 is also largest among the decile portfolios, with a monthly return of entire 11%, this is much larger than for portfolio X10, which has a January return of only 2,1%. These results support the theory of the January effect being a small-firm effect.

6.5 Has the January Effect Changed Over the Years?

Because we have found significant evidence that there exists a January effect for the EW portfolio, and especially for the smallest size portfolios, it would be interesting to see how this effect has changed during our test period. Maybe the effect has decreased over the years? To find this out, we divide our period into three sub-periods. First sub-period includes the years 1980 to 1990, second sub-period includes the years 1991 to 2002, and the third sub-period includes the years 2003 to 2014. The tests for normality and heteroscadatisity for both portfolios can be found in Appendix A3. We found that we had no problem with heteroscedatisity, but the samples were not normally distributed. To make the results more valid we use the bootstrap regression in this section. We choose to draw 50 000 bootstrap samples. The results are shown in table 6.11.

	1980-1990			1991-2002			2003-2014		
	Coef.	z	sig. level	Coef.	z	sig. level	Coef.	z	sig. level
α_1	0.096	5.12	***	0.052	3.15	***	0.028	1.81	*
α_2	-0.060	-2.34	**	-0.020	-0.89	-	-0.008	-0.44	-
α_3	-0.063	-2.53	**	-0.028	-1.26	-	-0.016	-0.89	-
α_4	-0.065	-2.68	***	-0.018	-0.80	-	-0.002	-0.10	-
α_5	-0.094	-3.95	***	-0.026	-1.38	-	-0.014	-0.64	-
α_6	-0.108	-4.71	***	-0.066	-3.24	***	-0.015	-0.73	-
α_7	-0.057	-2.57	***	-0.032	-1.44	-	-0.009	-0.49	-
α_8	-0.084	-3.92	***	-0.065	-2.20	**	-0.021	-1.09	-
α_9	-0.087	-3.62	***	-0.089	-3.89	***	-0.031	-1.28	-
α_{10}	-0.097	-3.48	***	-0.032	-1.4	-	-0.021	-0.85	-
α_{11}	-0.097	-4.04	***	-0.052	-2.05	**	-0.018	-0.90	-
α_{12}	-0.089	-3.37	***	-0.035	-1.56	-	0.005	0.29	-

Table 6.11: Results from the bootstrap regression for the EW portfolio, divided into three sub-periods

From table 6.11 we observe that the return in January has decreased over the period, from a 9,1% monthly mean return in first sub-period to a monthly mean return of 2,8% in the third sub-period. We also see that the December return in the third sub-period is higher than the return in January, which could indicate that the January effect has shifted more to a December effect or a turn-of-the-year effect. According to the results in table 6.11, we only find significant evidence for a January effect in the first sub-period. Here, all the coefficients are significant at a level of at least 5%. In the second sub-period there are only a few of the coefficients that are significant. When we look at the third sub-period, none of the coefficients are significant. This means that we do not find significant evidence for a January effect in the period 1991 to 2014, only for the period 1980 to 1990. Does this mean that the effect has disappeared totally? To find this out, we also see how the effect has changed for the smallest size portfolio (X1) from section 6.4. The results are shown in table 6.12.

	1980-1990			1991-2002			2003-2014		
	Coef.	z	sig. level	Coef.	z	sig. level	Coef.	z	sig. level
α_1	0.210	6.85	***	0.069	4.99	***	0.060	4.92	***
α_2	-0.145	-3.07	***	-0.039	-2.59	***	-0.030	-2.02	**
α_3	-0.127	-3.13	***	-0.015	-0.37	-	-0.050	-3.27	***
α_4	-0.148	-3.92	***	-0.015	-0.65	-	-0.054	-3.66	***
α_5	-0.196	-4.69	***	-0.031	-1.14	-	-0.059	-3.59	***
α_6	-0.228	-6.44	***	-0.064	-3.56	***	-0.046	-3.19	***
α_7	-0.164	-4.47	***	-0.040	-1.67	*	-0.036	-2.31	**
α_8	-0.192	-5.73	***	-0.058	-2.31	**	-0.053	-3.9	***
α_9	-0.176	-4.60	***	-0.082	-4.5	***	-0.061	-4.27	***
α_{10}	-0.196	-4.93	***	-0.066	-2.75	***	-0.049	-3.26	***
α_{11}	-0.182	-4.54	***	-0.065	-2.85	***	-0.051	-2.76	***
α_{12}	-0.208	-5.85	***	-0.041	-2.22	**	-0.051	-2.98	***

Table 6.12: Results from the bootstrap regression for the 10% smallest firms in the EW portfolio, divided into three sub-periods

From table 6.12 we see that the return in January has decreased considerably from the first sub-period to the following two sub-periods. In the first sub-period January had a monthly mean return of 21% and then it decreased to a monthly mean return around 6-7%. We see that in the first sub-period, all the coefficients are significant at a 1% significance level. The second sub-period only have a few coefficients that are not significant, March, April and May. For the third sub-period the coefficients are significant for at least a 5% significance level. This means that we only find significant evidence for a January effect for the period 1980 to 1990 and from 2003 to 2004. It seems like the January effect for the smallest firms existed in the first period then it disappeared in the second sub-period, before it reappeared in the third sub-period. The results from table 6.12 indicate that the January effect still exists in Norway and that it is mainly a small-firm effect.

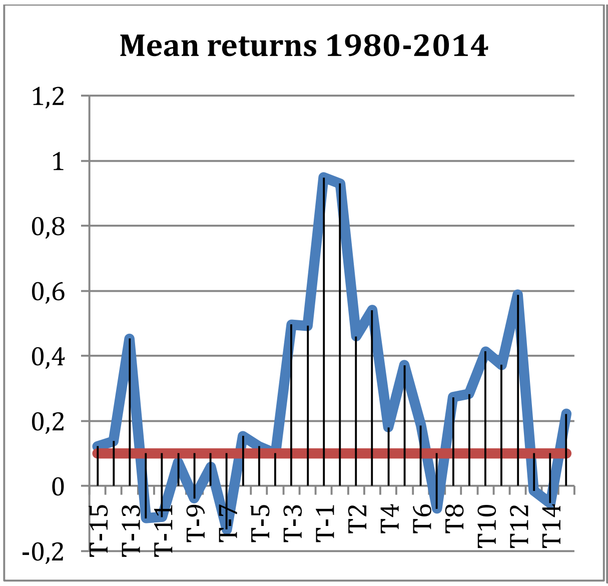
6.6 The Turn of the Year

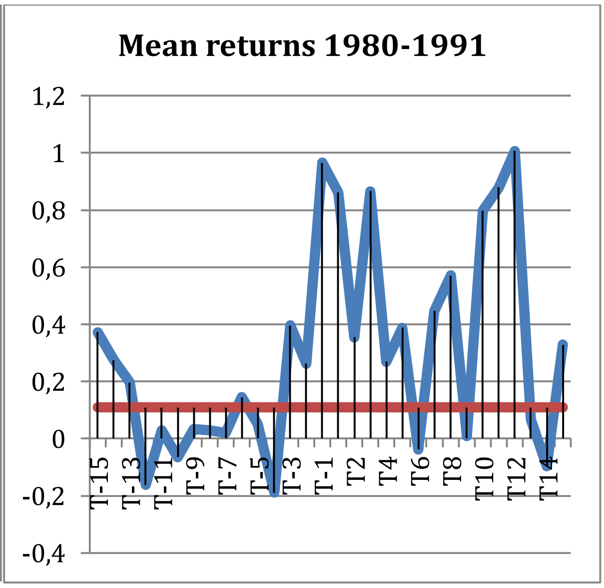
In recent years, the January effect has become more known as the turn-of-the-year effect. Researchers have indicated that the days when the returns are abnormally high have moved more to the first trading days in January, and even to the last trading days of December (Szakmary & Kiefer, 2004). In section 6.5 we found that for the last sub-period in the EW portfolio, December had a higher monthly mean return than January and the other ten months. We will therefore see which days in December and January that have higher returns than the mean return for the whole year. We use the EW daily returns for the last fifteen trading days in

December and for the first fifteen trading days in January. We have in total 34 year-turns, starting with the end of year 1980 and ending with the beginning of year 2014.

In this case we will use a descriptive approach to see which trading days during December and January the returns are higher than the global mean, an if this has changed during the period. We use line diagrams to present the results. T1 represents the first trading day in January (current month), T2 the second trading day in January, etc. T-1 represents the last trading day in December (previous month), T-2 the second last trading day in December, etc. We ignore days that do not fall into this interval. We also calculate the global mean return for each period, which consists of the average mean returns of all trading days in that period, and we assume 250 trading days a year.

First, we look at the mean returns for the trading days in December and January in the period 1980-2014 all at once, then we divide this period into three sub-periods. Global means for each period varies from around 0.08% until 0.11%. In figure 6.5 we see the line diagrams where the blue lines (▬) represent daily mean returns for each period, and the red lines (▬) represent the global daily mean return for each period. Trading days are plotted at the horizontal axes, and the daily returns (given in percent) are plotted at the vertical axes.





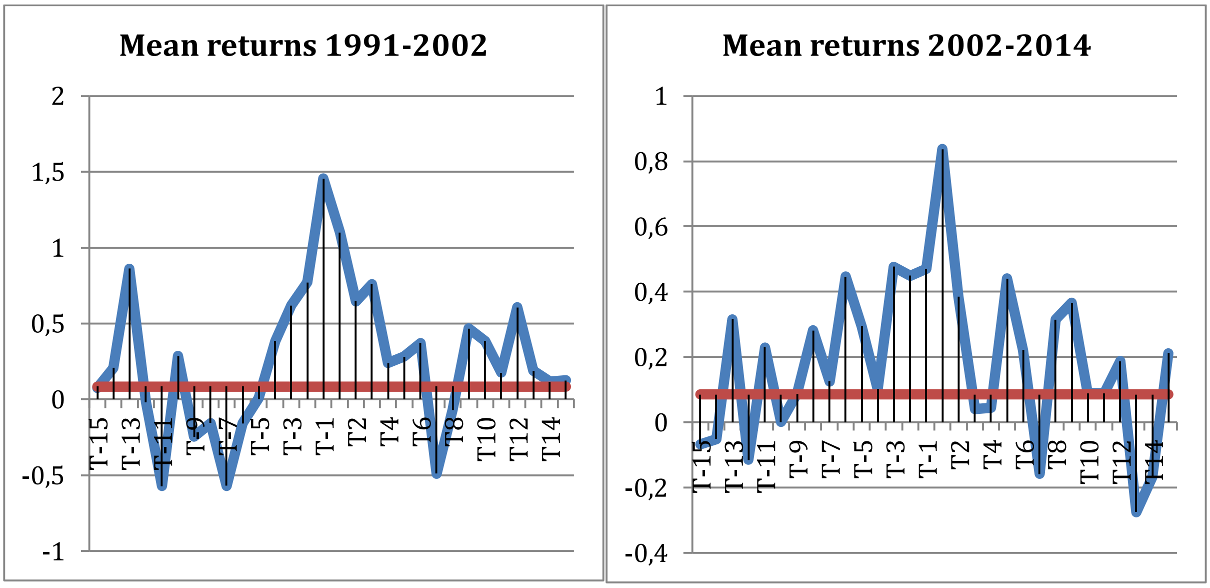


Figure 6.5: Line diagrams showing daily mean returns for trading days in December and January

When looking at the resulting line diagram for the whole period (1980-2014), we see that the high positive returns starts at the fourth last trading day of December and last until the sixth first trading day of January. This indicates that the "effect" seems to start already a few days before the month of January. When looking at the three sub-periods, we see that the daily returns vary widely. The first sub-period show most positive, high returns in January, starting on the third last trading day in December. Second sub-period show fewer high positive returns in January, and the high positive returns start from the fourth last trading day in December. The third sub-period does not show many high January returns either, and the high returns starts already from the eight last trading day in December. Overall, the line diagrams show that there exist higher returns during the trading days in January in the beginning of the period. The last trading day in December show higher returns the whole period, and this has expanded during the period. It is difficult to draw a conclusion from these graphs, but it seems like the January effect starts earlier for each period. One explanation for this change may be that investors are aware that the stock returns will increase in January, and thus they try to buy these stocks before the expected increase, leading to higher returns in the last trading days of December.

6.7 Possible Explanations for a January Effect in Norway

Two reasons for the January effect that is frequently mentioned in other studies, is the tax-loss selling hypothesis and the window-dressing hypothesis. We therefore want to see if these hypotheses could be relevant in Norway as well. First, we will look at tax-loss selling. The

Taxation Act in Norway says that, in general, gains on realization of shares etc. are considered as taxable income, and losses on realization of shares etc. may be deducted from the taxpayer's income, cf. § 10-31 (Skatteloven, 2006). This means that investors may have incentives to keep stocks with a high rise in prices in order to postpone tax payments, and to sell stocks that has decreased in value in order to get a deduction in tax payments. By the Tax Reform of 2006, a new law that prevent chain taxation within the corporate sector was introduced (Finansdepartementet, 2013). According to this law, corporate shareholders are exempt from taxation of income and does not have the right to deduct losses, cf. § 2-38 (1) (Skatteloven, 2012). The incentive to sell losing stocks may supports the tax-loss selling hypothesis and the January effect, but the Tax Reform of 2006 may have decreased the incentives for tax-loss selling in recent years, at least among the corporate shareholders.

Regardless of which country the institutional managers are located; we would guess that all of them would be hesitant in showing their portfolio holdings that have declined in value. We would therefore assume that the window-dressing hypothesis would exist in Norway just as in any other country. According to the Securities Funds Act in Norway, the fund management company should for each mutual fund publish an annual report and a half-year report cf. § 8-1 (Verdipapirfondloven, 2011). Publications of portfolio holdings might give incentives to window dressing, but a counterargument to this hypothesis is that is has become more common for managers to inform investors what stocks they have traded and when they were traded, this to create more transparency and to signal that they are serious with what they do.

It is difficult to conclude what reasons lie behind the existence of a January effect in Norway without doing a more thorough investigation. It is reasonable to assume that there is not one factor, but that there lies many explanations behind that jointly creates a January effect. This can both be behavioral factors, macroeconomic factors and other economic factors in the market, like taxes. We are not going to go deeper into this in this thesis, but it could be an interesting topic for further investigation.

7 Testing for the Other January Effect

Because many researchers have shown that the January effect exists in global stock markets, they have recently been interested in finding out if January returns have a predictive power for the following 11 months. This phenomenon is referred to as "the other January effect". In this chapter of the thesis, we want to see if this effect also exists in Norway, and that the mean returns for the following 11 months will likely be higher after positive January returns than after negative Januarys. To support our theory about the other January effect, we expect to find significantly positive coefficients for the remaining 11 months of the year if January returns are positive, and significantly smaller coefficients for the remaining 11 months of the year if January returns are negative.

7.1 Methodology

We follow the methodology proposed by Cooper, McConnell, and Octchinnikov (2006). We use a regression model with a dummy variable, and test the significance of parameter α_2 using the following model for EW and VW raw returns:

$$r_{feb-dec,t} = \alpha_1 + \alpha_2 D_{jan,t} + \varepsilon_t \qquad (3)$$

For EW and VW excess returns, the model is:

$$r_{feb-dec,t} - r_f = \alpha_1 + \alpha_2 D_{jan,t} + \varepsilon_t \qquad (4)$$

where $r_{feb-dec,t}$ is the yearly average raw return for February to December, $r_{feb-dec,t} - r_f$ is the yearly average excess return for February to December, t = year, α_1 is a constant, α_2 denotes the differences between the January returns and the returns in the 11 other months. $D_{jan,t}$ is a dummy variable that takes the value of one when the January returns are positive and the value zero when the January returns are negative. ε_t is the error term that we assume is normally distributed.

If we take an example with raw returns, and we have a constant that is -1 % and the difference between January and the 11 other months is 3%, model (3) would be:

$$r_{feb-dec,t} = -0.01 + 0.03 * 1 = 0.02$$

This result tells us that when the return in January is positive, then the rest of the year will have an average return of 2%. For negative Januarys the dummy variable would be equal to zero, and we would have a negative average return of 1% for the rest of the year.

The F-test's null hypothesis states that January does not have a predictive power for the following 11 months of the year in the Norwegian stock market. The alternative hypothesis states that January can predict the returns for the following 11 months of the year in the Norwegian stock market. Expressed in formal terms:

$$H_0: \quad \alpha_2 = 0$$
$$H_A: \quad \alpha_2 \neq 0$$

If the difference between the January returns and the returns in the 11 other months is equal to zero, then the parameter α_2 should be insignificant. This means that we fail to reject the null hypothesis.

7.2 Parametric Testing of the Equally-Weighted Portfolio

To test if the other January effect exists at the OSE, we use the OLS-method to estimate the parameters of the model. Given the estimates, we will perform parametric tests where we do a regular t-test and interpret the p-values of the test. Because these test procedures are only valid if the assumptions underlying model (3) and (4) hold, we therefore will perform some non-parametric tests if it appears that our residuals are not normally distributed. The processed results from our regression are shown in table 7.1, the unprocessed results are shown in appendix A4. We have divided the table into columns with positive and negative Januarys ($\alpha_1 + \alpha_2$ and α_1 respectively), and the coherent returns for the following 11 months are given under. We also show the spread between the 11 months' returns following positive Januarys and the 11 months' returns following negative Januarys. N stands for the number of months with positive or negative returns. The p-values for the mean return in the 11 months following positive Januarys are given in parentheses ( ), and in brackets [ ] for negative Januarys.

PORTFOLIO	POSITIVE JANUARYS		NEGATIVE JANUARYS		SPREAD	P-VALUE
	Returns %	N	Returns %	N		
EW	1.69	31	-1.74	4	3.43	(0.005) ** [0.110] –
EW-RF	1.10	31	-2.51	4	3.61	(0.004) *** [0.028] **
VW	2.10	25	0.67	10	1.43	(0.061) * [0.293] –
VW-RF	1.44	25	0.17	10	1.27	(0.112) – [0.801] –

Table 7.1: Processed results from the OLS regressions

From table 7.1, we see that in the case of the EW portfolio, we have positive mean returns in the 11 months following a positive return in January, and negative returns in the 11 months following a negative return in January. The spread between positive and negative Januarys is 3.43% and 3.61% for the raw and excess EW portfolio respectively. For the excess returns, we have a significant other January effect with a significance level of 5%, even though we only have four negative Januarys. For the raw returns, we see that only the positive returns are valid, whereas the negative returns are not statistically significant.

When looking at the VW portfolio, we have positive mean returns in the 11 following months both after a positive and a negative return in January, but the return is lower when January is negative. The spread between positive and negative Januarys is 1.43% and 1.27% for the raw and excess VW portfolio respectively. We only have one significant result, for positive January returns in the raw returns, the other values are not significant. We see that the returns for the VW portfolio are higher than the returns for the EW portfolio, both for positive and negative Januarys, thus the spread is larger for the EW portfolio.

Like the procedure in chapter 6 with the January effect, we will also here check for normality. We will look at the raw and excess residuals for both portfolios. We did not find a problem with heteroscedasticity, this test is shown in appendix A4. In figure 7.1, we see the density of the residuals, the normal density line (solid line) and the kernel density line (dashed line).

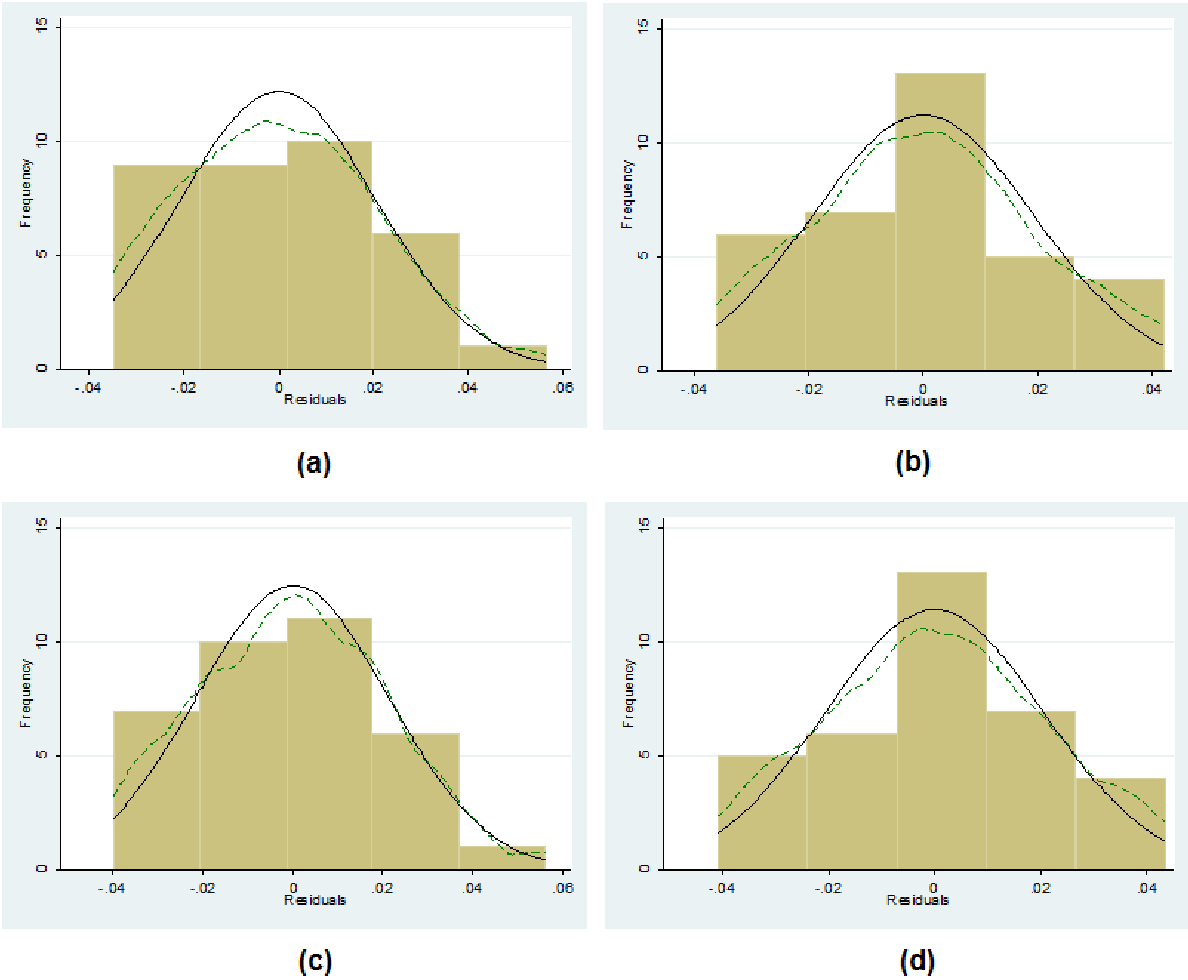


Figure 7.1: Distribution plots for the residuals

	RESIDUALS			
	EW (a)	VW (b)	EW-Rf (c)	VW-Rf (d)
SKEWNESS	0.418	0.147	0.260	0.042
KURTOSIS	2.941	2.527	2.859	2.435

Table 7.2: Skewness and kurtosis variables

In figure 7.1 and table 7.2, we see that the distribution of all the residuals slightly deviates from normality. The columns in table 7.2 are marked (a) to (d), corresponding to plots (a) to (d) in figure 7.1. In (a) we have the residuals for the EW portfolio (raw returns). We observe more values to the left of the mean, giving us a positive skewness (>0). The kurtosis is close to three, but the distribution is a little flatter than the normal distribution. For (b) we have the residuals for the VW portfolio (raw returns). The skewness is slightly positive (>0) and lies closer to the normal distribution. We see that the density is flatter with thicker tail than the normal density, this is confirmed by the kurtosis value lower than three. (c) shows the residuals for the EW excess returns. The residuals are positively skewed (>0) and the kurtosis is lower than three, giving a flatter density. (d) shows the residuals for the VW excess returns. The skewness lies close to the normal density (≈0), but the kurtosis is lower than three. Because we have so few sample years with negative Januarys, it is hard to draw a conclusion just from these histograms. Therefore, to determine if we can assume normality, we run a Shapiro-Wilks normality test.

SHAPIRO – WILK NORMALITY TEST

	P-VALUES
EW	0.636
EW-RF	0.726
VW	0.851
VW-RF	0.860

Table 7.3: Test statistics for the Shapiro-Wilk normality test

According to the values from table 7.3, we fail to reject the null hypotheses, which states that the residuals are normally distributed. This means that we do not need to perform any non-parametric tests, and we can use the original results and assume that our data and residuals are normally distributed.

We will now see if there exists a correlation between the average January returns and the average returns for the following 11 months of the year. This relationship can formally be represented by:

$$r_{feb-dec,t} = \alpha_1 + \alpha_2 r_{jan,t} + \varepsilon_t \qquad (5)$$

$$r_{feb-dec,t} - r_f = \alpha_1 + \alpha_2 r_{jan,t} + \varepsilon_t \qquad (6)$$

where $r_{jan,t}$ represents the mean return in January. In figure 7.2, the x-axis represents the average January returns, whereas the y-axis represents the average returns in the following 11 months of the year. To support the other January effect, this relationship (shown by the fitted line) should be increasing and positive.

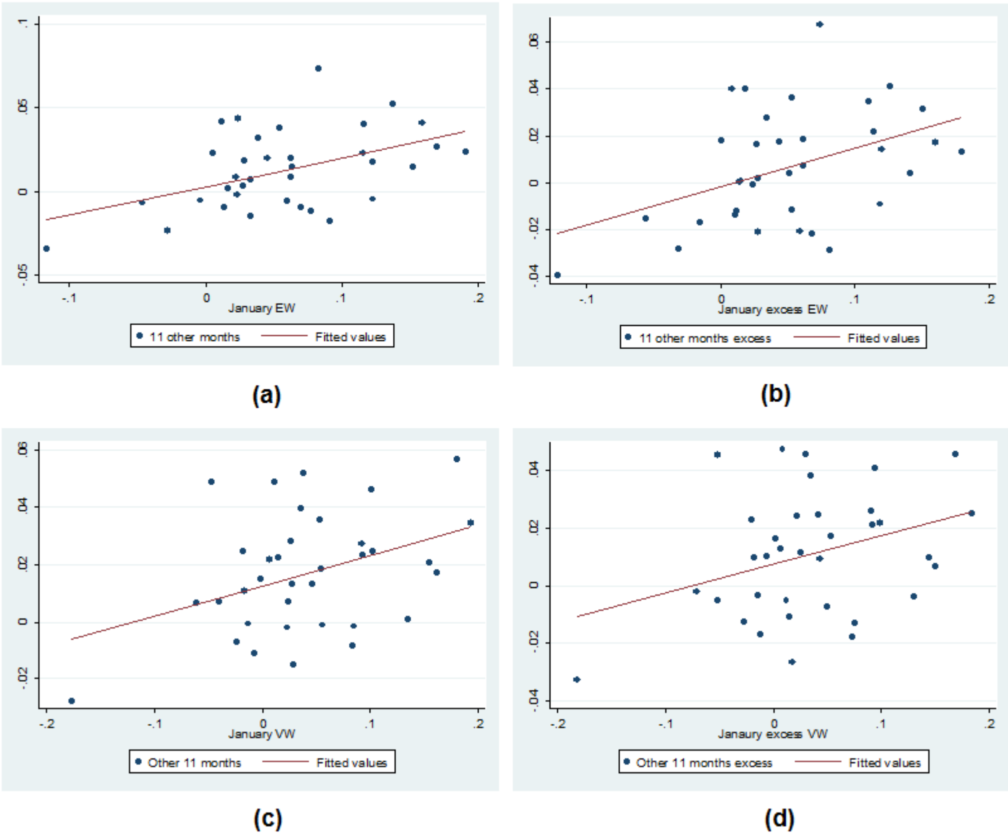


Figure 7.2: January vs. the other 11 months, for each portfolio

We see from the plots in figure 7.2, that there seems to be a positive correlation between January returns and the returns of the 11 following months, but the points are widely spread around the fitted line. Even if there are deviations from the fitted line, this indicates that if January has positive returns then the rest of the year tend to have positive average returns. If January has negative returns then the rest of the year tend to be negative or at least lower than if January has positive returns. This can be shown by the correlation coefficients in table 7.4.

CORRELATION

EW VS JAN	0.469
EW-RF VS JAN-RF	0.427
VW VS JAN	0.389
VW-RF VS JAN-RF	0.343

Table 7.4: Correlation coefficients between Januarys and the following 11 months

We see in table 7.4, that all the average returns for the following 11 months are positively correlated with January returns. This suggests that when January has positive (negative) returns, then the rest of the year also tend to have positive (negative) average returns.

Even though there exists a positive correlation between the average return of the portfolios and the average returns in January, it is only the excess return for the EW portfolio that has statistically significant values for both the positive and negative Januarys. The EW and VW raw returns have significant values only for positive Januarys. Our results finds evidence for the theory of the other January effect for the positive Januarys, except in the case of the excess VW portfolio, but we do not find evidence for the theory regarding the negative Januarys.

7.3 Testing Size Portfolios

Because we found evidence of the other January effect when looking at the EW portfolio, but not when looking at the VW portfolio, it would be interesting to compare the returns for the smallest firms with the returns for the largest firms to see if there is a difference with respect to the size of the firms. We do a linear regression for the 10% smallest firms, the second 10% smallest firms, and for the 10% largest firms, denoted by X1, X2 and X10 respectively. Our regression models are model (3) and (4) from section 7.1. For these portfolios we did not find a problem with heteroscedasticity. We failed to assume normality, therefore we will use the bootstrap method in this section. The tests are shown in appendix A5. We choose to draw 50 000 bootstrap samples for both the raw and the excess return. The results for the EW raw returns are shown in table 7.5.

			X1		
	Coef.	**t**	**P>t**	**Sig.level**	**Spread**
α_1	-0.001	-0.05	0.962	-	0.023
α_2	0.023	1.70	0.088	*	
			X2		
	Coef.	**t**	**P>t**	**Sig.level**	**Spread**
α_1	0.015	0.63	0.527	-	0.003
α_2	0.003	0.10	0.919	-	
			X10		
	Coef.	**t**	**P>t**	**Sig.level**	**Spread**
α_1	0.008	1.07	0.287	-	0.003
α_2	0.003	0.36	0.721	-	

Table 7.5: Results from the bootstrap regression for portfolios X1, X2 and X10 for EW raw returns

From table 7.5 we can take an example with X1. If January returns were positive then the mean return for the 11 following months would be:

$$\alpha_1 + \alpha_2 = (-0{,}001) + 0{,}023 = 0{,}022$$

If January returns are negative, then the mean return in the 11 other months is:

$$\alpha_1 = -0{,}001$$

In table 7.5 we see that the results are coherent with the theory of the other January effect, but only one coefficient is statistically significant at a 10% level. This means that we do not find significant evidence for the other January effect for any of the decile portfolios. We also see that the spreads are narrow, indicating that the difference between the returns in the 11 months following a positive and a negative January are quite small. This indicates that the other January effect is independent of the size of the firms. We now want to see if this is also the case when using EW excess returns, the results are shown in table 7.6.

	X1				
	Coef.	**t**	**P>t**	**Sig.level**	**Spread**
α_1	-0.004	-0.36	0.720	-	0.020
α_2	0.020	1.86	0.062	*	
	X2				
	Coef.	**t**	**P>t**	**Sig.level**	**Spread**
α_1	0.008	0.36	0.718	-	0.003
α_2	0.003	0.14	0.887	-	
	X10				
	Coef.	**t**	**P>t**	**Sig.level**	**Spread**
α_1	-0.011	-1.87	0.061	*	0.022
α_2	0.022	3.11	0.002	***	

Table 7.6: Results from the bootstrap regression for portfolios X1, X2 and X10 for EW excess returns

In table 7.6, we have results that are coherent with the other January effect. We fail to reject the null hypotheses for portfolio X1 and X2, but we reject the null hypothesis for the X10 portfolio. We also see that the spreads are low, indicating that the difference between the returns in the 11 months following a positive and a negative January are small. According to these results, the other January effect do not seem to be affected by the size of the firm.

8 Conclusion

In this thesis we have examined the two anomalies "the January effect" and "the other January effect". The January effect was first discovered by Wachtel in 1942, and has since then been widely discussed and researched. The other January effect is a more unfamiliar anomaly that was discovered by Hirsch in 1972, it has not been studied to the same extent as the January effect, but has become more familiar in recent years. Research has confirmed the January effect on a global scale, whereas the other January effect is not a global phenomenon.

When we tested for the existence of the January effect we used the non-parametric procedure because we failed to fulfil the assumption of normality. We found that the EW portfolio exhibit a January effect with a 10% significance level, whereas the VW portfolio did not show significant results. The mean return for the EW portfolio in January was 5.8%, whereas the other months had significantly lower mean returns. For example, April had the highest mean return among the other months with a return of 3.2%, whereas September had the lowest mean return with a return of -1.1%. The mean return in January was 2.6% higher than in April, and 6.9% higher than in September. For the VW portfolio there was only four of the other months that were significant, and the returns were much lower than the returns in the EW portfolio.

Because all coefficients for the EW portfolio were significant, and the EW portfolio gives relatively higher weight to small firms than the VW portfolio, we also tested for the January effect based on firm size. Our results showed that the January mean returns decreased with the size of the firms, with only two exceptions. The portfolio with the 10% smallest firms had a 11% monthly mean return in January, this was much higher than the second highest January mean return in the portfolio with the 10% second smallest firms, with a 6.8% mean return. We found that the smallest decile portfolio had significant levels of difference in the return between January and all the other months, at a 1% level. The largest size portfolios did not show a significant January effect.

During our period from 1980 to 2014, the January effect did change. When we divided the period into three sub-periods, we only found a significant January effect for the EW portfolio in the first sub-period. When we divided the EW portfolio consisting of the 10% smallest firms into three sub-periods, we found that the January effect was not significant in the period 1991 to 2002, whereas for the sub-periods before and after it was significant at a 1% level.

When testing for the other January effect we only found significant values for the EW excess return portfolio, though we only had four observations with negative January returns. Our result from the excess EW portfolio, indicated that if January returns were positive then the average returns for the following 11 months would be 1.10%, whereas it would be - 2.51% if January exhibited negative returns. We also found significant evidence for the positive Januarys, both for the EW and the VW raw portfolios. There was a slightly positive correlation between the return in January and the returns for the rest of the year. This contributed to the conclusion that if January exhibited positive returns, then the other 11 months of the year were more likely to have positive returns. We also tested if the other January effect was affected by the size of the firms, but we did note find such a relationship.

Our results indicate that there exists a January effect for the EW portfolio and a other January effect for the EW excess portfolio in the Norwegian stock market. We also find evidence that the January effect has disappeared in the latest years for the EW portfolio as a whole, but that it still exists for the smallest firms. According to these finding, the January effect seems to be a small-firm effect. The existence of the January effect might be due to a combination of tax-loss selling, window-dressing, and other economic factors.

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A APPENDIX

A1 More Details About the Data

As mentioned in chapter 5, the data we use is provided by Bernt Arne Ødegaard, Professor in finance at the University of Stavanger. He describes the data more closely in his two papers "Empirics of the Oslo Stock Exchange: Basic Results" and "Empirics of the Oslo Stock Exchange: Asset Pricing Results". We will here present some of it, but to get a more detailed description and some more descriptive information we recommend that you read Ødegaard's papers (links in the reference list).

Ødegaard's data starts in 1980 and ends in 2014. The raw data that he used was from the Oslo Stock Exchange Data Service, it contained volume and daily observations of prices of all stocks traded at the Oslo Stock Exchange (OSE), as well as dividends and factors necessary when calculating returns. When calculating representative returns for the OSE he did not use all the stocks. He omitted stocks that had less than 20 trading days, stocks that had a price below 10 NOK, and stocks with a total value outstanding of less than 1 million NOK. When constructing the market portfolios he constructed two indices, equally-weighted and value-weighted. For value-weighting, he has used end of year values at the previous yearend. He mostly used monthly and annual NIBOR rates as the estimate of the risk-free rate, and calculated two interest rates: one monthly risk-free rate and one yearly risk-free rate (Ødegaard, 2015b). Ødegaard also calculated several portfolios that are sorted by similar criteria. He constructed the portfolios by grouping stocks at the OSE according to for example industries, momentum, and spread. The one we use in our thesis is the portfolio with stocks at the OSE sorted by company equity size. This portfolio is divided into ten portfolios with increasing firm size from 1980 to 2014 (Ødegaard, 2015a)

A2 Testing Size Portfolios

We test for heteroscedasticity and normality for all of the ten decile portfolios. X1 represent the 10% smallest firms, X2 represent the 10% second largest firms etc, and X10 represent the 10% biggest firms. First, we present the OLS regression result in table A2.1:

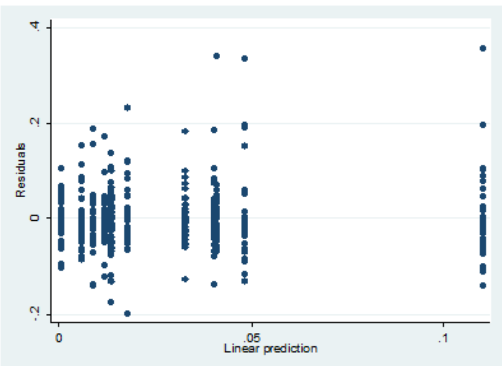
	X1			X2			X3			X4			X5		
	Coef.	t	sig. level	Coef.	t	sig. level	Coef.	t	sig. level	Coef.	t	sig. level	Coef.	t	sig. level
α_1	0.110	9.84	***	0.068	6.15	***	0.058	5.31	***	0.059	5.23	***	0.065	5.78	***
α_2	-0.069	-4.38	***	-0.012	-0.74	-	-0.021	-1.35	-	-0.040	-2.48	**	-0.022	-1.37	-
α_3	-0.062	-3.92	***	-0.055	-3.50	***	-0.028	-1.82	*	-0.039	-2.45	**	-0.043	-2.71	***
α_4	-0.070	-4.42	***	-0.038	-2.44	**	-0.024	-1.57	-	-0.027	-1.70	*	-0.036	-2.25	**
α_5	-0.092	-5.84	***	-0.048	-3.08	***	-0.041	-2.70	***	-0.045	-2.92	***	-0.049	-3.07	***
α_6	-0.110	-6.93	***	-0.065	-4.21	***	-0.065	-4.22	***	-0.056	-3.49	***	-0.068	-4.28	***
α_7	-0.077	-4.89	***	-0.031	-1.98	**	-0.035	-2.27	**	-0.039	-2.45	**	-0.036	-2.27	**
α_8	-0.098	-6.22	***	-0.057	-3.67	***	-0.053	-3.42	***	-0.062	-3.88	***	-0.059	-3.69	***
α_9	-0.104	-6.58	***	-0.064	-4.09	***	-0.071	-4.60	***	-0.062	-3.90	***	-0.077	-4.81	***
α_{10}	-0.101	-6.41	***	-0.070	-4.50	***	-0.060	-3.94	***	-0.038	-2.39	**	-0.050	-3.16	***
α_{11}	-0.097	-6.11	***	-0.046	-2.98	***	-0.058	-3.76	***	-0.064	-4.02	**	-0.068	-4.25	***
α_{12}	-0.097	-6.10	***	-0.067	-4.33	***	-0.049	-3.18	***	-0.055	-3.44	***	-0.040	-2.49	**
F-test		7.18	***		4.15	***		3.75	***		2.60	***		3.61	***

	X6			X7			X8			X9			X10		
	Coef.	t	sig. level	Coef.	t	sig. level	Coef.	t	sig. level	Coef.	t	sig. level	Coef.	t	sig. level
α_1	0.062	5.90	***	0.059	5.16	***	0.032	2.77	***	0.041	3.29	***	0.021	1.72	*
α_2	-0.033	-2.18	**	-0.038	-2.34	**	-0.012	-0.72	-	-0.026	-1.49	-	-0.012	-0.72	-
α_3	-0.041	-2.74	***	-0.040	-2.44	**	-0.011	-0.67	-	-0.022	-1.24	-	-0.004	-0.24	-
α_4	-0.024	-1.61	-	-0.036	-2.21	**	-0.002	-0.11	-	-0.010	-0.58	-	0.009	0.50	-
α_5	-0.049	-3.26	***	-0.042	-2.59	***	-0.012	-0.73	-	-0.039	-2.18	**	-0.005	-0.30	-
α_6	-0.067	-4.48	***	-0.067	-4.12	***	-0.041	-2.56	**	-0.058	-3.28	***	-0.029	-1.72	*
α_7	-0.045	-2.98	***	-0.036	-2.23	**	-0.003	-0.17	-	-0.004	-0.25	-	0.008	0.45	-
α_8	-0.068	-4.52	***	-0.059	-3.65	***	-0.037	-2.29	**	-0.055	-3.07	***	-0.020	-1.16	-
α_9	-0.076	-5.08	***	-0.080	-4.90	***	-0.058	-3.61	***	-0.057	-3.24	***	-0.036	-2.13	**
α_{10}	-0.052	-3.50	***	-0.056	-3.44	***	-0.021	-1.33	-	-0.037	-2.07	**	-0.014	-0.85	-
α_{11}	-0.059	-3.97	***	-0.056	-3.46	***	-0.026	-1.62	-	-0.048	-2.71	***	-0.020	-1.16	-
α_{12}	-0.032	-2.17	**	-0.025	-1.52	-	0.005	0.28	-	-0.004	-0.22	-	-0.001	-0.04	-
F-test		4.08	***		3.31	***		2.83	***		3.06	***		1.37	-

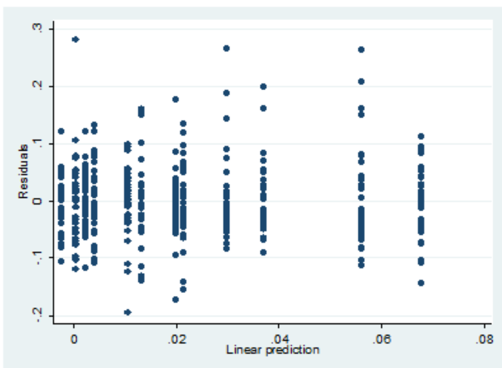
Table A2.1: Results from the OLS regression for the decile portfolios

Heteroscedatisity

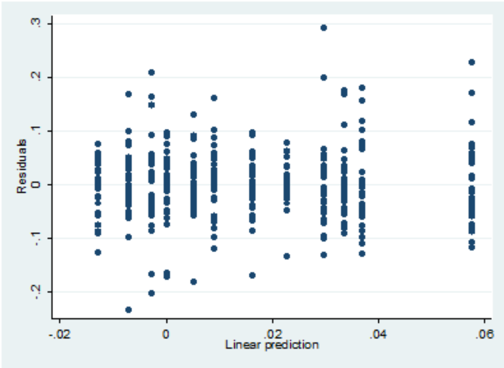
Second, we test for heteroscedasticity. We do this by plotting the residuals versus the fitted values, for all decile portfolios, to check for any patterns.



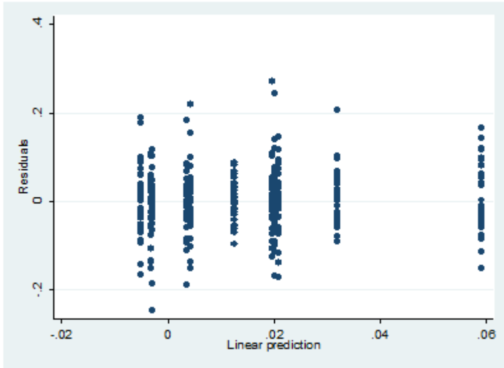
X1



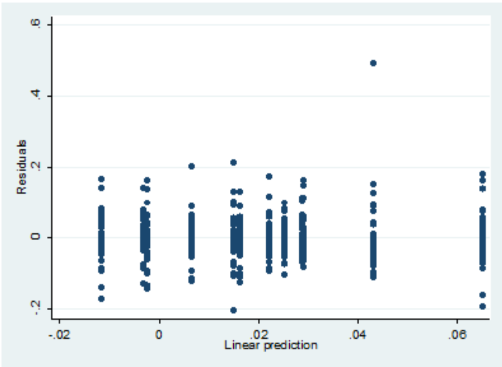
X2



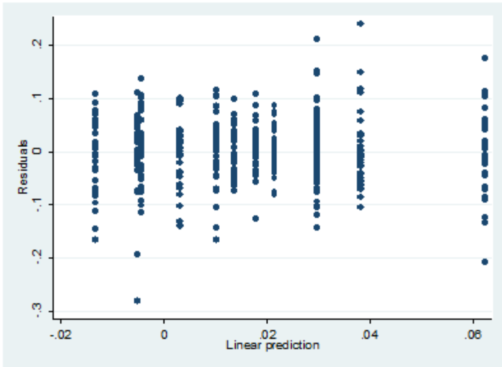
X3



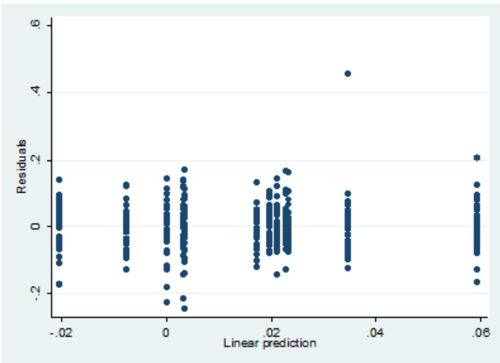
X4



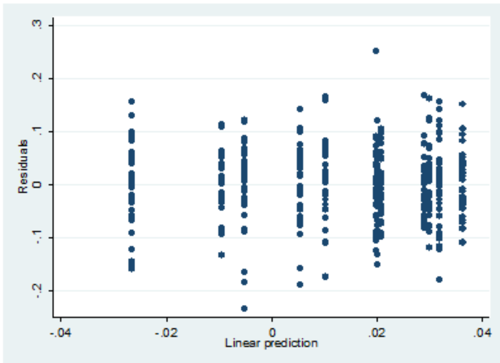
X5



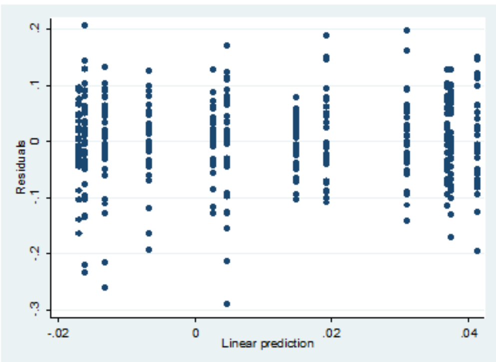
X6



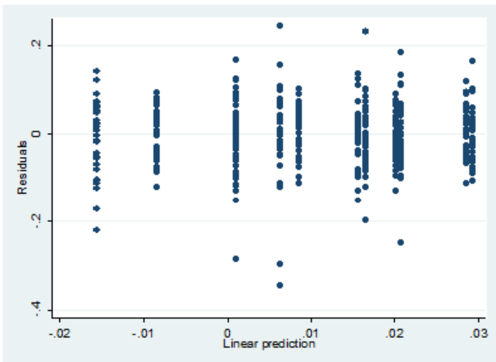
X7



X8



X9



X10

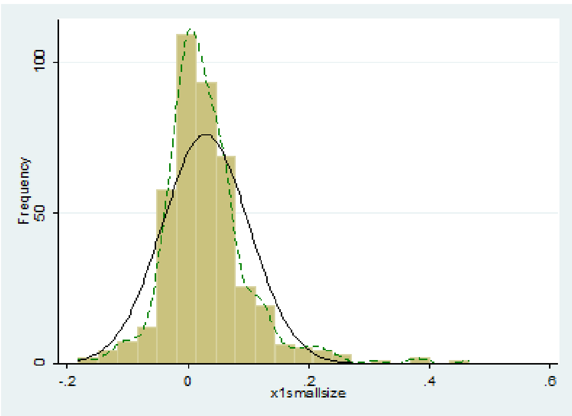
Figure A2.1: Plots of the residuals vs the fitted values for all decile portfolios

In figure A2.1, plot X1 represent the residuals versus the fitted values for portfolio X1, plot X2 represent the residuals versus the fitted values for portfolio X2 etc. We do not see any “visible” pattern from the plots, to confirm this we do an IM-test, the p-values are presented in table A2.1:

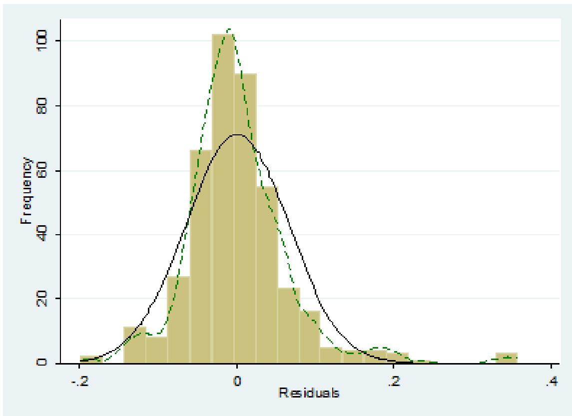
IMTEST	P-VALUES
X1	0.2452
X2	0.4994
X3	0.3551
X4	0.6290
X5	0.3059
X6	0.2096
X7	0.6040
X8	0.2676
X9	0.0382
X10	0.0443

Table A2.2: IM-test for all the decile portfolios

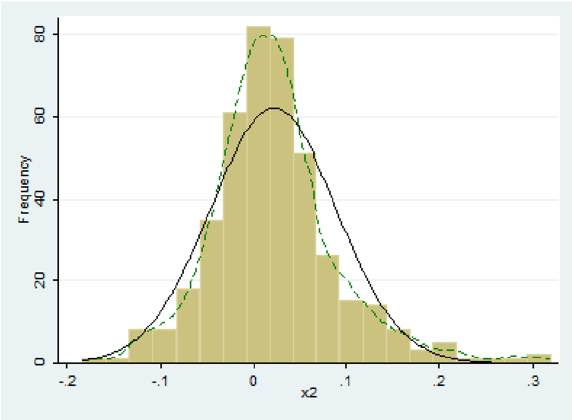
From the p-values in table A2.2, we can conclude that we do not have a problem with heteroscedasticity for all the portfolios. Because of this, we will not perform a regression with the robust option. Now we have to test for normality. We plot the distribution for all portfolios and for the residuals. The solid line is the normal density line and the dashed line is the kernel density line.



(a)



(b)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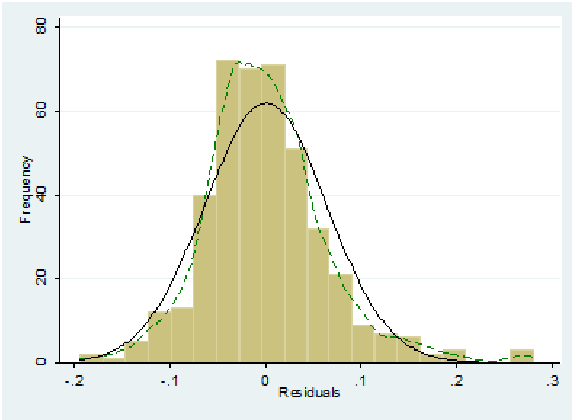
0
.1
.2
.3
x2

(c)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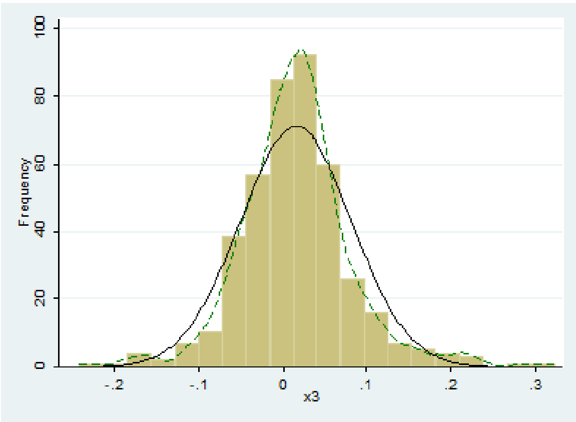
Residuals

(d)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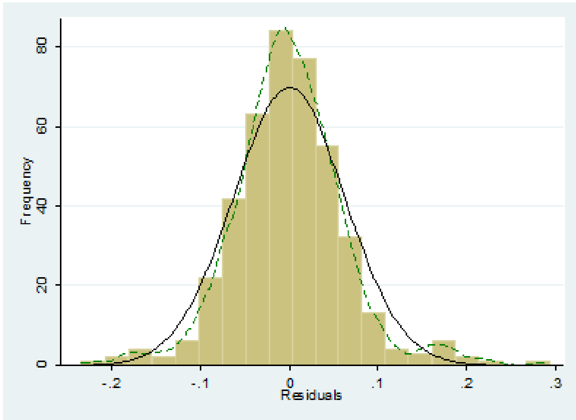
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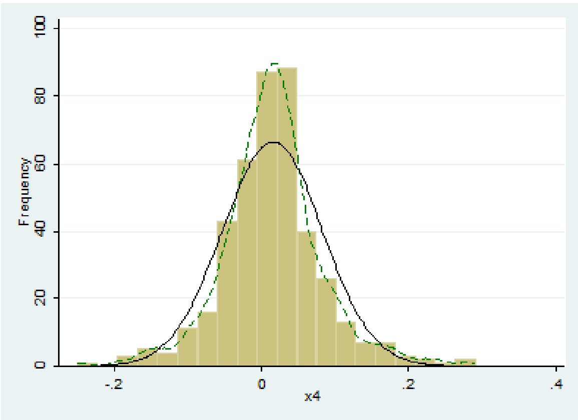
.2
.3
Residuals

(f)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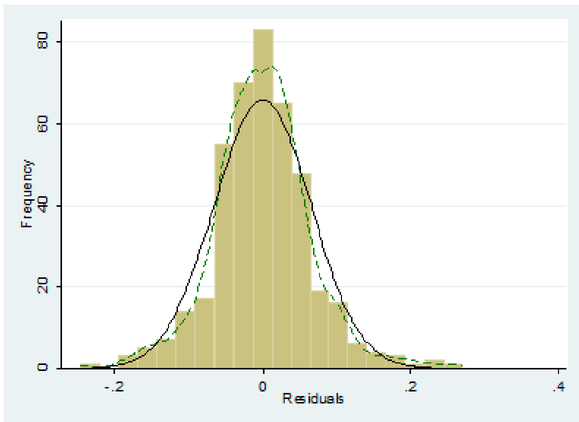
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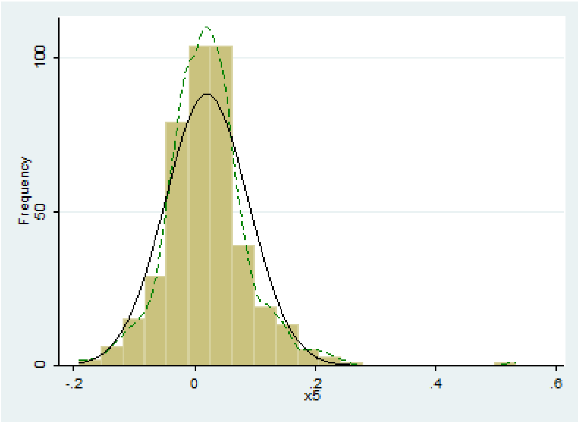
(h)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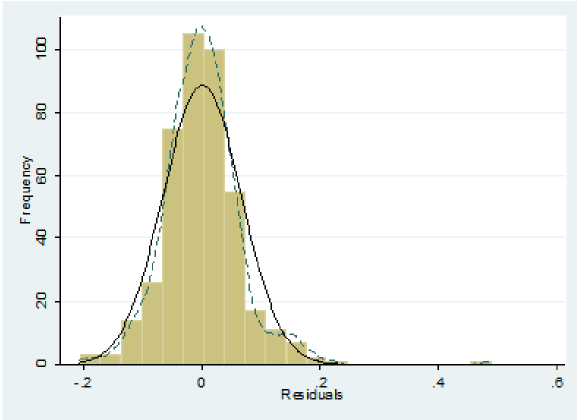
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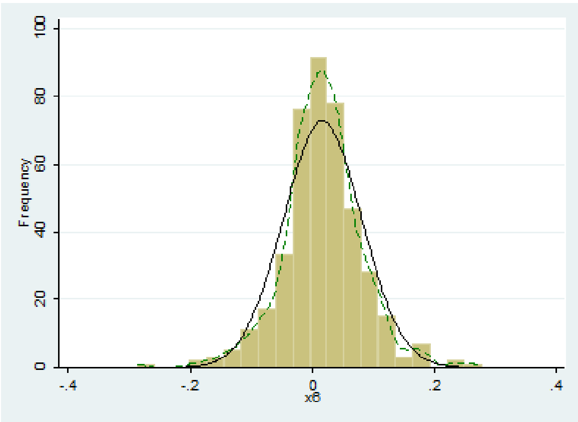
.2
.4
.6
Residuals

(j)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100
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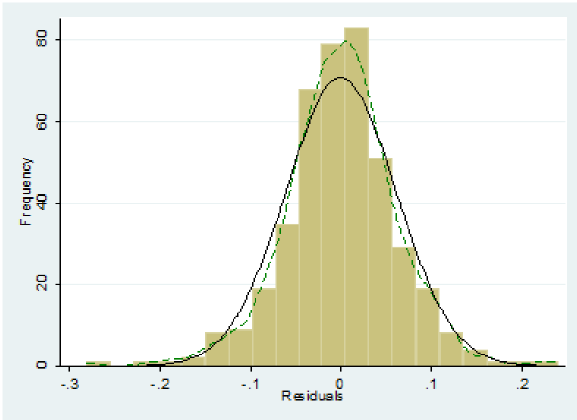
.4
x6

(k)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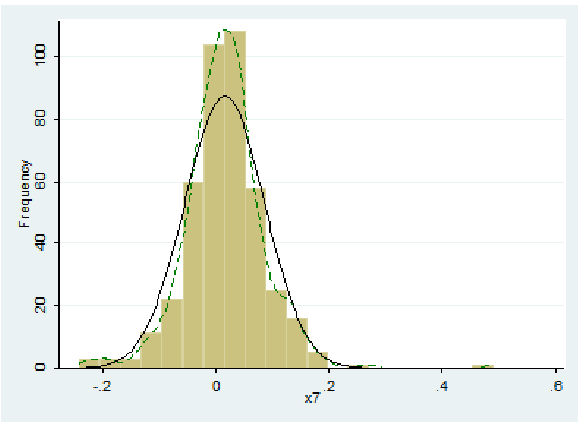
0
.1
.2
Residuals

(l)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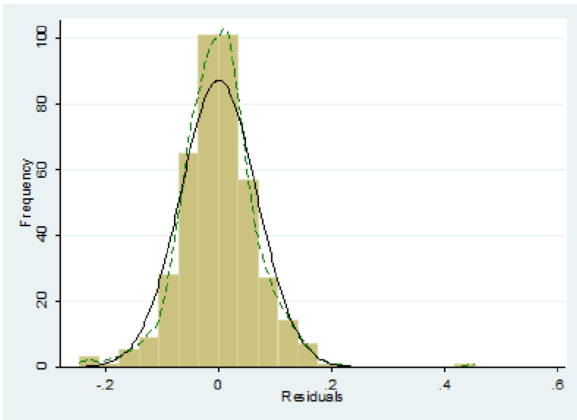
(m)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Residuals

(n)

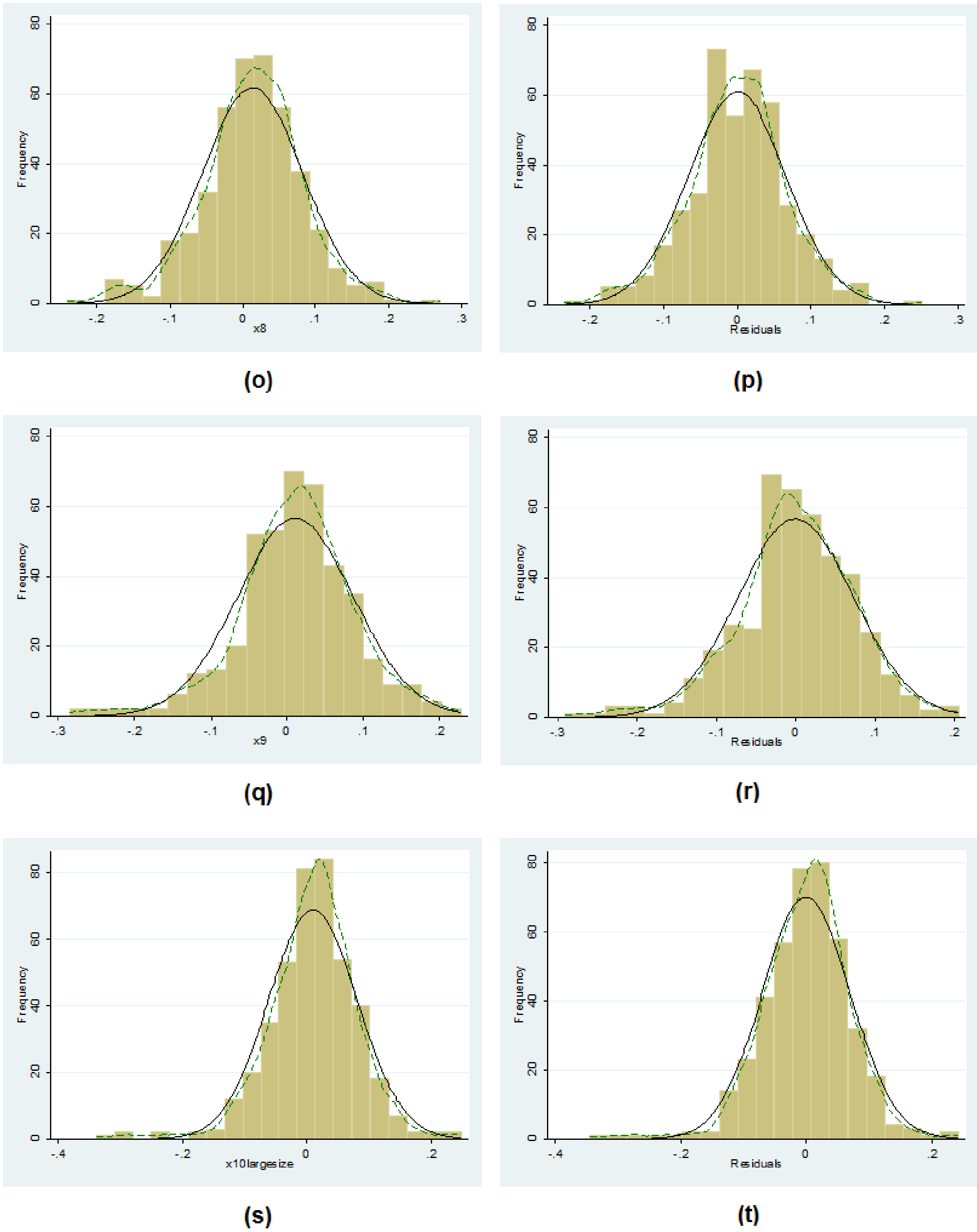


Figure A2.2: Distribution plots for all portfolios and residuals

In figure A2.2, plot (a) show the distribution for the X1 portfolio and plot (b) show the distribution of the residual for the X1 portfolio, plot (c) present the distribution of the X2 portfolio and plot (d) show the distribution of the residuals for the X2 portfolio, etc. We see deviations from the normal distribution in all the plots. The kurtosis and the skewness are presented in table A2.3

	SKEWNESS		KURTOSIS	
	EW	**Residuals**	**EW**	**Residuals**
X1	1.591	1.387	9.499	8.699
X2	0.818	0.780	5.293	5.241
X3	0.416	0.372	5.836	5.378
X4	0.261	0.259	5.028	4.813
X5	1.168	1.152	10.636	10.540
X6	-0.039	-0.158	5.264	4.761
X7	0.548	0.579	8.683	8.355
X8	-0.208	-0.116	4.020	3.739
X9	-0.457	-0.426	4.403	4.052
X10	-0.621	-.0582	5.829	5.736

Table A2.3: Values for skewness and kurtosis

The ten portfolios do not seem to be normally distributed. To confirm this we perform the Shapiro-Wilks test for normality:

	P-VALUE	
	EW	**Residuals**
X1	0.00000	0.00000
X2	0.00000	0.00000
X3	0.00000	0.00000
X4	0.00000	0.00000
X5	0.00000	0.00000
X6	0.00000	0.00009
X7	0.00000	0.00000
X8	0.00090	0.02460
X9	0.00001	0.00018
X10	0.00000	0.00000

Table A2.4: The Shapiro-Wilks normality test

We reject the null hypothesis. This means that the ten decile portfolios are not normally distributed, and we have to use the bootstrap method.

A3 Testing of the Sub-Periods for the EW and the X1 Portfolio

In this section we will test if the three sub-periods, both for the EW portfolio and the smallest EW size portfolio, are normally distributed and if we have a problem with heteroscedasticity. First, we perform the linear regression for the three sub-periods of the EW portfolio and the X1 portfolio.

	1980-1990			1991-2002			2003-2014		
	Coef.	t	sig. level	Coef.	t	sig. level	Coef.	t	sig. level
α_1	0.096	5.98	***	0.052	3.25	***	0.028	2.13	**
α_2	-0.060	-2.68	***	-0.020	-0.88	-	-0.008	-0.44	-
α_3	-0.063	-2.79	***	-0.028	-1.24	-	-0.016	-0.84	-
α_4	-0.065	-2.88	***	-0.018	-0.80	-	-0.002	-0.11	-
α_5	-0.094	-4.15	***	-0.026	-1.13	-	-0.014	-0.73	-
α_6	-0.108	-4.79	***	-0.066	-2.93	***	-0.015	-0.79	-
α_7	-0.057	-2.53	**	-0.032	-1.41	-	-0.009	-0.46	-
α_8	-0.084	-3.74	***	-0.065	-2.88	***	-0.021	-1.09	-
α_9	-0.087	-3.84	***	-0.089	-3.93	***	-0.031	-1.62	-
α_{10}	-0.097	-4.31	***	-0.032	-1.41	-	-0.021	-1.14	-
α_{11}	-0.097	-4.28	***	-0.052	-2.28	**	-0.018	-0.97	-
α_{12}	-0.089	-3.92	***	-0.035	-1.54	-	0.005	0.28	-
F-test		3.29	***		2.42	***		0.58	-

Table A3.1: Results from the linear regression or the three sub-periods for the EW portfolio

	1980-1990			1991-2002			2003-2014		
	Coef.	t	sig. level	Coef.	t	sig. level	Coef.	t	sig. level
α_1	0.210	8.49	***	0.069	3.62	***	0.060	6.20	***
α_2	-0.145	-4.15	***	-0.039	-1.43	-	-0.031	-2.22	**
α_3	-0.127	-3.63	***	-0.015	-0.54	-	-0.050	-3.66	***
α_4	-0.148	-4.23	***	-0.015	-0.56	-	-0.054	-3.90	***
α_5	-0.196	-5.63	***	-0.031	-1.14	-	-0.059	-4.27	***
α_6	-0.228	-6.54	***	-0.064	-2.38	**	-0.046	-3.38	***
α_7	-0.164	-4.70	***	-0.040	-1.48	-	-0.036	-2.59	**
α_8	-0.192	-5.49	***	-0.058	-2.15	**	-0.053	-3.88	***
α_9	-0.176	-5.04	***	-0.082	-3.05	***	-0.061	-4.40	***
α_{10}	-0.196	-5.63	***	-0.066	-2.46	**	-0.049	-3.60	***
α_{11}	-0.182	-5.21	***	-0.065	-2.39	**	-0.051	-3.70	***
α_{12}	-0.208	-5.96	***	-0.041	-1.51	-	-0.051	-3.67	***
F-test		5.72	***		1.71	*		2.89	***

Table A3.2: Results from the linear regression or the three sub-periods for the X1 portfolio

Now we will see if we have a problem with heteroscedasticity in these two portfolios.

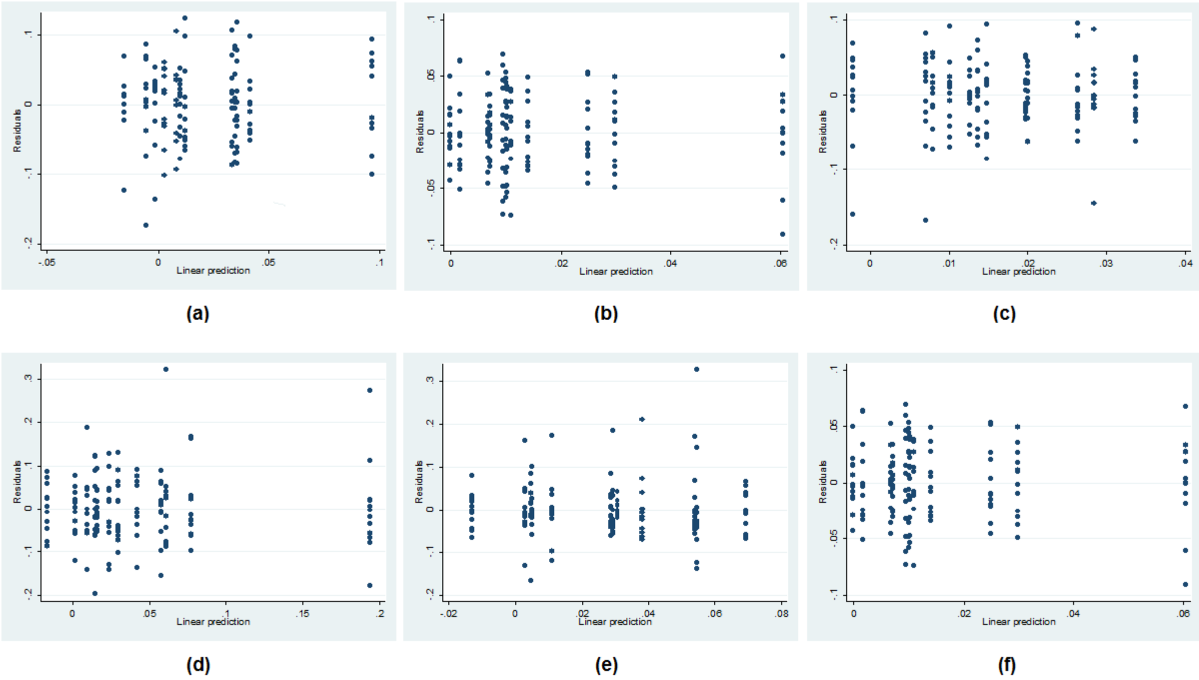


Figure A3.1: Residuals versus the fitted line

In figure A3.1, plot (a) represent the residuals versus the fitted values for the first sub-period for the EW portfolio (EW-1), plot (b) represent the residuals versus the fitted values for the second sub-period for the EW portfolio (EW-2), etc, plot (f) show the residuals versus the fitted line for the third sub-period for the X1 portfolio (SEW-3). We see no "visible" pattern in these plots. To confirm this we perform the IM-test.

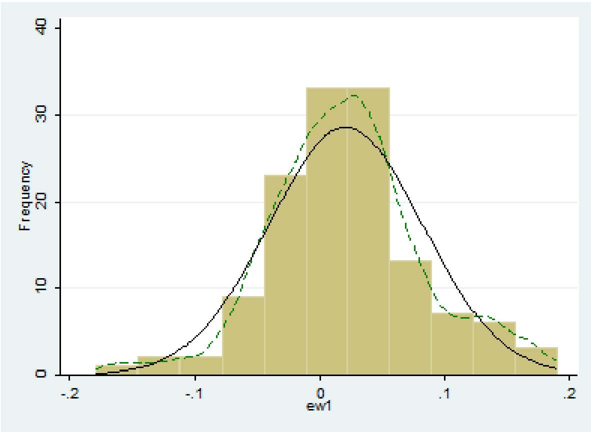
IM	P-VALUE
EW-1	0.7467
EW-2	0.2207
EW-3	0.4900
SEW-1	0.6189
SEW-2	0.2257
SEW-3	0.0715

Table A3.3: The IM-test for the three sub-periods

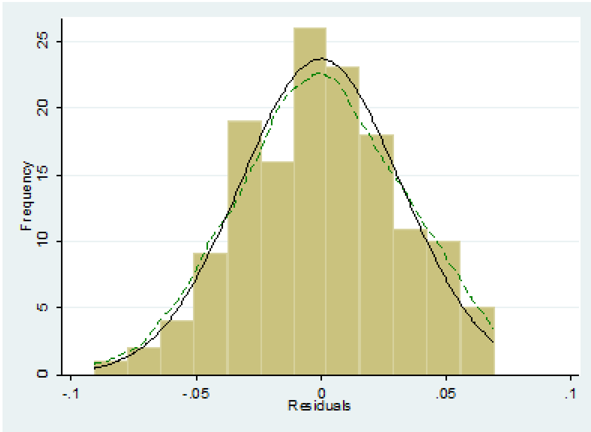
Beacause we fail to reject the null hypothesis we have no problem with heteroscedasticity, and we do not have to perform a regression with a robust option.

Normality

We will now test for normality, first by looking at the distribution plots. We plot the distribution for all portfolios and for the residuals. The solid line is the normal density line and the dashed line is the kernel density line.



(a)



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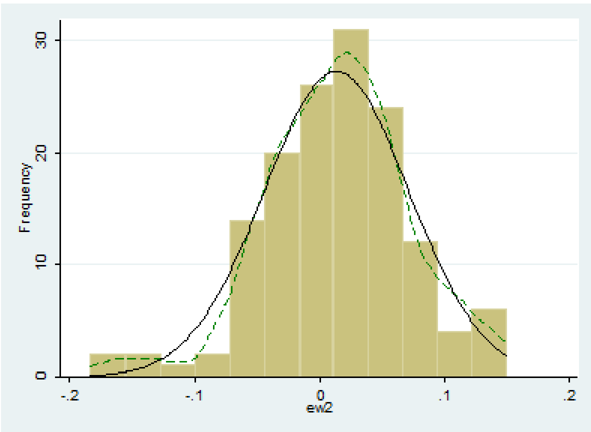

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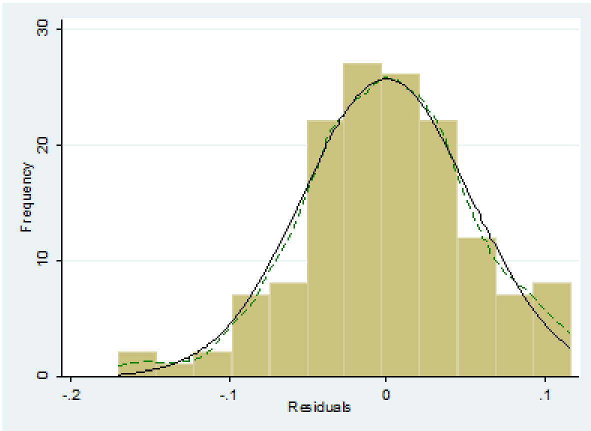

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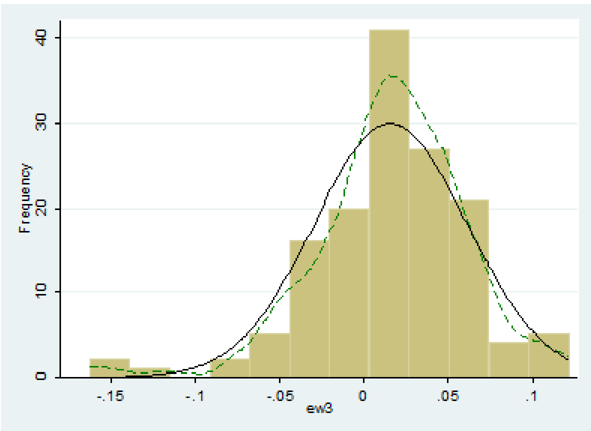

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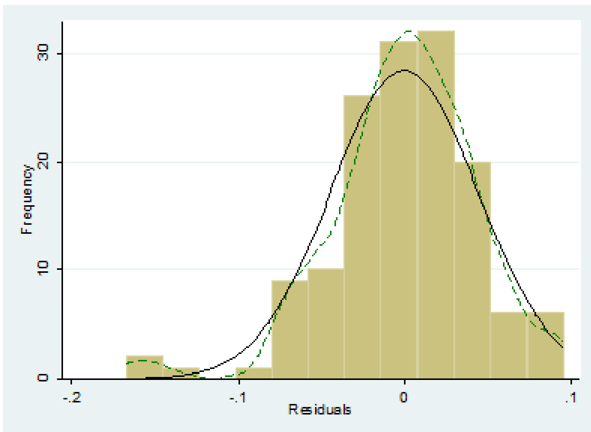

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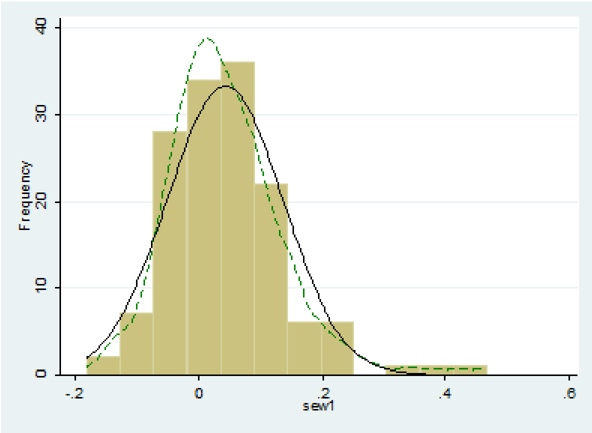

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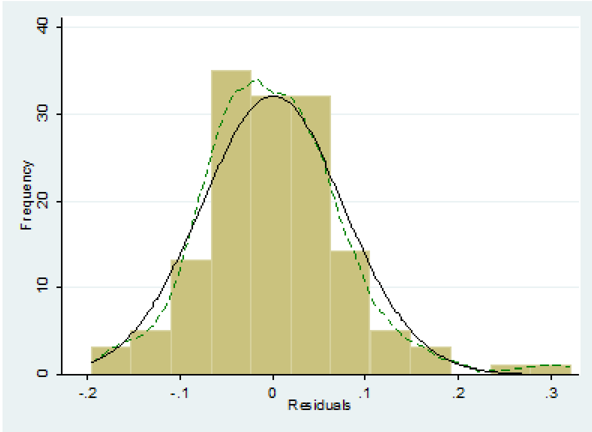

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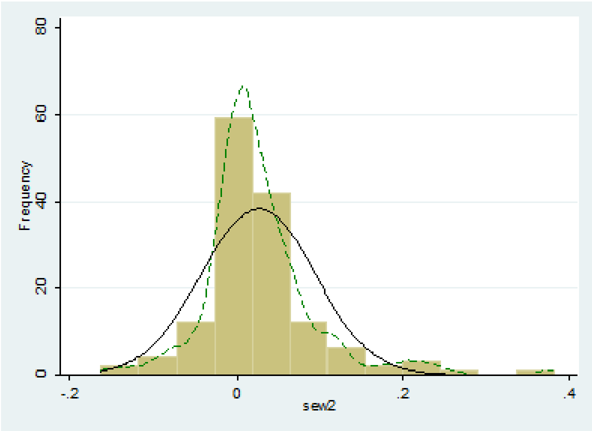

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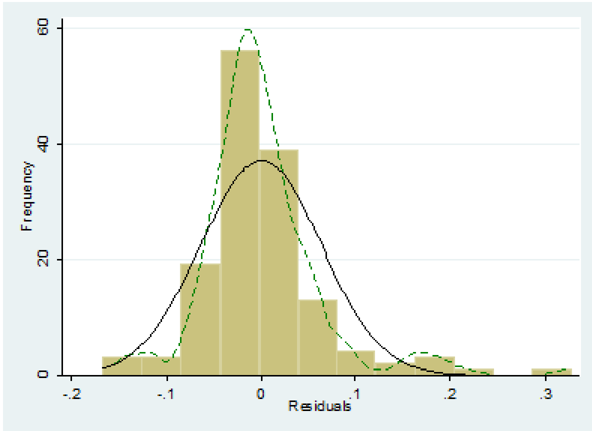

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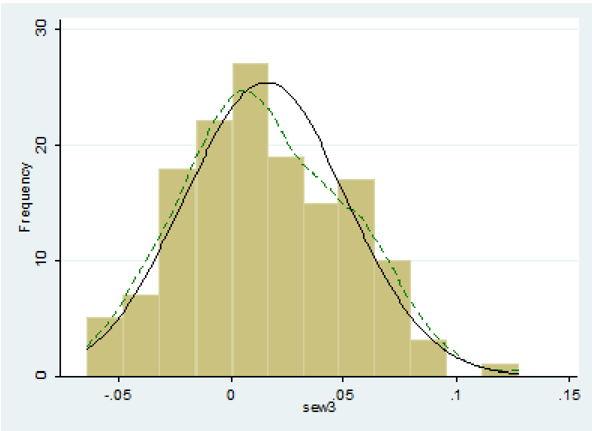

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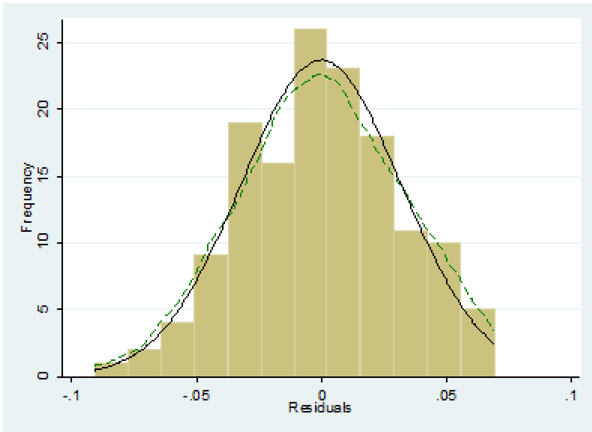


(l)

Figure A3.2: Distribution plots for the EW portfolio and size portfolio

In figure A3.2, plot (a) show the distribution for the first sub-period for the EW portfolio and plot (b) show the distribution of the residual for the first sub-period for the EW portfolio, etc., plot (k) present the distribution of the third sub-period for the X1 portfolio and plot (l) show the distribution of the residuals for the third sub-period for the X1 portfolio. We see deviations from the normal distribution in all the plots. The kurtosis and the skewness are presented in table A2.3

	SKEWNESS		KURTOSIS	
	EW	**Residuals**	**EW**	**Residuals**
EW-1	0.064	-0.227	3.855	3.216
EW-2	-.0354	-.0225	3.872	3.332
EW-3	-0.829	-0.744	5.410	4.968
SEW-1	1.140	0.729	6.225	5.248
SEW-2	1.542	1.529	8.979	8.785
SEW-3	0.241	-0.106	2.764	2.687

Table A3.4: Values for skewness and kurtosis

The ten portfolios do not seem to be normally distributed. To confirm this we perform the Shapiro-Wilks test for normality:

SWILKS	P-VALUES	
	EW	**Residuals**
EW-1	0.03759	0.64463
EW-2	0.03718	0.37806
EW-3	0.00012	0.00031
SEW-1	0.00001	0.00072
SEW-2	0.00000	0.00000
SEW-3	0.46862	0.77612

Table A3.5: The Shapiro-Wilks normality test

Only the residuals for EW-1, EW-2, SEW-3 and data on the dependent variable for SEW-3 are normally distributed. Because not all of the residuals are normally distributed we use the bootstrap method for all portfolios.

A4 The Other January Effect

In table A4.1 we present the unprocessed OLS regression results:

	EW				VW			
	Coef.	t	P>t	Sig.level	Coef.	t	P>t	Sig.level
α_1	-0.0174	-1.64	0.005	***	0.0067	1.07	0.293	-
α_2	0.0343	3.04	0.110	-	0.0143	1.94	0.061	*
	F-test	9.24	0.0046	***	F-test	3.76	0.0610	*
	EW-RF				VW-RF			
	Coef.	t	P>t	Sig.level	Coef.	t	P>t	Sig.level
α_1	-0.0251	3.11	0.004	***	0.0017	0.25	0.801	-
α_2	0.0361	-2.30	0.028	**	0.0128	1.63	0.112	-
	F-test	9.65	0.0039	***	F-test	2.66	0.1124	-

Table A4.1: The results from the OLS regression for the other January effect

Heteroscedasticity

To test for heteroscedasticity we plot the residuals against the fitted values to see if there exists any pattern between them. Plot (a) represents the residuals for EW raw returns, plot (b) the residuals for EW excess returns, plot (c) the residuals for VW raw returns, and plot (d) the residuals for VW excess returns.

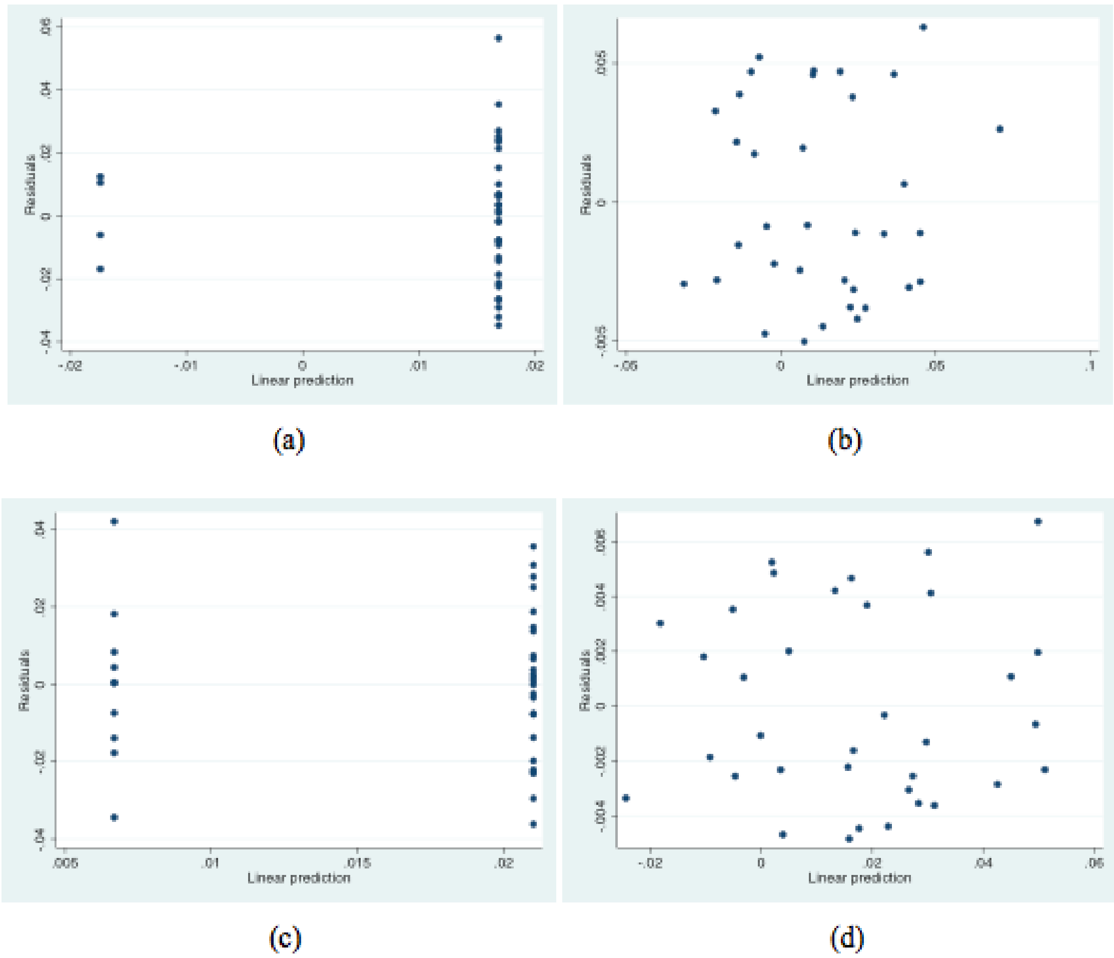


Figure A4.1: Plots showing the residuals against the fitted values

As we see in figure A4.1, there is no “visible” convincing systematic pattern with respect to the variance in the OLS residuals. This indicates that the residuals are homogeneous. To confirm this, we also perform the IM-test:

	IM–TEST
EW	0.319
EW – RF	0.683
VW	0.831
VW – RF	0.662

Table A4.2: The IM-test for the other January effect

Because the test statistics are larger than 0.05, we fail to reject the null hypothesis. This means that we do not have a problem with heteroscedasticity, and we can assume that the residuals are homoscedastistic.

A5 Testing Decile Portfolios

In this section, we will check if the six decile portfolios (raw and excess) are normally distributed and if we have a problem with heteroscedasticity. First, we present the OLS results:

			X1		
	Coef.	**t**	**P>t**	**Sig. level**	**Spread**
α_1	-0.001	-0.03	0.976	-	0.023
α_2	0.023	1.15	0.260	-	
	F-test	1.31	0.2603	-	
			X2		
	Coef.	**t**	**P>t**	**Sig. level**	**Spread**
α_1	0.015	1.15	0.257	-	0.003
α_2	0.003	0.18	0.862	-	
	F-test	0.03	0.8617	-	
			X10		
	Coef.	**t**	**P>t**	**Sig. level**	**Spread**
α_1	0.008	1.31	0.198	-	0.003
α_2	0.003	0.38	0.704	-	
	F-test	0.15	0.7038	-	

Table A5.1: Results from the OLS regression for portfolios X1, X2 and X10 for EW raw returns

X1					
	Coef.	t	P>t	Sig. level	Spread
α_1	-0.004	-0.22	0.826	-	0.020
α_2	0.020	1.23	0.228	-	
	F-test	1.31	0.2603	-	
X2					
	Coef.	t	P>t	Sig. level	Spread
α_1	0.008	0.63	0.530	-	0.003
α_2	0.003	0.24	0.815	-	
	F-test	0.03	0.8617	-	
X10					
	Coef.	t	P>t	Sig. level	Spread
α_1	0.003	0.48	0.637	-	0.001
α_2	0.001	0.09	0.931	-	
	F-test	0.15	0.7038	-	

Table A5.2: Results from the OLS regression for portfolios X1, X2 and X10 for EW excess returns

Heteroscedasticity

We plot the fitted line against the residuals. Plot (a), (b) and (c) refers to the raw portfolios X1, X2, X10, respectively, whereas plot (d), (e), (f) refers to the excess portfolios X1, X2, X10, respectively.

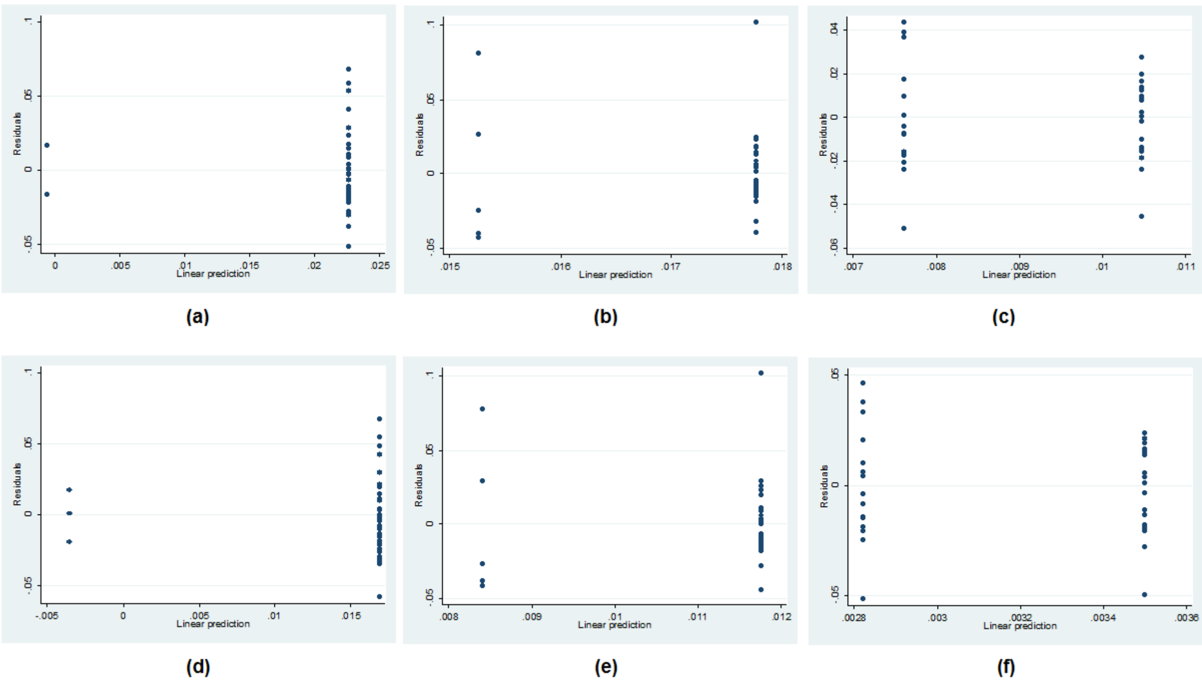


Figure A5.1: Fitted line versus the residuals for all six portfolios

There are no “visible” pattern in the plots, this indicates that the residuals are homoscedastic, to confirm this we do the IM-test. In table A5.3 we have the p-values from the IM-test on all six portfolios.

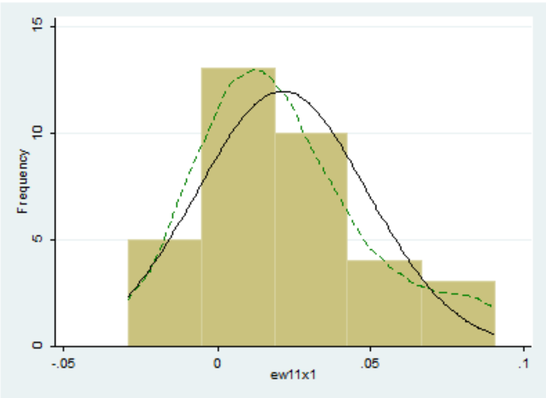
IM TEST	**P-VALUES**	
	Raw	Excess
X1	0.5412	0.3964
X2	0.0749	0.0985
X10	0.0771	0.2148

Table A5.3: The IM-test for three decile portfolios

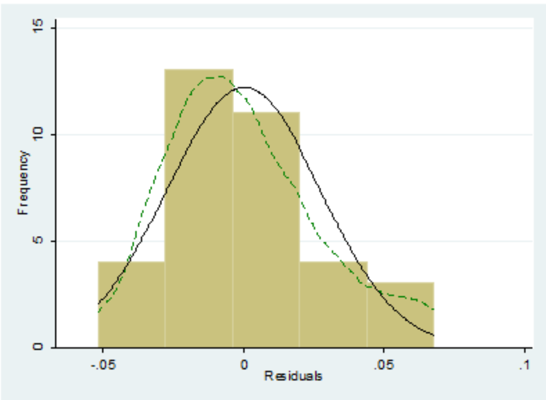
Because the test statistic are larger than 0.05 we fail to reject the null hypothesis and we do not have a problem with heteroscedasticity. Because of these results, we do not use the robust option regression.

Normality

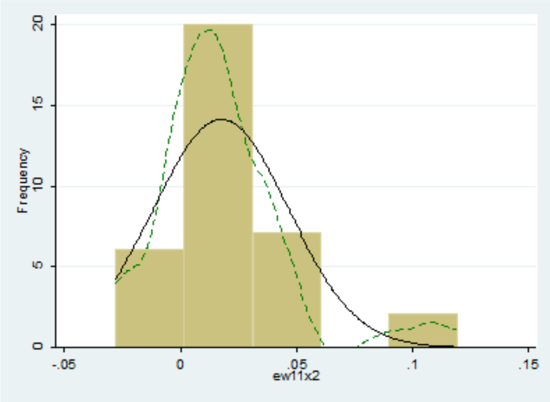
We will now test if the dependent variable and the residuals are normally distributed. We first look at the distribution plots. Plot (a) and (b) show the distribution of the raw X1 portfolio and the residuals, respectively, plot (c) present the distribution of the raw X2 portfolio and the residuals, respectively, etc., and plots (e) and (f) show the of the excess X10 portfolio and the residuals, respectively.



(a)



(b)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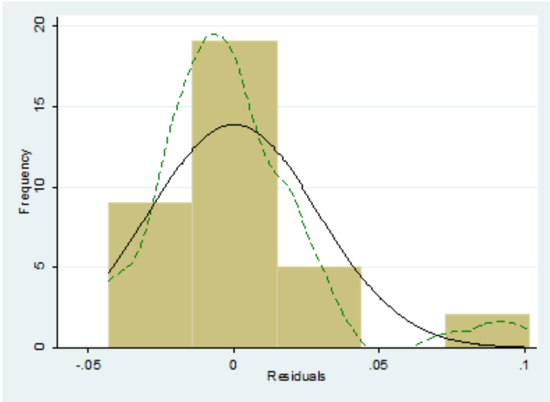
10
15
20
-.05
0
.05
.1
.15
ew11x2

(c)


Frequency
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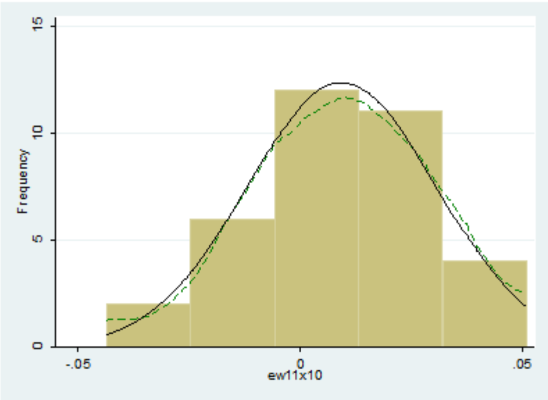
10
15
20
-.05
0
.05
.1
Residuals

(d)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15
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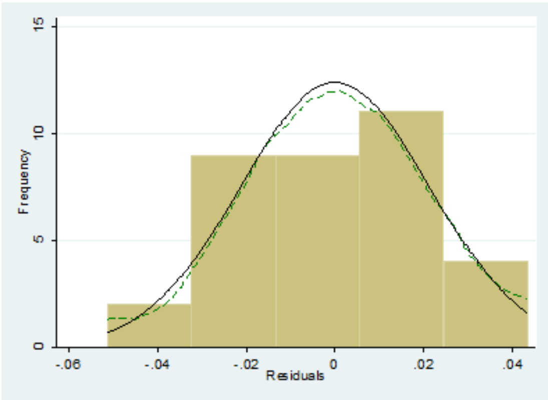
0
.05
ew11x10

(e)


Frequency
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15
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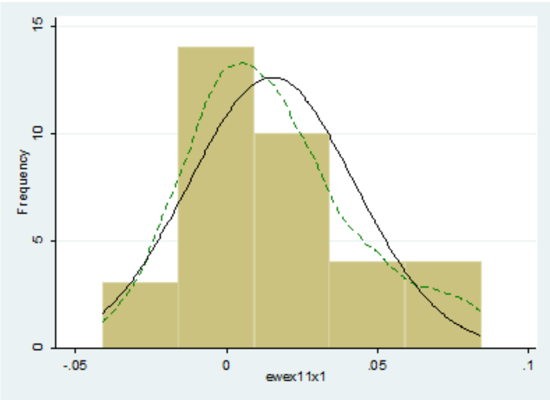
-.04
-.02
0
.02
.04
Residuals

(f)


Frequency
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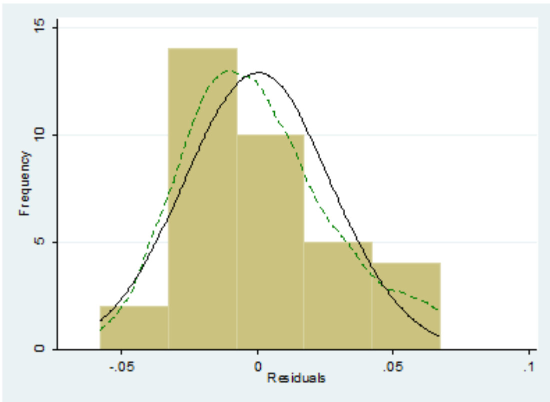
0
.05
.1
ewex11x1

(a)


Frequency
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10
15
-.05
0
.05
.1
Residuals

(b)

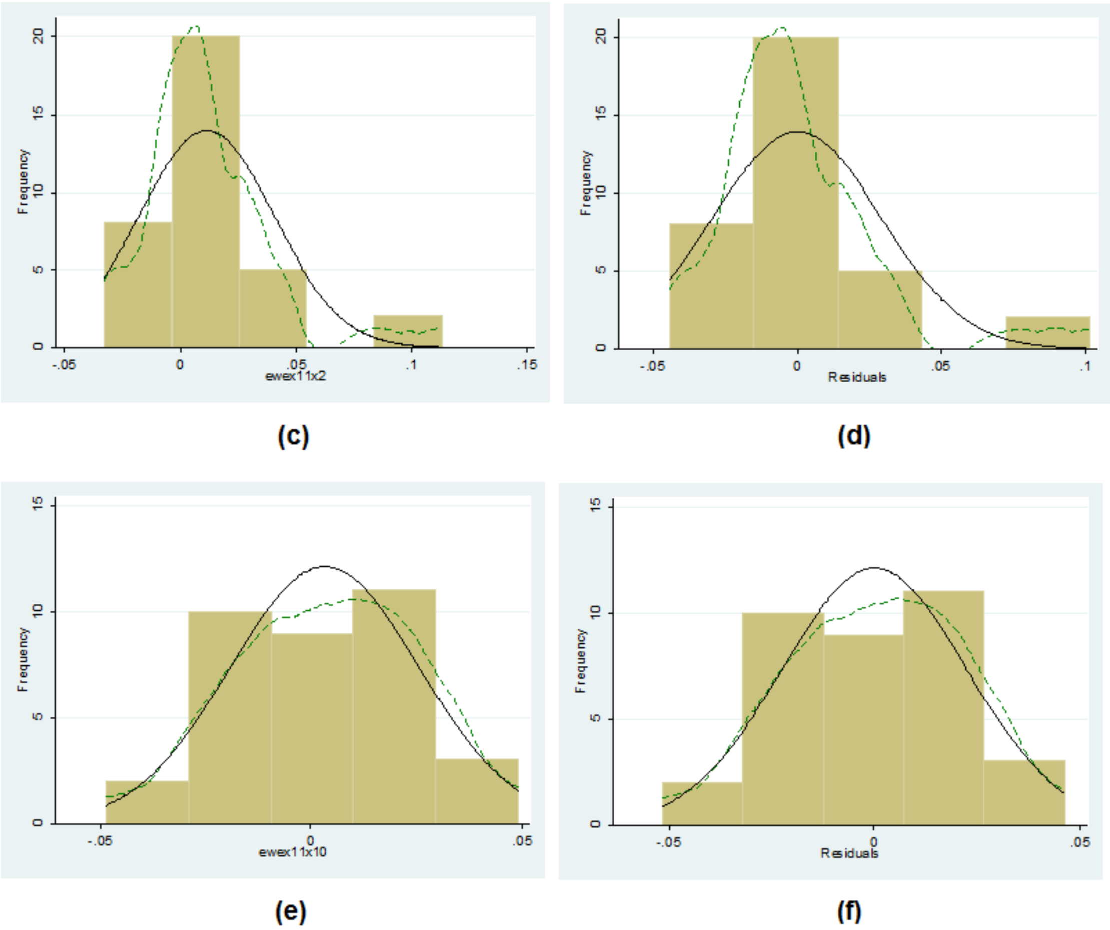

Figure A5.2: Distribution plots for the three decile portfolios

There are deviations from the normal density line. We will now look at the skewness and kurtosis.

	SKEWNESS		KURTOSIS	
RAW	EW	Residuals	EW	Residuals
X1	0.716	0.699	3.147	3.139
X2	1.596	1.665	6.766	6.851
X10	-0.243	-0.157	3.018	3.097
EXCESS				
X1	0.594	0.530	3.105	3.126
X2	1.499	1.583	6.405	6.490
X10	-0.266	-0.254	2.790	2.811

Table A5.4: The values for skewness and kurtosis

We see from table A5.4 that all portfolios deviate from the normal density, some more than others. To confirm this we do the Shapiro-Wilks test for normality.

SWILKS	P-VALUES	
RAW	EW	Residuals
X1	0.14959	0.14145
X2	0.00017	0.00027
X10	0.14959	0.74050
EXCESS		
X1	0.34444	0.41451
X2	0.00061	0.00039
X10	0.65626	0.65321

Table A5.5: Shapiro-Wilks normality test

From table A5.5 we see that only the X2 and excess X2 portfolios are normally distributed. Because not all of the portfolios are normally distributed, we will use the bootstrap regression for all of them.