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VOLATILITY LINKS IN THE NORWEGIAN STOCK MARKET

Oslo Stock Market Volatility Characteristics

Sammendrag

Denne masteroppgaven analyserer volatiliteten på Oslo Børs i et forsøk på å karakterisere volatiliteten på Oslo Børs fra 2005 til 2016. Ved å undersøke variabler vi mener kan karakterisere volatiliteten på Oslo Børs. Motivasjonen bak oppgaven er at det er få studier som prøver å karakterisere volatiliteten på Oslo Børs. Studien anses som nyttig i investerings- og risikostyringssammenheng. Begrunnelse bak er at ved å få en bedre forståelse av hva som karakteriserer volatiliteten, kan en bedre forstå risikoen på børsen. Vi fant at å bruke en asymmetrisk GARCH-modell ville gi de mest presise resultatene. Etter at vi kalkulerte volatiliteten, definerte vi enkle og multiple regresjonsmodeller med uavhengige variabler vi tror kan karakterisere volatiliteten på Oslo Børs. Vi fant at det amerikanske markedet har stor påvirkning på volatiliteten på Oslo Børs. Oljeprisens påvirkning på volatiliteten var også høy. OBX-indeksen består av de 25 mest likvide aksjene på Oslo Børs og replikerer volatiliteten til hele børsen nesten perfekt.

Abstract

In this master thesis, we will analyse the volatility on the Oslo stock exchange to characterise the volatility in the period between 2005 and 2016. We will examine variables we believe can explain the volatility on the Oslo stock exchange. The motivation of this thesis is that there are few studies that try to characterise the changes in volatility on the Oslo stock exchange. The thesis is considered useful for investment, risk management and for further academic research. The reason for this, is that by better understanding the characteristics of the volatility, one can better understand the risk on the exchange. We found that by using an asymmetric GARCH-model produces the most precise results of the volatility. After calculating the volatility, we defined simple and multivariate regression models that we think can characterise the volatility on the Oslo Stock exchange. Our findings show that the U.S market have a profound influence on the volatility of the Oslo stock exchange. In addition to this, our findings show that the oil price also affects the volatility to a high degree. The OBX-index consist of the 25 most traded companies on the Oslo stock exchange and almost perfectly replicates the volatility for all the shares on the exchange.

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Preface

This study is conducted as our Master's thesis at the department of Economics at School of Business, Oslo (HiOA). This thesis represents the final of our time at Oslo Business School, in finance as specialization. As far as we know, there exist no such research on the Norwegian market.

We would like to express our gratitude to our advisor Øystein Strøm for the encouragement, valuable academic support and feedback. Furthermore, we want to express our appreciation to Andreea Ioana Alecu for the quick response and valuable insight in Rstudio programming.

The process of structuring data and constructing the model we use in this thesis has been a demanding process, which also required a depth study in programming. The calculations in this thesis is exercised in R, which has been a time-consuming and educational process. We are researching the characteristics of the Oslo stock exchange market fluctuations from 2005 to 2016.

Oslo Business School, May 26, 2017

Andreas Tandberg Anfinsen and Mads Henriksen Johansen

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1 Introduction

In this thesis, we will look at the characteristics of the Oslo Stock Exchange volatility. To do so, we need to calculate the volatility of the data. We will define volatility in chapter 3. We have selected a set of variables that we think affect the volatility on the Oslo Stock Exchange. The variable we use to represent Oslo Stock Exchange is the Oslo Børs All-share index (OSEAX). The OSEAX is an index of all the listed shares on the Oslo Stock Exchange.

We gathered the data from the Thomson Reuters data stream, that Oslo Business School (HiOA) have available. The data range from year 2005 to 2016. We divide our data into commodity prices, interest rate, exchange rates and indexes. We will focus especially on the Crude Oil North Sea, an oil price index. The reason why we want to focus on oil, is that oil plays a crucial part in the Norwegian economy. In this period, there have been several incidents that will affect volatility, among other incidents, the financial crisis. Market fluctuations is measured by volatility. We hope to find the factors with the highest explanatory effect on the volatility. By the means of that, we hope to find a good risk measure for the volatility on the Oslo Stock Exchange, to adequately characterise the volatility between 2005 and 2016 on the Oslo Stock Exchange.

It is assumed that the volatility behaves different to stock movements, whether the stock is going to decrease or increase there should be an inconsistent rise or fall in the volatility when considering increase or decrease in the stock. These effects are not picked up by a normal autoregressive conditional heteroskedasticity model (ARCH), often used for calculating volatility. ARCH will be defined in chapter 3. Because of this, we will need to use a model that can pick up asymmetric effects. We need to use a modification of the generalized ARCH (GARCH) model. In chapter 6, we will present a Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model. By using a GJR-GARCH model we are adjusting for the leverage effect and hoping for a more precise outcome than by just using the standard deviations or a regular GARCH-model of the variables. This can give investors better information about the movement and characteristics of the volatility on the Oslo stock exchange and it can also give a better basis for making their investments decisions.

VIX, VDAX and the newly introduced Norwegian NOVIX, are implied volatility (IV, also called historical volatility) indexes that can be interpreted as the market expectation to future movements. These indexes are commonly called fear indexes. They also give information about option prices.

Previous studies prove that implied volatility contribute to better risk management. An example of this is Value-At-Risk models (Giot, 2005). Portfolio results are often evaluated against the outperformance of volatility.

Black and Scholes presented their option pricing model in 1973. Volatility is not observable in this model. We believe that by finding out what characterises the realized volatility, forecasting volatility will be more precise and efficient. The historical standard deviation has been used as a measurement of the volatility, but in recent times implied and realized volatility has been common measurements. Realized volatility can be observed daily and led to a breakthrough in volatility when first derived. While implied volatility is risk neutral and subjective to expectations about future volatility, is the realized volatility an objective and do not include any assumptions about the users in the marked. In this study, we will research realized volatility on Oslo Stock Exchange.

1.1 Research question

In this section, we will define our research questions.

- *What are the Oslo stock market volatility characteristics during 2005 to 2016 on Oslo Stock Exchange?*

- *How much does the oil price impact volatility on Oslo Stock Exchange?*

If we can find explanatory variables for the realized volatility, then the information can be used for investment strategies, risk management or maybe even for diversification. To answer the research question, we will use a GJR-GARCH-model to calculate volatility. GARCH- and GJR-GARCH-models will be defined in chapter 3. We will also calculate the volatility of our explanatory variables and use these in an OLS regression to see how much they can be linked with the volatility on the Oslo Stock Exchange. OLS regression will be defined in chapter 4.

ARCH was introduced to map and model observed time series. This model has problems with white noise in time series. A new model was derived from ARCH and is called GARCH. This model pick up the white noise of the time series. From GARCH, there are many sub models with their own features. TGARCH and GJR-GARCH are basically the same, but where GJR uses variance, TGARCH uses standard deviation. Both catch the asymmetric effects with stocks and adjust for the leverage effect. To calculate the volatility derived from the GJR-GARCH model we will use the programming tool Rstudio (URL: https://www.rstudio.com/).

The first research question is to find what characterises the volatility on the Oslo stock exchange during the period between 2005 and 2016. The second part is how much the oil price affects the OSEAX volatility. We expect to see that the oil price to be the most influential variable to characterise the volatility on the Oslo Stock Exchange volatility. We mentioned why earlier, but its due to its influence in the Norwegian economy.

1.1.1   Motivation

We wanted to find the gap in the literature to see what we could do about this and to find out what is already researched. Volatility has been a large research area ever since the CAPM-model was introduced. Most of the research we can find on this area has been done on the U.S market. In Norway, we have two volatility indices, the NOVIX and one presented daily in *Dagens Næringsliv* (a Norwegian finance newspaper). Both are calculated with the OBX total return Index. This index is made up of the 25 most traded companies on Oslo Stock Exchange. The NOVIX uses the same methodology as VIX and VDAX. While the one in Dagens Næringsliv is calculated from less information. From what we have found, there is no research using either index for prediction of future realized volatility.

Because of the massive research in foreign markets, we believe that the research on the Norwegian stock market is getting left behind. Therefore, we want to focus on the Norwegian market in this thesis. From previous literature, we have seen a lot of research use implied volatility to predict future volatility and realized volatility to predict future volatility, there is also research on the use of realized volatility to explain implied volatility. We have not encountered any research that tries to characterise volatility on the Oslo Stock Exchange. We want to find out which variables that can be linked with the volatility on Oslo Stock Exchange. We will do this by looking at several different explanatory variables. This type of research is similar to Schwert's (1989) study on the American market. We believe that using a GJR-GARCH model will produce more accurate results, than by using the ARCH (12) model used by Schwert (1989). By doing this, we believe that we will be closer to understanding and establish good measures for the future volatility on Oslo Stock Exchange. Hopefully our work will lead to results that investors and academics will take an interest in.

1.2 Oslo Stock Exchange

The Oslo Stock Exchange was founded in 1819 and is the only regulated security market in Norway. The exchange is tasked with conveying trades and sales by the auction principle. In 1988, the stock exchange introduced an electronic trade system. From 1819 to 1988 the stock exchange trades were based on meeting up in person to do the trades. Oslo Stock Exchange offers trade in stock, bonds, equity instruments, derivatives and interest rate products. Oslo stock exchange wants to be the market place for listing and trade in the previous mentioned products on their 5 different market places; Oslo Stock Exchange, Oslo Axess, Merkur Market, Nordic ABM and Oslo Connect. Oslo Stock Exchange is known for being a world leader in energy, seafood and shipping. Companies from all over the world has chosen to be listed on the exchange, with a network through their members reaches investors all over the globe (Oslo Børs, 2017).

Figure 1-1: OSEAX and Crude Oil price from 2005 to 2016.
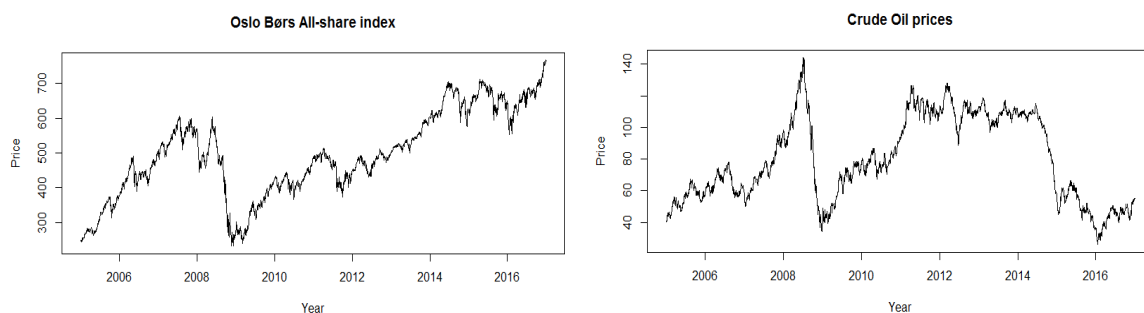
1.3 Macroeconomic incidents from 2005 to 2016

There are macroeconomic incidents in the period of 2005 to 2016 that we can assume have an impact on the volatility. A few years before 2005, there was an internet bubble burst. This may have impacted the volatility in the following years, which impacts our datasets. In May and June 2006, there was an increased nervousness. In 2008 was the start of the financial crisis. May 2010 the EU debt crisis blossomed, where Germany put a ban on short-selling of European government bonds. In August 2011, we had the downgrade of US credit rating and EU debt crisis. In addition to this, there was also the fear of Greece not being able to pay their debt and a European banking crisis. In the late fall of 2012 EU decided to let banks borrow from the EU crisis fund and the OPEC's boycott of Iran. In the fall of 2014 the oil price collapsed. The marked expected internal division in OPEC.

1.4 The data

The data we need to conduct for our analysis of the volatility characteristics consist of both weekly and daily data from 1.1.2005 to 31.12.2016. There are both quiet and noisy periods in our data set, which we mentioned in the previous section. The data has been gathered from the Thomson Reuters data stream, where we found data about OSEAX-index, OBX-index, commodity prices, exchange rates and volatility indexes. Commodity prices are oil, gold, aluminium and salmon. Exchange rates are NOK/EUR, NOK/USD, NOK/SEK and NOK/DKK. We ended up with 2848 observations for most of the variables expect for the NOXIV and salmon price. We also got the daily intra-day historical data, from the NOVIX database. Bugge, S., et al. (2016) calculated the volatility based on the VIX methodology. Since the Norwegian economy is very influenced by both the EU and oil, we expect the Euro and oil price to have high explanatory factor on the OSEAX volatility.

1.5 Structure

In part 2, we will have a closer look at what previous literature and research has found. In part 3 we will present theory related to explaining and finding volatility. In addition to this, we will present theory on time series. In part 4, we will present the methodology used in this thesis. We will present our methodology for regression and some test for out data and model. In part 5 we will go into the descriptive statistic and some of our results. In part 6, we will present the main results. In the last part, 7, we will conclude based on our results.

2   Previous literature

In this part, we will look further into previous research on volatility. We will then explain why we use our approach later in the paper.

In 1973, the Black and Scholes model was introduced, this model did not have a measure for the volatility. Thus, in the after math of the Black & Scholes model there has been written many articles about volatility.

Schwert, G. W. (1989) research the relation of stock volatility with real and nominal macroeconomic volatility, economic volatility, financial leverage, and stock trading activity. Schwert used monthly data from 1857 to 1987. He found that, while aggregate leverage is significantly correlated with volatility, it is supposed that it explains a relatively small part of the movements in stock volatility. Amplitude of the fluctuations in aggregate stock volatility may be difficult to explain by using simple models of stock valuation.

Latané and Rendleman (1976) presented a method to calculate implied volatility, it concluded with the statement of implied volatility giving a better prediction on future movements in stock return. Realized volatility was introduced by Andersen and Bollerslev (1998) as a measurement of volatility. Engle and Gallo (2006) used the information from realized volatility to predict implied volatility. By using high-low-price observations and daily squared return to predict implied volatility. Hansen and Lunde (2006) research micro noise effects in intra daily observations and concludes that micro noise effects influence the estimates of volatility. Corsi (2009) defined a simple model, that included both short and long-term effects in realized volatility, the HAR-RV model ("Heterogeneous Autoregressive model of Realized Volatility")

Ahoniemi (2006) used macro variables, ARIMA-models and GARCH-error terms, to test predictions accuracy on the VIX-index. Where some models got an accuracy over 60 % outside the range. These predictions were used to define an option-trade strategy that gives a positive profit. Fernandes et al. (2014) also used a HAR-RV with lagged IV-values. Some exogenous variables were significant, but with VIX persistent autocorrelation, they conclude that it is difficult to find a better prediction than the HAR-process.

From the financial marked research where they look at stock, commodity prices and so on try to figure out how these affect the marked. Akgirav V. (1989), Bollerslev et al. (1992), Frances and Dijk (1996), Brailsford and Faff (1996), Brooks and Persand (2002) and (2003),

Berkowitz, Christoffersen and Pelletier (2009) and Pagan (1990) all have in common upon the agreement that GARCH and other GARCH-models has a habit of working better when using financial time series than other technics as for example linear regression or moving average. ARCH-models was introduced in the late 80's. Predictions based on implied volatility was introduced after CBOE's launching the original VIX index (VXO) in 1993.

Some of the first articles published for predicting volatility by using ARCH-model was Taylor (1986) and Akigray (1989). Cao and Tsay (1992) found that using EGARCH best predicts future volatility. Other studies show that ARCH/GARCH-models are inferior models or models where implied volatility is used. ARCH/GARCH-models has an assumption of that it expects stationarity in the variance (variance stationarity). When the volatility changes significantly, that will result in making these models unprecise.

By using implied volatility in the prediction of future realized volatility produced high values for the R^2, which is a measurement of how much of the variation in the model that is explained by the independent variables. Fleming, Ostdiek and Whaley (1995) predicted the volatility for the next month for the S&P100, and found a R^2 of 15%. They found that implied volatility had the highest R^2, much higher than with historical data. And concluded that implied volatility was best to predict future volatility. Blair, Poon and Taylor (2001) got an even higher R^2, when they combined implied volatility with historical data. Where the historical data was as important and relevant as the implied volatility. They also used the S&P100. Canina and Figlewski (1993) gathered data for the period March 1983 to March 1987. What they found was that implied volatility contributed little relative to the historical data with respect to the explanatory power.

In the literature, the thing that is reoccur often, is that there exists an asymmetric context between volatility indexes and the return on a stock index. This mean that volatility indexes tend to increase more by a fall in the underlying stock index, that it will increase with a raise in the stock index. Dhanaiah et al. (2012) found this connection.

Tsay (2010) explains the weaknesses of ARCH models by 4 factors. First that the model assumes that positive and negative shocks have the same effect on volatility. In practice, it is well known that the price of financial assets responds differently to these shocks. Second is that the model is quite restrictive, meaning that for higher order of ARCH models the constraint gets complicated. In practice this limit the ability of ARCH models to capture excess kurtosis. Third factor is that the model does not give new insight for understanding the

source of variations of a financial time series. Fourth is that ARCH model reacts slowly to large isolated shocks to the return series and therefore is likely to overpredict the volatility. (Tsay, 2010, p. 119)

The ARCH model requires many parameters to adequately describe the volatility process of asset return, even though the model itself is quite simple. Schwert (1989) must use a 12 order ARCH model to describe the volatility in his article *Why does stock market volatility change over time.* As Tsay (2010) says; an alternative model must be sought. Bollerslev (1986) proposed the extension known as the generalized ARCH model. The model encounters the same weakness as the ARCH model. To overcome some of these weaknesses, an asymmetric GARCH model were introduced. This model type does not restrict the asymmetric effects between positive and negative asset returns. For example, the EGARCH (Nelson, 1991) and GJR-GARCH (Gloesten et al. 1993).

An asymmetric model leaves an opening for a better understanding of what affects the volatility on the Oslo stock exchange. Research on what affects the volatility on the Oslo stock exchange is practically non-existent. Schwert (1989) tried to explain stock market volatility change, the data used was on the American market. A different market can be dependent on different factors, and these factors can help investors get a better understanding of the volatility on the Oslo stock exchange. Using a different model than a high order ARCH, we can get a more precise understanding on what affects the volatility on the Oslo stock exchange.

3   Theory and methodological approach

In this chapter, we will present the theory used in this thesis. There are many difficult and complex concepts that we need to further explain before we can move on to our descriptive statistics and results. We will examine some theory about volatility and time series, ARCH, GARCH and GJR-GARCH.

3.1 Volatility theory

Volatility is a measure for uncertainty or risk in an underlying stock or option. Volatility is a measure for market fluctuations. The volatility will only tell you how much an asset is implied to move, but cannot predict whether the underlying asset will increase or decrease.

For financial institutions, it can be crucial to monitor the variables in the market that their portfolios depend on. These variables include interest rates, exchange rates, equity prices, commodity prices etc. Volatility is normally given by the Greek letter sigma (σ). It is defined as the standard deviation of the return provided by the variable per unit of time when the return is expressed using continuous compounding (Hull, 2012, p. 205).

In the business world, especially when we are referring to stocks, we often consider a year of 252 days. The reason for this is that we do not include weekends and holiday, when the exchange is closed. Research shows that volatility is much higher on business days versus non-business days (Hull, 2012, p. 206).

What causes volatility? One can assume that stock volatility or another asset, is caused by new information that is available to the market. This information cause people to reconsider their opinions about the asset value. A change in the price of an asset, change the volatility of the asset as well. However, the view of what causes volatility, is not supported by research.

With the years of daily data on an asset price, we can calculate the variance of asset's return between the closing prices and with that the volatility of the asset return. Research by Roll (1984) looked at the prices of orange juice futures showed that the most important news for orange futures was information about the weather. He also found that the variance between when the market is closed from Friday to Monday the variance was only 1,54 times greater than the one-day variance. Because of this, Hull (2012, p. 207) found that the only reasonable conclusion is that the volatility is caused by trading itself.

3.1.1 Different volatility measures

Taylor (2005) differentiates between four different volatility measures.

Measurement 1: *the standard deviation of previous returns*. With *n* trading periods/days, and returns $r_{t-n}, \dots, r_{t-1}$, with an average of r̄ is the historical standard deviation.

Equation 3-1: Standard deviation (Taylor, 2005, p. 190).

$$s = \sqrt{\left(\frac{1}{n-1}\right) \sum_{i=1}^{n} (r_{t-i} - \bar{r})^2}$$

This simple estimate of the standard deviation of return for *t* days with trading. Using intraday data, realized volatility have been calculated using trading periods measured in minutes. This is what newer research have been working with, when using realized volatility.

Measurement 2: *Conditional volatility* is the standard deviation of a future return. You get the future return from conditional on known information, this can for example be historical returns. Future return is calculated by using a time-series model on fitting data. By using ARCH, you get accurate equations for volatility expectations. Where h_t is conditional variance of the return in period t, this is done by using past data I_{t-1}. Taylor, S. presents an example of this. A weighted sum of squared excess return, defined by the recursive equation:

Equation 3-2: Recursive equation. (Taylor, 2005, p. 190)

$$h_t = \omega + \alpha(r_{t-1} - \mu)^2 + \beta h_{t-1}$$

By using the time series of return $\omega, \beta, \alpha \text{ and } \mu$ parameters are calculated.

Measurement 3: *Stochastic volatility*. From the fact that volatility changes over time the motivation for stochastic volatility came. Seeing that volatility is not constant. From this being able to see how volatility changes through time.

Measurement 4: *Implied volatility* is calculated from option prices. Because of this, they depend on the time until expire and the strike price of the option. Since the market for option are competitive and therefor the prices reflect the market's expectation of future volatility. The Black-Scholes pricing formula provides theoretical prices for European call options. From the formula, we get this definition of implied volatility:

$$c_M = c(\sigma)$$

Where $c(\sigma)$ is the theoretical price for European call options

c_M is the market price.

Assuming the asset price process is a geometric Brownian motivation with annual variance rate of σ^2.

The values of unobservable stochastic-, realized-, implied- and conditional volatility are typically different. When the different assumptions and data are used to calculate these values, it will be highly unlikely that they will be similar.

3.1.2 Characteristics of volatility

Stock volatility is special in the way that it cannot be directly observed. We might have daily log returns on a stock. We cannot observe the data directly, as there is only one observation in a trading day. But if we have 10-minute returns available, we have the possibility to estimate one-day volatility.

Experience and research shows that implied volatility is normally higher than historical volatility. This might be because of the risk premium for volatility (Tsay, 2010, p. 110-110). While volatility is not directly observable, asset returns has some characteristics that are commonly seen in volatility. Volatility clusters, that volatility may be high for certain periods and low for other. In a continuously manner volatility evolves over time, jumps in the volatility are rare. Volatility varies within some fixed range. A big price drop or a big price increase affects the volatility different, this is referred to as the leverage effect. As mentioned earlier, there are different GARCH models developed with the purpose of capturing these characteristics.

3.2 ARCH and GARCH

When modelling volatility, we need a systematic framework. Where ARCH and GARCH are popular choices.

There are many volatility models of this type. To mention a few, we have ARCH, GARCH, GARCH in the mean (GARCH-M), Integrated GARCH (IGARCH), exponential GARCH (EGARCH), threshold GARCH (TGARCH), GJR (Glosten-Jagannathan-Runkle model), Asymmetric parametric ARCH (APARCH) and Stochastic volatility (SV). ARCH is short for autoregressive conditional heteroskedastic model of Engle (1982). GARCH is short for Generalized ARCH model of Bollerslev (1986).

3.2.1 ARCH

The ARCH (autoregressive conditional heteroskedasticity) model of Engle (1982) was the first model that provided a systematic framework for volatility modelling. The model has two basic ideas. First that the mean corrected asset return is serially uncorrelated, but dependent. Second from a simple quadratic function of the lagged values can describe the reliance of a_t.

Equation 3-3: ARCH. (Tsay, 2010, p. 116).

$$a_t = \sigma_t \epsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2$$

The ARCH(m) model assumes that {t} is a series of independent and identically distributed random variables, where the mean is zero and variance is 1, $\alpha_0 > 0$, and $\alpha_i \geq 0 \ for \ i > 0$. For t, the assumption is standardized Student-t distribution or normal distribution. α_i coefficient should satisfy some regularity conditions for it to guarantee the unconditional variance of a_t is not infinite (Tsay, 2010, p. 115-116).

Why are we not going to use ARCH modelling? There are advantages and weaknesses considering ARCH modelling. On the positive end the model produces volatility clustering. On the other hand, the model assumes positive and negative shocks have the same effect on volatility, which depends on the square of previous shocks. The model may have restrictive constraints on the parameter values. Another weakness is that we may need many lags to capture evolution of volatility. For this reason, ARCH is not the best suit for our purposes and we should strive for a better model. GARCH purports to improve upon the short comings of the ARCH-model. (Tsay, 2010, p.119)

3.2.2 GARCH

While the ARCH model is simple, it requires more parameters to get a good enough calculation on the volatility process of an asset return. That is why an alternative model is needed. In 1986 Bollerslev published his extension on the ARCH model, commonly known as the generalized ARCH model. For log return series r_t, let $a_t = r_t - \mu_t$ be the innovation of time t. a_t follows a GARCH (m, s) model if autoregressive conditional heteroskedasticity.

Equation 3-4: GARCH (m,s) model. (Tsay, 2010, p. 132).

$$a_t = \sigma_r \epsilon_r$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{\max(m,s)} (\alpha_i + \beta_i) a_{t-i}^2 + \eta_t - \sum_{j=1}^{s} \beta_j \eta_{t-j}$$

where Tsay describes the parameters as *{ϵ}*.

Equation 3-5: GARCH (1,1). (Tsay, 2010, p. 132).

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

3.2.3 GJR-GARCH

Studies shows that a change in the stock market has a different impact on whether the stock rises or falls. Nelson (1991) found out that a fall has a greater impact than a rise of the same magnitude on future volatility. If the effects Nelson (1991) describes are true, a standard GARCH model will not be able to pick up these effects. We should consider using an asymmetric conditional volatility model. Hopefully this will later make our results more valid. The GJR-GARCH model is commonly used to handle leverage effects (Glosten et al. 1993). The model uses a threshold to separate the impacts of past shocks.

The GJR-GARCH is defined by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p}(\alpha_i + \gamma_j I_{t-i})\varepsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j \sigma_{t-j}^2$$

Where

$$I_{t-1} = \begin{cases} 0 \; if \; r_{t-1} \geq \mu \\ 1 \; if \; r_{t-1} < \mu \end{cases}$$

3.3 Time series

The foundation of time series analysis is stationarity. Time series are often referred to as random variables over time. Time series are data indexed in time order. In our case, these are stock prices, commodity prices, exchange rates etc. over time. We try to use time series to understand the behaviour of the data over time. Based on typical features of the data, one can decide on an expedient model to predict in the future. We are not going to predict future values; we are only interested in the historical data and its behaviour.

It is common to assume that an asset return series is weakly stationary, in financial literature. A common assumption using time series is that the data is stationary. We need to control whether the data is stationary or not. The reason for this, is that it affects the series attributes and behaviour in significant matter. The most commonly used way to control for stationarity is by an Augmented Dickey Fuller (ADF) test. We will come back to this matter in chapter 5, where we test for stationarity (Tsay, 2010, p. 30).

4   Methodology and data

In this chapter, we will go through the methods and data that will be used in the analysis.

4.1 Inspection of the data material

We collected 3016 observations in total. Some days have the same numbers, often due to holidays, where the exchange has been closed. For instance, we found that the price of the OSEAX all shares stock always was the same on first of May as the day before. This is because of the international workers' day. The most common holidays and double price dates we had to trim, were Christmas, Easter and other common holidays. We did the same for NOVIX. This means that we drop 168 observations from the full data set. The resulting data set is 2848 observations. We assume we will not meet any difficulties modelling with the data set, even though we have trimmed it. For the salmon price this was not necessary since the data was weekly observations. We have only removed a handful of observations from our data set, this means that the macroeconomic picture is intact.

4.2 The oil market

In 1960, several important oil exporting countries in the middle East and South Africa, together created OPEC. OPEC was founded with important countries as Saudi Arabia, Venezuela, Nigeria and the Emirates as its members. In practice, OPEC took over the oil price control after the 1974 crisis. Today this pricing happens through a conventional marked orientation, where buyers and sellers meet and agree directly or through a third party. There have also been created several reference indexes to check the price against. The three major is named Brent blend WTI and OPEC curve. Where the NYMEX in North-America and ICE in Europe exchanges, hold much of the oil trades. The contracts that is used here is used in the WTI, OPEC and Brent indexes.

The financial trade of oil happens through futures contracts and the psychical trades is negotiated through price reporting agencies. With these agencies, you place an order for buying or selling crude oil through price platforms. ICE has trading stations in New York, London and Singapore, and is open for nearly a continuously trade. The financial price can therefore be sensitive to media. When Dagens Næringsliv reports about the oil price, it is normally based on the financial reference index, that is derived from the futures market.

According to Pahl and Richter (2013) the Brent Blend Oil is the basis of two thirds of the world's oil trade.

4.3 Regression analysis

Regression analysis is a statistical method that is used to explain the effect one independent variable or variables has on the dependent variable. We divide the variables into a dependent and independent variable. We try to explain the reasons behind the change within a dependent variable with a similar change in one or more independent variables. In our case, we want to try to explain the change in the volatility of the Oslo Stock Exchange volatility. That means Oslo Stock Exchange volatility in this case is the dependent variable. We assume it is reasonable to believe that the oil price has its impact on the Oslo Stock Exchange volatility, because of the amount of oil export in the Norwegian market. By using regression analysis, we want to explain the effect of a change in the independent variables on the dependent variable.

The simplest form of regression is a simple linear regression model. It can be estimated as:

Equation 4-1: Simple linear regression (Wooldridge, 2013, p. 23).

$$y = \beta_0 + \beta_1 x + \varepsilon$$

Where   Y   is the dependent variable

            x   is the independent variable

            β_0 is the constant of the regression

            β_1 is the gradient of the regression and the

            ϵ is the error joint that represent all the other factors that, including x, affects y.

The simple linear model can be expanded with additional variables, this model we call a multivariate regression model. It is pretty much the same as a simple linear regression model, but with more independent variables. It can be estimated like:

Equation 4-2: Multiple linear regression (Wooldridge, 2013, p. 72)

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon$$

Where   Y   is the dependent variable

               X_k is the independent variables

               β_k is

The average value of the error joint is to be equal to 0, which gives the expected value of equal to 0, regardless of the value of the x variable; $E(\epsilon|x) = E(\epsilon) = 0$. (Wooldridge, 2013)

4.3.1   OLS

An often-used method to estimate the coefficients is ordinary least squares (OLS). We are going to estimate the connection between x and y variables. $\beta_0 \; and \; \beta_k$ from the model described over is necessary to estimate this connection, and to estimate this we are using the OLS method.

Using the available data, OLS will try to estimate a regression line. This line will rarely be perfect. Getting a difference (residuals) from the estimated values. OLS squares these residuals, and because of that one avoids that positive and negative residuals even out of each other. The regressions line will be adapted so that the residuals are diminished.
The method:

Equation 4-3: Mathematical presentation of the method

$$\hat{\epsilon}_t = (y_t - \hat{y}_t)$$

$$min \sum_{t=1}^{T} \hat{\epsilon}_t^2$$

Where y_t at time t the observation

               $\hat{y}_t$ estimated value on the regressions line at time t

               $\hat{\epsilon}_t^2$ is the residual error

The residuals sum of squares (RSS) is the sum of the residuals in the method over.

The estimated regressions line can be defined as:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$$

From the equation above we get:

$$\hat{y}_t = \hat{\beta}_0 + \hat{\beta}_1 x_t$$

Where $\quad \hat{\beta}_0 \quad$ is the estimated constant

$\quad\quad\quad\quad \hat{\beta}_1 \quad$ is the estimated change in $\hat{y}_t$ given a change in x_t

$\quad\quad\quad\quad x_t \quad$ is the value of x at time t

$\quad\quad\quad\quad \bar{y} \quad$ is defined as the sample average for y_t and $\bar{x}$ as the sample average for x_t. To find the constant the value of y when x is zero.

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

To find $\hat{\beta}_1$ the formula is:

$$\hat{\beta}_1 = \frac{\sum(x_t - \bar{x})(y_t - \bar{y})}{\sum(x_t - \bar{x})^2}$$

With these formulas, we can find by using ordinary least squares the estimates for a constant $\hat{\beta}_0$ and the gradient $\hat{\beta}_1$.

Ordinary least squares work so that it minimizes RSS.

$$RSS = \sum_{t=1}^{T}(y_t - \hat{y}_t)^2 = \sum_{t=1}^{T}(y_t - \hat{\beta}_0 - \hat{\beta}_1 x_t)^2$$

To make a multiple regression model, with for example 2 independent variables. The estimated regression line and the RSS formula will be:

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2$$

$$RSS = min \sum_{t=1}^{T}(y_t - \hat{\beta}_0 - \hat{\beta}_1 x_1 - \hat{\beta}_2 x_{t2})^2$$

4.3.2 Evaluating the result

After completing the regression, we will try to understand the outcome.

One of the most used measures is the R^2. This variable tells us the degree of variance that is explained in the dependent variable by the independent variables. The formula of R^2 is:

Equation 4-8: Equation for R^2

$$R^2 = 1 - \frac{RSS}{\sum_{t=1}^{T}(y_t - \bar{y})^2}$$

Where   RSS   is $\sum_{t=1}^{T}(y_t - \hat{y}_t)^2$

                      y_t is observed value for variable y at time t

                      $\bar{y}$ is population average for variable y

                      $\hat{y}_t$ is estimated value of variable y at time t

R^2 is a number between 1 and 0. R^2 is a percent, where the bigger the value of R^2, the better the explaining variables are. That means the estimated regression model is better fitted for the data used.

4.3.3 Hypothesis testing

Hypotheses testing is when you research if there is a connection between two variables $\alpha \; and \; \beta$. The null hypothesis is defined as H_0: there is a connection between $\alpha \; and \; \beta$. The alternative hypothesis, H_A: no connection between $\alpha \; and \; \beta$. We difference between one-sided and two-sided test. If H_0 is that the mean of a distribution is zero, H_A with a one-sided test for example be that the mean is greater than zero. With a two-sided test the H_A will be that the mean is not zero.

With hypotheses testing one will get one of two possible results. That there is enough evidence to support the alternative hypothesis and reject the null hypothesis, or that there is not enough evidence to reject the null hypothesis.

4.3.4 Significance testing

Is used to test if your results are statistically significant. When doing statistically analysis a regular test is the well-known t-test. The test is used to see if a value is significantly different from another. With a regression analysis one can use the t-test to see if one of the regression coefficients is significantly different from 0 (0 is mostly used, can be another value also).

The formula is:

Equation 4-9: T-test

$$t = \frac{\hat{\beta}_1 - \beta_1}{SE_1}$$

Where $\hat{\beta}_1$ is the estimated regression coefficient

                β_1 estimated value of the estimated regression coefficient $(E(\hat{\beta}_1)$

                SE_1 is the estimated standard error for $\hat{\beta}_1$

With degrees of freedom n-2 and a t-distribution. SE_1 is calculated using:

Equation 4-10: Calculation of SE₁

$$SE_1 = \frac{s_\varepsilon}{\sqrt{(n-1)_{s_x^2}}}$$

Where s_ε is the standard error of the estimate

                n   is the number of observations

                s_x^2 is the sample variance of the independent variable

In a regressions analysis one normally define the null hypothesis H_0: $\beta = 0$. H_A is then H_A: $\beta \neq 0$. The null hypothesis says that there is not a connection between two variables.

Another test is the t-difference test. With this test, you can see if two time-series have significantly different mean. If the observations are pared, they are from the same t, one can use a pared t-difference test. The formula is for a pared t-difference test:

Equation 4-11: Test observer of paired t-difference test

$$t = \frac{\bar{d}}{SE}$$

Where $\bar{d}$ is $\frac{1}{n}\sum_t^n(a_t - b_t)$

                SE   is given by: $SE = \frac{s}{\sqrt{n}}$. Where s is the standard deviation of $\bar{d}$ and n is the number of observations.

Then you should see how statistically significant the results are. By for example evaluate the tests observations against a critically limit, that you get by a chosen confidence interval. If the test observation is exceeding this limit, the null hypothesis is rejected.

Another method is by looking at the test p-value. The p-value represent the probability of getting this result if the null hypothesis is true. This means that if you have chosen a 2,5 % significant level and the p-value is 0,00001, the null hypothesis is rejected. It would be unlikely to a high degree to get that result if the null hypothesis is true.

4.3.5   Assumptions using OLS

When working with ordinary least squares, there are a few prerequisites that needs to be fulfilled. In this part, we will present these prerequisites and method for testing of these prerequisites. In addition, how violation of these prerequisites can be handled.

Assumption 1: this requisite explains that a time series needs to follow a linear model in its parameters. This prerequisite can be mathematically defined like this: the stochastic process $((x_{t1}, x_{t2}, \ldots, x_{tk}, y_t)$, where t = 1, 2, 3, …,) must be able to be adjusted for a linear regression model. This means that the relation between the dependent and the independent variable or variables should be linear. If we try to examine and analyse non-linear data with a linear model, the results will be very unreliable.

To test for linearity, we plot the residuals for the estimate values. If the plot is symmetric distributed, we can assume that the prerequisite about linearity is fulfilled.

Assumption 2: is that the expected value of the errors $\epsilon_t = 0$ for all t, given by the dependent variables for all time periods. This prerequisite is being held up by including a constant in the regression.

Assumption 3: The third prerequisite is that none of the independent variables can correlate perfect, if we are going to use ordinary least squares. This is often called multicollinearity and everything below perfect multicollinearity is allowed. As it comes to the point where we start to research data material, this prerequisite is rarely breached.

Assumption 4: If we are going to use ordinary least squares, the variance of the residual errors must be constant, regardless of the independent variables.

This can be expressed mathematically as:

$$VAR(\epsilon_t|X) = VAR(\epsilon_t) = \sigma^2 \qquad \text{this applies for all t.}$$

Constant variance for the errors is called heteroskedasticity, it implies that the variables are independent of each other. If this prerequisite is not fulfilled it means that there exist heteroskedasticity. If we have heteroskedasticity, it will not affect the regression coefficients, but their standard errors, t-values and p-values will be unreliable. If this is the case, this must be corrected for.

Assumption 5: This prerequisite is that there should not exist any autocorrelation in the data set. Mathematically it can be defined as:

$$Corr(\epsilon_t\epsilon_s|X) = 0 \qquad \text{for all } t \neq s$$

The most commonly used method to check for autocorrelation is to use a Durbin-Watson test. This test will give an answer for existence of first order autocorrelation. In other words, the test sees if there is a relation between the residual errors in following periods. Durbin-Watsons test is expressed:

$$DW = \frac{\sum_{t=2}^{n}(\hat{\epsilon}_t - \hat{\epsilon}_{t-1})^2}{\sum_{t=1}^{n}\hat{\epsilon}_t^2}$$

The value of DW will always be somewhere from 0 to 4. If there is no autocorrelation, then DW will be 2. The reason behind this is the relation between DW and the estimated correlation coefficient, ρ. In this case, $DW = 2(1 - \rho)$.

When testing for autocorrelation, the null hypothesis H_0 will be *no correlation*. Depending on the DW coefficient and two critical values, we should decide whether to reject or accept the null hypothesis. These critical values can be found in a Durbin-Watson table. It relies on how many observations we have, number of independent variables and chosen confidence level. The critical values are represented by d_L and d_U, lower and upper limit.

Assumption 6: The last prerequisite is about normality. This means that the residual errors are independent of the variables we use in the regression, as well as being independent and

identical distributed to a normal distribution. In addition, they should have, as mentioned earlier, have expected value equal to zero. We define this mathematically by: Normal $(0, \sigma^2)$.

This prerequisite can be tested by plotting a histogram and look at the residuals frequency along the y-axis and the residuals value along the x-axis. If the histogram looks normal distributed, the prerequisite of normality can be approved.

Another test for normality, is Jarque-Bera test. This is a test that uses number of observations, skewness and kurtosis to estimate a test observer. This test observer is then compared to a critical value we get from the Chi^2-table (Tsay, 2010, p. 10).

Equation 4-15: Jarque-Bera test (Tsay, 2010, p. 10)

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right)$$

Where   JB   test observer for Jarque-Bera test

                n   number of observations

                S   skewness of the time series

                K   kurtosis of the time series

4.3.6   Correlation

Correlation is used to measure to what degree to stochastic variables moves in comparing to each other. In our thesis, we will use correlation to get a preliminary analysis of the volatility. By doing this we hope to see how the variables move comparing to the Oslo stock exchange volatility. The formula used:

Equation 4-16: Correlation (Tsay, 2010, p. 30)

$$\rho_{\sigma OSEAX, \sigma varible} = \frac{Cov(\sigma OSEAX, \sigma varible)}{\sqrt{\sigma^2 OSEAX * \sigma^2 varible}}$$

Where

$\rho_{\sigma OSEAX, \sigma varible}$ is the correlation coefficient between the development in OSEAX volatility and the independent variables volatility

$Cov(\sigma OSEAX, \sigma varible)$ covariance between the development in OSEAX volatility and the independent variable volatility.

The scale is ranged from -1 to 1. Where 0 indicates that the variables are independent of each other. 1 indicates perfect correlation, meaning a linear dependence between the two variables. For -1 it is a perfect negative correlation, which indicates that the variables move opposite of each other.

For a financial point of view, correlation can be used to diversify parts of the unsystematic risk in a portfolio. A portfolio risk can be divided up by systematic and unsystematic risk.

4.4 Calculation of VIX, VDAX and NOVIX

In 1993, The Chicago Board Option Exchange (CBOE) introduced the VIX volatility index. VIX was a measure of the expected 30-day future market volatility (Taylor, 2005, p. 3). Being based on the Black-Scholes pricing model (Black & Scholes, 1973), the VIX was calculated as the average BS implied volatility from S&P 100 put and call options. The method uses eight near-the-money puts and calls for the nearby and second most nearby maturity. This VIX depends on the assumptions of the BS model, this makes it a model-based implied volatility index. While it does capture more information than a single strikes implied volatility, it does not capture all the information with the wide range of strikes available. Ten years later the VIX was revised in collaboration with Goldman Sachs. To be able to provide exchange traded volatility derivatives. The underlying index changed from the S&P 100 to the S&P 500. The method for calculating the index was replaced by a model-free approach. Based on the work of Derman and Kani (1994), Duprie (1994, 1997) and Rubinstein et al. (1994), Britten-Jones and Neuberger (2000) who first devised the concept of model-free implied variance. Using no-arbitrage settings to extract joint features of all stochastic processes that are consistent with detected option prices. This give the advantage that it is not dependent on any option pricing model and extracts information from all related option prices (Jiang & Tian, 2005). How a portfolio of standard options can replicate a variance swap and that the cost of the replicating portfolio is the fair price of a variance swap was show theoretically by Demeterfi et al. (1999). Basically, the VIX methodology discretization of the formula for the fair value of a variance swap. VDAX and NOVIX have followed the CBOE and used the same model-free approach. The VDAX did this in 2005 and renamed VDAX-NEW.

The formula used for this is:

$$\sigma^2 = \frac{2}{T} \sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T} \left(\frac{F}{K_0} - 1 \right)^2$$

Where σ VIX/100

         T   time to expiration

         F   Forward level of the underlying

         K_0 First strike below F

         K_i Strike price of the i-th out-of-the-money option

         ΔK_i $\frac{1}{2} \times (K_{i+1} - K_{i-1})$

         R   risk-free rate

         $Q(K_i)$ Midpoint of the bid-ask spread for option with strike K_i

For more details on the VIX method, we refer to the CBOE White Paper (Chicago Board Options Exchange, 2015).

5 Data & descriptive statistics

In this chapter, we will present the data and results of descriptive statistics. We will also present the data we have used in our analysis later in the paper. With descriptive statistics, we give a summary of the statistics we find important to mention from our data set. The descriptive statistic is chosen to adequately select a model with clean time series. The descriptive statistic we have decided to use is mentioned in section 5.2.

5.1 Data

To complete our analysis, we collected data that we think might affect the OSEAX (Oslo Børs All-share index). The data consist mainly of daily data. For the Fish pool salmon spot index, we used weekly data, as there was no available daily data on the salmon price.

The data is mainly gathered from 1.1.2005 to 31.12.2016. For the NOVIX, we found that there was missing data in 2016 between April and September. We decided to use data from 2005 to 2015 on the NOVIX. This index is calculated based on the VIX methodology S. Bugge, et al. (2016). The data has been gathered from the Thomson Reuters data stream, except the NOVIX. We decided it would be expedient to collect both the OBX total return index, which is the 25 most traded shares on Oslo Stock Exchange, and the OSEAX, which contains all stocks traded on Oslo Stock Exchange. We also collected data on commodity prices, exchange rates and volatility indexes.

This thesis will focus on the volatility and how these variables affect the volatility. Our focus will be the oil price and its link to the Oslo Stock Exchange. The reason why we particularly want to examine the oil price and its link to the Oslo stock volatility, is because oil is a very important part of the Norwegian economy. We will see what effect different exchange rates and interest rates has on the Oslo stock exchange volatility. With the Norwegian economic so entwined in both the EU and the oil price, we expect this to have the highest explanatory factor on the volatility on OSEAX.

Period	Name of data	Number of observations
03.Jan.2005-31. Des.2016	OSEAX	2848
03.Jan.2005-31. Des.2016	OBX total return index	2848
03.Jan.2005-31. Des.2016	Gold price in USD	2848
03.Jan.2005-31. Des.2016	Aluminium price in USD	2848
03.Jan.2005-31. Des.2016	Crude Oil North Sea price	2848
03.Jan.2005-31. Des.2016	NOK to Euro (exchange rate)	2848
03.Jan.2005-31. Des.2016	NOK to USD (exchange rate)	2848
03.Jan.2005-31. Des.2016	NOK to SEK (exchange rate)	2848
03.Jan.2005-31. Des.2016	NOK to DKK (exchange rate)	2848
03.Jan.2005-31. Des.2016	NORWEGIAN GOVERNMENT BOND 10 YEAR	2848
03.Jan.2005-31. Des.2016	VIX-NEW	2848
03.Jan.2005-31. Des.2016	VDAX-NEW	2848
03.Jan.2005-31. Des.2015	NOVIX	2613

Table 5-2: Data set of weekly observations.

07.Jan.2005-30. Des.2016	OSEAX	627
07.Jan.2005-30. Des.2016	Fish Pool Index Spot Salmon	627

Data collected from Thomson Reuters data stream and Bugge, S et al. (2016).

The data mentioned over is used in our descriptive statistics. The descriptive statistic is chosen to adequately select a model with clean time series.

5.2 Descriptive statistics

In this section, we will present the descriptive analysis. It is a brief presentation of the most important statistics regarding our choice of model to calculate the volatility. In this section, we will present the mean, median, mix, max, standard deviation, skewness, kurtosis, Jarque-bera test, Ljung Box-test, QQ-plots, two sample t-test, ACF/PACF and Augmented Dickey Fuller test (ADF).

In the table below we have presented the size of the data, mean, min, max, standard deviation, skewness, kurtosis and Jarque-Bera of the different data.

Table 5-3: OSEAX all share index and OBX total return index.

Statistical Analysis	OSEAX all share index	OBX total return index
Size	2848	2848
Mean	495.5032	395.8685
Min	232.29	162.9199
Max	766.17	621.02
Std.Dev	122.5724	109.0862
Skewness	−0.04582254	0.04412901
Kurtosis	−0.7712143	−0.8601618
Jarque-Bera	3508.1756	4325.1652
P-verdi	2.2e−16	2.2e−16

Table 5-4: VIX and VDAX.

Statistical Analysis	VIX	VDAX
Size	2848	2848
Mean	19.48763	22.59228
Min	9.89	11.65
Max	80.86	8.799531
Std.Dev	9.453958	22.59228
Skewness	2.479947	2.341263
Kurtosis	8.120843	8.046079
Jarque-Bera	1847.1953	878.1489
P-verdi	2.2e−16	2.2e−16

Table 5-5: Crude oil North Sea and Norske Bank 10-year bond benchmark.

Statistical Analysis	Crude Oil	NORSKE BANK 10 YEAR BOND BENCHMARK
Size	2848	2848
Mean	79.74365	3.145949
Min	26	0.8786716
Max	143.95	5.265768
Std.Dev	26.56123	1.125283
Skewness	0.1309606	−0.1915623
Kurtosis	−1.262032	−1.173194
Jarque-Bera	196.79	2307.6108
P-verdi	2.2e−16	2.2e−16

Table 5-6: NOK/EUR exchange rate and NOK/USD exchange rate.

Statistical Analysis	NOK/EUR - EXCHANGE RATE	NOK/USD - EXCHANGE RATE
Size	2848	2848
Mean	8.230496	6.401633
Min	7.27245	4.95835
Max	9.9515	8.97465
Std.Dev	0.5593586	0.9332688
Skewness	0.7597803	1.131495
Kurtosis	−0.178735	0.3306062
Jarque-Bera	2528.3638	1915.9549
P-verdi	2.2e−16	2.2e−16

Table 5-7: Descriptive statistics of NOK/SEK exchange rate and NOK/DKK exchange rate.

Statistical Analysis	NOK/SEK - EXCHANGE RATE	NOK/DKK - EXCHANGE RATE
Size	2848	2848
Mean	88.32824	110.4131
Min	76.43	97.68
Max	105.21	133.48
Std.Dev	5.212495	7.504752
Skewness	0.8982014	0.7667684
Kurtosis	0.4159257	−0.1789428
Jarque-Bera	1412.1531	4991.3773
P-verdi	2.2e−16	2.2e−16

Table 5-8: Descriptive statistics of Gold Buillion and LME-Aluminium.

Statistical Analysis	Gold	Aluminium
Size	2848	2848
Mean	1097.107	2076.28
Min	412.1	1251.75
Max	1898.25	3271.25
Std.Dev	375.8811	422.7601
Skewness	−0.11747	0.48725
Kurtosis	−0.8993939	−0.6287634
Jarque-Bera	2618.5834	356.765
P-verdi	2.2e-16	2.2e-16

Table 5-9: Descriptive statistics of OSEAX all share index and NOVIX.

Statistical Analysis	OSEAX all share index	NOVIX
Size	2613	2613
Mean	480.2308	23.87172
Min	232.29	10.7689
Max	711.22	84.24663
Std.Dev	115.8486	9.979465
Skewness	−0.002938669	1.914634
Kurtosis	−0.6378987	5.317802
Jarque-Bera	44.056	4684.6
P-verdi	2.713e-10	2.2e-16

Table 5-10: Descriptive statistics of OSEAX all share index and Fish Pool spot price salmon.

Statistical Analysis	OSEAX all share index	Fish pool
Size	627	627
Mean	495.6587	35.18376
Min	232.29	18.99
Max	764.66	79.37
Std.Dev	122.9788	11.25507
Skewness	−0.05417897	1.361991
Kurtosis	−0.7575932	1.864943
Jarque-Bera	15.020	287.17
P-verdi	0.0005475	2.2e-16

Most of the data has been collected by using the Thomson Reuters data stream, provided by Oslo Business School (HiOA). Except from the NOVIX that was provided to us by S. Bugge (2016) et al.

The tables present statistics we have calculated in Rstudio. The mean statistic is the mean value of the associated data. For instance, we can see that the mean of the Oslo All shares data is 495,5. The *Min* statistic is the number of the lowest value in the associated data. For the OSEAX data, the minimum value is 232,3. The *Max* statistic shows the highest value in the data. For Oslo All Shares, this value is 766,2. For the volatility indexes, VDAX has a higher *Mean* than the VIX and the NOVIX has the highest *Mean* of 23,87. The data on NOVIX is with one year less data, which can influence the results when compared together. Since the VIX has the lowest *Mean* of the volatility indexes, this can imply that the volatility on the S&P 500 has been lower than on the OSEBX and Frankfurt stock exchange.

For the exchange rates the results cannot be compared against each other on share value, as the volatility indexes can (because they are calculated the same way). We see that one euro has on average cost of 8,23 Norwegian kroner and one dollar a cost of 6,40 Norwegian kroner. While 100 Swedish kroner has a mean of 88,33 Norwegian kroner and 100 Danish kroner has a mean of 110,41 Norwegian kroner. The oil price has a mean of 79,74.

The *Min* and *Max* values are not particular complex nor hard to understand. For the volatility indexes, we see that VIX has the lowest max, but all the indexes range from approximately a *Min* of 10 to a *Max* of around 80, showing that the market have been volatile in the period. For the exchange rates the dollar also has a higher range between its *Min* and *Max* than Euro, maybe showing that this exchange rate has been more volatile than the euro against the Norwegian kroner. Amongst the Nordic countries, Sweden has the largest range between its *Min* and *Max*, but interesting enough it is the DKK that have the largest standard deviation. The most interesting *Min* and *Max* of our explanatory variables is the crude oil price. That has a *Min* of 26 and a *Max* of 143,95. Showing the largest range in percentage of all our variables. This might indicate that the oil price has been as or more volatile than the volatility indexes.

When we consider the next statistic, it became a little more complex and detailed. The next statistic we are going to look at is the standard deviation of the data. We cannot directly find this statistic, so this is calculated. This statistic is calculated by subtracting each observation by the mean. This number is squared and summed, which is the Sum of Squares (SS) value.

SS is now divided on the number of observations (n) or Size, as we have called this value in the descriptive table, minus 1. Now, have the variance to get standard deviation, we square root the number we get. This method can be presented by the following formula:

Equation 5-1: Sum of squares.

$$SS = \sqrt{\frac{\sum(X - \bar{X})^2}{(n-1)}}$$

Where   X   is the score of each observation

              $\bar{X}$ is the mean

              n   is the number of observations

Looking at the standard deviation we found that for the volatility indexes VDAX, the standard deviation is the greatest at 22,59, with VIX at 9,45 and NOVIX at 9,979. This might indicate that the US market has a greater influence on the volatility for the Oslo Stock Exchange, than the Frankfurt stock exchange have. Even if one could expect the Frankfurt stock exchange to follow the EU market. For the Oslo Stock Exchange the standard deviation is 122,57 and the benchmark indexes (25 most traded companies on the Oslo Stock Exchange) has a standard deviation of 109,09. This can be indicating that the 25 most traded companies on the stock exchange has a lot of influence in the market. The standard deviation for the oil is also high, at 26,56. Indicating that the price has been highly volatile in this period.

In the next section, we will present the more statistical advanced values, such as kurtosis, skewness and Jarque-Bera.

5.2.1 Skewness

Skewness is a measure to what degree the distribution is not symmetrical around the mean. This will then be the asymmetrical in the probability distribution. A positive skewness will mean that the distribution is skewed right and means that there are more likely to occur positive price jumps than negative ones. Negative skewness tells us that the distribution is skewed left which means that there is more likely to be negative price jumps than positive jumps (Brooks, 2008).

Figure 5-1: Skewness distribution.
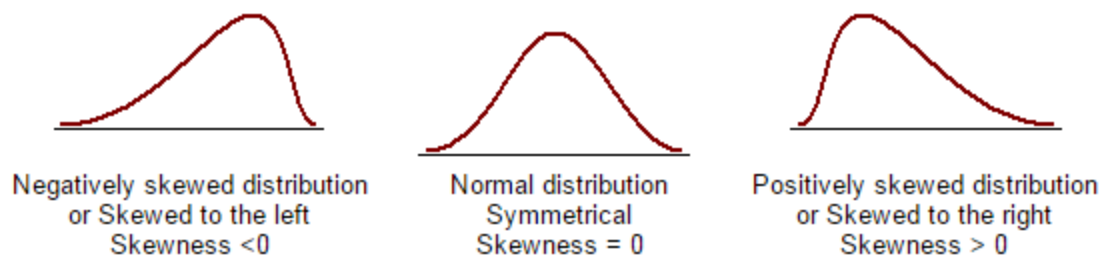
The tables above show that none of data is normally distributed, they are ranged from -0,192 to 2,48. Our main data from the Oslo Stock Exchange has a skewness of -0,046, with the OSEBX index having a skewness of 0.044. On the stock exchange, there is a higher probability that large negative price changes occur, than large positive changes. When we look at the Oslo stock benchmark index, there is a positive skewness. This means that there is more likely that a large positive price jumps occurs, than a negative one. Notice, that is the implied volatility on VIX and VDAX that has high positive skewness. Both at 2,48 and 2,34 respectively. This shows that the volatility on the S&P 500 and Frankfurt stock exchange have a high probability that higher volatility is more likely than lower volatility changes.

5.2.2 Kurtosis

Kurtosis is a measurement of distributions tails. Kurtosis means how fat the tails are. Normally we categorize a kurtosis of 3, a normal distribution. This figure below shows the various stages of kurtosis. (Brooks, 2008)

Figure 5-2: Kurtosis distribution.
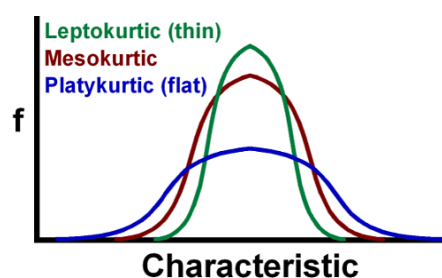
In the figure, we can see the various stages of kurtosis. If the kurtosis is 3, then this will mean a regular distribution. If the kurtosis is < 3 the distribution is flatter, called a Platykurtic distribution. When the kurtosis is > 3 it is a leptokurtic distribution (thin).

In the data for Oslo Stock Exchange Platykurtic distribution has been proven. We see that most of the data has the same Platykurtic distribution. Except the Volatility stock indexes, VDAX and VIX has Leptokurtic distribution.

5.2.3 Jarque-Bera test

With the Jarque-Bera test, we are testing the H_0 of normality. By using this test, we are checking if our data is normally distributed or not. The Jarque-Bera test uses kurtosis and skewness. Defined by Brooks (2008):

Equation 5-2: Jarque-Bera test

$$JB = T\left(\frac{\hat{y}^2}{6} + \frac{(\hat{\delta} - 3)^2}{24}\right)$$

where $\hat{y}^2$ is the skewness of the time series

                    T   is number of observations

                    $\hat{\delta}$ is the kurtosis.

Using a chi-squared distribution with two degrees of freedom, gives a critical value of 5,99 for 5% confidence interval. In other words, the null hypothesis is that the data is normally distributed, which implies a kurtosis is 3. If the observation is over 5.99, we reject the null hypothesis.

With few observations, one risk that the null hypothesis is rejected even if the null hypothesis is correct. Considering that we have 2848 or 2613 observations on the daily data and 626 on the weekly, it is reasonable to believe that this will not be a problem. The Jarque-Bera test shows that the data is not normally distributed, this is also confirmed by the skewness and kurtosis. This confirms our assumption that an asymmetric GARCH model will be better to calculate the volatility.

The Jarque-Bera test ranges from 357-4325. With the skewness and kurtosis mentioned earlier, we conclude that we can reject the null hypothesis.

5.2.4 Residual autocorrelation function (ACF) and Partial autocorrelation function (PACF)

ACF is a set of correlation coefficients between the series and lags of the series. PACF is the partial correlation coefficients between the series and the lags of the series. If it follows an autoregressive process, it tells us what we do not know compared to what we do know. If there is a sharp cut off in the PACF, ACF decays sharper and the result are significant in higher lags. We can than say that the series follows an autoregressive process.

We can also see if the series follow the Moving-average process (MA). If this is the case the ACF for the differentiated series shows a sharp cut off and/or if the prior results lags autocorrelation is negative, then we should consider an MA-model.

ACF and PACF will at one lag be the same. PACF measures the correlation between one observation for k periods and todays observation. The correlation between y_t and y_{t-k}.

Equation 5-3: ACF and PACF.

$$\hat{\tau}_\ell = \frac{\sum_{t=\ell}^{T}(r_t - \bar{r})(r_{t-\ell} - \bar{r})}{\sum_{t=1}^{T}(r_t - \bar{r})^2}, 0 \leq \ell < \text{T-1}$$

The correlation coefficient between r_t and $r_{t-\ell}$ is called lag-ℓ autocorrelation of r_t and is noted as τ_ℓ and $\hat{\tau}$ is the consistent estimate for τ_ℓ.

With 2 lag ACF and PACF will be different. PACF is then:

Equation 5-4: PACF 2-lag (Brooks, 2008 and Tsay, 2010).

$$\tau_{22} = \frac{(\tau_2 - \tau_1^2)}{(1 - \tau_1^2)}$$

τ_1 and τ_2 is the autocorrelation coefficients with lag 1 and 2. If you use lags greater than 2 will the formula be very complex (Brooks, 2008 and Tsay, 2010).

The ACF plots are shown under. By studying these plots, we see that OSEAX all share has a lag of 32, the OSEBEX 34, gold 30, aluminium 31, oil 28, 10-year government bond 33, NOK/EUR 23, NOK/USD 34, NOK/SEK 30, NOK/DKK 30, VDAX 33, VIX 12, NOVIX 22 and Salmon 27. Many of these stand out by having a significant negative autocorrelation. The data have high autocorrelation lags; they are positively correlated with the change in the past. The ACF of the data gives us these plots.

Figure 5-3: ACF plots for all variables in our data set.
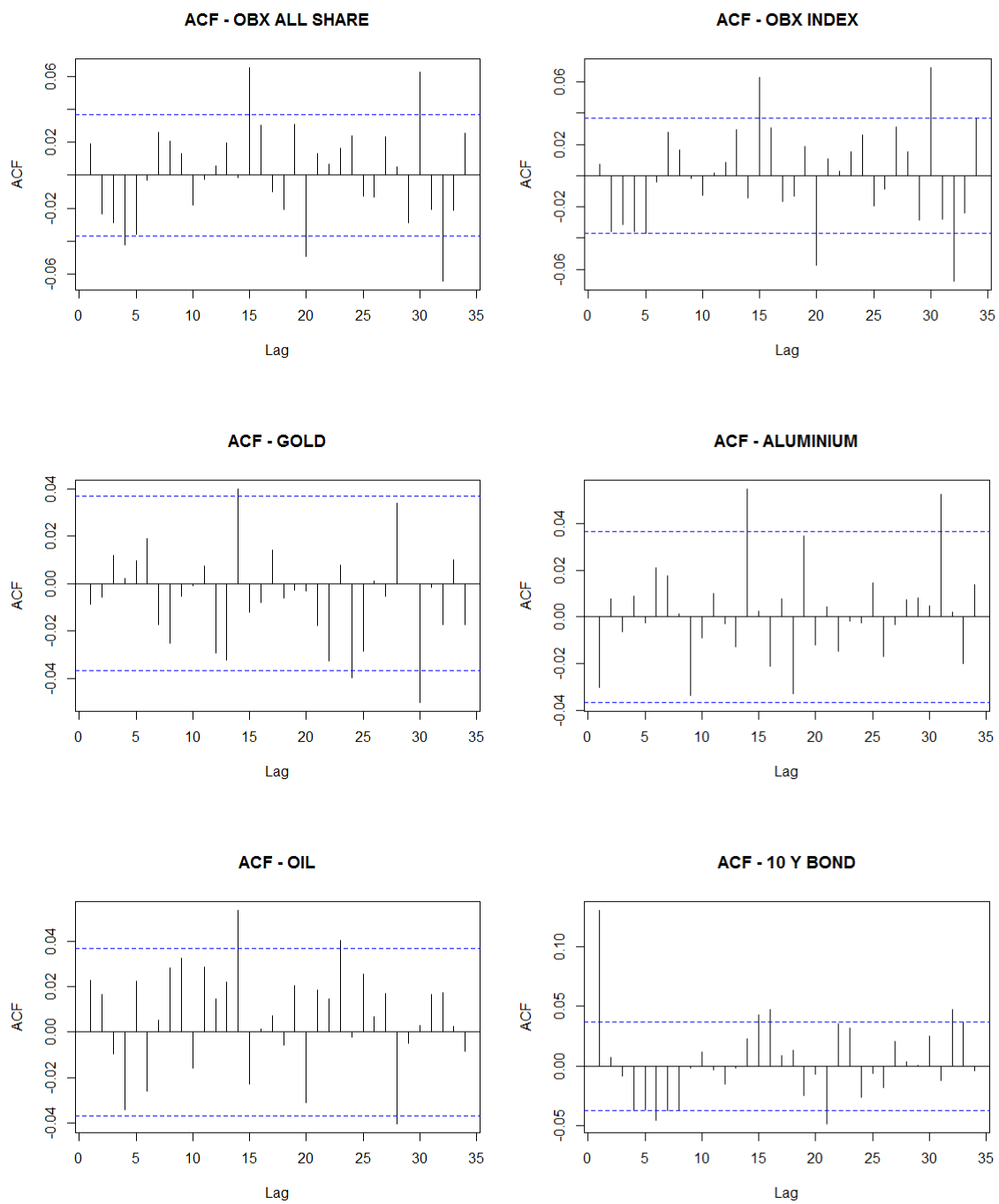
ACF - NOK/EUR
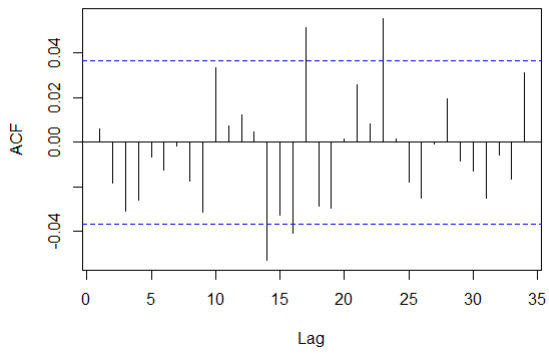
ACF - NOK/USD
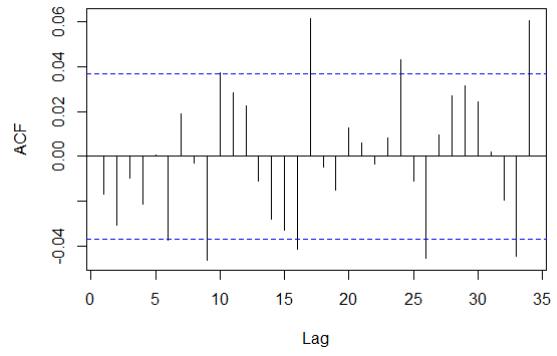
ACF - NOK/SEK
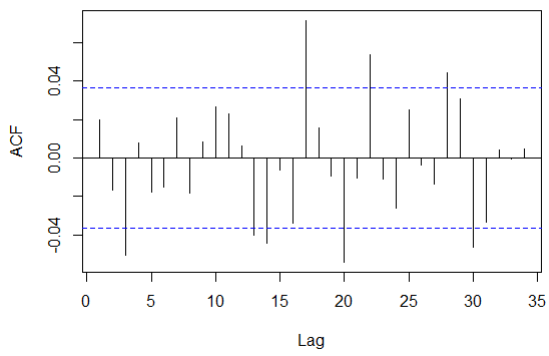
ACF - NOK/DKK
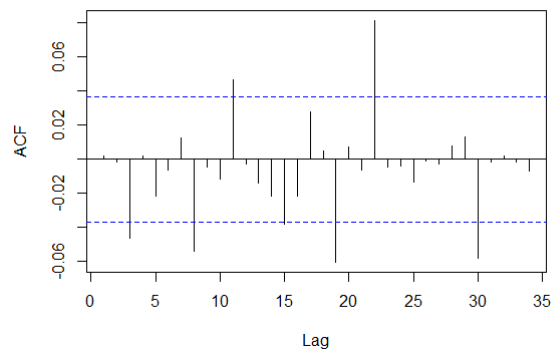
ACF - FISH POOL
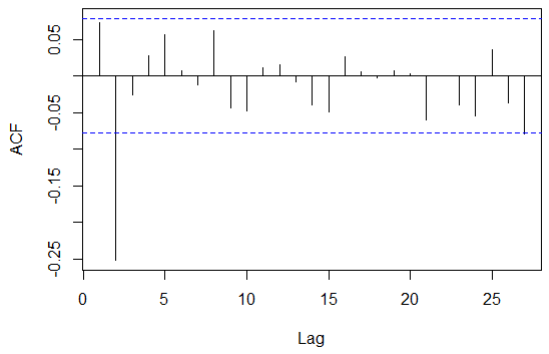
ACF - NOVIX
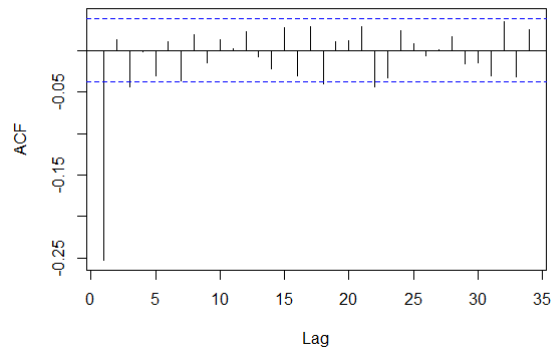
ACF - VDAX
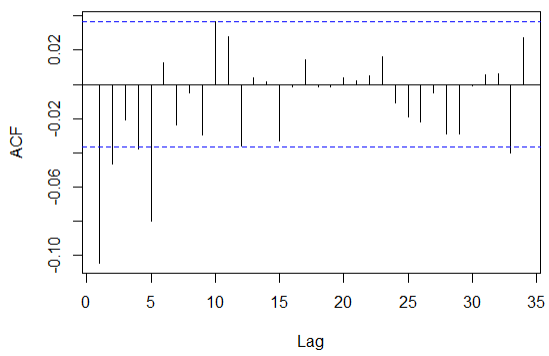
ACF - VIX
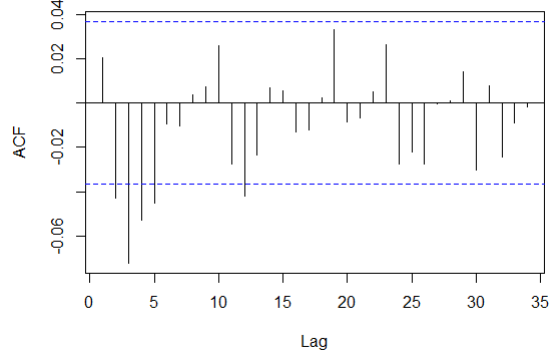
5.2.5 Ljung-Box test

With the Ljung-Box test, we test the adaption of the time series model. The null hypothesis is independence in the time series. The null hypothesis for this test checks if there is no autocorrelation. The formula is:

Figure 5-4: Ljung-box test.

$$Q^*(m) = T(T+2) \sum_{\ell=1}^{m} \left(\frac{\hat{\rho}_\ell^2}{T-\ell} \right)$$

Where ρ is the autocorrelation coefficient

              T   is the number of observations

Using a χ^2 chi-distribution with m degrees of freedom the test has a decision rule to reject H_0 if $Q(m) > \chi_\alpha^2$, where χ_α^2 denotes the $100(1-\alpha)$th percentile of a chi-squared distribution with m degrees of freedom. Meaning that ARCH-effects are non-existing in the data if we cannot reject the null hypothesis. Implying that an ARCH or GARCH model will not be a good fit (Tsay, 2010).

We selected a few of the variables that we found interesting to mention the results of. We chose OBX, NOVIX, VIX and oil. We are using the log returns of these.

In Rstudio we used ACF-plots to find the best fitting lags. We found that the best fitting lags of OBX is 32, Oil 28, VIX 12 and NOVIX 22. We ran the Box-test to see if there is serial correlation. The lags are higher than five lags, which indicates serial correlation in the data. The values from the box-test below shows that they are all over the critical value with a good margin. The degrees of freedom will be lower by (p+q), we are using a GJR-GARCH (1,1) model meaning that the degrees of freedom will be subtracted by 2. We can reject the null hypothesis from the results in the table under.

Table 5-11: Ljung-Box test

Ljung-Box test				
Data	OSEAX	OIL	VIX	NOK/USD
χ^2	77.385	47.176	45.039	82.734
df	30	26	10	20
p-value	4.663e-06	0.01605	2.14e-06	2.265e-06

5.2.6 Augmented Dickey Fuller (ADF) test

The Dickey Fuller test and the augmented Dickey Fuller test is known to test unit root (Lupi, 2009). What we hope to discover with this test is if the data follows a "*random walk*". The zero hypothesis that y_t is *"random walk"*, that will mean that $\Phi = 1$ against the H1 that $\Phi < 1$. In the expression $y_t = \Phi y_{t-1} + u_t$. This will mean that H_0: the time series contains unit root. $H_1 =$ the series is stationary. From Buveit (2014) we got this simplification of the formula and the augmented Dickey Fuller formula:

Equation 5-5: Dickey Fuller equation

$$\psi = \Phi - 1 \, , \Delta y_t = \psi y_{t-1} + u_t$$

H_0 is then, $\psi = 0$, and H_1 is $\psi < 0$. u_t is white noise. We dismiss the zero hypothesis if the t-value is lower than zero, the test follows a t-distribution.

There are some problems with this test. It only applies if u_t is white noise. u_t is also assumed to not be autocorrelated. If there is autocorrelation in the dependent variable, there will be autocorrelation in u_t. It also does not follow the t-distribution under the null hypothesis.

Buveit (2014) gave us the solution with the augmented Dickey Fuller formula. This will work as a solution, since it uses p lags of the dependent variable.

Equation 5-6: Augmented Dickey Fuller equation

$$\Delta y_t = \psi y_{t-1} + \sum_{i=1}^{p} \alpha_i \, \Delta y_{t-i} + u_t$$

To make this work, we must choose enough lags so that all the serial correlation is gone. This will also mean that by using too much lags the estimates will be less correct, since we are consuming up too much degrees of freedom (Brooks, 2008). We are using the daily log returns of the data to adjust for the exponential trending data.

Table 5-12: ADF coefficients calculated in Rstudio.

Variable (log returns)	ADF	P-value
OSEAX	-38,233	0,001
OBX total return index	-38,955	0,001
Oil	-36,678	0,001
Gold	-38,112	0,001
Alum	-38,198	0,001
NOK/EURO	-38,285	0,001
NOK/USD	-39,274	0,001
NOK/SEK	-37,954	0,001
NOK/DKK	-37,725	0,001
VDAX	-41,965	0,001
VIX	-38,947	0,001
10 year Gov. Bond	-35,49	0,001
NOVIX	-38,947	0,001
Salmon	-22,097	0,001

The table present that all the daily log returns are stationary at an 1 % level. They are all highly significant and stationary.

5.2.7   QQ-plots

Q stands for Quantile. So QQ-plot will be Quantile-Quantile plots. It is used to control validity of a dataset assumption of the distribution. If the QQ-plot follows the assumed distribution, the points in the plot will be approximately a straight line.

Figure 5-5: QQ-plots.
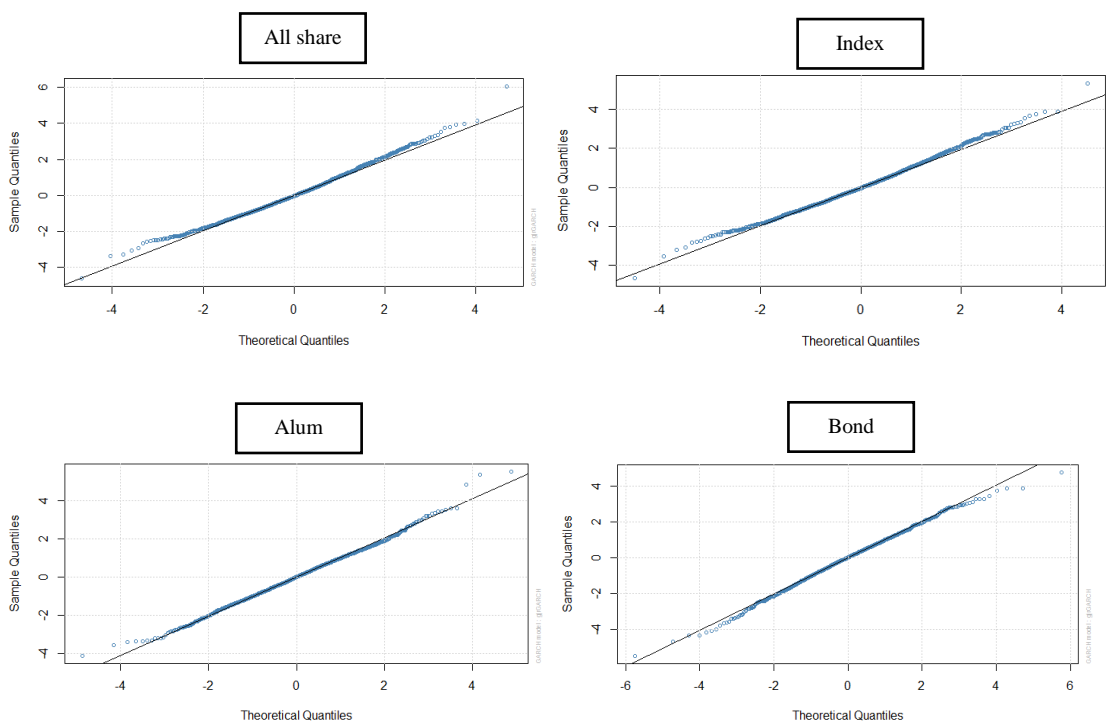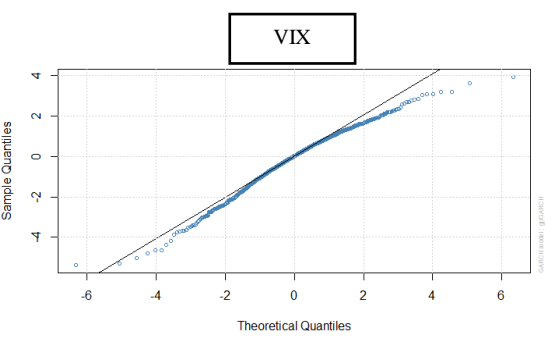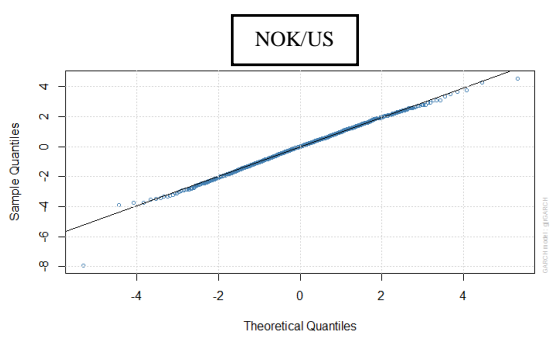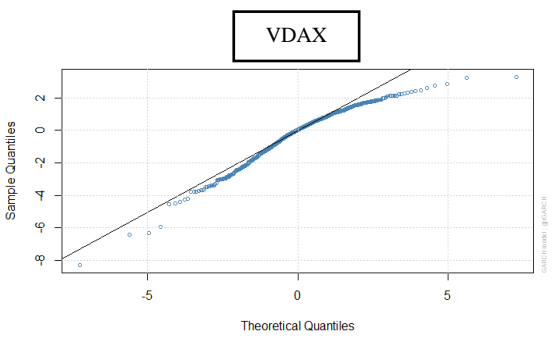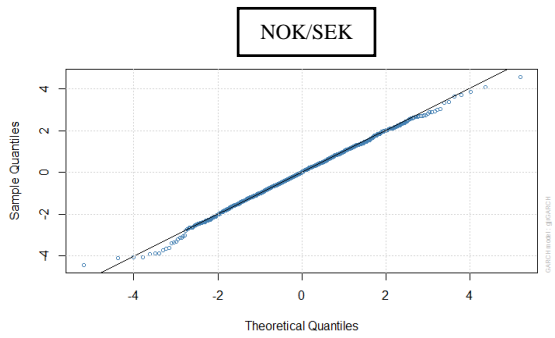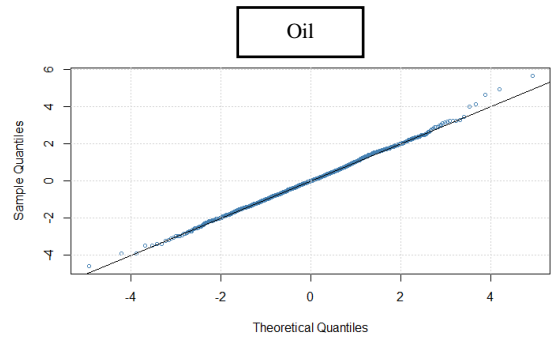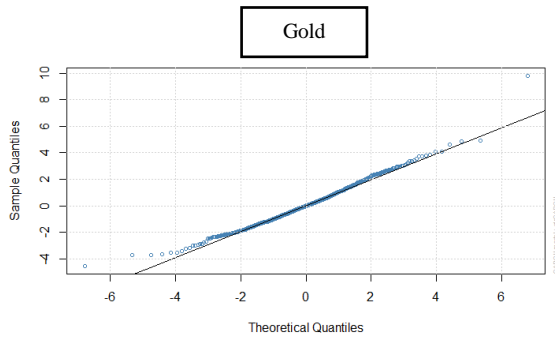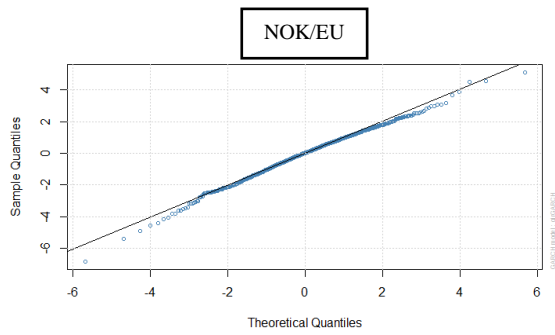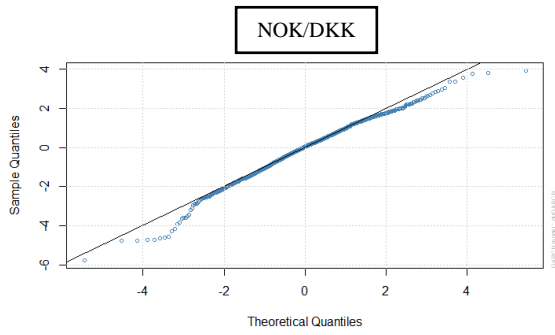
From the QQ-plots we can see that the series has fat tails and high kurtosis. We can also see that the fat tails are not perfectly symmetric.

5.2.8 T-test

The sample t-test is a test that decides if there is significant difference between the mean in two unrelated groups. The zero hypothesis is that the sample mean from the two separate groups is the same. If we find that the mean from the two separate groups are not the same, we can reject the null. To do this we choice the significant level of 5 %.

Equation 5-7: T-test

$$ t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\dfrac{s_1^2}{n_1} + \dfrac{s_2^2}{n_2}}} $$

$\bar{X}_1$ is the mean of sample 1 and $\bar{X}_2$ is the mean of sample 2. s_1^2 is the variance to sample 1 and s_2^2 is the variance of sample 2. n_1 is the number of observations in sample 2 and n_2 for sample 2.

Figure 5-6: Two sample t-tests calculated in R.

Two sample t-test of log returns	OSEAX vs OBX	OBSEAX vs OIL	OSEAX vs ALUM	OSEAX vs GOLD
t	-1,6349	-1,5745	-2,19	-1,8892
df	3472	3472	3472	3472
p-value	0,1022	0,1155	0,02859	0,05895

Two sample t-test of log returns	OSEAX vs EUR	OSEAX vs USD	OSEAX vs SEK	OSEAX vs DKK
t	-2,8265	-2,4683	-2,8851	-2,8285
df	3472	3472	3472	3472
p-value	0,004733	0,01362	0,003937	0,004703

Two sample t-test of log returns	OSEAX vs 10-year BOND	OSEAX vs VDAX	OSEAX vs VIX	OSEAX vs NOVIX	OSEAX vs SALMON
t	-2,2363	-0,59056	-0,72515	-0,22725	0,066168
df	3472	3472	3472	5222	1250
p-value	0,0254	0,5549	0,4694	0,8202	0,9473

The two-sample t-test show that the mean of the daily changes considering the exchange rates are significantly different from the OSEAX. While the volatility indexes are not significantly different from OSEAX, with NOVIX having the highest p-value. Since NOVIX is the implied volatility on OSEAX the mean of these two are not significantly different. The results from gold, aluminium and the 10-year government bond, we can conclude that these are significantly different from OSEAX. The OBX index and Oil are not significantly different from OSEAX. We expect that the variables that are not significantly different from OSEAX will have the most explanatory effect on the volatility of the Oslo Stock Exchange. That is

because if it is not significantly different we think the variable will move with the OSEAX, and can have a high explanatory factor on the Oslo Stock Exchange volatility.

5.3 Summary

The descriptive statistic is used to see what characterises the data, and with the results we must decide on what kind of model will get the cleanest time series. We see that the index and the stock exchange have comparable results. We see that the correlation between these two are almost perfect. We also see that the both exhibit high kurtosis and fat tails. They are also stationary. We can also see that the VIX and the oil price seem to be showing the same tendency. We see that all the exchange rates are highly volatile, as are the volatility indexes and the commodity prices.

All the variables show high kurtosis and skewness. They have fat tails. They also show high lags. This indicates that the volatility of oil on day t-1 can be used to characterise the volatility of Oslo Stock Exchange on day t. The volatility indexes have comparable results, with the standard deviation of VDAX standing somewhat out. The oil price shows tendencies of being highly volatile in the period.

We also see that the data is stationary and that there are ARCH-effects and serial correlation in the data sets. We see that most of the data has the same Platykurtic distribution, except the volatility stock indexes, VDAX and VIX has Leptokurtic distribution.

Due to some macroeconomic incidents, such as the financial crisis, we can see that there has been high uncertainty in the markets, that have affected the volatility. We can see that the volatility indexes also show a tendency to follow each other. This means that they are affected by each other or more likely that the VIX (US stock market) has a greater effect on VDAX and NOVIX.

The difference between *Min* and *Max* are great for all the variables. Probably because of the financial crisis. While the VDAX can have a higher standard deviation than VIX and NOVIX, which could be vecasue it was affected by the Greek debt crisis for example, we see that against the Norwegian kroner, it is the dollar that we expect have the highest volatility. Probably, because of the oil volatility.

As mentioned we found that the data had fat tails, high kurtosis and skewness. The data should tendency for high volatility with large standard deviations. From skewness, we found

that the data is not normally distributed. From kurtosis, we found that most of the data follow a platykurtic distribution (flat). The Jarque-Bera also shows that data is not normally distributed, indicating that an asymmetric model could better fit our data. The Ljung-Box test also showed that ARCH effect is existing in the data, indicating that an ARCH model can be used. We also found that the data is not perfectly symmetric.

From the result, we wanted to check what kind of different ARCH and GARCH models have the best fit with our data. With our tests and results, indicate that characterising the financial data with an asymmetric GARCH model will have the best fit. By doing this we will not have bias either way.

6 Econometric results and discussion

In this chapter, we will present the results of our analysis.

6.1 Preliminary analysis

We are researching which factors can characterise the volatility on the Oslo Stock Exchange between 2005 to 2016. In this section, we want to present some preliminary analysis, that is correlation analysis and graphical presentation of the volatilities we are trying to link the volatility on the OSEAX index with. Volatility has a graphical representation in GARCH. We decided to use the volatility output from the stock exchange and plot them against the variables we are trying to characterise the volatility with. Accumulating in ten graphs where the daily volatility calculated by a GJR-GARCH model is plotted (weekly for salmon).

Regression	Independent variable	β_0	β_1	R^2	t-value (β_1)	p-value	N
1	OBX Index	0,080498	0,860925	0,9809	381,89	2,00E-16	2848

Figure 6-1: GJR-GARCH (1,1) volatility plot and regression coefficients for OSEAX and OBX total return index.

Figure 6-1 is a presentation of the volatility calculated from the GJR-GARCH (1,1) model for OSEAX and OBX total return index from 03.01.2005 to 31.12.2016.

When looking at the plot of the volatility of OSEAX and the OBX index we see that the volatility is almost identical. The OBX index is as mentioned before made up of the 25 most traded companies on the stock exchange, this can imply that these 25 companies have a profound influence on the volatility for the stock exchange. There is approximately no

difference in the volatility for these two.

Regression	Independent variable	β_0	β_1	R^2	t-value (β_1)	p-value	N
2	Oil Volatility	0,15988	0,58794	0,3903	42 679	2,00E-16	2848
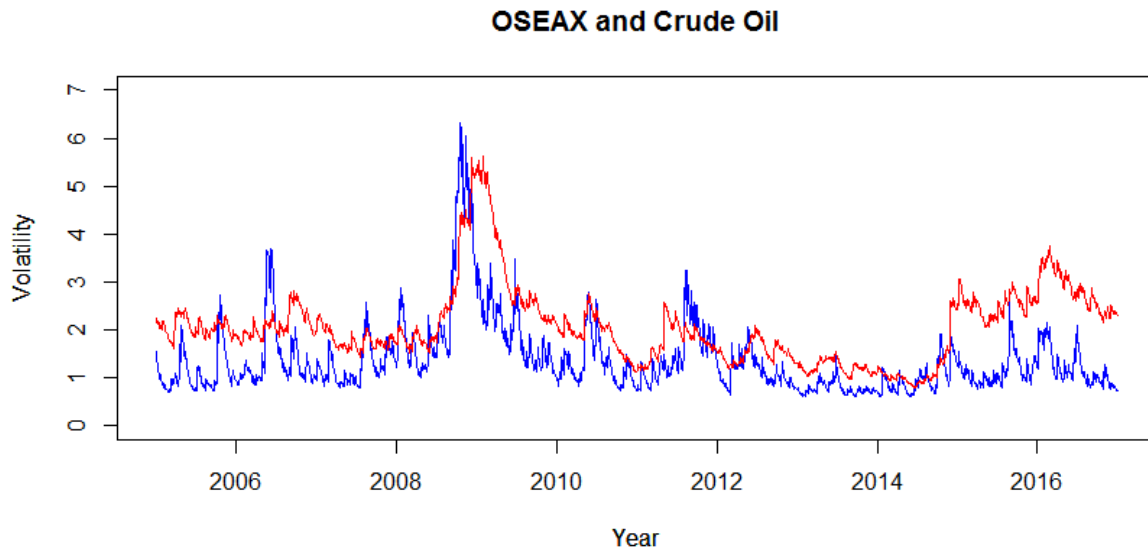
Figure 6-2: GJR-GARCH (1,1) volatility plot and regression coefficients for OSEAX and Crude Oil.

Figure 6-2 is a presentation of the volatility calculated from the GJR-GARCH (1,1) model for OSEAX and Crude oil price from 03.01.2005 to 31.12.2016.

We see that the oil volatility is higher on average than the OSEAX, but their movements are similar, relative to each other. When the volatility in oil price goes up, the volatility on the exchange also increases. It is worth mentioning that during the financial crisis, the volatility on the exchange is higher than the oil volatility. The same can be said for the end of 2006 and the end of 2011, when the exchange volatility is higher than the oil volatility. We would expect to see the oil price volatility to have a high and significant link to the volatility on the exchange.

Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta1$)	p-value	N
9	10 Year Bond Volatility	1,21471	0,09868	0,01071	5,64	2,00E-16	2848
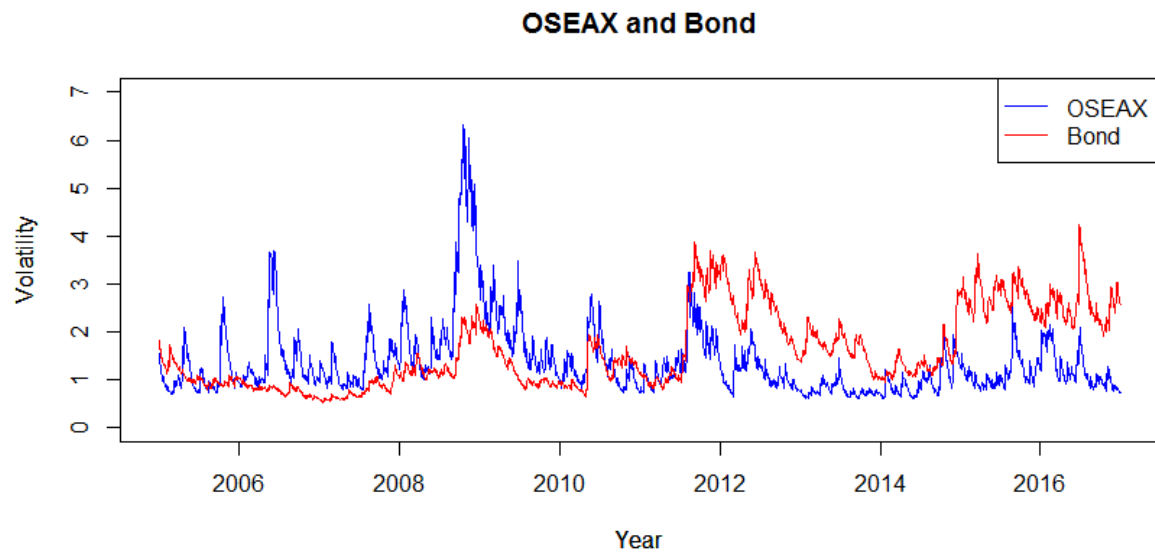
Figure 6-3: GJR-GARCH (1,1) volatility plot and regression coefficients for OSEAX and Norwegian 10-year bond.

Figure 6-3 is a presentation of the volatility calculated from the GJR-GARCH (1,1) model for OSEAX and 10-year movement bond from 03.01.2005 to 31.12.2016.

The volatility of the exchange seems to be moving sporadically with the government bond. At various times in the figure we can see that the volatility of the government bond (changes in the bond) gets higher when the volatility on the exchange goes down. At other points the opposite is the case. Mostly it seems that when the volatility on the bond is lower, the volatility on the exchange increases.

Regression	Independent variable	β_0	β_1	R^2	t-value (β_1)	p-value	N
5	NOK/EUR Volatility	0,18706	2,36094	0,2636	31,94	2,00E-16	2848
6	NOK/USD Volatility	-0,12874	1,83870	0,3995	43,534	2,00E-16	2848
7	NOK/SWE Volatility	0,29632	2,30063	0,1368	21,264	2,00E-16	2848
8	NOK/DKK Volatility	0,27329	2,23267	0,2264	28,882	2,00E-16	2848
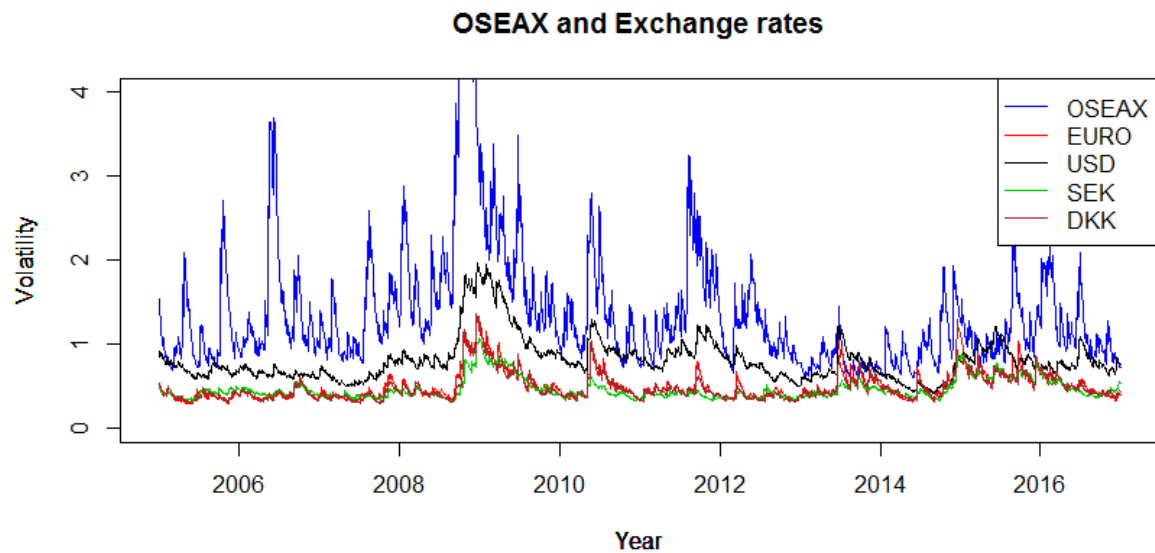
Figure 6-4: GJR-GARCH (1,1) volatility plot and regression coefficients for OSEAX and exchange rates.

Figure 6-4 is a presentation of the volatility calculated from the GJR-GARCH (1,1) model for OSEAX and the different exchange rates from 03.01.2005 to 31.12.2016. Notice the graph is scaled with a *Max* of 4, to make the exchange rate volatilities readable.

The exchange rate between NOK and USD stands out, the volatility is higher at all points than the other exchange rates. The EURO, DKK and SEK moves approximately the same as each other. We see that the daily volatility for all the exchange rates are lower than for the NOK/USD, expect in the late 2013.

Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta1$)	p-value	N
3	Gold Volatility	-0,27005	1,35117	0,4698	50,232	2,00E-16	2848
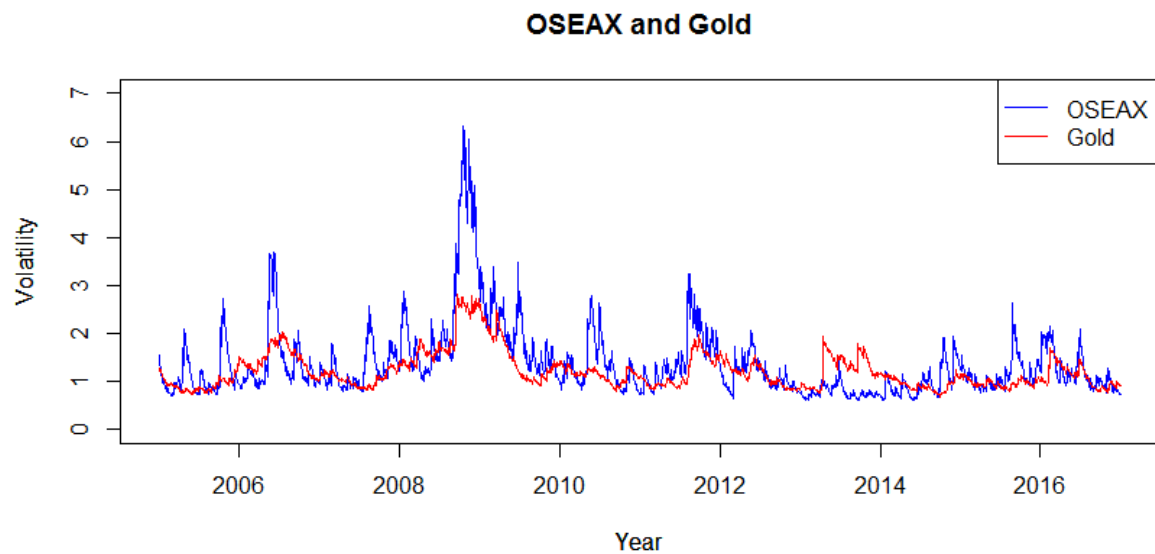
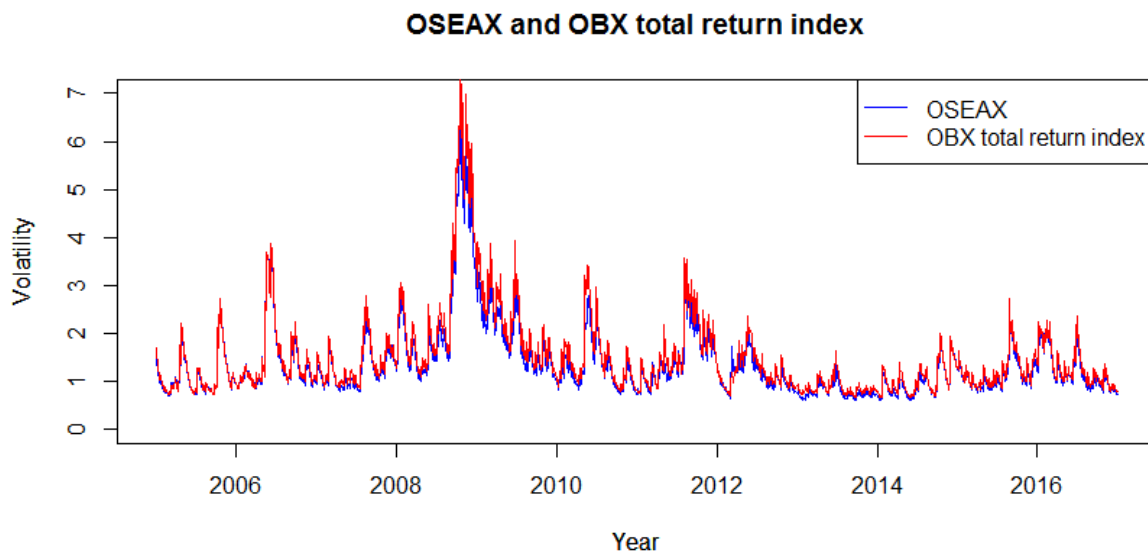*Figure 6-5: GJR-GARCH (1,1) volatility plot and regression coefficients for OSEAX and Gold Bullion.*

Figure 6-5 is a presentation of the volatility calculated from the GJR-GARCH (1,1) model for OSEAX and Gold price from 03.01.2005 to 31.12.2016.

The daily volatility for the gold price is normally lower than the volatility on the exchange, but we can see that they move quite similar. The exception looking to be from 2013 to 2014.

Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta1$)	p-value	N
4	Aluminium Volatility	0,35011	1,16682	0,2792	33,224	2,00E-16	2848
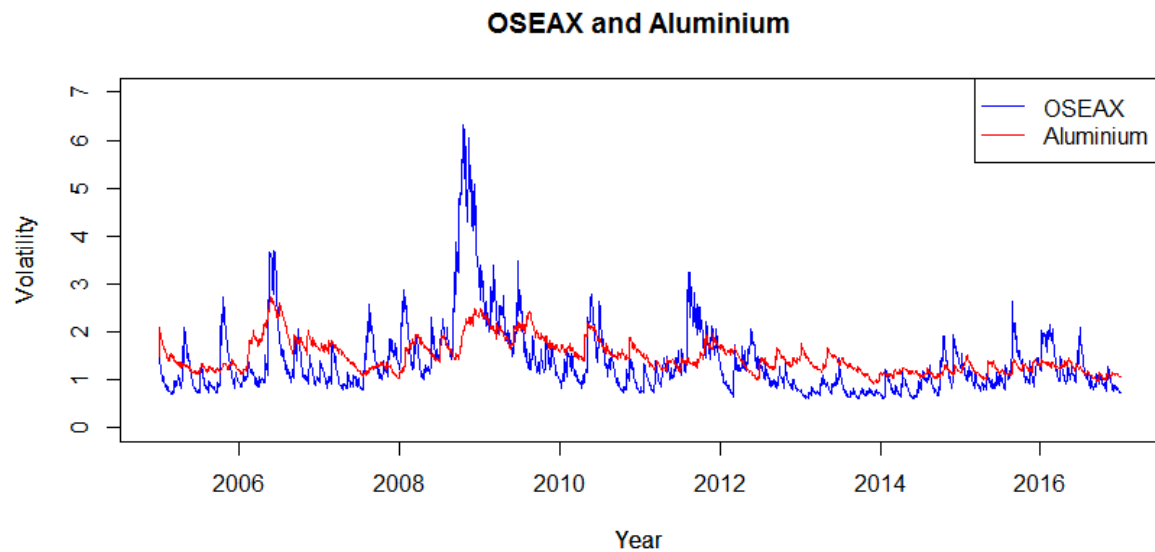
Figure 6-6: GJR-GARCH (1,1) volatility plot and regression coefficients for OSEAX and Aluminium.

Figure 6-6 is a presentation of the volatility calculated from the GJR-GARCH (1,1) model for OSEAX and Aluminium price from 03.01.2005 to 31.12.2016.

The daily volatility of aluminium price seems to have a very stable volatility. The volatility of the stock exchange has much higher peaks. When the volatility of the stock exchange is lower, the movement is more in synch.

| Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta1$)	p-value	N
10	VIX Volatility	-0,382122	0,305687	0,2613	31,749	2,00E-16	2848
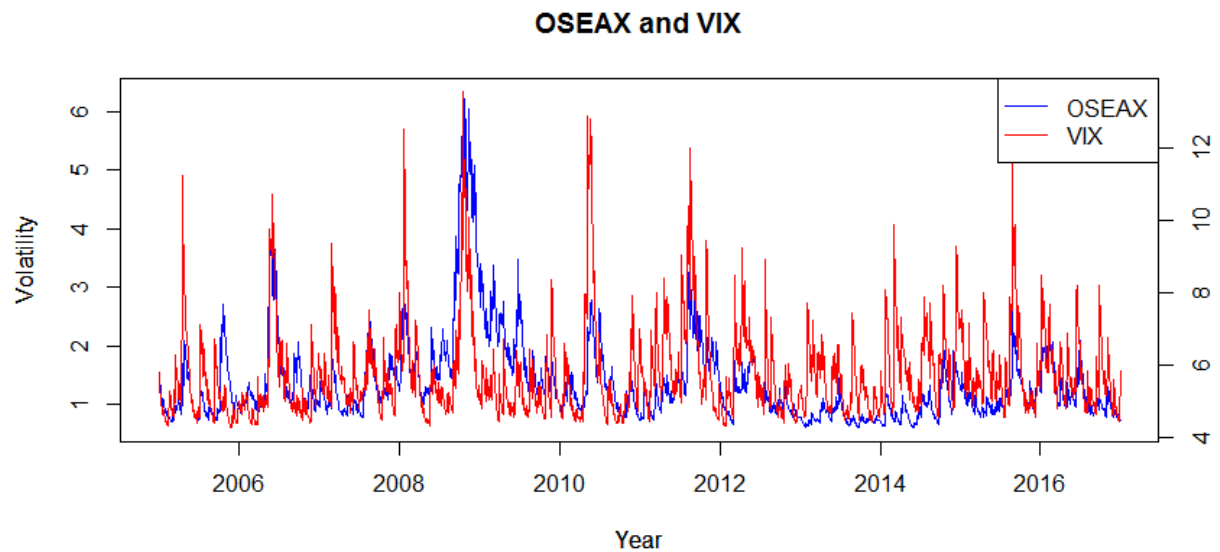
OSEAX and VIX

Figure 6-7: GJR-GARCH (1,1) volatility plot and regression coefficients for OSEAX and VIX.

Figure 6-7 is a presentation of the volatility calculated from the GJR-GARCH (1,1) model for OSEAX and VIX index from 03.01.2005 to 31.12.2016. Notice different axis for VIX.

For this plot, we had to use a z-axis to scale the volatilities differently. The reason is that the historical volatility for VIX and the other volatility indexes are much higher than for the stock exchange. The peaks of the volatility still do follow each other. OSEAX and VIX have the same peaks, but the peaks are much higher for the VIX.

| Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta1$)	p-value	N
11	VDAX Volatility	0,432233	0,130257	0,1878	25,68	2,00E-16	2848
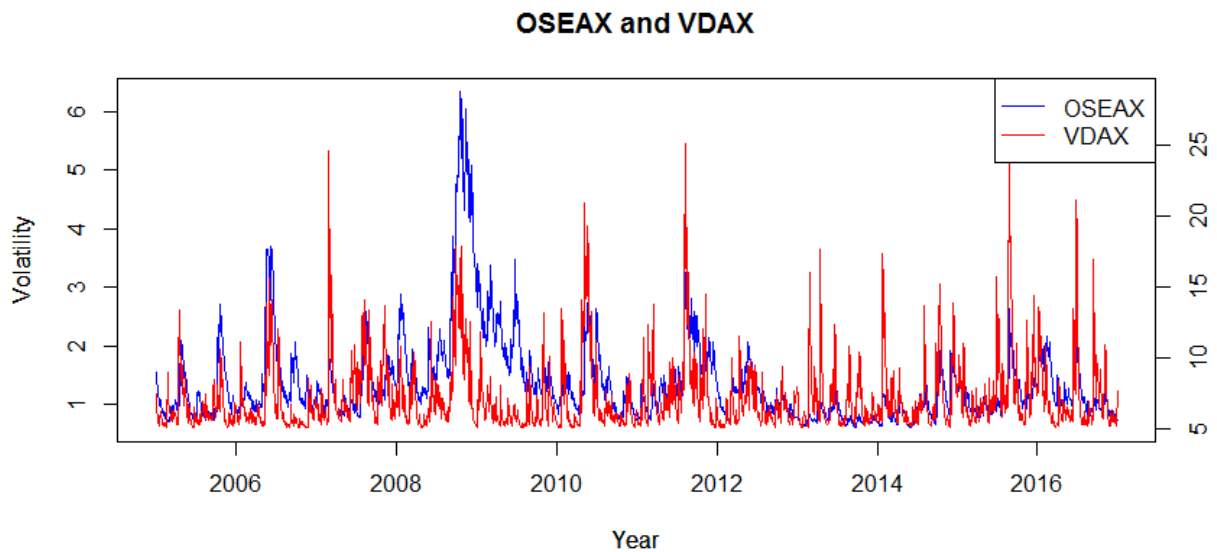
OSEAX and VDAX

Figure 6-8: GJR-GARCH (1,1) volatility plot and regression coefficients for OSEAX and VDAX.

Figure 6-8 is a presentation of the volatility calculated from the GJR-GARCH (1,1) model for OSEAX and VDAX index from 03.01.2005 to 31.12.2016. Notice different axis for VDAX.

From 2005 to 2008 the volatilities seem to be moving quite similar. Even though that the VDAX like the VIX have a much higher volatility than the OBX. But after this period, the results seem to vary more.

| Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta 1$)	p-value	N
13	NOVIX Volatility	0,878782	0,095563	0,05315	12,15	2,00E-16	2613
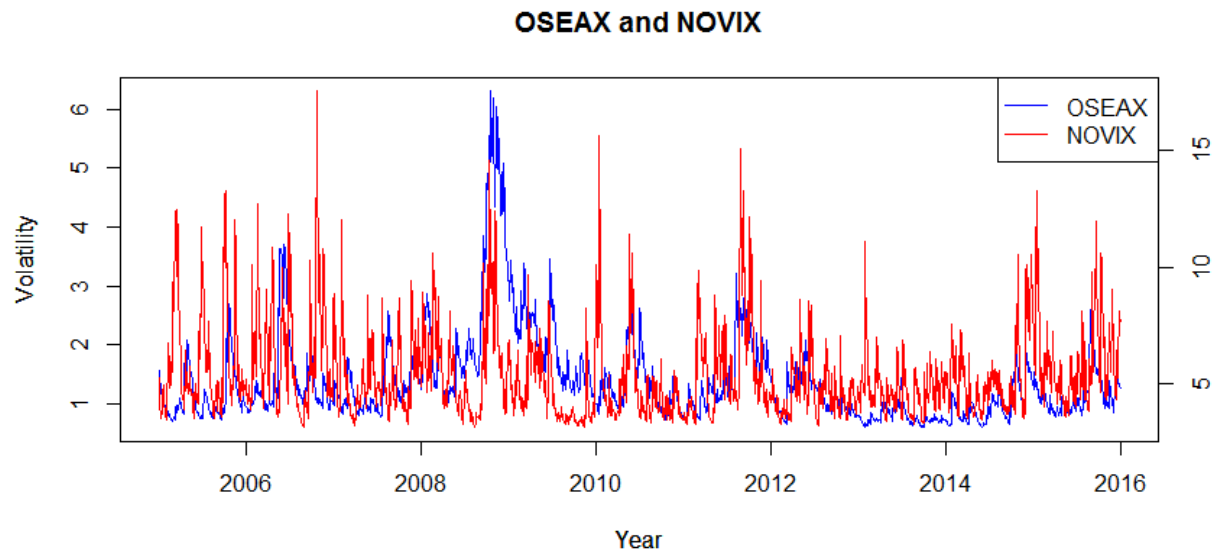
Figure 6-9: GJR-GARCH (1,1) volatility plot and regression coefficients for OSEAX and NOVIX.

Figure 6-9 is a presentation of the volatility calculated from the GJR-GARCH (1,1) model for OSEAX and NOVIX index from 03.01.2005 to 31.12.2016. Notice different axis for NOVIX.

Quite surprising the NOVIXs daily volatility (changes in the implied volatility) are different from the OBX. Except for the financial crisis, the volatilities seem to be moving quite different.

Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta1$)	p-value	N
12	Fish Pool Volatility	2,3622	0,0967	0,001044	1,286	1,99E-01	267
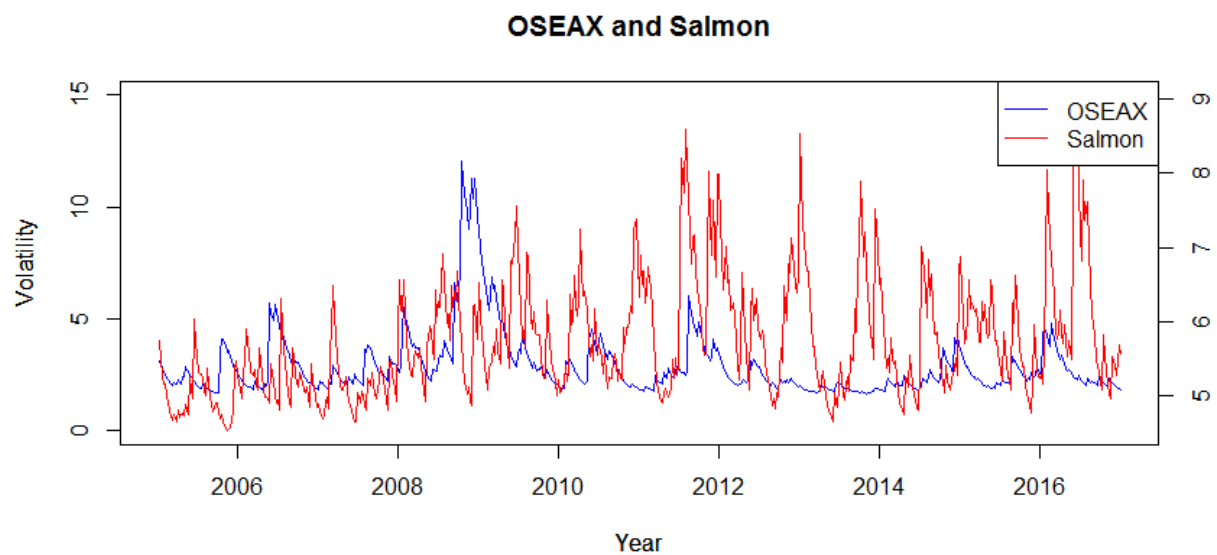
Figure 6-10: GJR-GARCH (1,1) volatility plot and regression coefficients for OSEAX and Fish Pool salmon index.

Figure 6-10 is a presentation of the volatility calculated from the GJR-GARCH (1,1) model for OSEAX and Salmon price from 03.01.2005 to 31.12.2016.

The difference between the volatilities seem to be correlated negatively. When the Salmon volatility is high, OSEAX volatility seem to be more stable and low. And when the OSEAX was at an all-time high for the period, the salmon price volatility was almost at its lowest.

Table 6-1: Correlation table.

Correlation analysis daily	From 2005-2016
OSEAX and OBX totalt return	0,99
OSEAX and Gold	0,69
OSEAX and Alum	0,53
OSEAX and Oil	0,62
OSEAX and EURO	0,51
OSEAX and USD	0,63
OSEAX and SEK	0,37
OSEAX and DKK	0,48
OSEAX and Bond10Y	0,11
OSEAX and VIX	0,51
OSEAX and VDAX	0,43

Correlation analysis daily	From 2005-2015
OSEAX and NOVIX	0,23

Correlation analysis weekly	From 2005-2016
OSEAX and Salmon	0,59

The results from the correlation analysis is presented on a scale from -1 to 1. Where -1 is a perfect negative correlation and 1 is a perfect positive correlation. The interesting statistics for us is the correlation between OSEAX and the other variables. We see that 10-year bond (interest rate) have the lowest correlation with the volatility of the stock exchange at 0,11. Amongst the exchange rates NOK/USD have the highest correlation with the stock exchange at 0,63. NOK/EURO, NOK/SEK and NOK/DKK have respectfully correlations at 0,51, 0,37, 0,48. The NOK/USD had the highest correlation as we expected from the volatility plots. NOK/SEK have the second lowest correlation of all and can imply that this exchange rate influence over the volatility on the exchange is minimal. Among the commodity prices, aluminium and salmon have the lowest correlations, as we expected from the volatility plots. While we expected oil to have a higher correlation than gold, where they have respectfully correlations at 0,62 and 0,69. As we mentioned it looked like the volatility of gold and the exchange moved quite similar. For the volatility indexes the results are for NOVIX surprising. NOVIX having the lowest correlation at 0,23. VIX and VDAX respectfully having a correlation of 0,51 and 0,43. We can also mention that the correlation between VIX and VDAX is 0,69. So they move quite similar.

For the OBX total return index the correlation is surprisingly high, as the movement where surprisingly similar in the plots as well. With a correlation of 0,99, we believe that the 25 most traded companies on the exchange have a profound influence on the stock exchange.

6.2 Finding the volatility

The next step is to calculate the volatility of the variables. We used Rstudio in the calculations. To find out which model we should use, we need to compare the different GARCH-models towards each other. To calculate the volatility based on our data we must figure out what model works best with our data, which is why we try to see which model have the best fit to our data. After the illustration, we will try to pinpoint the best-fitting relation.

Our model selection criteria are the AIC and BIC. We have calculated the AIC and BIC for some few different ARCH (q) and GARCH (p, q) models on the OSEAX data.

The equation for AIC is defined as:

Equation 6-1: AIC equation

$$AIC = 2k - 2\ln(L)$$

Where k   is number of coefficients

L   is the maximum likelihood-value to the likelihood function

The formula for BIC is defined as:

Equation 6-2: BIC equation

$$BIC = T^{-1}(k\ln(T) - 2\ln(L))$$

Where   k   is number of coefficents

L   is the maximum likelihood-value to the likelihood function

T   is number of observations in the data set

The results are presented in the table below:

Table 6-2: AIC and BIC for OSEAX

Model	AIC	BIC
ARCH (1)	3,4993	3,5118
ARCH (3)	3,4978	3,5145
GARCH (1,1)	3,2732	3,2878
GARCH (2,1)	3,2741	3,2908
GARCH (1,2)	3,2727	3,2894
GARCH (2,2)	3,2748	3,2936
GJR-GARCH (1,1)	3,2557	3,2724
GJR-GARCH (2,1)	3,2517	3,2726
GJR-GARCH (1,2)	3,2557	3,2745
GJR-GARCH (2,2)	3,2512	3,2742

In table 6-2 we have the different AIC and BIC values for the different conditional variance models. We have highlighted the lowest value for AIC and BIC in green. We see that the lowest AIC-value is in the GJR-GARCH (2,2) model and the lowest BIC-value is found in the GJR-GARCH (1,1).

We decided to continue with the GJR-GARCH (1,1) model. We do not want to over complicate our model and the AIC and BIC values disagree upon whether we should use the GJR-GARCH (1,1) or GJR-GARCH (2,2) model. The AIC of (1,1) and (2,2) GJR-GARCH do not differ too much, we feel safe to continue with a GJR (1,1). The interesting result is that using a GJR-GARCH significantly improves the model fitting from an even an ARCH (3) model and GARCH (2,2). Supporting our assumption that using an asymmetric GARCH model gives a better model fitting and give a better understanding of the volatility, than using a regular GARCH or an ARCH model.

6.2.1 GARCH (1,1) specification for OSEAX

Table 6-3: Table for the GARCH (1,1) coefficients. Calculated in Rstudio.

GJR-GARCH (1,1)	μ	γ	ω	α	β	LLF
OSEAX	-0.074114	-0.136131	0.030230	0.163163	0.887836	-4628.02

Equation 6-3: GJR-GARCH (p,q) formula Glosten et al. (1993).

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} (\alpha_i + \gamma_j I_{t-i})\varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

Equation 6-4: OSEAX GJR-GARCH (1,1)

$$\sigma_{OSEAX,t}^2 = \omega_{OSEAX} + (\alpha_{OSEAX} + \gamma_{OSEAX} I_{t-i})\varepsilon_{t-i}^2 + \beta_{OSEAX}\sigma_{t-j}^2$$

Equation 6-5: OSEAX GJR-GARCH (1,1) with calculated parameters from Rstudio.

$$\sigma_{OSEAX,t}^2 = 0.030230 + (0.163163 - 0.136131)\varepsilon_{t-i}^2 + 0.887836\sigma_{t-j}^2$$

$$\sigma_t^2 = 0.030230 + 0.000032\varepsilon_{t-i}^2 + 0.887836\sigma_{t-j}^2$$

6.3 Regression models

As mentioned earlier in our research question, we try to figure out what affects the volatility on the Oslo Stock Exchange the most and how these are related to each other. Our background to use the GJR-GARCH model, unlike what Schwert (1989) did with his 12 lag ARCH model, was that we took the leverage effect into the model. That a GJR-GARCH (1,1) model gives more accurate result than a GARCH model, is supported by our model fitting results. Our hypothesis is also that the volatility of the oil price will affect the volatility greater than other variables. Intuitively we expect a greater R^2 in our regression model when the oil price is used as the independent variable. While also looking at the link between volatility indexes and volatility on the stock exchange.

To see if our null hypothesis is correct we must make regressions models to test this out. We are first going to use the simple regression models, then increase the independent variables to see if we get a better result with more and what variables work together. As mentioned in our theory chapter (chapter 4).

To make this section as straightforwardly as possible we are going present the results of the regression models one after another. Then go to the multiple regression model. The first regressions models will be made by using the sigma (volatility output) from the GJR-GARCH (1,1) model, expressed as σ.

All the results will be commentated in this section.

Our regression models in simultaneous time is:

Equation 6-6: Simple regression models for our data set:

$$\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{oil} + \varepsilon_t$$

$$\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{OBX} + \varepsilon_t$$

$$\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{Gold} + \varepsilon_t$$

$$\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{alum} + \varepsilon_t$$

$$\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{exchange\ rate} + \varepsilon_t$$

$$\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{10Ybond} + \varepsilon_t \text{ (interest rate)}$$

$$\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{salmon} + \varepsilon_t \text{ (weekly data)}$$

$$\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{VDAX} + \varepsilon_t$$

$$\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{VIX} + \varepsilon_t$$

$$\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{NOVIX} + \varepsilon_t$$

For the exchange rate, we calculate first a simple regression for each of the exchange rate variables. The exchange rates we use are NOK/EURO, NOK/SEK, NOK/USD and NOK/DKK.

Equation 6-7: Multivariate regression models:

1. $\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{OBXindex} + \beta_2 \sigma_{oil\ price} + \varepsilon_t$

2. $\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{OBXindex} + \beta_2 \sigma_{NOK/USD} + \varepsilon_t$

3. $\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{oil\ price} + \beta_2 \sigma_{NOK/USD} + \varepsilon_t$

4. $\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{NOK/EUR} + \beta_2 \sigma_{NOK/USD} + \beta_3 \sigma_{NOK/SEK} + \beta_4 \sigma_{NOK/DKK} + \varepsilon_t$

5. $\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{oil\ price} + \beta_2 \sigma_{gold\ price} + \varepsilon_t$

6. $\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{oil\ price} + \beta_2 \sigma_{NOK/EUR} + \beta_3 \sigma_{NOK/USD} + \beta_4 \sigma_{NOK/SEK} + \beta_5 \sigma_{NOK/DKK} + \varepsilon_t$

7. $\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{oil\ price} + \beta_2 \sigma_{alum\ price} + \beta_3 \sigma_{gold\ price} + \varepsilon_t$

8. $\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{VIX} + \beta_2 \sigma_{VDAX} + \varepsilon_t$

9. $\sigma_{OSEAX} = \beta_0 + \beta_1 \sigma_{VIX} + \beta_2 \sigma_{VDAX} + \beta_3 \sigma_{NOK/USD} + \beta_4 \sigma_{NOK/EURO} + \varepsilon_t$

We are using the volatility output from the GJR-GARCH (1,1), calculated in Rstudio for each of these independent variables. By doing so, we can see if there are links in volatility change for oil price is affecting the volatility on the OSEAX. The variables are explained earlier, so we will not go through them once more.

β_0 is the constant

β_i is the independent variables coefficients, where i is the number of independent variables.

ε_t is the residual

The regression model can be explained with that we first see how each of the variables are linked with the volatility. Then we use this information to see if a multivariate regression will

give a better result. By that we first analysed the volatility of each of the variables. Then we analyse the information in these against each other, regarding historical volatility.

In our hypothesis, we expect that the β_i will be significantly different from 0 and characterise some of the volatility on the exchange. The null hypothesis will then be that $\beta_i = 0$. We should also see that the estimate does not deviate too much, and see how the variables affect each other. We should also see how these estimates are correlated with one another.

6.4 Linking OSEAX volatility with simple regression

Table 6-4: Summary of simple regression coefficients. Calculated in Rstudio.

	Dependent variable - OSEAX Volatility						
Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta1$)	p-value	N
1	OBX Index	0,080498	0,860925	0,9809	381,89	2,00E-16	2848
2	Oil Volatility	0,15988	0,58794	0,3903	42 679	2,00E-16	2848
3	Gold Volatility	-0,27005	1,35117	0,4698	50,232	2,00E-16	2848
4	Aluminium Volatility	0,35011	1,16682	0,2792	33,224	2,00E-16	2848
5	NOK/EUR Volatility	0,18706	2,36094	0,2636	31,94	2,00E-16	2848
6	NOK/USD Volatility	-0,12874	1,83870	0,3995	43,534	2,00E-16	2848
7	NOK/SWE Volatility	0,29632	2,30063	0,1368	21,264	2,00E-16	2848
8	NOK/DKK Volatility	0,27329	2,23267	0,2264	28,882	2,00E-16	2848
9	10 Year Bond Volatility	1,21471	0,09868	0,01071	5,64	2,00E-16	2848
10	VIX Volatility	-0,382122	0,305687	0,2613	31,749	2,00E-16	2848
11	VDAX Volatility	0,432233	0,130257	0,1878	25,68	2,00E-16	2848
12	Fish Pool Volatility	2,3622	0,0967	0,001044	1,286	1,99E-01	267
13	NOVIX Volatility	0,878782	0,095563	0,05315	12,15	2,00E-16	2613

The constant for all the variables are significant at a 0,1% level.

6.4.1   Linking OSEAX volatility with OBX total return index volatility

Table 6-5: OSEAX and OBX simple linear regression.

Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta1$)	p-value	N
1	OBX Index	0,080498	0,860925	0,9809	381,89	2,00E-16	2848

From table 6-5 the results from the simple regression analysis is presented. The OBX total return index is by far the one with the highest correlation and R^2. The R^2 is at a staggering 0,9809 on a scale where 1 is the highest possible result. The index is made to follow the market movement, which our result show that in this period the volatility at least has been the same. It is made up of the 25 most traded companies on the exchange. In the period, we are considering the index have had approximately 40 % of its companies in the energy sector during this period.

We see that the t-value is the highest of all the variables at 381,89. An argument can be made that our variables have substantial number of observations so we are going to get a significant result either how, but the index t-value is so great that we can reject the null hypothesis that $\beta_1 = 0$ and conclude that the coefficient is different from 0. As mentioned earlier, the constant is significant with the OBX total return index as the independent variable.

With a high coefficient at 0,861 who is significant different from null, indicate that the OBX total return index volatility is related to the stock exchange volatility. With the highest R^2 of all the variables we see that the 25 most traded companies on Oslo Stock Exchange, have the greatest influence on the volatility.

6.4.2 Linking volatility with oil price volatility

Table 6-6: OSEAX and Oil simple linear regression.

Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta1$)	p-value	N
2	Oil Volatility	0,15988	0,58794	0,3903	42 679	2,00E-16	2848

When we run a simple linear regression for Crude Oil on the OSEAX we get a $R^2 = 0,3903$. We can see from the table 6-6 that the oil variable is significant, we get a t-value of 42,679. We can reject the null hypothesis of $\beta_1 = 0$. The coefficient is 0,588, which is a high coefficient. Which can indicate an economic interesting number. The intercept is at 0,16 and significant as all the others.

As we expected, the R^2 for oil price is high and the coefficient is significantly different from 0, with a high t-value. Which can indicate that the oil price volatility is related to the stock exchange volatility.

6.4.3 Linking volatility with commodity price volatility

In this section, we will look at the commodity prices in regression to. These variables are three different simple regression, so this is not a multivariate regression. These commodity prices are gold, aluminium and fish price.

Table 6-7: Simple linear regression for Gold, aluminium and Fish Pool against OSEAX

Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta1$)	p-value	N
3	Gold Volatility	-0,27005	1,35117	0,4698	50,232	2,00E-16	2848
4	Aluminium Volatility	0,35011	1,16682	0,2792	33,224	2,00E-16	2848
12	Fish Pool Volatility	2,3622	0,0967	0,001044	1,286	1,99E-01	267

For gold, aluminium and fish we get R^2 in respectively order of 0,4698, 0,2792 and 0,001044. We can see that gold and aluminium has a high R^2 and should therefore have a relative high impact on the OSEAX. These variables are significant for both the OSEAX and the independent variables, gold and aluminium. When we look at the Fish Pool, we see that the R^2 is very low, but significant. It is reasonable to think that the fish price does not have much impact on the OSEAX volatility.

We can see that we have high t-values for gold and aluminium. These are 50,232 for gold and 33,224 for aluminium. The t-value for Fish Pool is 1,286 and is much lower. The variable is not significant.

Gold have the second highest R^2 of the independent variables. With a high t-value and a coefficient different from 0 we reject the null that the coefficient is not significantly different from 0. As mentioned the coefficient is high, at 1,35 its one of the highest from the regression. Which can indicate some economic interest for investors. The gold price is affected by the USD, probably explaining the result this commodity has on the exchange.

Aluminium have a lower R^2 at 0,2792, but still indicate that the aluminium volatility is related to the volatility on the exchange. With a high coefficient of 1,17 it can indicate some financial interest. The t-value is high, and we reject the null that the coefficient is 0.

6.4.4 Linking volatility with exchanges rate volatility

Is this section, we look at the exchange rates. The rates we look at are NOK/EUR, NOK/USD, NOK/SWE and NOK/DKK. These variables are also simple regressions towards the OSEAX index.

Table 6-8: Simple regressions of exchange rates as independent variable and OSEAX as dependent.

Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta1$)	p-value	N
5	NOK/EUR Volatility	0,18706	2,36094	0,2636	31,94	2,00E-16	2848
6	NOK/USD Volatility	-0,12874	1,83870	0,3995	43,534	2,00E-16	2848
7	NOK/SWE Volatility	0,29632	2,30063	0,1368	21,264	2,00E-16	2848
8	NOK/DKK Volatility	0,27329	2,23267	0,2264	28,882	2,00E-16	2848

We see from the table that NOK/USD has the highest R^2 of 0,3995. It is reasonable to believe that the OSEAX volatility is more sensitive to the volatility of the US market than the European, Swedish or Danish market.
We notice that all the coefficients are high and all are different from 0 with a high t-value. While looking at the graphs earlier in this section we expected NOK/USD to be more linked

with the OSEAX volatility. Which is intuitive, that the Norwegian market is more vulnerable against the dollar or the euro, because of trade and the share size of the markets. Another interesting observation from the exchange variables is that the euro has the highest coefficient and the USD have a negative intercept.

6.4.5 Linking volatility with volatility indexes

In this section, we look at the volatility of the volatility indexes of VIX, VDAX and NOVIX towards the volatility of the OSEAX index.

Table 6-9: Volatility indexes simple regressions. OSEAX as dependent variable and indexes as independent variable.

Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta 1$)	p-value	N
10	VIX Volatility	-0,382122	0,305687	0,2613	31,749	2,00E-16	2848
11	VDAX Volatility	0,432233	0,130257	0,1878	25,68	2,00E-16	2848
13	NOVIX Volatility	0,878782	0,095563	0,05315	12,15	2,00E-16	2613

The table shows that the VIX R^2 is 0,2613, which is a high number for explaining the variation in the OSEAX. With a t-value of 31,749 there is no doubt that the VIX is significant and reject the null of $\beta_1 = 0$. The VDAX have a coefficient close to zero, which can indicate less economic interesting result. The VDAX have a high t-value. For the NOVIX we see that coefficients are marginally lower than the VDAX, it also has one of the lowest t-values. Surprisingly enough we are finding that link the implied volatility has on the exchange is quite low.

The VIX is showing the most promising results of the 3 volatility indexes. In share explanatory factor of the model as well as size of the coefficient. All the indexes are significantly different from 0.

6.4.6 Linking OSEAX volatility with interest rate volatility

In this section, we will look at how the volatility on OSEAX is affected by the Norwegian 10-year bond.

Table 6-10: OSEAX – Norwegian 10-year government bond.

Regression	Independent variable	β_0	β_1	R^2	t-value ($\beta 1$)	p-value	N
9	10 Year Bond Volatility	1,21471	0,09868	0,01071	5,64	2,00E-16	2848

We can see that the R^2 is 0,01071. The R-squared is very low. This indicate that the Norwegian interest rate has a minimal impact on the OSEAX volatility. Using the interest rate volatility, we get a little direct effect on the volatility for the stock exchange. Worth

mentioning that the coefficient is the second lowest for all the simple regressions and the R^2 is the second lowest. The t-value of the interest rate is significantly lower than for most of the other variables. One could argue that that the coefficient is only significant because of the number of observation used.

6.5 Linking OSEAX volatility with multivariate regression

Table 6-11: Table of all multivariate regressions we ran.

		Dependent variable - OBX Volatility						
Regression	Independent variable	β_0	β_1	β_2	β_3	β_4	β_5	R^2
1	OBX + Oil	0.075680 (***)	0.858584 (***)	0.004034 ( )				0.9809
2	OBX + USD	0.120548 (***)	0.875855 (***)	-0.076427 (***)				0.9812
3	Oil + USD	-0.21533 (***)	0.33251 (***)	1.10432 (***)				0.4604
4	Exchange rates	0.10142 (*)	0.79079 (***)	1.73736 (***)	-0.92738 (***)	0.72645 (**)		0.4242
5	Oil + Gold	-0.53950 (***)	0.35035 (***)	0.97778 (***)				0.5723
6	Oil + exchange rates	0.28760 (***)	0.50046 (***)	1.13624 (***)	0.92945 (***)	-3.73402 (***)	0.95640 (***)	0.535
7	Oil + Alum + Gold	-0.72510 (***)	0.32954 (***)	0.24114 (***)	0.87273 (***)			0.5796
8	VIX + VDAX	-0.350972 (***)	0.242269 (***)	0.045065 (***)				0.2733
9	VIX + VDAX + USD + EUR	-1.388188 (***)	0.197188 (***)	0.043441 (***)	1.75566 (***)	-0.239281 (**)		0.5858

The stars in parentheses is a representation of the significance level of the dependent and independent variable. There are five various levels of significance, where (***) means that the variable is significant on a 0,001 level. (**) means significance on a 0,01 level, (*) on a 0,05 level, (.) on a 0,1 level and ( ) on a 1 meaning not significant. Second column shows which independent variables that are run against the dependent variable OSEAX. In regression 4 the independent variable says exchange rates, these are all the exchange rates we have in our data set; NOK/EUR (β_1), NOK/USD (β_2), NOK/SEK (β_3) and NOK/DKK (β_4). In regression 6, Oil price volatility is (β_1). The exchange rates in regression 6 are; β_1 is oil, β_2 is NOK/EUR, β_3 is NOK/USD, β_4 is NOK/SEK and β_5 is NOK/DKK.

We note that all of intercept are significant, with the exchange rates regression having the lowest significant intercept at a 5 % level. Note that all multivariate regressions are with OSEAX volatility as dependent variable.

6.5.1   Linking OSEAX volatility with OBX total return index- and oil volatility.

Table 6-12: Multivariate regression of OBX and Oil volatility.

Regression	Independent variable	β_0	β_1	β_2	R^2
1	OBX + Oil	0.075680 (***)	0.858584 (***)	0.004034 ( )	0.9809

We also calculated an OLS multivariate regression with the OBX total return index and oil volatility as the independent variables. As we see from the table over the result of putting oil

volatility in with the index gave a minor change in the result from the index alone, maybe not surprising as the index already have a staggering R^2. The coefficient for the oil volatility is also not significant and close to zero. So, we should reject the null that oil volatility gives more information on how the volatiles are related to the stock exchange volatility. Commentating on the values from the OBX will be the same as for the simple regression.

6.5.2 Linking OSEAX volatility with OBX total return index and NOK/USD volatility.

Table 6-13: Multivariate regression of OBX and NOK/USD volatility.

Regression	Independent variable	β_0	β_1	β_2	R^2
2	OBX + USD	0.120548 (***)	0.875855 (***)	-0.076427 (***)	0.9812

From the table, we see that indifference to the oil volatility the NOK/USD volatility gives a marginally better explanatory effect than the index alone. By improving the R^2 0,0003. While the explanation for the index have changed marginally from the simple regression. The coefficient for NOK/USD volatility is significant at a 0,0001 level. We see that the value of the coefficient is not very different from 0 and that it is negative at -0,076. Indicating that higher volatility on the NOK/USD exchange rate effect the volatility on the stock exchange negatively. The higher volatility in the NOK/USD gives lower volatility on the stock exchange. The result is so close to zero, so the effect NOK/USD volatility have with the index volatility on charactering the stock exchange volatility is difficult to determine.

6.5.3 Linking OSEAX volatility with Oil price and NOK/USD volatility

Table 6-14: Multivariate regression of oil and NOK/USD volatility.

Regression	Independent variable	β_0	β_1	β_2	R^2
3	Oil + USD	-0.21533 (***)	0.33251 (***)	1.10432 (***)	0.4604

We notice that using this multivariate regression the R^2 for oil alone is improved by approximately 0,07. While for the NOK/USD the improvement is 0,06. The coefficients are both significant and both have a high value different from zero. Indicating that NOK/USD and oil price volatility together gives better information on the stock exchange volatility than alone. With an R^2 of 0,46 and high significant coefficients we reject the null that the information from the independent variables is zero. The result from the multivariate regression can indicate that these two together gives better information on the stock exchange volatility link with the variables.

6.5.4 Linking OSEAX volatility with exchange rates.

Table 6-15: Multivariate regression of exchange rates volatility.

Regression	Independent variable	β_0	β_1	β_2	β_3	β_4	R^2	R^2
4	Exchange rates	0.10142 (*)	0.79079 (***)	1.73736 (***)	-0.92738 (***)	0.72645 (**)	0.4242	0.4242

The coefficients for the exchange rates in regression 4 are:

$\beta_1 = NOK/EURO\ volatility$

$\beta_2 = NOK\ /\ USD\ volatility$

$\beta_3 = NOK\ /SEK\ volatility$

$\beta_4 = NOK\ /\ DKK\ volatility$

The R^2 for the exchange rates multivariate regression is at 0,4242. A small improvement from NOK/USD volatility alone. While for the other variables it is a larger improvement. All the coefficients are significant. Where NOK/DKK volatility have the lowest significant level at 1 %. The intercept is as mentioned previously at 5 % significant level. We notice that all the coefficients are significantly different from 0 with high t-values. The NOK/USD volatility have the highest coefficient, while the NOK/SEK volatility have a negative value at -0,927. Indicating that the NOK/SEK volatility having a negative relationship against the exchange in this scenario. Meaning that when the volatility NOK/SEK is higher, the volatility on the exchange gets lower, not considering the other volatilities. Looking at the results the improvement from NOK/USD volatility alone is probably too low to justify a model with higher difficulty. Meaning that the NOK/USD volatility characterise the volatility on the exchange almost as efficient alone.

6.5.5 Linking OSEAX volatility with oil volatility and gold volatility

Table 6-16: Multivariate regression of oil and gold volatility.

Regression	Independent variable	β_0	β_1	β_2	R^2
5	Oil + Gold	-0.53950 (***)	0.35035 (***)	0.97778 (***)	0.5723

We notice that all the coefficients and intercept are significant. There is a negative intercept at -0,54. The values of the coefficients are high and significantly different from zero. The R^2 is 0,5723, an improvement from oil volatility alone at 0,3903 and gold volatility 0,4698. We see that these together characterise the volatility on the stock exchange better than alone. Where gold has the highest coefficients at 0,978.

6.5.6 Linking OSEAX volatility with oil- and exchange rates volatility.

Table 6-17: Multivariate regression of oil and exchange rates volatility.

Regression	Independent variable	β_0	β_1	β_2	β_3	β_4	β_5	R^2
6	Oil + exchange rates	0.28760 (***)	0.50046 (***)	1.13624 (***)	0.92945 (***)	-3.73402 (***)	0.95640 (***)	0.535

The coefficients for the oil and exchange rates in regression 6 are:

$\beta_1 = Oil\ volatility$

$\beta_2 = NOK/EURO\ volatility$

$\beta_3 = NOK\ /\ USD\ volatility$

$\beta_4 = NOK\ /SEK\ volatility$

$\beta_5 = NOK\ /\ DKK\ volatility$

The effect of putting oil in with the exchange rates gives an improved R^2 at 0,535 from 0,4242 with just exchange rates and 0,3903 from oil volatility. From the oil and NOK/USD volatility the improvement is 0,0746. We notice that the coefficients for NOK/SEK volatility is very different from zero at -3,73 and that the NOK/USD volatility has the highest positive value at 1,136. When used in multivariate regression the NOK/SEK volatility has a negative value.

6.5.7 Linking OSEAX volatility with oil, aluminium, and gold volatility.

Table 6-18: Multivariate regression of oil, aluminium and gold volatility.

Regression	Independent variable	β_0	β_1	β_2	β_3	R^2
7	Oil + Alum + Gold	-0.72510 (***)	0.32954 (***)	0.24114 (***)	0.87273 (***)	0.5796

The difference from the multivariate regression on just oil and gold volatility is marginally. The R^2 gets 0,0073 higher and the coefficients changes are not too large. Implying that putting the aluminium volatility in with the gold and oil volatility does not have too much effect. The information we get on the stock exchange volatility from oil and gold volatility seem to be the same without the aluminium volatility. Meaning that aluminium does not seem to give any addition information on the stock exchange volatility.

6.5.8 Linking OSEAX volatility with the volatility of the VIX and VDAX indexes.

Table 6-19: Multivariate regression of VIX and VDAX volatility.

Regression	Independent variable	β_0	β_1	β_2	R^2
8	VIX + VDAX	-0.350972 (***)	0.242269 (***)	0.045065 (***)	0.2733

When using the volatility from the VIX and VDAX indexes the difference from the VIX alone is marginally. Giving an improvement on the R^2 of 0,012. But the VDAX coefficient is still close to zero, it is closer to zero with the VIX volatility than alone. The coefficient and intercept for from the VIX simple regression, changes marginally when adding the VDAX volatility. Implying that VIX volatility gives almost the same information on the stock exchange volatility alone.

6.5.9 Linking OSEAX volatility with VIX, VDAX, NOK/USD and NOK/EURO volatility.

Table 6-20: Multivariate regression of VIX, VDAX, NOK/USD and NOK/EUR volatility.

Regression	Independent variable	β_0	β_1	β_2	β_3	β_4	R^2
9	VIX + VDAX + USD + EUR	-1.388188 (***)	0.197188 (***)	0.043441 (***)	1.75566 (***)	-0.239281 (**)	0.5858

The VDAX coefficient is still not greatly different from zero, meaning that the additional information we get from this independent variable is close to zero. While the R^2 is significantly different from the VIX alone. It is also an improvement from the exchange rates, approximately 0,16 in the R^2. Indicating that putting the VIX volatility with the NOK/USD and NOK/EURO volatility gives addition information on the stock exchange volatility. Indicating that the exchange rate volatility with the VIX gives better information on the stock exchange volatility link. Looking at the coefficients it seems that the synergy of VIX and NOK/USD volatility is large. The coefficients on the NOK/USD volatility is quite high at 1,756. Worth mentioning that this regression gives the highest R^2 when the index is not used in the regression.

6.6 Volatility in the data, comparing the different models.

In the data, we see that the OBX total return index has the highest explanatory factor. VDAX has the highest volatility, when the volatility is calculated with daily changes. The variable with the lowest volatility is NOK/SEK. We also see that the volatility on Oslo Stock Exchange has a mean of 1.375 and a maximum at the financial crisis at 6.332. We notice that the exchange rates have a similar average volatility around 0.5, expect for the NOK/USD volatility which is significantly higher.

For the volatility indexes VIX has an average volatility of 5,748, VDAX - 7,237 and NOVIX - 5,382. We see that the implied volatility indexes have larger day to day changes than the other variables. Also, we see that the standard deviation is highest for these three variables. This can be because the volatility indexes are used to forecast volatility, and using them to characterise the volatility of the same day will give poor results. Although, adding NOK/EURO and NOK/USD to the VIX index regression, gave a high R^2. This might imply that using this relationship can help investors better predict future volatility.

The reason why the OBX total return index has the largest R^2, is probably because the index is made up of the 25 most traded companies in the OSEAX. It also implies that economic trading activity can be the reason behind the volatility, meaning that economic activity can have a profound influence on the stock exchange.

We see that by using the exchange rate for Swedish and Danish kroner, the link of the volatility variation is quite low. The NOK/USD especially and NOK/EURO have a higher R^2 on the volatility on the OSEAX in comparison to the NOK/SEK and NOK/DKK. Alone it seems that the NOK/USD volatility is more related to stock market volatility.

When we use the commodity prices, aluminium and salmon prices gave few results for relating to the volatility to the OSEAX index. Whereas the gold and oil prices seemed to give a better picture of the stock market volatility. The oil price seems to impact the volatility on the stock exchange, where the oil price volatility with the NOK/USD volatility seemed to give an accurate picture of high R^2 of the volatility on the OSEAX. The effect oil price volatility has on the stock exchange volatility, even though it seems profound, is not as impactful as we would have first expected. We see that the link between oil price volatility and the stock market volatility is approximately the amount of the companies the OBX total return index has in the energy sector.

7 Conclusion

The origin of this thesis was to examine the volatility characteristics of the OSEAX. Data was collected using the Thomson Reuters DataStream, expect for the NOVIX which was provided by S. Bugge et al. (2016).

7.1 Conclusion

With this thesis, we have tried to characterise volatility on the Oslo Stock exchange from 2005 to 2016. We have looked at how much the oil price is linked to the volatility of the OSEAX. Our study has shown that different macro and marked variables are related to the volatility on Oslo stock exchange from 2005 to 2016. For investors and academics, this thesis should be interesting for a better understanding of the Oslo Stock exchange volatility. We believe that knowing more of characteristics of the volatility, investors can make more accurate investment choices and academics can research further on how we can use this to predict future volatility on the Oslo Stock exchange.

From Schwert (1989) we wanted to see if we could find a better fitted-model to the fluctuations in the stock market. To do so, we had to choose variables we believe could characterise the Oslo stock exchange volatility. For commodity prices, we looked at oil, salmon, gold and aluminium. We had an idea the volatility of oil is linked with the stock exchange volatility. The reasoning behind selecting the salmon price, was that the last year's companies in this industry have been doing quite well on the stock exchange. We chose gold and aluminium because they are profound commodity prices around the world. We wanted to see how the exchange rates from the markets the Norwegian economy have a profound number of its trades with and the interest rates in Norway to see if these are related to the volatility. We included volatility indexes with the reason being that the expectation on future volatility in markets have an influence on Oslo stock exchange volatility. We also included the NOVIX (Norwegian fear index) as a variable, to check if the future volatility expectations on the exchange would better characterise the volatility on the exchange than the foreign expectations.

To see what model could best interpret our results, we used descriptive statistic to see what characterised the data. We found that the data had fat tails, high kurtosis and skewness. The data should have a tendency for high volatility with large standard deviations. From the skewness, we found that the data was not normally distributed. From kurtosis, we found that

most of the data follow a platykurtic distribution (flat). The Jarque-Bera also showed that data is not normally distributed. Indicating that an asymmetric model could better fit our data. The Ljung-Box test showed that ARCH effects exist in the data, indicating that an ARCH model can be used. We also found that the data is not perfectly symmetric.

From the result, we wanted to check what different kind of ARCH- and GARCH-model have the best fit for our data. Our results indicate that to characterise the financial data, an asymmetric GARCH model would be the best fit. When we checked different models against each other we found that a GJR-GARCH (1,1) and GJR-GARCH (2,2) having the best result, showing significantly better fit than a GARCH (2,2) and ARCH (3).

We ran multiple regressions to see which of the volatility variables could best characterise the volatility on Oslo stock exchange. We used both simple and multivariate regressions. When using the multiple simple regressions, we found that the OBX total return index had the highest amount of explanation on the Oslo stock exchange volatility. The OBX total return index is made up from the 25 most traded companies on the stock exchange. Perhaps this indicates that the trading activity have a profound influence on the exchange volatility. These 25 companies have a large amount of the total value on the stock exchange. The volatilities on the stock exchange followed the index almost perfectly.

From the oil volatility, we found that the oil price does characterise the volatility on the stock exchange. The oil price contains information about the volatility. From the other commodity prices, gold was the only one who was higher related than oil. For salmon price, we did not get significant results. This indicates that the price contains little to zero characterisation about the volatility on the Oslo stock exchange. Gold shows the most promising result of the commodity prices.

For the exchanges rate, we found that the NOK/USD gave the most promising result. This indicates that the U.S market is related to the volatility on the Oslo stock exchange in this period. This is backed by the VIX expectation to future volatility, which gives the most promising result of the volatility indexes.

We used the result and correlations to base some of our multivariate regressions. Where the OBX total return index and NOK/USD giving the highest R^2, indicating that the US market affects the 25 most traded companies and the stock exchange volatility. For the multivariate regression where we used NOK/USD, gave us the largest improvement in R^2. We found that

the volatility can be characterised with, beside the total return index, the U.S market expectation to future volatility and NOK/USD exchange rate gave the strongest result.

7.2 Suggestion for further research

We do not have unlimited time for this thesis and because of that, we had to put limitations to how much and how deep we could dig into this matter. For further research, it can be very interesting to see if there are any other variables that can be related to the characterisation of the volatility on the OSEAX.

It could be possible to research the asymmetric tendencies shown by the Oslo stock exchange, by using different models and see if there are other models that has a better fit than the models used in this thesis. Using the characterisation of the volatility, we have found, further research can divide our results into different periods. Then it is possible to see if the characterisation changes in periods with high volatility (Bank crisis in Greece and financial crisis being examples) and periods with a low volatility. Maybe this can contribute to better understanding of risk control in periods of financial distress. We believe that for our thesis that by dividing the data into different periods, we could have gotten more accurate characterisation of the volatility.

Previous research has found that using implied volatility will give the most accurate forecast of future volatility. On the contrary, some papers found that when using historical volatility with implied volatility the predictions becomes more accurate. By digging deeper further into our findings, we think that implied volatility predication can be improved. Historical volatility has shown tendency to not predict future volatility as good as implied volatility. By having a better understanding on what characterise the volatility, one can use this information to make better models for predicting the future volatility. Our hope is to get a better understanding on the existing risk factors on the Oslo stock exchange and help investors to have a better understanding of their risk they encounter.

References

Ahoniemi, K. (2006). *Modeling and forecasting implied volatility – an econometric analysis of the VIX index*. PhD, Helsinki School of Economics. URL: https://helda.helsinki.fi/handle/10138/16698

Akgirav V. (1989). *Conditional heteroskedasticity in time series of stock returns: Evidence and forecasts.* The journal of business vol.62, 55-80. URL: http://www.jstor.org/stable/2353123

Andersen, T. G. and Bollerslev, T. (1998). *Deutsche mark-dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies. The Journal of Finance.* Vol 53, 219-265. DOI: http://dx.doi.org/10.1111/0022-1082.85732

Berkowits, J. Christoffersen, P and Pelletier, D. (2009). *Evaluating Value-at-Risk Models with Desk-Level Data*. Management Science, Articles in Advance. Vol 57, 1-15. DOI: http://dx.doi.org/10.1287/mnsc.1080.0964

Black, F. and Scholes, M. (1973). *The pricing of options and corporate liabilities. Journal of Political Economy*. Vol 81, 637-654. DOI: https://doi.org/10.1086/260062

Blair, B., Poon, S. and Taylor, S. (2001). *Modelling S&P 100 volatility: The information content of stock returns. Journal of Banking & Finance, 25(9)*, p. 1665-1679. DOI: https://doi.org/10.1016/S0378-4266(00)00157-6

Bollerslev, T. (1986). *Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics*, 31(3), pp.307-327. DOI: https://doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, T., Chou, R., Kroner, K., and Jayaraman, N. (1992). *ARCH modeling in finance: a review of the theory and empirical evidence. Journal of Econometrics.* Vol 52, 5-59. DOI: https://doi.org/10.1016/0304-4076(92)90064-X

Brailsford, T and Faff, R. (1996). *An evaluation of volatility forecasting techniques. Journal of Banking and Finance.* Vol 20, 419-438. DOI: https://doi.org/10.1016/0378-4266(95)00015-1

Brooks, C. (2008). *Introductory Economics for Finance.* 2nd ed. [ebook] New York: Cambridge University Press. Available at: http://www.afriheritage.org/TTT/3%20Brooks_Introductory%20Econometrics%20for%20Finance%20(2nd%20edition).pdf. [Accessed 23 Mar. 2017].

Brooks, C and Persand, G. (2002). *Model choice and value-at-risk performance. Financial Analysts Journal.* Vol 58 (5), 87-97. URL: http://www.jstor.org/stable/4480420

Brooks, C and Persand, G. (2003). *Volatility forecasting for risk management. Journal of Forecasting.* Vol 22, 1-22. DOI: http://dx.doi.org/10.1002/for.841

Britten-Jones, M., and Neuberger, A. (2000). *Option price, implied price processes, and stochastic volatility. The journal of finance*, 55(2), DOI: http://dx.doi.org/10.1111/0022-1082.00228

Bugge, S., Guttormsen, H., Molnár, P. and Ringdal, M. (2016). *Implied volatility index for the Norwegian equity market. International Review of Financial Analysis*, 47, pp.133-141. DOI: https://doi.org/10.1016/j.irfa.2016.07.007

Buveit, O., E., (2014). *Analysis of market integration at Nord Pool Spot with one-day-ahead Vaue at Risk estimation.* URL: https://oda.hioa.no/nb/analysis-of-market-integration-at-nord-pool-spot-with-one-day-ahead-value-at-risk-estimation/asset/dspace:7165/Butveit_Ellingsen_Oda.pdf

Canina, L. and Figlewski, S. (1993). *The informational content of implied volatility. The Review of Financial Studies*. Vol 6, 659-681. DOI: https://doi.org/10.1093/rfs/5.3.659

Cao, C. and Tsay, R. (1992). *Nonlinear time-series analysis of stock volatilities. Journal of Applied Econometrics*, 7(S1), p. 165-185. DOI: http://dx.doi.org/10.1002/jae.3950070512

Chicago Board Options Exchange (2015). *VIX White Paper*. URL: https://www.cboe.com/micro/vix/vixwhite.pdf

Corsi, F. (2009). *A Simple Approximate Long-Memory Model of Realized Volatility. Journal of Financial Econometrics*, *7*(2), 174-196. DOI: http://dx.doi.org/10.1093/jjfinec/nbp001

Demeterfi, K., Derman, E., Kamal, M. and Zou, J. (1999). *A Guide to Volatility and Variance Swaps. The Journal of Derivatives*, 6(4), p. 9-32. DOI: http://dx.doi.org/10.3905/jod.1999.319129

Derman, K., E., Kamal, M., and Zou, J. (1999). *More than you ever wanted to know about volatility swaps*. In: Goldman Sachs quantitative strategies research notes 41.

Derman E., and Kani, I. (1994). *Riding on a smile*. Risk, 7(1). URL: https://www.researchgate.net/publication/239059413_Riding_on_a_Smile

Dhanaiah, G., Reddy, D. R., Prasad, T. N. L. (2012). *India VIX: Examining the Negative and Asymmetric Volatility Index – Market Return Relationship. India Journal of Finance*. Vol 6. DOI: http://dx.doi.org/10.2139/ssrn.2078164

Duprie, B. (1994*). Pricing with a smile. Risk*, 7(1). URL: https://www.scribd.com/document/101527176/Dupire-Pricing-With-a-Smile-1994

Duprie, B. (1997*). Pricing and hedging with smiles. Mathematics of derivative securities.* Dempster and Pliska eds., Cambridge Uni. Press.

Engle, R. (1982). *Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica*, 50(4). DOI: https://dx.doi.org/10.2307/1912773

Engle, R. F. and Gallo, G. M. (2006). *A multiple indicators model for volatility using intra-daily data. Journal of Econometrics.* Vol 131, 3-27. URL: http://www.stern.nyu.edu/rengle/EngleGallo.pdf

Fernandes, M., Medeiros, M. C. og Scharth, M. (2014). *Modeling and predicting the CBOE market volatility index. Journal of Finance.* Vol 40, 1-10. URL: https://pdfs.semanticscholar.org/25c7/c35c01d7560edef1aea2c693aaf346b6ab2d.pdf

Fleming, J., Ostdiek, B. and Whaley, R. (1995). *Predicting stock market volatility: A new measure. Journal of Futures Markets*, 15(3), p. 265-302. DOI: http://dx.doi.org/10.1002/fut.3990150303

Frances, P and Dijk, D. (1996). *Forecasting stock market volatility using non-linear GARCH models. Journal of Forecasting*. Vol 15, 229-235. DOI: https:dx.doi.org/10.1002/(SICI)1099-131X(199604)15:3<229::AID-FOR620>3.0.CO;2-3

Giot, P. (2005). *Implied volatility indexes and daily Value at Risk models. The Journal of Derivatives.* Vol 12, 54-64. DOI: https://dx.doi.org/10.3905/jod.2005.517186

Glosten, L., Jagannathan, R., & Runkle, D. (1993). *On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. The Journal of Finance, 48*(5), 1779-1801. DOI: https://dx.doi.org/10.2307/2329067

Hansen, P.R. and Lunde. A. (2006). *Realized variance and market microstructure noise. Journal of Business & Economic Statistics.* Vol 24, 127-167. URL: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.467.3402&rep=rep1&type=pdf

Hull, J. (2012). *Risk management and financial institutions.* 3rd ed. Hoboken: Wiley.

Jiang, G. J. and Y. S. Tian. (2007). *Extracting model-free volatility from option prices: An examination of the VIX index*. In: Journal of Derivatives 14.3. DOI: http://dx.doi.org/10.2139/ssrn.880459

Latané, H.A. and Rendleman, R. J. (1976). *Standard deviations of stock price ratios implied in option prices. The Journal of Finance.* Vol 31, 1540-6261. DOI: http://dx.doi.org/10.2307/2326608

Lupi, C. (2009). *Unit Root CADF Testing with R. University of Mlise. Vol 32.* URL: https://cran.r-project.org/web/packages/CADFtest/vignettes/CADFtest.pdf

Nelson, D. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica, 59*(2), 347-370. DOI: http://dx.doi.org/10.2307/2938260

Oslo Børs. (2017). *Om Oslo Børs / Oslo Børs / Home - Oslo Børs*. [online] Oslobors.no. Available at: https://www.oslobors.no/Oslo-Boers/Om-Oslo-Boers/ [Accessed 11 Mar. 2017].

Pagan, A. (1990). *Alternative models for conditional stock volatility. Journal of Econometrics.* Vol 45, 267-290. URL: http://schwert.ssb.rochester.edu/je90_ps.pdf

Pahl, N., and Richter, A. (2013). *Oil Price Developments-Drivers, Economic Consequences and Policy Responses.*

Roll, R. (1984). *Orange juice and weather. The American Economic review, 73*(5), 861-880. URL: http://rady.ucsd.edu/faculty/directory/valkanov/pub/classes/mfe/docs/Roll_AER_1984.pdf

Rubinstein, M., Britten-Jones, M., and Neuberger, A. (1994). *Implied binomial trees. The journal of finance.*, 49(3). DOI: http://dx.doi.org/10.1111/j.1540-6261.1994.tb00079.x

Schwert, G. (1989). *Why Does Stock Market Volatility Change Over Time?* 1st ed. *The Journal of Finance.* URL: http://schwert.ssb.rochester.edu/jfin89a.pdf

Taylor, S. J. (1986). *Modeling Financial Time Series.* Chichester, UK: John Wiley and Sons

Taylor, S. J. (2005). *Asset Price Dynamics, Volatility, and Prediction*. 3rd ed. New Jersey: Princeton Univeristy Press.

Tsay, R. (2010). *Analysis of financial time series*. 3rd ed. Hoboken, N.J.: Wiley.

Wooldridge, J. (2013). *Introduction to econometrics* (1st ed.). Andover: Cengage Learning.