MASTER THESIS

Course code: EN310E

Candidate name: Magnus Bakken

The dynamics of oil price shocks and stock market movements in Norway. A bivariate GARCH approach.

Date: 22/05/2017

Total number of pages: 52

NORD University

www.nord.no

Chapter 1

Preface

This thesis marks the end of a Master of Science in Business with a specialization in Energy Management.

The work on this thesis has been challenging and interesting experience from start to finish.

I want to thank my supervisor Thomas Leirvik who first presented me with the initial idea for my chosen topic and for introducing me to financial modeling using the Rstudio software. All constructive criticism and tips along the way have been of great help.

I also want to thank all my fellow students for invaluable support in times of desperation and despair.

Abstract

This thesis examines the co-movements of stock returns on Oslo Stock exchange and the Brent crude oil price. By employing different statistical methods this thesis aims to provide a clearer picture of how these two assets move in relation to each other. The analysis is done on price data of the OSEBX index and the Brent crude oil from year 1996 to 2016. This period covers several interesting events such as the financial crisis and the recent oil price downfall of 2014. The choice of method is made on the basis of research suggesting that a fair share of financial data may suffer from time-varying variance. The results show evidence of time-varying conditional correlation between the oil price and OSEBX, suggesting volatility interdependence between the two assets.

Three sub-periods were also analysed separately. Before the financial crisis, financial crisis and post financial crisis. While no obvious patterns were found, the results showed that the time-varying correlation dropped significantly along with the oil downfall of 2014, marking somewhat of a shift in how the assets move in relation to each other. This is also backed up by a cointegration analysis which yielded negative results when considering the entire dataset, but indicating a cointegrated relationship when excluding the period of the oil downfall. The granger-causality analysis was applied in order to make inference about causality. Results shows a bi-directional granger-causality which may be caused by too infrequent data-sampling or what is referred to as a common-cause fallacy.

This thesis aims to provide valuable information in understanding how the oil price and returns on the Norwegian stock markets move together. This could be of interest for portfolio managers, speculators and policy makers working with reducing risk.

Structure and practical info

In this thesis I will start by giving an introduction to the subject of oil price - stock return linkages before proceeding to present a short litterature summary. The properties of the norwegian stock market is presented in the same section. In chapter 3 I will introduce the models to be used before presenting the empirical results and analysis in the fourth chapter of the thesis. Conclusion and suggestions for further research is presented in the fifth and final chapter.

With the exception of some initial data cleaning done in Microsoft Excel, this thesis in its entirety is written and produced in Rstudio version 1.0.44 using Rmarkdown and the LaTeXsyntax for all parts concerning text layout. Plots, graphs and calculations are all made in RStudio mainly using the packages tseries, rugarch and rmgarch.

If read in a digital format: All in-text references to previous chapters, figures, tables or equations are clickable to allow for effortless review.

References were handled in Mendeley reference manager.

All potential errors are my own.

Contents

List of Tables

List of Figures

Abbreviations

ACF Autocorrelation

ADF Augmented Dickey Fuller

ARCH Autoregressive Conditional Heteroskedasticity

DCC Dynamic conditional correlation

GARCH Generalized Autoregressive Conditional Heteroskedasticity

GCC Gulf Cooperation Council

OSE Oslo Stock Exchange

OLS Ordinary Least squares

OSEBX A stock index on Oslo Stock Exchange designed to be representative of the entire exchange.

QQ-plot Quantile-Quantile plot

VAR Vector AutoRegression

WTI West texas intermediate

Introduction

The aim of this thesis is to examine the co-movement of the crude oil price and the Norwegian stock market. By applying a general method for this purpose, I show that the returns of OSEBX and Brent crude are correlated with each other. Moreover, I show that the magnitude of the correlation changes quite drastically between different time periods. Testing for cointegration, a way to check for a causal relationship between variables, I further provide evidence that the two data sets follows each other very closely up until the oil crash of 2014. In the period after 2014, there is only a weak link between the two markets. These results indicates that the more research is needed to test if the breakdown in the linkage is permanent or only temporary.

There already exists extensive research on the topic of how the oil price influences stock markets. Both in countries of net-import and in oil-exporting countries. The results have however, been varied. For example, Kling (Kling 1985) found that increase in crude oil prices gave a decline in the stock market while Cheng (Cheng 1996) found no link between oil price and the stock market. Considering the importance and the impact oil prices have on the Norwegian economy, modelling the linkages between the oil price and the Norwegian stock market is interesting. Specific research on the Norwegian markets is limited which is the reason for choosing to compliment the research in this area.

Oil is used in hedging strategies and plays a big part in the risk management and policies of many countries and corporations. Therefore, monitoring the co-movements between different capital markets have become increasingly important to actors in the financial sector in line with the increasing financial globalization. Even more so, in light of the later year's financial crisis, oil crisis, and market crashes, identifying possible linkages could prove an important tool not only for portfolio managers and speculators but also for policy makers in order to reduce systematic risk.

An important property of financial time-series data is that the volatility changes over time, i.e the volatility is not constant; there are periods of calm followed by periods of large swings in prices from day to day. Using a model which does not account for this variation in volatility can produce inaccurate inference and fail to provide a clear picture of the true movements of our data. Robert Engle was the first to come up with a model which addressed this problem and he proposed the Autoregressive conditional heteroskedasticity model (ARCH) in 1982 (Engle 1982), this work earned him the Nobel Prize in economics in 2003. Bollerslev (Bollerslev 1986) generalized the ARCH-model into the GARCH-model (generalized autoregressive conditional heteroskedasticity). The models of both Engle and Bollerslev have been extended in many directions. This paper will consider one of these extensions, the DCC-GARCH model, which allows us to compare the two variables and also analyze the linkages between them. In order to unveil potential linkages between the two markets. The research will be done by considering the Norwegian stock market index OSEBX as the proxy for the Norwegian stock market, and the price of Brent crude oil as a proxy for the oil price.

Chapter 2

Theoretic Framework

Literature Review

Extensive research already exists on the subject of linkages between oil price and stock markets. See for example (Driesprong, Jacobsen, and Maat 2008; L. Kilian and Park 2009; Nandha and Faff 2008). This section will present some of the research done on the subject, what methods were applied and what results and conclusions can be drawn from these reports. The rapid evolution of advanced computers and new statistical methods has made sure there are now many ways of doing calculations and interpreting big sets of data. Against this background the focus will mainly be on litterature from the last ten years in the review. Papers applying Multivariate Generalized AutoRegressive Conditional Heteroskedasticity methods will be the main focus, but some other methods are also considered. The literature review will be summarized in the form of a table in the end of the chapter.

Robert Engle (R. Engle 2002) emphasizes that correlation estimates between financial variables have many important uses, such as portfolio optimization, asset allocation or risk assessment. Engle (R. Engle 2002) developed the Dynamic Conditional Correlation (DCC) framework enabling us to obtain reliable measures of time-varying correlation coefficients. While correlation estimates in themselves are useful, it is important to be aware that correlation does not imply cause. The correlation estimates simply gives us a picture of how different assets move together, but making any conclusions about causality requires further analysis.

An asymmetric causality test performed by Hatemi et al.(Hatemi-J, Al Shayeb, and Roca 2017) shows a positive relationship between increasing oil prices and stock prices in world, U.S. and Japanese markets, while it found that the German stock market reacted negatively on decreasing oil prices. Hatemi et al argued that this may imply the U.S and Japanese markets consider oil price increases an indicator of good news while the

German markets view decreasing crude prices as a contraction of the economy (Hatemi-J, Al Shayeb, and Roca 2017).

Alsalman (Alsalman 2016) carried out a research considering the U.S. stock market using a Generalized Autoregressive Conditional Heteroskedasticity Vector AutoRegression model (VAR-GARCH). The results showed there were no significant effect of oil price volatility on U.S. stock returns. Alsalman proceeds to argue that this could be due to effective hedging against fluctuating oil prices or even the ability of corporations to effectively transfer the increased costs of oil to consumer. Alsalman also found that while there was no transfer of volatility, oil price movements had symmetric effects on aggregate US stock returns. Meaning that oil price changes had an equal and opposite effect on the U.S. markets. This follows the notion set by the discounted cash-flow method. Increased oil prices will in theory lead to higher costs, decrease corporate earnings and cause stock prices to drop.

Park and Ratti (J. Park and Ratti 2008) applied a Multivariate VAR analysis to estimate effects of oil price shocks and oil price volatility on stock returns in the U.S. and 13 European countries. The study was based on data from 1986-2005. The results showed that oil price had a significant impact on stock returns intra-month and up to one month later. In this study, Norway was the only country which showed a statistically significant positive response in stock returns following an increase in oil prices. This could be attributed to the fact that Norway is an oil exporting country where revenues from oil-related business plays a big role in the Norwegian economy. With this in mind, it is interesting to look at the research of Nandha and Faff (Nandha and Faff 2008) who introduced an oil factor into their standard market model in order to unveil linkages between oil price shocks and equity pricing. Applying the model to different sectors, Nandha and Faff found that out of 35 industries, only the mining and the oil and gas industry returned positive "oil-coefficients". This means that the 33 remaining industries showed negative "oil-coefficients", meaning that increase in oil price had a negative impact on stock returns, where most of these were statistically significant. This is in line with other studies which suggest that oil price increases have adverse effects on output and in turn on corporate profits where oil is used as input.

Both Lee and Chiou (Lee and Chiou 2011) and Aloui and Jamazzi (Aloui and Jammazi 2009) applied versions of regime-switching Markov models in order to measure effects of oil price movements on stock markets. Empirical results from Lee & Chiou showed a negative relationship between movements in oil price and stock markets. Aloui and Jamazzi state that "We find evidence that the net oil price increase variable play a significant role in determining both the volatility of real returns and the probability of the transition across regimes". (Aloui and Jammazi 2009)

A study on return and volatility linkages between oil prices and stock markets of the Gulf Cooperation Council countries (GCC) by Arouri, Lahiani and Nguyen (Arouri, Lahiani, and Nguyen 2011) showed the existence of substantial return and volatility linkages between the oil price and GCC stock markets. Arouri, Lahiani and Nguyen applied a bivariate VAR-GARCH model to look at the interdependence between the oil prices and the stock markets. While the results were not consistent for all the GCC countries, oil price changes tended to significantly and positively affect GCC stock markets. (Arouri, Lahiani, and Nguyen 2011)

Bouri (Bouri 2015) also applied a VAR-GARCH model in order to model the return and volatility linkages between oil prices and the Lebanese stock market in crisis periods. The results showed a positive causal effect from oil price change to stock market returns. The volatility linkages were found to be unidirectional for the entire period running from oil prices to the Lebanese stock market. Both the return and the volatility linkages became stronger in crisis periods. Bouri argues that the VAR-GARCH framework has several advantages over a simple VAR-model in that it considers both nonlinearities and heteroscedasticity. The research of Bouri builds on the work of Dagher & El Hariri (Dagher and El Hariri 2013) which applied a VAR framework to examine interactions between Brent prices and stocks in the Lebanese markets. The research found that oil prices did in fact Granger cause stock prices, but no evidence was found of the opposite (Dagher and El Hariri 2013) .

Driesprong, Jacobsen, & Maat (Driesprong, Jacobsen, and Maat 2008) made a significant contribution in showing that changes in oil price forecast stock-returns. By running a regression analysis on 48 different developed and developing countries they found that a rise in oil price drastically lowers future stock returns. The research also found results in line with the delayed reaction hypothesis. Meaning that investors tend to take some time to react to the changes in the oil price. Driesprong et.al found that the explanatory power of their regression model was at its largest when applying a lag of 6 trading days between changes in the oil price and the reaction of the world markets (Driesprong, Jacobsen, and Maat 2008).

As this chapter shows, there already exists extensive research on the topic of oil price influence on stock markets. In the literature reviewed the method applied differs in several ways. First of all, there are differences in the statistical methods applied, different data sets, different time series frequencies and different time periods analysed. Secondly, the attributes of different countries stock markets may be diverse considering what sectors are most widely represented or which stocks carries the highest trading volume. In light of this, drawing any general conclusion is inappropriate. Therefore, this paper will consider the Norwegian stock market and how it moves together with fluctuating oil prices. There are few papers which focus especially on the Norwegian markets, especially when it comes to the linkages between return and volatility between stocks and oil. The Norwegian market is interesting because of the large part that oil revenues play in the countrys economy. By applying the DCC-GARCH framework, this thesis will analyze the co-movements of oil prices and the Norwegian stock market. This is somewhat in contrast to other research which in large part focuses on measuring volatility spillover effects between oil price and stock markets.

Table 2.1: Litterature summary

Year	Author	Method	Results
2008	Driesprong, Jacobsen & Maat	Regression analysis	Significant negative impact of oil price increase on stock markets in both developing and developed countries.
2008	Park & Ratti	Multivariate VAR	Norway showed a statistically significant positive response in stock returns following an increase in oil price.
2008	Nandha & Faff	Standard market model with an oil price factor	Applying their model to different industry segments, the results showed that only the mining and oil & gas industries had a positive impact from the introduced oil-factor.
2009	Aloui & Jammazi	Markov-Switching EGARCH model	Evidence is found that net oil price increase play a significant role in determining both volatility of real returns.
2011	Arouri et al.	VAR-GARCH model.	Non-conclusive across all countries. Oil-price changes tended to significantly and positively affect GCC stock markets.
2011	Lee & Chiou	Markov Regime-Switching model	Significant fluctuations in oil prices give a negative impact on stock market returns (S&P 500). Lower levels on fluctuations did not reproduce the same impact.
2015	Bouri	VAR-GARCH model.	Positive causal effect from oil price change to stock returns. Unidirectional volatility linkages from oil price to stock market.
2016	Alsalman	GARCH-in-mean VAR model.	No significant effect of oil volatility on U.S. Stock returns. Oil price movements have symmetric, opposite effect on U.S. Stock market returns.
2017	Hatemi et al.	Assymetric causality test.	Increasing oil prices cause increasing stock prices in world, U.S. And Japanese markets. Decreasing oil prices cause decreasing stock prices in Germany.

Oslo Stock Exchange

Founded in 1819, Oslo Stock Exchange, then named Christiania Exchange, started out by dealing mostly in currency trading and sale of bills of exchange. The first listings for stocks and shares were made in 1881, and the market was mostly made up of railway shares. Today, Oslo Stock Exchange is the only regulated market for trading securities in Norway.

In 1969 Norway discovered the first commercially exploitable oil reserves in the Ekofisk field in the North Sea. This marked the start of the Norwegian oil adventure and consequently the Norwegian stock markets have seen the effects of this through the listing of a significant amount of oil & gas related corporations on the exchange.

The OBX Total Return Index constitutes the 25 most traded securities on Oslo Stock exchange based on six months turnover rating ("Oslo Børs" 2017). As of December 16th 2016, the OBX index, by weight of stocks, consists of 31,3% stocks within the Global Industry Classification Standard (GICS) classification of Energy companies, 20,6% in financials, 19,9% in Consumer staples and the rest are spread within the sectors consumer discretionary, industrials, information technology, materials and telecommunication services, see Table 2.2. The OSEBX benchmark index is "an investable index which compromises the most traded shares listed on Oslo Stock exchange" ("Oslo Børs" 2017). This index is different from the OBX index as it contains more securities and is meant to be a selection of stocks representative for the entire exchange. The OSEBX index is revised semi-annually and as of December 16th 2016, the index is made up of 62 stocks. Of these 62 stocks, 9 are within the Energy sector and 14 stocks are listed within the Industrials sector. Of these 14, 7 are Shipping-companies, which mean these are companies heavily influenced by the oil market. A time series plot of weekly OSE and Brent prices from 1996 to 2016 presented in Figure 2.1 shows an observable similar

OBX Weights by sector	Weight	OSEBX by Industry	Count	Percentage of total
Consumer Discretionary	1,7 %	Consumer Discretionary	6	9,7 %
Consumer Staples	19,9 %	Consumer Staples	5	8,1 %
Energy	31,4 %	Energy	9	14,5 %
Financials	20,6 %	Financials	7	11,3 %
Industrials	0,9 %	Health Care	4	6,5 %
Information Technology	0,3 %	Industrials	14	22,6 %
Materials	13,7 %	Information Technology	9	14,5 %
Telecommunication Services	11,5 %	Materials	2	3,2 %
Total	100,00 %	Real Estate	3	4,8 %
		Telecommunication Services	1	1,6 %
		Utilities	2	3,2 %
		Total	62	100,0 %

Table 2.2: OBX index with weights on the left. OSEBX index by sector on the right.

trend in the price development.

The argument that OSE is indeed heavily influenced by the oil & gas sector is strengthened further when we look at the statistics of the most traded stocks for 2016. Statoil ASA is the most traded stock (by value) with 14,94% of the total, followed by DNB which stands for 9,06% of the total value. In total, about 1,2 billion statoil shares were traded in 2016. The 40 most traded stocks on OSE stands for 89,11% of the total traded value, and among these 40 we find several companies within the oil and gas industry such as Subsea 7, Seadrill and Aker BP ("Oslo Børs" 2017). Oslo stock exchange is the second largest in Europe for energy companies, and as of 2013, the exchange was the worlds second largest stock exchange for oil service, both in terms of number of companies listed, and in terms of market capitalization ("Oslo børs," n.d.).

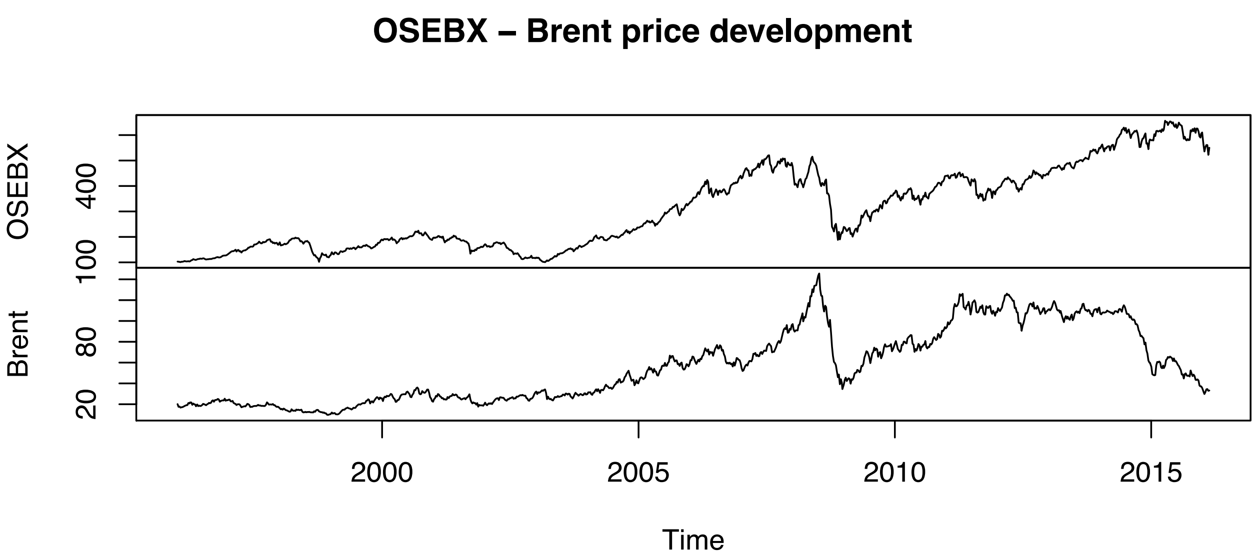

Figure 2.1: OSEBX/Brent price plot, 1996 - 2016.

As this section shows, the Norwegian stock market have for the last few decades been dominated by companies within sectors related to the oil and gas industry. Intuitively, this could be an indication that the Norwegian markets are prone to fluctuations in the oil prices. The following chapters will try to unveil wheter or not this is factual. The next chapter will consider historical movements in the crude oil price and what drives these movements.

Oil Price uncertainty

Globally, oil is still the most important source of energy we have and it is also the one we consume the most of. Oil is used not only for fuel, transportation and power production but also for production of consumer goods, furniture, cars, and fertilizers. Hence, fluctuations in the oil price is important not only for the big oil producers and consumers, but affects the global economy as a whole. While the growth in supply is expected to slow down in the coming years, IEA still forecast global capacity to grow by 5.2 million barrels by day by 2020, up from a supply of about 97 million barrels by day in 2016 ("International Energy Agency" 2017).

Historically, the oil prices have experienced large swings over time. The size of these swings is measured by the standard deviation of the price changes. We call this the volatility of the asset. Natural resources as an asset class has, in general, highly volatile price movements. Oil is no exception, however, identifying the drivers behind the oil prices has shown to be a complex issue (Zhang and Yao 2016). Following theory, oil prices should follow fundamentals such as supply and demand, but the oil price is also influenced by politics, speculation and other non-fundamental factors. Baumeister and Kilian (Baumeister and Kilian 2016) looked at oil price fluctuations over the last forty years and have identifyed three main price shock determinants. A price shock is defined by Baumeister and Killian as the gap between the expected price of oil and the actual price outcome. The determinants are, shocks to:

- Global crude production
  - This mainly concerns political events in oil-producing countries and discovery of new reserves.
- Demand of crude oil
  - Mainly related to changes in global business cycles.
- Above-ground inventory demand.
  - This determinant reflects shifts in expectations about future shortfalls of supply relative to demand in the market.

From 1948 up until the end of the 1960s crude oil prices remained rather stable, ranging between \$2.50 and \$3.00. In 1973, the Yom Kippur War started and marks one of the biggest oil price shocks in recent times. Many western countries, including the US expressed their support for Israel. Following this, exporting Arab nations imposed an oil embargo on countries who supported Israel. The subsequent fall in production seemingly led to a major price increase. In 1972, before the war broke out the price was about \$3.50 and by the end of 1974 the price had risen to more than \$12/bbl. However, Baumeister and Kilian (Baumeister and Kilian 2016) suggests, that there is evidence which points to an increase in oil demand as the explaining factor for the price increase and not the decline in supply.

The oil crisis in Iran and Iraq led to a new price shock in the end of the 1970s. By 1980, the price of West Texas intermediate Crude oil (WTI) was almost at $40. Traditionally, this price increase is attributed to the fall in Iranian oil production following the revolution. Baumeister and Kilian (Baumeister and Kilian 2016) points out that empirical oil market models suggest that one third of the price increase was due to increased inventory demand in anticipation of future shortages. Two thirds could be attributed to effects of flow demand shocks triggered by a strong global economy.

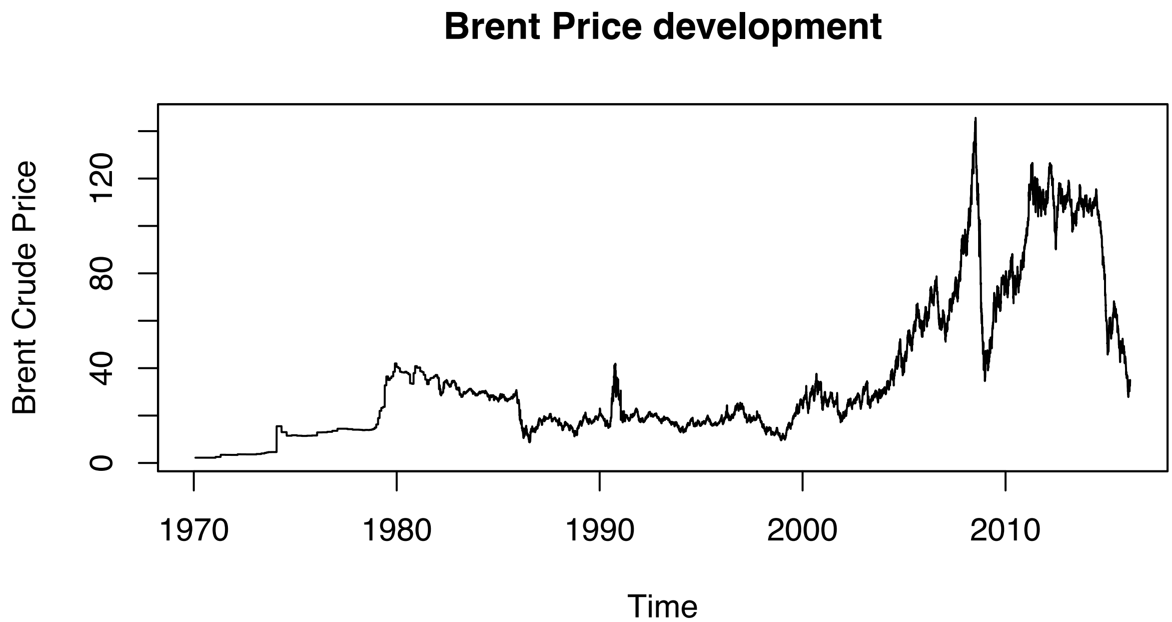

Figure 2.2: Brent price development 1970-2016.

From 1980 to 1990 the oil price saw a general negative trend which in part can be attributed to non-OPEC countries starting their production and increasing global supply.

In the late 1990s the crude oil price was at its lowest in recent times and the price of WTI bottomed out at $11 per barrel. This decline can be attributed somewhat to a sliding decrease in oil demand coupled with the Asian financial crisis of 1997. Starting in 1999 the oil price started to gain momentum again. A combination of factors such as increasing demand due to a recovering global economy and some production cuts helped the price increase.

The biggest increase in oil price since 1979 happened between 2003 and 2008. This increase is widely recognised to be caused not by any single event, but rather incremental increases in demand for crude oil. This again is attributed to the development of the world economy with growth in the asian market leading the way. In 2008 the price was at its all-time high at $145/bbl. Come the Financial crisis, the decrease in demand for industrial commodities sent the price down before the price once again rose above the $100 mark in 2014.

The situation today started with a fall in the price in the last half of 2014. Between June 2014 and January 2015 Brent prices went from \$112 to \$47, a decline upwards of 50%. This decline is connected to the unexpected growth in US shale oil production and other sources of unconventional oil and gas as well as the increased production from Russia and Canada.

As this short summary of oil price movements show, as well as Figure 2.2, oil prices have historically been a volatile asset. By plotting the return series of both Brent Crude and OSEBX we can examine the volatility closer. Looking at the return series presented in Figure 2.3 we clearly see that big fluctuations happen more frequently for the Brent Crude return series. As the section on descriptive statistics also will comment, the mean return of OSEBX (0,160%) is about three times that of Brent crude (0,048%), while the standard deviation (volatility) of Brend crude (4,837%) is still about 1,5 times that of OSEBX (3,160%). Further evidence of this volatility will be presented later in the paper.

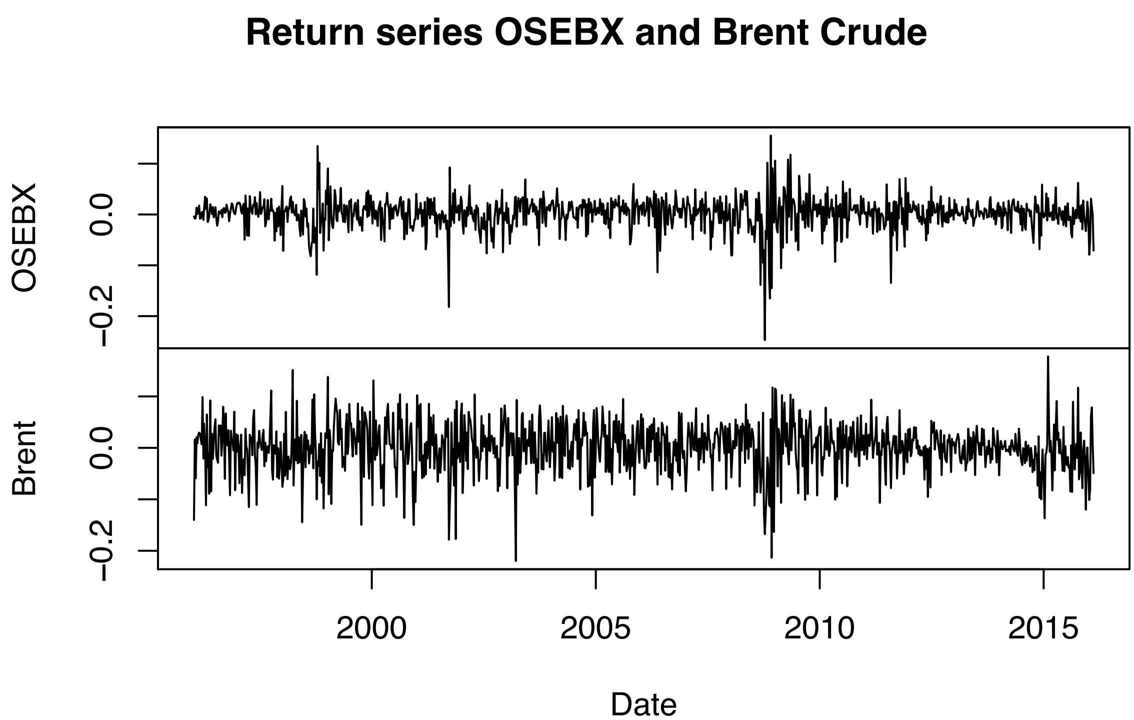

Figure 2.3: Return Series for OSEBX and Brent Crude.

Price processes

Several different methods exist for modelling commodity prices. Both qualitative and quantitative. This section will briefly look at the attributes of the quantitative methods.

The main methods applied in the quantitative methods includes introducing a stochastic variable. A stochastic process can be defined as a collection of random variables which may affect (in our case) the price of oil. Stochastic modeling attempts to forecast the changes in for example prices or returns over time. In price modelling we often encounter Weiner processes, also referred to as Brownian motion processes, which is simply a continuous-time stochastic process.

Most commodity prices also follow a mean-reverting process. Meaning the prices typically return to some central value (Hull 2009); it reverts to its long-term mean. Schwartz (Schwartz 2008) looked at three models of the stochastic behaviour of commodity prices, all which took into account mean reversion. The analysis revealed strong mean reversion in commercial commodity prices. The mean reverting property of commodity prices contrasts those of equities, which does not show the same tendency of a mean reverting price movement.

While the purpose of this thesis is not to model oil prices, having an idea of how commodity prices can be modelled can be valuable. As the previous chapter shows, the oil price can be affected by external shocks which are not possible to model, for example, a political event. In particular, understanding the significant size of volatility compared to e.g. stocks and bonds, is valuable in understanding what drives returns on large equity indices like the OSEBX.

Chapter 3

Method

As already mentioned, the main tool of this thesis will be the application of the DCC-GARCH framework. In order to understand the GARCH-model, we will start with a short look at the underlying idea of the model before looking at one of the most widely used models of financial modelling, namely the least squares model. The attributes, assumptions and limitations of this model will be assessed before continuing to look at how the GARCH model can be helpful and possibly fill the gaps when the least-squares method is insufficient.

A cursory view of ARCH/GARCH

Benoit Mandelbrot (Mandelbrot 1963) suggested that, when looking at financial data, large price changes tend to be followed by large changes, and similarly small changes tend to be followed by small changes. This time-dependency is called autocorrelation and is often referred to as volatility clustering. If we plot the return series for our OSEBX and brent crude price data we can see indications of this volatility clustering, see Figure 2.3. Furthermore, we often see in financial data series that these clusters of volatility are not spread randomly but rather seem to be affected by some degree of autocorrelation where autocorrelation refers to the situation where lagged values of the same data correlates with previous values.

The ARCH model was developed by Engle in 1982 and was meant to explain the property of certain financial variables where the volatility would shift from high to low and vice versa as described above. Where prior models would assume constant volatility or make som arbitrary estimates of volatility, the ARCH-model treat this non-constant variance, also called heteroskedasticity, as a variance to be modelled. (R. Engle 2001)

Engle got great recognition for his work on the ARCH-model and he won the Nobel memorial Price in Economics for his work in 2003. The ARCH-model was further generalized by Bollerslev in 1986 into what is now called the GARCH-model. This model has shown to be superior to the ARCH-model in predicting volatilities and is now one of the main tools used in financial analysis regarding volatility.

Introducing the model

OLS regression

The OLS model aims at explaining the move in a dependent variable Y, with the movements in one or more independent variables $X_1, ..., X_k$.

The first least squares model was first published in 1805 by Adrien Marie Legendre, but some evidence argues that it was in fact the german mathematician Carl Friedrich Gauss who invented the model in 1795 (Stigler 1981). Today, the model is the most used method in statistical analysis. There exists many variations of the least squares model, but for this short introduction we will consider only the simplest form of linear regression, Ordinary Least Squares (OLS).

If we let Y be our dependent variable, i.e the left hand side, the variable which we want to predict, and $X_1, ..., X_k$ denote our independent variables, sometimes also called our predictors, then the notion is that Y can be explained by the following expression

$$Y = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + ... + \beta_k X_{kt} + \varepsilon_t \tag{3.1}$$

Where β_0 is the constant of the equation and represents the value of Y when all values of $X = 0$. The other betas $(\beta_1, \beta_2 ...)$ are coefficients of our predictor variables X. This means that the beta is the slope of the regression line and shows the change in Y given a change in X. The noise-term ε is assumed to be independent and identically distributed random variables with a mean of zero. However, the error term ε is often dropped from most regression equations. From this, we can state our expression for the predicted values of Y, $\hat{Y}$.

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X_{1t} + \hat{\beta}_2 X_{2t} + ... + \hat{\beta}_k X_{kt} \tag{3.2}$$

Equation 3.2 is an example of a linear multiple regression. The equation shows that $\hat{Y}$ is explained by our predictor values $X_1, ..., X_k$ and the beta coefficients which are estimated to minimize the sum of squared errors, meaning the (absolute) value by which the linear regression line misses the actual observations. The linear fit with error terms are illustrated by an example in Figure 3.1.

In order to arrive at this model we do make some important assumptions:

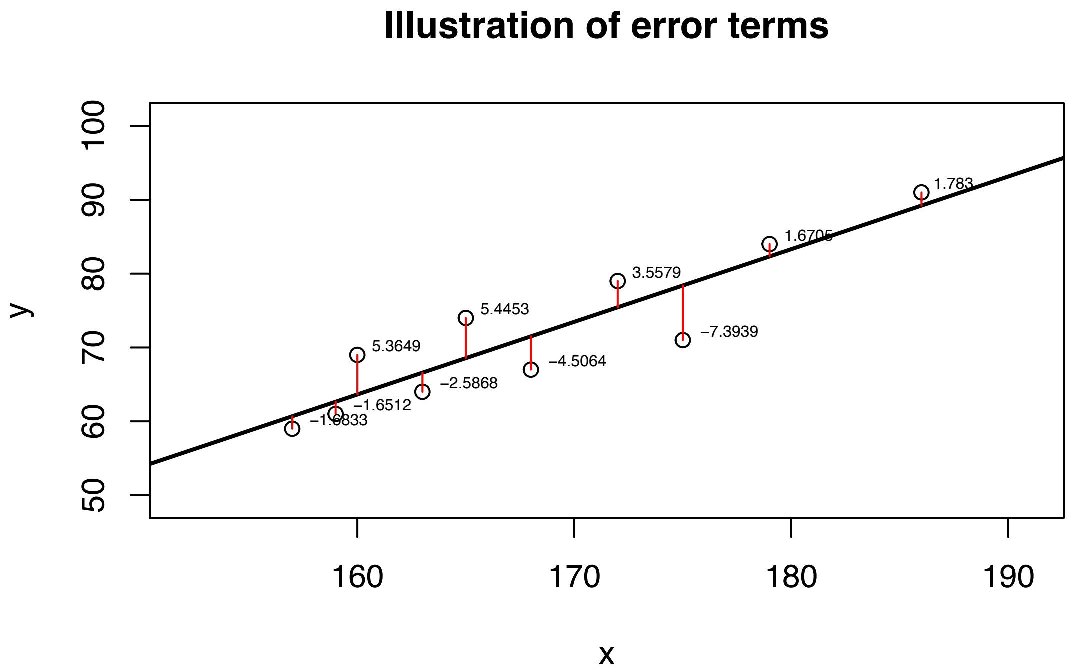

Figure 3.1: Illustration of error terms in OLS regression.

1. We assume a linear relationship between the independent and the independent variables.
2. We assume the independent variables are independent, i.e. we assume no autocorrelation.
3. We assume homoskedasticity, meaning we assume that the variance is constant for all the squared error terms. This will often give the model an incorrect measure of precision if the data are in fact heteroskedastic, meaning the variance of our observations are not constant.

Heteroskedasticity

In order to understand the concept of heteroskedasticity we can consider two examples. The first one is that of grocery spending relative to income. Families earning a very low income have limited choice in what groceries they buy because they will always have to choose the cheapest alternatives and in turn, the amount spent on groceries among poor families will have a low dispersion. Wealthier familes have the opportunity to buy what foods they want. Some wealthy families will want to spend a large amount of money on groceries whereas some wealthy families still choose to buy cheap groceries; the dispersion will be larger among the families earning more money.

The same case can be considered for total income predicted by age. Typically, most teenagers and younger individuals will have a low income due to natural reasons. However, as these people grow older, some will start earning larger wages rather quickly, while some will climb the wage-ladder more slowly, and some will not increase their salary at all. In short, the dispersion of total income will tend to increase with age.

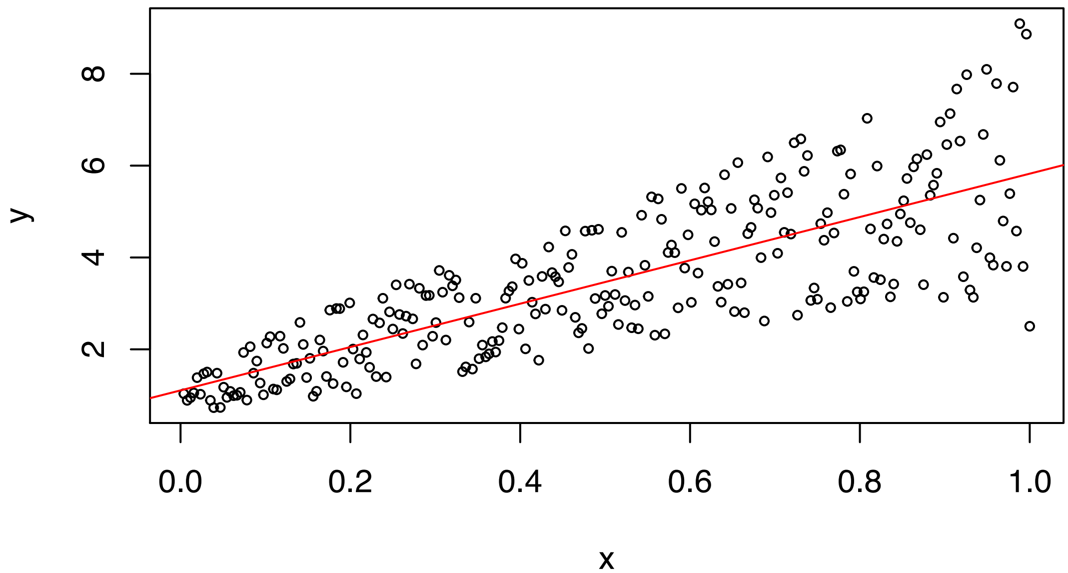

Figure 3.2: Illustration of heteroskedastic data.

In Figure 3.2 I have simulated a dataset which shows typical signs of heteroskedasticity. Keeping in mind the two examples above, we see that the dispersion of the values relative to the linear fit (red line) increases as the x-values become bigger and form a cone-shape. This effectively illustrates the essence of heteroskedasticity, namely the fact that the variance of the error terms differ (are unequal) across our dataset. Our example plot in Figure 3.2 effectively shows the problem of heteroskedasticity related to linar regression. When heteroskedasticity is present, the coeficcients of the regression equation will still be unbiased, but we see that the precision of the model could indeed be low and biased.

ARCH model

As briefly mentioned in the last section, one of the assumptions of OLS models is the assumption of homoskedasticity, and this is also the assumption which is addressed by the ARCH and GARCH models. Robert Engle (Engle 1982) emphasizes that it has become increasingly interesting in finance to model the size of the errors of our models. If heteroskedasticity is in fact present in an OLS regression, then the standard errors of our estimates will be biased, which in turn means we can not use the normal t-statistic or F-statistics for drawing statistical inference because the estimates of the error terms and confidence intervals will be too narrow. By treating heteroskedasticity as a variance to be modeled, the ARCH-model seeks to fill the deficiencies of the OLS model and at the same time, predictions for the variance of each variance term is computed.

The ARCH model consists of two equations, the conditional mean, and the conditional variance. The conditional mean equation can be written as:

$$Y_t = x_t\theta + \epsilon_t \tag{3.3}$$

Where ϵ_t is simply a random shock or innovation. We specify ϵ_t as:

$$\epsilon_t = \sigma_t + z_t \tag{3.4}$$

Where z_t is a standard normal shock, meaning it is normally, independent and identically distributed with a mean of 0 and a variance of 1, notated as $z_t \sim NIID(0, 1)$.

We can then proceed to give the equation for the conditional variance of ϵ_t:

$$\sigma_t^2 = C + \alpha\epsilon_{t-1}^2 \tag{3.5}$$

We set the restrictions $C > 0$ and $\alpha \geq 0$ to ensure the variance is positive.

As we can see from Equation 3.5, the variance σ_t^2 is given by a constant and the squared error of the preceeding period.

GARCH model

The notation in the following two sections follows the work in (Orskaug 2009).

We can define the model GARCH(q,p) in the following terms:

$$r_t = \mu_t + a_t \tag{3.6}$$

$$a_t = h_t^{1/2} z_t \tag{3.7}$$

$$h_t = \alpha_0 + \alpha_1 a_{t-1}^2 + ... + \alpha_q a_{t-q}^2 + \beta_1 h_{t-1} + ... + \beta_p h_{t-p} \tag{3.8}$$

Where:

r_t: Logarithmic returns of some asset at time t.

μ_t: Expected value of r_t

a_t: Return of some asset at time t

h_t: Squared volatility, the conditional variance at time t.

z_t: A sequence of iid (identical and independently distributed) random variables.

$\alpha_0, \alpha_1, ..., \alpha_q$: Alpha-coefficients

$\beta_1, ..., \beta_p$: Beta-coefficients

Equation 3.8 can be re-written to:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i a_{t-1}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{3.9}$$

And we can see that h_t will vary with time, depending on the squared returns a_{t-i}^2. Meaning that a big swing in the market up to q days earlier will show in an increased volatility h_t. This will result in a_t tending to be large meaning that a large shock will be followed by a large shock. This describes the periodical dependence of volatility as described by Mandelbrot (Mandelbrot 1963). It is important to note that a_t does not *have* to be large even in a period of high volatility, it just means the probability of a_t being high is increased. As we also see from the model, GARCH models do not separate positive and negative movements of markets as all returns are squared. See Equation 3.8. This can be considered a weakness of the GARCH model, and has been generalized by so-called asymmetric GARCH-models allowing for negative returns.

When speaking of a GARCH model we often see the model written as some version of "GARCH(q,p)" or "GARCH(1,1)". The first position of the parenthesis refers to the number of autoregressive lags, or ARCH-terms we consider in our equation, whereas the second number refers to the number of moving average lags in our equation, also called the number of GARCH terms.

Multivariate DCC-GARCH model

In finance and econometrics, understanding the comovements of assets is valuable in order to make better decisions in matters such as portfolio optimization, hedging or even Value at risk forecasts. Extending the GARCH-models from a univariate to a multivariate process recognizes that volatilities move together and across markets and makes us able to create more relevant models as opposed to just working with univariate models.

The DCC-GARCH model was introduced by Robert Engle in 2001. See (R. Engle 2002) for the complete presentation of the model. The model can be written as:

$$r_t = \mu_t + a_t \tag{3.10}$$

$$a_t = H_t^{\frac{1}{2}} z_t \tag{3.11}$$

$$H_t = D_t R_t D_t \tag{3.12}$$

Where:

r_t: n x 1 vector of logreturns at time t.

μ_t: n x 1 vector of expected value of r_t.

a_t: n x 1 vector of mean-corrected returns at time t. $a_t = r_t - \mu_t$

H_t: n x n matrix of conditional variances of a_t at time t.

$H_t^{1/2}$: n x n matrix at time t where H_t is the conditional variance matrix of a_t.

D_t: n x n diagonal matrix with conditional standard deviations of a_t

R_t: n x n conditional correlation matrix of a_t.

z_t: n x 1 vector of iid errors.

The standard deviations in D_t are given from the univariate GARCH model which gives the following matrix.

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 & \dots & 0 \\ 0 & \sqrt{h_{2t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sqrt{h_{nt}} \end{bmatrix} \tag{3.13}$$

And in line with Equation 3.9 we see that

$$h_{it} = \alpha_{i0} + \sum_{q=1}^{Q_i} \alpha_{iq} a_{i,t-q}^2 + \sum_{p=1}^{P_i} \beta_{ip} h_{i,t-p} \tag{3.14}$$

R_t denotes the conditional correlation matrix of the process ϵ_t.

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \dots & \rho_{1n,t} \\ \rho_{21,t} & 1 & \rho_{23,t} & \dots & \rho_{2n,t} \\ \rho_{31,t} & \rho_{32,t} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & 1 & \rho_{n-1,n,t} \\ \rho_{n1,t} & \rho_{n2,t} & \dots & \rho_{n,n-1,t} & 1 \end{bmatrix} \tag{3.15}$$

In short, we can say that the DCC-GARCH framework allows us to make accurate estimates of the time-varying correlations of our data while taking into account the conditional variance. The idea of a constant correlation matrix across a long period of time seems unlikely, especially considering the proven volatility of the assets in question. The DCC-GARCH framework allows for the exploration of a time-varying correlation matrix giving us insight in how these assets have moved together over time. In addition to this the model will give us insight in the conditional variances of the two assets and lets us examine if the variance of the two assets have any linkages.

Chapter 4

Analysis

This section will present all statistical analysis done on our dataset. As the previous chapter shows, a DCC-GARCH approach is suitable for data where we have signs of volatility clustering (heteroskedasticity). This, combined with the common notion that Norwegian Stock market returns are heavily linked to the oil crude price is the main reason for choosing a DCC-GARCH framework to explore this further. The analysis will follow a natural build-up towards the concluding results of the DCC-GARCH results. The first part will cover descriptive statistics in order to illustrate how our data looks. Tests will also be done to actually prove if our data is heteroskedastic. Furthermore, I will test whether or not the data is stationary, stationary data is needed in order to make statistical inference. A cointegration analysis is also performed to discover whether or not our two assets react to the same shocks in the market. The DCC-GARCH results lets us look at the time-varying correlations as well as looking at the volatility linkages between the two assets. Concluding the chapter is a Granger Causality analysis which will allow us to infer whether or not there is a causal relationship between Brent Crude and OSEBX.

Data and descriptive statistics

The basis for this analysis are time-series data of oil-prices and the norwegian stock market. Brent spot prices were used for the oil price as the Brent price is considered an international benchmark for crude oil prices. The OSEBX index, which is designed to be representative for the Norwegian Stock market, is chosen as a proxy for the norwegian stock market. (See the chapter about **Oslo Stock exchange**).

The brent prices were gathered from Thomson Reuters DataStream while the price info on OSEBX were taken from the TITLON database. According to data availability, the time period spans from January 1996 until February of 2016. This period gives an interesting timeframe and covers both the period of the financial crisis and the current period of oil price decline, starting in 2014. The choice of data-point frequency was guided by the research of Driesprong et. al. (Driesprong, Jacobsen, and Maat 2008). Driesprong et als research supports the hypothesis that there exists an underreaction to oil price changes in the stock market. Meaning that it takes time before information about oil price changes are reflected in stock market prices. When modelling the influence of oil on stock markets, Driesprong et. al. found that the explanatory power of their model was at the strongest when introducing a lag of six trading days between the oil prices and the stock market. Considering this, choosing weekly prices is appropriate. (Driesprong, Jacobsen, and Maat 2008).

In the analysis, all price info is converted into weekly returns by taking the first difference of the logarithmic weekly closing prices.

$$R_t = log(Y_t/Y_{t-1})$$

R_t denotes the return at time t and Y_t denotes the weekly closing price at time t. Running descriptive statistics on our dataset gives us the results presented in table Table 4.1.

Table 4.1: Descriptive statistics for OSEBX and Brent Crude return series, 1996-2016

	OSEBX	Brent
Mean	0,160 %	0,048 %
Standard Error	0,0009	0,0014
Median	0,0046%	0,0033%
Volatility	3,160 %	4,837 %
Sample Variance	0,0001	0,0023
Kurtosis	7,7661	1,3903
Skewness	-1,1152	-0,5010
Jarque-Bera	2869,5***	129,04***
Range	0,4025	0,3976
Minimum	-0,2471	-0,2200
Maximum	0,1553	0,1776
Sum	1,6753	0,5010
Count	1050	1050
Unconditional correlation	0,3916	

[1] *** denotes significance on 1% level. In this table, the Jarque-Bera test is the only hypothesis test, which is why it is the only value with a significance-level.

Both OSEBX and Brent Crude have a positive mean return. OSEBX had a higher average return (0,160%) than Brent Crude (0,048%) when we consider our full data period. We also see that the return series for Brent were more volatile (4,837%) than OSEBX (3,160%) which gives an indication that the Norwegian stock market has remained slightly more stable than the Brent Crude market in our selected time period. The two assets exhibit similar weekly maximum and minimum changes, denoted by the minimum and maximum values

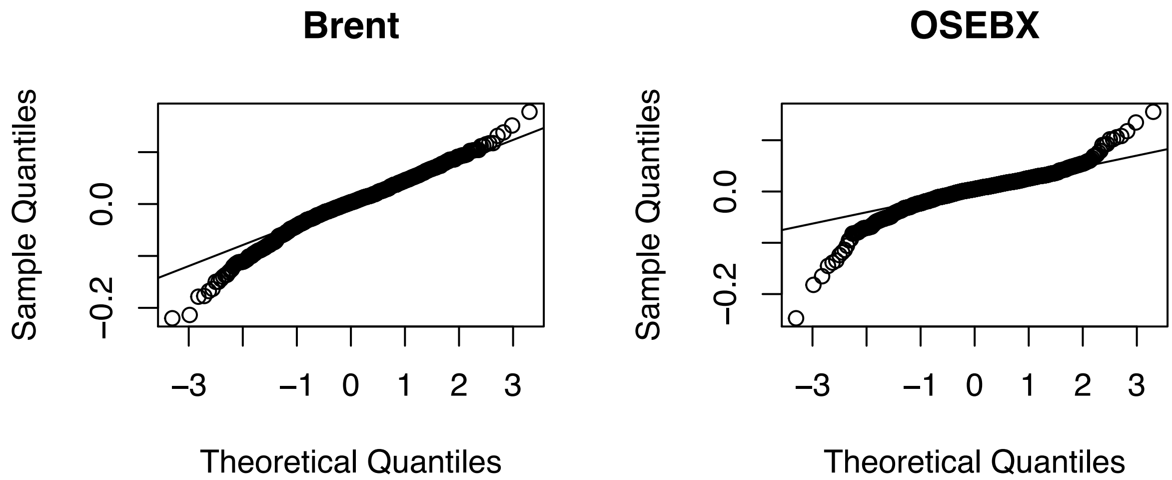

Figure 4.1: QQ-plots of Brent and OSEBX returns.

listed in Table 4.1. Both return series show a negative skewness, indicating that negative shocks tend to be bigger than positive shocks. This can also be seen from the quantile-quantile-plots (QQ-plot) in Figure 4.1 shown below. The QQ-plots lets us assess whether or not our data comes from some type of theoretical distribution, for example a normal distribution. For a normally distributed dataset, the QQ-plot would show a more or less straight line, whereas our plots seem to curve off in the extremities, usually indicating our data have more outliers than what would be expected in a Normal distribution. The Jarque-Bera test tests the return series for normality and the results listed in Table 4.1 confirm we can reject the null hypothesis of a normal distribution in both return series as indicated by both the skewness and QQ-plots. We also see from both the QQ-plots and the Jarque-Bera tests that Brent crude is closer to a normal distribution than OSEBX. The last line of Table 4.1 tells us that the unconditional correlation coefficient is 0,3916 which is in line with the discussion in the chapter about Oslo Stock exchange that OSE is dominated by large amounts of oil & gas related stocks which intuitively will fluctuate with the changing oil price.

Testing for heteroskedasticity

Even though visual inspection of the return series in Figure 2.3 show quite clear signs of heteroskedasticity, this should be clarified by running further tests. This will be done by applying another graphical method as well as a statistical test represented by what is called the Breusch Pagan test.

The graphical method consists of analyzing the residuals of a linear regression model. That means the first step is to fit our data into a regression model. The results of our fit is presented in Table 4.2.

Table 4.2: Linear regression analysis, OSEBX - Brent Crude

	Dependent variable:
	OSEBX
Brent	0.256^{***}
	(0.019)
Constant	0.001
	(0.001)
Observations	1,049
R^2	0.154
Adjusted R^2	0.153
Residual Std. Error	0.029 (df = 1047)
F Statistic	189.992^{***} (df = 1; 1047)
Note:	*p<0.1; **p<0.05; ***p<0.01

The results indicate that Brent Crude has a significant impact on OSEBX returns (0,256), giving us that $OSEBX = 0,001 + 0,256\beta$, where β is the change in Brent Crude price.

The regression analysis in itself is not the most important in our case. However, we can use the residuals of this model in order to check for heteroskedasticity.

Figure 4.2 on the next page shows us some diagnostics on the residuals of our regression model. The most interesting plots for evaluating heteroskedasticity are the top and lower left plots. In the absence of heteroskedasticity we should see a random, equal distribution of observations through the X-axis and a straight, flat, red line. As we see in our plots, the red line is slightly curved in both cases, meaning we have reason to assume there is some heteroskedasticity present.

The Breusch-Pagan test lets us stastically test whether or not there is heteroskedasticity in our residuals. The null hypothesis of the test is homoskedasticity. Table 4.3 shows significance on 1%-level, meaning we can reject the null hypothesis of homoskedasticity and assume that our data is in fact heteroskedastic.

From the section about **heteroskedasticity** we now know that when heteroskedasticity is present, the

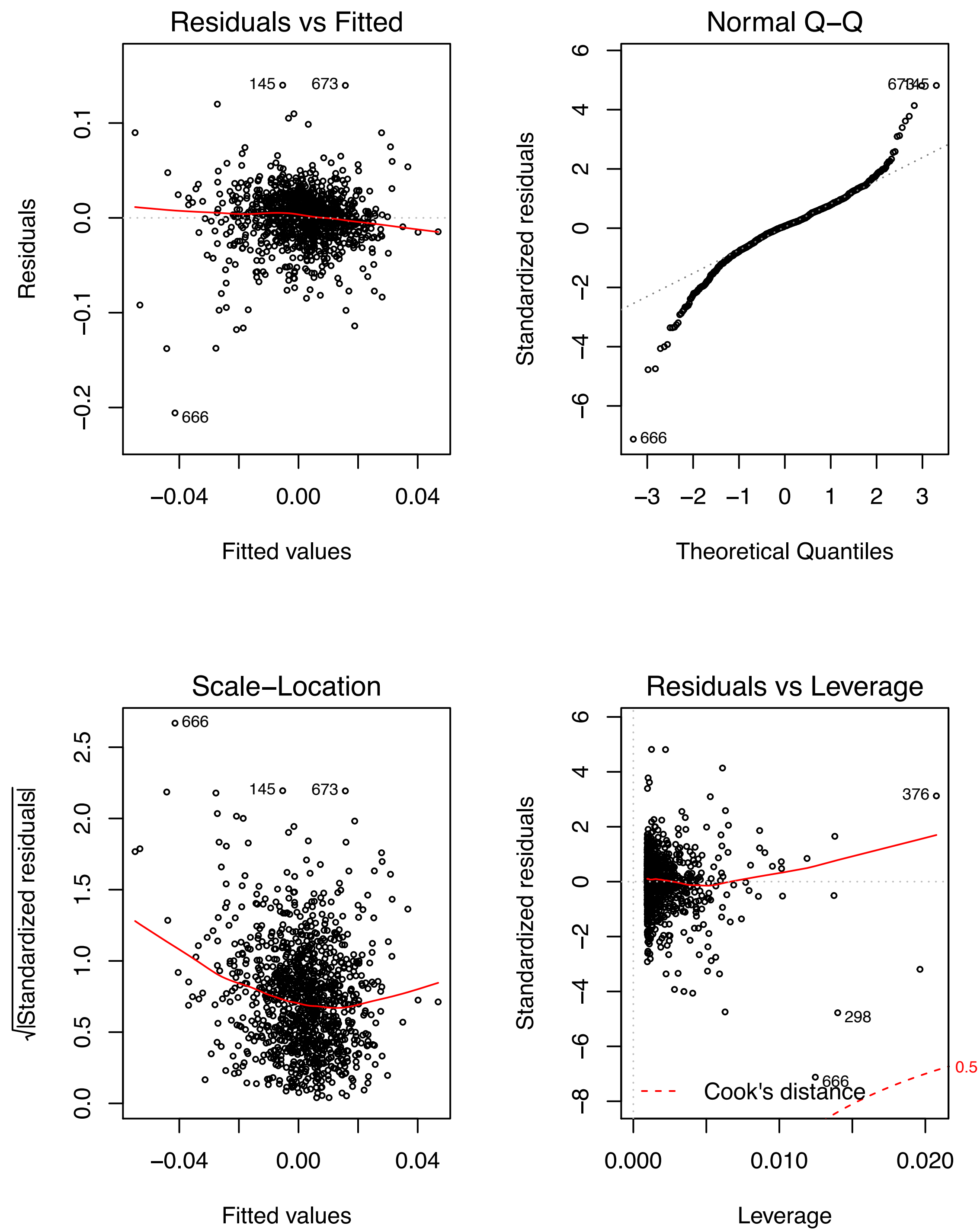

Figure 4.2: Diagnostic plots of residuals for linear regression OSEBX - Brent Crude. If our data was homoskedastic, the two plots on the left would show more or less straight horizontal lines. The top right plot illustrates the distribution of the error terms (residuals). As we can see, the residuals do not follow a normal distribution because of the curving in the extremities of the plot. This indicates fat tails caused by the outliers in our dataset. The most extreme outliers are marked with numbers in the plots, indicating what week the particular extreme event occured. The lower right plot lets us identify if one ore more outliers influence the regression results. Typically, if we see outliers outside of the dotted red line (cooks distance), then the regression result can be altered by removing this outlier. No outliers seem to affect the results in our case.

Table 4.3: Result of Breusch-Pagan test

	Test value	p-value
Breusch-Pagan	36,621	0,000***

[1] *** indicates significance on 1%-level.

coefficients of our regression will remain unbiased, but the standard errors and confidence intervals will not be evaluated correctly, giving low precision in our model. The issue of heteroskedasticity in regression analysis can be dealt with in a few different ways, an example is the application of a weighted least-squares method where the values of X and Y are given different weights depending on the variance of the error terms. The weighted least squares method is beyond the scope of this thesis, and will not be discussed further. The fact that these tests proves heteroskedasticity further reinforces the choice of using a GARCH-method as this method is designed to deal with heteroskedastic data.

Properties of Time-Series Data

Before making any statistical inference about Time-series data we need to make some assumptions about our data. One of the most important assumptions we make is the one concerning stationarity. Loosely speaking, if there is no observable trend in our data, then the observations are stationary. We can say that our data is stationary if the probability laws deciding the behaviour of the process does not change over time (Chan and Cryer 2008). For example, we can say that a process is strictly stationary if the joint distribution of $Y_{t_1}, Y_{t_2}, ..., Y_{t_n}$ is the same as the joint distribution of $Y_{t_1-k}, Y_{t_2-k}, ..., Y_{t_n-k}$ for all times $t_1, t_2, ..., t_n$ and all time lags k. Or more intuitively, we can say that all realizations of our time series, $Y_t, Y_{t_2}, ..., Y_{t_n}$ are draws from identical distributions. A Time series process is said to be stationary when three conditions are satisfied:

1. The mean is independent of time i.e. constant mean.
2. The variance is independent of time i.e. constant variance.
3. The covariance between values depends only on the time distance between the points, and not on time.

This definition is what we call *weak stationarity.*

We can use simulated data in order to illustrate what a stationary and a non-stationary time-series typically will look like. Figure 4.3 shows two plots of simulated data. There are 200 observations in each plot and we can see how the stationary series keep returning to an average value whereas the non-stationary series tends to wander off from its starting value. So, why is stationarity important in time-series analysis? When we are dealing with non-stationary data such as seen on the right in Figure 4.3, we see that for example the mean expected value can potentially be drastically different between two time points. This means that stationarity is important in order to ensure that sample statistics such as mean or variance gives a unified picture of the data for all time points.

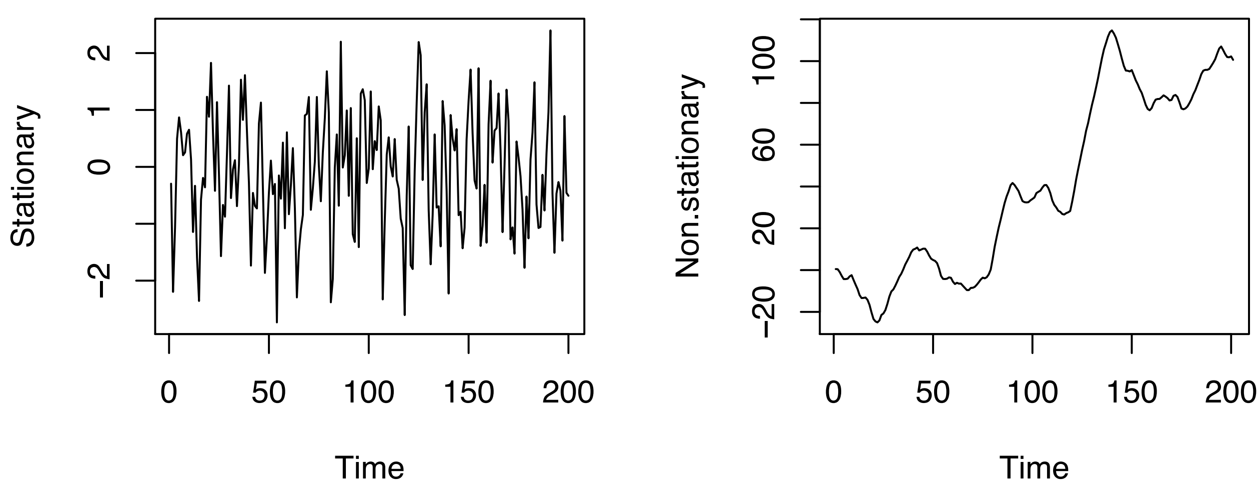

Figure 4.3: Simulated stationary and non-stationary time-series.

Testing for stationarity

In order to check whether or not our data are stationary we can perform different statistical tests. The most common test to test for stationarity is the Augmented Dickey Fuller test. We can also do a visual inspection of an autocorrelation-plot (ACF-plot) in order to make up some initial thoughts about stationarity or not.

The ACF-plot such as the one shown in Figure 4.4 have the correlation coefficient on the Y-axis and the number of lags on the X-axis. If the observed value at lag n exceeds the significance bounds (blue dotted lines) then we have significant autocorrelation at lag n.

Typically, an ACF-plot for a non-stationary time-series will look like the plot in Figure 4.4 with high values of autocorrelation which decays very slowly over time. The specific ACF-plot shown in Figure 4.4 is done on the raw price data for OSEBX and Brent, and one would typically expect raw price data to be non-stationary. We can perform the Augmented Dickey-Fuller test (ADF-test) on the raw price data to confirm. As Table 4.4 shows, we obtain p-values of 0,2905 for OSEBX and 0,5774 for Brent. The null-hypothesis of the ADF-test is non-stationarity. Our p-values are not significant and hence, we cannot reject the null-hypothesis of non-stationarity.

	Test-value	p-value
OSEBX	-2,68	0,2905
Brent	-2,00	0,5774

Table 4.4: ADF-test on raw price data, OSEBX and Brent Crude

Moving on to the return series of OSEBX and Brent, our ACF-plots indicate stationarity. As shown in Figure 4.5 for OSEBX, we can see that very few lags are significant, and those which fall outside the significance bounds only barely fall outside. We can confirm this by performing the ADF-test on the dataset. As Table 4.5 show, we now obtain p-values significant on the 1%-level and we can reject the null hypothesis of non-stationarity and conclude our return series are stationary.

	Test-value	p-value
OSEBX	-8,692	$<$0,01
Brent	-8,78	$<$0,01

Table 4.5: ADF-test on OSEBX and Brent return series

These initial results of testing for heteroskedasticity and stationarity combined with what we observed in our descriptive statistics do support the choice of applying a DCC-GARCH framework for further analysis of the return series.

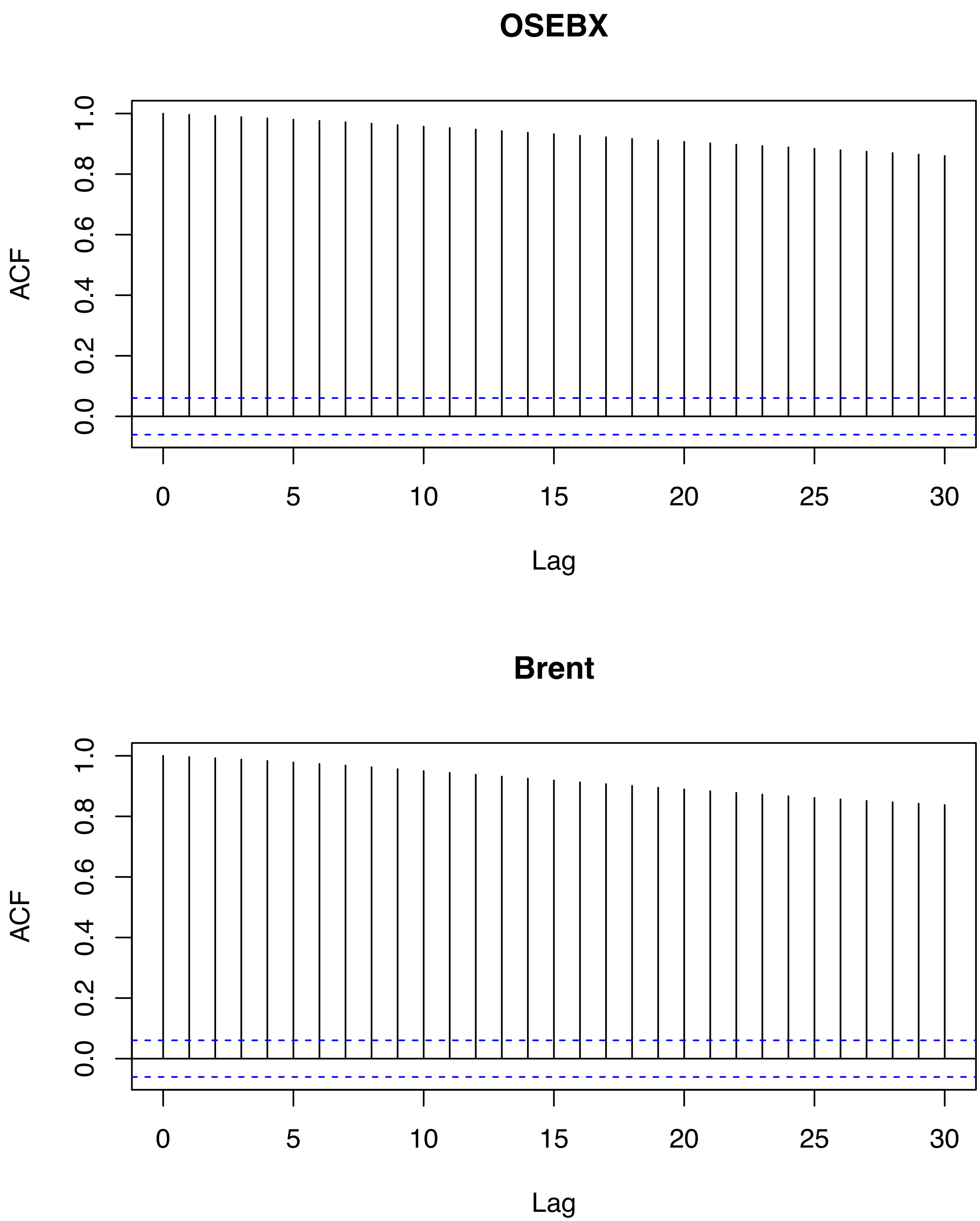

Figure 4.4: ACF plots for OSEBX and Brent Crude raw price data. The vertical lines indicate if there is a trend in the observations. If the vertical lines consistently stretch beyond the dotted blue lines, this indicates a trend in our observations, which in turn indicates non-stationarity. As expected, the raw price plotted above has a clear trend.

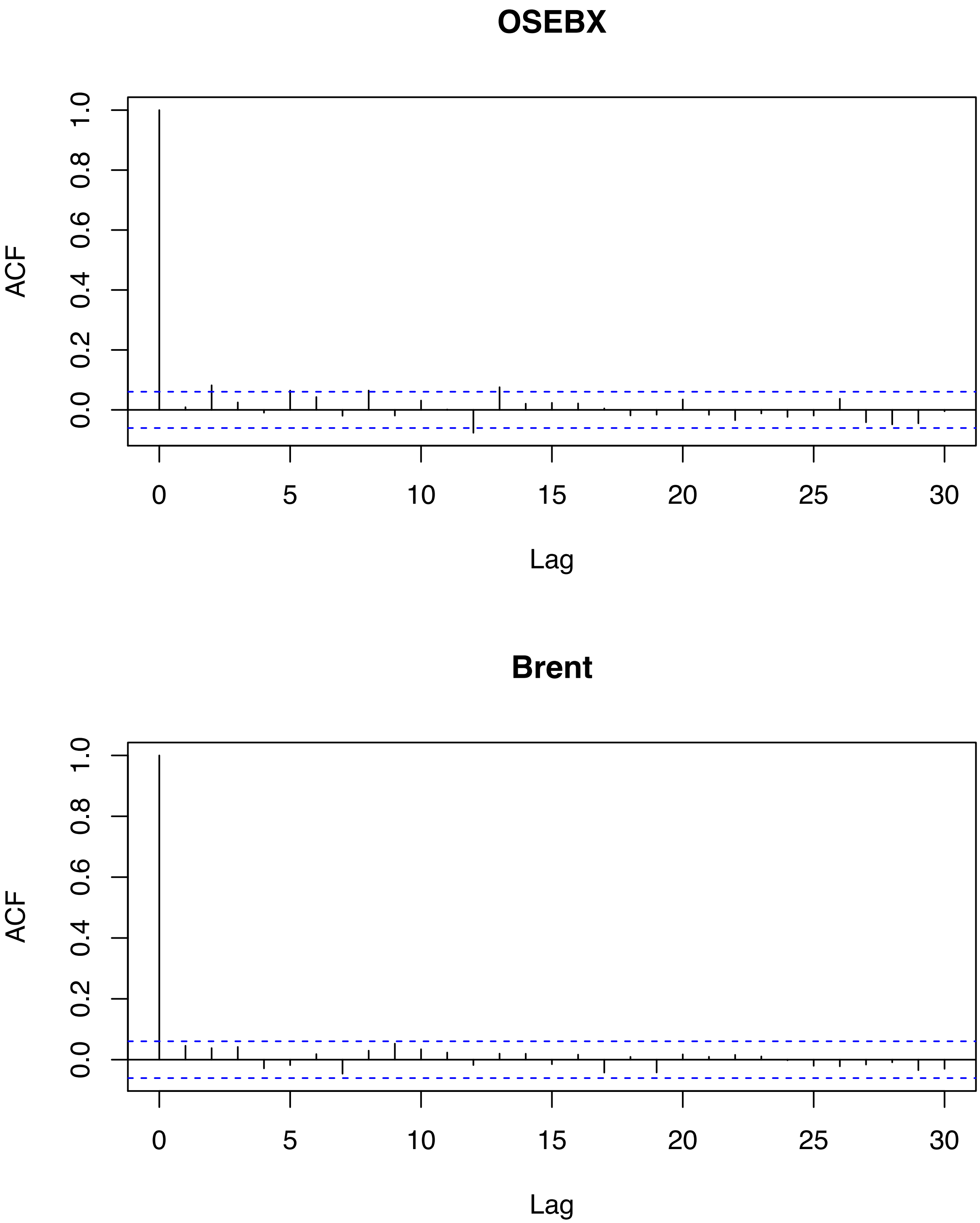

Figure 4.5: ACF plots for OSEBX and Brent Crude return series. We see that the vertical lines stay inside the signifiacance bounds, indicating a ack of trend. We can conclude our return series are stationary.

Testing for cointegration

In order to better understand the co-movements of our two datasets we can examine whether the two are cointegrated or not. While this test is not related to the DCC-GARCH model we are applying, performing a cointegration test will allow us to have an idea of how the two assets move together, and if they react to the same shocks in the market. The notion of cointegration was first introduced by Granger in 1981 (Granger 1981). To understand cointegration we must understand what the term *integrated series* mean. For example, let us consider two nonstationary timeseries, i.e. two series with some kind of trend. If the time series become stationary after differencing n times, then we can say that the series are integrated of order n. Looking back to the previous section we established that our time series were nonstationary at raw price levels but we also saw that after transforming the prices into return series (which is the same as taking the first difference) we concluded with stationarity. Our data is therefore integrated of order 1, notated by I(1). This can be written in the following way:

$$P_t = I(1) \tag{4.1}$$

Difference of first order gives us diff(1):

$$diff(1) = P_2 - P_1 \tag{4.2}$$

And since our return series are both stationary we can write that

$$diff(1) = I(0) \tag{4.3}$$

A given set of data can be considered cointegrated if a linear combination of these series is integrated of order less than n. In empirical terms, we can consider a simple regression:

$$Y_t = \alpha + \beta X_t + \epsilon_t \tag{4.4}$$

Then we can say that Y_t and X_t are cointegrated if there is some value of β that makes the linear difference between Y_t and X_t a stationary process, I(0).

$$Y_t - \beta X_t = I(0) \tag{4.5}$$

Murray (Murray 1994) quite accurately compares cointegration to the relationship between a drunk person walking home from the pub and this persons dog. The drunk person may wander off randomly into the night, the dog will stay more or less closely to its owner, but may also wander off at times. The owner will at times call for the dog, and the distance between them will be corrected so that they always will stay more or less close together. So, despite the more or less nonstationary paths of both human and dog, the distance between the paths can be considered stationary. We say that the two separate paths followed by dog and human are cointegrated; they are not equal, but their paths are driven by the same shocks.

The Johansen and Engle-Granger test lets us examine if there is cointegration between our two variables. The test results of the full period of OSEBX and Brent Crude data showed no cointegration. This could for example be caused by the two asset prices moving in opposite directions for too long making it impossible to find a stationary linear relationship. If we look back at the price plot in Figure 2.1 we see that the price movements move in separate directions towards the end of the plot. This represents the oil price crash in 2014. When excluding this period and simply testing the time series from 1996 through 2013 the test results imply that our series are cointegrated. The results from the tests are presented in Table 4.6

Table 4.6: Cointegration tests results.

	Test	Test Value
Full period	Johansen	2,7945
	Engle Granger	-0,0721
1996-2013	Johansen	20,2327
	Engle Granger	-2,5462

[1] The critical value for the Johansen test on 5% level is 19,96, and 24,50 on 1% level. For the Engle-Granger test the critical values are -2,58 on 1% level and -1,95 in 5% level. We see that our results are significant on a 5% level in both tests.

The fact that our series are cointegrated up until 2013, but not beyond, is explained by the oil price crash of 2014. This price crash was evidently so specific to the oil price that the norwegian stock market did not follow suit. In this case, the OSEBX index did not react to the same shock as the oil price. When the two assets “part ways” like we can see for example in Figure 2.1, there is no longer a stationary relationship to be found between the price series, which causes negative results when looking for cointegration.

Results of the DCC-GARCH fit

The preceeding tests have shown us that we are in fact dealing with data that show clear signs of heteroskedasticity. The test for stationarity helped us ensure that we are infact dealing with stationary time series data, suitable for further statistical analysis. The cointegration analysis confirmed initial assumptions that our two assets historically have indeed had a close relationship, reacting similarly to the same shocks. These results support the use of the DCC-GARCH framework to further investigate the dynamics of our assets.

Choosing the number of ARCH and GARCH terms for our estimation is important to ensure best possible description of our data. One way to do this is to compute an information criteria. For example, Akaike (Akaike 1981) proposed a measure which gives the optimal number of lags in a statistical model. When applied on my dataset I find that one lag for each input is reasonable. This means that I will apply the GARCH(1,1) in this case. This means we will only have one ARCH-term and one GARCH-term in our estimation. AIC measures the quality of statistical models and gives us a basis on which we can select the best fitting model (Burnham and Anderson 2004). It could be argued that a GARCH (2,1) could also be used, but as the differences showed to be minimal, GARCH(1,1) has been applied. This means we will only have one ARCH-term and one GARCH-term in our estimation.

The results of the conditional variances are presented in Table 4.7. The ARCH coefficients represented by $OSEBX_{\alpha}$ and $Brent_{\alpha}$ are significant on a 1%-level. The ARCH terms measure the impact of past innovations on current conditional volatility, meaning the current conditional volatility is a result of the previous time periods error terms. Considering the magnitude of the coefficients, this effect is stronger in OSEBX stock returns (0,179201) than in Brent crude (0,065484). $OSEBX_{\beta}$ and $Brent_{\beta}$ represents the GARCH terms which measure the impact of past volatility on current volatility. The GARCH-coefficients are significant on a 1% level for both Brent Crude (0,928168) and for OSEBX (0,771196). The magnitude of the coefficients indicate that there is more volatility persistence in oil price than in the stock returns implying that average variance will remain higher since an increase in the conditional variance due to shocks will decay slowly. In line with the descriptive statistics in Table 4.1, we see that the higher GARCH-term for Brent Crude suggests higher volatility.

Table 4.7: Conditianal variance estimates

Parameter	Coefficient	t-statistic	P-value
$OSEBX_{\alpha}$	0,179201	3,32101	0,000897
$OSEBX_{\beta}$	0,771196	12,88036	0,000000
$Brent_{\alpha}$	0,065484	3,4588	0,000543
$Brent_{\beta}$	0,928168	44,34451	0,000000

The DCC-GARCH parameters shows us the existence of time-varying correlation between asset prices. In our case, the results presented in Table 4.8 shows us that the DCC-ARCH-coefficient (0,026745) is statistically

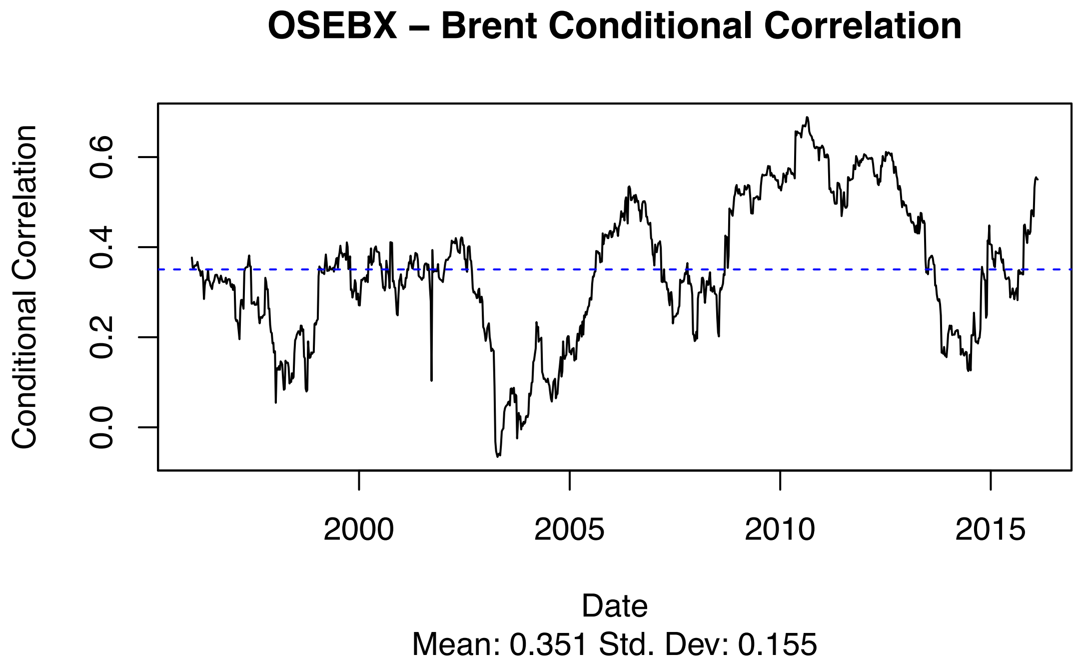

Figure 4.6: Dynamic Conditional Correlation for our full period. The blue dotted line indicates the mean for the full period.

significant on a 1%-level. In other words, we see that there is a co-movement in the manner that innovations from previous periods affects current volatility for both Brent and OSEBX. Similarly, the DCC-GARCH coefficient (0,967736) is also significant on a 1%-level and indicates strong evidence of dynamic conditional correlation in the GARCH effect between OSEBX return volatility and oil price volatility. The evidence of time-varying conditional correlation provides support for volatility interdependence between the two assets.

Table 4.8: Parameters of the DCC-GARCH estimation

Parameter	Coefficient	t-statistic	P-value
$DCC\alpha$	0,026745	2,90333	0,003692
$DCC\beta$	0,967736	93,63902	0,000000

As we can see in Figure 4.6, the Dynamic Conditional Correlation for the entire period has a mean of 0,351 and a standard deviation of 0,155. This correlation is similar to that which was presented in Table 4.1. As the plot also shows, the correlation was at its strongest from around 2009 until about year 2012 when it started declining again. This relatively strong correlation suggests poor diversification benefits from investing in both markets. Furthermore, this correlation supports the points made in the chapter about **Oslo Stock exchange** where it was implied a strong integration between the two markets because of the number of oil&gas and energy-related companies listed on OSE.

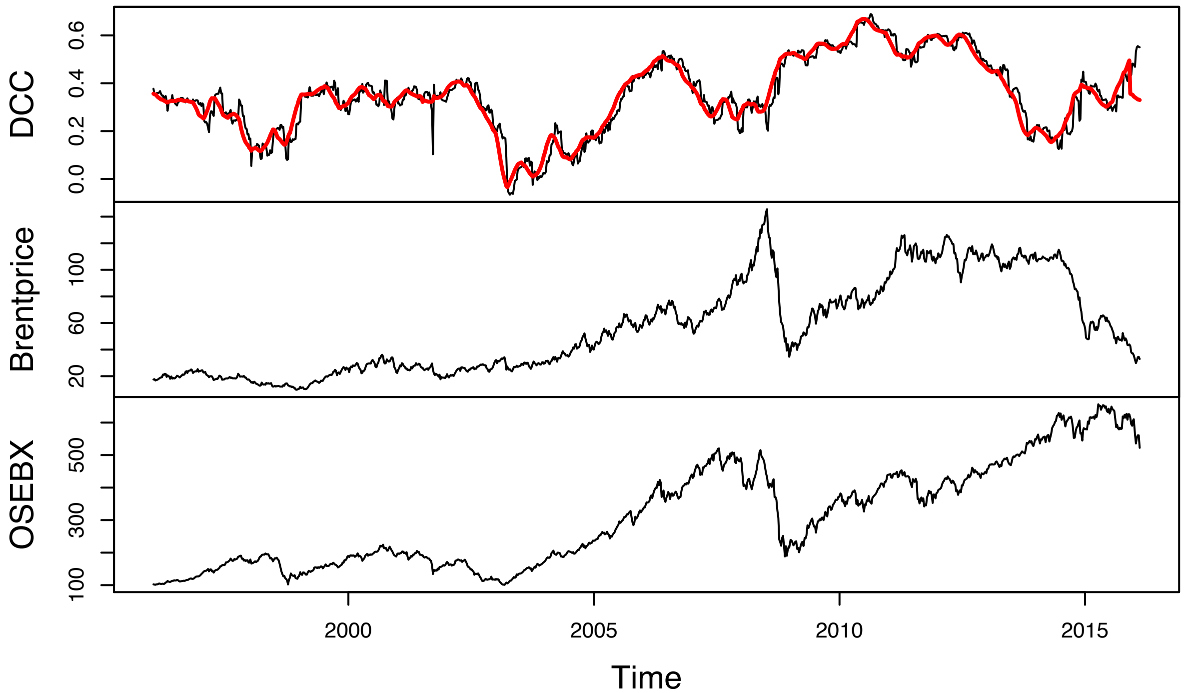

Figure 4.7: Movements of DCC, Brent Crude and OSEBX in the time period 1996-2016. The red line represents a 12-week rolling average for the DCC-values.

Analysis of correlation in sub-periods

When looking at time-varying correlation between two variables it is also interesting to see how the correlation changes and behaves in certain time periods or in relation to specific events. I have chosen to look at the period preceding the most recent financial crisis, the period of the actual crisis and the period following the crisis. The period of the financial crisis has been defined as the time between December 2007 until June 2009. The preceding period will be all data before the crisis (January 1996- November 2007) and the period following the crisis will span from July 2009 until the end of our dataset, february 2016. In order to get a visual overview of whether there are some immediate patterns to be recognized between the price movements of our two assets and the DCC-coefficients it can be helpful to first visually inspect all three values at once. Figure 4.7 shows a plot containing the Time-varying correlation (DCC), Brent prices and OSEBX in the period 1996-2016. I have also included a 12-week rolling average plot of the DCC-values indicated by the red line in order to help identify possible trends. From looking at the figure, any clear patterns are not obvious. However, we do see some patterns which are quite natural. Such as the DCC was strengthened in the financial crisis where both assets fell substantially.

From the plots in Figure 4.8 we see that the period before the financial crisis had a lower average DCC (0,285) compared to the whole period (0,351). The average DCC during the financial crisis (0,389) was a little higher than the full period and we especially see that the DCC was strongest at the end of the financial crisis where we see a DCC coefficient of about 0,5. Of the three sub-periods the period after the financial crisis until february 2016 is the one which displays the highest average DCC-coefficient (0,459). Interestingly, we see that the DCC declines quite drastically towards the end of 2013 and in the beginning of 2014 before hitting the lowest point in this sub-period in mid 2014 which is also when the oil price started experiencing a quite dramatic fall, see the chapter about Oil Price uncertainty.

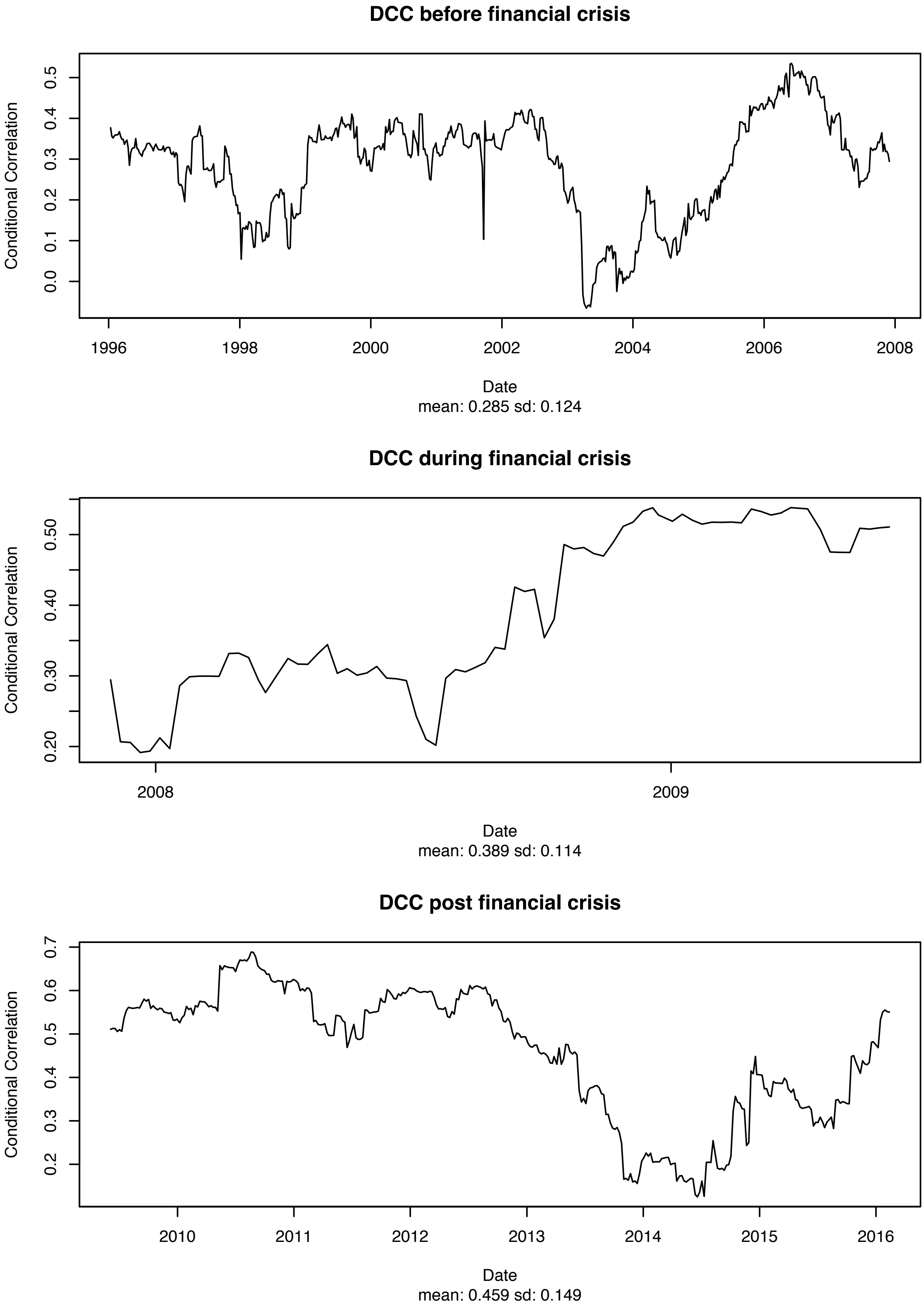

Figure 4.8: Dynamic Conditional Correlation in different time periods.

Causality

It is a well-known fact in methodology and statistical litterature that correlation does not imply causation. Even though we have seen that the correlation between Brent Crude and OSEBX is periodically quite strong, this does not, however, give us enough evidence to conclude with any causation between the two variables.

Clive Granger (Granger 2016) developed a paper in 1969 on investigating causal relations between economic variables. His work has led to what we call the test for Granger causation. We can say that some variable, X, Granger-causes some other variable Y if past values of X help predict Y in a more precise way than simply looking at past values of Y alone. In other words, having knowledge about the development X will reduce the forecast error of Y which in turn implies that Y does not move independently of X. We see that this is not exactly similar to what we normally think of as causality, but it is nevertheless an interesting indicator of some causal relationship.

Running a Granger Causality test on our data provides the results presented in Table 4.9

Table 4.9: Results of Granger-Causality tests

	p-value	Reject null?
H_0: Brent does not Granger-cause OSEBX	0,04104	Yes
H_0: OSEBX does not Granger-cause Brent	0,001065	Yes

The test indicates that brend Crude returns does in fact Granger-Cause OSEBX returns. However, we also see that the test indicates that OSEBX returns Granger-causes Brent returns, i.e we obtain a bidirectional granger-causality between our two variables. There are a number of factors which may affect the results of the Granger Causality test. It is especially sensitive to the choice of number of lags to include when running the test. In this case, the Akaike Information Criteria (AIC) was used, the same as was used for choosing lags for the GARCH estimation. See Burnham (Burnham and Anderson 2004) for more info. Maziarz (Maziarz 2015) also suggests that when finding a bidirectional relationship this could be caused by what he calls a "common cause fallacy" which means that both OSEBX and Brent are both affected by some third variable Z. Maziarz also argues that rejection of the null hypothesis in the Granger Causality test could be due to causes such as the sampling not being frequent enough or time series integration. In my case, however, the more probable cause is the large share of oil and energy firms listed in the OSEBX. This implies a feedback effect: oil goes up which leads to oil firms going up, when the oil firms go up, OSEBX goes up. When OSEBX go up, this could drive oil firms up again.

Chapter 5

Conclusions and further research

By applying different statistical analytical tools such as cointegration analysis, Granger causality and the DCC-GARCH framework I have looked into the co-movement between the Brent Crude price and OSEBX in the period between 1996 and 2016. The main analysis was built around the application of the DCC-GARCH framework which has allowed me to discover the time-varying correlation between the two chosen assets as well as the conditional variances. I have also performed analysis on three different sub-periods. Pre-financial crisis (January 1996 - November 2007), the financial crisis (December 2007 - June 2009) and post financial cris (July 2009 - February 2016). The analysis was based on end of week price data. The choice of frequency was based primarily on the theory of a delayed investor reaction to changes in oil price (Driesprong, Jacobsen, and Maat 2008). The analysis of the time-varying correlation showed that the highest mean correlation occured in the period following the financial crisis. The analysis showed no obvious patterns as far as conditional correlation goes, but I did identify a substantial drop in conditional correlation during the recent oil price downfall of 2014. The conditional correlation was at its strongest between 2010 and 2011, reaching a coefficient of almost 0,7.

The cointegration analysis was performed by utilizing the Engle-Granger and Johansen methods. This analysis shows that we could not prove a cointegrated relationship between our two assets when considering the full period (1996-2016). This is due to the oil downfall starting in 2014 where our two asset prices moved more or less in opposite directions. When analyzing only the period prior to the oil downfall (1996-2013) I was able to prove a cointegrated relationship.

The causal relationship between oil was analyzed by using a Granger-causality test. Through this test we found that Brent crude prices do Granger-cause returns on OSEBX. However, we also found a bi-directional relationship meaning that the returns on OSEBX also Granger-caused the Brent crude prices. This result could occur due to the close relationship of the assets, or even a bias in the test through e.g. a “common cause fallacy" or too infrequent sampling.

This study provides insight to the co-movements of returns on OSEBX and the Brent crude oil price. The insight can be valuable for portfolio optimization and risk assessment.

Moving forward, a more in-depth research including different indices on OSE could be interesting together with applying this method in order to derive portfolio optimizations with stocks or indicies on OSE. Furthermore, applying a VAR-GARCH framework for measuring volatility spillovers will provide even stronger insight into the relationship between our two assets.

References

Akaike, Hirotugu. 1981. "Likelihood of a model and information criteria." *Journal of Econometrics* 16 (1): 3–14. doi:10.1016/0304-4076(81)90071-3.

Aloui, Chaker, and Rania Jammazi. 2009. "The effects of crude oil shocks on stock market shifts behaviour: A regime switching approach." *Energy Economics* 31 (5). Elsevier B.V.: 789–99. doi:10.1016/j.eneco.2009.03.009.

Alsalman, Z. 2016. "Oil price uncertainty and the U.S. stock market analysis based on a GARCH-in-mean VAR model." *Energy Economics* 59: 251–60. doi:10.1016/j.eneco.2016.08.015.

Arouri, M. E. H., A Lahiani, and D K Nguyen. 2011. "Return and volatility transmission between world oil prices and stock markets of the GCC countries." *Economic Modelling* 28 (4): 1815–25. doi:10.1016/j.econmod.2011.03.012.

Baumeister, Christiane, and Lutz Kilian. 2016. "Forty Years of Oil Price Fluctuations: Why the Price of Oil May Still Surprise Us." *The Journal of Economic Perspectives* 30 (1): 139–60. doi:10.1257/jep.30.1.139.

Bollerslev, Tim. 1986. "Generalized autoregressive conditional heteroskedasticity." *Journal of Econometrics* 31 (3): 307–27. doi:10.1016/0304-4076(86)90063-1.

Bouri, E. 2015. "Return and volatility linkages between oil prices and the Lebanese stock market in crisis periods." *Energy* 89: 365–71. doi:10.1016/j.energy.2015.05.121.

Burnham, K. P., and R.P. Anderson. 2004. "Multimodel Inference: Understanding AIC and BIC in Model Selection." *Sociological Methods & Research* 33 (2): 261–304. doi:10.1177/0049124104268644.

Chan, Kung-Sik, and Jonathan Cryer. 2008. In *Time Series Analysis with Applications in R*.

Cheng, A. C. S. 1996. "Economic factors and stock markets: Empirical evidence from the UK and the US." *International Journal of Finance and Economics* 1 (4): 287–302.

Dagher, L, and S El Hariri. 2013. "The impact of global oil price shocks on the Lebanese stock market."

Energy 63: 366–74. doi:10.1016/j.energy.2013.10.012.

Driesprong, Gerben, Ben Jacobsen, and Benjamin Maat. 2008. "Striking oil: Another puzzle?" *Journal of Financial Economics* 89 (2): 307–27. doi:http://dx.doi.org/10.1016/j.jfineco.2007.07.008.

Engle. 1982. "Autoregressive Conditional Heteroscedacity with Estimates of variance of United Kingdom Inflation." *Journal of Econometrica* 50 (4): 987–1008. doi:10.2307/1912773.

Engle, Robert. 2001. "GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics." *Journal of Economic Perspectives* 15 (4): 157–68. doi:10.1257/jep.15.4.157.

———. 2002. "Dynamic Conditional Correlation." *A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models* 20 (3): 339–50. doi:10.1198/073500102288618487.

Granger, C W J. 1981. "Some properties of time series data and their use in econometric model specification." *Journal of Econometrics* 16 (1): 121–30. doi:http://dx.doi.org/10.1016/0304-4076(81)90079-8.

———. 2016. "Investigating Causal Relations by Econometric Models and Cross-spectral Methods." *Econometrica* 37 (3): 424–38.

Hatemi-J, A, A Al Shayeb, and E Roca. 2017. "The effect of oil prices on stock prices: fresh evidence from asymmetric causality tests." *Applied Economics* 49 (16): 1584–92. doi:10.1080/00036846.2016.1221045.

Hull, John C. 2009. *Futures, Options and Other Derivatives.*

"International Energy Agency." 2017. https://www.iea.org/topics/oil/.

Kilian, L, and C Park. 2009. "The impact of oil price shocks on the U.S. stock market." *International Economic Review* 50 (4): 1267–87. doi:10.1111/j.1468-2354.2009.00568.x.

Kling, John L . 1985. "Oil Price Shocks and Stock Market Behavior." *The Journal of Portfolio Management* 12 (1): 34–39. doi:10.3905/jpm.1985.409034.

Lee, Yen Hsien, and Jer Shiou Chiou. 2011. "Oil sensitivity and its asymmetric impact on the stock market." *Energy* 36 (1). Elsevier Ltd: 168–74. doi:10.1016/j.energy.2010.10.057.

Mandelbrot, Benoit. 1963. "The Variation of Certain Speculative Prices." *Source: The Journal of Business* 36 (4): 394–419. doi:10.1007/978-1-4757-2763-0_14.

Maziarz, Mariusz. 2015. "A Review of the Granger-Causality Fallacy." *The Journal of Philosophical Economics* 8 (2): 86.

Murray, Michael P. 1994. "A drunk and her dog: An Illustration of Cointegration and Error Correction."

doi:10.2307/2685084.

Nandha, Mohan, and Robert Faff. 2008. "Does oil move equity prices? A global view." *Energy Economics* 30 (3): 986–97. doi:10.1016/j.eneco.2007.09.003.

Orskaug, Elisabeth. 2009. "Multivariate DCC-GARCH Model -With Various Error Distributions." *Norwegian Computing Center*.

"Oslo Børs." 2017. Accessed February 7. https://www.oslobors.no/Oslo-Boers/Statistikk/AArsstatistikk/Aksjer/2016-Mest-omsatte-verdipapir.

"Oslo børs." n.d. https://www.oslobors.no/ob{_}eng/Oslo-Boers/About-Oslo-Boers/News-from-Oslo-Boers/Oslo-Boers-oil-service-index-becomes-tradable.

Park, Jungwook, and Ronald A. Ratti. 2008. "Oil price shocks and stock markets in the U.S. and 13 European countries." *Energy Economics* 30 (5): 2587–2608. doi:10.1016/j.eneco.2008.04.003.

Schwartz, Eduardo S. 2008. "The Stochastic Behavior of Commodity Prices : Implications for Valuation and Hedging Author (s): Eduardo S . Schwartz Source : The Journal of Finance , Vol . 52 , No . 3 , Papers and Proceedings Fifty-Seventh Annual Meeting , American Finance Associatio" 52 (3): 923–73.

Stigler, Stephen M. 1981. "Gauss and the Invention of Least Squares." *The Annals of Statistics* 9 (3): 465–74. doi:10.1214/aos/1176345451.

Zhang, Yue Jun, and Ting Yao. 2016. "Interpreting the movement of oil prices: Driven by fundamentals or bubbles?" *Economic Modelling* 55. Elsevier B.V.: 226–40. doi:10.1016/j.econmod.2016.02.016.