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MASTER'S THESIS

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ABSTRACT

Value at Risk (VaR) is an important calculation in risk management. It is a commonly used measure of risk in finance, and is used by corporations to estimate potential future loss. With a significance level, VaR gives the worst potential loss within a specific time period. VaR is easy to understand, and provides important information about risk.

This thesis uses data from the oil and gas industry to compare different methods of calculating the VaR. The approaches compared are the non-parametric and the parametric methods, whereas the latter is calculated based on the simple standard deviation, EWMA and GARCH (1,1). The thesis also studies the price fluctuations in the oil and gas market, which are mainly affected by changes in supply and demand.

In the oil and gas market, the minimum price is set by the last supplier needed to fulfill the demand. Production will not be profitable for that supplier if the price is less than this.

Expectations about the future have great influence on the price development. Geopolitical tensions, and other factors that could lead to reduced supply make the price increase. New discoveries, which lead to increased supply or reserves, tend to lower the price.

As this thesis will show, the period from 2002 until the summer of 2008 was a period of steady growth for oil prices, whereas the prices for natural gas also started falling in 2008 due to the financial crisis.

The normal and student-t distributions were assumed in the parametric approach, and were compared to a non-parametric approach, the historical simulation, as a benchmark.

The Kupiec-test and the Christoffersen-test were both used to test the validity of the approaches.

For all three time periods considered (250, 500, 1000 days), the non-parametric approach was without doubt the one that got accepted most by the back-tests. The VaR estimates for the 99% confidence level were dominantly better than the ones for the 95%, which the back-tests confirmed.

PREFACE

This report is my master thesis and completes my education for a Master of Science (M.Sc) degree in Industrial Economy at the University of Stavanger with Risk Management, Project Management and Contract Management as fields of study.

The thesis has been a great opportunity for me to combine my fields of study with my Bachelor's degree in Petroleum Technology, and interest for trading.

Microsoft Excel has been used for the analysis of data and the calculations performed for this study. The three Excel workbooks, containing the data and calculations executed for this study, are included on the CD provided with this thesis.

I would like to thank my instructor, Roy Endré Dahl, for being an excellent guide. Firstly for helping me specify the contest of this thesis and for providing me with the collection of data necessary to perform this study. I have really appreciated all the assistance he has provided during this process.

I would also like to extend my gratitude to my dad, Per Ove Staveland, and Francisco Cardona for their feedback and support.

Lastly I would like to thank my family for all their assistance and support throughout this arduous time.

Stavanger, December 20, 2012

Line K. Staveland

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1 INTRODUCTION

This chapter will outline the scope of the thesis, and give a quick introduction to Value at Risk (VaR). It will also give an overview of the layout of this thesis.

1.1 Scope

This thesis is focusing on extreme risk management in the oil and natural gas market. Different approaches to estimate the risk involved in the market is calculated. These approaches are all estimating the Value at Risk, but with different usage of the market histories. Thus, the calculations differ.

The scope of this thesis is to compare the individual approaches, which one(s) are the best, and their validity.

To test their validity, the approaches are all back-tested by the use of the Kupiec–test and the Christoffersen–test.

1.2 Value at Risk

Risk can be defined in a various amount of ways. The word risk can have a different meaning for people. Most of the things we do (if not all) involve some kind of risk. Usually we think of risk as a possibility of something negative to happen. If the negative outcome of an activity will give a serious consequence, we may decide not to go forward with the activity the assosiated risk is considered too high.

In a financial texture, risk is usually thought of with regard to profit and loss. A high risk will give a better chance of resulting in a greater profit, but can also result in a greater loss.

The volatility, of the assets return is commonly used in finance to describe the risk of an investment. The volatility, which normally is the standard deviation of the assets historical returns, measures both sides of the mean. When thinking about risk, we usually consider the amount that we might lose. To measure the potential loss, or the negative risk of the investment, we can calculate the value that is at risk.

Value at Risk is a measurement of how much the potential loss could be in a worst-case scenario. There are two inputs needed, together with information about the market (i.e. historical prices), to calculate the VaR of an asset or a portfolio of assets. These two inputs are the level of significance and the time period.

The level of significance is a measure of how accurate the results are going to be; do we want to know with 95% certainty what the worst potential loss can be, or do we want another level of confidence? The most commonly applied confidence levels within the oil and gas industry are 95% and 99%, whilst banks mainly prefer the 99% confidence level.

For what time horizon do we want to get the estimates for? The time horizons can be days, weeks, years etc. A commonly used time horizon is 250, 500 and 1 000 days, which represent the trading days of one, two and four years.

With the above two parameters given, we can give statements of the future potential loss (i.e. "Tomorrow (time horizon), 95% (level of confidence) of the outcomes will be greater than -150k (VaR)").

The approaches used to calculate the VaR are:

- Historical simulation (non-parametric)
- Variance-covariance (parametric)
- Monte – Carlo simulation

The historical simulation, also called the non-parametric approach, is based on historical data. It sorts the data according to returns, and gives the VaR as the return that has the property that X% (level of confidence) of the returns are greater than this value, and 1-X% (level of significance) of the returns are less. The non-parametric approach equally weighs all previous data in the chosen timeframe in which data are collected.

The variance-covariance approach assumes that the returns are following a specific mathematical distribution like the normal distribution, student t-distribution, gamma distribution, etc. When a distribution is chosen, the only parameter needed is the expected standard deviation. Instead of basing the calculation of VaR on the historical data, the future expected curve of returns are used.

There are different approaches to calculate the standard deviation. The regular way, in which is mostly thought in lectures in mathematics, is the standard deviation that equally weighs the data considered. To put more weight on the more recent data the Exponentially Weighted Moving Average (EWMA) or Generalized Autoregressive Conditional Heteroscedasticity (GARCH) can be calculated. GARCH puts more weight to the recent data, and also assumes an average value. EWMA is a special case of GARCH as will be discussed in chapter 3.

Monte–Carlo simulation is used to simulate the data, given an average and a standard deviation. Monte–Carlo is mostly used in calculations of VaR for portfolios.

1.3 Layout

Chapter one, **Introduction**, presents the scope of the thesis together with an introduction to Value at Risk. It also introduces the parameters needed to perform the calculations.

*Chapter two***, Price variability in the oil and gas market**, gives an introduction to the oil and gas industry and its high price fluctuations. The market's volatility, together with factors affecting its supply and demand, is presented.

Chapter three, **Risk**, presents risk, risk management and risk measurement. The three mathematical methods that have been used to calculate the volatilities used in this study are discussed and compared. Value at Risk will be more thoroughly described, and its three different approaches will be presented. Lastly portfolio management will be introduced.

Chapter four, **Analysis of data**, presents the statistical characteristics of the products studied in this thesis. The products will be presented, and their return distributions discussed and compared with the normal distribution. The portfolios will be presented together with diversification and product correlations. Figures, illustrating the price and the volatilities for the time period considered in this study, of the selected assets will also be presented in this chapter.

Chapter five, **Empirical results**, gives the results obtained from the calculations. A description of how the calculations were executed will also be given.

Chapter six, **Conclusion**, will provide conclusions of the study, and discuss them. Lastly, suggestions for further studies will be given.

Chapter seven, **References**, gives the references. The bibliography studied for this thesis will be presented.

An appendix, with the Microsoft Excel workbook for all the calculations, will be given at the end of the thesis.

2 PRICE VARIABILITY IN THE OIL AND GAS MARKET

This chapter will discuss the oil and gas market, identifying the factors influencing demand and supply, and illustrate historical data and future forecasts.

2.1 The market

The oil and gas industry includes everything related to the process of getting oil and gas products out to the consumers, including exploration, extraction, transportation, distillation, etc. The processes listed below describe the steps necessary to bring a petroleum product like gasoline from the ground and to the gas station.

Exploration is the first step performed to locate the reservoir. Once the reservoir has been found, drilling of wells and recovery of the hydrocarbons follow. When the oil and gas have been produced they need to be processed and transported away from the production site to the refinery.

Through a process called distillation, refineries process the raw materials into different oil and gas products such as Kerosene, Asphalt, Gasoline, Propane, etc. This process is possible due to the properties of the hydrocarbon molecules. During distillation, the crude oil is heated and separated. The separation by distillation is possible because of the hydrocarbons´ different boiling points.

The various products are then traded, meaning that sellers and potential buyers negotiate to reach an acceptable price for the products considered. With both sellers and buyers being spread all around the world, the trading market is a global market. A set of trading alternatives offers both sides opportunities to share risk, as presented in 2.1.2.

Lastly, the products need to be distributed and marketed to the consumer.

The above steps, describing the processes that take place within the oil and gas industry, can be divided into three different sectors:

- Upstream
- Midstream
- Downstream

The Upstream sector consists of the steps necessary to extract oil and gas from underground deposits. In other words; this sector encompasses the exploration and production of hydrocarbons.

The Midstream sector consists of the processes taking place after the production, but before the products reach the retailers. This sector includes the processing, refining, trading, storing and transportation of hydrocarbons.

Lastly, the Downstream sector is comprised of the steps taken to bring the products to the consumers; the marketing and distribution as well as the actual sale of the products.

For simplicity, the market is sometimes divided into two sectors instead of three, Upstream and Downstream. If a two model sector is used, then the Midstream sector is included in the Downstream sector.

2.1.1 Storage and transportation

Consumers of oil and gas products are spread all over the world. The vast majority of consumers typically do not live in the areas where production takes place. In order to reach all consumers, the products need to be transported and stored. As a consequence of this, transportation and storage play an important role in the industry.

Boats, trucks and pipelines are among the utilities provided to make the transportation possible. Oil and gas are transported from the production site to the refinery, and the output from the refinery is either stored or transported to be distributed.

Transporting hydrocarbons using a pipeline system instead of by boat or motor vehicle is more efficient and economical. The hydrocarbons are transported by pipeline to distribution hubs.

Below is a map showing the pipeline network in the United States.

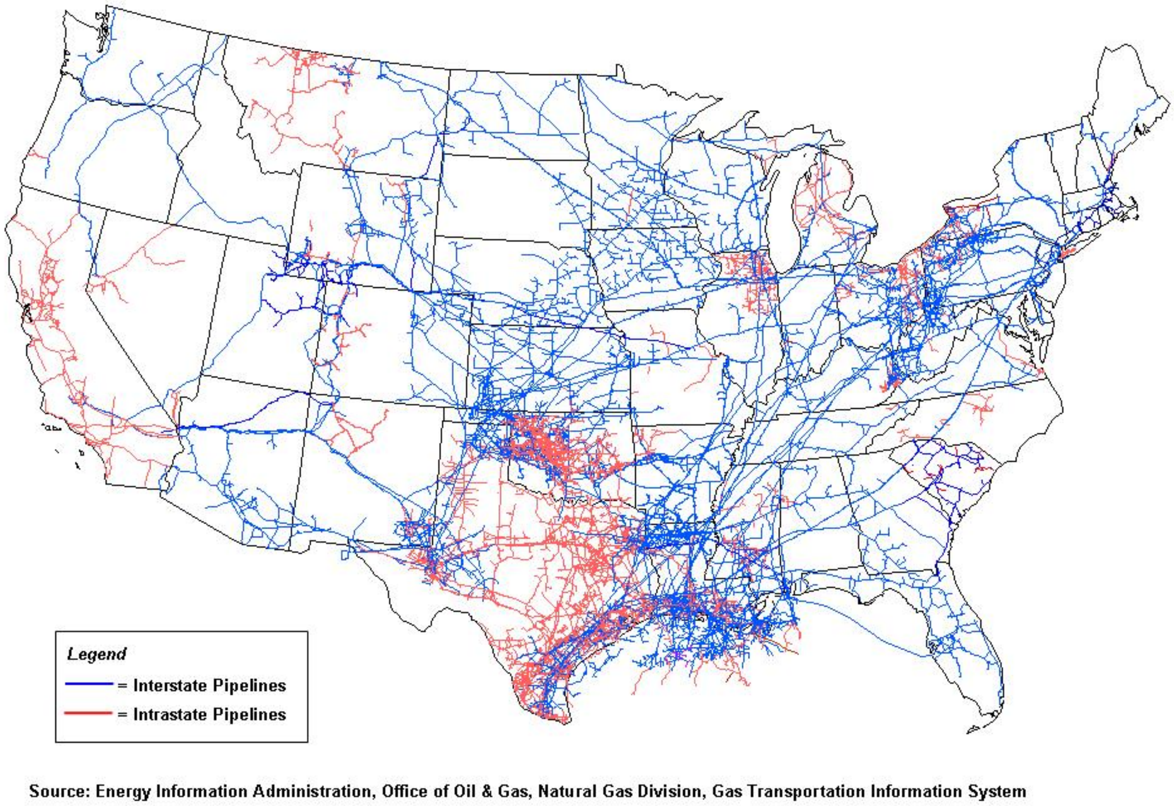


Figure 2.1: *Map of the pipeline network in the United States (EIA.gov), including pipelines up to 2008.*

Oil and gas products are usually first sold to either the nearest buyers, or to buyers in areas where an integrated transportation system already exists (i.e. pipelines), due to the lower transportation costs.

Oil and natural gas differ in how they can be transported. While oil can be readily stored in barrels and shipped globally, gas, due to its nature, is dependent on pipelines for transportation. Otherwise, gas has to be liquefied into Liquefied Natural Gas (LNG) in order to be transported by vehicle. The additional procedures involved in the liquefying and re-gasifying processes require facilities capable of converting the gas. As a consequence, the natural gas market is much more regionally defined, while the oil market is global. Today, LNG exports are limited to exports from Europe to USA and Japan.

2.1.2 Trading

Oil and gas products are traded in different markets around the world. The prices of the products that are described in this thesis are derived from the New York Mercentile Exchange (NYMEX), The InterContinental Exchange (ICE) and the Independent Chemical Information Services (ICIS). ICIS publishes the European Spot Gas Markets (ESGM), every working day of the year, following the British calendar.

The physical delivery of hydrocarbons are organized through long-term contracts and the spot market.

There are three main ways of pricing the products:

- Spot–price
- Futures
- Bilateral contracts

Spot trading is the most fundamental method of trading. In essence, the seller and buyer agree on a price over the counter (OTC). Parties usually engage in spot trading in order to buy and sell quantities of oil or gas not covered by long-term contracts (Fattouh, 2011).

In a bilateral contract the two parts agree on a specific delivery of quantity and quality with a certain time and place of delivery. While the price is fixed, since the delivery and payment takes place in the future, both parties incur a counterparty risk (e.g. the seller may not be able to deliver the specified quantity and quality, or the buyer may not be able to pay for the goods due to financial distress).

A future contract removes this counterparty risk, by allowing the buyer and seller to agree via a third party: the futures exchange market. In a future contract, the quality, quantity and delivery location is predefined by the exchange, thus limiting the buyer and seller to only agree on price. Each day the positions for both buyer and seller of the future are marked-to-market, thus removing the counterparty risk. Typically the contracts will be defined for several time periods, and buying (selling) multiple futures allows the buyer (seller) to vary both the time and quantity. However, since the quality is predefined, both buyer and seller may experience a basis risk, due to the difference in the product defined in the futures compared to the product supplied or purchased (e.g. an oil company may produce a certain oil quality like oil from the Brage oil field, while future contracts is traded using another quality, i.e. Forties blend at ICE).

2.2 Price

This section discusses the impact that different factors have on the price of oil and natural gas. The main factors discussed include the microeconomic model of supply and demand, geopolitical events and the global economy.

The prices of oil and gas products are considered to be among the most volatile in the global market, and any prediction of the oil market will be highly uncertain due to its large volatility (Foote & Little, 2011; Hamilton, 2009).

Originally, the oil price was set through oligopoly, by the largest oil companies in the world (Fattouh, 2011). However, in the late 1950´s the power to set the price shifted to the Organization of Petroleum Exporting Countries (OPEC).

The OPEC administered pricing system collapsed in the late 1980´s, and the "market" became the controlling pricing authority. Due to the emergence of many new suppliers and buyers, the largest oil companies (also called "the Seven Sisters") and OPEC lost the power to determine the price. Since 1988 the "market related pricing system" has been the main method for pricing crude oil in international trade. Fattouh (2011) describes the market related pricing system.

Historically, the oil price has been dominated by periods of high and low volatility. It is difficult to predict when these periods of rapid price change will occur. However, reasons for a price change can in most cases be found when studying historical price data. As demonstrated in figure 2.2 below, these periods of rapid change usually occurred contemporaneously during times of war and geopolitical unrest.

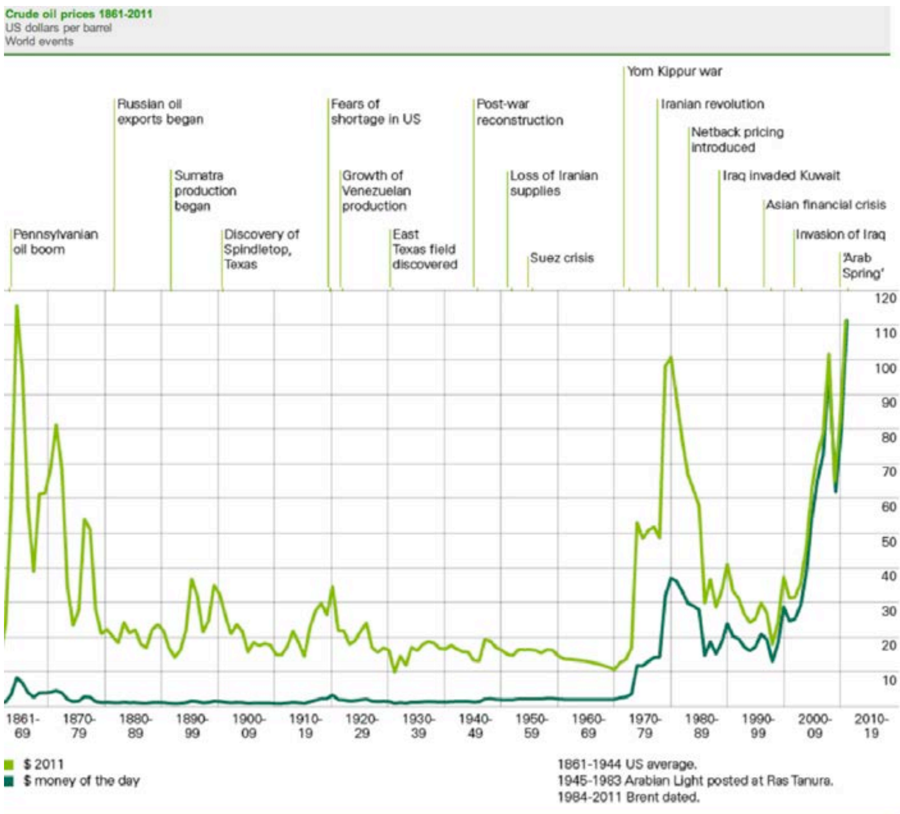


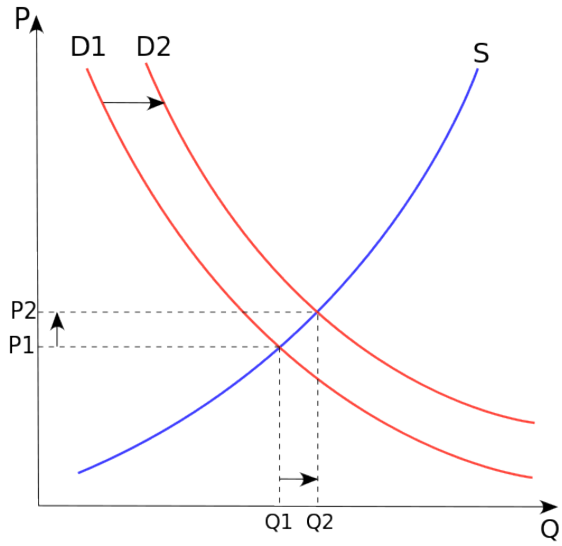
Figure 2.2: *The historical price of crude oil in US Dollars. Light green is the 2011 Dollar value, dark green is the Dollar value at the time. (BP.com, 2011)*

The following sections will introduce the microeconomic model of demand and supply together with elasticity, and discuss how it applies to the petroleum industry. Additionally, the impact of geopolitical tension will be included in the sections discussing supply and demand.

2.2.1 The microeconomic model

In microeconomics, the market price of a product is found at the point where the demand and supply curves meet. According to the microeconomic theory, the relationship between supply and demand decides the price and quantity of a product in a market.

The microeconomic model of "quantity vs. price for supply and demand" is illustrated in figure 2.3 below.



Where Q_1*: Quantity in market before demand shift* P_1*: Price before demand shift*

Q_2*: Quantity in market after demand shift* P_2*: Price after demand shift*

S: Supply

Figure 2.3: *The microeconomic supply and demand curve (Wikipedia.com, 2012).*

The above figure illustrates the connection between the price, quantity supplied and the quantity demanded of a product in a market. These are the laws of supply and demand.

An increase in price will effectively reduce the demand. At the same time, if suppliers can get a higher price for their product they tend to produce more, thus increasing the quantity of supply.

The positive shift in demand, as illustrated in figure 2.3 (where demand is shifting from D1 to D2), indicates that the product is in higher demand. The increased demand can for example be caused by a community's increased wealth. This will lead to an increase in both price and quantity.

In a perfect market with perfect competition, the price of a product will be equal to the marginal costs that suppliers face to offer the product.

The above statement is also applicable to the petroleum industry. The high demand of hydrocarbon products drives its selling price. Therefore, its prices are higher than what the related costs of producing said products for the suppliers with the lowest costs. This is due to the inability of one, or a few suppliers, to meet the demand. With perfect competition, the price in this market will be set by the last supplier needed to meet the demand (i.e. the supplier that experiences the highest costs of production).

It follows from the law of demand that as the price of a product drops, the demand for it will increase. Conversely, the law of supply states that as the price drops, its supply will decrease. How much the reduction in price impacts the quantity demanded or the quantity supplied depends on the goods elasticity.

According to market equilibrium theory, a shortage in supply versus demand will lead to a price increase. This is a result of consumers' willingness to pay extra to be able to get the product. The increase in price will induce more producers, increasing supply until the market reaches equilibrium, as illustrated in figure 2.3.

2.2.2 Price Elasticity

Price elasticity is a measure of how much the quantity demanded (supplied) reacts to a change in the market price. The formula for the elasticity is presented below:

$$E_d = \left(\frac{P}{Q_d}\right) x \left(\frac{dQ_d}{dP}\right)$$

Where	*P:*	*is the price*	*Q_d:*	*is the quantity demanded*
	dP:	*is the price change*	*dQ_d:*	*is the change of Q_d*

An E_d value below -1 indicates that the good is following the microeconomic law of demand (i.e. the demand for a specific good will increase if the price of it is reduced, given that all else remains equal). A product is said to be elastic if a change in price causes the quantity demanded to change significantly (Mankiw, 2012). The opposite is true for an unelastic product; the quantity demanded will not react substantially to a change in price. According to Mankiw, there are no universal rules for what determines the elasticity. However, Mankiw points out four factors, which he describes as a "rule-of-thumb" to determine elasticity: availability of close substitutes, necessities versus luxuries, definition of the market, and the time horizon.

For oil and gas, there may be substitution alternatives in several dimensions, e.g. a power generating company substituting between different energy sources may use the availability and timing to substitute.

As shown by Hamilton (2009), Kilian (2009), and Baumeister and Peersman (2012), the elasticity in the oil and gas market is very low and near zero in the short-term. This is due to demand for oil and the cost of substituting to other energy sources. As a consequence most of the increase in price is passed on to consumers without reduction in consumption.

On the other hand, long-term elasticity is higher. This is because industries to some degree can switch to alternative energy sources (e.g. coal instead of natural gas in power plants). Additionally, high oil and natural gas prices will provide incentives for research and development of alternative energy sources, which may provide more viable substitutes in the future.

2.2.3 Supply, demand and the impact of geopolitics

Oil and gas play a vital role in the global economy, and together with coal the fossil fuels are the number one energy source of the world (Carollo, 2012; BP, 2012). The price of oil impacts the global economy and is considered a leading factor that affects the prices of most energy sources. An increase in oil prices affects the net importing economies negatively, while net exporters benefit from it.

The demand for oil and gas products increases as the world's demand for energy increases. Not only is the average energy demand per person increasing, the number of people on earth is also increasing rapidly. A particularly high increase in demand is experienced by developing countries and Asia. Currently, China's emergence as a developing nation has led to a tremendous increase in its demand for energy. Meanwhile, the consumption in Western Europe and the United States has experienced a slight decrease over the last years (BP, 2012).

The commodities price development over the last 40 years reflects the shortcomings of these industries – the global production of oil and gas has been unable to meet the global demand for these energies (Inkpenn, Moffett, 2011).

But the price is not solely based on the supply and demand in the market. Even though the demand for the most time has been higher than the supply, there are also other factors affecting the price of oil and gas. Geopolitical tensions, wars and other possible sources that impose a threat of the market to be in shortage of petroleum make the price position north.

However, oil production has increased over the last year, and on April 30th 2012 it outpaced the global demand. Improved technology and new findings, together with OPEC´s 10% production increase over the last year (as of June 2012) are some of the factors that lead to this increase (Phillips, 2012). At the same time the world's demand for oil has declined since December 2011. This is illustrated in the demand vs. supply figure below.

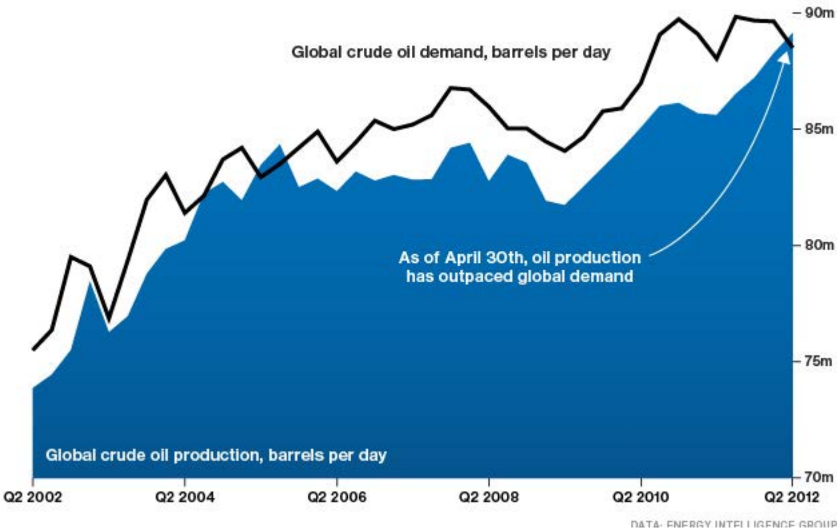


***Figure 2.4: Demand** vs. **Supply** (Energy Intelligence Group, 2012).*

The laws applicable to pricing with regard to supply and demand (presented in 2.2.1 The microeconomic model) also apply to oil and gas products. In order to better understand the commodities price fluctuations, one must understand which factors influence the demand and supply for the given commodities.

In the following sections demand and supply will be discussed. The impact of geopolitical tensions on supply and demand will also be explored in these sections.

2.2.3.1 Demand

According to the International Energy Agency (IEA), who is one of the world's leading authoritative sources for energy statistics, the worlds demand for energy will increase by an average of 1.5% each year through 2030. By 2030, the world's energy demand will be 60% higher than it was in the year 2000.

IEA predicts that 80% of the increased demand will come from countries that are not affiliated with the Organization for Economic Cooperation and Development (OECD) nations (Inkpenn, Moffett, 2011).

The following figure presented below illustrates a publicized forecast by United States Energy Information Administration (EIA, 2011) of global energy consumption.

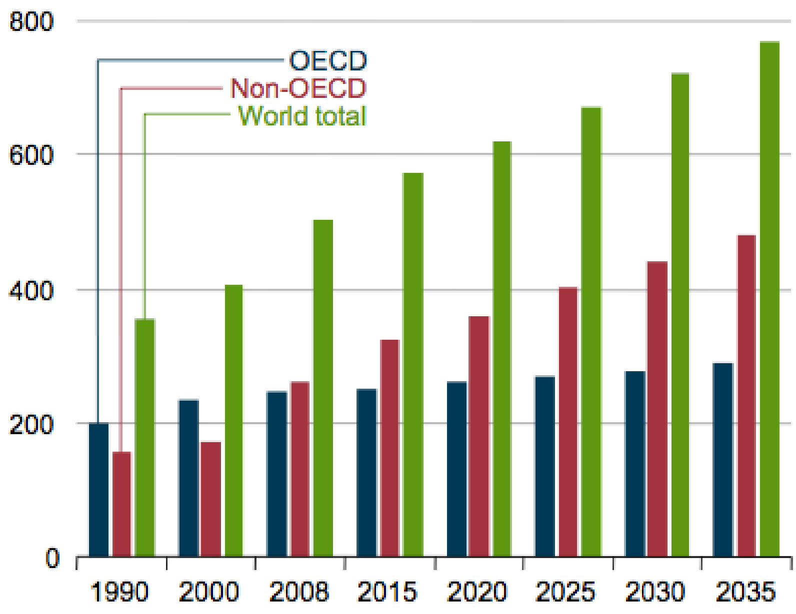


Figure 2.5: *Forecast of the World´s energy comsumption. Data from 1990 until 2008 is calculated based on actual numbers, the data after 2008 are estimations performed by the EIA (EIA, 2011)*

China is a major contributor to the Non-OECD countries increase in consumption. In 2009, the total energy consumption in China surpassed the consumption of the United States. It is estimated that China's energy demand will continue increasing, and that by the year 2035 will be about 68% higher than the total energy consumption of the United States.

The following figure, compares the EIA's forecast of energy consumption of China, India and the United States through 2035.

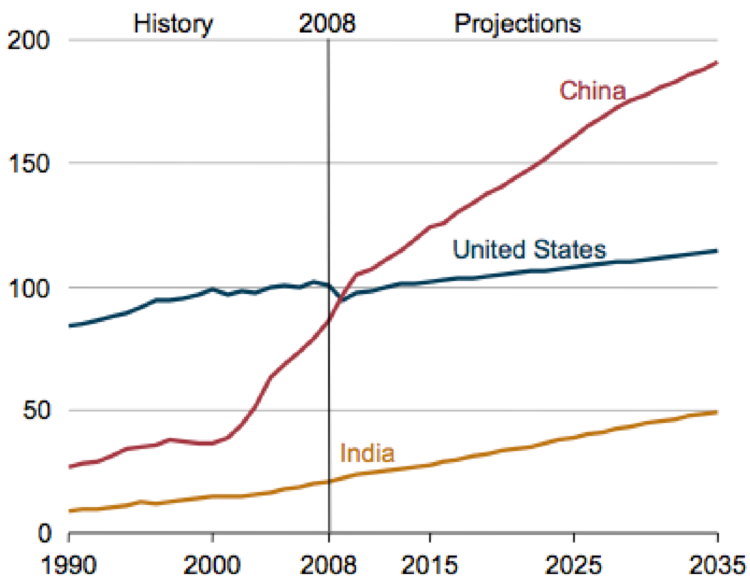


Figure 2.6: *Comparison of the historical and projected energy comsumptions for the United States, China and India (EIA, 2011).*

Although new technologies make products and processes more energy efficient, it will take time before the market adjusts to them. These new technologies are most likely to be more expensive to invest in, and that it takes a long time for society and governments to adjust to new technologies in general, these "energy savers" will most likely not contribute much, in the sense of decreasing, to the demand for the next following years. The fact that, as mentioned above, the non-OECD nations are predicted to stand for 80% of the increased demand also supports this hypothesis.

Fossil fuels (coal, oil and gas) are the energy source that has the most practical uses in the world (Follett, 2011). They provide electricity, heating, transportation, they are easy to store and transport, and they are cheaper than other energy sources.

If the technology of other energy source (such as solar or wind) transmissions enhance, resulting in a reduced price for the energy, that is likely to switch the energy demand over to focus more on the cheaper energy source. This may impact the price for oil and gas products.

Environmental concerns may also impact the prices of oil and gas products, since it may change the demand. It is already widely known that fossil fuels most likely have a bad impact on the environment, but further developments about this topic may affect the prices depending on the outcome of the news.

Kathrine Follett (2011) argues, in her book "Energy Sources for the 21st Century", that all of the energy sources can be said to have some kind of bad impact on the environment. For example, solar cells are manufactured with toxic heavy metals, wind turbines cause noise pollution and injure or kill birds, and hydropower dams cause rivers to dry up, disturbing the environment for animals that rely on the water (for example fish that spawn in the river). Follett further argues that cutting edge technology makes fossil fuels clean and safe (Follett, 2011).

Last year's nuclear accident in Japan, was a consequence of the earthquake at Fukushima, and this incident reminded the world of the dangers of relying on nuclear energy.

In situations when people believe that a shortcoming is most likely to occur, i.e. because of geopolitical tensions, they may want to get the product before its too late, and by doing so the temporary demand for the product increase, resulting in a higher price.

A major act of nature, like a hurricane, tsunami or earthquake, will also impact the price of oil and gas products in the short run. Even though this impact is short it is worth mentioning.

For example, during the fall of 2012, the eastern coast of the United States was struck by hurricane Sandy. As the storm approached, production and refining, as well as storage facilities were shut down in anticipation of its arrival. Because of the shutdown, a surplus volume of oil products was created, affecting the wholesale network and the price of oil and gas declined due to the excess of supply.

The impact felt on the price of oil following an act of nature is usually felt on a short-term basis. The prices will re-adjust back to normal once the storm (or other act of nature is over) (Moor, 2012). Even though the prices initially fell following the storm, due to the shut-down of the supply, prices on gasoline and diesel rose in anticipation of the approaching hurricane. This price increase can also be explained by the increased demand, since people filled up their cars with fuel, in fear of not being able to get it during and following the storm.

During the Conference on the Oil and Market held at the Federal Reserve Bank of Boston in June 2010, experts surmised that the price fluctuations experienced during the 1970´s (price increase) and 1980´s (price decrease) are most likely never to be experienced again (Foote & Little, 2011). Their conclusion is based on the current lack of methods for a major net importing country to reduce its demand for oil, would a sudden price increase be experienced. During the 1970´s and 1980´s however, net importers could choose from other sources of energy, or simply increase their own domestic production.

The oil price is highly dependent on the world's fuel demand. Economic growth is a positive indicator with regard to this demand. Wood et Al (2004) argue that "Where high demand growth exists it is primarily due to rapidly rising consumer demand for transportation via cars and trucks powered with internal combustion engines".

Because the asset price is dependent on market expectations, what was given a lot of positive indications for the asset implying that it would very likely increase in value could as likely be wrong, and make the price go back to what it was before. In addition, a large increase in price may provide an opportunity to secure profits for some agents. Opposite, a large decrease may provide purchasing incentives for several agents as the commodity/stock is relatively cheaper.

News about decreasing growth, or growth being lower than expected may lead to a decrease in price due to a fear of a decreasing demand on fuel. The fact that the Chinese economy in October showed less growth than expected, together with the economic weaknesses in Europe and a decreased level of fuel usage in the United States made the global demand not follow the supply (Wall Street Journal, 2012). When this happens, that the supply is larger than the demand, a decrease in price is experienced. In May 2012, the supply curve passed the demand curve, and the price started to fall (see figure 2.4 above).

The oil and gas price is measured in US Dollars, a currency that has weakened over the last decade. A weakening of the US Dollar, assuming that everything else remains the same, will result in a cheaper price of oil relative to the local currency for a given country with a different currency. The reason for this being the lower conversion factor between the local currency and the U.S. Dollar.

Hamilton (2012) argues that “a lower value for the U.S. dollar would mean a greater quantity demanded worldwide at a given dollar price of oil”, which supports the reasoning given in the above paragraph.

Setser (2008), who is a fellow for Geoeonomics for the Council on Foreign Relations, also supports this statement. He further explains the correlation between oil prices and the value of the US Dollar to be the interest rates in the United States being so low that it made investments in other forms than savings accounts more popular. This includes commodities. Considering that the United States is the world’s largest net importer of oil, it is logic that they will be the country most impacted by a rise in the oil price.

2.2.3.2 Supply

Oil and Gas are products resulting from the decomposition process taking place when dead organisms are buried underneath the ground. This process, which transforms the dead organisms to oil and gas, only takes place under specific conditions and a long period of time is required for it to occur. Chilingar (2005) describes this process, which takes millions of years. Due to the fact that the process takes a long time, it is easy to understand that there is a finite amount of oil and gas present.

For a field to be considered an economically recoverable resource it has to be profitable to produce. Thus a decrease in the price may lead to premature field shutdowns, or field development projects being delayed or cancelled. This might again lead to a reduction of oil supply, whereas the severity depends on how many fields that will become uneconomical.

The decline in production could then create a shortage in the market, which would stimulate an increase in the price. Thus, a higher oil price will result in more fields becoming profitable, which again will lead to a potential increase in supply. Because of the optimism in the market, companies would be willing to spend more money on research.

Only 50-70% of the hydrocarbons are recovered from the reservoir with today’s technology. This means that 30-50% of the hydrocarbons is left behind in the reservoir. As the technology advances, the recovery factors are likely to improve, making it possible to increase the supply of hydrocarbons to the market. With new techniques one may be able to reduce production costs, and extend the life of fields. This can turn unprofitable reservoirs into recoverable resources.

As the conventional, easy to produce, fields have been in operation for many years, more and more of the global production is now supplied from unconventional fields. These fields have higher production costs, and are therefore more sensitive to price changes.

The marginal costs related to oil production greatly differs between fields. The fields with the lowest marginal costs are the ones that can best withstand a reduction in the oil price and still remain profitable. The marginal costs are low in the fields located in Middle-Eastern countries, while the Tar Sands in Canada and offshore oil production have the highest marginal costs, as seen in figure 2.7 below.

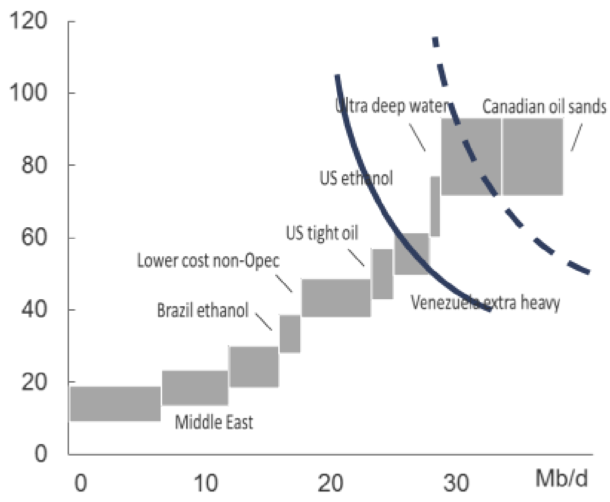


Figure 2.7: *The figure illustrates the different marginal cost in production of oil from a set of oil resource types. (Mohn, 2012).*

Even though all countries are consumers of products originating from the oil and gas industry, only a few nations contribute as producers. The ability of these countries to produce oil and gas has allowed relatively small nations to become heavily influential in the world economy. One can only speculate if the United States and other developed countries would have shown the same interest in Middle-Eastern countries if it were not for the oil and gas resources available in Arab nations.

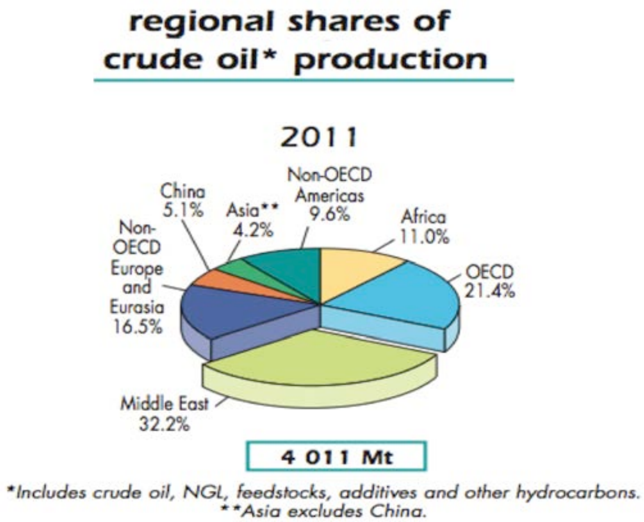


Figure 2.8: *The figure illustrates the global production of oil, and how much each "group" produces. The Middle East stands for almost one third of the world's production (International Energy Agency, 2012).*

Politics highly influence the price of oil and gas products. The influence exercised by politicians is demonstrated through government regulations, taxes, fees, environmental concerns, wars, as well as geopolitical tensions.

Particularly, geopolitical tensions and war are very likely to affect the oil price. Especially if one or more of the nations involved are exporters of oil. Even speculation that a war may occur is enough to cause an increase of the oil price. A good example of this is the Yom Kippur War in the early 1970´s when Arab nations refused to export petroleum to Europe and the United States.

The Organization of Petroleum Exporting Countries (OPEC) is an intergovernmental organization comprising of twelve non-OECD oil producing nations.

"In accordance with its Statute, the mission of the Organization of the Petroleum Exporting Countries (OPEC) is to coordinate and unify the petroleum policies of its Member Countries and ensure the stabilization of oil markets in order to secure an efficient, economic and regular supply of petroleum to consumers, a steady income to producers and a fair return on capital for those investing in the petroleum industry."

(The Organization of Petroleum Exporting Countries, 2012)

OPEC decides how much petroleum its member countries are allowed to produce. However, the organization has had problems controlling the quotas provided to its members, since an individual member always has economic incentives to deviate from the agreed allocation. Saudi Arabia is by far the most important member of OPEC, and is generally considered the swing producer, having the capacity to influence the oil price by adjusting its production.

A reduction of supply is an almost certain indicator of a future price increase, given that the demand has not decreased more than the supply. This theory is supported by Peak Oil Theory, which in short says that the production of oil in any region will follow a bell-shaped curve. There will be an initial phase of increased production until it reaches a maximum, and as the oil fields mature, the production will decline. This theory was introduced by Hubbert (1956). He predicted that the U.S. oil production would peak in the beginning of the 1970s. He later also predicted that global oil production would peak in 1995. Although his global prediction was inaccurate, it is now debated that we are currently peaking the production of conventional crude oil.

3 RISK

This chapter will give an introduction to risk and risk management. Different approaches to calculate risk will be presented. Volatility will be introduced and the different approaches used to calculate it will be discussed.

3.1 Risk and risk management

Risk is something we encounter every day; when we are in the car, out walking, taking an exam, etc. Aven and Renn (2010) state that no agreed definition of risk exists. They list several definitions of risk defined by different authors. These definitions can be divided into two categories;

(1) Risk is expressed by means of probabilities and expected values.

(2) Risk is expressed through events/consequences and uncertainties.

Based on the above two categories, nothing is risk free. This is due to the fact that nothing can be said to be 100% predictable

When it comes to trading, risk basically boils down to profits and losses. The risk is money. There is always a chance that an investments actual return will differ from its expected return. Prices are prone to change and may increase or decrease, resulting in a potential gain or loss for investors. Ross et Al (2011) defines the true risk of any investment to be “the unanticipated part of the return, that portion resulting from surprises”.

Risk can be divided into two categories; systematic risk and unsystematic risk.

The factors affecting the systematic risk, also called market risk, can be defined as the surprises that influence the entire market. Examples can be an increase or decrease in interest rates, GDP or inflation. These are factors that impact most companies.

A surprise may only impact a specific company, or a few companies, but not have consequences for anyone else. An example can be the sudden loss of key personnel, announcement of a strike or positive/negative publicity. These types of risks are unsystematic.

By taking certain measures one can reduce risk, but it can never be removed entirely. Risk management is about understanding and assessing potential risks, and controlling or mitigating the effects of possible damaging events.

The oil and gas markets are susceptible to being affected by a wide variety of factors. Many of these were discussed in Chapter 2Price Variability in the oil and gas market. However, some issues that may affect the oil and gas market remain unknown.

The price of an asset varies over time, and by studying these price changes one may get a better impression of how sensitive the asset is. The most common way of describing a set of data is by using the mean and the standard deviation (Gravetter et Al, 2011). It measures the dispersion about the mean of a distribution, and is a sufficient risk metric if the returns are following a normal distribution.

In finance, volatility is used to describe risk. Volatility can be used to forecast different profit and loss scenarios for the future. Alexander (2008) defines volatility as the annualized standard deviation of the returns on an investment. However, the volatility can also be presented for other periods of time, the most common being daily, weekly or monthly. In other words – the volatility is a measure of the spread of data.

A high standard deviation implies that the data values are widely spread. If these were the data of the prices for a specific stock, a high standard deviation would imply that the price changes have been substantial over the period considered, and thus the specific stock would be said to have a high volatility.

The standard deviation, and thus the volatility, will vary with the observations horizon. Comparison of standard deviations calculated from data sets of different quantity will therefore not be comparable as they are. The standard deviation can be transformed into annualized terms, and expressed as a percentage (Alexander, 2008).

To transform the standard deviation of a one-period log return (generated by a stationary i.i.d process with mean, μ, and standard deviation, σ) to a standard deviation of a h-period log return, the standard deviation of the one-period must be multiplied by the squared root of h.

It is common to express the volatility on an annualized basis, which reflects the volatility of a one-year period. This can be done by following the 4-step procedure described below:

1. Calculate the variance in log-return for each day from the given set of data
2. Calculate the average daily variance
3. Calculate the daily volatility by taking the squared root of the average daily variance
4. Calculate the annualized volatility by multiplying the daily volatility by the squared root of 250/1*

*On average there are 250 trading days in a year. The daily volatility is for a period of 1 day. If we had the two days volatility we would have to multiply this volatility by the squared root of 250/2 to get the annualized volatility.

The particular focus of this thesis will be on the volatility of oil and gas products. It will consider the volatility for a one-year period (250 trading days), a two-year period (500 trading days) and a four-year period (1000 trading days). Different models and approaches to calculate the volatility and to assess risk will be discussed and presented.

3.2 Risk measures

There are different approaches to calculate the historical volatility. This thesis will present and discuss three: Simple, EWMA and GARCH. Which one to choose depends on how the historical data is to be weighted.

The approaches all share the same first two steps;

1. Calculate the rate of return
2. Assign the data weight

It is the outcome of step two that decides the type of approach and the steps that will follow.

The daily return (from one day to the next) of an asset can be calculated using the logarithmic return, R_t;

$$Rt = ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where *P_t: Price today* *P_{t-1}: Price the day before*

The logarithmic return is preferred in finance due to its many properties that help simplifying calculations.

3.2.1 Simple volatility

The simple volatility is the standard deviation calculated the regular way, giving each of the data equal weight. Even though this is not the most accurate volatility, it is the easiest to understand and calculate, and can be used as input to calculate other historical volatilities such as EWMA and GARCH.

The historical standard deviation over a specific period of time, n days, can be expressed as stated below.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}, \quad where\ \mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Where *N: the number of observations* *x_i: the ith observation*

The simple standard deviation emphasizes the historical data equally. Hence, 5-year old data is considered to influence today's volatility with the same magnitude as does yesterday's data. During short periods of time, a day of high volatility is very likely to be followed by another day of high volatility (Berry, 2012). Volatility clustering can be better explained through an example; say that a stock's price rose significantly the previous day, one would believe that it is more likely to decrease or rise even more during the following day(s). It is highly volatile.

The standard deviation will not accurately reflect the current market conditions because of the equal weighting afforded to the historical data. Hence, it does not take into consideration that recent data is more likely to reflect today's market than the data collected years ago.

The standard deviation is a function of squared returns deviation, thus making them more sensitive to outliers that can dominate the result. As an example, Ederington & Guan (2006) looks at S&P 500 market over a 35-year period. From July 5th 1967 to July 11^{th} 2002. When calculating the volatility by using the simple standard deviation, the 1% largest daily return accounted for 24.5% of the total squared return deviations!

The weakness of the above approach (the volatility estimator assigns equal weight to all observations) can be fixed by giving the historical data different weight.

3.2.2 Exponentially Weighted Moving Average (EWMA)

The Exponentially Weighted Moving Average (EWMA) places the most emphasizes on the most recent observations. This method was first introduced by Roberts (1959) and later by Hunter (1986). The emphasis decreases exponentially as the data gets older. By doing this one avoids big shocks from an earlier period influencing the result as much as it does with the simple volatility/standard deviation.

As one moves back in time, the data is given less and less weight. By doing this one assumes that the more recent the data is, the more important it is and the better it represents today's market.

The EWMA is calculated using the formula presented below

$$\sigma^2_{\ n} = (1-\lambda)\, r^2_{\ n-1} + \lambda\sigma^2_{\ n-1} \qquad , 1 > \lambda > 0$$

Where $\sigma^2_{\ n}$: *Variance*

λ: *The smoothing parameter /exponential weight coefficient*

$r^2_{\ n-1}$: *The squared return of the day before*

The first term on the right hand side of the equation represents the intensity of reaction, which determines how much weight should be given to the squared return of the previous day. The last term on the right hand side of the equation is called the smoothing effect, and determines how much weight should be given to the lagged variances.

λ is called the exponential weight coefficient, and decides how much weight the returns will be given. The value of λ is normally between 0.9 and 0.975 (Alexander, 2008). JP Morgan, who developed the EWMA in 1989, assigns a value of 0.96, which has become the most used value for λ among analysts.

The mean simple variance is used as the first variance in the calculation of the EWMA. The resulting EWMA variance is then used as variance for the following calculations.

Compared with the Standard Deviation, the EWMA is a better interpretation of the volatility with regard to the financial stock market due to its higher emphasis of the most recent observations.

The EWMA is a special, simplified version of the Generalized Autoregressive Conditional Heteroscedasticity (GARCH), which is described below.

3.2.3 Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) is the most popular method for estimating volatility and was introduced by Engle (1982) and Bollerslev (1986). It assumes that the volatility will revert to an expected value over the long run. The assumption of mean reversion is an improvement compared to the EWMA, and limits the significant effects on the mean that can be caused by the influence of larger fluctuations.

Apart from the above, the same conditions as the EWMA apply; as data gets older, the weight it is afforded is reduced exponentially.

The formula for calculating the GARCH variance is presented below

$$\sigma^2_n = \omega + \alpha r^2_{n-1} + \beta\sigma^2_{n-1}$$

Where	*σ^2: variance*	*σ: volatility*
	r: return	*α: weight on periodic returns*
	ω: Expected long run variance	*β: Weight of variance*

To estimate the weight parameters for both EWMA and GARCH (1,1) the Maximum Likelihood Estimation (MLE) method is used. By maximizing the value of the equation for the logarithm of the normal distribution's likelihood function, the optimal parameters can be found. Brooks (2008), Alexander (2008), Eliason (1993) and Khadska (2004) describe Maximum Likelihood Estimation, and presents examples.

Because the likelihood function is based on the normal distribution, it assumes that the returns follow a normal distribution. Therefore, if applied to a non-normal distribution, the result may not be correct.

A GARCH variance with an expected long run variance, ω, of zero, and $\alpha = (1 - \lambda)$,

$\beta = \lambda$, makes the GARCH identical to the EWMA. This illustrates that the EWMA is a special case of GARCH.

3.2.4 Other measures (kurtosis, skewness)

Both kurtosis and skewness are used to describe the distribution of the empirical returns. Moreover, their values can be used to compare the distributions to a normal distribution, which is often used as a base assumption in the analysis.

3.2.4.1 Kurtosis

Kurtosis is used to describe a distributions peakedness and measures how concentrated the data are around its mean.

The excess kurtosis of a student-t distribution can be calculated using the formula presented below.

$$Excess\ kurtosis = \frac{6}{(v-4)} \qquad v > 4$$

Where v represents the degrees of freedom.

The normal distribution has a kurtosis of 3. Deviations from this value indicate that a set of data is not normally distributed. Hence, to assume normal distribution in calculations then can lead to wrong answers. This is discussed by Lee, Lee & Lee (2000).

Figure 3.1 below illustrates the forms of distributions with kurtosises of infinity, 2 and 0.

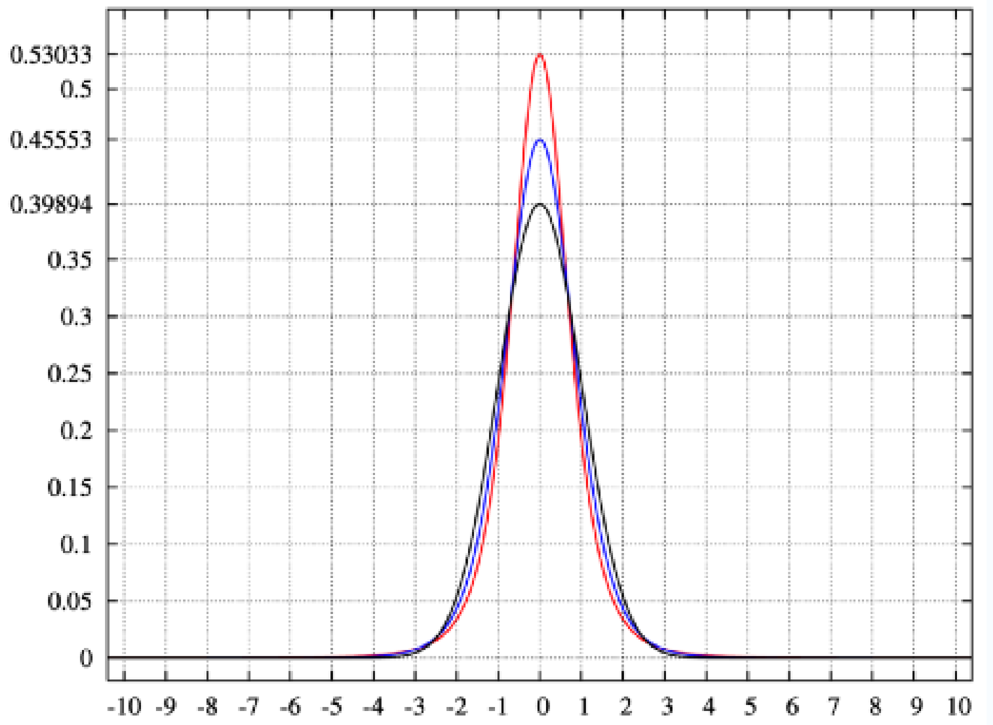


Figure 3.1: *Illustration of different kurtosis values. X-axis is the number of standard deviations and y-axis is probability. The black curves represents the normal distribution (Wikipedia, 2012).*

A kurtosis higher than 3 indicates that the dataset consists of more extreme values than that of the normal distribution, and thus resulting in the VaR being too high. The opposite is true for kurtosis values below 3.

The return distributions of products in the oil and gas industry commonly have fat tails, which results in a higher kurtosis compared with the normal distribution.

3.2.4.2 Skewness

The skewness is used to describe the form of the distribution. It tells whether or not the data are distributed symmetrically around its mean. A normal distribution has perfect symmetry, and hence a skewness of 0. Skewness compares the symmetry of a distribution with the normal distribution, and tells how skewed it is compared to the normal distribution.

A distribution can be positively or negatively skewed. This is illustrated in the figure below.

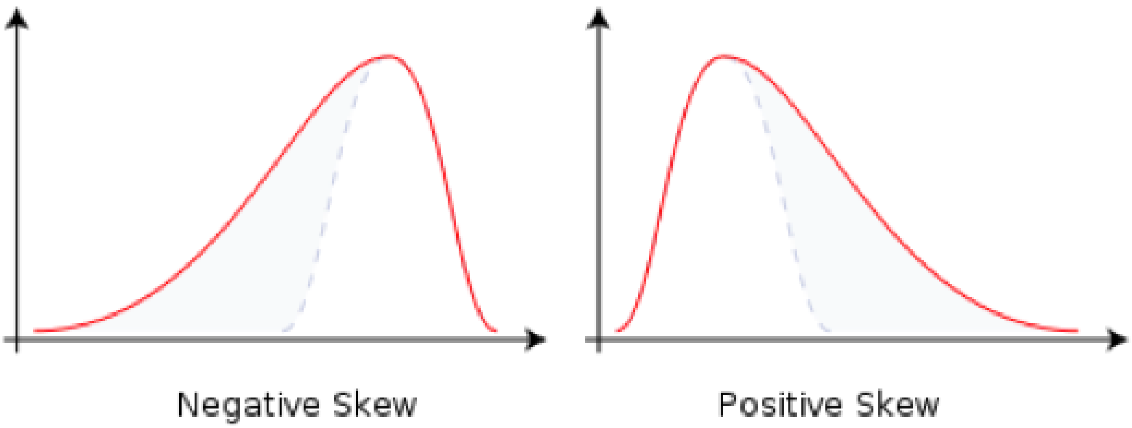


Figure 3.2: *Illustration of data sets with a negative skew and a positive skew (Wikipedia, 2012)*

The parametric approach may miscalculate the VaR of a skewed distribution because it assumes that the data are normally and symmetrically distributed. As can be seen in the figure above, a negative skew would underestimate the risk whereas a positive skew would overestimate it. This is supported by Lee, Lee & Lee (2000).

3.3 Portfolio management and diversification

On any given day, the price of a stock can have three different outcomes in the end of the trading day; it can close on a price lower, higher or equal to the one it had on the day before. Some stocks have a wider price variation than others; they might be more sensitive to change.

By studying the historical price data of stocks, one can get a picture of how the price reacts to a specific market change; does the change have a positive or negative influence on the price? Compared with other stocks, how does this stock react?

A portfolio generally consists of more than one asset or stock. It can consist of assets, stocks and bonds, all of which induce some risk, but also offer more "risk–free" solutions like money in the bank, or currency. All of these investments may be combined in a portfolio, or some of them. By spreading investments over several assets, the risk is reduced through diversification, as explained in portfolio theory by Markowitz (1959) and Samuelsson (1967). Lower portfolio risk can also be obtained by investing in assets with low correlation (Jorion, 2001)

Diversification can be explained as risk spreading.

Ex: The President and the Vice President are not allowed to travel together. This is to make sure that if something happens to the President, the Vice President will be able to step in for the President in his absence.

The above example illustrates that by diversifying the transportation, the risk of something happening to both the President and the Vice President at the same time is greatly reduced.

In a financial texture diversification reduces the risk related to profits and losses. A diversified portfolio contains different products.

As mentioned in section 3.1 Risk and risk management, the total risk of an investment has two components; the systematic risk and the unsystematic risk. The systematic risk affects most companies, and is therefore a component that will remain equal no matter what company you decide to invest in. However, by combining different stocks in a portfolio, the unsystematic risk can be dramatically reduced.

By adding different kinds of stocks to a portfolio one reduces the expected std of Profits and Losses (P&L). Ross et Al (2011) explains that this is because the diversifying of the portfolio combines the unsystematic risks for each investment. By doing this, the unique events, positive and negative, tend to cancel each other out when the portfolio consists of a variety of assets, rather than a few.

Assets may react differently to news and market change. A general market change is very likely to affect most assets. That is what happened during previous economic crises like the financial crisis of 2007 and the Wall Street Crash of 1929. These are examples of systematic risk, and cannot be reduced by portfolio diversification.

3.3.1 Correlation

Correlation is a statistical measure of how different data relate to each other. It is used to see if a connection between the behaviors of two different data sets exists, if they are dependent on each other.

The correlation is defined as:

$$Corr(X,Y) = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}$$

The correlation varies between the values -1 and 1. A correlation value of -1 indicates a strong negative correlation, which means that when the data values of one dataset increase, the values of the other dataset considered will decrease. If the trends of the two datasets are the same, meaning both of their values increase or decrease, the two datasets are said to be strongly correlated – thus giving a correlation value of 1. A value between 0 and 1 indicates correlation, while a value between 0 and -1 indicates a negative correlation. The closer the value is to 0, the less of a correlation we have. 0 means no correlation at all.

Combining assets that lack strong positive correlation will reduce the overall risk of the portfolio.

Correlation is an important component when explaining diversification. Samuelsson (1967) proves that adding assets to a portfolio will always reduce the risk, due to some imperfect correlation. Only if the extra asset is perfectly and positively correlated (r = 1), the risk will not be reduced (Mayo, 2011). However, reducing risk by adding assets will also reduce the expected return, as a result of common risk-return tradeoff.

A portfolio which contains assets that have strong correlation between each other is not as diversified as it would be if the assets had negative or lower correlation. The portfolio in this thesis is a single-asset portfolio. All of the products are from the same industry and expected to be highly correlated. The correlation between the natural gas and the oil products are not expected to be as correlated as the correlation between the individual oil products, but they are expected to show some degree of correlation.

Figure 3.3 illustrates how the risk is reduced when 2 assets with different levels of correlation are combined.

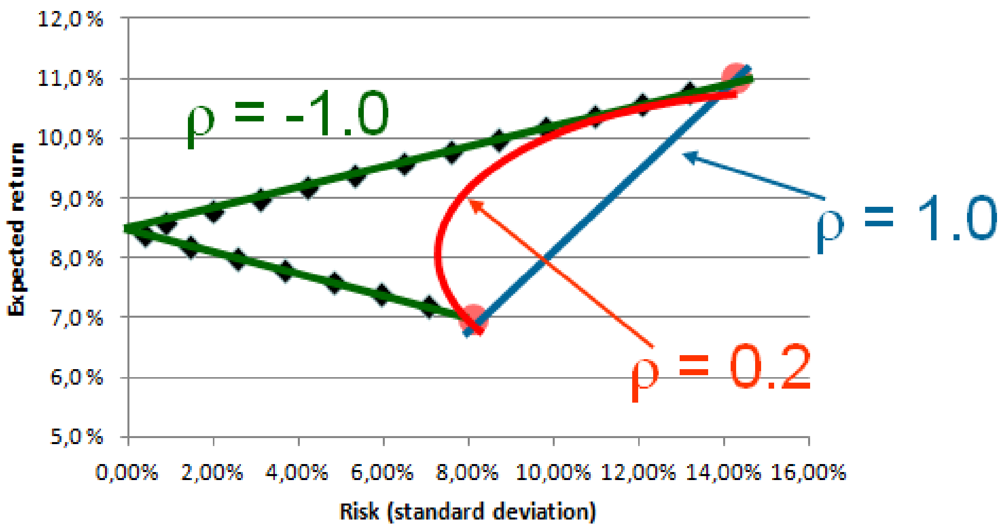


Figure 3.3: *Illustration of combining 2 assets with different levels of correlation (ρ = {-1.0, 0.2, 1.0}) and the effect on the risk and return tradeoff.*

3.4 Value at Risk (VaR)

"Value at risk (VaR) is a probability-based metric for quantifying the market risk of assets and portfolios. (...) VaR measures are forward-looking approximations of market risk" (Culp, Mensink, Neves, 1999).

VaR is a statistical definition that estimates the maximum potential loss in a given period of time. The VaR calculation serves as a good summary of financial investments in terms of risk management (Culp, Mensink, Neves, 1999).

Matemathically, VaR can be described as the probability $\boldsymbol{P}$ for the potential loss $\boldsymbol{L}$ being less than the amount $\boldsymbol{x_l}$, given a significance level $\boldsymbol{p}$. This is illustrated in equation (1.1) below.

$$\mathrm{P}\ (L < x_l) = p$$

VaR represents the potential worst-case scenario of loss based on different confidence levels. With a specific confidence, the VaR estimate attempts to identify the worst expected loss. The probability of the loss being less than what it was estimated to be by the risk measure is given by the confidence level (Hendricks, 1996).

Corporations may use this calculation to estimate how much money they should have in easy access to avoid bankruptcy.

Lets illustrate this with an example:

> *Suppose that a given corporation estimates that they have a probability of 0.02% of defaulting within the next two-year period. The company wants to know how much they will need to have in equity to have a good chance at surviving a potential default.*
>
> *To calculate this they use a VaR analysis with a confidence level of 99.98% and a time period of 2 years. If VaR(2-years, 99.98%) = $ 24.5 million, this means that there is a 0.02% chance of the company going bankrupt if they have an equity of $ 24.5 million. In other words – We have a confidence of 99.98% that the total loss over the given 2-year period will be maximum $ 24.5 million dollars.*

As seen in the above example, a confidence level of X% for the VaR gives us the outcome in which X% of the data is better, which implies that only (1-X)% of the data is worse. In other words – there is only a (1-X)% chance that the loss will be higher than the calculated VaR.

The potential loss depends on the chosen confidence level. The Value at Risk will increase when the confidence level is increased. This is due to the higher level of accuracy, which includes a larger percentage of the data, and thus also the worse returns. The opposite is true for decreasing levels of confidence.

Choudhry (2006) describes the four steps for calculating VaR:

(1) Determine the time horizon over which one wishes to estimate a potential loss
(2) Select the degree of certainty required, which is the confidence level that applies to the VaR estimate
(3) Create a probability distribution of likely returns for the instrument or portfolio under consideration
(4) Calculate the VaR estimate

The VaR is based on data, and can be calculated using three different approaches (Etukuru, 2011):

1. Historical simulation (non-parametric approach)
2. Variance - Covariance (Parametric approach)
3. Monte Carlo Simulation

The three different approaches presented above differ in how the data is going to be used for the calculation of the VaR. The approaches are supposed to make estimates that are as close to future distributions of returns as possible. The challenge of calculating the VaR lies mostly in selecting the approach that gives the best fit to the future distribution.

This thesis will calculate the VaR for oil and gas related products. The three different approaches above will all be used, whereas the Parametric approach will be based on EWMA and GARCH (1,1), both of which assume that the data is normally distributed.

The Value at Risk can be back tested, which means that it is possible to test the validity of the estimation. If the VaR estimation is accurate, the amount of losses larger than the estimated VaR will only occur x% of the time, where x is the specified level of confidence.

3.4.1 Historical simulation (non-parametric)

The Non-parametric approach assumes that the future is going to behave exactly like the past. It is based on data from previous observations and is therefore often called "The Historical approach".

The historical returns are sorted numerically from worst losses to best gains. Because the data are sorted, the historical VaR can also be found by calculating the xth first data, which is the xth worst loss based on which x-percentile that is chosen for the VaR calculation.

Lets say we want to calculate a 99% confidence VaR. Then we are interested in finding the worst 1% of the data. If we are basing our calculation on a set containing 2000 historical data, that would mean that the 99% VaR would give us the 20th (2000 x 1%) lowest value in the set considered.

To better illustrate the Historical approach, a histogram representing the historical returns is presented below. The confidence level is drawn as a straight vertical line in the figure, representing the VaR at that confidence level.

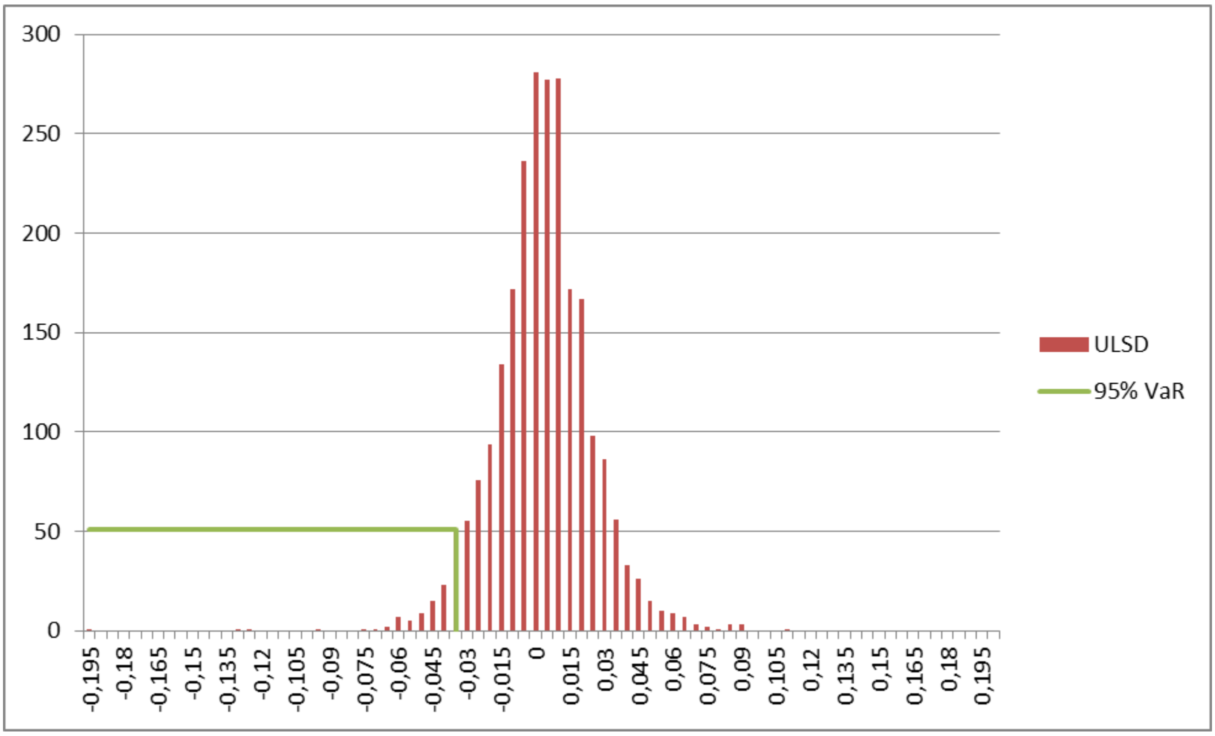


Figure 3.4: *Histogram of returns for ULSD (red bars) and 95% VaR.*

Figure 3.4 illustrates that 95% of the actual historical returns will be on the right hand side of the confidence level line, which means that were better than this level. The remaining 5% is on the left hand side, and thus worse than the chosen level of confidence. Where the vertical line is drawn depends on the chosen level of confidence.

A weakness of the historical simulation approach is that it does not say anything about the magnitudes of the losses that are in excess of the chosen level of confidence. These losses may be of significant magnitude, and therefore also of significant importance for risk management purposes.

Yet another shortcoming of the historical simulation is that it requires a lot of data to provide a realistic result, and that all data are weighted equally. There has been performed several tests and written many papers about the historical simulation approach.

It has been concluded several times that the performance of the approach depends heavily on the amount of data considered. The trend is that historical approaches give more accurate estimates as the sample size increases (Hendricks, 1996, Vlaar, 2000).

The historical approach is easy to understand and very easy to calculate when a sufficient amount of data is available.

3.4.2 Variance – covariance (parametric)

The Variance – Covariance (parametric) approach assumes that the future data will follow or approximately follow a specific distribution (e.g. Gaussian). This approach is also known as "the variance based VaR estimate" (Culp, Mensink, Neves, 1999) because of its dependency on the future distribution's assumed variance.

The assumption that the future data will follow a normal distribution makes the calculation of VaR more straightforward and easy to both understand and perform. To present a normal distribution the only two variables needed are the distribution's mean and its standard deviation. This thesis assumes that the log returns follow a normal distribution.

It is assumed that changes in instrument values will be linear with respect to changes in risk factors. This is a property that makes the parametric approach a linear approach (Etukuru, 2011). The requirement of parameters like the mean, standard deviation and correlation (the latter which is used on portfolios) is the reason why this approach is called parametric.

To decide which mean and standard deviation that best represent the Gaussian curve for the future distribution, different models can be applied. To get an idea of what is going to happen in the future, an obvious thing to do would be to use the information available today, which amongst others is the historical data. There are a wide variety of models applicable to estimate the future data. This thesis uses the simple volatility, the EWMA and the GARCH (1,1), whom of all are described in Chapter 3.2 Risk measures, to calculate the historical standard deviation which is used to forecast the future standard deviation used in the estimation of the VaR.

The simple volatility, EWMA and GARCH (1,1) differ in the approach they use to calculate the volatility (standard deviation). This means that the output, the volatility, from the different approaches may differ.

The VaR, assuming normal distributed data can be calculated using the formula presented below (Etukuru, 2011);

$$VaR_{\alpha} = (\sigma * z_{\alpha} + \mu) * \text{Asset value}$$

Where σ*: The standard deviation of asset per holding period in percentage*
α*: The significance. (1- α) is the level of confidence*
Z : The z-value according to alpha-level

If the entailed assumptions about the form and shape of the distribution are incorrect, the given VaR calculated with the parametric approach will not be reliable. This is the most significant weakness of the parametric approach. The calculated VaR will underestimate the actual VaR if one assumes normal distribution when in fact the data shows that they are not normally distributed.

When calculating the VaR we are only interested in the outer left tail, in which we find the potential losses. Typically, the tails of a financial data series is found to be fat (Mandelbrot, 1963), meaning that extreme events occurs more often than predicted by a normal distribution (Embrecht et al., 2002). Statistically this can be checked using kurtosis, as a fat tail will have excess kurtosis indicating fat tails. Financial returns tend to have a much higher kurtosis than the normal distribution (Coleman 2012; McNeil et al. 2005). This makes the shape of the financial returns higher and with fatter tails than the normal distributions bell shaped curve. Leptokurtic distributions have kurtosis higher than three, and are more likely to represent the distribution of returns in finance (Brooks, 2011).

The standard deviation and the mean will be influenced by major fluctuations in the historical data. Previous market shocks will affect the standard deviation differently depending on how extensive the data collection has been and on the decision of how to weigh the data.

An advantage of the parametric approach is that once the standard deviation and the mean are decided it is typically much faster to calculate compared to Monte-Carlo simulation or historical simulation.

3.4.3 Monte-Carlo simulation

This approach is intended for calculations of VaR with regard to portfolios. The Monte-Carlo simulation simulates the prices over a horizon. These prices are the data that is used for the VaR estimation, which then can be calculated using the same approach as is used to calculate the historical VaR. The only difference is that instead of using the historical data for the calculation, the simulated data will be used for the calculation. In other words – If we have simulated 2000 prices, the VaR on a 99% confidence level will then be today´s price minus the 20th lowest simulated price (2000 x (1-0.99) = 20).

The Monte-Carlo simulation performs random selections of data from a distribution. The degree of uncertainty and the average yield are amongst the assumptions that need to be taken to perform the simulation.

3.5 Backtesting of VaR

After the Value at Risk calculations have been performed and the results are given, it is necessary to examine the results and to verify that the methods chosen is in fact valid. A good method has to satisfy two equally important requirements;

(1) The amount of times that the true values exceed the VaR is the same as expected, as indicated by the level of confidence.
(2) The exceptions are independent of each other.

The data is expected to not exceed the 95% VaR estimate more than a total of 5% of the time (1-95%). This means that for the VaR estimate to be good, the losses can only exceed the VaR a reasonable amount of times, this depending on its level of confidence.

Different tests can be used to examine an approach used to calculate the VaR. The simplest tests only consider the first requirement (1), whereas more advanced tests also takes requirement (2) into account.

To compare the different approaches to Value at Risk, this study examines the amount of times the market change exceeds the individual VaR estimates. The good estimates will be the ones that experience an acceptable amount of times where the market changes exceed the estimate.

In this study two tests have been used to test if the amount of exceeding losses are significant or not, thus resulting in the VaR to be rejected or accepted. The two tests used are the Kupiec test and the Christoffersen test.

The next two sections will give a brief introduction to the two backtesting methods.

3.5.1 The Kupiec test

In 1995 Kupiec suggested a method to test if the number of exemptions is consistent with the level of confidence or not. This is one of the simple tests, and it only considers requirement (1).

By using the binomial distribution Kupiec calculates the probability of the specific amount of VaR breaks to occur within a specified number of trading days. He then uses the cumulative binomial distribution to find a confidence interval in which the amount of VaR breaks has to fall for the approach to be accepted (Gustafsson, Lundberg, 2009).

The probability of x numbers of outcomes in n tries is calculated by using the formula for the binomial probability:

$$P(x|n,p) = \binom{n}{x} p^x (1-p)^{n-x}$$

Where: *x: is the number of VaR breaks* *n: is the number of days*

p: is the level of significance

In short, the Kupiec test considers whether or not the amount of VaR breaks differs considerably from the level of significance. The underlying risk model is rejected if the amount of VaR violations significantly exceeds the expected amount with respect to the level of confidence.

3.5.2 Christoffersen test

In 1998 Peter Christoffersen published his three steps procedure for evaluating the ability of VaR models to predict the future. This test is more advanced, and considers both requirement (1) and (2).

The Christoffersen test is a conditional test in the sense that it does not accept "clustering". It considers when the actual data exceed the calculated VaR, and if the deviations are closely together in time.

The test does not only estimate if the number of times the calculated VaR is exceeded by the actual data differs significantly from the level of significance (like the Kupiec test does), but also takes the time when this happens into account. Even though a VaR value has been accepted by the Kupiec test, it can be rejected by the Christoffersen test due to clustering.

Good presentations of the above two back-tests for VaR can be found in Kupiec (1995) and Christoffersen (1998).

4 ANALYSIS OF DATA

This chapter will provide information about the products that the calculations have been done for.

4.1 The Products

The prices of 10 products from the oil and gas industry are examined and used for the calculations performed for this thesis (with a brief explanation of them) are:

- **Propane NWE FOBSeagoing Platts Mid As Quoted(US$:F/T)**
  (*Propane is a byproduct of petroleum refining and natural gas processing)*
- **Jet/Kerosene NWE CIF ARA Platts Mid As Quoted(US$:F/T)**
  (Jet/Kerosene is a blend of hydrocarbons, a product of petroleum refining which belongs to the middle distillate group. Normaly used in commercial airliners. (ICIS, 2012)
- **HSFO 3.5% NWE CIF ARA Platts Mid As Quoted(US$:F/T)**
  (High Sulphur Fuel Oil, fuel oil containing 3.5% sulphur)
- **No.6 1%/LSFO NWE CIF ARA Platts Mid As Quoted(US$:F/T)**
  (Low Sulphur Fuel Oil, fuel oil containing 1% sulphur)
- **Naphtha NWE FOB Barges Platts Mid As Quoted(US$:F/T)**
  (Naphtha is a colorless, volatile petroleum distillate, usually an intermediate product between gasoline and benzine, used as a solvent, fuel, etc.)
- **ULSD 10ppm NWE FOB Barges Platts Mid As Quoted(US$:F/T)**
  (Ultra Low Sulphur Diesel is diesel fuel with substantially lowered sulfur. Almost all of the petroleum-based diesel fuel available in Europe and North America is of a ULSD type)
- **NYMEX Henry Hub Nat Gas Monthly Rollover Series 1st Month Close As Quoted(US$:F/MMBTU)**
  (Natural gas located at the Henry Hub, USA)
- **ICE NBP Nat Gas Monthly Rollover Series 1st Month Close As Quoted(US$:F/MMBTU)**
  (National Balancing Point, natural gas in the U.K)
- **Zeebrugge Monthly Rollover Series 1st Month ICIS Heren Mid As Quoted(US$:F/MMBTU)**
  (The price for natural gas bought from the Zeebrugge hub)
- **ICE Brent Combined Monthly Rollover Series 1st Month Close As Quoted(US$:F/BBL)**
  (The price listed by ICE for Brent)

Below follows explanations for some of the abbreviations presented above.

- NWE stands for North West Europe. Products with this in their name are traded from the North West Europe oil and petrochemicals market.
- Mid means that the price is an arithmetic average between high and low quotations of the day. This is the case for most of the products.
- ARA stands for Amsterdam-Rotterdam-Antwerp. Products termed ARA are used in shipping when discharge or loading occur in one of the three ports in Amsterdam-Rotterdam-Antwerpen.
- FOB and CIF stands for Free On Board and Cost Insurance Freight. They are two different types of insurance. The type of insurance decides the responsibility for risk of the cargo during freight. CIF is generally more expensive because the freight is insured and the price is for the product at the delivery port. With FOB the price is for the product(s) at the departure port, and excludes the cost for shipping and insurance. The buyer has to pay for this by himself.
- NYMEX stands for the New York Mercantile Exchange. Products termed with NYMEX are traded from this market.
- NBP stands for the National Balancing Point, and is a virtual trading location for the sale, purchase and exchange of UK natural gas. Products with NBP in their name are traded from this market.
- ICE stands for InterContinental Exchange and is an American financial company that operates Internet-based marketplaces. Products with ICE in their name are traded from one of the markets operated by ICE.
- ICIS is a publisher of the European Spot Gas Markets (ESGM).
- Zebrugge and Henry Hub are hubs located in Zeebrugge, Belgium and Louisiana, USA. They are distribution hubs for the natural gas markets in Europe and the US respectively. Products with one of the two names included indicates that the quoted price is for the product sold from one of these locations.
- Platts is a pricing reporting agency (PRA). Most of the products in this study have Platts in their name, meaning that their price is quoted by Platts.
- (US$:F/T) means that the price is quoted in US Dollars per Tonn.
- (US$:F/MMBTU) means that the price is quoted in US Dollars per million BTu. BTu is the British Thermal unit. 1 MMBTU = 1,000,000 British Thermal Units = 293.071 kWh

- (US$:F/BBL) means that the price is quoted in US dollars per barrel.

4.2 Statistical characteristics

4.2.1 10-year history of price and volatility

All of the oil products have been following the same trend over the last ten years. Their prices have all increased steadily from 2002 until 2008, when the financial crisis led to a dramatic decrease in price. From July 2008 prices decreased dramatically throughout the year (i.e. the price of Jet/Kerosene fell from a summer high in 2008 of above 1400 USD/T to a low of below 400 USD/T the following winter!) In 2009 prices started to move steadily upwards again.

The fact that the products have been following the same trend indicates that they are closely linked together and most likely impacted by the same factors. The 10-year price history for the seven oil products are given in figure 4.1 below. By looking at the figure, it is easy to observe that they all are strongly correlated. The reason why ICE Brent combined has a much lower value than the other products is only because its price is listed as dollars per barrel, instead of per ton. The conversion factor from barrels to tons are approximately seven, thus giving ICE Brent combined a value in the same range as the other products in the figure.

The 10-year price histories for the thesis´ oil products are illustrated in figure 4.1.

The price developments for the three natural gas hubs considered in this thesis indicate a strong link between them. The price trend for the natural gas markets is also affected by the financial crisis. From 2002 until 2006, the price development followed a positive trend. Between 2006 and 2007 the market price decreased. In 2007 the prices increased again, until the effects from the financial crisis forced prices downwards, to bottom levels of 2007. After the financial crisis, prices for the Zeebrugge hub and ICE NBP have increased, whereas the Henry hub continues to decrease.

From 2002 until 2005, the natural gas prices had several peaks. These four price peaks can be explained by the season variation of natural gas. During the winter season, more natural gas is used, leading to an increase in demand. As described in chapter 2 Price variability in the oil and gas market, the increased demand most likely leads to an increase in price. Another explanation may because companies have changed their contracts to include a larger range of volumes. There are no sudden peaks after 2005. This can be a result of contracts taking larger volumes into account and more trading in the post market. But also increased supply, new technology and discoveries have made more natural gas available.

It is expected that the prices of NBP (red in figure 4.2) and Zeebrugge (green in figure 4.2) will have a high correlation due to the fact that they both are sold on the European natural gas market. As mentioned in 2.1.1 Storage and Transportation, the gas market is more regionally defined due to its limited transportability, and thus it is not too surprising if the price for gas on the American natural gas market differs to some degree, when compared to the European market. The Henry Hub price differs a little from the two other prices, but can be said to follow the same trend until 2009/2010. The main reason for the decrease in price after this is the shale gas in the United States, increasing the supply of natural gas in the country. These reserves have become profitable to produce, thanks to new technologies within hydraulic fracturing. These discoveries may turn the United States from being a net importer of energy to a net exporter.

The 10-year price histories for the thesis´ three natural gas products are illustrated in figure 4.1 below.

There are similarities in the price variability between figure 4.1 and 4.2. The fact that they share the same trends can be explained by their prices being impacted mostly by the same factors. These factors are mentioned in chapter 2. The exception is the natural gas peaks in figure 4.2, which most likely are the effect of the increased demand due to seasonal winter weather.

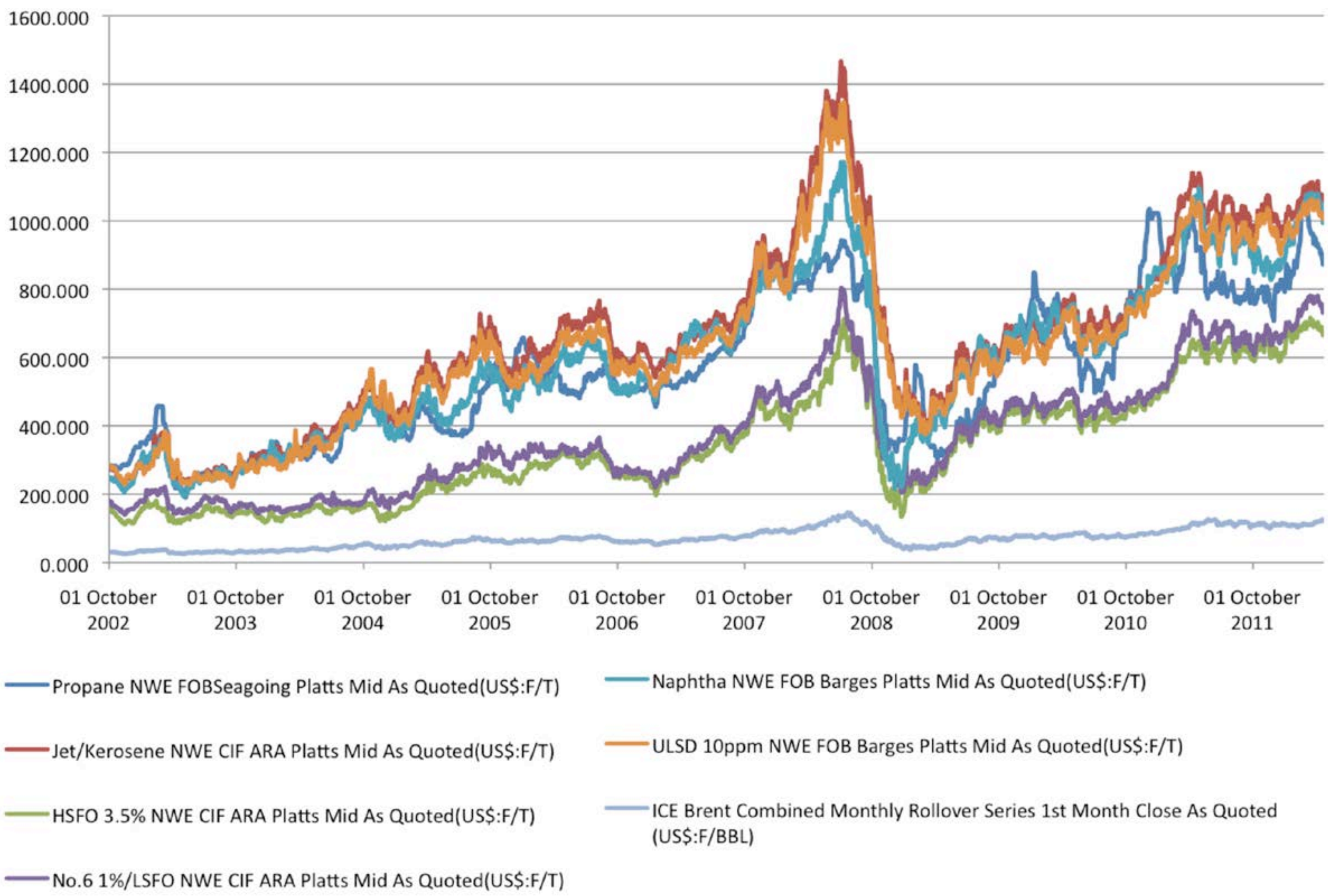


Figure 4.1: *10-year price history for the seven oil products considered in this thesis. ICE Brent is listed as US$/BBL, the other products are listed as US$/T. Conversion factor from BBL to T is approximately 7.*

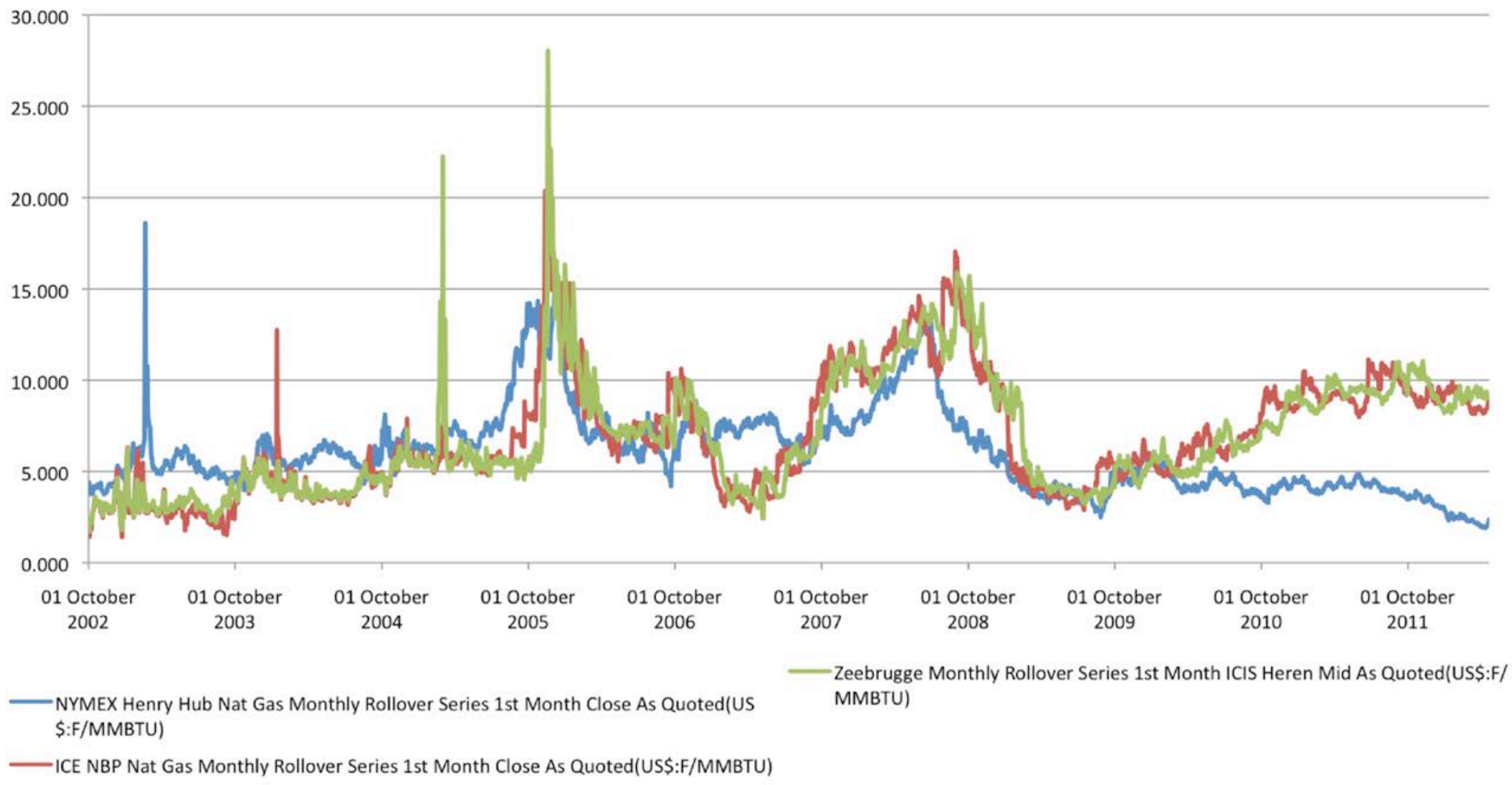


Figure 4.2: *Price history for natural gas.*

The one-year volatilities for the seven oil products followed a downward trend from 2002 until 2008. Then, due to the financial crisis, the volatilities increased dramatically throughout the year, and a downward trend did not begin until late in 2009. In 2010 the volatilities were back to where they were before the major increase, and after that have since demonstrated a slightly decreasing trend.

The one-year volatilities for the seven oil products show an inverse connection with the products price developments presented in figure 4.1, but with a delay. The reason for the slight shift east is due to the calculations of the volatilities being based on a period of 250 days. This is also true for the volatilities represented in figure 4.4.

The volatilities for the seven oil products are presented graphically in figure 4.3 below.

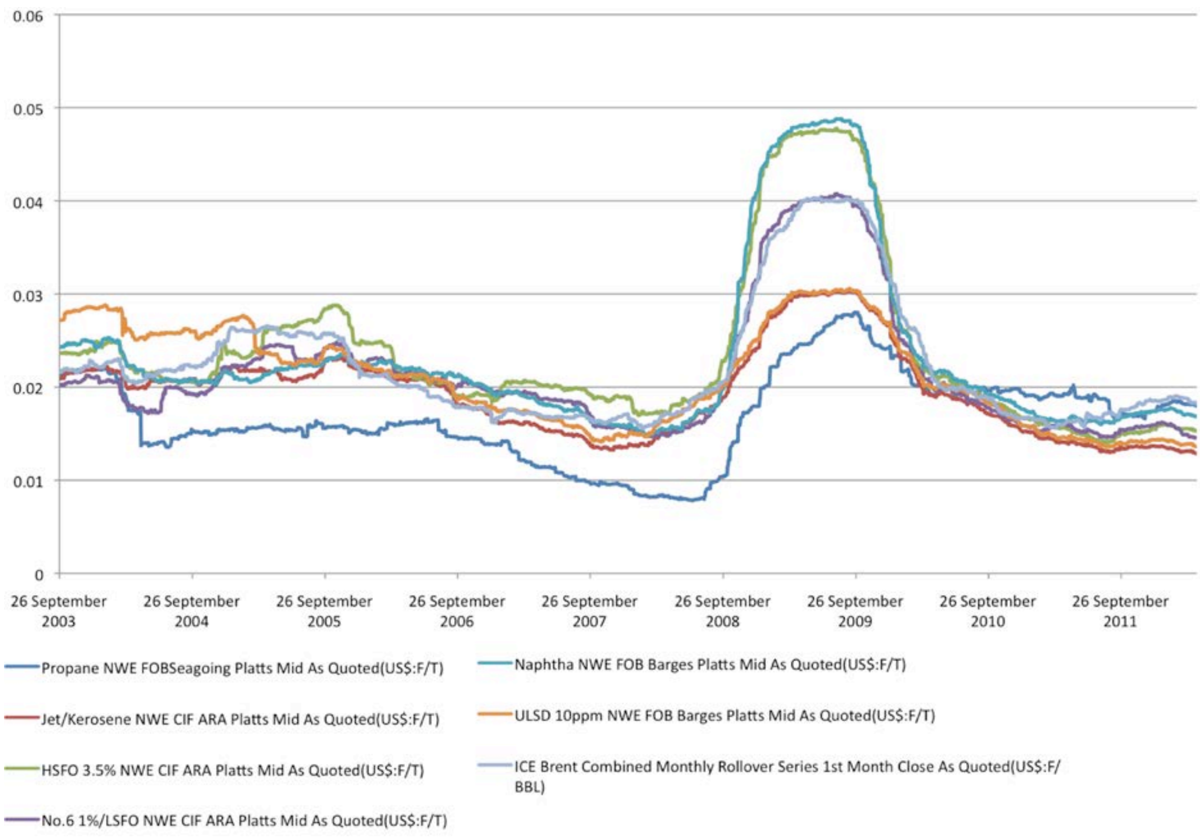


Figure 4-3: *The volatilities of the seven products over the 10 year-period, measured by the standard deviation over the last 250 days.*

The volatilities for the three natural gas products show a downward trend. The one-year volatilities of the natural gas on the European market are dominantly higher than the one-year volatility of the natural gas from the Henry Hub until late 2009. This can again be explained by the new technology, resulting in an increased volume of economically recoverable reserves of natural gas in the United States. The general downward trend can be explained by increased supply, in addition to this, companies have started to use new contracts, allowing them to get more flexibility with regard to future volumes.

The differences in volatility over time are more pronounced for the natural gas series. This may be a result of temporary demand shocks from seasonal variations, but also due to temporary supply shocks as for instance seen in Europe with gas supply from Russia/Ukraine having experienced troubles during this period. There seems to be a convergence for all 3 products from 2008, which is of particular interest when considering the price fluctuations between Zeebrugge/NBP and Henry Hub, as seen in figure 4.2.

The volatilities of the three natural gas products are shown in figure 4.4 below.

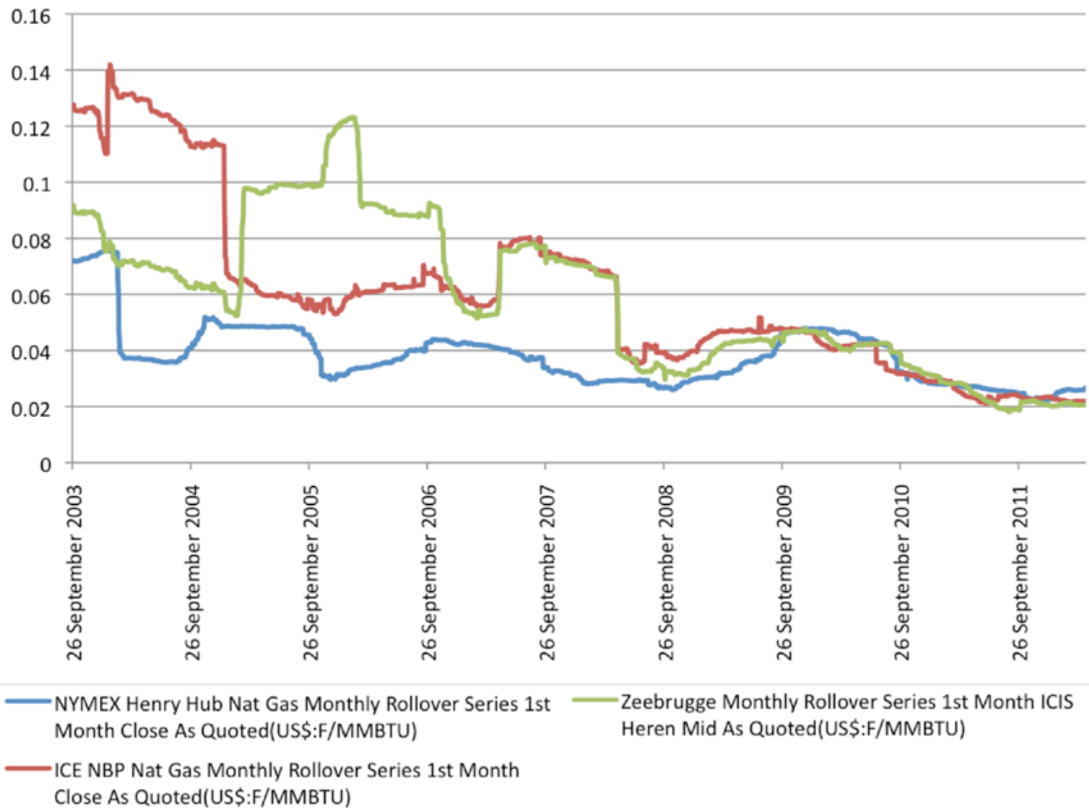


Figure 4.4: *The volatilites for the three natural gas products, measured by the standard deviation over the last 250 days.*

4.2.2 Properties of the return distributions

A set of data will, according to the Central Limit Theorem, approach a normal distribution as the number of observations increase. By investigating the properties of the products´ return distributions, they can be compared with the normal distribution.

A normal distribution will have a mean and skewness of zero, and a kurtosis of three. The return distributions for the ten products all differ from the normal distribution, but to different degrees.

All the products have a mean return close to zero, but none have a kurtosis of three or a skewness of zero.

The kurtosis of the natural gas form the European and North American market differs significantly from the one of the normal distribution. They are 7 to 10 times larger. The Henry Hub and NBP both have a skewness close to 1. This implies that they do not follow the normal distribution, and thus their VaR is not expected to be accurate if it assumes normal distribution.

Jet/Kerosene, No.6 and Brent are the three products that have kurtosis and skewness most similar to the normal distribution.

The properties of the 10 different products return distributions are presented in table 4.1 below.

Product	Mean	Median	1.quartile	3. quartile	Standard Deviation	Kurtosis	Skewness
Normal distribution	**0**	**0**			**Varies**	**3**	**0**
Propane	0.00048	0.0000	-0.00617	0.00656	0.0176	9.8464	0.4101
Jet/ Kerosene	0.00056	0.00087	-0.01123	0.01182	0.0197	1.9934	0.0890
HSFO	0.00060	0.00077	-0.01233	0.01370	0.0247	6.8113	0.3924
No.6	0.00059	0.00052	-0.01130	0.01260	0.0220	4.7290	0.0997
Naphtha	0.00058	0.00126	-0.01192	0.01381	0.0244	7.2108	-0.1071
ULSD	0.00053	0.00090	-0.01101	0.01215	0.0216	5.0433	-0.3545
Henry Hub nat. gas	-0.00026	-0.00099	-0.02087	0.01829	0.0420	37.6268	0.8380
NBP nat. gas	0.00073	-0.00181	-0.02182	0.01765	0.0705	39.5820	0.7443
Zeebrugge nat. gas	0.00064	-0.00124	-0.02315	0.01917	0.0653	21.3410	0.3143
Brent	0.00057	0.00126	-0.01168	0.01354	0.0229	2.8943	-0.2221

Table 4.1: *Properties of the ten products´ return distributions are compared with the normal distribution.*

More than 30% of the returns of Propane were 0, thus making the distributions curve differ significantly to the normal distribution despite its closeness to zero mean, zero median and 0.4101 in kurtosis. This may be a result of the product not being traded in large volumes daily, as the data used in this analysis are based on daily returns.

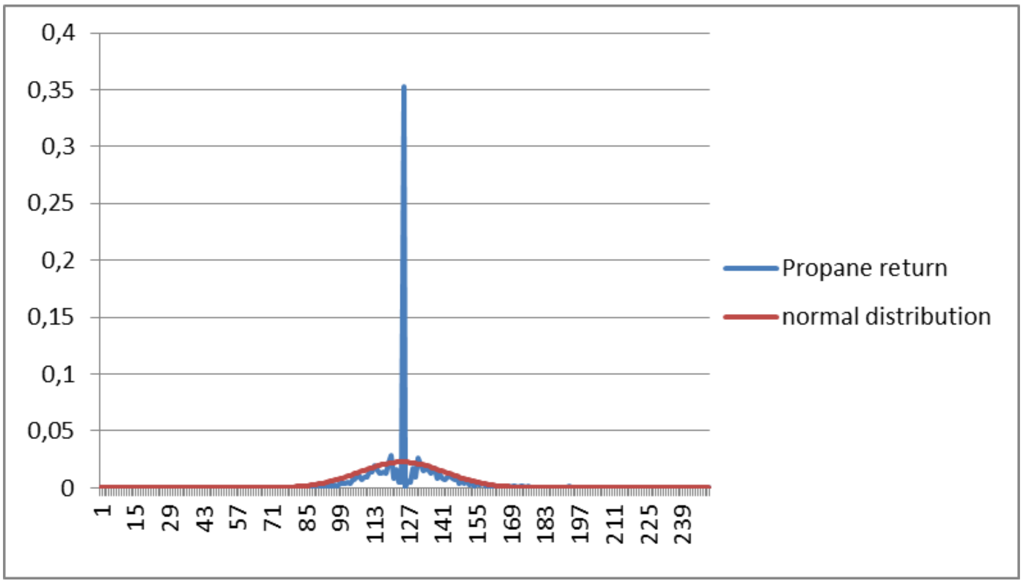


Figure 4.5: *The distribution of the returns for Propane, based on the last 10 years of price history. Propane is the blue curve, while the red curve illustrates how a normal distribution with the same standard deviation would look like.*

All distributions had a kurtosis higher than three except the distributions for Jet/Kerosene and Brent, who both were close to three. The distributions of NBP and Zeebrugge differ greatly from the normal distribution as illustrated in figure 4.6 below.

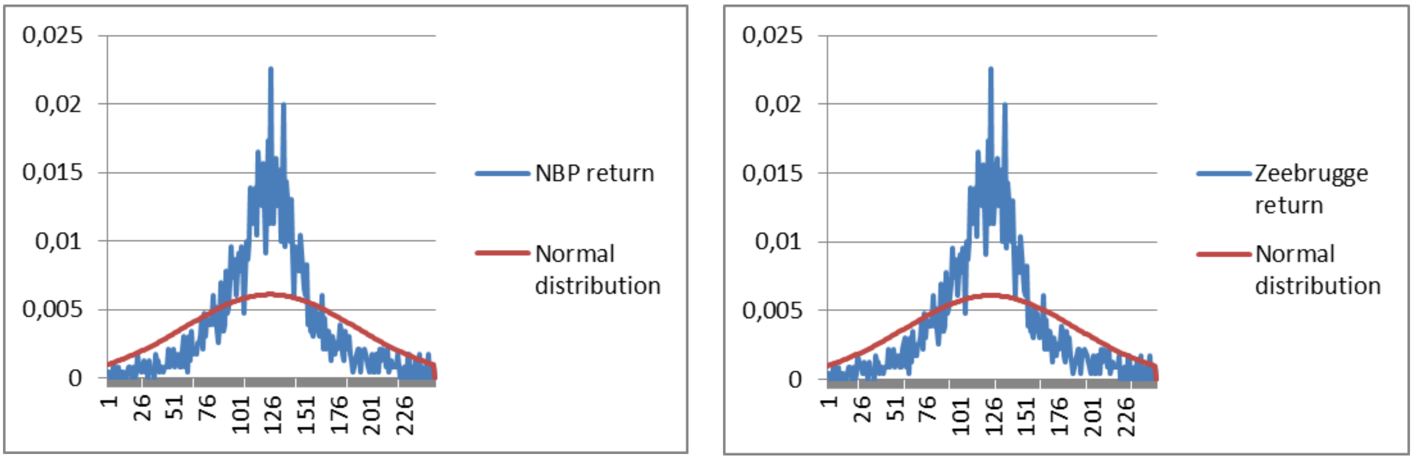


Figure 4.6: *The return distributions of NBP and Zeebrugge natural gas. The blue curves illustrate the distribution of the returns whilst the red curves showes the normal distribution curves with standard deviations with the same as the ones of the return distributions.*

Jet/Kerosene, No.6, ULSD and Brent are the four products that have curves most similar to the normal distribution curve. As mentioned above, Jet/Kerosene, No.6 and Brent are the three products with kurtosis and skewness nearest to the normal distribution. ULSD have a negative skew of -0.3545, but has a kurtosis and mean close to that of the normal distribution. The curves of the four distributions are illustrated in figure 4.7 below.

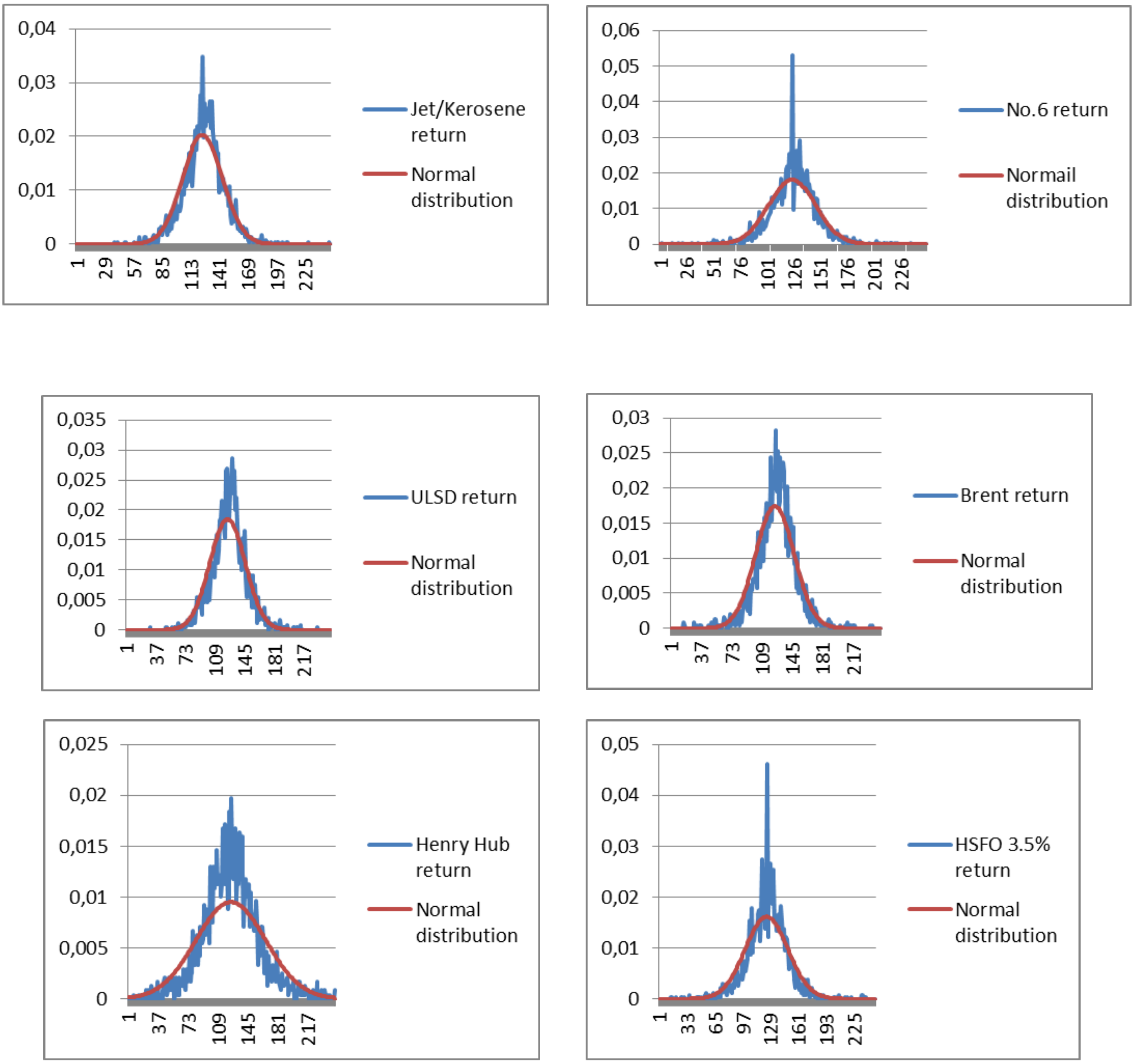


Figure 4.7: *Illustration of the distributions of Jet/Kerosene, No.6, Henry Hub, HSFO, ULSD and Brent compared with the normal distribution. The curves of the products returns are in blue, the normal distribution is in red.*

The return distributions are not normally distributed. However, most of them have a shape similar to the bell curve, with the exception of a higher peak and thicker tails. This implies that the distributions have properties more similar to a student-t distribution.

Due to the similarities of the student-t and the normal distribution, the returns are assumed to be normally distributed in the calculations that follow. This makes it possible to use the MLE method to estimate the variables needed to calculate EWMA and GARCH (1,1). The VaR for the portfolios will be calculated assuming both distributions, to compare the results. For the student-t distributions, 6 degrees of freedom are chosen, as the standard is between 5-7 degrees of freedom for financial returns.

4.3 Portfolio diversification and product correlation

The four portfolios created consist of several of the ten products given above. Each product is not invested in more than once. The four portfolios are listed in table 4.2 below.

Portfolio #	Propane	Jet/ Kerosene	HSFO 3.5%	No.6 1% /LSFO	Naphtha	ULSD 10ppm	**Henry Hub Nat Gas**	**NBP Nat**	**Zeebrugge Nat Gas**	**Brent**
A	1	1	0	0	0	0	0	0	1	1
B	1	0	0	1	0	0	1	0	1	0
C	0	1	0	0	1	1	1	1	1	0
D	0	1	0	0	0	1	1	1	1	1

Table 4.2: *The four different portfolios.*

The seven oil products are highly correlated, meaning that their price variations follow each other. This is as expected considering the descriptions of their price and volatility histories presented in section 4.2 Statistical characteristics. The natural gas are not as correlated with the oil products.

The two prices for natural gas on the European market (NBP and Zeebrugge) are also very correlated, as discussed in section 4.1 Statistical characteristics. On the other hand, the price for natural gas from the Henry Hub in the United States is not very correlated to any of the other nine products. The Henry Hub is, as the only one, even slightly negatively correlated with HSFO and LSFO. Table 4.3 below, shows the correlation between the products.

Correlation	Propane	Jet/ Kero- sene	HSFO 3.5%	No.6 1%/LSFO	Naphtha	ULSD 10ppm	**Henry HubNat Gas**	**NBP Nat**	**Zee- brugge**	**Brent**
Propane	1.0000	0.9124	0.9041	0.9080	0.9483	0.9120	0.0236	0.6954	0.6563	0.9014
Jet/Kerosene	0.9124	1.0000	0.9259	0.9395	0.9664	0.9981	0.1185	0.7382	0.7077	0.9772
HSFO 3.5%	0.9041	0.9259	1.0000	0.9946	0.9584	0.9243	-0.1739	0.5994	0.5693	0.9458
No.6 1%/LSFO	0.9080	0.9395	0.9946	1.0000	0.9587	0.9386	-0.1281	0.6293	0.5998	0.9546
Naphtha	0.9483	0.9664	0.9584	0.9587	1.0000	0.9637	0.0010	0.6469	0.6029	0.9546
ULSD 10ppm	0.9120	0.9981	0.9243	0.9386	0.9637	1.0000	0.1126	0.7396	0.7085	0.9750
HenryHub Nat Gas	0.0236	0.1185	- 0.1739	-0.1281	0.0010	0.1126	1.0000	0.3887	0.3347	0.0400
NBP Nat	0.6954	0.7382	0.5994	0.6293	0.6469	0.7396	0.3887	1.0000	0.9075	0.7196
Zeebrugge	0.6563	0.7077	0.5693	0.5998	0.6029	0.7085	0.3347	0.9075	1.0000	0.6879
Brent	0.9014	0.9772	0.9458	0.9546	0.9582	0.9750	0.0400	0.7196	0.6879	1.0000

Table 4.3: *Correlation between the ten products. Henry Hub, NBP and Zeebrugge are the natural gas, whilst the remaining seven products are oil products.*

The four portfolios have different degrees of diversification due to the fact that they all have a mix between the oil products and the natural gas. General portfolio theory as described in Chapter 3 provides a set of opportunities for a risk manager. The portfolios used should therefore have lower risk due to diversificiation. The return distributions all have a mean and median close to zero as seen in table 4.4. However, their kurtosis differ significantly from the one of the normal distribution.

Product	Mean	Median	1.kvartil	3.kvartil	Standard Deviation	Kurtosis	Skewness
Normal distribution	**0**	**0**			**Varies**	**3**	**0**
Student-t, 6°	0	0			Varies	6	
Portfolio A	0.00056	0.00034	-0.00870	0.00918	0.01929	10.0654	0.2754
Portfolio B	0.00036	0.00039	-0.01015	0.01017	0.02096	8.9499	0.1776
Portfolio C	0.00046	0.00012	-0.01051	0.01025	0.02240	13.4458	-0.0369
Portfolio C	0.00046	4.46E-6	-0.00914	0.00959	0.02143	15.6082	-0.0264

Table 4.4: *Properties of the distributions of the four portfolios, compared with the normal distribution.*

All the four curves for the four portfolios` return distributions are similar. They are dominated by thin high peaks, thus differing from the normal distribution. Because of the returns high kurtosis, they are more likely to fit better with a leptokurtic distribution as presented in chapter 3.4.2 – Variance-covariance.

The curves of the four distributions are illustrated in figure 4.8 below.

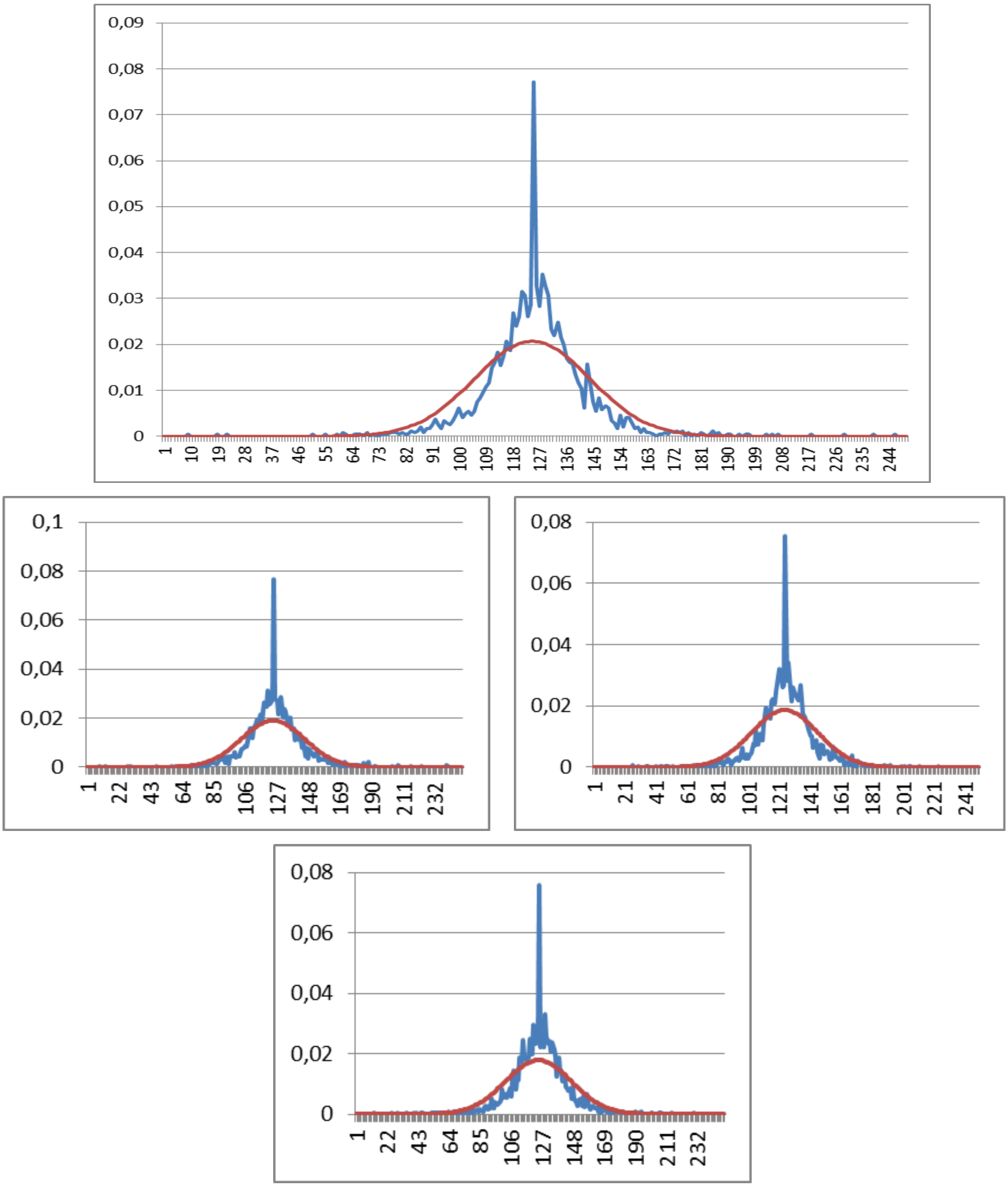


Figure 4.8: *Portfolio A – D respectively. Blue line is portfolio distribution of daily log returns. Red line is normal distribution.*

5 EMPIRICAL RESULTS

In this chapter the results of the VaR calculations are presented and discussed. The different approaches are calculated for 250, 500 and 1000 days, and back-tested by using the Kupiec test and the Christoffersen test. The tests are performed based on two different levels of significance; 95% and 99%.

A description of how the calculations have been performed is presented, and the results from the back-tests will be presented and discussed.

5.1 The VaR estimation methods

The historical price data of 10 different petroleum products have been collected. The prices are given for each trading day from 1. October 2002 until 20. April 2012.

The logarithmic profits and losses were calculated for each day using the formula presented below:

$$P\&L = ln\left(\frac{t_n}{t_{n\text{-}1}}\right)$$

Excel's **SUMPRODUCT** was used to calculate the P&L for the portfolios.

The standard deviations for the P&L data were calculated by considering different time periods. The calculations were done for the span of 250, 500 and 1000 trading days. Excel's formula **STDEV** was used to perform the calculations.

The P&L results were used to calculate the EWMA and GARCH (1,1). The Maximum Likelihood Estimation (MLE) was used to estimate the different parameters needed to solve the calculations for the EWMA and GARCH (1,1).

Excel's **Solver** has been used to perform the MLE for each individual product.

EWMA and GARCH (1,1) were calculated for different periods of time; 250, 500, and 1000 trading days.

The historical prices together with the results from the standard deviation, EWMA and GARCH (1,1) calculations were then used as input for the estimations of the different products´ Value at Risk.

The VaR was calculated with two significance levels; 95% and 99%. Eight VaR calculations were performed for each product and each portfolio per time period. The different approaches used to calculate VaR:

The VaR was calculated with two significance levels; 95% and 99%. Eight VaR calculations were performed for each product and each portfolio per time period. The different approaches used to calculate VaR:

- Historical Simulation
- Variance-covariance
  - Simple (by using the standard deviation as input)
  - EWMA
  - GARCH (1,1)

The VaR was calculated based on different time spans. The time periods were 250, 500 and 1000 trading days. The normal distribution was used in the calculations of all products, whereas both the normal and student-t distributions were used for the portfolios.

The calculation of VaR, under the assumption of normal distributed data is:

VaR_{normal} = volatility*Z

When the data is assumed to follow a student-t distribution, the degrees of freedom can be converted to a Z value by using Excels function **TINV** , and the calculation is the same as for the normal distribution:

$VaR_{Student\text{-}t}$ = volatility*Z_t

To be able to comment on and compare the different approaches, the extreme values were counted by using a formula to count the times the estimated VaR was exceeded by the actual change in the market.

The number of times that the actual change exceeded the estimated VaR were then used as input to backtest the approaches. The backtesing methods, Kupiec (1995) and Christoffersen (1998) test, were calculated using Excel macros.

5.1.1 The VaR estimations

The Value at Risk has been calculated with regard to three different periods (250 days, 500 days and 1000 days), in order to measure the market volatility for one, two and four trading years. Confidence levels of 95% and 99% were used, as these are the most common confidence levels to use in this industry.

The Parametric and the Non-parametric approaches have been used to calculate the Value at Risk for the ten different products, assuming a normal distribution. For the portfolios, both normal and student-t distributions were assumed, due to the high kurtosis. For the Parametric approach, three different volatilities have been used to calculate the Values at Risk: standard deviation, EWMA and GARCH (1,1).

The results for ULSD and Henry Hub will be presented to illustrate the products with the best back-test results among the oil products and among the three natural gas hubs. The results for the one-year period will be presented in a table of products and a portfolio table, while the results for the other periods will be discussed in the text (no table will be provided). However, all the results for the back-tests can be found in the appendix. The one-year period has the highest "update rate", and will be presented in the tables and figures in this chapter. The results from the back-tests performed on the two-and four-year periods will be discussed in the text together with the results of the one-year period (no table will be provided). However, all results and calculations can be found in the Excel workbooks in the appendix found on the CD.

5.2 Back-testing the different VaR approaches

The two back-testing methods, described in section 3.5 Back-testing of VaR, by Kupiec and Christoffersen has been used to investigate the validity of the VaR approaches and their results.

The number of VaR breaks for each approach is calculated, with confidence levels of 95% and 99%, for each product and portfolio. The Extreme events are found when the actual return exceeds the one that has been predicted. This results in 36 different VaR estimates for each approach, 20 come from the VaRs for the individual products, and 16 from the portfolios. The back-tests are used to investigate whether the amount of VaR breaks is significantly different (or not), from what is expected by the significance level.

For the estimation method to be accepted, the estimated VaR cannot differ from the actual data more times than what is accepted by the level of confidence (as described in section 3.5 Backtesting). The number of VaR breaks is calculated for each approach on each product/portfolio with the confidence levels of 95% and 99%. The back-tests are used to calculate if the amount of VaR breaks is significantly different from what is expected by the significance level.

5.2.1 Products

The one-year VaR estimates obtained the best results from the back-tests. As the time period considered increased, so did the number of back-test rejections. This may be a result of the impact that the financial crisis had on the return data. Because the one-year period only is based on the previous 250 trading days at a time, its rate has a higher level of refreshment compared to the two- (500 trading days) and four-year (1000 trading days) periods. Although the one-year period provides the most updated rate, its volatility is greater due to the smaller amount of data.

ULSD was the only product that got accepted by both tests for all three time periods. The VaR breaks for the 95% confidence level are illustrated in figure 5.1 below.

For simplicity, only the 95% VaR is presented for one oil product (ULSD) and one gas product (Henry Hub). The results for 99% are similar, although all estimates are more extreme resulting in fewer breaks.

Henry Hub was accepted most times in the 500-day period. Then it was accepted for all methods on a 99% level, whereas the non-parametric approach (Simple) and the EWMA approach accepted it on the 95% level. Kupiec accepted all of the VaR on the 99% level for the one-year periodwhilst Christoffersen accepted the simple approach on the 95% level, and both EWMA and GARCH (1,1) for the 99% level.

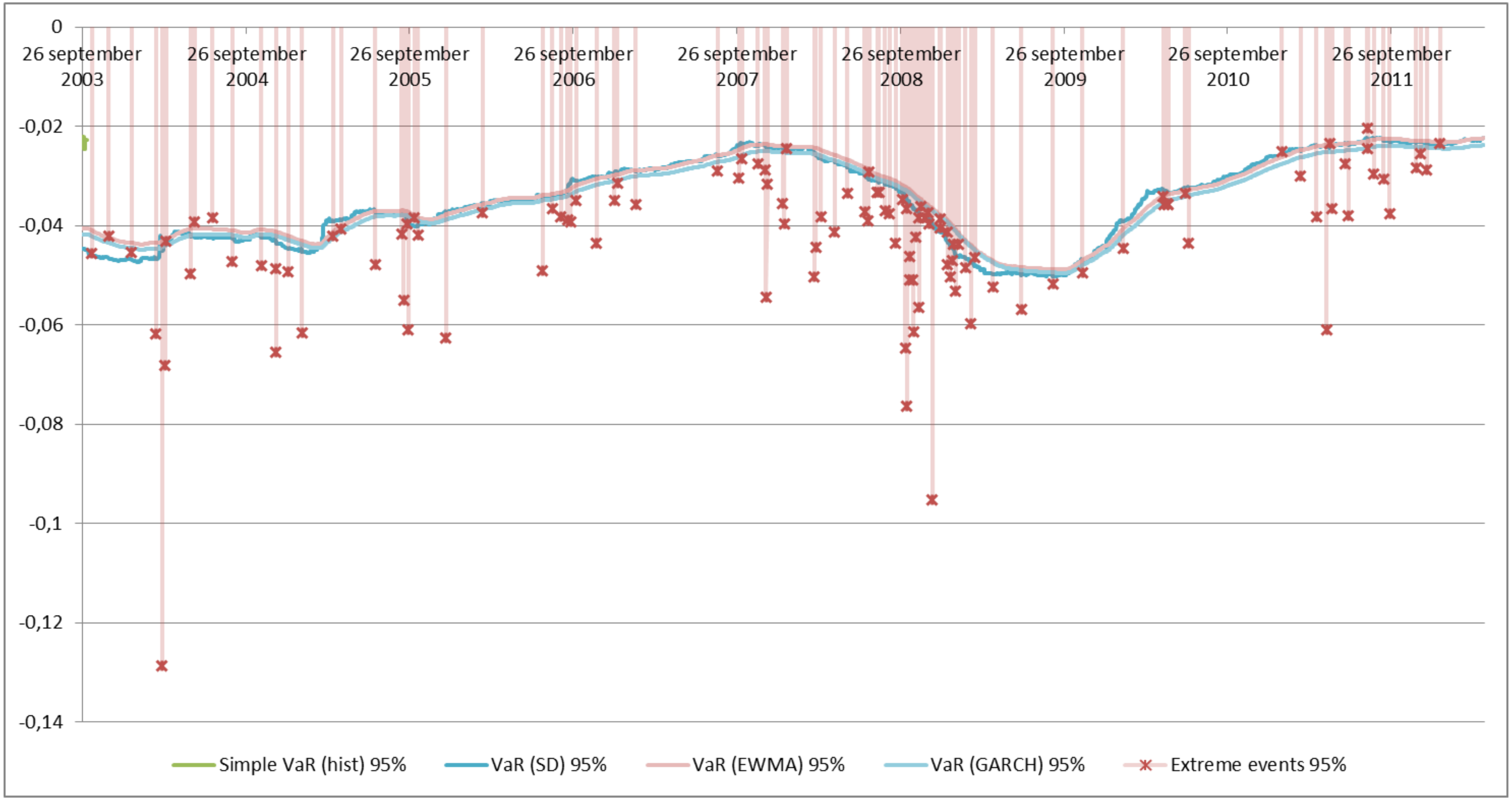


Figure 5.1: *Illustration of VaR breaks (in red) for ULSD, with a 95% confidence level for the one-year time period. The Extreme events are found when the actual return exceeds the one that has been predicted.*

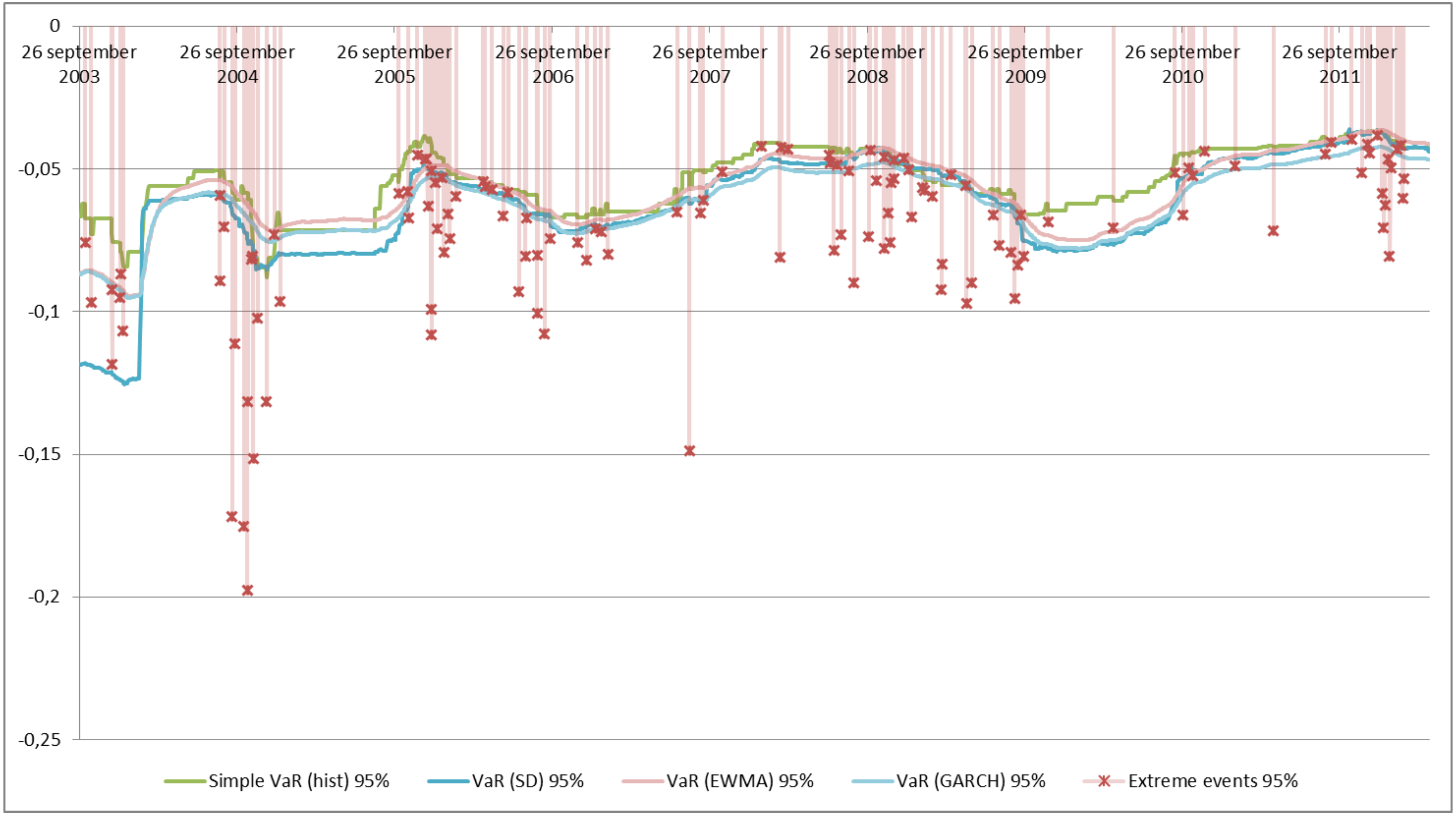


Figure 5.2: *Illustration of VaR breaks (in red) for Henry Hub, for the 95% confidence level, for the one-year time period. The Extreme events are found when the actual return exceeds the one that has been predicted.*

All of the VaR approaches were rejected for the five-year period for Zeebrugge, whilst they were accepted on the 99% confidence level for the two-year period. Christoffersen did not accept the historical VaR for the 99% confidence level, but approved the 95% confidence level for this approach. Both tests accepted the remaining three approaches for the 99% confidence level. NBP was rejected on both confidence levels for both the two- and the five-year period. For the one-year period all approaches were accepted by both tests for the 99% level.

The Christoffersen test rejected all of the VaRs calculated for Propane and No.6, for all three periods. Due to the fact that Kupiec accepted them both, this indicates that their VaR breaks are too clustered.

The Historical (Simple) approach was the estimation method that was accepted the most by both tests for all three time-periods considered and both levels of significance.

For the one-year period, the Kupiec test approved the VaR for this approach for all of the products, while the Christoffersen test only disapproved of 8 out of 20 VaR breaks. With four of these times coming from Propane and No.6, this leads one to question whether this is limited to these products and how this may be explained considering their properties.

The Variance-Covariance approach did not have as many acceptances as the Historical approach. The VaR based on the standard deviation (SD) was accepted 70% of the time by the Kupiec test, and 45% of the times by Christoffersen.

The VaR based on the EWMA was accepted in 50% of the tests. Kupiec accepted it in 12 of 20 tests.

The amount of VaR breaks for the VaR based on GARCH (1,1) was determined by Kupiec to be significant in 8 of the 20 calculations. The Christoffersen test accepted the test for 6 out of 20 calculations. This results in the GARCH (1,1) being the test with the lowest score in the one-year period VaR.

The amount of VaR breaks are summarized and presented in table 5.1 below, together with the results from the two back tests. The values are given for a 95% confidence level on the first line, whereas the second line of data gives the data for a confidence level of 99%. A method accepted by one of the tests will be marked with either K (Kupiec) or C (Christoffersen).

VaR 95% 99%	VaR breaks	VaR breaks Simple	VaR breaks SD	VaR breaks EWMA	VaR breaks GARCH (1,1)
Propane	0.0568 0.0236	0.0513^{K} 0.0134^{K}	0.0402 0.0203	0.0430^{K} 0.0222	0.0374 0.0194
Jet/ Kerosene	0.0531 0.0125	0.0471^{KC} 0.0111^{KC}	0.0457^{KC} 0.0083^{KC}	0.0481^{KC} 0.0106^{KC}	0.0134 0.0028
HSFO	0.0564 0.0217	0.0522^{KC} 0.0120^{K}	0.0457^{KC} 0.0176	0.0481^{KC} 0.0199	0.0203 0.0079^{K}
No.6	0.0564 0.0199	0.0485^{K} 0.0134^{K}	0.0481^{K} 0.0148^{K}	0.0522^{K} 0.0189	0.0485^{K} 0.0171
Naphtha	0.0555 0.0208	0.0494^{KC} 0.0116^{KC}	0.0485^{KC} 0.0143^{K}	0.0527^{K} 0.0199	0.0494 0.0185
ULSD	0.0536 0.0134	0.0476^{KC} 0.0083^{KC}	0.0439^{KC} 0.0120^{KC}	0.0508^{KC} 0.0134^{KC}	0.0467^{KC} 0.0111^{KC}
Henry Hub nat. gas	0.0587 0.0185	0.0560^{KC} 0.0125^{KC}	0.0421^{K} 0.0152^{KC}	0.0504^{KC} 0.0176	0.0388 0.0143^{KC}
NBP nat. gas	0.0439 0.0097	0.0434^{K} 0.0088^{KC}	0.0217 0.0069^{KC}	0.0166 0.0051^{KC}	0.0171 0.0060^{KC}
Zeebrugge nat. gas	0.0467 0.0157	0.0462^{KC} 0.0102^{K}	0.0263 0.0106^{KC}	0.0296 0.0139^{KC}	0.0250 0.0106^{KC}
ICE Brent	0.0596 0.0236	0.0550^{K} 0.0129^{KC}	0.0494^{K} 0.0180	0.0508^{K} 0.0222	0.0328 0.0134^{KC}
Sum K		10 10	7 7	8 4	2 6
Sum C		6 6	4 5	4 4	1 5

Table 5.1: *Percentage of VaR breaks for each approach and product. Numbers accepted by the Kupiec test and the Christoffersen test are market with K (Kupiec) and/or C (Christoffersen). The data are calculated based on a one-year period.*

A trend is noticeable when comparing the results from the three different time periods: As the time period considered increased, so did the back-test rejections. This is true for all of the four approaches used to calculate the VaR. This can be caused by the impact of the financial crisis that occurred within the price histories collected. As the amount of data considered increase, data from the financial crisis have a greater influence on the amount of VaR breaks. This because they are accounted for more times (remain in the same dataset) as the considered days increase. On the other hand, the extreme events occurring in the financial crisis will impact the VaR estimates of small data sets (i.e. 250 days) more than it will for larger sets of data (i.e. 500 and 1000 days).

The data from the financial crisis are more extreme, and as a result calculations taking them into account tend to result in an overestimation of the VaR.

The back-tests were performed for three time periods for the portfolios, in order to compare how the tests performed for the periods before, during and after the financial crisis. The tests were performed on the oil product Brent, and on portfolio B. Brent confirms the assumption that the data in the financial crisis are more volatile and therefore rejected by the back-tests.

For the calculations of the separation of periods, the financial crisis is defined to last from June 5th 2008 to June 4th 2009. It must be pointed out that these dates are very roughly estimated and the amount of data for the calculations may not be sufficient to provide good results. The table for the results from the VaR back-tests for the three periods (before, within, after the financial crisis) are presented in table 5.2 below. The table for portfolio B can be found in section 5.2.2 Portfolios.

Brent 95% 99%	**VaR Simple**	**VaR SD**	**VaR EWMA**	**VaR GARCH (1,1)**
Total	K KC	K -	K -	- KC
Before the Financial Crisis	KC KC	K KC	KC KC	- KC
Within the Financial Crisis	- -	- -	- -	- -
After the Financial Crisis	**K** **KC**	**-** **KC**	**-** **KC**	**-** **KC**

Table 5.2: *The results from the VaR back-tests for the three periods (before, within, after the financial crisis) for Brent. The financial crisis is defined to last from June 5th 2008 to June 4th 2009*

5.2.2 Portfolios

The VaR methods got rejected significantly more when the calculations were based on the data from the portfolios instead of the individual products. Even though the VaR was calculated for both normal and student-t distributions, both portfolios A and B got the same amount of VaR breaks for the two different distributions. For portfolios C and D, the amounts of VaR breaks for the student-t distribution were less than for the normal distribution. Despite this, the student-t distribution assumption provided more rejections than the normal distribution assumption. A reason for this may be that the VaR got over estimated due to the thicker tails associated with the leptokurtic student-t distribution.

The non-parametric approach was accepted the most for the 250-day period, and was the only method that got accepted by the Christoffersen test. Kupiec accepted the approach for all four portfolios, whereas Christoffersen only accepted the approach for portfolio C.

All of the approaches obtained better results for the 99% confidence level. This may be a result of the lower significance level, making the estimates more extreme. By doing this, more of the subsequent breaks experienced at 95% VaR are removed, and as a result the likelihood of accepting the method increases when using a Christoffersen test.

The amounts of one-year VaR breaks are given in table 5.3 below, together with the results from the back-tests. Student-t data are given in the parentheses. An empty parentheses means that the value is the same as for the normal distribution. For the historical simulation (VaR breaks Simple in the table), it is independent of any assumptions about the underlying distribution.

VaR Norm (Stud-t) 95% 99%	VaR breaks	VaR breaks Simple	VaR breaks SD	VaR breaks EWMA	VaR breaks GARCH (1,1)
Portfolio A	0.0504 (0.0467) 0.0185 (0.0139)	0.0467^{K} 0.0134^{K}	0,0236 () 0,0055^{K} (^{K})	0,0268 () 0,0065^{K} (^{K})	0,0231 () 0,0060^{K} (^{K})
Portfolio B	0.0541 () 0.0171 ()	0,0471^{K} 0,0111^{K}	0,0374 () 0,0139^{K} (^{K})	0,0439^{K} (^{K}) 0,0166 ()	0,0379 () 0,0120^{K} (^{K})
Portfolio C	0.0545 (0.0522) 0.0171 (0.0116)	0,0513^{KC} 0,0116^{KC}	0,0384 (0.0240) 0,0111^{K} (0.0037)	0,0416 (0.0268) 0,0143^{K} (0.0046)	0,0351^{K} (0.0226) 0,0134^{K} (0.0032)
Portfolio D	0.0297 (0.0283) 0.0057 (0.0042)	0,0499^{K} 0,0120^{K}	0,0370 (0.0226) 0,0134^{K} (0.0028)	0,0393 (0.0273) 0,0152^{K} (0.0046)	0,0342 (0.0226) 0,0120^{K} (0.0032)
Sum K		10 10	7 7	8 4	2 6
Sum C		6 6	4 5	4 4	1 5

Table 5.3: *The amount of VaR breaks for the different approaches on the portfolios. The results from the assumption of student-t distributed returns are given in the parentheses. Parentheses are left blank when the two distributions got the same value.*

The results from the periods based on 500 and 1000 trading days are presented in table 5.4 below. The data are from the VaR assuming student-t distribution, and it is evident that the non-parametric (Simple) approach achieves significantly better results than the parametric approaches.

Portfolio 95%500 (1000) 99% 500 (1000)	Simple VaR	SD VaR	EWMA VaR	GARCH (1,1) VaR
A	K (K) K (K)	- (-) - (-)	- (-) KC (-)	- (-) - (-)
B	K (K) KC (KC)	- (-) - (-)	- (-) - (-)	- (-) - (-)
C	KC (KC) KC (KC)	- (-) - (-)	- (-) - (-)	- (-) - (-)
D	- (-) K (K)	- (-) - (-)	- (-) - (-)	- (-) - (-)
Sum K	3 (3) 4 (4)	- (-) - (-)	- (-) 1 (-)	- (-) - (-)
Sum C	1 (1) 2 (2)	- (-) - (-)	- (-) 1 (-)	- (-) - (-)

Table 5.4: *The results from the back-tests performed on the different portfolios based on 500-day data (1000-day data).*

Portfolio B and C were the portfolios that obtained the best results for the back-tests over all. Project B was accepted for more than the non-parametric approach, and is therefore chosen to illustrate the difference when dividing the VaR breaks into three time periods. Results for Portfolio B are given in table 5.5 below.

For the calculations of the separation of periods, the financial crisis is defined to last from June 5th 2008 to June 4th 2009. It must be pointed out that these dates are very roughly estimated and the amount of data for the calculations may not be sufficient to provide good results.

Portfolio B – Stud-t 95% 99%	VaR Simple	VaR SD	VaR EWMA	VaR GARCH (1,1)
Total	K K	- K	K -	- K
Before the Financial Crisis	- K	- K	- K	- K
Within the Financial Crisis	- -	- -	- -	- -
After the Financial Crisis	**KC KC**	**- KC**	**- KC**	**- KC**

Table 5.5: The results from the VaR back-tests for the three periods (before, within, after the financial crisis) for Portfolio B. The financial crisis is defined to last from June 5th 2008 to June 4th 2009.

The back-tests done for the period of the financial crisis rejects more of the VaR values compared with the other periods. For portfolio B, the VaRs in the financial crisis were rejected for all approaches. The normal distribution assumption results in more rejections within the financial crisis than if a student-t distribution is assumed.

6 CONCLUSION

The results presented in the previous chapter will be discussed in this chapter.

The results obtained in this study do not clearly state one or more of the approaches as a correct approach of calculating the VaR. Because this study was limited to a few products withing the oil and gas industry, the conclusions drawn based on the results may not apply for other products and other industries.

None of the approaches were accepted by all tests. One would believe that the parametric approach, based on the more complex volatility calculations EWMA and GARCH (1,1), would provide the best estimates of VaR. However, in fact the more simplistic historical simulation test provided the best results.

Even though this study proves the historical simulation to be the most successful, this conclusion cannot be drawn in general. The parametric approach is more complicated than the historical simulation, and relies on several parameters. Wrong parameters may affect the accuracy of the approach, and result in a rejection by the back-tests.

The MLE performed to estimate the parameters for both EWMA and GARCH (1,1) may not be correct due to the fact that Excel's Solver finds the local maximum, and not the global. Even though the estimation has been done several times, it cannot be guaranteed that the maximum found is the global maximum.

The results from this study indicate that the validity of the approach is not only dependent on the approach, but also on the specific product or asset being studied. It is evident that for some of the products/assets, none one of the approaches are accepted for the longer time periods (500, 1000). Therefore, one may further conclude that the distributions cannot be generalized; and that each asset/product has to be studied individually to determine its distribution.

The reason why the parametric approach did not obtain good results from the back-tests is very likely due to the normal distribution assumptions. Even though the VaR for the student-t assumed portfolios did not result in many acceptances, one can conclude that the data did not follow a normal distribution.

When the portfolios were assumed to be student-t distributed, the back-tests rejected more of the approaches for the majority of portfolios and time periods (one, two and five years). However, the student-t accepted more of the VaRs within the financial crisis.

As the time period considered was increased, so did the back-test rejections. This was especially significant for the products, because the one-year period is only based on the previous 250 trading days, its rate has a higher level of refreshment compared to the two- (500 trading days) and four-year (1000 trading days) periods. Although the one-year period provides the most updated rate, its volatility is greater due to the smaller amount of data.

One would believe that the accuracy of the estimations would increase with increasing observation period, due to the central limit theorem (however, the financial crisis occurred during the time span when the data for this thesis was collected). Nevertheless, by increasing the time period considered, a higher emphasis will be placed on the data derived from the financial crisis, and it will be calculated for a longer period of time when the VaR is calculated. For the shortest observation period, the financial crisis will have a substantial impact for a short, temporary period.

Most of the return distribution curves of the ten products had a shape similar to that of the normal distribution curve. Nevertheless, the tails were to some extent thicker than a normal distribution tail, which was confirmed by the kurtosis. Logically, this will tend to underestimate the true VaR if a normal distribution is assumed.

For the portfolios all of the approaches get sufficiently better results for the 99% confidence level.

All of the approaches get better results for the 99% confidence level. This may be a result of the lower significance level, making the estimates more extreme. By doing this, more of the subsequent breaks experienced at 95% VaR are removed, and as a result the likelihood of accepting the method increases when using a Christoffersen test.

All of the above can be summed into one conclusion; due to the fact that VaR estimations are meant for periods of normality, and that the parametric approach got rejected so many times, the approaches are not applicable when data from the financial crisis is involved. As a consequence it may be more accurate to include a regime shifting method to adjust for extreme periods.

Conclusion 1: The validity of the approach is not only depending on the approach, but also on the specific asset.

Conclusion 2: This study does not provide enough information to conclude whether or not the historical simulation approach is better than the parametric approach.

Conclusion 3: As the time period considered increased, so did the back-test rejections.

Conclusion 4: More VaR approches got accepted on the 99% confidence level evaluating VaR using a Kupiec and Christoffersen test.

Further studies

This thesis studies the VaR of ten different products from the oil and gas industry. The results drawn from this work may not be accurate for other products. It would be interesting to study the properties of other products´ return distributions and determine how the approaches would perform when applied to them.

In addition, it would be interesting to conduct further studies on the parametric approach, and to estimate the best parameters. As well as compare different distributions, i.e. Student-t and Delta Gamma, and try to find a similar distribution for different product returns. Furthermore, it would be ideal to study the effects of the financial crisis, to determine when it began to influence the returns, and perform the back-tests for the three periods (before, during and following the financial crisis).

Lastly, it would be interesting to have an opportunity to study more back-testing methods.

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