Universitetet
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FACULTY OF SCIENCE AND TECHNOLOGY

MASTER'S THESIS

Study programme/specialisation: Industrial economics/Finance	Spring / ~~Autumn~~ semester, 20.17.. Open/~~Confidential~~
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Programme coordinator: Roy Endre Dahl Supervisor(s):	
Title of master's thesis: A Comparison Study of Value at Risk and Expected Shortfall	
Credits: 30 sp	
Keywords: • Value at Risk • Expected Shortfall • Market Theory • Backtesting	Number of pages: ..75……………… +supplemental material/other: ..32… Stavanger,..15. June 2017……… date/year

Preface

This master thesis was carried out at the University of Stavanger (UiS), at the Department of Industrial Economics, Risk Management and Planning, spring 2017.

The thesis was written with my supervisor, associate Professor Roy Endre Dahl who has provided me with data and insightful discussions in forming the outline and given me constructive feedback. I am very thankful for his guidance during the project. In addition, I would like to thank PhD student Henrik Langdalen for feedback, help and support.

Stavanger 04.06.2017

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Abstract

This thesis evaluates the performance of Value at Risk (VaR) and Expected Shortfall (ES) for four portfolios during different scenarios. Both historical VaR and normal VaR together with ES have been calculated for two significance levels, α=1% and α=5%, and two time horizons, h=250 days and h=1000 days. The portfolios represent three commodities markets and a diversified portfolio containing assets from the three markets, grains, energy and metals. Total sample period starts from 2nd of July 2001 until 17th of March 2017 and the scenarios are selected periods during the sample period that have had an influence on the commodity prices. The risk metric performance is evaluated by backtesting the predicted VaR and ES with actual return data. Backtesting has been performed by comparing ratio of violations and observations with significance level, Kupiec test and Christoffersen test.

VaR is a common risk metric tool, and has been implemented in the Basel regulations for financial institutions since the revised Basel I was published in 1996. However, sevarl studies criticize VaR for underestimating risk during times of crisis. During the financial crisis, VaR was unable to predict the severity of the additional loss. This has been investigated for the portfolios in this thesis, and the additional loss was in the worst case 8,4%. Historical VaR is generally better at predicting risk than normal VaR, especially at h=1000 days.

It has been suggested to replace VaR with ES as a standard risk metric for financial institutions that follows the Basel regulations. Thus, the VaR and ES results are compared in order to examine whether ES is a better risk metric, and if ES is able to predict sufficient losses during times of crisis. The results shows that ES is better than VaR to predict losses at high confidence levels. However, during the worst day in the financial crisis, even the best ES metric had an additional loss of 6,1%.

A comparison of the performance to the different portfolios has also been conducted to investigate whether there is a difference between the commodity markets and the diversified portfolios. However, the results shows that there are no significant difference, but the diversified portfolio is generally slightly better in predicting risk.

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1 Introduction

In the revised Basel regulations that were published in 1996, Value at Risk (VaR) was implemented as a risk-modelling tool in order to predict financial risk. It has since then been used by industry and financial institutions to predict potential loss. It has been argued that the model underestimates risk during times of crisis, and that the drawbacks are greater than the benefits, especially by Persaud (2000) and Danielsson (2002). Already in early 2000s, they were critical to VaR and suggested that the models would not sustain a crisis. In 2008, the world economy experienced one of the major financial crisis through all time. The VaR models failed several days in a row, which had devastating consequences and the metric was criticised in a report by Turner (2009) for the UK Financial Services Authority (FAS, 2009)

Since 2008 several Master thesis have been written about VaR with the financial crisis as the base period. However, most of the thesis have had objectives related to optimising mathematical models to investigate if they would have been able to estimate the losses experienced in 2008. Other master students have used interest rates to look at credit risk (Osmundsen, 2016), energy commodities (Dahl, 2009) and derivatives (Kierulf, 2010). In this thesis, commodities from grain, energy and metals markets will be used in a model with dynamic allocations. The minimum variance portfolios for each market in addition to a diversified portfolio containing assets from all three markets will be used to calculate daily VaR and ES. Both historical and normal distributed methodologies will be evaluated. Instead of only looking at the financial crisis and try to find a model that could have predicted the losses, a scenario analysis will be conducted for several periods in order to investigate when and if the risk models actually work.

1.1 Objectives

Evaluating Value at Risk and Expected shortfall as risk metrics in commodity markets is the base of the thesis. In order to understand the results an introduction with theory related to statistics, prices, and risk management is presented. Furthermore, a market analysis of the commodities is conducted. The market analysis is an aid in understanding the price changes during the sample period and identify important market events that affected the related commodities.

The purpose of this thesis has been to compare several scenarios to when the different risk metrics behave the best. The models have been calculated based on dynamic portfolios where the allocations change daily. The allocations are solved by minimising the portfolio variance. In this thesis, we will try to answer the following questions.

- *Which risk metric is the best in risk evaluating?*
- *Is the VaR performance affected by diversification?*
- *How is the performance during times of crisis?*
- *Does time horizon and significance level affect the VaR and ES performance?*

In order to obtain the answers to the objectives, the thesis has the following configurations.

- **Chapter 2** introduces general statistics and portfolio theory. The most important statistical properties for this thesis are briefly presented.
- **Chapter 3** gives a brief summary of price theory. Market definition and economic terms are presented.
- **Chapter 4** introduces various types of risk and risk management tools.
- **Chapter 5** defines value at risk and expected shortfall. The chapter provides different models for VaR and three backtesting approaches for evaluating the risk metrics performances. "regular", Kupiec and Christoffersen backtesting models are introduced.
- **Chapter 6** presents the data that is used in the thesis and gives a careful market analysis of all the twelve commodities. Both the assets and portfolios descriptive statistics can be found in this chapter.
- **Chapter 7** presents the risk models and workflow together with the results complimented with discussion and evaluation.
- **Chapter 8** gives the concluding remarks together with recommendations for future work.
- **Chapter 9** gives the bibliography with all the references used in this thesis.
- **Appendix** supplies the results and discussion part with additional results.

2 Basic Portfolio Theory

2.1 Statistics

This chapter presents formulas for basic statistics used in portfolio theory.

2.1.1 Expected Return

The expected value *E[X],* of a probability distribution *X* is also called the sample mean, and is the centre of the distribution. (Alexander, 2008)

Equation 1 Expected Return

$$\mu = E[X] = \int_{-\infty}^{\infty} x f(x) dx$$

2.1.2 Variance

The variance of a probability distribution of a random variable, is defined as the dispersion about the centre of the density (Alexander, 2008).

Equation 2 Variance

$$Var(X) = \sigma^2 = \int_{-\infty}^{\infty} (x-\mu)^2 f(x) dx$$

$$Var(X) = E[(X-\mu)^2]$$

2.1.3 Standard Deviation

The standard deviation of a probability distribution is the square root of the distributions variance, and is a measure the amount of dispersion of a set of data. A high standard deviation indicates that the data set is spread over a wide range from the sample, while a low standard deviation indicates that the data points are close to the expected value.

Equation 3 Standard Deviation

$$St.dev = \sigma = \sqrt{Var(X)}$$

2.1.4 Covariance

Covariance is a measure of the joint variability of two risky assets return. The covariance is positive if the assets tend to show similar behaviour, and is negative if the assets returns move inversely. The covariance can also be said to be the expected product of their deviations of two random variables, X and Y from their expected returns μ_x and μ_y (Everitt, 2002).

Equation 4 Covariance

$$Cov(X,Y) = E[(X-\mu_x)(Y-\mu_y)]$$

$$Cov\ (X,Y) = \frac{1}{n}\sum_{i}^{n}(x_i-\bar{x})(y_i-\bar{y})$$

The value of covariance is determined by the degree of dependency between X and Y and the size of X and Y, which means that the magnitude of the covariance between two assets calculated on monthly return will normally be greater than covariance between the same two assets calculated on daily return. There correlation is a preferred statistic measure of the linear relationship between two assets is the correlation (Alexander, 2008).

2.1.5 Correlation

Correlation is the dependency between two random variables (Alexander, 2008). The correlation coefficient between two assets can be a number between -1 and 1. If asset X tends to increase when Y increases, and tend to decrease when Y decreases, the two assets are positively correlated. If asset X decreases when Y increases and vice versa, the two assets are negatively correlated. If the two assets are independent of the movement of the other they have zero correlation.

Equation 5 Correlation

$$Corr(X,Y) = \rho = \frac{Cov\ (X,Y)}{\sigma_x\sigma_y}$$

2.1.6 Portfolio variance

The variance of a portfolio with two assets X and Y where the nominal amount *w* is invested in X and 1-*w* is invested in Y, is given by:

Equation 6 portfolio variance, two assets

$$Var\ (p) = w^2\sigma_x^2 + (1-w)^2\sigma_y^2 + 2\rho w(1-w)\sigma_x\sigma_y$$

For a portfolio with several assets, the portfolio variance has to be solved by using vectors. The variance – covariance matrix for the portfolio is denoted ***Var(p)*** and is a function of assets weights and assets returns. The assets return is an *n* x *n* matrix of variances and covariances and is denoted ***V*** and may be written as ***V=DCD*** where ***D*** is the *n x n* diagonal matrix of standard deviations and ***C*** is the correlation matrix of assets returns. The *n* x *1* vector for assets non-negative weights is denoted ***w***.

Equation 7 Portfolio Variance

$$Var(p) = w'Vw = w'DCDw = x'Cx$$

Where, $\boldsymbol{x} = \boldsymbol{Dw} = (w_1\sigma_1, \dots, w_n\sigma_n)$

2.1.7 Skewness

Skewness is a measure of the asymmetry of the probability density function (PDF) (Walpole, 2007). The skewness can be a positive or negative value. A negative skew indicates that the left sided tail is longer and fatter than the right side tail, while a positive skew indicates the right sided tail is longer and fatter than the left side tail. However, in the case of an asymmetric distribution with a fat short tail and a long thin tail, the skewness evens out to zero as for a symmetrical distribution (Alexander, 2008). A normal distribution is a symmetrical distribution, so for the commodities price return, the skewness should be zero for the VaR assumption of i.i.d Normal distribution to hold.

2.1.8 Kurtosis

The kurtosis of a distribution is used to describe the distribution of observed data around the mean. For a normal distribution the kurtosis is 3. For normal distributions it is normal to express the kurtosis as *excess kurtosis* which is kurtosis minus 3. A distribution with positive excess kurtosis is referred to as *leptokurtic.* A leptokurtic distribution has fatter tail such as the student-t and poisons distributions e.g.(Alexander, 2008).

3 Price Theory

This chapter will introduce the underlying economics in order to understand the market analysis in chapter 6.2. The term “market” will be defined together with general theory behind price setting of commodities.

3.1 Definition of a Market

Underlying the definition of a market is the theory of supply and demand, which assumes there exists a market of a certain commodity, bundle of commodities or a good. Given all other relevant variables constant, the interactions between quantity supplied and quantity demanded of the commodity leads to a price setting of the commodity. The price represent the market equilibrium so that the asking price of the last unit supplied equals the last buyer’s willingness to pay (Tveterås, 2000).

A price change for one commodity in a market will yield a change in demand for another commodity. The demand may increase or decrease, depending on the commodities are considered complements or substitutes (Tomek & Kaiser, 2014). Stigler made a well-known definition of the extent of a market in 1966:

“the area within which the price of a good tends to uniformity, allowance being made for transportation” (Stigler, 1966).

Stigler’s definition states that the price difference of two commodities can differ in the short terms, but arbitrage opportunities will force the prices back into market equilibrium so that there is a long-term price relationship between the commodities in the market. An arbitrage opportunity is when there exist a price difference within or between markets so that the commodity can be bought at a low price and sold at a higher price leading to a risk free certain profit investment (Langdalen, 2016).

3.2 Supply and Demand

Figure 1 contains supply and demand curves for two commodities that are traded in two markets at a normalised price *p.* What impact a change in supply in *market 1* has on *market 2* is determined by a *cross-price-elasticity,* which gives the degree of substitutability between the two commodities.

If the markets are perfectly integrated and the two commodities are perfect substitutes, a positive shift in supply (S1 to S1’) of commodity 1 will shift the demand of commodity 2 to the left (D2 to D2’). As the commodities are perfect substitutes, the consumer is indifferent to the two products, and will select commodity 1 over commodity 2, as it is cheaper. Based on the *law of one price (LOP)*, the price in market 2 will be adjusted to p’ in a market equilibrium with market 1. These two markets are perfectly integrated, as a price change in one of the markets will have a response in the other market, giving an equal price in the two markets (Tveterås, 2000).

If the commodities are not perfect substitutes, an increase in supply in market 1 will result in a lower demand in market 2. However, the decrease in demand will not be in the same extent as for two commodities that are perfect substitutes. D’’ marks the shift in demand in market 2 due to the shift in supply in market 1 for commodities that are not perfect substitutes.

In the case where there is no change in market 2 after a change in supply or demand in market 1, the markets are uncorrelated and the cross-price elasticity is zero. Furthermore, the price of commodity is unchanged.

In the case of a positive shift in demand in market 2 as a result of a positive shift in supply in market 1, the products are complements (Asche, Gordon, & Hannesson, 2003). The market impact of changes in supply and demand reveals information about the relationship between commodities. This will later be observed in the market analysis.

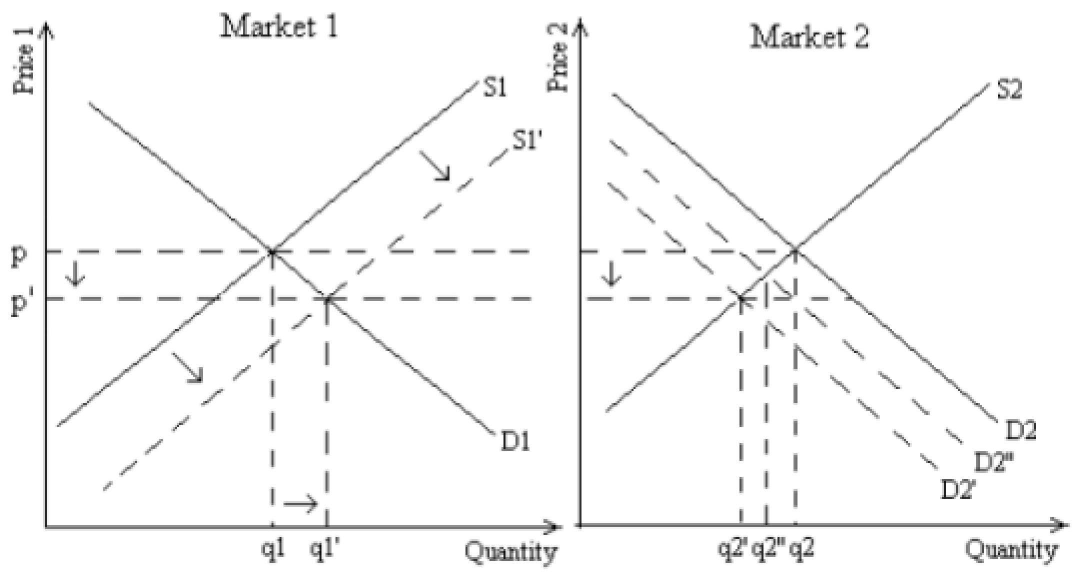

Figure 1: Supply and demand curves for two commodities competing in two markets (Asche et al., 2003).

3.2.1 Exogenous factors affecting short term supply and demand

The price theory explains how the price of a good changes on a long-term basis as a consequence to changes in supply and demand based on new technology, increased production costs, political regulation e.g. On a short term basis, the prices changes daily as a consequence of new information. The information can be numerous exogenous factors that affects the supply and demand and thus the price of a commodity. Example of factors can be geopolitical, climate, technology, speculations, rumours, expectations e.g.

In risk management, the price volatility is one of the major concerns. The VaR and ES risk metrics uses the daily return in order to estimate the potential future loss. The exogenous factors that makes the price fluctuate from day to day by causing uncertainties around the supply and demand are very important in understanding the risk measures. For instance, will speculative news regarding whether or not OPEC will increase or decrease their oil production the next six months, make the oil price fluctuate in the opposite direction of the predicted supply. In chapter 6 during the market analysis, the price changes of the commodities in this thesis will be evaluated. The exogenous factors that have caused the major changes during the sample period will be identified together with their impact on the commodity price.

4 Risk Management

Risk is often defined as the possibility of loss. In financial terms, risk is related to loss on an investment. Risk cannot be eliminated, but proper risk management can mitigate risk and minimize the impact of risk (Tarantino & Cernauskas, 2010)

An investor can be defined as risk averse, risk neutral and risk lover. Depending on the risk type, the investors obtain a utility function that is used to make decisions about investment opportunities. The considered value of an investment is described by the utility function and depends on the trade-off between risk and return. A risk averse investor will try to hedge away the risk with his investment, while a risk lover may select risky assets in order to maximize his potential gain. Figure 2 illustrate the trade-off between risk and return for the three risk attitude profiles.

There are different types of risks. Risk can for instance also be associated with hazards for health injury, quality, black swans etc. In this thesis, the focus will be on financial risk and especially market risk.

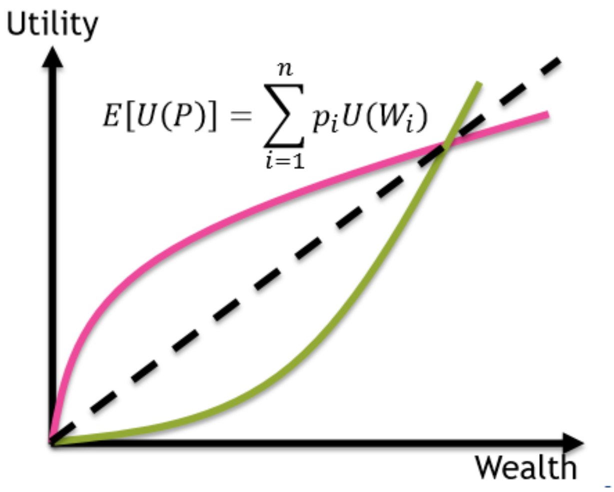

Figure 2: The relationship between risk and return where the pink curve illustrate the utility of a risk averse, the green is for risk lover, and the dotted line is for a risk neutral (Dahl, 2016b)

4.1 Financial Risk

Financial risk can generally be defined as the possibility of losing on an investment. The loss can for example be a result of a transaction or loan default. Risk associated with financial investments can further be categorised into credit risk, market risk, liquidity risk and operational risk (Tarantino & Cernauskas, 2010). The underlying causes of investments risk can be political issues, new governmental regulations, currency changes etc. However, risk is not all bad. By investing in risky assets, the potential gain is also correspondingly larger. There is a risk premium associated with an investment in a risky asset, and is the excess return of the risk-free rate of return. The risk free rate is often associated with the interest rate you get from the bank.

4.1.1 Market Risk

A general definition of market risk is given by James Lam as *"the exposure to potential loss that would result from changes in market prices or rates"(Lam, 2014).*

Market risk can also be called trading risk, as it involves the risk a trader faces on its investment due to changes in equity prices, commodity prices, interest rate and foreign currency exchange rate. For large international corporations, risk associated with currency changes is a major concern. At the time being, Marine Harvest who is based and has most of its production in Norway profit on this risk. The Norwegian krone is weak, and the dollar is strong. Marine Harvest has production costs in Norwegian krone and export and sell their products in dollars, and hence profit from the currency risk today. Figure 3 illustrates why currency changes is a major risk for large international corporations with operations in Norway.

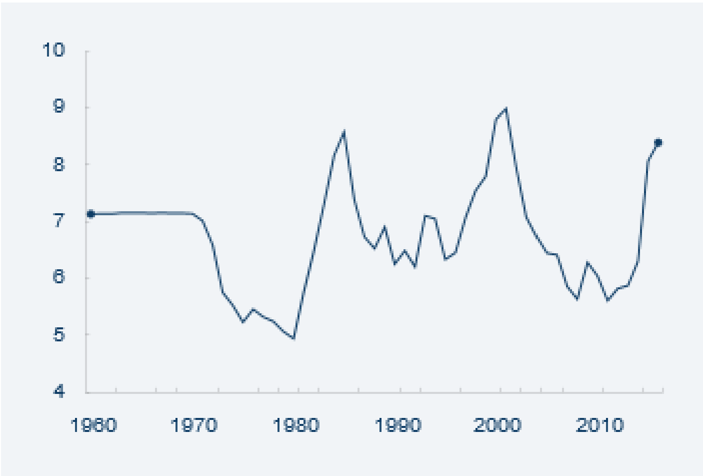

Figure 3: Annual average of USD vs NOK from 1960 to 2016 (Norges-Bank, 2017)

In this thesis, the focus will be on market risk in commodities markets. The risk associated with commodities markets is price fluctuations (Lam, 2014). For a baker who needs to buy wheat to produce bread, he is dependent on buying wheat to a certain price or less in order break even. To minimize his risk for high wheat prices, the baker can buy a forward contract with delivery date sometime in the future. However, if the spot price at delivery date is less than the bakers' price on his forward contract, he has lost on his investment.

In order to have control on the market risk, Value at Risk is a key risk management tool. Based on historical data, Value at Risk is calculated to give the worst loss an investor can expect in one day under normal market conditions and with a given confidence interval (Lam, 2014). Market risk, risk management and Value at Risk will be discussed more carefully in the next chapters.

4.1.2 Credit Risk

Credit risk can be defined as the possibility of a legal contract to be reduced in value or become worthless because the counterparty defaults or go out of business (E. Anderson, 2013). It can be a private person losing his job, and can no longer pay his debt commitments on his mortgage. The bank has security in the house itself, but if the value of the house decrease to less than the debt, this is credit risk. That is what happened with the sub-prime mortgages in US during the financial crisis in 2008 and led to huge losses for the banks. Another example is that a company goes bankruptcy and cannot pay its obligations.

4.1.3 Liquidity Risk

Liquidity risk is generally the risk of being unable to sell an asset fast enough to avoid loss. It is divided into asset liquidity and funding liquidity. *Asset liquidity* is related to not being able to liquidate value that is bound up in fixed asset into cash. For instance, if a person buys a new house before the old house is sold. He takes an asset liquidity risk that he is able to sell the old house at a value larger than his debt. *Funding liquidity* is the risk of being unable to pay a liability leading to a default. Stocks and bond is considered to have lower liquidity risk because they are traded daily.

Following the financial crisis in 2008. A liquidity risk in financial institutions rose. The illiquidity ratio, which reflects a high price impact of trades, tripled from 2007 to 2008 (Næs, Skjeltorp, & Ødegaard, 2011). A liquidity crisis implies that there is a lack of cash in the market, and results in companies are not able to pay their liabilities which in the end results in bankruptcy. The Lehman brother's bankruptcy marked the peak of the financial crisis, as it also had great impact on other companies (Steffensen, 2008).

The liquidity crises further led to crashes in commodities markets, as the demand for resources collapsed. The collapse was a consequence of construction companies, the real-estate business, car-industry and other businesses related to production and turnover of enduring values were hit hard by the financial crisis. As these are companies holding large values in fixed assets, they experienced liquidity crisis and many went bankrupt. These companies uses commodities in their production, and as the demand for their products and their ability to purchase resources as metal and oil fell, so did the commodity prices.

4.1.4 Operational Risk

Operational risk is an unsystematic risk and is associated with breakdown of procedures, systems, human errors or poor management decisions. A good example is Samsung's poor management decision when they launched the mobile phone Samsung Note 4 before it was properly tested. The phone battery caught fire and Samsung had to pull the product from the market. This led to huge losses for Samsung, both the investment in Note 4, but also the stock price fell.

4.2 Risk Management

Risk management can be defined as identification, analysis and prioritisation of risk. Furthermore, risk management is also the response to risk. Different types of response can be: avoidance, mitigation, acceptance, transfer of risk, absorption or research (Gardiner, 2005). Risk cannot be ignored and need a response no matter how small the investment is. It can be as simple as “can I afford the gamble on a 5 week coupon on the lottery”. The potential gain can be millions, but there is a high risk on losing the investment. Do you accept this risk and make the investment?

A more applicable example on risk management will be making an investment alternative to the risk free alternative, savings account in the bank. By taking risk, the investor has to make a decision about the risk and return trade-off discussed earlier in this chapter. The investor should identify investment opportunities, and analyse which investment will most likely give him his expected return, and what risk (potential loss) must he except for this return. If the investors finds the risk to be too high, he can trade some of the risk by diversify his portfolio, that way he will mitigate his risk of loss.

Another way of risk management is to hedge against risk, by investing in financial instruments that has opposite payoff function. This will be discussed more carefully in the next subchapter.

For Banks and other financial institutions, there are strong governmental rules for how much risk they can take. These rules and regulations must be part of their risk management.

4.2.1 Hedging risk with derivatives

In order to reduce risk, an investor can buy an asset that is inversely correlated to the asset he possess. A perfect hedge is when the two assets are perfectly uncorrelated, meaning that if asset X rises 10%, asset Y will fall 10%. A hedge minimize the risk of loss, but it also reduces the potential return.

The most common ways to hedge is by buying financial instruments (also called derivatives) that has the opposite payoff expectations than the position that the investor already hold. For example, an oil company who is naturally long on oil price can hedge by buying a derivative, such as a short future contract on jet fuel. As shown by the simple sketch in Figure 4, When the oil price increase, the investor will gain on his long position in oil, but lose on his short position on jetfuel future, resulting in a small return on the hedging position. Other derivatives that are used to hedge the risk are forward, options contracts and swaps.

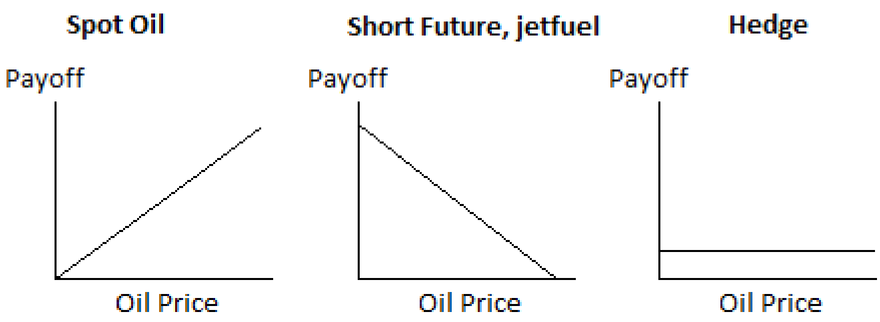

Figure 4: Payoff function for Spot price, jetfuel future and hedge. Source: author.

4.2.2 Bank Regulations: Basel

In 1974, the committee of Banking Regulations and Supervisory Practises, later knowns as the Basel committee, was founded. It was founded in order to enhance financial stability by improving the quality of banking supervision. The committee has announced three standards since late 1980s, which includes regulations on capital to risk requirements. The standards are called Basel I (1989), Basel II (2004) and Basel III (2010). In addition, Basel I was adjusted in 1996 to incorporate market risk accorded for the banks risk exposers to market risk; foreign currency, traded debt securities, equities, commodities and options. This adjustment led the banks to use their own models, Value at Risk, for measuring their capital requirements. (Basel-Committee, 2017).

After the financial crisis in 2008 leading to the bankruptcy of Lehman Brothers, and the saviour of several large banks as HBOS, Merrill Lynch etc, the Basil committee implemented Basel III with stronger capital to risk requirements (Mathiason, 2008),(Basel-Committee, 2017). The regulations in Basel III includes stricter capital requirements for the banks in their investments. In addition, it also requires that the banks have more liquidised capital (Åvitsland, 2014). The purpose of the regulations is that in case of a new crisis, the banks will be better prepared and to sustain the losses in case of a new crisis. The potential socioeconomics loss is tremendous in case one of the greater banks go bankrupt.

There has been raised questions to whether the Value at Risk model is sufficient to calculate the potential loss as it has its limitations. This issue will be further discussed in the chapter about Value at Risk.

4.2.3 Diversification of risk with Portfolio allocations

By investing in various assets that have no correlation or are negatively correlated with each other the risk of loss is reduced by the diversification effect. This is because the assets do not move in the same direction. For a portfolio containing the assets X and Y, which are negatively correlation with each other, when the price of asset X increase, the price of asset Y decreases. The magnitude of the change in Y when X changes is determined by the correlation. Thus, a price increase in X will cause a ρ change in Y.

Figure 5 below shows an example of the relation between a portfolios volatility (standard deviation) and correlation for a portfolio with two risky assets. The closer to -1 the correlation is, the less volatile is the portfolio. When two assets has a correlation of -1, they are said to be a perfect hedge.

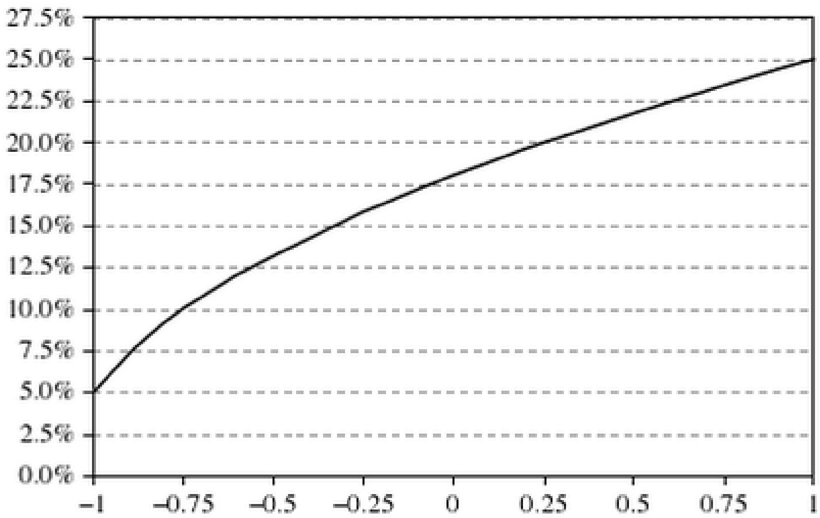

Figure 5 The effect of correlation on portfolio volatility (Alexander, 2008).

The purpose of portfolio allocation is to minimise risk and maximise return. This effect can be explained by applying the Markowitz problem which minimises the portfolio variance but adds constraints to the expected return. That way an investor can obtain the allocations that gives him a risk he is comfortable with and payoff to an acceptable criteria.

Equation 8 Markowitz Problem

$$\min_{w} \boldsymbol{w}'\boldsymbol{V}\boldsymbol{w} \ \textit{such that} \ \sum_{i=1}^{n} w_i = 1 \ \textit{and} \ \boldsymbol{w}'E(\boldsymbol{r}) = \bar{R}$$

Where $E(\boldsymbol{r})$is the vector of expected returns on each asset and $\bar{R}$ is the target level of the portfolio return (Alexander, 2008).

5 Analysis tools for financial risk management

This chapter will present some of the most common analysis tools to risk management in financial investments.

5.1 Approaches to Risk Management

5.1.1 Scenario analysis

A scenario analysis of an investment is the process of estimating the expected return assuming specific changes in the portfolios assets of key factors such as interest rate. Scenario analysis is used to analyse a theoretical worst-case scenario, in order to identify the potential loss given a scenario. A typical approach is to apply the securities volatility and compute the expected return for the portfolio if each security generates returns that are two or three times the assets volatility above and below the average return. A market crash is an example of a scenario where the assets volatilities are larger than normal times. These extreme volatiles can be simulated and the result will be a reasonable certain change in portfolio value due to this extreme scenario (Investopedia, 2017).

When applying historical data to analyse the worst case scenario with regards to investment loss. An approach can be to use only data from a period where an event occurred that resulted in a market crash, for instance the financial crisis in 2008. Such a scenario analysis will be carried out in this thesis.

5.1.2 Sensitivity analysis

A sensitivity analysis recognises the uncertainty associated with the variables by isolating single variables and records the range of possible outcomes (Dahl, 2016a). For investments in agriculture spot market, an analysist can isolate factors as net margin, supply and demand. Based on historical data the results of the analysis will be how much a 1% change in a variable will affect the price of the commodity. A sensitivity analysis is often called a “what if” analysis. The sensitivity analysis measures the sensitivity to a risk factor, ignoring the risk of the factor itself, which is the major disadvantage of sensitivity analysis (Alexander, 2009).

5.1.3 Loss distribution

When analysing financial risk, a good starting point is to look at history and analyse the impact events have had on different markets. For instance, what happened with the wheat price during the Arabic spring? What was the influence on the oil price during the Gulf war, OPECs embargo against USA after the Yom Kippur war, financial crisis in 2008 etc. By analysing the tails of a frequency histogram or a distribution function of returns, the potential loss with an investment can be estimated at different significance levels (E. J. Anderson, 2013).

5.2 Value at Risk

Value at Risk (VaR) is a risk management approached applied by financial institutions. The risk metric is based on the loss distribution approach defined in previous sub chapter. From the 1990s regulators and large international banks started using VaR as a risk metrics, and is today used by almost all financial institutions (Alexander, 2009). VaR has been accepted as a good method to predict the potential loss of an investment as the market behaviour generally falls within the prediction of VaR. However, the financial crisis in 2008 showed that risk metric did not work during times of crisis and was not able to capture the amount of losses that occurred (Daníelsson, 2008; A. D. Persaud, 2008; Wong, 2013). Both (A. Persaud, 2000) and (Daníelsson, 2002) argued long before the financial crisis that the statistical models as VaR would not be able to capture crisis as the one we experience in 2008. The reason is that market data is endogenous. During normal times, people or investors act individually, where some are selling and others are buying assets. In times of crisis investors acts together, selling away risky assets and buy safer securities. Thus, the statistical properties of financial risk are endogenous. The models that are based on market behaviour and statistical analysis made in "normal" and stable markets that does not give sufficient guidance to severity of losses in times of crisis.

Value at Risk has a wide range of applicability, which is one of the major advantages. However, the metric has also several disadvantages. A disadvantage that is often used as an argument against the metric is that VaR is not necessarily sub-additive (Alexander, 2009; Artzner, Delbaen, Eber, & Heath, 1999; Daníelsson, Jorgensen, Samorodnitsky, Sarma, & de Vries, 2012). Meaning that VaR does not consider diversification, which contradicts with the modern portfolio theory. It is in other words possible to construct two portfolios X and Y so that VaR(X+Y) > VaR (X) + VaR (Y). Expected shortfall (ES) is another risk metric, closely associated with VaR which *is* sub-additive (Alexander, 2009; Daníelsson et al., 2012). In this thesis, a comparison between ES and VaR will be carried out.

Danielsson published in 2002 an article where he pointed out the major disadvantages of VaR. The first is already mentioned, VaR is not necessarily sub-additive and thus not coherent. Second, VaR does not indicate potential loss. It only answers the question "With 1-α confidence, the portfolio will not lose more than the Value at Risk". Furthermore, VaR is only concerned with the losses at its confidence level that implies that VaR have very little relevance to the probability of bankruptcy, finical crashes and systematic failures.

The advantages of VaR as a risk metric are several, and one of them is the simplicity. It is easy to understand, carry out and the method provides an actual number for potential loss at a significance level. Other features are listed below and are taken from (Alexander, 2009).

- It measures the risk of the risk factors as well as the risk factors sensitivities.
- It can be compared across different markets and different exposures.
- It is a universal metric that applies to all activities and to all types of risk.
- It can be measured at any level, from an individual trade or portfolio, up to a single *enterprise-wide VaR measure* covering all the risks in the firm as a whole.
- When aggregated (to find the total VaR of larger and larger portfolios) or disaggregated (to isolate component risks corresponding to different types of risk factors) it takes account of dependencies between the constituent assets or portfolio.

5.2.1 Defining value at risk

Value at Risk is the loss quantile of the profit and loss distribution (Wong, 2013). VaR has two basic parameters, a significance level α, and a time horizon h, which is trading days over which VaR is measured.

The most common ways of calculating VaR is by applying one of the three parametric methods, Historical VaR, Normal distribution VaR and Monte Carlo analysis. The methods are based on historical data under the assumption that history will repeat itself. VaR is the exposure of risk associated with an investment in a portfolio. In this thesis, the focus will be on linear risk, related to long positions in commodities markets.

5.2.2 Historical VaR

Historical VaR is the easiest method for calculating the potential loss of an investment. The method applies historical data directly by using return data and does not assume any distribution model and is applied by industry and financial institutions (Pérignon & Smith, 2010). It is hard to argue that the ease of the model is its strongest advantage. The fact that the model does not assume any distribution model can be said to be an advantage. It is clearly favourable if the model is poor. A poor model will provide poor results. However, if the sample size is too small, then the historical simulation will not contain enough large losses to provide a VaR at a high confidence level. If the sample size is too large, then the most recent observations that are presumably the most relevant to tomorrows results, will carry little weight and be sufficiently responsive to recent returns (P. F. Christoffersen, 2012). In order to overcome some of the drawback of sample size sensitivity, a *weighted historical simulation (WHS)* can be applied. WHS uses assigns the data (returns) in a sample with probability weights that is declining exponentially through the past (P. F. Christoffersen, 2012). That way the most recent observations will be weighted heavier than data from the far past.

The methodology of historical VaR: For a model of 1000 days, the expected VaR for day 1001 can be found by sorting the data and finding the 10^{th} worst outcome with a 99% confidence.

5.2.3 Normal VaR

The basic assumption of normal VaR is that the returns on the portfolio is *i.i.d.* independent and identically distributed with a normal distribution (Alexander, 2009). Normal VaR is calculated using daily returns and basic portfolio theory from chapter 2. The following equations will lead to the normal VaR expression.

Equation 9 Value at Risk

Value at risk can be calculated from the below formula.

$$VaR_{hr,\alpha} = -x_{ht,\alpha}$$

Let X denote returns under the assumption that X is i.i.d.

$$X_{ht} \sim N\left(\mu_{ht}, \sigma_{ht}^2\right), \qquad \mu_{ht} \approx 0 \; for\; daily\; returns$$

Want to derive a formula for the α quantile return, $x_{ht,\alpha}$ such that:

$$P\left(X_{ht} < x_{ht,\alpha}\right) = \alpha$$

Standard normal transformation

$$P\left(X_{ht} < x_{ht,\alpha}\right) = P\left(\frac{X_{ht} - \mu_{ht}}{\sigma_{ht}} < \frac{x_{ht,\alpha} - \mu_{ht}}{\sigma_{ht}}\right) = P\left(Z < \frac{x_{ht,\alpha} - \mu_{ht}}{\sigma_{ht}}\right) = \alpha$$

Where $Z \sim N(0,1)$

By definition:

$$\frac{x_{ht,\alpha} - \mu_{ht}}{\sigma_{ht}} = \phi^{-1}(a) \;\rightarrow\; P\left(Z < \phi^{-1}(a)\right) = \alpha$$

Where ∅ is the normal distribution function. Using this formula and solve for $x_{ht,\alpha}$ and substitute it into $VaR_{hr,\alpha} = -x_{ht,\alpha,}$we will obtain the function for Value at Risk.

$$VaR_{ht,\alpha} = \phi^{-1}(1-a)\sigma_{ht} - \mu_{ht}$$

Which will give VaR as the percentage of the portfolio value. By multiplying the result with the investment, the monetary value will be obtained.

Normal linear VaR assumes a normal distribution. For most samples, this is not the case and the model may therefore be poor to obtain an accurate VaR at high confidence level. The distributions may be affected by skewness or kurtosis. Chrisoffersen made in 2012 a comparison for VaR by using a normal distribution model and non-normal model with a kurtosis of 3. The comparison showed that for significance levels less than 2,5%, the non-normal VaR was much larger than for the normal. This results shows the weakness of normal VaR in the end of the tails where the extreme risk is hidden. The figure below presents the relative difference in VaR between the non-normal model and the normal model (P. F. Christoffersen, 2012).

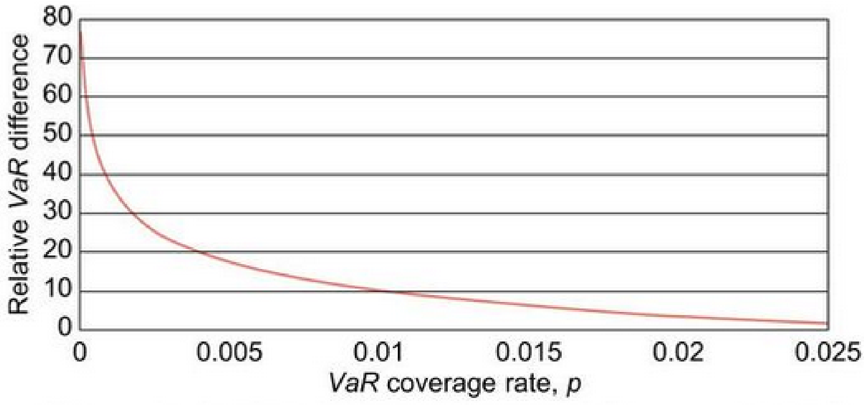

Figure 6: Relative difference in VaR between the nonnormal model and the normal model (P. F. Christoffersen, 2012).

5.2.4 Monte Carlo

Monte Carlo simulation uses random sampling of returns to obtain a distribution of possible outcomes. The method can potentially map other underlying risk factors more accurately by using more suited distributions and correlations. However, the method can become very complex. Another downside is that the method uses random draws from the distribution. Because of that, the simulation should be carried out at least 10 000 times.

The estimation method:

1. Identify the return distribution with skewness and kurtosis, expected return and standard deviation.
2. Estimate the dependencies and correlation between the assets in the portfolio
3. Draw randomly from the distribution.
4. Use historical or normal VaR to calculate the potential loss based on the Monte Carlo simulation.

5.3 Expected Shortfall

Expected shortfall (ES) is another method to estimate distribution loss. ES focuses on the extreme events in the tail and gives information on the range of possible extreme losses with associated probability for each outcome. ES accumulates this information into a single number by computing the average outcomes in the tail, weighted by their probabilities (P. F. Christoffersen, 2012). Thus, ES gives the expected loss given that the investment will actually get a loss in the α tail, while VaR only gives the loss at α with a 1-α confidence that the loss will not be worse than this.

Another advantage of ES is that it is a coherent risk metric also implying it is sub-additive and thus considers diversification. Because ES consider diversification and the extreme losses, it is said to be a better risk metric than VaR (Alexander, 2009; P. F. Christoffersen, 2012).

Equation 10 Defining ES mathematically

Let denote X as the return on the *h*- day.

$$VaR_{h,\alpha} = -x_\alpha$$

Where x_α denotes the significance α of the distribution X, i.e. $P(X < x_\alpha) = \alpha$.

ES expressed as a percentage of portfolio value is then

$$ES_\alpha(X) = -E(X|X < x_\alpha)$$

Since ES is a conditional expectation, it is obtained by dividing the probability-weighted average of values of the X distribution that are less than $x_\alpha$by $P(X < x_\alpha)$ so when X has the density function *f(x)*:

$$ES_\alpha(X) = -\frac{1}{\alpha}\int_{-\infty}^{x_\alpha} xf(x)dx$$

For the normal linear VaR model, ES can be derived according to (Alexander, 2009).

Equation 11 Expected Shortfall for normal linear Value at Risk

Let the random variable X denote the return on the *h*-day. If $X \sim N(\mu_h, \sigma_h^2)$ then

$$ES_{h,\alpha}(X) = -\frac{1}{\alpha}\varphi\left(\phi^{-1}(\alpha)\right)\sigma_h - \mu_h$$

Where φ and ϕ are the density and distribution functions so that $\phi^{-1}(\alpha)$ is the significance α of the standard normal distribution and $\varphi(\phi^{-1}(\alpha))$ is the height of the standard normal density at this point. The proof of the equation can be found in (Alexander, 2009).

5.4 Backtesting VaR

Backtesting is a simulation of a model with past data to measure the accuracy and effectiveness of the VaR model. The value at risk model claims that: For a significance level of α, in 1- α of the days in the time horizon *h*, the loss will not exceed VaR. Let say α=5% and *h*=1000 days, then the VaR model is acceptable if the loss does not violate the VaR more than 50 days. Backtesting of the past data will reveal how many days the VaR is violated. For α=5%, the model is not acceptable if the actual loss is larger than VaR in more than 5% of the measures during the time horizon *h.*

Furthermore, a VaR model may be acceptable regards to fewer violations than α% within the time horizon but still be a poor model due to the clustering effect. For a 5% VaR model over 1000 days, let assume the losses exceeds VaR in 40 of these days. Then the model will be acceptable. However, if all these 40 days are within a very short period as three months, then there is a clustering of days with losses. The investor may not be able to handle these extremes and the risk of a default would be much higher than if these violations came scattered randomly within the time period (P. F. Christoffersen, 2012).

In this thesis, the VaR and ES models will be tested using "regular" backtesting based on number of VaR/ES violations, observations and significance level. In addition, Kupiec and Christoffersen tests will be carried out.

If $I_t(\alpha)$ is the variable associated to the ex-post observation of a α% VaR exceedance at time t, and r_t is the return at time t:

$$I_t(\alpha) = \begin{cases} 1 \; if \; r_t < \; -VaR_{t|t-1}(\alpha) \\ 0 \; else \end{cases}$$

The regular test is carried out as a hypothesis test with:

$$H_0: \frac{\sum I_t(\alpha)}{N} \leq \alpha$$

H₀ is rejected if $I_t(\alpha) > \alpha$.

5.4.1 Kupiec test

The Kupiec test and model is described on Mathworks webpage, and their work is republished in this chapter (MathWorks, 2017). In 1995, Kupiec introduced a proportion of failures (POF) test. It uses a likelihood ratio to test whether the probability of exceptions is synchronised with the probability *p* implied by the VaR confidence level.

Equation 12 Kupiec POF test statistics

$$LR_{POF} - 2log\left(\frac{(1-p)^{N-x}p^x}{\left(1-\frac{x}{N}\right)^{N-x}\left(\frac{x}{N}\right)^x}\right)$$

Where x is the number of failures, N is the number of observations and p=1-VaR level.

The Kupiec test is asymptotically distributed as a chi square variable with one degree of freedom. The VaR model is rejected if the likelihood ratio exceeds a critical valued that is determined by the VaR level.

5.4.2 Christoffersen Test

When the return of an assets is a loss that exceeds the VaR models prediction, the VaR model breaks for that day. It has often been observed that these violations occurs in clusters.

Christoffersen presented a backtesting model in 1998 that rejects VaR with clustering violations. The model is an independence test and uses a likelihood ratio with a chi distribution with one degree of freedom to test the risk metric model. The model uses the violation from regular dependence backtest and estimates what is the probability of getting a violation tomorrow, given that today was also a violation, π_{11}. Together with the probability of a violation tomorrow given that today was not a violation, π_{01}. This gives the probabilities of no violation tomorrow given that todays was π_{10} or no violation tomorrow, given that today was not a violation, π_{00}.

If the violations are independent, then, π_{01}.= π_{11}=π which can be considered as a hypothesis and can be tested with the following likelihood ratio.

Equation 13: Christoffersen Test

$$LR = -2ln\left[L\left(\widehat{\Pi}\right)/L\left(\widehat{\Pi_1}\right)\right] \sim \mathcal{X}_1^2$$

Where $L\left(\widehat{\Pi}\right)$ is the likelihood and

$$\widehat{\Pi} = \begin{bmatrix} 1-\hat{\pi} & \hat{\pi} \\ 1-\hat{\pi} & \hat{\pi} \end{bmatrix}$$

The test is rejected if the p-value is less than the significance level α of the risk metric.

A more careful deviation of the Christoffersen test can be found in (P. Christoffersen, 2011).

6 Data Analysis

All data is collected from the Thomson Reuters Eikon (DataStream) database. The data is collected on trading days in the sample period from July 2nd 2001 until March 17th 2017. Full description of the instruments is presented in Appendix B. The data has been processed so that all commodities are traded on the same dates in the sample period. For the durum wheat and barley, it was difficult to obtain complete daily data for the whole sample period. By assuming that durum and barely increase and decrease linearly with wheat in these periods, the data has be calculated by using linear interpolation. The historical data is unadjusted, since all data is presented in USD and VaR is calculated with the price change data.

The data has been collected from three commodities markets, grains, energy and metals. For the analysis in next chapter, the assets will be divided into four portfolio, one for each market and a fourth with assets from each market to investigate the diversification effect. In the following subchapters, an overview with analysis of the prices will be presented together with a short market analysis explaining the major booms and bursts in price for the different assets.

6.1 Statistical properties

In this subchapter, descriptive statistical properties for the dataset will be presented together with the distribution analysis. In the further analysis, the logarithmical percentage change will be used:

Equation 14: logarithmic percentage change

$$X_i = \log\left(\frac{x_i}{x_{i-1}}\right)$$

In this thesis, VaR will be calculated based on the assumption that the dataset is normal distributed. Form most datasets this is not true, as they usually have skewness and kurtosis. To investigate the normality of the dataset, a Jarque Bera goodness of fit test will be carried out as a hypothesis test.

6.1.1 Descriptive statistics commodities

The Jarque Bera goodness to fit methodology uses skewness and kurtosis to test the sample of observation distribution to the statistical normal distribution (Walpole, 2007). The Jarque Bera statistic asymptotically converges to a chi-squared distribution (χ^2) with two degrees of freedom for increasing sample size. The observations of the commodities have been tested using the JB- test for a significance level of 5%. The critical value of the chi-squared distribution with a significance level of 5% and 2 degrees of freedom is 5,991. The test has been carried out as a hypothesis test:

H_0= the distribution is a normal distribution vs.
H_1= the distribution is not a normal distribution.

The null hypothesis is rejected if the Jarque- Bera test of the commodity is bigger than $\chi^2_{0,05,2}$=5,991. The Jarque-Bera (JB) is calculated by applying the following formula.

Equation 15 Jarque Bera test

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

Where *n*= number of observations, *k*=degrees of freedom, *S*=skrewness, *C*=kurtosis.

The results of the Jarque Bera test is presented in Table 1. It is obvious that the null hypothesis is rejected for all commodities.

Table 1: Descriptive Statistic for commodities.

	WHEAT	DURUM	BARLEY	BRENT	WTI	NG-ZEE	NG-HH	COPPER	BRONZE	PT	PD	AU
Count	3969	3969	3969	3969	3969	3969	3969	3969	3969	3969	3969	3969
Mean	1,26E-04	1,12E-04	1,28E-04	1,77E-04	1,53E-04	1,99E-04	-1,33E-05	3,30E-04	2,33E-04	1,19E-04	5,42E-05	3,66E-04
St. Error	3,56E-04	3,68E-04	2,88E-04	3,61E-04	4,17E-04	1,08E-03	7,54E-04	2,93E-04	3,19E-04	2,48E-04	3,80E-04	2,71E-04
Median	0	0	0	0	0	0	0	0	0	0	0	0
Mode	0	0	0	0	0	0	0	0	0	0	0	0
St.Dev	0,0224	0,0232	0,0182	0,0228	0,0263	0,0680	0,0475	0,0184	0,0201	0,0156	0,0239	0,0171
Var	5,02E-04	5,36E-04	3,30E-04	5,18E-04	6,91E-04	4,62E-03	2,26E-03	3,40E-04	4,05E-04	2,44E-04	5,73E-04	2,92E-04
Kurtosis	7,017	287,151	69,041	3,130	14,670	26,442	175,168	17,592	312,424	22,323	64,867	555,389
Skew	-0,170	-7,007	-0,104	-0,147	0,372	-0,529	0,434	-0,158	-7,519	0,180	0,357	0,671
JB	2,69E+03	1,34E+07	7,21E+05	1,71E+01	2,26E+04	9,10E+04	4,90E+06	3,52E+04	1,59E+07	6,18E+04	6,33E+05	5,04E+07
Range	0,398	1,097	0,629	0,271	0,614	1,711	2,073	0,478	0,947	0,352	0,818	1,105
Min	-0,212	-0,704	-0,318	-0,149	-0,243	-0,961	-1,011	-0,249	-0,652	-0,160	-0,389	-0,550
Max	0,186	0,393	0,310	0,121	0,370	0,750	1,062	0,230	0,295	0,193	0,428	0,555

6.1.1.1 Distribution

As the JB- test above showed together with the kurtosis and skewness results, none of the commodities have a price change distribution that is normal distributed. This can also be visually observed by figure below. The commodities frequency histogram is plotted together with the normal distribution bell curve. The normal density probability function, PDF (=norm.dist in excel) has been calculated for the steps between the max and min observed data. However, for visualisation purpose an x-axis (returns) from -0,15 to 0,15 has been used for the distribution plots.

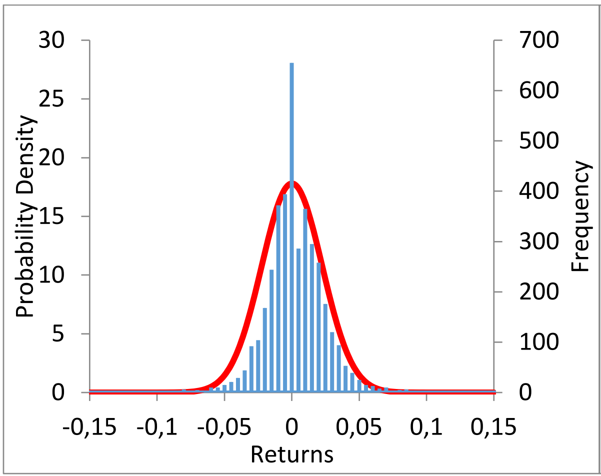

Figure 7: Wheat - Histogram and PDF, price changes

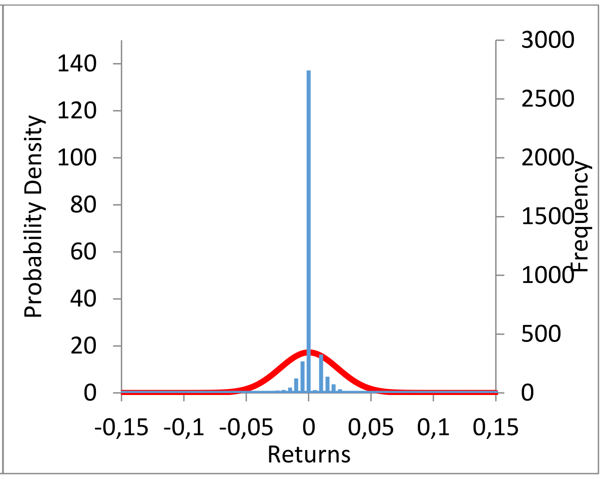

Figure 8: Durum - Histogram and PDF, price changes

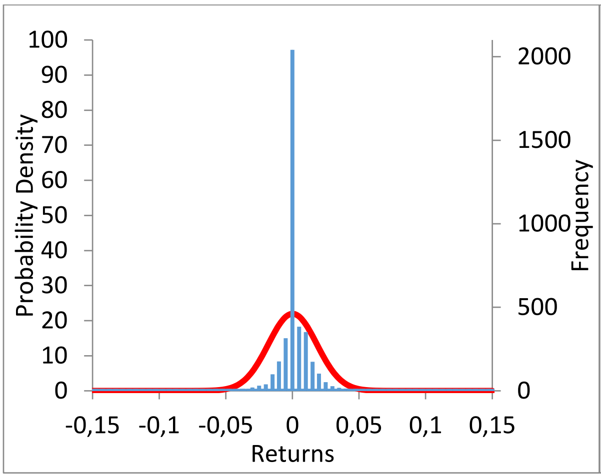

Figure 9: Barley - Histogram and PDF, price changes

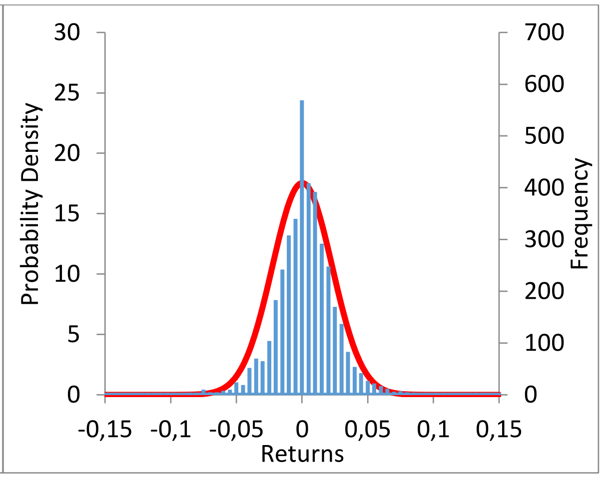

Figure 10: Brent - Histogram and PDF, price changes

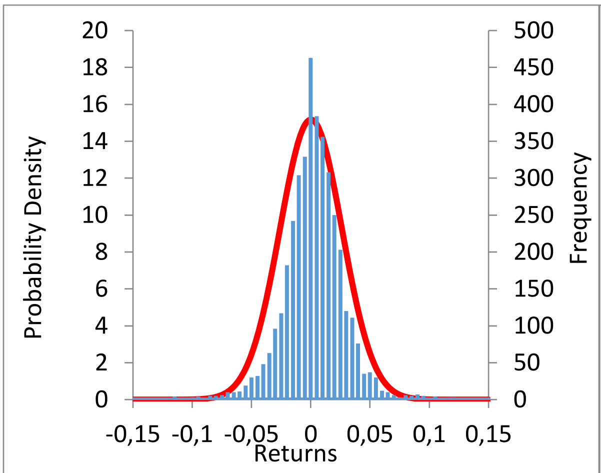

Figure 11: WTI - Histogram and PDF, price changes

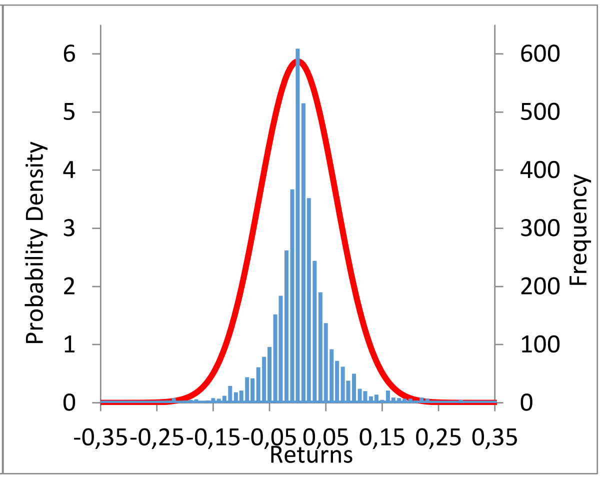

Figure 12: NGAS ZEE - Histogram and PDF, price changes

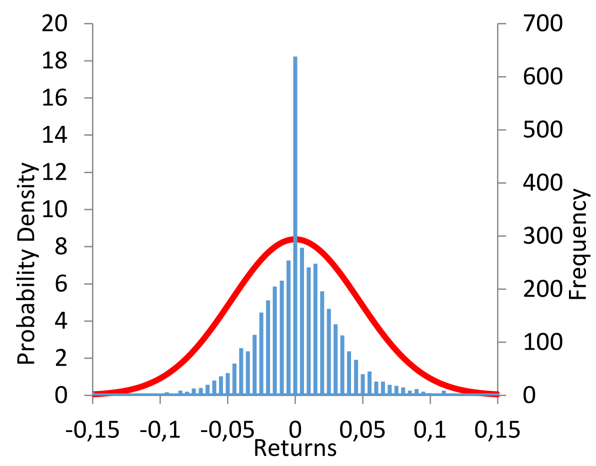

Figure 13: NGAS HH - Histogram and PDF, price changes

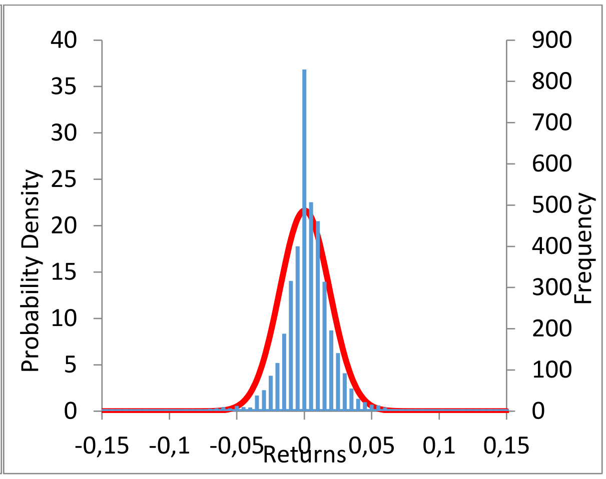

Figure 14: Copper - Histogram and PDF, price changes

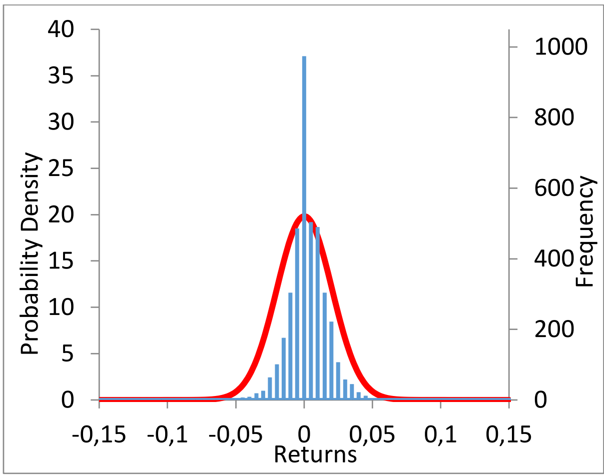

Figure 15: Bronze - Histogram and PDF, price changes

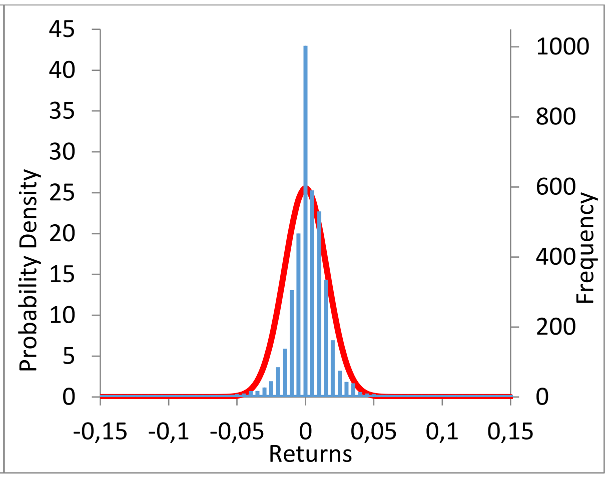

Figure 16: Platinum - Histogram and PDF, price changes

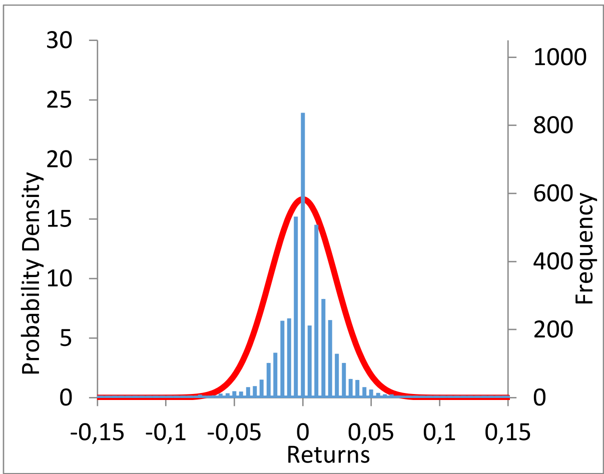

Figure 17: Palladium - Histogram and PDF, price changes

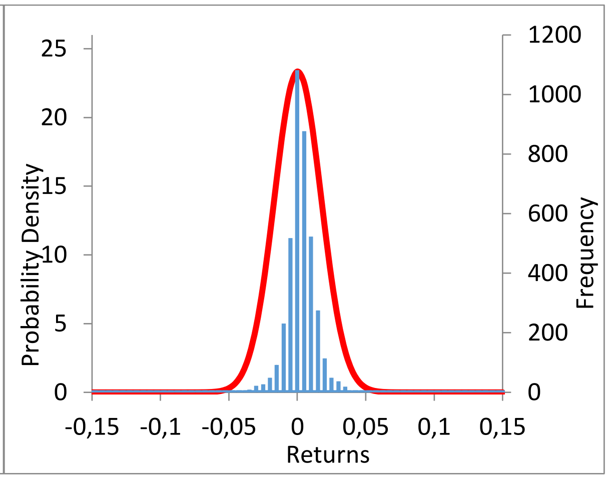

Figure 18: Gold - Histogram and PDF, price changes

6.1.2 Descriptive statistics portfolios

This chapter presents the descriptive statistics for the four portfolios with daily returns based on minimum variance allocations for 250 days rolling window. As mention in the introduction to chapter 6, the fourth portfolio contains assets from each commodity market. The assets are Wheat, Brent oil, Henry Hub Natural Gas, Copper, Gold. The reason for selecting these assets will be explained in 6.2.4.

The portfolios also have high values of kurtosis and skewness and fail the JB test for normality, and cannot be said to be normal distributed. The data is presented in the table below.

Table 2: Descriptive statistics portfolio P1-P4.

	P1	P2	P3	P4
Count	3718	3718	3719	3718
Mean	-2,88E-05	5,22E-05	3,18E-04	3,19E-04
Standard Error	2,02E-04	3,14E-04	1,76E-04	1,68E-04
Median	0,00	-8,61E-05	3,94E-04	3,57E-04
Mode	0,00	0,00	0,00	0,00
Standard Deviation	0,0123	0,0191	0,0107	0,0102
Sample Variance	1,51E-04	3,67E-04	1,15E-04	1,04E-04
Kurtosis	302,884	5,925	37,035	50,553
Skewness	-10,182	-0,315	-0,342	0,999
JB	1,40E+07	1,39E+03	1,80E+05	3,51E+05
Range	0,531	0,307	0,328	0,341
Minimum	-0,376	-0,216	-0,171	-0,156
Maximum	0,155	0,090	0,157	0,184
Sum	-0,107	0,194	1,183	1,184

6.1.2.1 Portfolio Distributions

The portfolios frequency histogram is plotted together with the normal distribution bell curve. The normal density probability function, PDF (=norm.dist in excel) has been calculated for the steps between the max and min observed data. However, for visualisation purpose an x-axis (returns) from -0,15 to 0,15 has been used for the distribution plots.

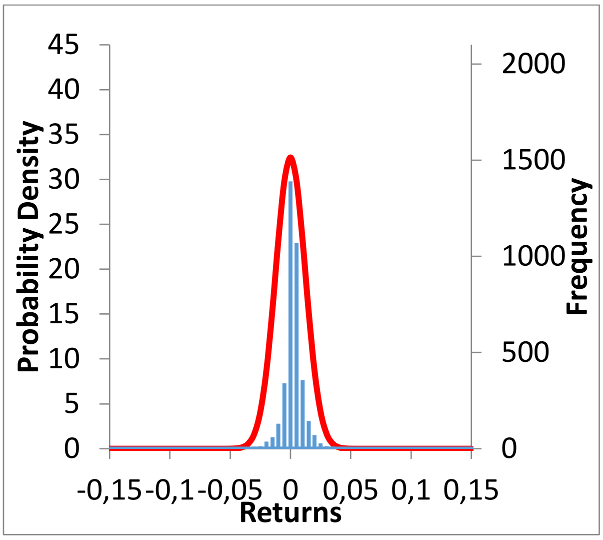

Figure 19: P1, grains - Histogram and PDF, price changes.

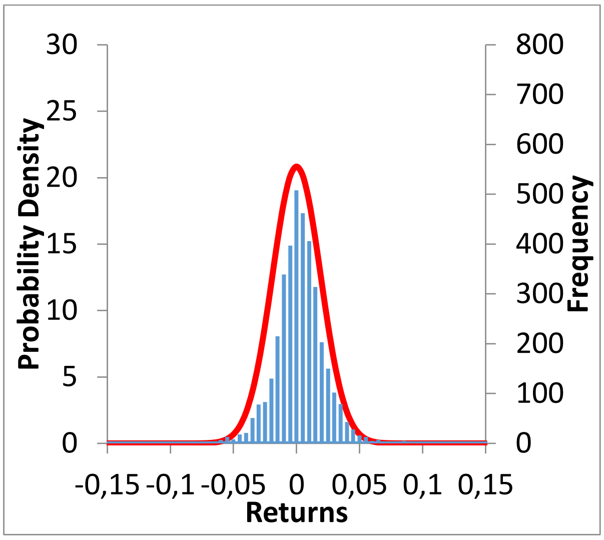

Figure 20: P2, energy - Histogram and PDF, price changes

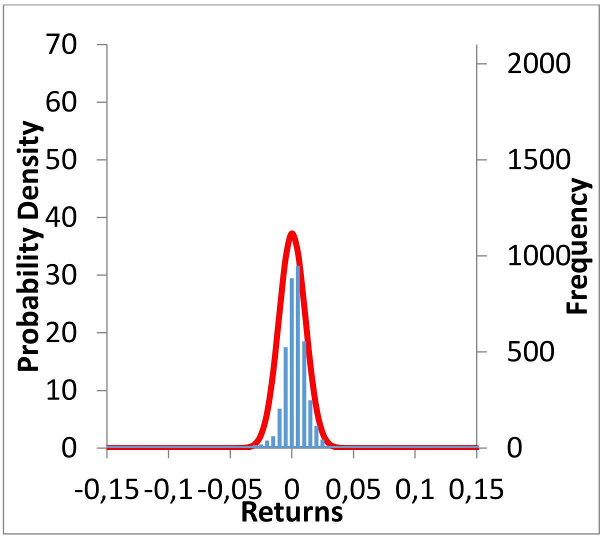

Figure 21: P3, metals – Histogram and PDF, price changes.

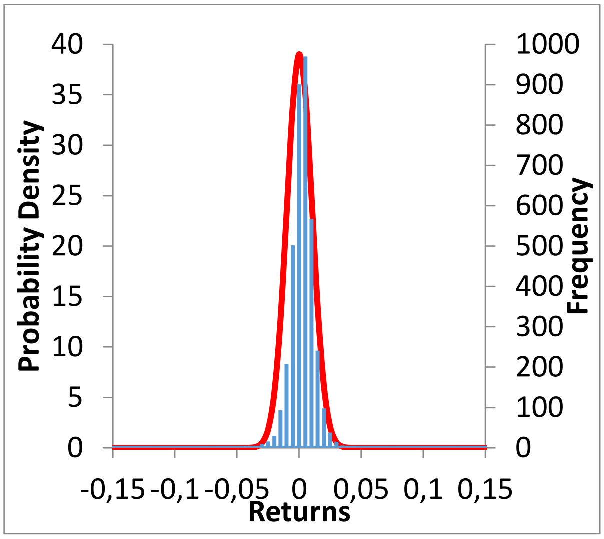

Figure 22: P4, diversified – Histogram and PDF, price changes

6.2 Market Analysis

For all markets, demand and supply of the commodity is the major influencer of asset price. When the demand is high and supply is low, the prices increase and vice versa. However, the extraneous factors that affects the supply and demand for the various assets depend on the market. For instance is the supply and demand of oil is unaffected of a drought in Europe, while it may be a major influencer of the supply of grains.

In this subchapter a market analysis of the commodities spot prices will be carried out.

6.2.1 Grain Market, Portfolio P1

Portfolio 1 contains three commodities, wheat, durum wheat and barley. Figure 23 shows the price development from 2nd of July 2001 until 17th of March 2017 for the three assets and a comparison. Figure 24 shows two major booms and bursts that are common for all three assets occurring in 2007-2009 and 2010-2013. Durum wheat has an additional burst followed by a boom in 2014-2015.

As explained in chapter 3, the price is determined by the supply and demand of the commodity. In the grain market, the major influencer on the supply is weather. Droughts, floods and cold long winters will provide poor harvest, destroy the crop or delay the planting of seeds. If either of these incidents occur in a large area of producers, there will be a shortcoming of grain in the market leading to increased prices.

The grain prices are strongly correlated with each other as presented in Table 3. This is also evident by the curves in Figure 23 and Figure 24, which shows how the prices increase and decrease almost simultaneously. This means that when an incident for instance affect the wheat production so that price increase or decrease, the durum and barely price is also likely to increase or decrease as per definition in chapter 2.1.5.

Table 3: Correlation matrix for grain prices

	Wheat	Durum	Barley
Wheat	1,000		
Durum	0,736	1,000	
Barley	0,862	0,774	1,000

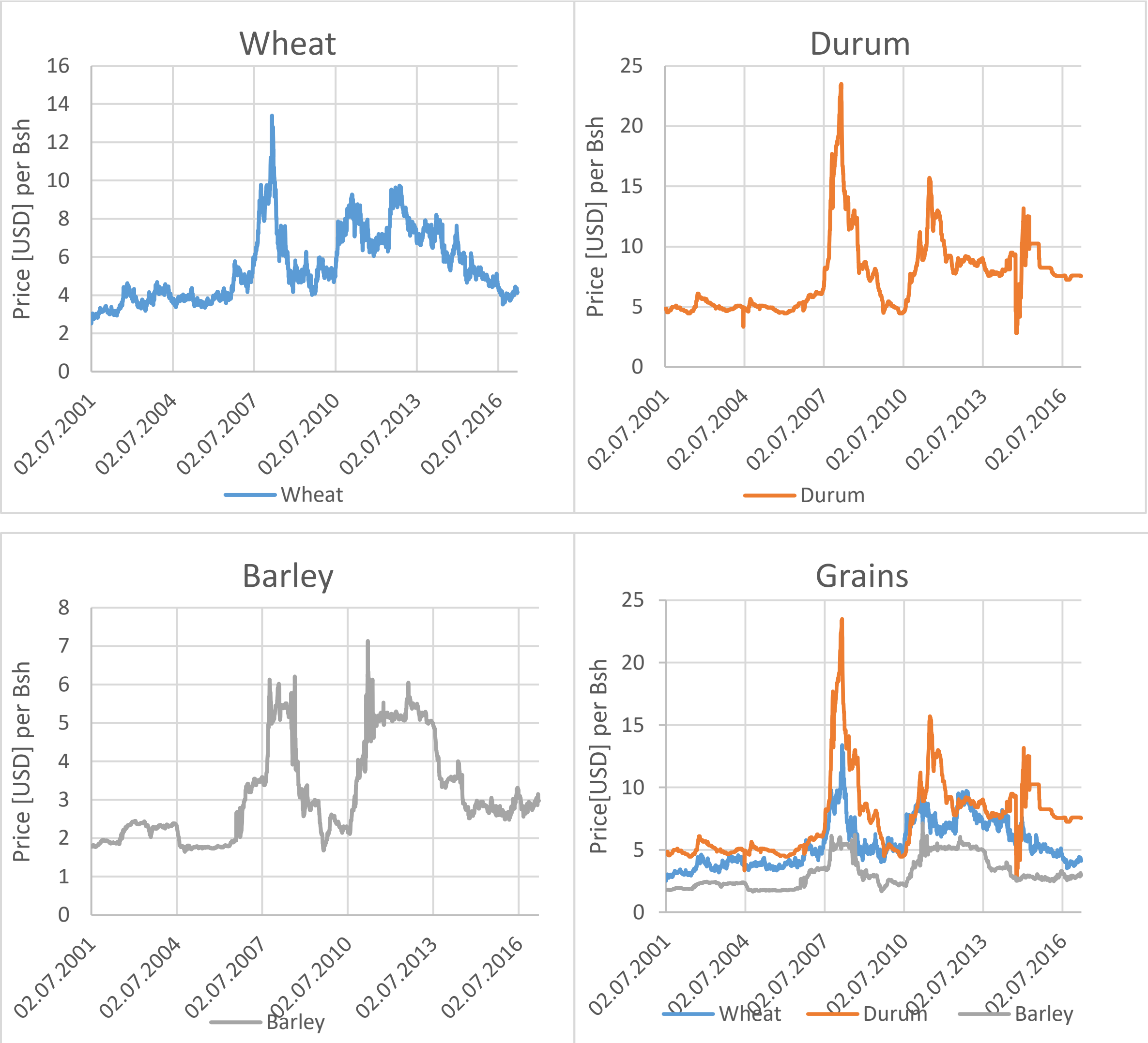

Figure 23: Grain prices from 02.07. 2001 until 17.03.2017

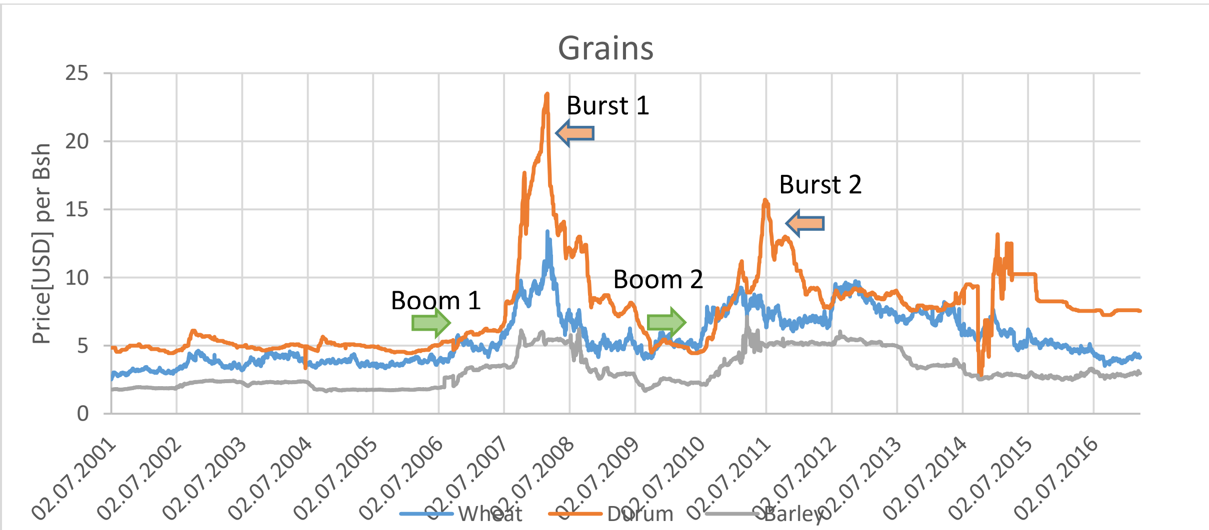

Figure 24: Marking of booms and bursts in the sample period. Boom 1: second half 2007, Burst 1: second half 2008, Boom 2 second half 2010, Burst 2 for durum already in July 2011, Barley price was fluctuating until the price together with Wheat price fell in July 2013.

As presented in Figure 24, during the sample period, there were two large booms in the grain price. During the first, the price started to rise in second half of 2007 and peaked in the first half of 2008. The reason was droughts in Ukraine, Australia and USA who also experienced a long winter in 2008 (McMahon, 2008). This led to a shortcoming in supply and consequently higher prices. A well functional market strives to reach an equilibrium between supply and demand at a price that is acceptable for both producer and buyer. When the shortcoming resulted in high prices, farmers worldwide who were not affected by weather conditions increased their acreage of productions and the prices started to fall at the end of first half 2008 (McMahon, 2008). Furthermore, due to the following financial crisis and weak macro economy the price fell further until beginning of 2009 at the same price level as before the droughts in 2007/2008. The market was in equilibrium again.

The second boom period is of interest as it has been blamed to be the cause of Arab spring breaking out in the end of 2010 (Lagi, Bertrand, & Bar-Yam, 2011; Perez, 2013; Zurayk, 2011). The Arab spring is the common denomination of riots, protests and demonstrations against the governments in Arab countries in North Africa and Middle East. Undemocratic governments had run these countries and the people had been neglected for a long period. After the financial crisis in 2008 the worldwide macroeconomic was week. When the grain prices again started to rise in second half of 2010 the poor people in the Arab region became even more desperate due to lack of governmental security. The governments did not help its people by sufficiently lowering taxes and giving farmers subsidence to grow crops (Zurayk, 2011). The protests accelerated leading to the outbreak of the Arab Spring in the end of the same year. However, the grain market prices were rising due to another drought and in Russia, Ukraine, China and Argentina together with torrential storms in Canada, Australia and Brazil which consequently diminished the global supply of grains driving the commodity prices up (Perez, 2013). In 2013, all assets in the grain market portfolio came back in equilibrium.

Final notation on the grain market is regarding the durum wheat asset. As Table 3 showed, durum is the least correlated with the two other assets in the portfolio. This can also be seen from Figure 24. The reason is that the demand for durum has increased, while the crop did not before 2016 when the market again reached an equilibrium. Figure 25 presents the production (supply) and use (demand) in US, Canada and European Union from 2000 – 2017 which explains the boom and following burst in durum wheat. However, in the dataset, the durum wheat has a burst before this rise in price in the end of 2014. As explained in the introduction to this chapter, some assumptions had to be made for the durum data, and this period is interpolated. That can explain the behaviour, as no reasonable explanation for this burst has been found.

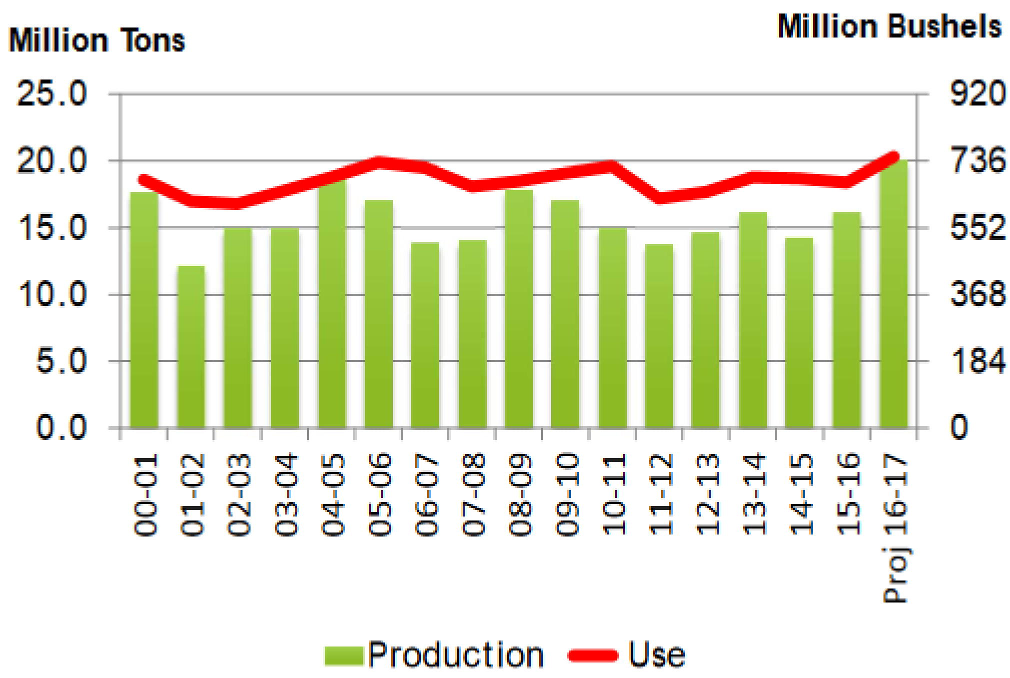

Figure 25: Durum wheat production and use in USA, Canada and European Union from 2000 until 2017 (NorthDakotaWheatCommission, 2017) .

6.2.2 Energy: Oil and Gas Market, Portfolio P2

Portfolio 2 contains two oil commodities and two gas commodities. The assets are Brent and WTI crude oils, and natural gas from Zeebrugge (ZEE) and Henry Hub (HH) pipeline distributers. Brent and ZEE are commodities from Europe while WTI and HH are commodities from USA. There is a price offset between the crudes because Brent oil is lighter and has therefore a better quality. However, the prices are strongly correlated due to arbitrage, which can be seen from Table 4.

Gas is much harder and expensive to transport to other markets, the gas prices therefore have a regional price behaviour while the other commodities in this thesis have a global price behaviour. To transport gas between Europe and USA for instance, the gas would have to be liquefied first and shipped to the other geomarkets. The liquidation and shipping costs of gas are high compared to transportation through pipelines. Therefore, countries as USA strives to be self-sufficient of natural gas.

The correlation matrix for the commodities throughout the whole sample period shows that Brent and WTI prices are almost perfect correlated (Table 4). The natural gas assets are also positively correlated with oil; however, the HH gas has a weak correlation particularly with the oil assets. By studying the price curves in Figure 26 it is clear that the HH price curve starts to move in the opposite direction from mid-2010. In 2010, USA shale gas production increased with 72% compared to 2009 level (Figure 57).

The increased gas supply in USA further led to a price decrease on HH natural gas. A correlation matrix from before and after the increased shale gas supply is therefore also presented to show the impact shale gas had on the energy commodity market. The correlation for the period 02.07.2001 – 30.07.2010 presented in Table 5, while Table 6 presents the correlation for the period 02.08.2010-02.03.2017. The correlation between all the energy assets are strong again in the final sample period. From Figure 26 it can also be observed, that all the four commodities have the same trend from 2013.

Table 4: Correlation matrix – Energy assets throughout sample period.

	BRENT	WTI	NGAS-ZEE	NGAS-HH
BRENT	1,000			
WTI	0,974	1,000		
NGAS-ZEE	0,762	0,760	1,000	
NGAS-HH	0,082	0,221	0,263	1,000

Table 5: Correlation matrix – Energy assets from 02.07.2001 – 30.07.2010

	BRENT	WTI	NGAS-ZEE	NGAS-HH
BRENT	1,000			
WTI	0,997	1,000		
NGAS-ZEE	0,672	0,683	1,000	
NGAS-HH	0,588	0,608	0,662	1,000

Table 6: Correlation matrix – Energy assets from 02.08.2010- 17.03.2017.

	BRENT	WTI	NGAS-ZEE	NGAS-HH
BRENT	1,000			
WTI	0,972	1,000		
NGAS-ZEE	0,863	0,838	1,000	
NGAS-HH	0,582	0,630	0,531	1,000

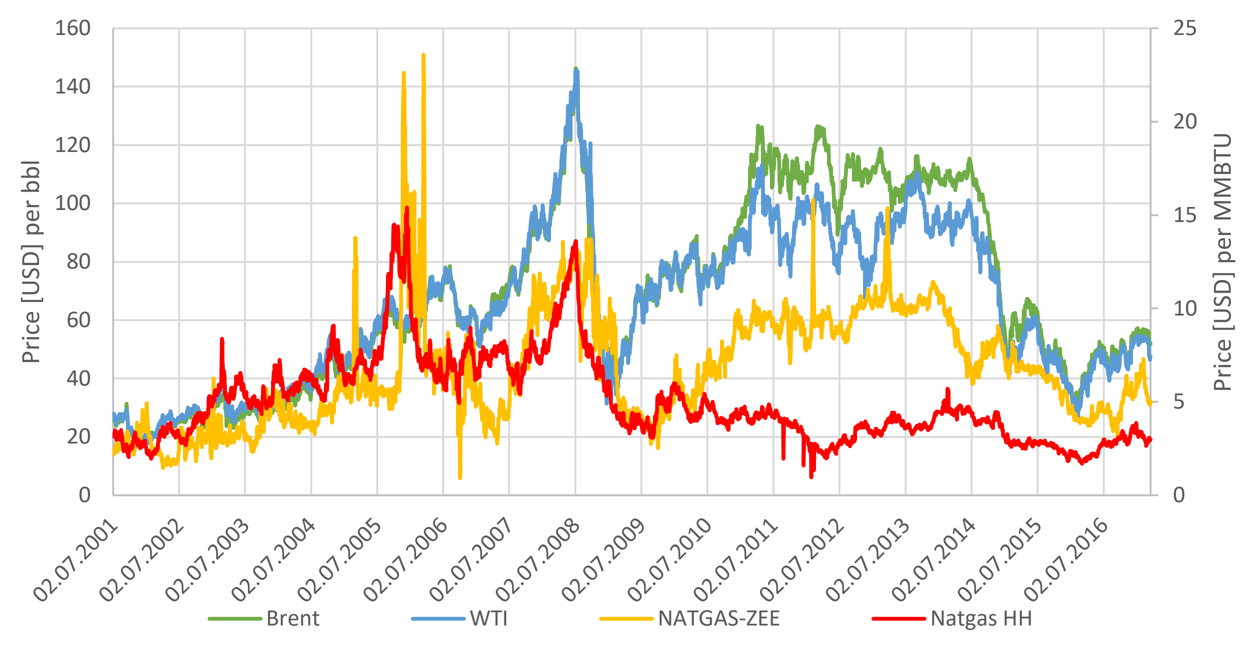

Figure 26: Energy prices throughout the sample period. Brent and WTI are following each other closely with a price offset due to quality on Brent oil.

The oil prices are affected by supply and demand, which are again affected by factors as geopolitical issues, technology, stock market crash, recession (Sungurov, 2015). Oil is used as a transportation fuel and fuel for heating and electricity generation. Throughout the history of the oil price, there have been many peaks and crashes. A large part of the production is controlled by member countries in the Organisation for Petroleum Exporting Countries (OPEC), where Saudi Arabia is the major contributor and influencer as the world's second largest oil producing country in 2016 (EiA, 2016b). When OPEC decides to increase or decrease production their decision has showed to have an impact on the oil price, as the decision affects the supply.

By studying Figure 27, two booms and bursts are marked. Since the price data has not been adjusted to 2017 terms, it is not obvious from the figure that the oil price starts with a drop due to oversupply in the market pressing the prices down. The prices started to increase in early 2002 as a consequence of the tension in the world after 9/11 and invasion of Iraq early 2003 (Sungurov, 2015). This incident is marked as the beginning for Boom 1. This boom later gets fuel on fire by the increased commodity demand in emerging countries led by China. In addition, the OPEC countries experience a limitation in their spare capacity. They were thus unable to boost their production in order to reduce the oil price (EiA, 2017). The shortcoming in supply drove the oil prices to an all-time high of 144$/bbl. in 2008 before it collapsed as the result of the recession in the world economic after the financial crisis, marked as burst 1. In the beginning of 2009 the commodity demand slowly started to increase again by the lead of China (Sungurov, 2015). Moreover, as the Arab Spring evolved with riots and wars in North Africa and Middle East disturbing their production, there was yet again a shortcoming in supply leading to another boom. With high oil prices and new technology as long horizontal producing wells, and commercialised shale oil fields, the oil production was increased leading to stabilisation in oil price around 110$/bbl for Brent and 90$/bbl for WTI. The high oil price made more fields commercial either by expensive infill drilling in old reservoirs, EOR treatments or new heavy oil fields. The oil producing companies invested in these fields, and in 2014 the investments lead to increased production. The surging North America shale supply and a weaker demand lead to a flood of oil in the market and the prices burst again. OPEC decided to maintain their production as USA and Russia would be the two countries that suffered the most from low oil price, as their shale oil production is not commercial at low prices. The prices fell from July 2014 until spring 2016 when the rumours regarding whether OPEC will cut production started to blossom (Ottosen, 2016). At their autumn meeting, OPEC decided to cut production in order to achieve a supply/demand equilibrium in order to stop the price fall. OPECS cut led to some optimism and increased prices. It looks like the worst of the ongoing oil crisis is over.

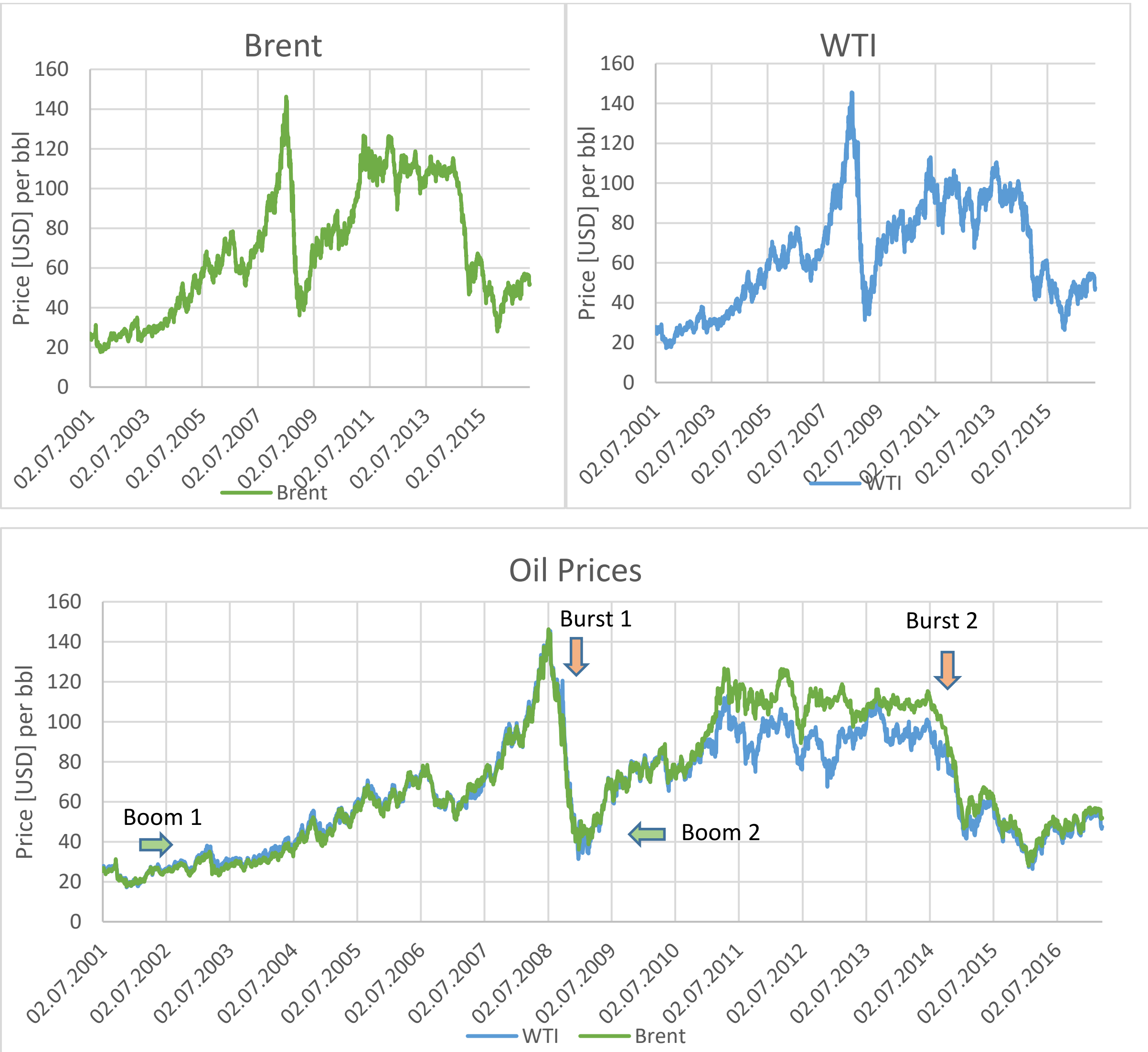

Figure 27: Oil prices during the sample period and a comparison of Brent and WTI.

The natural gas prices have a weak correlation to the oil market. In many cases natural gas is produced together with oil. The oil and natural gas are used for heating and electricity generation, the correlation between the assets may appear surprisingly low. However, oil is a worldwide market, while natural gas are regional markets. Therefore, a war in Middle-East may affect the oil price greatly, while HH natural gas price will carry on without a change, as it is produced and distributed domestically in U.S. This is also the reason for the weak correlation between HH and ZEE natural gas prices. However, if there is a shortcoming in supply in the U.S, Europe can supply U.S with additional LNG leading to increased demand in both markets and increased prices. Therefore, the prices are correlated.

Historically the gas price has followed the oil price with a delay of a few months. This pattern is also observed in this thesis sample period in Figure 26 and in the correlation matrixes. The reason is that gas has been traded with oil-indexed prices, as gas has been considered a close substitute to oil (Winje, Naug, & Stavseng, 2011) . However, as the gas spot market evolved in USA and Great Britain, the gas marked in these countries has distanced itself from the oil market. Natural gas in HH and oil marked are no longer integrated markets and the Natural gas price response to changes in oil price has become weaker and weaker since 2009. For continental Europe natural gas, the prices are still indexed to the oil price (Winje et al., 2011). This explains the results in correlation matrix, where natural gas ZEE has a quite strong correlation to WTI and Brent.

The natural gas prices are quite volatile and are strongly affected by short term events as low temperature, leading to instant increased demand for heating. In addition is cold weather challenging for gas transportation in pipelines that can lead to hydrates and plugs that prevent the distribution and delayed supply (EiA, 2016a). The natural gases are mainly affected by supply and demand. The most important factors affecting the supply are gas production, import and export of gas, storage level. The demand side is affected by the economic growth in regional market, weather, prices of alternative fuels (EiA, 2016a).A weather phenomenal that affect the natural gas prices are extreme storms, like the Katrina hurricane that hit Gulf of Mexico the last week of August 2005 (Helman, 2013). Katrina affected the natural gas supply by the evacuation of platforms in the Gulf, and shut-ins on land rigs in states hit by the hurricane. The natural gas production was down with as much as 83%(Helman, 2013; Romero, 2005). In addition, Katrina destroyed many of the land rigs and pipelines. The consequences was a shortage in natural gas supply that is the cause of boom 1 in Figure 28. Due to the shortage in natural gas supply in the U.S, Natural gas from Europa was imported leading to a boom in ZEE gas also.

When the damages from Katrina was maintained and the production came up to a sufficient level to supply U.S, the prices burst in HH and especially ZEE gas as U.S import demand fell. The gas prices in Europe and USA increased again in2007 until autumn 2008. This increased can be explained by the increased demand for energy and oil, and the high oil prices. Due to high oil prices the demand for the cheaper gas increased (Winje et al., 2011). As explained earlier in this chapter the increase for energy and oil was due to growth in macro economic led by China. After the financial crisis, the natural gas prices also burst as most other commodities.

When the oil prices started to evolve again after the financial crises. The petroleum producers experienced high level of income, and had investments opportunities and technology to start commercialize shale gas production in U.S. This led to a high supply for gas in the U.S marked, and the prices on Henry Hub burst from 2010. The prices trend has been decreasing and volatile since then.

In the same period the continental European ZEE gas price followed the oil price with a delay of a few months leading to boom late 2009 with a following burst in 2014, in line with the oil price. However, the burst was actually six months premature to the oil price burst. This can be traced back to a lower consumption during the winter of 2014 and an increased import from Russia and Norway (EU, 2016).

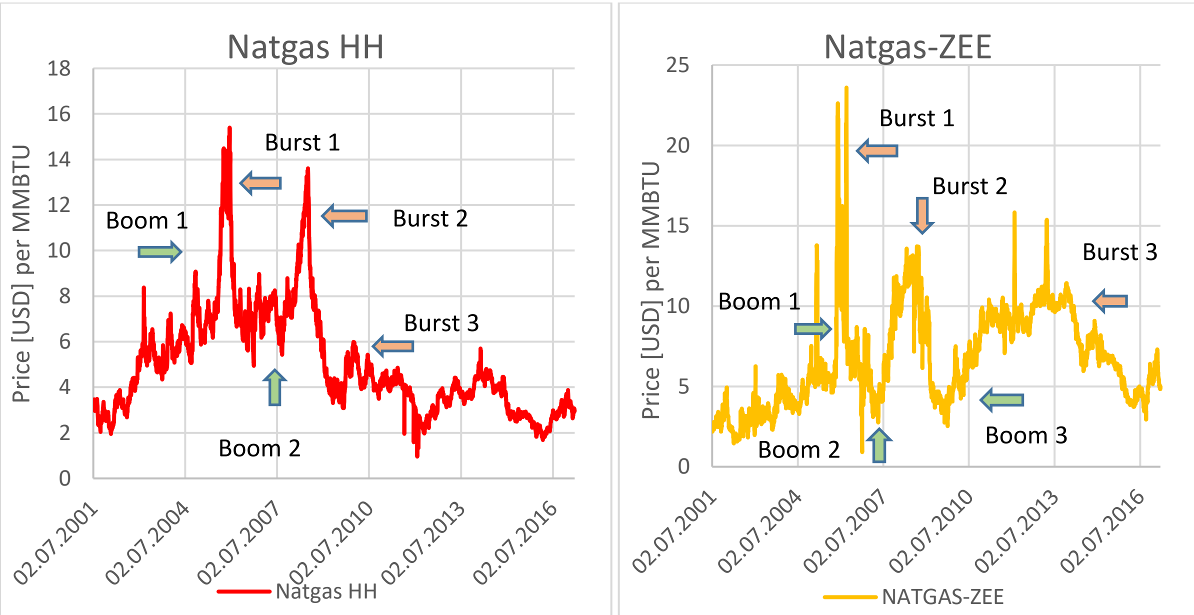

Figure 28: Natural gas prices from Henry Hub (HH) and Zeebrugge (ZEE) respectively.

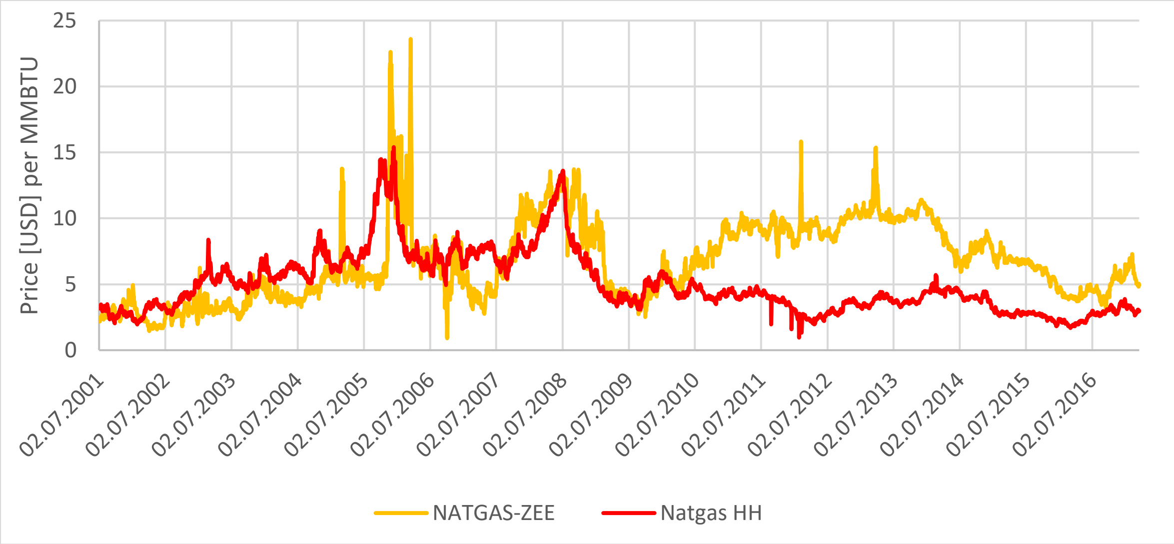

Figure 29: Comparison of Natural gas ZEE and HH.

6.2.3 Metal Market, Portfolio P3

Portfolio 3 contains five metals, copper, bronze, platinum, palladium and gold. Copper is an industrial metal that is commonly used alone or in alloys. Bronze is an alloy while platinum, palladium and gold are precious metals. Precious metals is the denotation of metals that are rare and/or have a high economic value. All the metals are positively correlated with each other (see Table 7)

Even though the metals are correlated, there are different reasons for their booms and bursts. For instance, the gold price rose 3,75% during the financial crisis (01.07.2008-31.12.2008), while the four other metals, commodity prices fell drastically. The prices fell more than 50% compared to the price before the crisis. Therefore, this analysis will be carried out looking at each metal and describing the factors responsible for their price volatility.

Table 7: Correlation Matrix – Metals

	COPPER	BRONZE	PLATINUM	PALLADIUM	GOLD
COPPER	1,000				
BRONZE	0,976	1,000			
PLATINUM	0,918	0,915	1,000		
PALLADIUM	0,589	0,681	0,511	1,000	
GOLD	0,754	0,836	0,749	0,807	1,000

Bronze is an alloy containing ~88% copper, and the two metals are therefore strongly correlated. By comparing the price history during the sample period, their curves are moving more or less simultaneously (Figure 30). Bronze has added value compared to raw copper. It is more resistant to corrosion and is stronger, and thus more expensive. Copper is mainly used in constructions, electrical wires and industrial machineries. Bronze is also used in industrial manufacturing, and has a wider application area than copper due to the corrosion resistant.

As the Figure 31 shows, there has been two great booms and bursts in the copper and bronze prices during the sample period. The first blooming period lasted from start of 2000 century until the financial crisis in 2008. The main cause of the price increase was the increase in demand coming from G20 countries, in particular China. Chinas growths during the start of 2000 led to a great bloom in demand for metal commodities (Sanderson, 2016). Due to the geopolitical situations, as strikes in Chile and Peru, the supply was not sufficient to meet the rising demand, and hence the prices increased. In the financial crisis in 2008, the macro economy of the world was very poor. The governments did not make investments, and the construction and housing market stopped. This led to a sharp decrease in demand for copper and bronze that resulted in a burst in price. As the worst of the crisis was over, and investors started to believe in the market again, the demand started to rise in 2009, leading to an all-time high copper price in 2011. Due to investments among the supplier in machineries and more efficient mining equipment, in addition to developing countries higher contribution to the metal market, the supply boomed from 2011 (Matsumoto, 2015). The supply has increase by 17% from 2011-2016 (USGS, 2017). At the same time the Chinese industrial production is not growing at the same high rate any longer (Sanderson, 2016). Therefore, the increase in supply is a large contributor to the price fall during the second burst from all-time high in 2011 to almost financial crisis low in 2016.

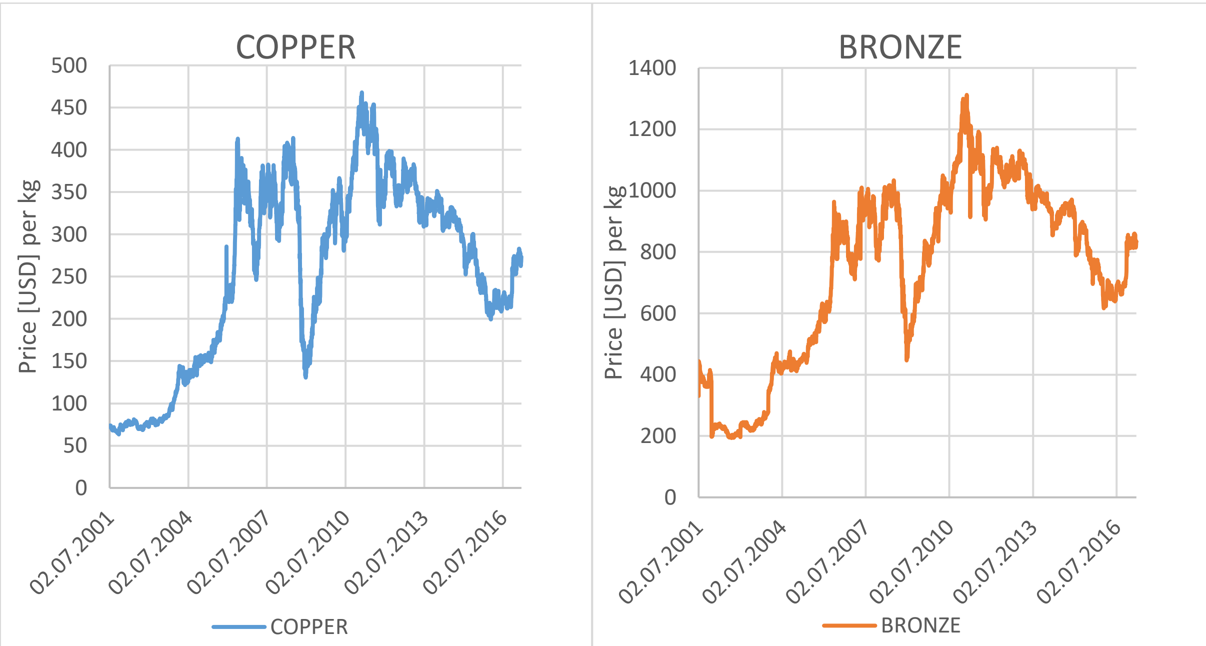

Figure 30: Copper and bronze prices during the sample period.

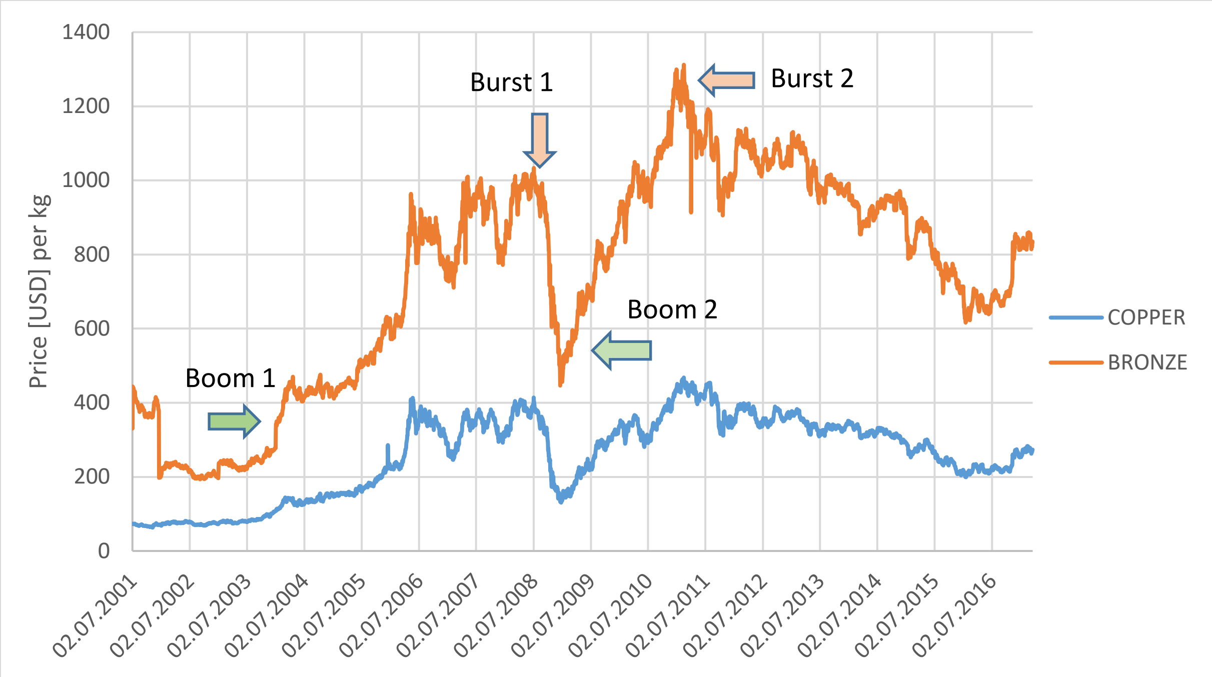

Figure 31: Comparison of Copper and Bronze prices. Two large booms and burst incidents have been marked.

Platinum is a very rare and valuable metal. South Africa is the primary producer, which in 2014 stood for 68% of the world production while Russia is the second largest producer (U.S.GeologicalSurvey, 2015). The main demand for platinum comes from the vehicles industry, which uses platinum in engines as catalyst, and from the jewellery industry. Since platinum is even more valuable than gold, there is also a demand from investors as a security (Scott, 2010).

The demand for platinum increased in line with copper and bronze due to the extensive industrial growth in China, which is reflected as the first boom in Figure 32. The price reached the top just before the financial crisis in 2008 where the price burst (number 1) in line with other commodities, before the demand again increased leading to a price recovery (boom 2). As for copper and bronze, the platinum price started to fall after 2011 (burst 2) due to abundant supply and lacklustre demand (Prakash, 2015; Terazono, 2011). The supply increased even further as a long lasting strike in South Africa ended in 2014 (Topf, 2016). After the Volkswagen scandal in 2015, a general concern about the diesel motors future raised, leading to an even steeper decrease in the platinum price, as platinum is used in diesel catalysts (Topf, 2016). At the end of the sample period it can be observed, that the platinum price has started to increase again. The increase is a result of increase in demand for automobile vehicles in the US and China, and a decrease in supply from South Africa due to wage negotiation and locked mines (Els, 2016).

Palladium is a metal part of the “platinum group metals” definition. The metal is a substitute to platinum, though with a poorer quality. It is for instance less efficient in catalysts (Scott, 2010). Russia is the largest producers of Palladium, where it is a luxurious by-product from their Nickle mining. South Africa is the second largest contributor.

As Table 7 showed, the prices of platinum and palladium are correlated, however not as strong as platinum, copper and bronze during the sample period. Since they are substitutes, it can be explained by the example in the price theory chapter. By looking at the curves for the palladium and platinum, this result is also obvious (Figure 33) as the palladium curve often moves in opposite direction or increase at a much higher or lower rate. In the beginning of the sample period, the palladium price was falling rapidly. The reason was that in the period 1998-2000 Russia had severe delays with production and shipping of palladium leading to undersupply in the market and a surge in price (Scott, 2010). In addition, the demand for vehicles increased sharply which made the consequences of Russian production delay more severe. When the production caught up again in the late 2000, the demand for palladium had fallen as consumers substituted palladium with the at the time cheaper platinum leading to an overload of palladium in the market (EuropaPublications, 2003). The palladium price fell while the platinum price rose together with the other commodities to satisfy the blooming macro economy in the world. In 2005, the palladium demand finally caught up with the supply and the price rose with the other commodities until the financial crisis in 2008. Of the metals in our portfolio, only copper experience a more drastic price drop than palladium from 01. July 2008 until 31. December 2008. The financial crisis and the macroeconomic uncertainties was the main cause of palladiums burst number 2 in the sample period.

After the financial crisis, the palladium price increased to a new all time high in 2011. The explanation for this growth can be traced back to the uncertainty regarding Russia’s stockpile of palladium (Scott, 2010) and Chinas demand for industrial commodities. The price fell in 2012, however it soon caught up again as South Africa’s miners went on a strike for 20 months until end of 2014. When the strike was over South Africa increased their palladium production to a new record, leading to an abundant supply which together with the Volkswagen scandal caused palladiums third burst in 2015 (Prakash, 2015; Topf, 2016). The palladium soon recovered and the price boosted again in 2016.

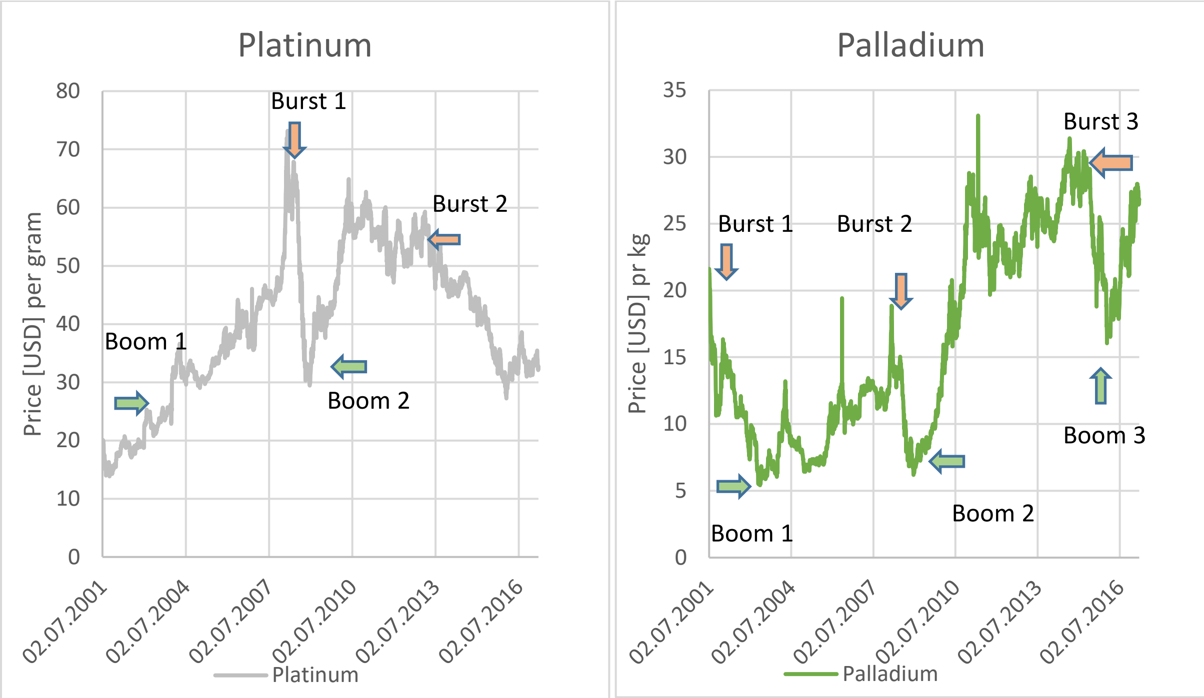

Figure 32 Platinum and palladium prices during the sample period.

Figure 33 Comparison of platinum and palladium prices in the sample period.

The gold price has always been hard to analyse, as it does not follow clear patterns. For instance, the consumer demand is rather affected by the gold price, than vice versa (Ash, 2014). The founder of the Rothschild Group, N.M Rothschild expressed in the 19th century the complexity of the gold price (Ash, 2014; Stammer, 2015).

"I know of only two men who really understand the value of gold, an obscure clerk in the basement vault of the Banque de France and one of the directors of the Bank of England.

"Unfortunately, they disagree." N.M Rothschild

In the sample period, the gold price has had an increasing trend from start until end of 2011. Also during the financial crisis the gold price increased by 3,74% from July 1st until December 31st 2008. The price growth ended in end of 2011 and the price fluctuated around 55000 USD/kg before it started to drop quite rapidly during year 2013. The price has been fluctuating around 40000 USD/kg since beginning of 2014 with a quite sharp fall during 2015. The supply of gold comes from several countries in most continents in addition to recycling. The demand is from jewellery where China and India are the major consumers, technology and medicine, and as securities for investors (Ash, 2014; Hagen, 2014).

According to Adrian Ash the head of research at Bullion Vault ltd. in London there are seven input factors to the gold price: inflation, interest rates, stock markets, geopolitics, the U.S dollar, the oil prices, Asian jewelry demand (Ash, 2014). He has drawn his conclusion from investigating the correlation between gold price and the above input factors. However, none of these input factors exclusively correlates positively or negatively with the gold price. This is also one of the reason why gold is attractive by investors as a hedging assets in portfolios.

Robert Næss in Nordea Investment Management found that gold could diversify risk in a global stock portfolio. Based on MSCIs global index from 2004, Næss found that a portfolio of one third gold and two third stocks, would have had a volatility of 12,9 percent against 18,7 and 15,7 percent for respectively gold and stocks alone (Redaksjonen, 2016). In addition, he found that the return for the diversified portfolio would have been approximately 1 percent higher.

Looking at Figure 34, one long price booming period and one big burst can be observed. Due to the complexity of the gold price, several inputs factors affected the gold price leading to the boom during first decade of 21st century. First USA experience the slowest inflation of all time from 2000 (Ash, 2014). The world bank's interest rate has been falling throughout the whole sample period leading to low operations costs of holding gold (OECD, 2017). The weak U.S dollar. The uncertain investment market after the financial crises in 2008 led to investors searching secure holdings (Hagen, 2014). Furthermore, unstable geopolitical matters as Iran holding atom weapons (2006), Greece and the Eurozone collapse (2011) and finally the Arab spring leading to an all-time high gold price in the end of 2011 (Ash, 2014).

The high gold price led to a decrease in demand for gold as jewelry in Asia in 2013, marking the beginning of the gold price burst in the sample period. In addition, investors gained faith in the stock marked as the tense situation between Russia and Ukraine started to cool down. As stocks severs higher and faster pay-off opportunities, investors prefer investing in stocks when the risk of loss is at an acceptable level (Hagen, 2014).

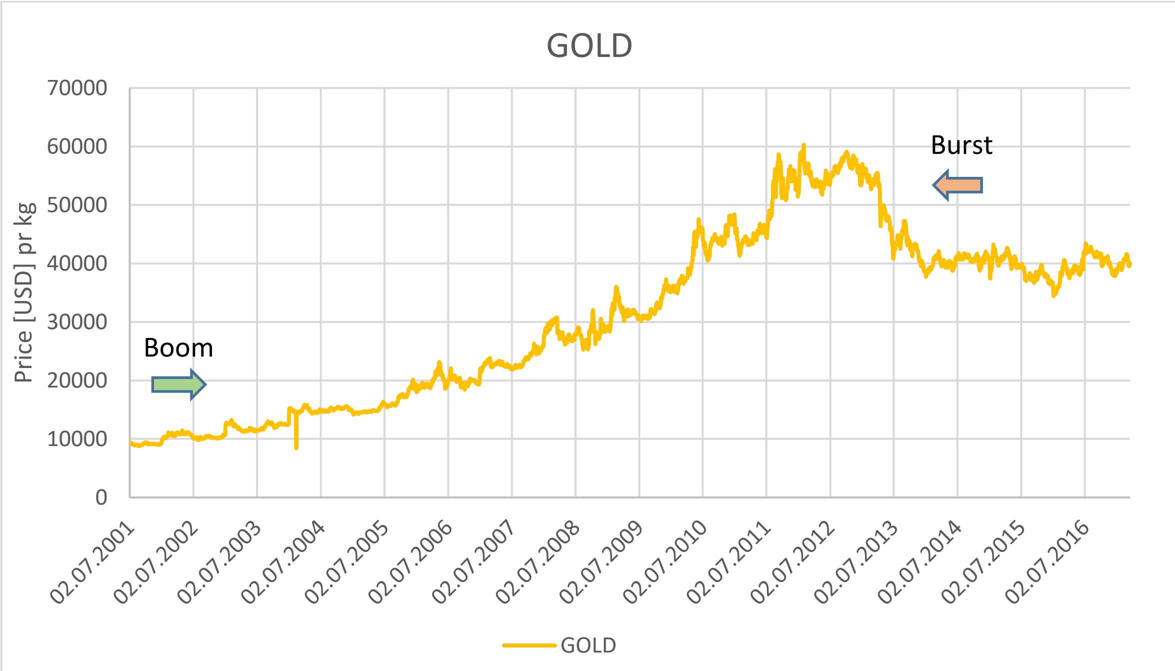

Figure 34: Gold Price during sample period.

Figure 35 shows a comparison of the metal prices throughout the sample period. The figure demonstrates the results of the market analysis and the results in **Feil! Fant ikke referansekilden.**. The gold and palladium prices are during some periods not following the same trends are the three other metals.

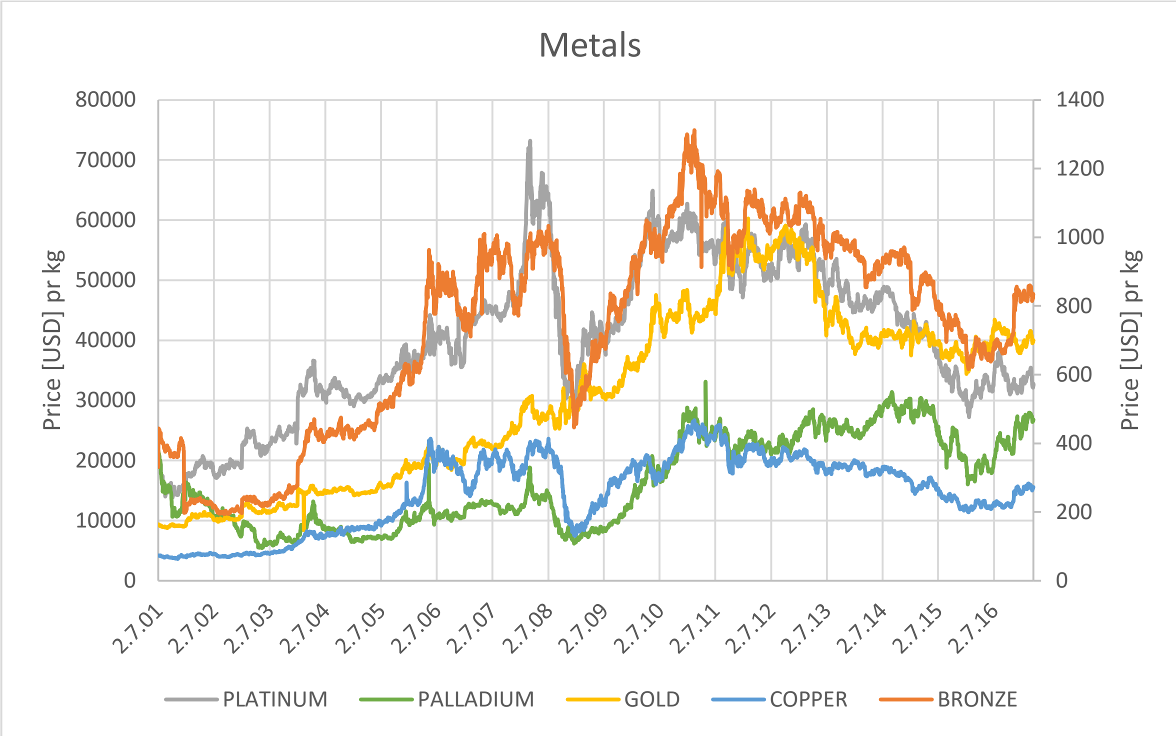

Figure 35: Metal price through sample period. Platinum, palladium and gold prices on left axis, copper and bronze prices on right axis.

6.2.4 Price comparison, portfolio P4

Based on the market analysis and price correlation matrix (Table 8) for all the commodities a fourth portfolio with assets from grain, energy and metal market has been selected. Portfolio P4 has been selected to obtain diversification by including assets from the various markets. In the grain market, all three commodities are quite correlated, and wheat has therefore been chosen to represent the grain market. The market analysis of the energy commodities showed that Henry Hub (HH) natural gas only has a weak correlation with the other three assets who are more correlated. Therefore two commodities have been selected from the energy market, Brent and HH. In the metal market analysis, the results revealed that copper, bronze and platinum (PT) had correlated price behaviour, while palladium (PD) and gold (AU) were not as strongly correlated with the other metal. Therefore, Copper (CU) and gold have been chosen to represent the metal market in portfolio P4.

Table 8: Correlation Matrix, all assets.

	WHEAT	DURUM	BARLEY	BRENT	WTI	ZEE	HH	CU	BRONZE	PT	PD	AU
WHEAT	1,00											
DURUM	0,74	1,00										
BARLEY	0,86	0,77	1,00									
Brent	0,82	0,58	0,79	1,00								
WTI	0,78	0,57	0,74	0,97	1,00							
ZEE	0,67	0,54	0,63	0,76	0,76	1,00						
HH	-0,04	0,03	-0,06	0,08	0,22	0,26	1,00					
CU	0,78	0,54	0,70	0,89	0,88	0,66	0,04	1,00				
BRONZE	0,78	0,53	0,70	0,88	0,85	0,65	-0,07	0,98	1,00			
PT	0,82	0,56	0,72	0,90	0,89	0,68	0,12	0,92	0,91	1,00		
PD	0,54	0,38	0,49	0,56	0,45	0,39	-0,53	0,59	0,68	0,51	1,00	
AU	0,69	0,47	0,67	0,74	0,64	0,53	-0,43	0,75	0,84	0,75	0,81	1,00

In Figure 36 the relative price change in the sample period between the commodities in portfolio P4 is presented. The relative price change has been obtained by dividing every price observation throughout the sample period with the price at the first observation on July 2nd 2001. The figure and Table 9 show that these commodities do not have a strong correlation if any. In the further VaR analysis in next chapter, the diversification effect will be studied, as basic portfolio theory claims the variance of a diversified portfolio with asset X and Y should be less than the variance of X and Y respectively.

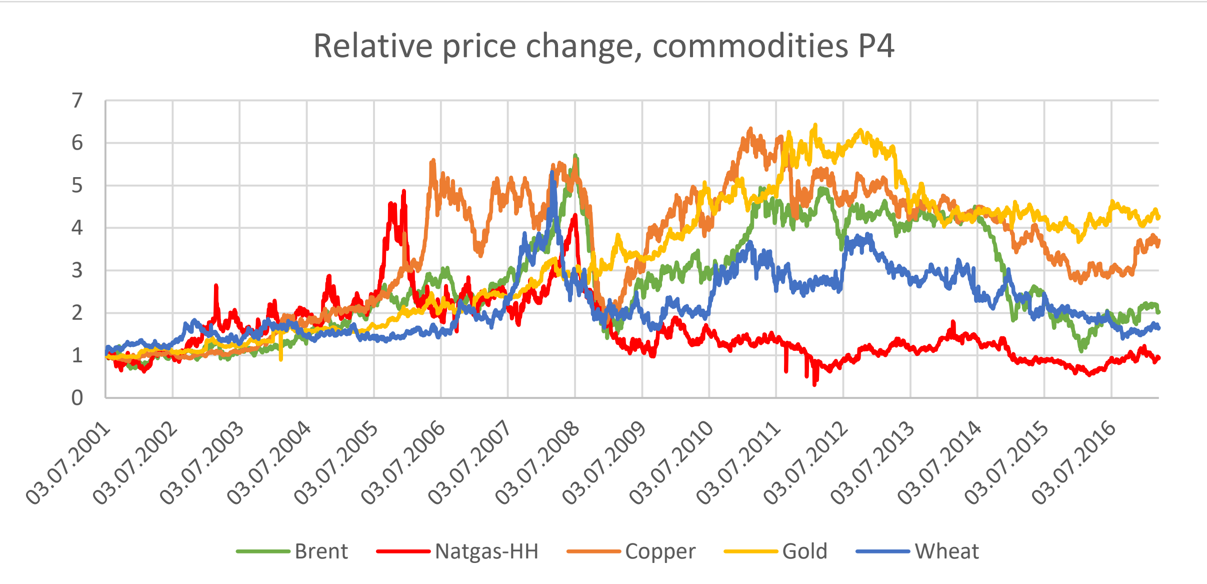

Figure 36: Relative price relationship for commodities in portfolio P4.

Table 9: Correlation matrix for commodities in portfolio P4

	WHEAT	BRENT	NATGAS HH	COPPER	GOLD
WHEAT	1,000				
BRENT	0,816	1,000			
NATGAS-HH	-0,041	0,082	1,000		
COPPER	0,778	0,889	0,043	1,000	
GOLD	0,695	0,740	-0,430	0,754	1,000

6.3 Standard deviation

The portfolios return data have been evaluated in terms of standard deviation. The reason is to investigate if the basic portfolio theory with regards to diversification applies. The portfolios standard deviations have been plotted vs time together with the single assets standard deviations. The figures shows that all the portfolios are less volatile than their single assets.

Portfolio 4 is a diversified portfolio as it contains commodities from all three markets. Based on portfolio theory, this portfolio should therefore have a lower risk than P1-3. However, in the scenario where the minimum variance portfolios have been calculated based on a 250days rolling window, the P1 has actually lower standard deviation than P4.

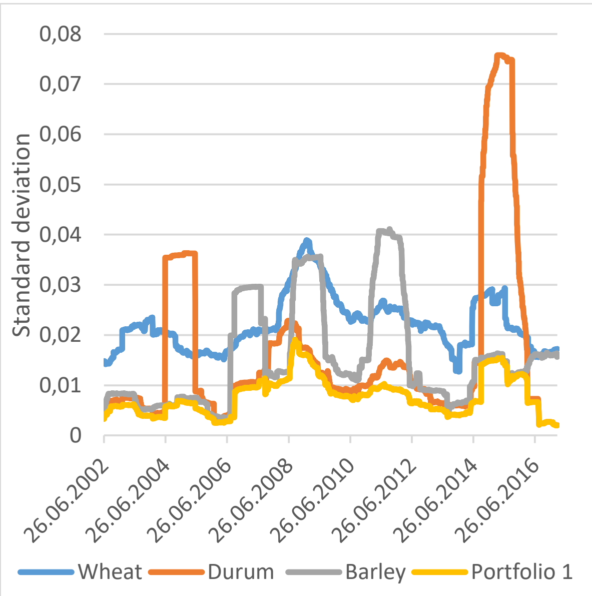

Figure 37: Standard deviation Grains

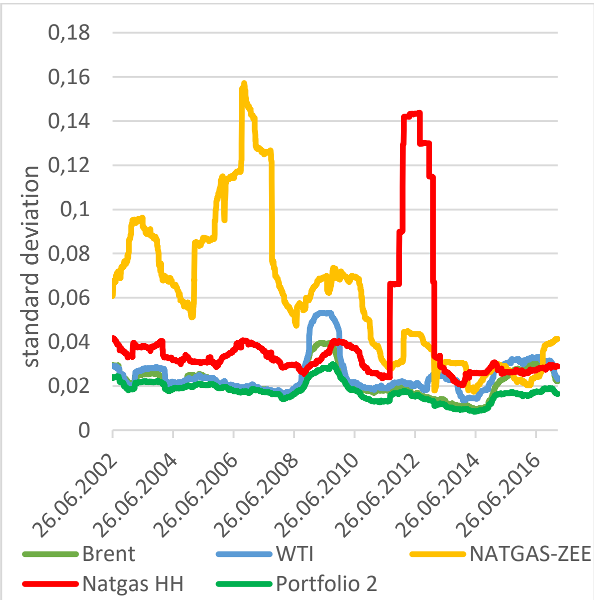

Figure 38: Standard deviation Energy

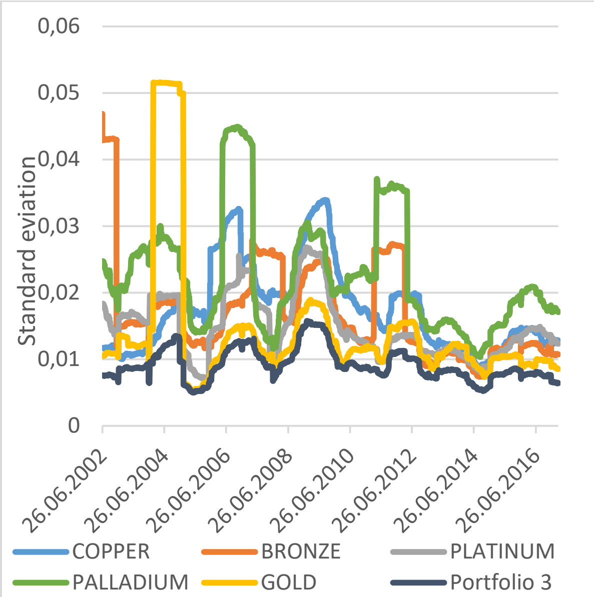

Figure 39: Standard deviation Metals

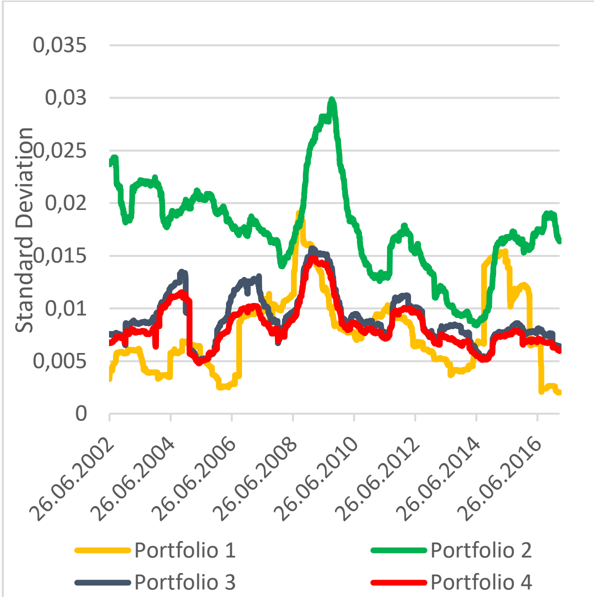

Figure 40: Standard deviation portfolios

7 Results and Discussion

In this chapter the results from the VaR and ES calculations will be presented and discussed. VaR and ES have been calculated for the four different portfolios presented in previous chapter. The portfolios have dynamic assets allocations, meaning that their allocations varies from day to day.

The VaR and ES have been calculated with two different time horizons, 250 days rolling window and 1000 days rolling window at 99% and 95% confidence level. Both historical and Normal VaR have been calculated. Furthermore, the results have been backtested with the three approached presented in chapter 5.4, *regular, Kupiec and Christoffersen test.*

In the next subchapter, a description of the VaR and ES model will be described.

7.1 The VaR model

The VaR calculations have been done using Microsoft Excel 2013 and Visual Basic for Application (VBA). VBA is excels programming language and gives the opportunity to define function for the users purpose. VBA has been selected for the task due to its simplicity and direct application for presentation of results using excel. Other programming tools that were considered are R and Mathlab.

7.1.1 The process

Since the object with the thesis is to calculate VaR with daily return data and dynamic allocation portfolios, a function for covariance had to be defined in VBA. The function calculates a new covariance as the rolling time horizon window propagates through the sample period. Furthermore, a VBA model using Excels solver to ensure the portfolios allocations gives the minimum variance. The only constraint is that the sum of allocations has to be 100%.

The allocations have been calculated based on a rolling window of 250 days and 1000 days, meaning that the first day with minimum variance portfolio allocations is 250 and 1000 days after the start of the sample period. Since historical and normal VaR are calculated on historical data, the first day with risk metric results comes another 250 or 1000 days after the first date with minimum portfolio allocations. ES has been calculated based on both the historical VaR and normal VaR breaks.

Figure 41: Float chart VaR calculations

In the market analysis in chapter 6.2, several global market incidents that affected the commodity prices were identified. Eight periods have been selected in order to test VaRs and ES performance during times of stress and optimisation. The periods have various lengths and have been chosen based on the findings in the market analysis. All periods have had an influence on at least one of the markets, and have been tested for significance level 1% and 5%, for both 250 days and 1000 days. Table 10 presents the testing periods. However, for the 1000 days time horizon, period 1 and 2 have not been conducted due to the data sample period does not contain 1000 days of data before the start of these periods

Table 10 Testing periods, VaR and ES.

Period	Scenarios
1	Commodity growth 18.06.03-18.06.07
2	Financial crisis 1.07.08-31.12.08
3	Growth after financial crisis 01.01.09 + 250 days
4	Arab Spring 01.07.2010 + 250 days
5	After Arab Spring 01.07.11 + 250 days
6	Oil crisis 01.07.2014 - 01.01.2016
7	Stabilised markets 01.02.2016 - 17.03.2017
8	Whole sample period 18.06.03 - 17.03.2017

7.1.2 Backtesting approach

All the VaR and ES results for 99% and 95% confidence level and 250 and 1000 days time horizon have been backtested using the three approaches presented in chapter 5. Christoffersen test have not been conducted for the 1000 days time horizon. Due to short sample period, it would only have been possible to test the last 970 days or period 6-8. The floatchart for backtesting is presented below.

Figure 42: Float chart, backtesting approach.

7.2 Portfolio Allocations

The portfolio allocations have been calculated by solving for minimum portfolio variance based on historical returns. This chapter presents two figures showing the allocations for portfolio P4 for the 250 days and 1000 days time horizon. The figures show that the metal assets gold and copper counts for a large portion of the allocations. The market analysis showed that the gold price was increasing even during the financial crisis before it started to fall in 2013. Gold has therefore been a good hedging asset. It can be observed from the plots that the gold allocation decreases when the gold price fell. In the same period the oil price was increasing, so the oil assets allocation also increased. When the oil crisis started the oil allocation part fell while the gold allocation grew as the gold price started to stabilize. The allocations in the 250 days portfolio fluctuate much faster than the allocations in the 1000 days portfolio. In both figures a major shift in allocations are observed. The reason is that an outlier in the gold price 250 and 1000 days before the shift has made a disturbance. Since the outlier was discovered in the finalising of the thesis, it has not been corrected for and must be seen as a source of error to the VaR calculations in period 1 for the 250 days case and period 3, 4 for the 1000 days case.

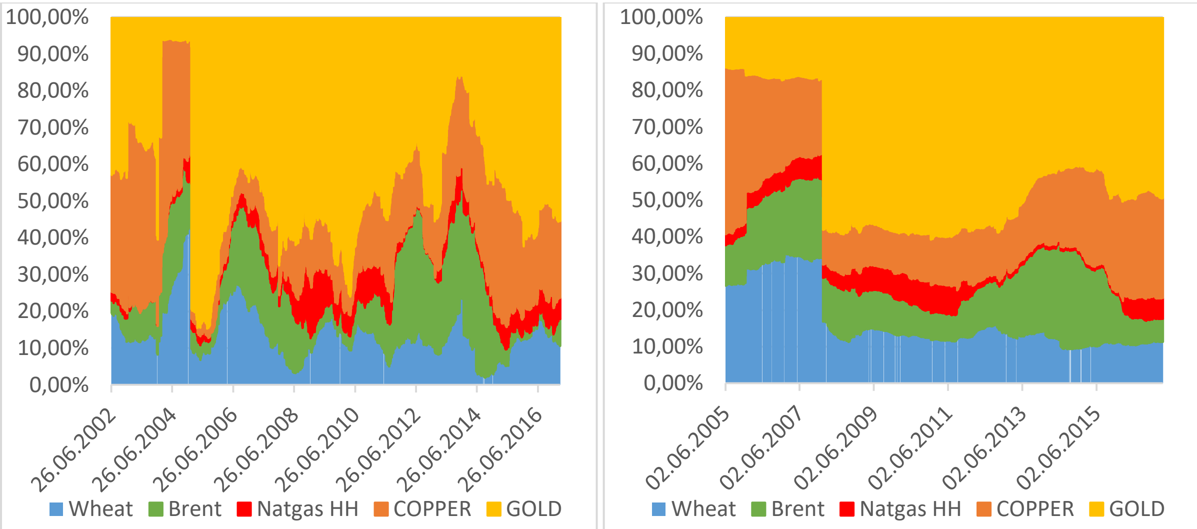

Figure 43 a, b: Allocations for P4 for the 250 days and 1000 days scenario respectively.

7.3 Normal VaR and ES Results

7.3.1 250 Days time approach

The results for the 250 days time horizons are presented below for all the portfolios. VaR and ES are plotted together with daily losses. It can easily be observed that ES predicts a higher expected loss than VaR for all cases. This is naturally true as expected shortfall is the expected loss given that VaR does not hold. It can also be observed that most losses comes in clusters. Therefore, the most loss predictions fails the Christoffersen test. For portfolio 1, Christoffersen test never holds.

Equivalent plots for the 1000 days time horizon are presented in Appendix C

Notation: for the results presented, the following abbreviations are used:

N-VaR = Normal VaR; N-ES= Normal ES; H-VaR= Historical VaR; H-ES= historical ES.

7.3.1.1 *99% Confidence Level*

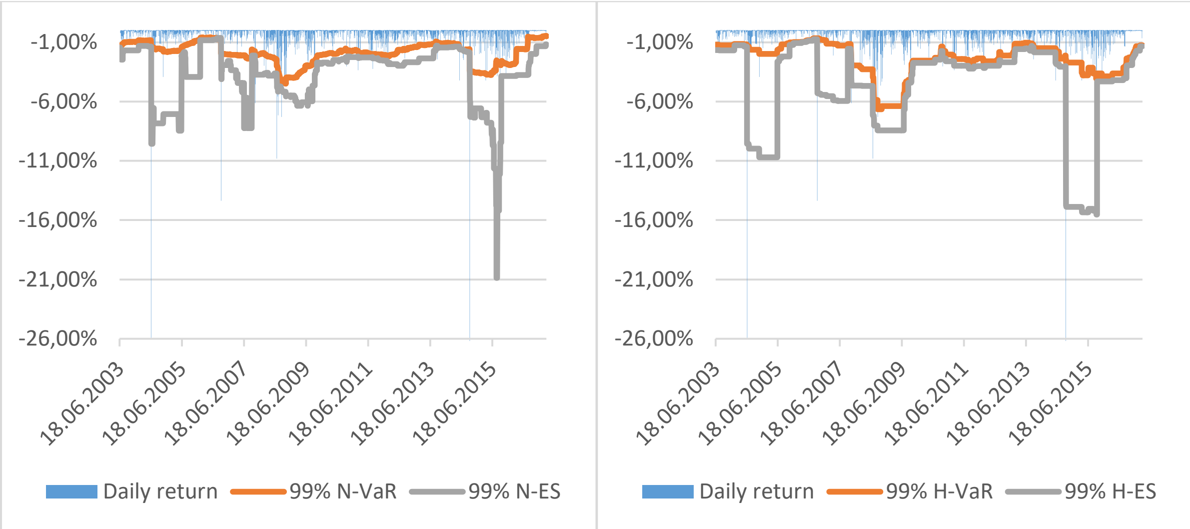

Figure 44 a,b: P1 VaR and ES results at 1% significance and 250 days time horizon for normal and historical respectively.

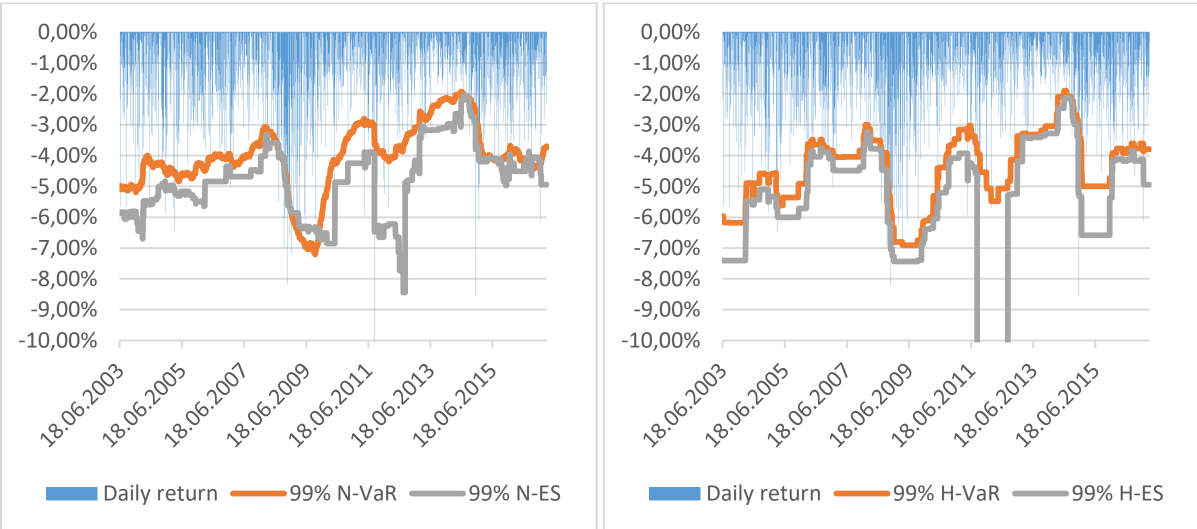

Figure 45 a,b: P2 VaR and ES results at 1% significance and 250 days time horizon for normal and historical respectively.

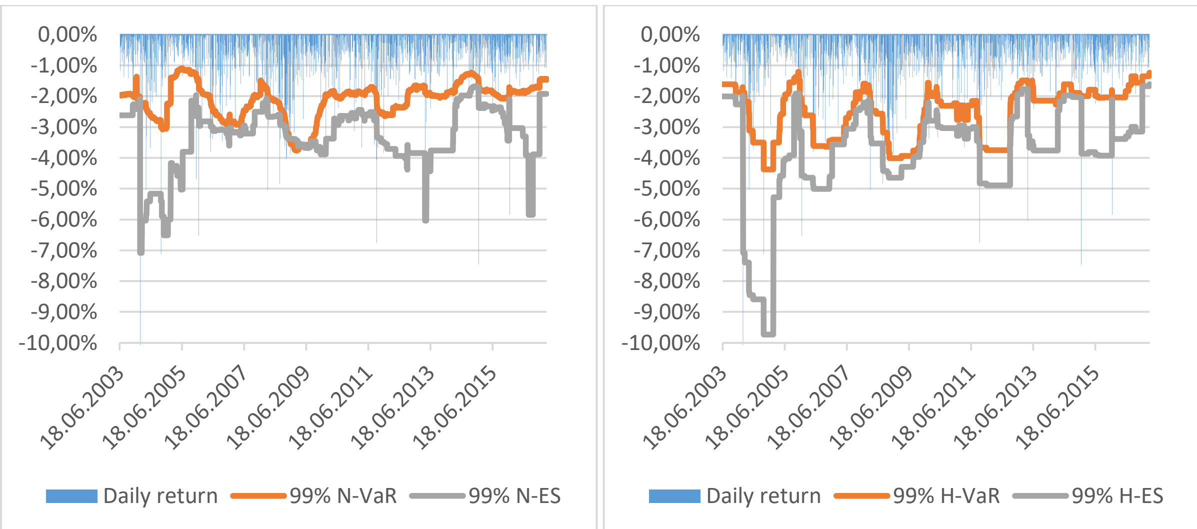

Figure 46 a, b: P3 VaR and ES results at 1% significance and 250 days time horizon for normal and historical respectively.

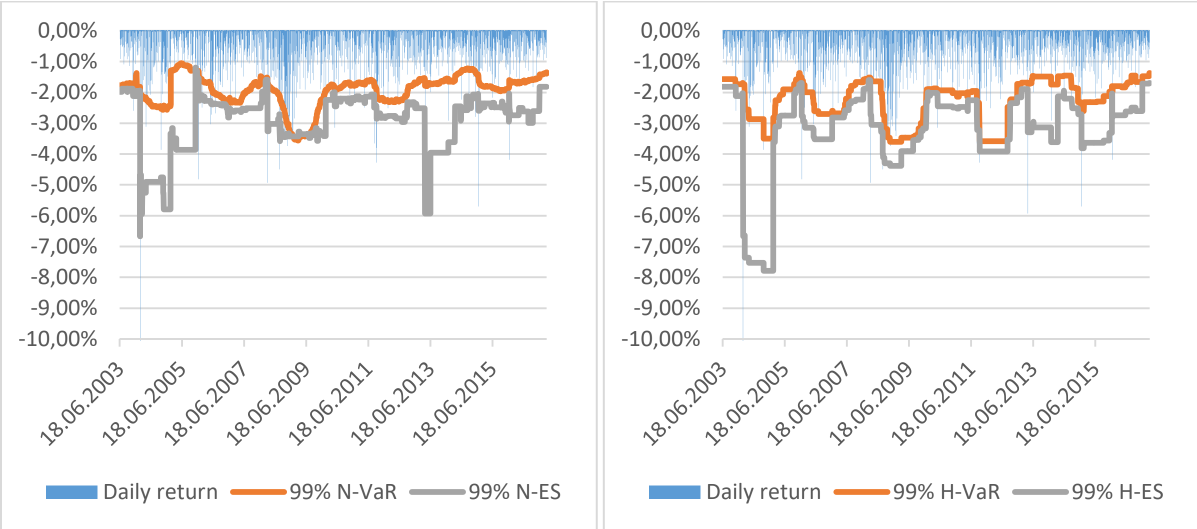

Figure 47 a, b: P4 VaR and ES results at 1% significance and 250 days time horizon for normal and historical respectively.

7.3.1.2 95% Confidence Level

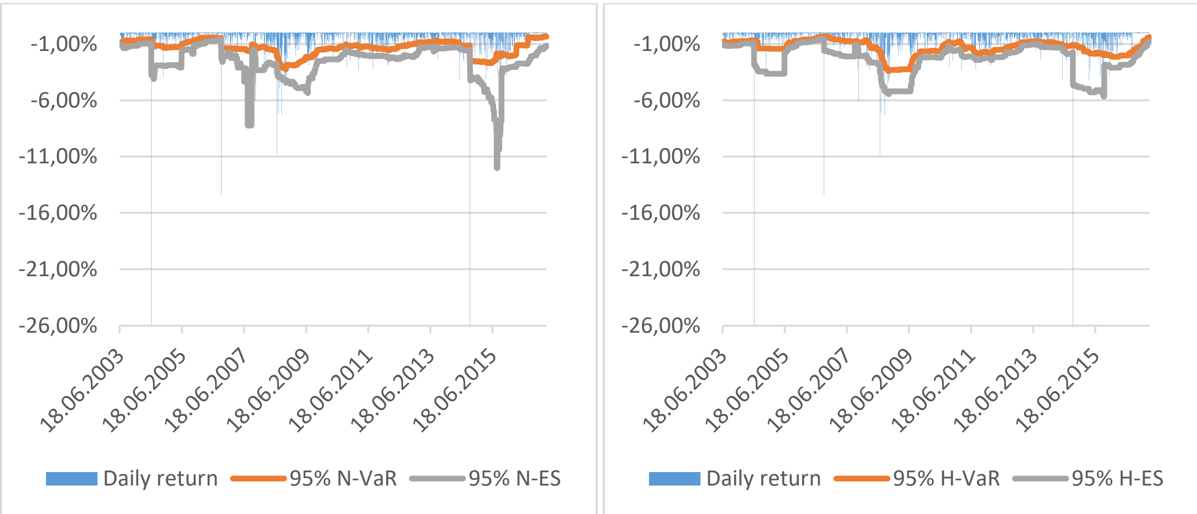

Figure 48 a, b: P1 VaR and ES results at 5% significance and 250 days time horizon for normal and historical respectively.

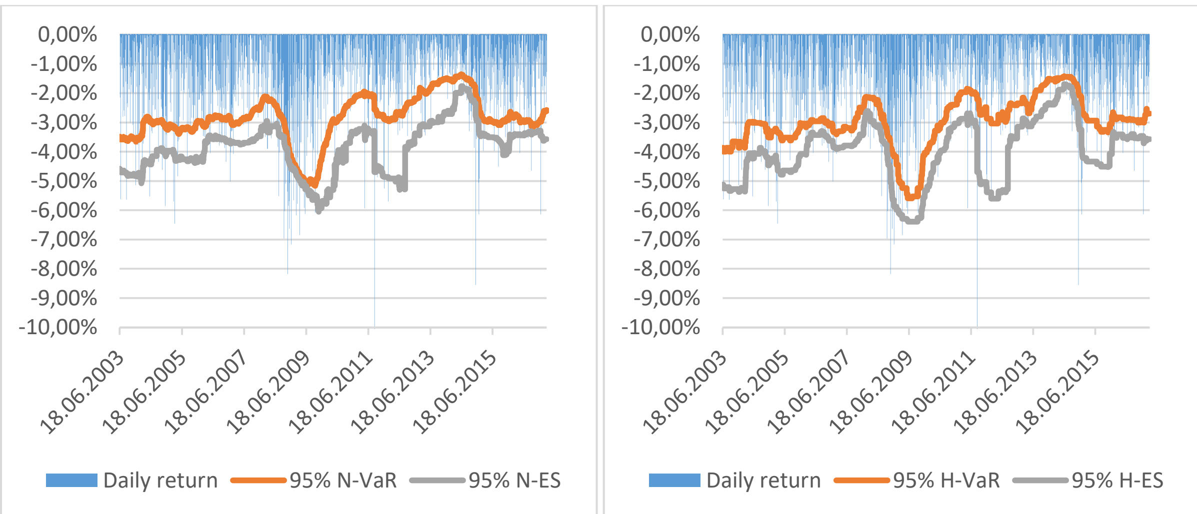

Figure 49 a, b: P2 VaR and ES results at 5% significance and 250 days time horizon for normal and historical respectively.

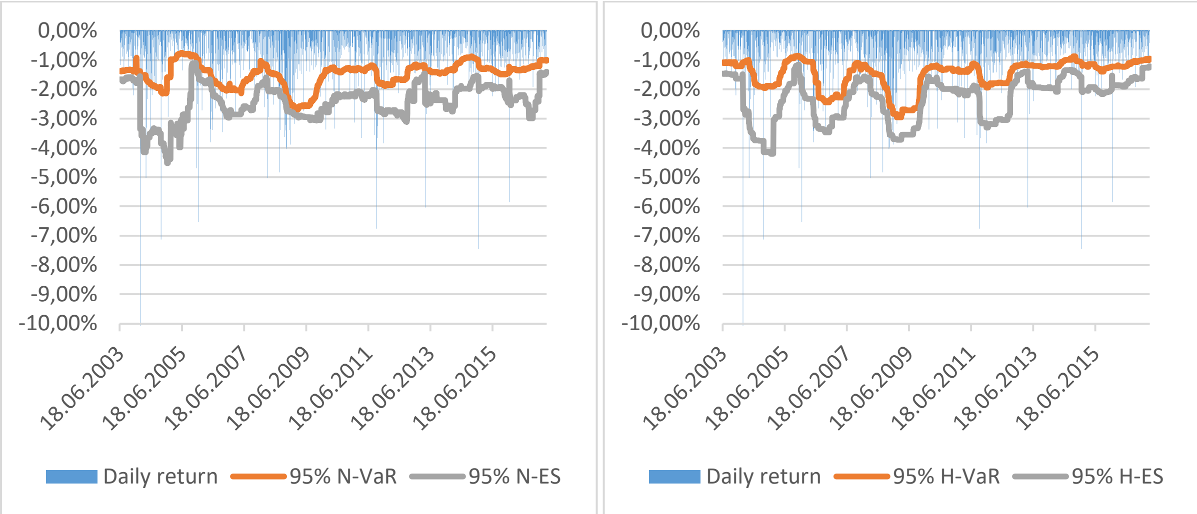

Figure 50 a, b: P3 VaR and ES results at 5% significance and 250 days time horizon for normal and historical respectively.

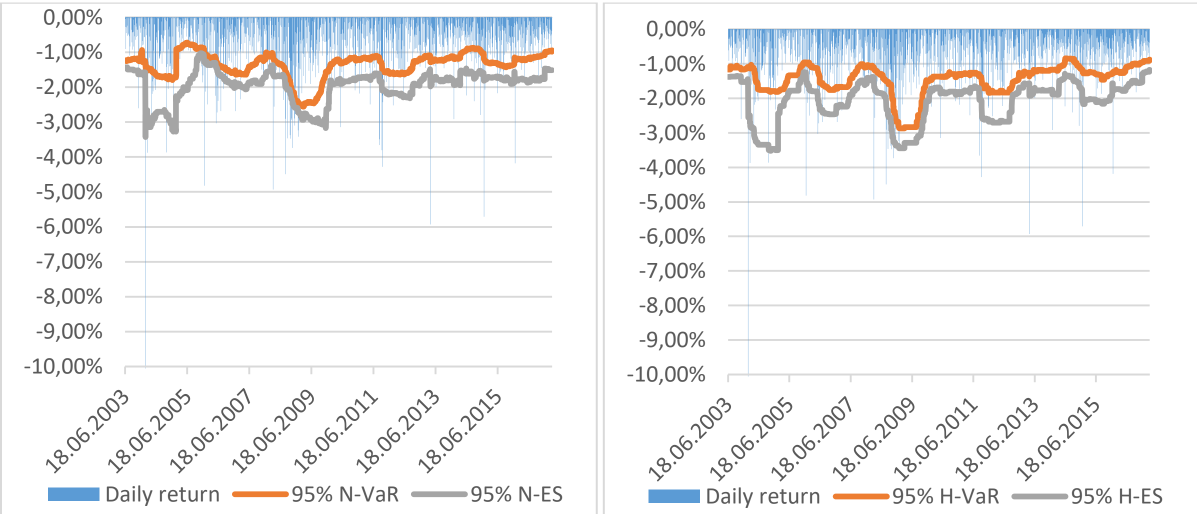

Figure 51 a, b: P4 VaR and ES results at 5% significance and 250 days time horizon for normal and historical respectively

7.3.2 VaR and ES portfolio comparison

In the following plots, the VaR and ES calculations for the four portfolios have been plotted together for each risk metric method at 99% confidence level and 250 days time horizon. The equivalent comparisons plot for the 1000 days time horizon can be found in Appendix C. The 95% risk metrics follows the same patterns and are therefore excluded. The comparison of the risk metric curves show that P4 generally has the lowest value at risk for all risk metrics. However, for Normal VaR, P1 has on average a slightly lower VaR than P4. It can also be observed that P3 is following P4 as a shadow. P3 has more or less exclusively higher VaR, but follows the same fluctuations. From the allocation plot in section 7.2, it is clear that P4 contains of at least 50 % metal assets, and is therefore correlated with P3, which explains the similar behaviour between the portfolios. Since P4 is a diversified portfolio containing assets from grain, energy and metal markets and its allocations are dynamic and solved for minimum variance, P4 is expected to have a lower standard deviation than the other portfolios. In Figure 3940 it can be seen that the standard deviation curve to P1 fluctuating around the more stable curve for P4. On average P1 has a slightly lower standard deviation than P4, which can explain why normal VaR is slightly lower for P1 than P4 as standard deviation is one of the input factors. Historical VaR and ES does not consider any distribution. Thus neither standard deviation and is therefore not affected. Historical VaR, normal ES and historical ES are all less for P4 than for P1-3, which is expected as the portfolios allocations are solved for the minimum variance. However, lower VaR/ES is not intuitive with a better risk metric performance. This will be investigated further in the backtesting chapter.

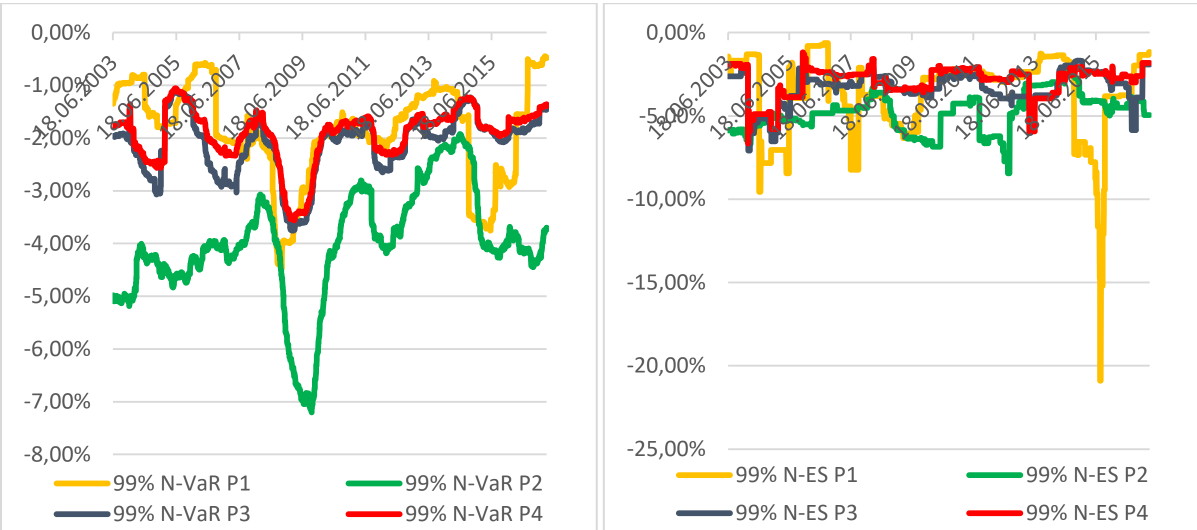

Figure 52 a, b: Portfolio comparison of 250 days 99% Normal VaR and Normal ES respectively.

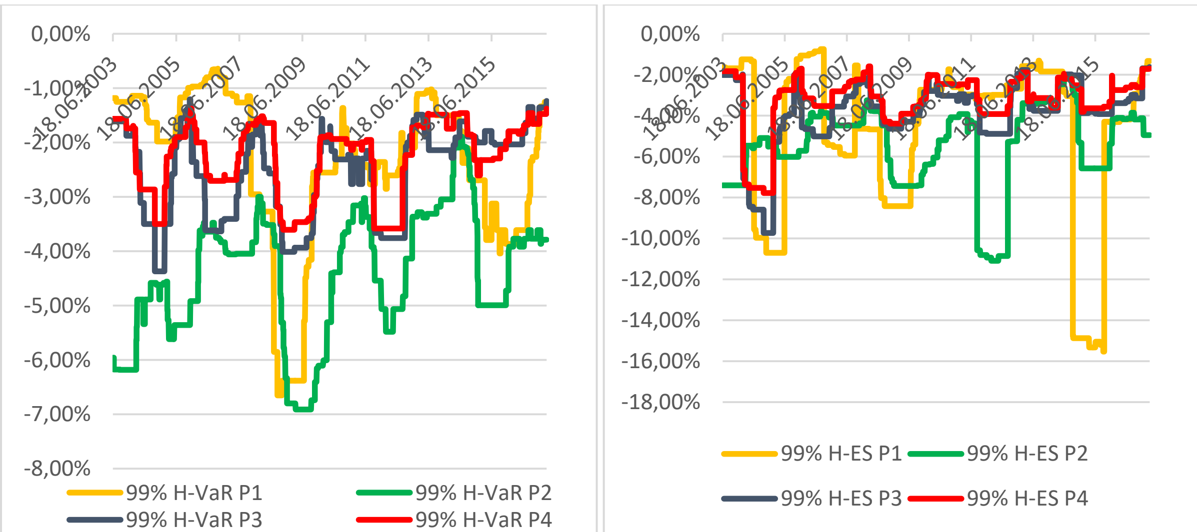

Figure 53 a, b: Portfolio comparison of 250 days 99% Historical VaR and Historical ES respectively.

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7.4 Backtesting Results

In total 1152 backtesting calculations have been conducted. This is equivalent with 288 tests per portfolio or per VaR/ES model. All the eight periods in Table 10 are tested at 99% and 95% confidence interval for 250 and 1000 days time horizons. The complete overview of the results are summarised in tables that are presented in Appendix C. In this chapter, the main findings from the backtesting will be presented.

After sorting the result data for models and portfolios, it is clear that expected shortfall is the best method for estimating potential future loss. ES calculated based on Historical 99%VaR with a 1000 days' time horizon is approved by all the tests. However, the 1000 days time horizons models have not been tested during the financial crisis. As this is a stressed period it can be argued, that the results may be different with a longer sample period. On the other hand, for the 250 days 99% Historical ES, tested 100% during the financial crisis for portfolio 4 and 75% in total for all portfolios. A more detailed presentation about the performance during selected periods will be presented later.

The following tables (11-13) present the percentages of how many tests each model passes under three different sorts. Historical ES is the best method at 1% significance level followed by Normal ES. The normal VaR and historical VaR score high or even best at 5% significance level. The VaR models score relatively poor at high confidence level. The portfolios descriptive statistics showed high positive kurtosis (Table 2), which means that the portfolios distributions have fat tails can explain this. It is in the tail area of the distribution the extreme losses are accumulated. VaR does not see beyond the 1% significance limit and fail to estimate the extreme losses.

For the calculations at 5% significance level, ES is no better than VaR and perform poorer than at high significance level. This is a bit unexpected and proves how difficult it is to get a good prediction of tail losses. However, it can be explained by the calculations. Expected shortfall is calculated based on the average of the losses that exceeds the VaR expectations. For 95% VaR, as much as 5% of the VaR calculations can fail and the test will still be approved for at least regular backtesting. The ES will be the average of all the losses higher than VaR. The 95% VaR is naturally lower than the 99%VaR because the calculations solve for the 5% worst outcome instead of the 1% worst outcome. Furthermore, when the pot of losses is large, the extreme losses that will be weighted equally with a loss that is just slightly higher than the VaR. The size of the losses "evens out". Hence, the ES will not be much larger than VaR. At high confidence level, 99%, the pot with losses higher than VaR are extreme, and therefore the average of these losses will be high enough to be able to estimate the potential loss so that ES holds more often .

Table 11: Percentage of how many tests the models pass.

h	N-VaR	N-ES	H-VaR	H-ES	1-α
250D	26%	52%	39%	**63%**	**99%**
250D	43%	40%	**44%**	43%	**95%**
1000D	52%	90%	81%	**100%**	**99%**
1000D	**69%**	54%	65%	**69%**	**95%**

Table 12: Percentage of how many tests the models pass, Christoffersen is excluded.

h	N-VaR	N-ES	H-VaR	H-ES	1-α
250D	36%	70%	53%	**83%**	**99%**
250D	58%	58%	56%	**61%**	**95%**
1000D	52%	90%	81%	**100%**	**99%**
1000D	**69%**	54%	65%	**69%**	**95%**

Table 13: Percentage of how many tests the models pass, excluding Christoffersen test and period 1 and 2.

h	N-VaR	N-ES	H-VaR	H-ES	1-α
250D	44%	77%	58%	**98%**	**99%**
250D	**69%**	65%	65%	65%	**95%**
1000D	52%	90%	81%	**100%**	**99%**
1000D	**69%**	54%	65%	**69%**	**95%**

The VaR performance is more or less the same for the four different portfolios. On average, the portfolios succeed in approximately 52% of the tests. That means that the portfolios are 52% efficient in predicting the potential loss. As Table 14 shows, the portfolios perform better in a 1000 Days time interval. This is also apparent from the tables presented and discussed above. The risk metric scenarios also perform better at the 1000 days scenario. As discussed in the historical VaR theory in 5.2.2, one of the risk metrics weakness is its sensitivity to the length of sample period. If the sample period is too short for historical VaR, the test fails to predict any large future loss if there are not any correspondingly losses in the sample period. However, for 95% H-VaR, there is no difference in performance between the 250 and 1000 days cases when they are evaluated for the same number of periods and Christoffersen test is excluded (Table 13). It can therefore not be concluded that the sample length is the sole reason for better performance in the 1000 days scenario.

It is not surprising that the four different portfolios do not differ in regards to performance. The backtests are not able to differ between high and low value at risk.

Table 14: Portfolios VaR and ES performance in percentage.

	P1	P2	P3	P4
250 Days	42%	**44%**	43%	**44%**
1000 Days	73%	70%	70%	**77%**
Overall	52%	52%	52%	**55%**

7.4.1 Backtesting periods

The periods presented in Table 10 have been backtested for regular, Kupiec and Christoffersen. As mentioned earlier, Christoffersen test is not conducted at 1000 days time horizon, due to the short test interval. The number of tests conducted and their approved ratios are presented in the table below. This count is the sum for all tests. The table shows that Christoffersen is a very hard test to pass, and kupiec and regular backtests approves approximately 65% each. Kupiec and regular are coverage tests that fails the risk metric fails to predict according to significance level. The regular fails a test if actual return is less than expected shortfall or value at risk. Furthermore, if the sum of violations divided by observations is higher than significance level, than the risk metric for the given period has failed.

Kupiec also test coverage, but is a likelihood test with a chi distribution with one degree of freedom (v=1). Chi distribution is the sum of v independent normal distributions and have two critical values. Kupiec fails the test period if the risk metric has over- or under-estimated the loss at the given significance level.

Christoffersen is an independence backtest and is hard to pass at it fails tests where the violations appears in clusters. As explained in the theory section, it tests the likelihood of a loss given one of four scenarios. The Christoffersen test uses a chi distribution with two degrees of freedom and calculates the p-values based on the critical values for significance level. The p-values are tested against the significance level and the test for the current day fails if the p-value is less than significance level. If the sum of failed Christoffersen tests divided by number of Christoffersen tests performed in the period is higher than significance level, then the period has failed Christoffersen test for the risk metric.

Table 15: Overview total backtests conducted and approved.

	Regular	Kupiec	Christoffersen
Tests Conducted	448	448	256
Approved Test	286	296	30
Approved Ratio	64%	66%	12%

Backtesting is a measure of VaR and ES's performance. It has earlier been investigated which risk metric performs best under different scenarios and if there is any difference in the portfolio performance. We have so far seen that for all the tests, historical ES is the best risk metric and there are barely any difference between the portfolios loss prediction performance. In the following tables, the results based on the different periods in Table 10 will be presented. Only a sample of the most interesting results are presented here. A complete collection of the results tables will be presented in Appendix C.

In this thesis, for simplicity, the "regular" backtest has only tested the hypothesis: *"accept the model if the ratio of violations is less than significance level α"*. For statistical models as VaR this is not statistically correct, and may be considered a source of error for the VaR regular backtesting results. For a 99% VaR model, the best model is the model that gives exactly the expected 1% violations. A model with zero violations may be a poor model as it overestimates the value at risk, and gives an opportunity cost. It is possible to use a binomial confidence interval (lower and upper limit) for number of violations that is accepted given the number of observations, confidence level and expected number of violations. Kupiec test, which is also conducted, considers such limits and rejects tests that has a number of violations that is under or over the tests confidence interval around the expected number of violations. However, it is chosen to reject all tests with more violations than expected, and accept all tests with violations equal or less than expected.

The results in Table 16Table 177 gives the regular backtesting results for normal VaR and historical ES respectively at 99% confidence and 250 days time horizon. The results are colour coded in terms with severity of violations. All accepted tests are green, while tests that are rejected have different shades of "warm red-ish colour". The least severe is light pink and the most severe are red, the colours get one tone darker per percentage away from the expected significance level. The tables represent the worst and best risk metric under these conditions for all 8 periods. Normal VaR holds only in period 3 and 7, which are periods for growth and market stabilisation. The risk metric fails tremendously during the financial crisis (period 2) and underestimates the value at risk. These observations are also true for historical VaR. In period 6, during the oil crisis the severity of the VaR performance is not as tremendous as during the financial crisis, but still generally poor for normal VaR. However, for historical VaR it is only P2, the energy portfolio, the risk metric fails as poorly as normal VaR. P1-P3 also fails the regular backtest for historical VaR, but just barely.

The historical ES actually succeeds in 50% of the regular backtests in both period 2 and 6, while normal ES fails all. In addition, the severity of the tests that fails are not as extreme as for the VaR metrics. As seen earlier in the results presented above, the historical ES is the best risk metric and especially at

99% confidence level. This is clear from Table 17 below. Normal ES is not as successful, but the risk metric also passes the backtesting in period 3 and 7.

Remember from the price analysis in chapter 6.2, period 3 is the time after the financial crisis in 2008 where all the commodity prices increased after the markets had crashed. Investors started to gain more confident in the macro economy and invested in industries that used commodities in the production line. The increased demand for commodities led to increased prices and hence less and reduced losses. In addition, since the risk metrics are calculated based on historical data, in the period after the crisis the predicted loss for the next day is based on the α% worst loss in markets in crisis. Therefore, the models are pessimistic and predict losses in line with what was experienced in the times of crisis. The "small" losses in the following period therefore goes under the predicted VaR and ES limits and the regular backtesting models approve the period. The same results are observed for period 7 after the markets had stabilized from the recession in industries and commodity demand in period 6.

Table 16: Results for 99% 250 days Normal VaR regular backtesting calculation.

		P1		P2		P3		P4	
Period	**Obs.**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	1020	13	1,27 %	14	1,37 %	28	2,75 %	21	2,06 %
2	128	8	6,25 %	12	9,38 %	13	10,16 %	11	8,59 %
3	250	1	0,40 %	1	0,40 %	0	0,00 %	1	0,40 %
4	250	10	4,00 %	5	2,00 %	8	3,20 %	5	2,00 %
5	250	7	2,80 %	7	2,80 %	7	2,80 %	10	4,00 %
6	365	9	2,47 %	17	4,66 %	11	3,01 %	11	3,01 %
7	290	4	1,38 %	2	0,69 %	1	0,34 %	2	0,69 %
8	3468	76	2,19 %	73	2,10 %	84	2,42 %	71	2,05 %

Table 17: Results for 99% 250 days Historical ES regular backtesting calculation.

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	1020	3	0,29 %	9	0,88 %	4	0,39 %	4	0,39 %
2	128	2	1,56 %	5	3,91 %	1	0,78 %	1	0,78 %
3	250	0	0,00 %	0	0,00 %	0	0,00 %	0	0,00 %
4	250	3	1,20 %	1	0,40 %	2	0,80 %	1	0,40 %
5	250	1	0,40 %	1	0,40 %	3	1,20 %	4	1,60 %
6	365	1	0,27 %	7	1,92 %	3	0,82 %	4	1,10 %
7	290	0	0,00 %	2	0,69 %	0	0,00 %	0	0,00 %
8	3468	18	0,52 %	29	0,84 %	19	0,55 %	19	0,55 %

In Table 18, the results for historical ES at 99% confidence and 250 days time horizon are presented. This is the best metric with regards to Christoffersen test, and is therefore chosen to represent the results in this thesis. The complete results can be found in Appendix C.

Christoffersen test fails the risk metric if the risk metrics violations appears in clusters. Christoffersen can therefore fail a test that is approved by regular backtest if the violations come in clusters. In the price analysis part, several periods of big market fluctuations were observed. Times of recessions comes with great losses, and often in short periods, before the market stabilises. During the worst periods of recessions, there are great losses that often comes in clusters. This can be observed by either at look at the price change plots in section 6 or by looking at the daily losses in section 7. Therefore, it is not hard to understand why Christoffersen fails most tests. Usually the losses appears in clusters.

Christoffersen can also approve a test that has failed the regular, if the violations of the risk metric do not behave in clusters. A bit surprising, this is what happens during the financial crisis for expected shortfall. For historical ES P2 and normal ES, P4, Christoffersen approves the risk metric calculations despite the tests fails for regular backtest. At 95% significance Christoffersen approves ES for P3 and P4 during financial crisis. In figure Figure 44-Figure 47 it can be observed that the daily losses that exceeds the VaR and ES limits come in clusters for P1 during 2008, while for P3 and P4, it looks like the big losses that exceeds the predicted loss are more spread. This observation explains why Christoffersen approves tests that regular backtesting rejects.

The results for the Kupiec test is not considers as carefully, because the test either "accepts" or "reject" a period. It does not give a percentage, which can be evaluated in regards to how extreme the violation was. Kupiec is also a coverage test as the regular backtest that uses number of violations, observations and significance level as input factors. Therefore, the tests approves approximately the same tests as regular. The exception is at 95% confidence level and the 1000 days time horizon. The 95%ES regular backtest results are presented in the additional tables in Appendix C.8. All tests are approved by regular backtest for both normal and historical ES. However, the Kupiec test only approves 11 tests in total during the same period in which the regular approves all 46 tests (see summary tables). This is also reflected in Table 13 which presents in total how large fractions of all tests conducted are approved for the given α and h. The results shows that in total Kupiec and regular only approves 54% and 69% of all tests for normal ES and historical ES respectively given α=95% and h=1000 days. The reason is that ES overestimates the loss at this significance level. Kupiec rejects the test because the number of violations are too far away from the expected. Because the Kupiec test uses a chi distribution it has two critical values, and in this case, the ES performance is rejected for most tests because the model overestimates risk. Thus in this scenario Kupiec show the added test value compared to regular coverage test that does not take overestimated risk into account.

Table 18: Results for 99% 250 days Historical ES Christoffersen backtesting calculation. (Period 1 is for Christoffersen from 10.06.04-18.06.07).

		P1		P2		P3		P4	
Period	**Obs.**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	771	329	42,67 %	48	6,23 %	337	43,71 %	346	44,88 %
2	128	81	63,28 %	0	0,00 %	0	0,00 %	0	0,00 %
3	250	116	46,40 %	42	16,80 %	105	42,00 %	103	41,20 %
4	250	69	27,60 %	214	85,60 %	2	0,80 %	2	0,80 %
5	250	3	1,20 %	1	0,40 %	2	0,80 %	191	76,40 %
6	365	71	19,45 %	43	11,78 %	49	13,42 %	6	1,64 %
7	291	291	100,00 %	161	55,33 %	62	21,31 %	62	21,31 %
8	3220	1545	47,98 %	916	28,45 %	948	29,44 %	1151	35,75 %

The tables (20,21,22) on the next pages show the performance of all the tests in period 2, 6 and 7. The summary tables for the other periods are presented in Appendix C. These tables show for each portfolio, which risk metrics are approved and by which tests. These summary tables lay the foundation for the conclusions drawn with regards to which risk metrics performs best and to the portfolio performance comparison. Table 19 present a summary of how many tests are approved for each portfolio during all the periods. Remember that period 1 and 2 only contain tests for 250 days time horizon. The table shows that for most periods, there is also one portfolio that underperforms. During the two crisis in period 2 and 6, portfolio 2 is the major underperformer. Portfolio 2 represent the energy market. During the price analysis in chapter 6.2 it was discussed how the oil prices dropped from all time highs during the financial crisis and later in the oil crisis. The risk metrics were not able to predict these huge losses and underperformed. Only the Kupiec and Christoffersen tests approved historical ES for P2 during the financial crisis, all other tests were rejected. For period 6, quite a few more backtests were approved for P2, which still was the portfolio that had the worst performance. The approved tests were for the 1000 days time horizon and most of them at 95% confidence level, which is easier to pass.

In period 4, the Arab spring, portfolio 1 was not performing at the same level as P2-4. During this time period, the grain prices were fluctuating around the uncertainty in demand and supply described in chapter 6.2. By investigating the price curves for all grains, it is observed that this is a period with increasing price trend, though with fluctuating prices. The risk metrics at high confidence level have during this period underestimated the VaR and ES, and hence given a poor performance. Moreover, the other portfolios have several tests during this period that has been approved by Christoffersen.

In period 5, portfolio 4 is underperforming. Compared to the other portfolios, it at high confidence level for the 250 days period compared to the other portfolio. By studying the VaR/ES to daily losses plots for the portfolio, there are not any obvious reasons behind why the diversified portfolio underperform in this period. All commodities are in a growth period, and P1-P3 all performs well.

The metal portfolio P3 does not have a period where it is performance much worse than the other three. The portfolio performance is slightly worse in Period 3 and 8, but inly with two test results.

These observations adds up under the conclusion about there are no major difference in the portfolio performance between the different markets and the diversified. Only some major market changes as crisis and unstable markets may influence the performance to the worse for the markets that are affected the most.

Table 19: Summary table portfolio performance during the different periods.

Period	P1	P2	P3	P4	Sum
1	10	11	9	7	**37**
2	7	2	7	7	**23**
3	26	28	23	25	**102**
4	23	27	27	30	**107**
5	25	26	26	20	**97**
6	17	14	18	19	**68**
7	22	27	26	30	**105**
8	21	17	15	20	**73**
Sum	151	152	151	158	

Table 20: Overview of tests approved and failed during period 2: financial crisis 2008.

Confidence Level	Time Horizon	Risk Metric	P1			P2			P3			P4		
			Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen
99 %	250D	N-VaR	-	-	-	-	-	-	-	-	-	-	-	-
		N-ES	-	v	-	-	-	-	-	-	-	-	v	v
		Hist-VaR	-	v	-	-	-	-	-	V	-	-	-	-
		Hist-ES	-	v	-	-	v	v	v	V	v	v	v	v
95 %	250D	N-VaR	-	-	-	-	-	-	-	-	-	-	-	-
		N-ES	v	v	-	-	-	-	-	-	v	-	-	-
		Hist-VaR	-	-	-	-	-	-	-	-	-	-	-	-
		Hist-ES	v	v	-	-	-	-	-	V	v	-	v	v
99 %	1000D	N-VaR	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		N-ES	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		Hist-VaR	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		Hist-ES	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
95 %	1000D	N-VaR	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		N-ES	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		Hist-VaR	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		Hist-ES	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

Table 21: Overview of tests approved and failed during period 6: oil crisis.

Confidence Level	**Time Horizon**	**Risk Metric**	**P1**			**P2**			**P3**			**P4**		
			Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen
99 %	250D	N-VaR	-	v	-	-	-	-	-	-	-	-	-	-
		N-ES	-	v	-	-	-	-	-	v	-	-	v	-
		Hist-VaR	-	v	-	-	-	-	-	v	-	-	v	-
		Hist-ES	v	v	-	-	v	-	v	v	-	-	v	-
95 %	250D	N-VaR	v	v	-	-	v	-	-	v	-	-	v	-
		N-ES	v	-	-	-	v	-	v	-	-	v	-	-
		Hist-VaR	-	-	-	-	v	-	-	v	-	-	v	-
		Hist-ES	v	-	-	v	v	-	v	-	-	v	-	-
99 %	1000D	N-VaR	-	-	NA	-	-	NA	-	-	NA	-	v	NA
		N-ES	-	v	NA	v	v	NA	-	v	NA	v	v	NA
		Hist-VaR	-	v	NA	-	v	NA	v	v	NA	-	v	NA
		Hist-ES	v	v	NA	v	v	NA	v	v	NA	v	v	NA
95 %	1000D	N-VaR	-	-	NA	-	-	NA	-	v	NA	v	v	NA
		N-ES	v	v	NA	v	-	NA	v	-	NA	v	-	NA
		Hist-VaR	-	-	NA	-	-	NA	v	v	NA	v	v	NA
		Hist-ES	v	v	NA	v	v	NA	v	-	NA	v	-	NA

Table 22: Overview of tests approved and failed during period 7: stabilised markets post oil crisis

Confidence Level	**Time Horizon**	**Risk Metric**	**P1**			**P2**			**P3**			**P4**		
			Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen
99 %	250D	N-VaR	-	v	-	v	v	-	v	V	-	v	v	v
		N-ES	v	v	-	v	v	-	v	V	-	v	v	-
		Hist-VaR	v	v	-	-	v	-	v	V	-	v	v	v
		Hist-ES	v	v	-	v		-	v	V	-	v	v	-
95 %	250D	N-VaR	v	-	-	v	v	v	v	-	-	v	v	-
		N-ES	v	-	-	v	-	-	v	-	-	v	-	-
		Hist-VaR	v	-	-	-	v	v	v	V	-	v	v	v
		Hist-ES	v	-	-	v	-	-	v	-	-	v	-	-
99 %	1000D	N-VaR	-	-	NA	-	v	NA	-	V	NA	v	v	NA
		N-ES	v	v	NA	v	v	NA	v	V	NA	v	v	NA
		Hist-VaR	v	v	NA	v	v	NA	v	V	NA	v	v	NA
		Hist-ES	v	v	NA	v	v	NA	v	V	NA	v	v	NA
95 %	1000D	N-VaR	-	v	NA	-	v	NA	v	V	NA	v	-	NA
		N-ES	v	-	NA	v	-	NA	v	-	NA	v	-	NA
		Hist-VaR	-	v	NA	v	v	NA	v	-	NA	v	-	NA
		Hist-ES	v	v	NA	v	v	NA	v	V	NA	v	v	NA

7.4.2 The severity of VaR and ES violations

Finally, the severity of a VaR and ES violation has been investigated. For α=1%, VaR just gives the answer "*with a 99% certainty, your loss will not exceed the calculated VaR*". The risk metric does not say anything about how much you can lose in 1% of the times the loss may exceed VaR. The magnitude of the loss for that 1% error may be severe enough to cause economical damage for the investor.

The expected shortfall has the advantage to predict the expected magnitude of the loss by taking the average of losses beyond the VaR limit for the last *h* days. However, if there is a market crisis, with losses larger than any loss in the historical time period *h*, ES is not able to forecast the loss.

The figures below show the additional loss for the VaR and ES violations during the financial crisis, period 2. The additional loss is the daily loss minus the predicted VaR or ES of the day the violation occurred. There is one plot for each portfolio and the VaR and ES are calculated at 99% confidence level and 250 days. The severity of the losses are for most cases worst for the VaR, both in number of violations and in excess of loss. These models shows one of VaR and ES major weaknesses as risk metrics. They underestimate the severity of losses.

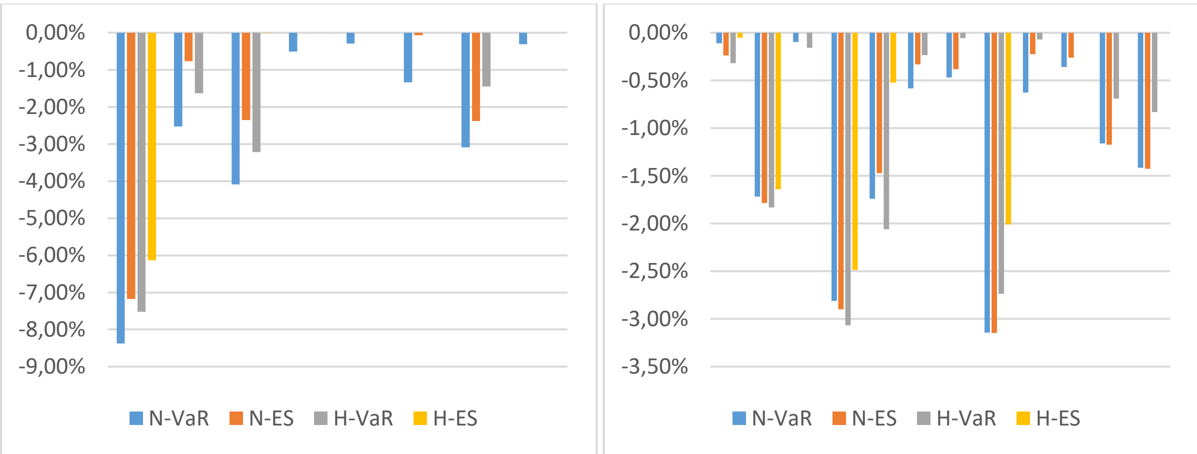

Figure 54 a, b: Difference between predicted loss and actual loss for P1 and P2 respectively in period 2, the financial crisis.

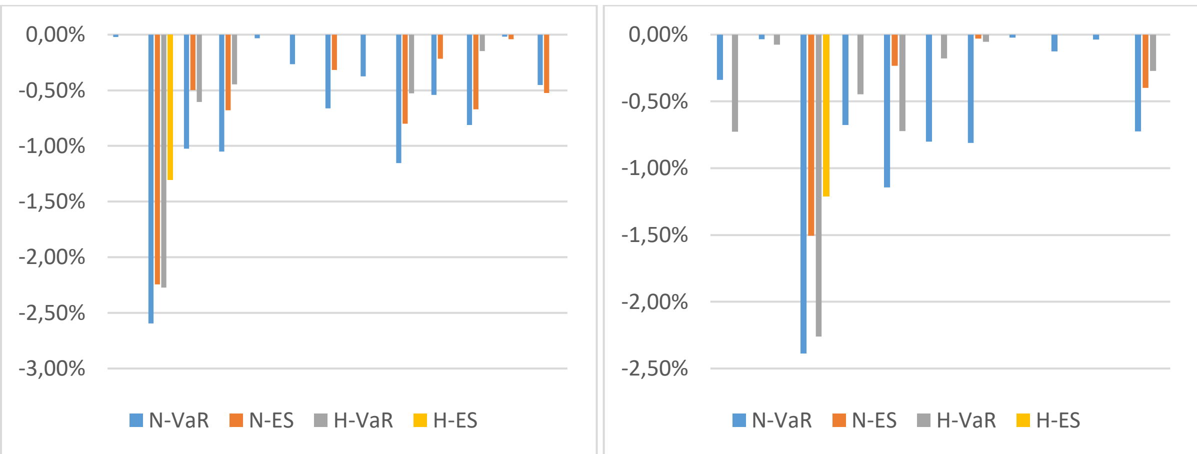

Figure 55 a, b: Difference between predicted and actual loss for P3 and P4 respectively in period 2, the financial crisis.

8 Conclusion and Recommendations

Eight conclusion remarks can be drawn from the results and discussion part in the previous chapter. The conclusions and recommendation for further work will be presented in this chapter.

- The diversified portfolio P4 showed that metals and particular gold accounted for a large portion of the allocation. Gold is seen as a good hedging asset. This thesis showed that this is true for our commodities, as the portion of gold generally was high and increased trough the financial crisis and the oil crisis.
- The energy commodities are more risky than grains and metals. The energy portfolio, P2 has higher standard deviation and also a higher VaR and ES than the other portfolios. The diversified portfolio, P4 is less risky and also have the lowest VaR and ES.
- 99% historical expected shortfall has proven to be the best risk metric in regards to predict the potential loss. While historical VaR is generally better than normal VaR, thus providing evidence to the high usage of historical VaR in financial industry (Pérignon & Smith, 2010).
- There is only minor difference in the VaR and ES performance between the portfolios. So that the diversification of risk in portfolio assets allocations, does not affect the performance of VaR. This is related to the none- coherency issues reported in earlier studies (Artzner et al., 1999).
- VaR performs poorly at high confidence level and ES performs best at high confidence. The performance on a 1000 days time horizon are generally slightly better.
- The risk metrics perform well during stable markets and times of growth. During times of recession and crisis the VaR models performs extremely poor, while historical ES succeeds for some portfolios. This confirms pervious critics by Danielsson (2002) and Persaud (2000) and the report by Turner (2009).
- When the risk metrics fail to predict the loss, the additional loss can be extreme. The consequences may be dramatic for the investors if he has not put aside sufficient securities to handles such losses. Again, this confirms previous studies.
- Christoffersen only approves 12% of the tests. It can thus be concluded that the majority of violations come in clusters, which is a consequence of the models’ moment of inertia and low ability to adapt to new information.

For further work, it is suggested to try the student-t distribution to predict value at risk and expected shortfall. In the descriptive statistics it was found that the return data of the portfolios and commodities were not normal distributed. Normal VaR turned out to be a poor risk metric, which is not surprising as the model assumes the data to be normal distributed. Student- t takes skewness and kurtosis into account with regards to degrees of freedom. It is therefore suggested to obtain the appropriate number for degrees of freedom for each portfolio, calculate VaR and ES and backtest with the same approach as in this thesis.

It is also suggested to Backtest the VaR results with a binomial confidence test to find acceptable upper and lower limits for number of violations. This may show somewhat better VaR performance results as the acceptance interval is larger.

Furthermore, it is suggested to run a case with restriction with regards to allocations. In this thesis the only constraint has been the sum of allocation has to be 100%. Especially for the 250 days rolling window, this has led to very fluctuating allocations. In a real case scenario, this comes along with transactions costs. In order to reduce the fluctuation in the allocations, it is suggested to put a constrain on allocations of minimum 5 % in all assets in the portfolio.

The results show that ES and historical ES in particular at 99% confidence level is the best risk metric for the four commodities portfolios in this thesis. Based on these results I recommend using ES as a risk metric model rather than VaR. Then maybe the next recession will not be as severe?

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Appendix A

A.1 Additional Figures

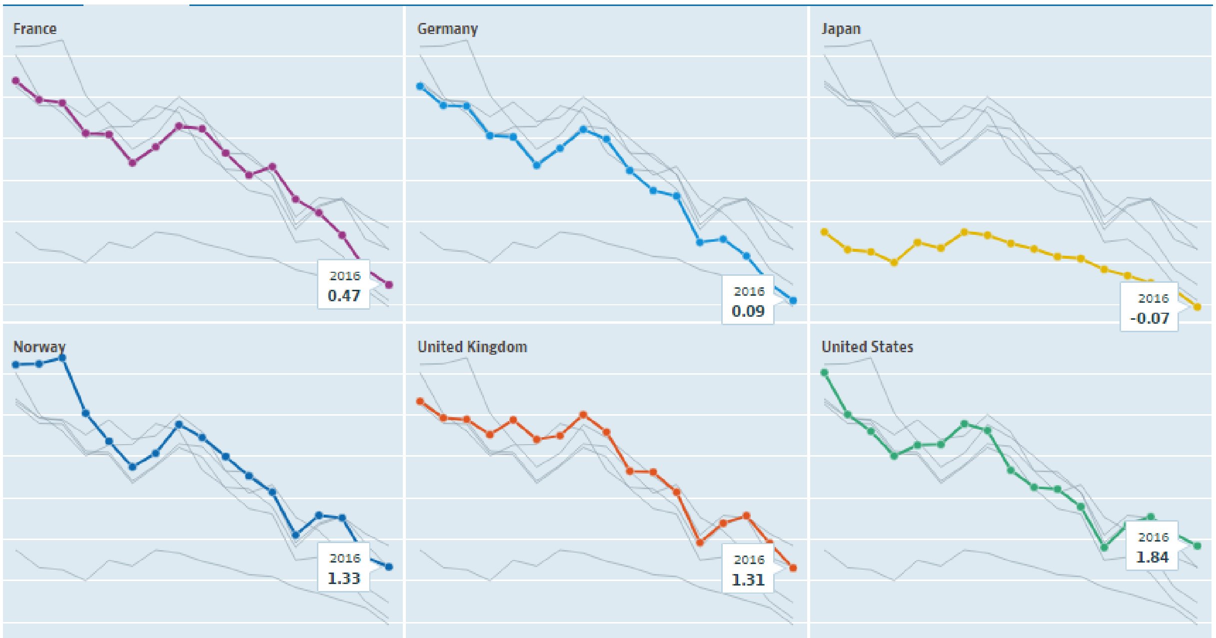


Figure 56: Long-term interest rates for France, Germany, Japan, Norway, UK, USA from 2000-2016. The figure shows decrease rates, leading to decreasing operation costs for holding gold as security (OECD, 2017).

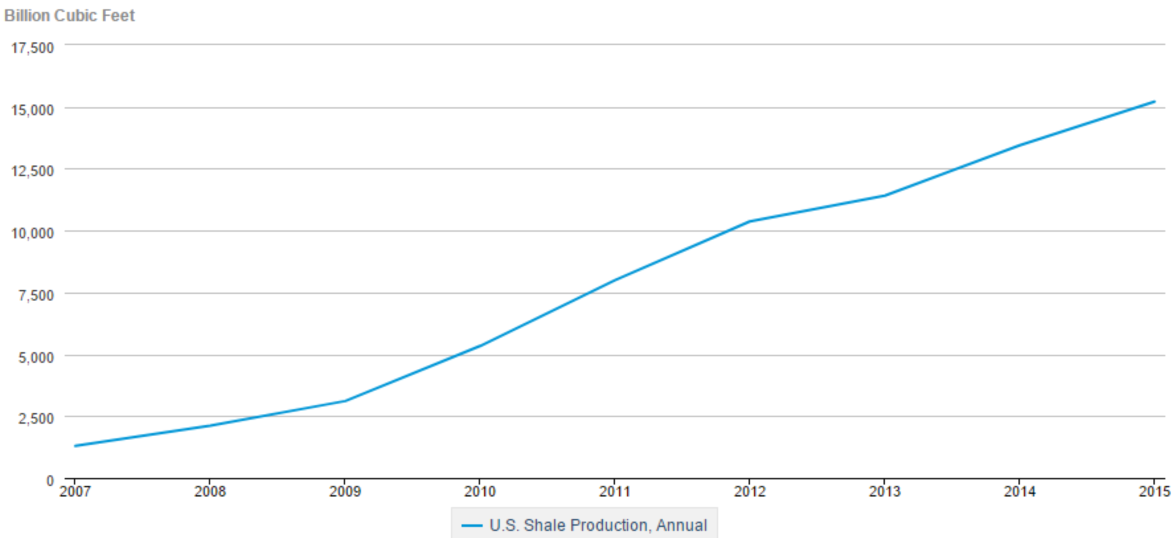


Figure 57: U.S Shale Production, Annual, 2007-2015 (EiA, 2016c)

Appendix B

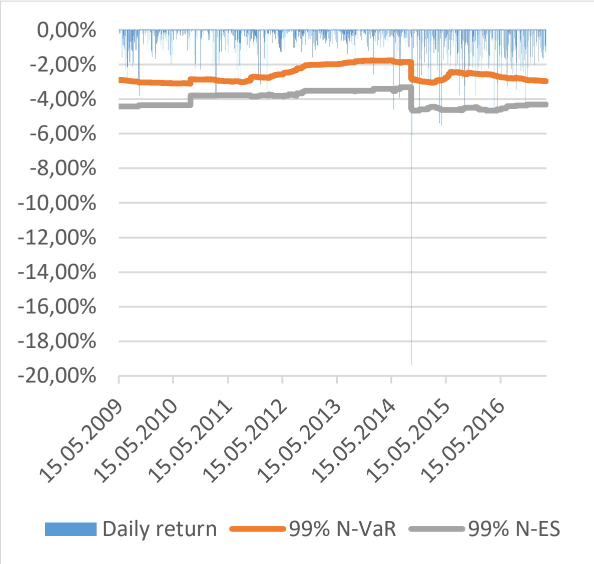
B.1 Data description

Category	Commodity	Asset Category Description	Instrument Description	Name	Currency	Units
GRAINS	Wheat	Commodity Spot	US Soft Red Winter Wheat New Orleans Terminal Prices	LousianaSRW Term	USD	BSH
GRAINS	Durum wheat	Commodity Spot	Thomson Reuters :US DURUM WHEAT MINNEAPOLIS TERMINAL PRICES CCS USD Contract	MPLS Wheat	USD	BSH
GRAINS	Barley	Commodity Spot	Thomson Reuters :US BARLEY MINNEAPOLIS TERMINAL PRICES CCS USD Contract	Mpls Term	USD	BSH
ENERGY	Brent	Commodity Spot	Brent Forties Oseberg Crude 1 Month USA Free On Board	BFO 1M USA	USD	BBL
ENERGY	WTI	Commodity Spot	Crude Oil WTI Midland US FOB	WTI-Midl	USD	BBL
ENERGY	Natgas Zee	Commodity Spot	Spectron Natural Gas Zeebrugge (ZEE) EOD Day Ahead Contract	MXS ZEE Gas DA	USD	MMBTU
ENERGY	Natgas HH	Commodity Spot	Natgas Nymex Herny Hub 2nd Month	NATGAS STRIP 2M	USD	MMBTU
METALS	Copper	Commodity Spot	Thomson Reuters : THOMSON REUTERS: WESTERN COPPER DELIVERED US CCS USD Contract	Cu Merchant	USD	kg
METALS	Bronze	Commodity Spot	Bronze MTLBASIS	Bronze MTLBASIS	USD	kg
METALS	Platinum	Commodity Spot	Platinum	Platinum UMIC	USD	kg
METALS	Palladium	Commodity Spot	Palladium	Palladium UMIC	USD	kg
METALS	Gold	Commodity Spot	Gold	Gold	USD	kg

Appendix C

C.1 99% VaR and ES 1000 Days

N-VaR= Normal VaR; N-ES= Normal ES: H-VaR= Historical VaR; H-ES= Historical ES



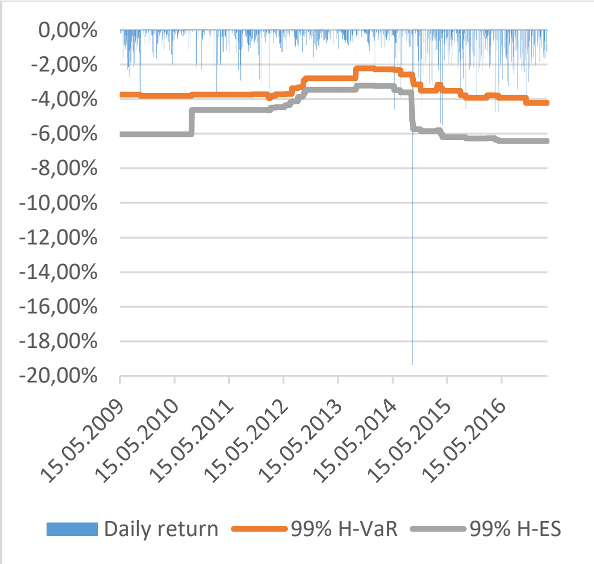
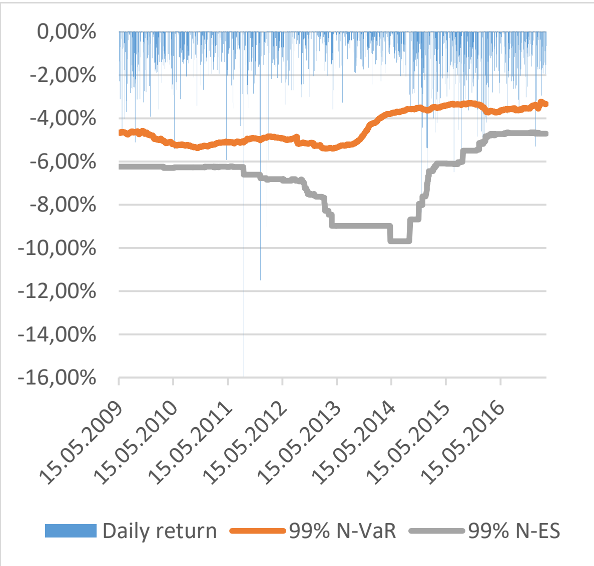


Figure 58 a, b: P1 VaR and ES results at 1% significance and 1000 days time horizon for normal and historical respectively.



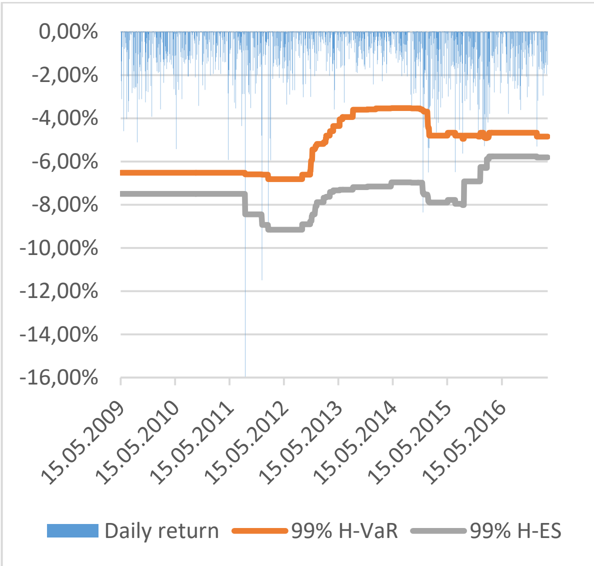
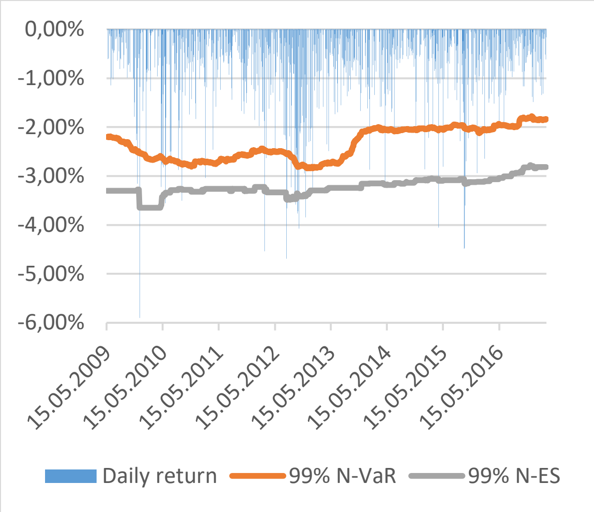


Figure 59 a, b: P2 VaR and ES results at 1% significance and 1000 days time horizon for normal and historical respectively.



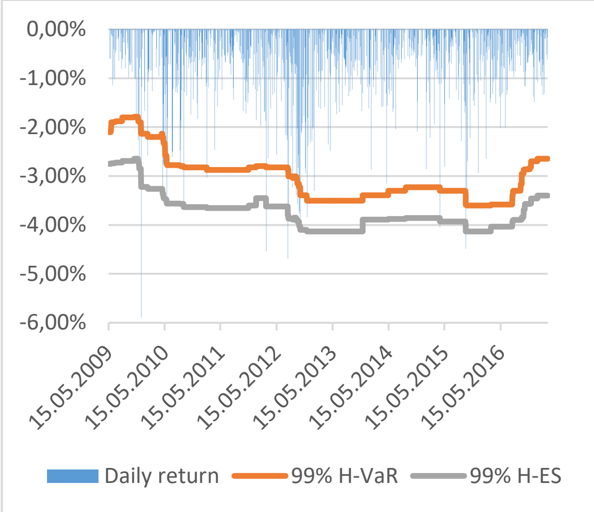
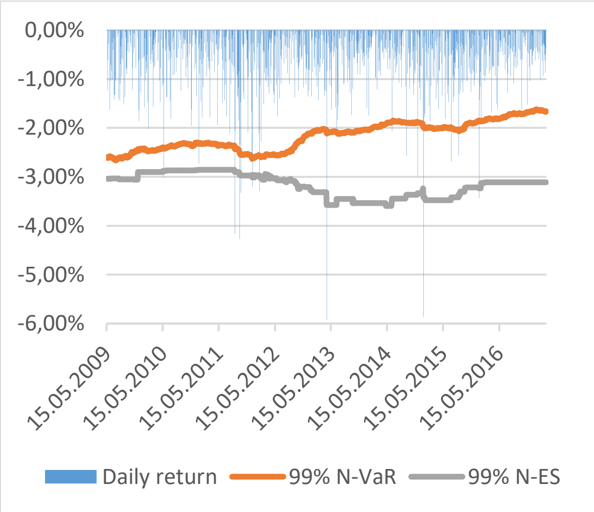


Figure 60 a, b: P3 VaR and ES results at 1% significance and 1000 days time horizon for normal and historical respectively.



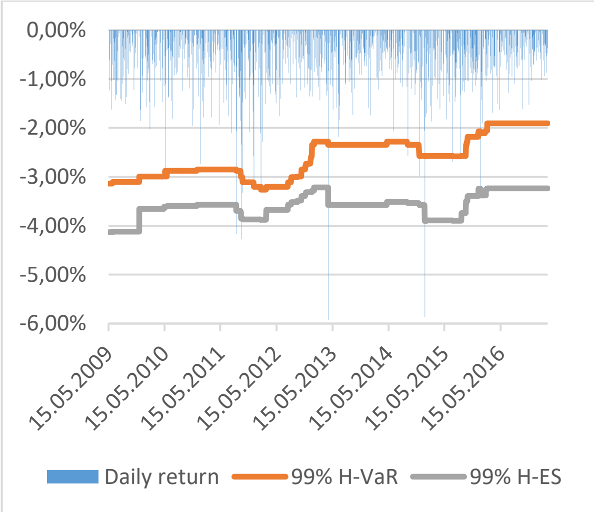
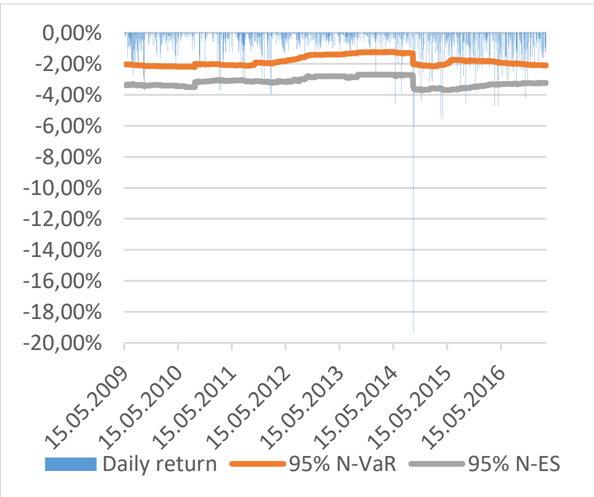


Figure 61 a, b: P3 VaR and ES results at 1% significance and 1000 days time horizon for normal and historical respectively.

C.2 95% VaR and ES 1000 Days



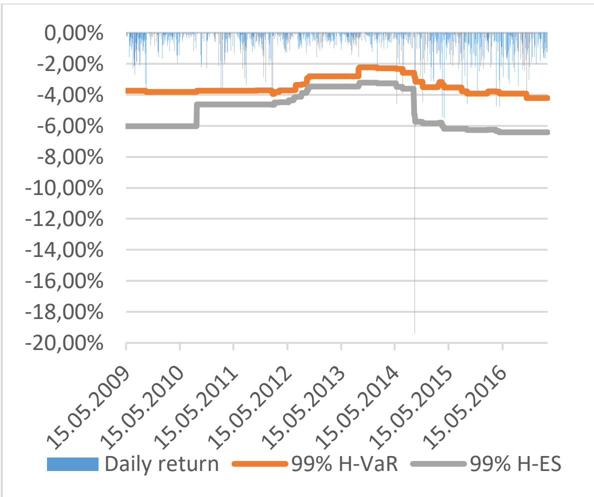


Figure 62 a, b: P1 VaR and ES results at 5% significance and 1000 days time horizon for normal and historical respectively.

Appendix C

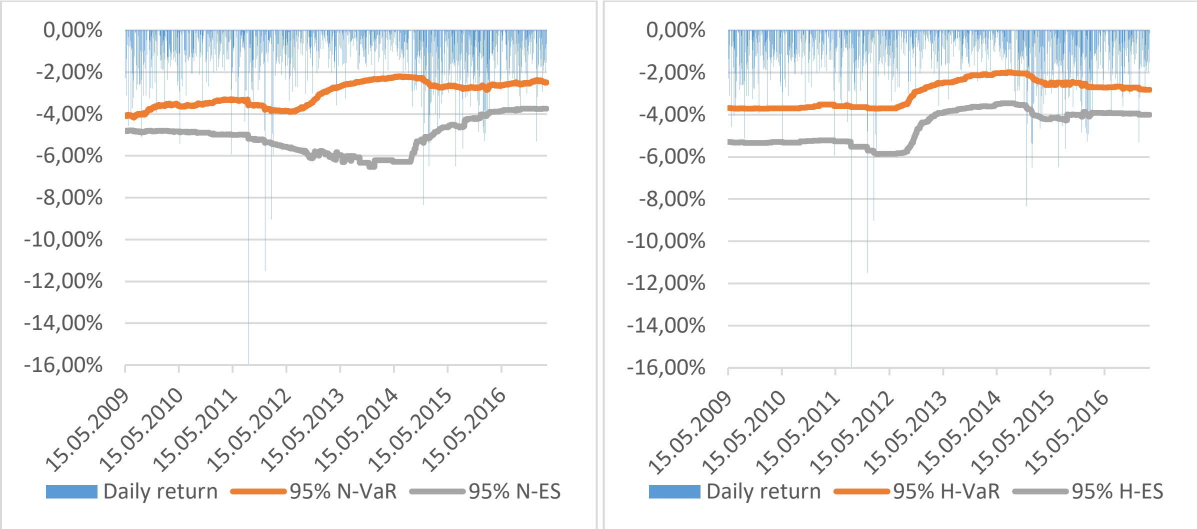


Figure 63 a, b: P2 VaR and ES results at 5% significance and 1000 days time horizon for normal and historical respectively.

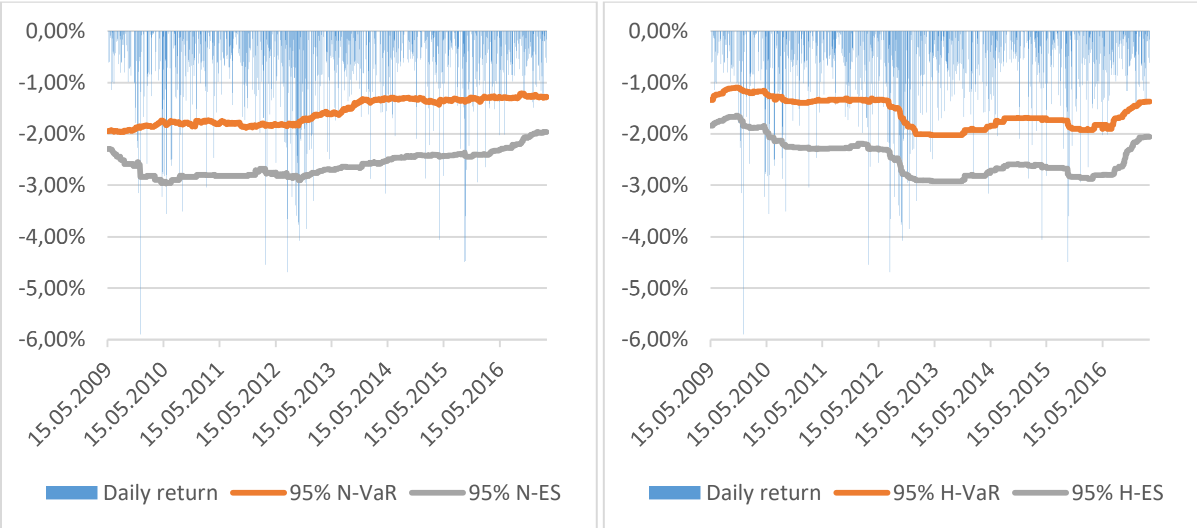


Figure 64 a, b: P3 VaR and ES results at 5% significance and 1000 days time horizon for normal and historical respectively.

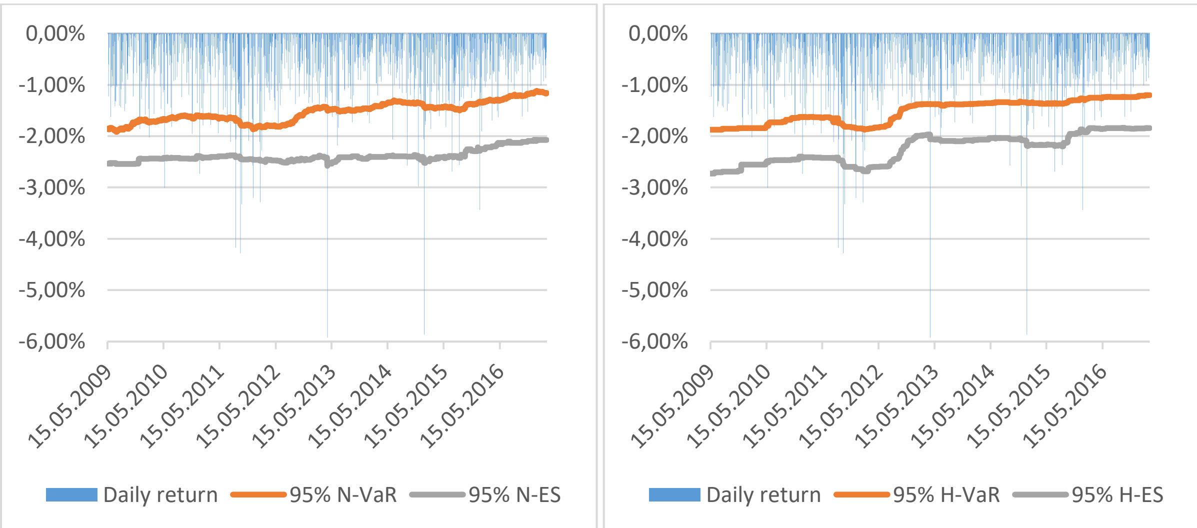


Figure 65 a, b: P4 VaR and ES results at 5% significance and 1000 days time horizon for normal and historical respectively.

C.3 Regular Backtesting additional results 99% 250 Days

Table 23: 99%N-VaR Backtest 250 days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	1020	17	1,67 %	14	1,37 %	17	1,67 %	18	1,76 %
2	128	4	3,13 %	11	8,59 %	5	3,91 %	8	6,25 %
3	250	0	0,00 %	1	0,40 %	0	0,00 %	0	0,00 %
4	250	5	2,00 %	4	1,60 %	3	1,20 %	3	1,20 %
5	250	4	1,60 %	6	2,40 %	5	2,00 %	4	1,60 %
6	365	8	2,19 %	13	3,56 %	6	1,64 %	4	1,10 %
7	290	0	0,00 %	3	1,03 %	1	0,34 %	2	0,69 %
8	3468	52	1,50 %	60	1,73 %	53	1,53 %	51	1,47 %

Table 24: 99%N-ES Backtest 250 days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	1020	3	0,29 %	5	0,49 %	10	0,98 %	14	1,37 %
2	128	5	3,91 %	11	8,59 %	9	7,03 %	4	3,13 %
3	250	0	0,00 %	2	0,80 %	0	0,00 %	0	0,00 %
4	250	4	1,60 %	1	0,40 %	2	0,80 %	1	0,40 %
5	250	4	1,60 %	2	0,80 %	5	2,00 %	4	1,60 %
6	365	4	1,10 %	13	3,56 %	4	1,10 %	4	1,10 %
7	290	0	0,00 %	2	0,69 %	0	0,00 %	0	0,00 %
8	3468	30	0,87 %	40	1,15 %	36	1,04 %	30	0,87 %

C.4 Christoffersen Backtesting additional results 99% 250 days

Table 25: 99%N-VaR Christoffersen Test 250 days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	771	62	8,04 %	178	23,09 %	288	37,35 %	203	26,33 %
2	128	128	100 %	67	52,34 %	115	89,84 %	63	49,22 %
3	250	113	45,20 %	196	78,40 %	213	85,20 %	203	81,20 %
4	250	181	72,40 %	1	0,40 %	30	12,00 %	4	1,60 %
5	250	170	68,00 %	138	55,20 %	135	54,00 %	193	77,20 %
6	365	141	38,63 %	282	77,26 %	114	31,23 %	191	52,33 %
7	291	6	2,06 %	24	8,25 %	4	1,37 %	2	0,69 %
8	3220	1199	37,24 %	965	29,97 %	1100	34,16 %	982	30,50 %

Appendix C

Table 26: 99%H-VaR Christoffersen Test 250 days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	771	255	33,07 %	33	4,28 %	338	43,84 %	194	25,16 %
2	128	81	63,28 %	67	52,34 %	102	79,69 %	87	67,97 %
3	250	91	36,40 %	191	76,40 %	100	40,00 %	105	42,00 %
4	250	247	98,80 %	1	0,40 %	4	1,60 %	3	1,20 %
5	250	73	29,20 %	98	39,20 %	2	0,80 %	192	76,80 %
6	365	14	3,84 %	223	61,10 %	4	1,10 %	6	1,64 %
7	291	90	30,93 %	65	22,34 %	3	1,03 %	1	0,34 %
8	3220	1217	37,80 %	845	26,24 %	748	23,23 %	793	24,63 %

Table 27: 99%N-ES Christoffersen Test 250 days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	771	329	42,67 %	208	26,98 %	277	35,93 %	350	45,40 %
2	128	81	63,28 %	34	26,56 %	49	38,28 %	0	0,00 %
3	250	90	36,00 %	202	80,80 %	171	68,40 %	44	17,60 %
4	250	69	27,60 %	214	85,60 %	1	0,40 %	1	0,40 %
5	250	5	2,00 %	1	0,40 %	2	0,80 %	191	76,40 %
6	365	49	13,42 %	286	78,36 %	50	13,70 %	50	13,70 %
7	291	87	29,90 %	24	8,25 %	62	21,31 %	62	21,31 %
8	3220	1175	36,49 %	1309	40,65 %	951	29,53 %	1094	33,98 %

C.5 Regular Backtesting Additional Results 95% 250 Days

Table 28: 95%N-VaR Backtest 250 Days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	1020	36	3,53 %	57	5,59 %	54	5,29 %	71	6,96 %
2	128	15	11,72 %	27	21,09 %	23	17,97 %	21	16,41 %
3	250	6	2,40 %	8	3,20 %	4	1,60 %	5	2,00 %
4	250	14	5,60 %	9	3,60 %	12	4,80 %	15	6,00 %
5	250	16	6,40 %	15	6,00 %	18	7,20 %	22	8,80 %
6	365	17	4,66 %	28	7,67 %	20	5,48 %	28	7,67 %
7	290	6	2,07 %	14	4,83 %	6	2,07 %	7	2,41 %
8	3468	152	4,38 %	200	5,77 %	176	5,07 %	218	6,29 %

Appendix C

Table 29 95%H-VaR Backtest 250 Days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	1020	51	5,00 %	44	4,31 %	58	5,69 %	57	5,59 %
2	128	14	10,94 %	25	19,53 %	20	15,63 %	24	18,75 %
3	250	4	1,60 %	8	3,20 %	3	1,20 %	4	1,60 %
4	250	14	5,60 %	10	4,00 %	11	4,40 %	12	4,80 %
5	250	10	4,00 %	15	6,00 %	15	6,00 %	17	6,80 %
6	365	30	8,22 %	27	7,40 %	23	6,30 %	28	7,67 %
7	290	1	0,34 %	15	5,17 %	10	3,45 %	8	2,76 %
8	3468	171	4,93 %	179	5,16 %	190	5,48 %	198	5,71 %

Table 30: 95%N-ES Backtest 250 Days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	1020	6	0,59 %	24	2,35 %	26	2,55 %	26	2,55 %
2	128	8	6,25 %	21	16,41 %	14	10,94 %	16	12,50 %
3	250	0	0,00 %	8	3,20 %	1	0,40 %	3	1,20 %
4	250	9	3,60 %	3	1,20 %	4	1,60 %	5	2,00 %
5	250	7	2,80 %	5	2,00 %	7	2,80 %	11	4,40 %
6	365	4	1,10 %	19	5,21 %	7	1,92 %	8	2,19 %
7	290	0	0,00 %	6	2,07 %	0	0,00 %	2	0,69 %
8	3468	47	1,36 %	96	2,77 %	70	2,02 %	81	2,34 %

Table 31: 95%H-ES Backtest 250 Days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	1020	8	0,78 %	23	2,25 %	22	2,16 %	20	1,96 %
2	128	5	3,91 %	15	11,72 %	9	7,03 %	9	7,03 %
3	250	0	0,00 %	2	0,80 %	1	0,40 %	1	0,40 %
4	250	10	4,00 %	6	2,40 %	6	2,40 %	4	1,60 %
5	250	5	2,00 %	4	1,60 %	7	2,80 %	5	2,00 %
6	365	4	1,10 %	15	4,11 %	8	2,19 %	6	1,64 %
7	290	0	0,00 %	5	1,72 %	1	0,34 %	2	0,69 %
8	3468	52	1,50 %	82	2,36 %	72	2,08 %	63	1,82 %

C.6 Christoffersen Backtesting Additional Results 95% 250 Days

Table 32: 95%N-VaR Christoffersen test 250 Days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	771	654	84,82 %	42	5,45 %	362	46,95 %	553	71,73 %
2	128	128	100,00 %	66	51,56 %	102	79,69 %	128	100,00 %
3	250	163	65,20 %	206	82,40 %	195	78,00 %	186	74,40 %
4	250	250	100,00 %	21	8,40 %	9	3,60 %	12	4,80 %
5	250	173	69,20 %	9	3,60 %	70	28,00 %	193	77,20 %
6	365	82	22,47 %	260	71,23 %	89	24,38 %	103	28,22 %
7	291	72	24,74 %	14	4,81 %	177	60,82 %	19	6,53 %
8	3220	2151	66,80 %	738	22,92 %	1298	40,31 %	1676	52,05 %

Table 33: 95%H-VaR Christoffersen test 250Days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	771	676	87,68 %	34	4,41 %	593	76,91 %	535	69,39 %
2	128	128	100,00 %	65	50,78 %	102	79,69 %	128	100,00 %
3	250	136	54,40 %	202	80,80 %	203	81,20 %	240	96,00 %
4	250	250	100,00 %	213	85,20 %	13	5,20 %	10	4,00 %
5	250	169	67,60 %	10	4,00 %	10	4,00 %	174	69,60 %
6	365	228	62,47 %	259	70,96 %	80	21,92 %	149	40,82 %
7	291	123	42,27 %	13	4,47 %	45	15,46 %	14	4,81 %
8	3220	2419	75,12 %	1023	31,77 %	1322	41,06 %	1721	53,45 %

Table 34: 95%N-ES Christoffersen test 250 Days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	771	481	62,39 %	433	56,16 %	717	93,00 %	416	53,96 %
2	128	128	100,00 %	33	25,78 %	0	0,00 %	27	21,09 %
3	250	250	100,00 %	188	75,20 %	78	31,20 %	43	17,20 %
4	250	188	75,20 %	250	100,0 %	250	100,00 %	165	66,00 %
5	250	250	100,00 %	73	29,20 %	61	24,40 %	162	64,80 %
6	365	333	91,23 %	88	24,11 %	341	93,42 %	138	37,81 %
7	290	217	74,83 %	96	33,10 %	290	100,00 %	290	100,00 %
8	3220	2481	77,05 %	1982	61,55 %	2590	80,43 %	2155	66,93 %

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Table 35: 95%H-ES Christoffersen test 250 Days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	771	770	99,87 %	457	59,27 %	603	78,21 %	438	56,81 %
2	128	81	63,28 %	25	19,53 %	1	0,78 %	2	1,56 %
3	250	228	91,20 %	112	44,80 %	73	29,20 %	96	38,40 %
4	250	250	100,00 %	245	98,00 %	6	2,40 %	83	33,20 %
5	250	158	63,20 %	17	6,80 %	59	23,60 %	249	99,60 %
6	365	154	42,19 %	121	33,15 %	221	60,55 %	333	91,23 %
7	290	290	100,00 %	286	98,62 %	290	100,00 %	290	100,00 %
8	3220	2846	88,39 %	2088	64,84 %	2060	63,98 %	2325	72,20 %

C.7 Regular Backtesting Additional Results 99% 1000 Days

Table 36: 99%N-VaR Backtest 1000Days

		P1		**P2**		**P3**		**P4**	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-
3	250	2	0,80 %	1	0,40 %	5	2,00 %	0	0,00 %
4	250	2	0,80 %	1	0,40 %	3	1,20 %	1	0,40 %
5	250	5	2,00 %	5	2,00 %	3	1,20 %	6	2,40 %
6	365	16	4,38 %	19	5,21 %	12	3,29 %	6	1,64 %
7	290	9	3,10 %	5	1,72 %	3	1,03 %	0	0,00 %
8	1970	37	1,88 %	37	1,88 %	44	2,23 %	19	0,96 %

Table 37: 99%H-VaR Backtest 1000Days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-
3	250	0	0,00 %	0	0,00 %	8	3,20 %	0	0,00 %
4	250	0	0,00 %	0	0,00 %	3	1,20 %	0	0,00 %
5	250	1	0,40 %	3	1,20 %	1	0,40 %	5	2,00 %
6	365	9	2,47 %	9	2,47 %	3	0,82 %	4	1,10 %
7	290	2	0,69 %	1	0,34 %	0	0,00 %	0	0,00 %
8	1970	14	0,71 %	15	0,76 %	27	1,37 %	12	0,61 %

Table 38: 99%N-ES Backtest 1000Days

		P1		P2		P3		P4	
Period	Obs	Violations	%	Violations	%	Violations	%	Violations	%
1	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-
3	250	0	0,00 %	0	0,00 %	1	0,40 %	0	0,00 %
4	250	0	0,00 %	0	0,00 %	1	0,40 %	0	0,00 %
5	250	2	0,80 %	3	1,20 %	1	0,40 %	6	2,40 %
6	365	7	1,92 %	2	0,55 %	4	1,10 %	1	0,27 %
7	290	2	0,69 %	1	0,34 %	0	0,00 %	0	0,00 %
8	1970	12	0,61 %	7	0,36 %	16	0,81 %	10	0,51 %

Table 39: 99%H-ES Backtest 1000Days

		P1		P2		P3		P4	
Period	Obs	Violations	%	Violations	%	Violations	%	Violations	%
1	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-
3	250	0	0,00 %	0	0,00 %	2	0,80 %	0	0,00 %
4	250	0	0,00 %	0	0,00 %	0	0,00 %	0	0,00 %
5	250	0	0,00 %	2	0,80 %	1	0,40 %	2	0,80 %
6	365	3	0,82 %	1	0,27 %	3	0,82 %	1	0,27 %
7	290	0	0,00 %	0	0,00 %	0	0,00 %	0	0,00 %
8	1970	4	0,20 %	3	0,15 %	7	0,36 %	5	0,25 %

C.8 Regular Backtesting Additional Results 95% 1000 Days

Table 40: 95%N-VaR Backtest 1000 Days

		P1		P2		P3		P4	
Period	Obs	Violations	%	Violations	%	Violations	%	Violations	%
1	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-
3	250	8	3,20 %	3	1,20 %	8	3,20 %	2	0,80 %
4	250	5	2,00 %	2	0,80 %	11	4,40 %	6	2,40 %
5	250	8	3,20 %	7	2,80 %	6	2,40 %	15	6,00 %
6	365	31	8,49 %	37	10,14 %	25	6,85 %	15	4,11 %
7	290	18	6,21 %	15	5,17 %	14	4,83 %	6	2,07 %
8	1970	78	3,96 %	73	3,71 %	118	5,99 %	58	2,94 %

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Table 41: 95%H-VaR Backtest 1000Days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-
3	250	14	5,60 %	5	2,00 %	15	6,00 %	2	0,80 %
4	250	7	2,80 %	1	0,40 %	16	6,40 %	6	2,40 %
5	250	9	3,60 %	7	2,80 %	15	6,00 %	15	6,00 %
6	365	50	13,70 %	43	11,78 %	14	3,84 %	16	4,38 %
7	290	24	8,28 %	12	4,14 %	4	1,38 %	6	2,07 %
8	1970	115	5,84 %	80	4,06 %	104	5,28 %	61	3,10 %

Table 42: 95%N-ES Backtest 1000Days

Period	Obs	Violations	%	Violations	%	Violations	%	Violations	%
1	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-
3	250	1	0,40 %	1	0,40 %	3	1,20 %	0	0,00 %
4	250	2	0,80 %	1	0,40 %	2	0,80 %	1	0,40 %
5	250	3	1,20 %	4	1,60 %	1	0,40 %	7	2,80 %
6	365	10	2,74 %	7	1,92 %	8	2,19 %	5	1,37 %
7	290	4	1,38 %	2	0,69 %	1	0,34 %	0	0,00 %
8	1970	21	1,07 %	20	1,02 %	30	1,52 %	16	0,81 %

Table 43: 95%H-ES Backtest 1000 Days

		P1		P2		P3		P4	
Period	**Obs**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**	**Violations**	**%**
1	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-
3	250	2	0,80 %	0	0,00 %	9	3,60 %	0	0,00 %
4	250	2	0,80 %	1	0,40 %	8	3,20 %	1	0,40 %
5	250	4	1,60 %	4	1,60 %	3	1,20 %	6	2,40 %
6	365	17	4,66 %	14	3,84 %	7	1,92 %	5	1,37 %
7	290	4	1,38 %	2	0,69 %	0	0,00 %	0	0,00 %
8	1970	32	1,62 %	26	1,32 %	45	2,28 %	17	0,86 %

C.9 Summary Tables Backtest results

Table 44: Summary Table Period 1: Commodity growth

Confidence Level	Time Horizon	Risk Metric	P1			P2			P3			P4		
			Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen
99 %	**250D**	N-VaR	-	v	-	-	v	-	-	-	-	-	-	-
		N-ES	v	-	-	v	v	-	v	v	-	-	v	-
		Hist-VaR	-	v	-	-	v	-	-	v	-	-	v	-
		Hist-ES	v	-	-	v	v	-	v	v	-	v	v	-
95 %	**250D**	N-VaR	v	v	-	-	v	-	-	v	-	-	-	-
		N-ES	v	-	-	v	-	-	v	-	-	v	-	-
		Hist-VaR	v	v	-	-	v	v	-	v	-	-	v	-
		Hist-ES	v	-	-	v	-	-	v	-	-	v	-	-
99 %	**1000D**	N-VaR	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		N-ES	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		Hist-VaR	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		Hist-ES	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
95 %	**1000D**	N-VaR	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		N-ES	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		Hist-VaR	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
		Hist-ES	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

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Table 45: Summary Table Period 3: Growth after Financial Crisis

Confidence Level	Time Horizon	Risk Metric	P1			P2			P3			P4		
			Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen
99 %	**250D**	N-VaR	v	v	-	v	v	-	v	v	-	v	v	-
		N-ES	v	v	-	v	v	-	v	v	-	v	v	-
		Hist-VaR	v	v	-	v	v	-	v	v	-	v	v	-
		Hist-ES	v	v	-	v	v	-	v	v	-	v	v	-
95 %	**250D**	N-VaR	v	v	-	v	v	-	v	-	-	v	v	-
		N-ES	v	-	-	v	v	-	v	-	-	v	-	-
		Hist-VaR	v	-	-	v	v	-	v	-	-	v	-	-
		Hist-ES	v	-	-	v	-	-	v	-	-	v	-	-
99 %	**1000D**	N-VaR	v	v	NA	v	v	NA	-	v	NA	v	v	NA
		N-ES	v	v	NA	v	v	NA	v	v	NA	v	v	NA
		Hist-VaR	v	v	NA	v	v	NA	-	-	NA	v	v	NA
		Hist-ES	v	v	NA	v	v	NA	v	v	NA	v	v	NA
95 %	**1000D**	N-VaR	v	v	NA	v	-	NA	v	v	NA	v	-	NA
		N-ES	v	-	NA	v	-	NA	v	-	NA	v	-	NA
		Hist-VaR	-	v	NA	v	v	NA	-	v	NA	v	-	NA
		Hist-ES	v	-	NA	v	-	NA	v	v	NA	v	-	NA

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Table 46 Summary Table Period 4: Arab Spring

Confidence Level	Time Horizon	Risk Metric	P1			P2			P3			P4		
			Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen
99 %	**250D**	N-VaR	-	-	-	-	v	v	-	-	-	-	v	-
		N-ES	-	v	-	v	v	-	v	v	v	v	v	v
		Hist-VaR	-	v	-	-	v	v	-	v	-	-	v	-
		Hist-ES	-	v	-	v	v	-	v	v	v	v	v	v
95 %	**250D**	N-VaR	-	v	-	v	v	-	v	v	v	-	v	v
		N-ES	v	v	-	v	-	-	v	-	-	v	v	-
		Hist-VaR	-	v	-	v	v	-	v	v	-	v	v	v
		Hist-ES	v	v	-	v	v	-	v	v	-	v	-	-
99 %	**1000D**	N-VaR	v	v	NA	v	v	NA	-	v	NA	v	v	NA
		N-ES	v	v	NA	v	v	NA	v	v	NA	v	v	NA
		Hist-VaR	v	v	NA	v	v	NA	-	v	NA	v	v	NA
		Hist-ES	v	v	NA	v	v	NA	v	v	NA	v	v	NA
95 %	**1000D**	N-VaR	v	v	NA	v	-	NA	v	v	NA	v	v	NA
		N-ES	v	-	NA	v	-	NA	v	-	NA	v	-	NA
		Hist-VaR	v	v	NA	v	-	NA	-	v	NA	v	v	NA
		Hist-ES	v	-	NA	v	-	NA	v	v	NA	v	-	NA

Table 47: Summary Table Period 5: After Arab Spring

Confidence Level	Time Horizon	Risk Metric	P1			P2			P3			P4		
			Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen
99 %	**250D**	N-VaR	-	v	-	-	v	-	-	v	-	-	-	-
		N-ES	-	v	-	v	v	v	-	v	v	-	v	-
		Hist-VaR	-	v	-	-	v	-	-	v	v	-	v	-
		Hist-ES	v	v	-	v	v	v	-	v	v	-	v	-
95 %	**250D**	N-VaR	-	v	-	-	v	v	-	v	-	-	v	-
		N-ES	v	v	-	v	v	-	v	v	-	v	v	-
		Hist-VaR	v	v	-	-	v	v	-	v	v	-	v	-
		Hist-ES	v	v	-	v	-	-	v	v	-	v	v	-
99 %	**1000D**	N-VaR	-	v	NA	-	v	NA	-	v	NA	-	v	NA
		N-ES	v	v	NA	-	v	NA	v	v	NA	-	v	NA
		Hist-VaR	v	v	NA	-	v	NA	v	v	NA	-	v	NA
		Hist-ES	v	v	NA	v	v	NA	v	v	NA	v	v	NA
95 %	**1000D**	N-VaR	v	v	NA	v	v	NA	v	v	NA	-	v	NA
		N-ES	v	-	NA	v	-	NA	v	-	NA	v	v	NA
		Hist-VaR	v	v	NA	v	v	NA	-	v	NA	-	v	NA
		Hist-ES	v	-	NA	v	-	NA	v	-	NA	v	v	NA

Table 48: Summary Table Period 8: Whole Sample Period

Confidence Level	Time Horizon	Risk Metric	P1			P2			P3			P4		
			Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen	Regular	Kupiec	Christoffersen
99 %	**250D**	N-VaR	-	-	-	-	-	-	-	-	-	-	-	-
		N-ES	v	v	-	-	v	-	-	v	-	v	v	-
		Hist-VaR	-	v	-	-	-	-	-	-	-	-	v	-
		Hist-ES	v	-	-	v	v	-	v	-	-	v	-	-
95 %	**250D**	N-VaR	v	v	-	-	v	-	-	v	-	-	v	-
		N-ES	v	-	-	v	-	-	v	-	-	v	-	-
		Hist-VaR	v	v	-	-	v	-	-	v	-	-	v	-
		Hist-ES	v	-	-	v	-	-	v	-	-	v	-	-
99 %	**1000D**	N-VaR	-	-	NA	-	-	NA	-	-	NA	v	v	NA
		N-ES	v	v	NA	v	-	NA	v	v	NA	v	v	NA
		Hist-VaR	v	v	NA	v	v	NA	-	v	NA	v	v	NA
		Hist-ES	v	v	NA	v	v	NA	v	v	NA	v	v	NA
95 %	**1000D**	N-VaR	v	v	NA	v	-	NA	-	v	NA	v	-	NA
		N-ES	v	-	NA	v	-	NA	v	-	NA	v	-	NA
		Hist-VaR	-	v	NA	v	v	NA	-	v	NA	v	-	NA
		Hist-ES	v	-	NA	v	-	NA	v	-	NA	v	-	NA