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Value-at-Risk and Expected Shortfall for oil & gas related securities during the oil price slide

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Abstract

Value-at-Risk and Expected Shortfall are assessed for their suitability as risk measures for oil & gas related securities during the oil price slide of 2014-15. The descriptive statistics of the analysed financial returns indicate non-Gaussian properties. This discourages the use of parametric approaches in oil & gas related investments for the estimation of Value-at-Risk and Expected Shortfall. The analysis also shows that volatility dynamics in oil & gas investments increased visibly during 2015 and might persist at high levels. Finally, Expected Shortfall shows a clearly superior performance to Value-at-Risk as a risk measure during turbulent times. These findings might be useful for investors exposed to the oil & gas sector and could be complemented by backtesting in further research.

Keywords: Value-at-Risk, Expected Shortfall, oil & gas equities, 2014 oil price slide

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Own work declaration

I hereby declare that this work was written solely by myself and that the work of other authors is recognised and appropriately referenced.

Colchester, 24th August 2016

Place, Date

Ahmad Nazmy

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1. Introduction

The recent drop in oil prices came unexpected and made oil & gas equities fall sharply. An investor in the oil & gas sector is surely interested in a suitable risk measure for his or her portfolio. While the classic Value-at-Risk (VaR) approach is widely used and intuitive to grasp, Expected Shortfall (ES) is gaining huge popularity because of its ability to consider tail risk. But which risk measure is better for oil & gas related securities during turbulent times? And is it appropriate to use a parametric approach (relying on specific distributional characteristics) for estimating VaR and ES for oil & gas related investments? These are the main questions investigated in this work.

This work provides a comparison of VaR and ES, in terms of their exceedance rates, applied on an equally weighted oil & gas equity portfolio, crude oil and the S&P 500 index. The analysis in this work relies on historical data from 2014-15, in order to emphasize pure empirical facts about the period of the oil price slide and “let the data speak”. This is important, as many investors and institutions often rely on parametric approaches for calculating their VaR and ES estimates.

The following chapter provides an introduction to VaR, ES and the nature of oil & gas related securities. This is followed by the “Data & Methodology” section which describes the data and methods used in this work. Further, descriptive statistics and rolling standard deviations of the equally weighted oil & gas equity portfolio, crude oil and the S&P 500 index are provided. The exceedance rates of the calculated VaR and ES estimates are presented for the analysed assets. The results are interpreted in a following section and some suggestions for additional research are proposed. The final section summarises the results and concludes the analysis.

2. Background

2.1 What is Value-at-Risk?

VaR is a simple and very popular measure of risk. It tries to answer a question every investor asks: “How much could I lose over a specific time horizon?”. A practitioners’ definition states that “*VaR is the maximum loss over a target horizon such that there is a low, prespecified probability that the actual loss will be larger*” [1]. From a statistical point of view, VaR is basically a specified percentile of financial returns [2], [3], [4]. Therefore, VaR can be described as the “*maximum loss not exceeded with a given high probability*” [5]. While it might be more useful to know the maximum possible loss on an investment, this is often not possible due to the fact that some financial returns are distributed in such way that the maximum loss is infinity [5]. This makes VaR an interesting alternative to the maximum possible loss.

More formally, the VaR of an investment with a loss of L and a confidence level of α (α ∈ (0, 1)) can be represented by the smallest number l . Thereby, the probability of L exceeding l shall not be larger than $1 - \alpha$ [5]. This is represented by the following equation. [5]

$$VaR_{\propto}(L) = \inf\{l \in \mathbb{R}: P(L > l) \leq 1 - \propto\}$$

This means that with α percent certainty, an investment will not lose more than the amount of l during a certain time period [2], [6]. In practice, VaR is often calculated with confidence levels between 90% and 99% [2], [4]. The time horizon for VaR estimation depends on the type and flexibility of the underlying portfolio [2].

As mentioned, VaR is very intuitive and easy to calculate. In order to explain VaR to somebody with a non-finance background, it would be enough just to describe it as follows: “You can be α percent sure that the losses on your portfolio will not exceed l during T days”.

However, VaR just focuses on a specific value and ignores the tail of the return distribution. In other words, once VaR is exceeded we do not know how bad our losses will be, as return distributions might be very fat-tailed or even double-peaked [2]. Other drawbacks of VaR will be discussed more in-depth in section 2.4.

2.2 Approaches for estimating Value-at-Risk

This section presents the main approaches for estimating VaR, outlining the advantages and disadvantages of each method. There are mainly three ways for estimating VaR: The historical simulation, the Monte Carlo method and the variance-covariance method [7]. While historical simulation and Monte Carlo simulation are non-parametric approaches, the variance-covariance method assumes specific properties of the distribution of financial returns and is, therefore, a parametric approach [1]. Knowing the underlying distribution of financial returns is crucial, in order for VaR to make sense [1], [3].

The *parametric variance-covariance approach* often assumes financial returns to be normally distributed, such as in the RiskMetrics approach developed by J.P. Morgan in the 1990ies [3], [8]. This is a very dangerous assumption as lots of empirical contributions show that financial returns are often not normally distributed, especially during turbulent times [1], [2]. However, there are many modifications, allowing for more flexibility in the parametric variance-covariance approach, such as combining it with GARCH and EWMA models or assuming that financial returns follow a student's t-distribution [2], [5]. These extensions might make the variance-covariance approach for estimating VaR more flexible, however, it is still a parametric approach, relying on special distribution-specific features. This approach is called the variance-covariance approach, as it requires calculating the variances and covariances of various assets in a portfolio [3].

The *Monte Carlo method* for estimating VaR is more flexible than the variance-covariance approach and allows to generate more complex distributions of financial returns with fat tails and other distributional characteristics [2], [1]. However, the higher degree of flexibility in the Monte Carlo method comes at the price of running Monte Carlo simulations with a random number generator, following very specific parameters [8]. This erodes the flexibility provided by the simulation to some extent, as it is difficult and research-intensive to create an ideal random number generator [2], [3].

The *historical simulation* is more intuitive and does not assume any characteristics of the underlying distribution of financial returns [3], [4]. Thereby, the historical simulation simply assumes that future financial returns will roughly follow the same distribution they were following in the past, making the historical simulation an empirical, non-parametric approach [8], [7]. Using historical data over a prespecified look-back period and a specific confidence level, we can estimate VaR by considering the losses and gains that would have been realised for the portfolio [9]. While the simplicity and the non-parametric nature of this approach seem very attractive, one major drawback is the necessity to collect enough relevant data, in order to capture extreme events [5]. On the other hand, taking too much data with extreme events might lead to a very conservative VaR estimate, rarely being exceeded [5].

Obviously, these three approaches could lead to different estimates [10]. This should be taken into consideration, especially when comparing various VaR estimates. This work will make use of the historical simulation approach because it relies on pure empirical facts.

2.3 What is Expected Shortfall?

ES is also known as Conditional VaR (CVaR) or Expected Tail Loss (ETL) [1]. It is very closely related to VaR and is often suggested as a better alternative [5]. Basically, ES could be regarded as a more sophisticated extension of VaR [10].

ES is a bit more complicated than VaR and less intuitive to explain. While VaR gives us a specific loss not be exceeded with a certain probability, ES gives us the average loss once our VaR point has been exceeded. In other words, ES measures the average loss "*conditional on the fact that it is greater than VaR*". [1]

This is probably the reason why ES is also known as Conditional VaR. Therefore, ES tries to describe the losses beyond our specified confidence interval [2], [5]. ES and VaR are illustrated in figure 2.3.1.

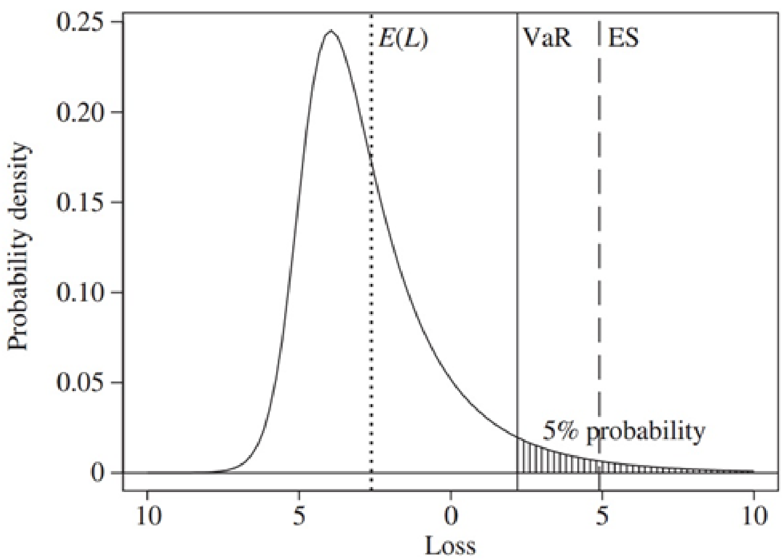

Figure 2.3.1: Illustration of the 95% VaR and the 95% ES (ES). While VaR represents a specific point, ES averages the shaded area. Source: McNeil, Frey and Embrechts [5].

ES emerged as an alternative measure of risk as it overcomes some shortcomings of VaR regarding desired mathematical properties a risk measure should have [11], [12], [13]. These properties describe the so-called "coherence" of a risk measure which is meant to classify a risk measure as suitable or not. The concept of coherence was introduced by Artzner et al. in [11].

It is important to keep in mind that ES will not give us the worst possible loss, however, by averaging the losses beyond our VaR it gives us a more conservative estimate of possible losses than VaR at the same confidence level. This means that a 95% ES will be more conservative than a 95% VaR. [9]

Formally, ES can be defined as follows [5]:

$$ES_{\propto} = \frac{1}{1-\propto}\int_{\propto}^{1} \mathrm{VaR}_{\mathrm{u}}(L)\mathrm{d}u$$

This shows that ES averages VaR over all levels $u \geq \propto$, in order to present an estimate, describing the expected tail loss [5]. This feature is probably the reason why ES is also referred to as expected tail loss.

The lack of capturing tail losses in VaR led to financial disasters which could have been partially avoided if banks would have used ES instead [14]. The consideration of tail losses made ES attractive to regulators across the world [9].

While ES is superior to VaR in terms of considering tail risk, the main problem associated with ES is its sensitivity to sample sizes and difficult backtesting [2]. Various backtesting techniques are proposed in recent academic literature, however, those techniques are still subject to further research and investigation [15], [16], [17]. Further advantages and disadvantages of ES are compared to those of VaR and discussed in the following section.

2.4 Value-at-Risk vs. Expected Shortfall

This section compares both measures of risk, VaR and ES, contrasting their advantages and disadvantages. VaR and ES have been discussed extensively in academic and practical literature. Thereby, ES is often described as being superior to VaR due to its coherence [5], [12], [18].

It was shown by various authors that VaR does not always satisfy the subadditivity feature, making it a non-coherent risk measure [2]. Subadditivity is one of the properties a coherent risk measure should have [11]. It states that merging many securities into a portfolio should yield an amount of risk smaller or equal to the sum of each individual security's risk [2]. The non-coherence of VaR might lead to a situation where the overall VaR of a portfolio is greater than the sum of the VaRs of each security in the same portfolio [1], [12]. In this case, diversification power is clearly ignored and the subadditivity property is violated [1]. However, Jorion [7], [1] states that lacking subadditivity in VaR occurs in exceptional cases and thus might be regarded as a more theoretical phenomenon. On the other hand, it is important to bear in mind that Jorion is a keen supporter of VaR, as demonstrated by some of his publications [19]. ES is often praised as it overcomes the lack of subadditivity and satisfies all other coherence requirements [20], [18], [21]. Acerbi in particular [22], [12], [15], presents a very positive picture of ES, describing it as an alternative to VaR due to its coherence.

However, we recall that neither ES nor VaR provide the worst possible loss on an investment [1], [9]. Here one could argue that VaR is a solid measure of risk if understood correctly [7]. Nevertheless, the fact that ES takes losses beyond VaR into account makes it a more useful and more attractive risk measure than VaR, especially in times where the market exhibits strong volatility dynamics. [20], [18], [21], [22].

Overcoming the main limitations of VaR, ES seems to be a more suitable measure of risk. Indeed, some opinions clearly suggest that VaR should be replaced by ES [22]. However, this draws an idealistic picture of ES, not considering its shortcomings.

Empirical studies have shown that ES requires larger sample sizes, in order to reach the same accuracy level as VaR [9], [21]. Furthermore, ES exhibits a larger estimation error and is more complicated to calculate and to backtest than VaR [2], [9]. In fact, the issue of the backtestability of ES is subject to a heated, ongoing discussion in academic and practitioners' literature [16]. However, this work does not intend to contribute to the ongoing, controversial debate about backtesting ES. The interested reader should refer to various new contributions, dedicated to discussing the backtestability of ES, such as [17], [16], [23] and [15].

One more basic disadvantage of ES is its less intuitive interpretation, in contrast to VaR which is easier to understand [9]. Both, VaR and ES, have advantages and disadvantages. Interestingly, regulatory requirements are currently favouring ES over VaR, despite complications regarding the backtestability of ES [2], [5], [14].

Investing in a fat-tailed portfolio would make ES the preferred risk measure, as it takes tail losses to some extent into account [21]. Apart from the complications arising from the backtestability of ES, the requirement of a large sample and the larger estimation error than VaR might be further limitations which must be considered [9], [21]. This shows us that it is not possible to label ES as definitely superior to VaR without any further considerations.

2.5 Oil & gas prices and equities

In order to understand the dynamics of oil & gas investment risks, it is useful to describe some significant factors influencing oil & gas prices and equities. This section gives a brief overview of various driving factors and properties of oil & gas prices and equities.

Various contributions show that changes in oil & gas prices have an impact on oil & gas equity prices [24], [25]. This is illustrated beautifully by figure 2.5.1 which shows the co-movement of the oil price and the price of the oil & gas equity portfolio used in this work. This seems plausible, as the oil & gas sector relies on energy prices [25]. Furthermore, it was shown that there are volatility transmissions between oil & gas markets and oil & gas equities [26]. Therefore, it is important to investigate oil & gas price movements for a better understanding of oil & gas equities.

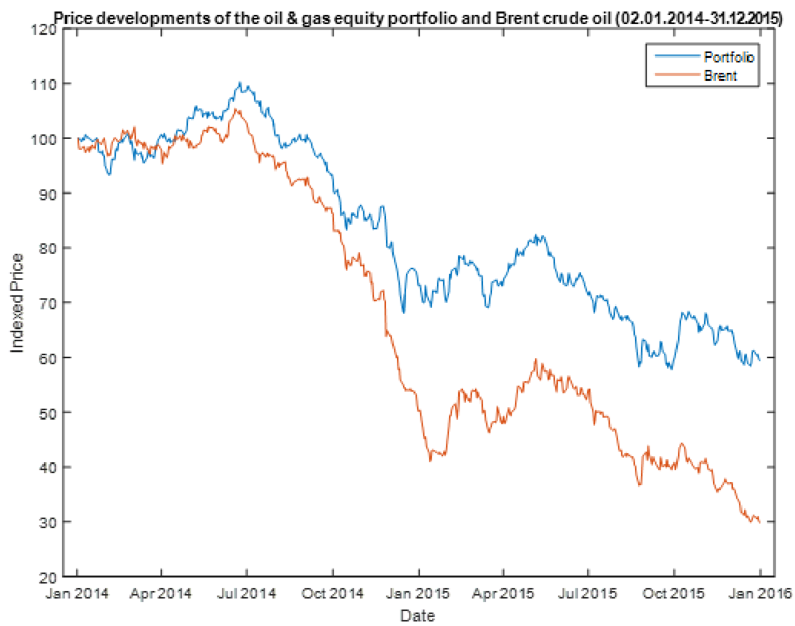

Figure 2.5.1: Price development of the oil & gas equity portfolio and Brent crude oil (02.01.2014-31.12.2015). Prices indexed at 100 on 02.01.2014. Source: Author's own analysis.

But what is driving oil & gas prices? This question is very heavily discussed in literature. One main current driving factor of oil & gas prices is demand coming from emerging countries, such as China or India [27], [28]. This is based on the fact that these rapidly expanding economies are dependent on commodities to ensure their growth, bearing in mind that oil & gas are crucial commodities for various producers and consumers [27], [8]. Furthermore, political uncertainty in major oil & gas producing countries, financial speculation and resource depletion contribute to higher volatility in oil & gas prices [29], [30]. These various driving factors seem to confirm that oil & gas prices are very volatile when compared to other assets [8], [31]. One more notable fact is that oil prices are subject to various shocks, resulting from the previously described factors [32]. These shocks were already observed during the nineteenth century and include the well-known 1973 oil price shock and the 2007-08 oil price spike [32].

Being highly volatile, financial returns of oil & gas related securities will not necessarily follow a normal distribution [33]. Another interesting property of oil & gas prices is mean-reverting behaviour, a typical property for commodity prices [29]. Mean-reversion makes oil & gas prices revert to a long-term mean (in real terms) [29]. This property might limit the application of widely used geometric Brownian motion models for describing oil & gas equity prices. Therefore, a Monte Carlo simulation approach for estimating VaR and ES for oil & gas equities could take the mean-reversion of prices into consideration which would require a lot of additional research to make this method efficient [8].

Due to various complicated factors and interesting dynamics, oil & gas prices still surprise experienced economists and finance professionals [34]. This is shown by the recent oil price slide, starting in 2014 [34], [35]. We can also see that oil & gas related assets are volatile and very difficult to predict. This has very important implications for managing and measuring risk of an oil & gas related investment.

3. Data & Methodology

This section describes the data and the methodologies used in the conducted analysis. The emphasis is on letting the data speak, by using unmodified, pure historical data, in order to determine the suitability of ES and VaR as risk measures for oil & gas related securities during turbulent times. The analysis should also show whether a parametric approach for VaR and ES estimation is appropriate or not.

3.1 Data

The portfolio analysed in this work consists of 10 equally weighted equities of major international oil & gas companies, namely: *The Royal Dutch Shell (UK/NL)*, *BP (UK)*, *Exxon (USA)*, *Chevron (USA)*, *OMV (Austria), Total (France), Eni (Italy), Lukoil (Russia), Gazprom (Russia)* and *Statoil (Norway).* The equities included in this portfolio were chosen to represent US, European and Russian oil & gas companies. Furthermore, this work also looks at Brent crude oil price, West Texas Intermediate (WTI) oil price and the S&P 500 index, in order to compare various descriptive statistics and the exceedance rates of VaR and ES.

All daily prices were extracted from Thomson Reuters DataStream in USD, in order to allow for a direct comparison. The analysed period starts 2nd January 2014 and ends at the 31st December 2015. This period consists of 521 daily closing prices or 520 daily returns for the period between 3rd January 2014 and 31st December 2015. Choosing this specific time period is meant to cover the oil price slide, starting in 2014. Calculations were conducted using Matlab.

3.2 Methodology

3.2.1 Continuously compounded daily returns

The analysis makes use of daily continuously compounded returns, calculated using Matlab's "*price2ret*" function [36]. The mathematical formula for calculating daily continuously compounded returns can be represented as follows:

$$r_t = \ln(P_{t+1}) - \ln(P_t)$$

Where r_t represents the continuously compounded daily return at day t, P_{t+1} and P_t represent the daily closing prices at day $t+1$ and day t, respectively.

3.2.2 Rolling standard deviation

The 3-day rolling standard deviation is calculated over the period from 3rd January 2014 to 31st December 2015, in order to show the volatility dynamics over time. This rolling-window approach is used in practice and is intuitive [1], [37]. It might be not suitable for forecasting purposes due its poor forecasting performance [38], however, it is very good to show how the volatility behaves over time as it is a "model-free representation" [39] and it lets the data speak for itself. The goal of this work is not to forecast any volatilities and therefore, the rolling window approach is absolutely sufficient to illustrate past volatility dynamics. Thereby, the standard deviation is calculated in rolling 3-day blocks. The 3-day rolling standard deviation $\widehat{\sigma_t}(3)$ can be represented as follows:

$$\widehat{\sigma_t}(n) = \sqrt{\frac{\sum_{i=1}^{n}(r_i - \bar{r}_{t,n})^2}{n-1}}$$

$\bar{r}_{t,n}$ represents the n-day mean of the analysed return series at time t and r_i is the daily return of the i-th day in the corresponding three-day block with $n = 3$. In addition to this, the "usual" standard deviations are calculated for the periods between *3rd January 2014 - 1st January 2015*, *2nd January 2015 - 31st December 2015* and *3rd January 2014 - 31st December 2015*.

3.2.3 Skewness & Kurtosis

Skewness is a measure of asymmetry for the probability distribution of the analysed financial returns around their mean. A negative skewness means that the distribution of the analysed returns has a long tail to the left, indicating few extreme losses. A positive skewness means that the distribution of the analysed returns has a long tail to the right, indicating few extreme gains. [40]

The skewness of a sample over time *t* can be represented mathematically as follows [40]:

$$Skewness_t = \frac{\frac{\sum_{i=1}^{n}(r_i - \bar{r}_t)^3}{n-1}}{{\sigma_t}^3}$$

Where r_i is the daily return of the *i*-th day, *n* is the number of observations, $\bar{r}_t$ is the mean of daily returns over time period *t* and σ_t is the standard deviation of the daily returns over time period *t*.

The kurtosis indicates the "tailedness" of the probability distribution of our financial returns [40]. A normally distributed sample has a kurtosis of 3 and is called mesokurtic. If the kurtosis is above 3, the distribution is said to be leptokurtic and, thus has fatter tails than a normal distribution. Kurtosis can be represented mathematically by the following formula [40]:

$$Kurtosis_t = \frac{\frac{\sum_{i=1}^{n}(r_i - \bar{r}_t)^4}{n-1}}{{\sigma_t}^4}$$

The skewness and kurtosis of the analysed financial returns are calculated for the following time periods: *3rd January 2014 – 1st January 2015*, *2nd January 2015 – 31st December 2015* and *3rd January 2014 – 31st December 2015*.

Kurtosis and skewness are important indicators of how the analysed financial returns are distributed [41]. They might indicate, whether a parametric approach (e.g. assuming normally distributed financial returns) for estimating VaR and ES is appropriate or not.

3.2.4 Jarque-Bera test

The Jarque-Bera test helps to determine if a set of financial returns is normally distributed or not by checking how good the kurtosis and skewness of the analysed dataset fit those of a normal distribution [40]. The test statistic *JB* [5] is represented as follows:

$$JB = \frac{1}{6}n(Skewness^2 + \frac{1}{4}(Kurtosis - 3)^2)$$

The null hypothesis of the Jarque-Bera test states that the analysed dataset follows a normal distribution, while the alternative hypothesis states that the analysed dataset does not follow a normal distribution [5]. The test statistic follows a chi-square distribution with 2 degrees of freedom [5]. However, Matlab uses a different approach for samples with less than 2000 observations by comparing the test statistic to critical values obtained from a Monte Carlo simulation for higher accuracy [42]. The Jarque-Bera test at the 95% confidence level is conducted for the following time periods of the analysed returns: *3rd January 2014 – 1st January 2015*, *2nd January 2015 – 31st December 2015* and *3rd January 2014 – 31st December 2015*.

3.2.5 Negative 3-sigma returns

Portfolio managers are interested in knowing how often large losses occur. Calculating the amount of losses beyond three negative standard deviations from the mean is a simple but clear indicator of extreme events. [41]

The negative 3-sigma returns are calculated for the portfolio, Brent oil, WTI oil and the S&P 500 index over the following time periods: *3rd January 2014 – 1st January 2015*, *2nd January 2015 – 31st December 2015* and *3rd January 2014 – 31st December 2015*.

3.2.6 Value-at-Risk and Expected Shortfall

The basics of VaR and ES are described in previous sections. This work makes use of the historical simulation approach for estimating daily VaR and ES. Hereby, the dataset of the analysed financial returns is split into two parts. The first part includes the financial returns from 3rd January 2014 to 1st January 2015 and the second part includes the financial returns from 2nd January 2015 to 31st December 2015. The first part is used to find the 95% VaR and the 95% ES, while the second part is used to see how often these estimates are exceeded. The exceedance rates of the portfolio, oil prices and S&P 500 index returns are calculated, in order to check whether the losses exceeded the VaR and ES estimates by more than 5%. This should give a basic intuition about the performance of both measures of risk which is a major goal of this work.

VaR and ES estimates will be presented as daily possible losses in percentages and in USD, based on an initial investment of 1 m. USD in the corresponding security.

4. Results

This section presents the results of the analysis done in this work, in order to proceed with interpretation and further discussion in a later section. Descriptive statistics over various periods are presented, followed by the exceedance rates from the VaR and ES analysis. Histograms representing the distribution of the analysed returns and other diagrams, illustrating the financial returns and price developments of securities analysed in this work can be found in Appendix B.1.

4.1 Descriptive Statistics

3rd January 2014 – 31st December 2015

Almost all analysed financial daily returns exhibit negative mean returns over the period from 3rd January 2014 to 31st December 2015. The daily returns of the S&P 500 index constitute an exception with a slightly positive mean return of +0.02%. The equally weighted oil & gas equity portfolio exhibits a mean return of -0.09% while Brent crude and WTI crude have mean returns of -0.21% and -0.18%, respectively.

Further, all analysed daily returns exhibit excess kurtosis with kurtosis values ranging from 4.85 to 7.07. The portfolio daily returns have a kurtosis of 4.85 while the S&P 500 daily returns have a kurtosis of 5.39. The daily returns of Brent crude oil have a kurtosis of 7.07 and their counterparts from WTI crude oil have a kurtosis of 5.53. Brent and portfolio daily returns are slightly positively skewed, while WTI and S&P 500 daily returns are slightly negatively skewed.

With respect to standard deviations, the S&P 500 daily returns are the least volatile with a daily standard deviation of 0.84%. On the other hand, Brent and WTI daily returns have daily standard deviations of 1.87% and 2.37%, respectively. Portfolio daily returns have a daily standard deviation of 1.32%.

While WTI, S&P 500 and portfolio daily returns all had 4 negative 3-Sigma returns, Brent daily returns only exhibit 2 negative 3-Sigma returns.

The Jarque-Bera test at the 95% confidence level indicates that all analysed financial returns are not normally distributed. Table 4.1.1 summarises the descriptive statistics of the analysed financial returns.

	Mean returns in %	Skewness	Kurtosis	Standard Deviation	Neg. 3-Sigma Returns
Brent	-0.21%	0.38	7.07	1.87%	2
WTI	-0.18%	-0.05	5.53	2.37%	4
S&P 500	0.02%	-0.32	5.39	0.84%	4
Portfolio	-0.09%	0.05	4.85	1.32%	4

Table 4.1.1: Summary of the calculated descriptive statistics for the daily returns of Brent crude oil, WTI crude oil, the S&P 500 index and the equally weighted oil & gas equity portfolio over the period of 3rd January 2014 – 31st December 2015. Source: Author's own analysis.

As visible in Appendix B.2, the daily returns of the portfolio exhibit stronger volatility dynamics than those of the S&P 500. While the 3-day rolling volatility of portfolio daily returns have a spike around March 2014, most volatility dynamics took place in 2015 with values reaching 4.5%. It is also noteworthy that both rolling volatilities peaked together around 4% in August 2015. However, the volatility dynamics of the S&P 500 remain calmer than those of the oil & gas equity portfolio.

WTI crude oil daily returns exhibit the strongest volatility dynamics. Not surprisingly, WTI crude oil 3-day rolling volatilities have similar patterns with their Brent crude oil counterparts in the sense that volatility dynamics in both series increased visibly during 2015, as visible in Appendix B.2.

However, the volatility of WTI crude oil daily returns remains higher than the volatilities of Brent crude oil, portfolio and S&P 500 returns, as visible in Appendix B.2.

We can observe strong volatility dynamics in Brent daily returns, starting around the end of November 2014 with 3-day rolling volatility values around 6% during the end of November 2014, February 2015 and September 2015. Furthermore, Brent daily returns volatility is higher and more dynamic than the volatility of S&P 500 daily returns. S&P 500 3-day rolling volatilities peaked in August 2015 around 4%. All volatility dynamics are represented graphically in Appendix B.2.

3rd January 2014 – 1st January 2015

The time period between 3rd January 2014 and 1st January 2015 exhibits negative mean returns for almost all analysed daily returns. The daily returns of the S&P 500 once again are slightly positive with a value of +0.04%. With regards to skewness, Brent crude oil returns show a value of -2.17, followed by WTI crude oil returns with a value of -1.46. The portfolio and the S&P 500 daily returns are also negatively skewed.

Both crude oil daily returns seem to have fat tails, indicated by a kurtosis of 15.64 for Brent and 10.82 for WTI. The S&P 500 daily returns have the lowest kurtosis value of 4.49. The analysed portfolio exhibits a kurtosis of 5.98.

WTI crude oil daily returns remain the most volatile over the analysed time period with a daily standard deviation value of 1.65%, followed by Brent daily returns, showing a daily standard deviation of 1.17%. The oil & gas equity portfolio has a daily standard deviation of 1.06% and the S&P 500 has the least volatile daily returns with 0.70% daily standard deviation. Interestingly, the S&P 500 daily returns have the highest number of negative 3-Sigma returns, while Brent daily returns have only 2 negative 3-Sigma returns, despite being more volatile. These findings are summarised by table 4.1.2.

	Mean returns in %	Skewness	Kurtosis	Standard Deviation	Neg.-3-Sigma Returns
Brent	-0.26%	-2.17	15.64	1.17%	2
WTI	-0.22%	-1.46	10.82	1.65%	3
S&P 500	0.04%	-0.44	4.49	0.70%	4
Portfolio	-0.11%	-0.12	5.98	1.06%	3

Table 4.1.2: Summary of the calculated descriptive statistics for the daily returns of Brent crude oil, WTI crude oil, the S&P 500 index and the equally weighted oil & gas equity portfolio over the period of 3rd January 2014 – 1st January 2015. Source: Author's own analysis.

The Jarque-Bera test at the 95% confidence level shows that all analysed financial returns are not normally distributed over the analysed time period.

2nd January 2015 – 31st December 2015

Brent, WTI and portfolio daily returns have negative mean returns for the period of 2nd January 2015 – 31st December 2015. The S&P 500 daily returns have a slightly negative mean of -0.0028%. It is noteworthy that almost all analysed daily returns exhibit positive skewness except the S&P 500 daily returns.

Furthermore, the kurtosis values range from 3.69 to 5.06 which is lower than the values obtained for other analysed time periods. Both crude oil daily returns show higher daily standard deviations than portfolio and S&P 500 daily returns.

The S&P 500 has the highest number of negative 3-Sigma returns, while Brent daily returns do not show any negative 3-Sigma returns. These statistics are summarised in table 4.1.3.

The Jarque-Bera test at the 95% confidence level shows that all analysed financial returns are once again not normally distributed over the analysed time period.

	Mean returns in %	Skewness	Kurtosis	Standard Deviation	Neg.-3-Sigma Returns
Brent	-0.17%	0.59	4.48	2.38%	0
WTI	-0.14%	0.18	3.69	2.91%	1
S&P 500	-2.80E-05	-0.23	5.06	0.96%	3
Portfolio	-0.07%	0.07	3.92	1.54%	1

Table 4.1.3: Summary of the calculated descriptive statistics for the daily returns of Brent crude oil, WTI crude oil, the S&P 500 index and the equally weighted oil & gas equity portfolio over the period of 2nd January 2015 – 31st December 2015. Source: Author's own analysis.

4.2 Value-at-Risk and Expected Shortfall violations

We recall that the 95% VaR and 95% ES values were estimated using daily data from 3rd January 2014 to 1st January 2015 and tested for exceedances using daily data from 2nd January 2015 to 31st December 2015.

Table 4.2.1 summarises the 95% VaR and 95% ES values as possible daily losses in percentages and in USD, based on an initial investment of 1 m. USD. As expected, the ES estimates are more conservative than the VaR estimates. WTI crude oil exhibits the largest 95% VaR and 95% ES possible daily losses. The S&P 500 has the lowest possible daily losses according to the corresponding 95% VaR and 95% ES estimates. The oil & gas equity portfolio has a possible daily loss of 18,635.20 USD according to its 95% VaR estimate and 27,436.72 USD according to its 95% ES estimate, based on an initial investment of 1 m. USD.

	95% VaR (loss in USD)	95% ES (loss in USD)	95% VaR (in percentage)	95% ES (in percentage)
Brent	22,195.04	36,378.64	-2.22%	-3.64%
WTI	32,524.62	49,294.78	-3.25%	-4.93%
S&P 500	12,616.51	17,778.91	-1.26%	-1.78%
Portfolio	18,635.20	27,436.72	-1.86%	-2.74%

Table 4.2.1: 95% VaR and 95% ES loss estimates in USD (based on 1 m. USD investment) and in percentages. Source: Author's own analysis.

The exceedance rates and number of exceedances for the 95% VaR and the 95% ES for Brent, WTI, S&P 500 and portfolio daily returns are presented in table 4.2.2. Brent crude oil daily returns show the highest exceedance rates for both, the 95% VaR and the 95% ES estimates. The 95% VaR estimate for Brent daily returns was exceeded 18.46% of the time instead of the expected 5%. The 95% ES estimate of Brent daily returns was exceeded 6.15% of the time, rather than 5%. On the other hand, S&P 500 daily returns exhibit the lowest exceedance rates for the corresponding 95% VaR estimates. The S&P 500 95% VaR estimate was exceeded

8.85% of the time instead of the expected 5%. Further, the 95% ES estimate of S&P 500 daily returns was exceeded 3.46% of the time, which is below the expected 5%. As for the analysed oil & gas equity portfolio, the corresponding 95% VaR estimate was exceeded 9.62% of the time which is higher than the expected value of 5%. On the other hand, the exceedance rate for the 95% ES estimate of portfolio daily returns was only 3.08% of the time. This is visibly below the expected value of 5%.

	Exceedances of 95% VaR	Exceedances of 95% ES	Exceedance rate 95% VaR	Exceedance rate 95% ES
Brent	48	16	18.46%	6.15%
WTI	30	12	11.54%	4.62%
S&P 500	23	9	8.85%	3.46%
Portfolio	25	8	9.62%	3.08%

Table 4.2.2: Number of exceedances and exceedance rates for the 95% VaR and 95% ES estimates for Brent, WTI, S&P 500 and portfolio daily returns. Source: Author's own analysis.

5. Interpretation of results

The presented results are discussed and interpreted in this section. This includes interpreting and discussing some presented statistical properties and the exceedances of VaR and ES estimates. The main findings are that:

i) The analysed returns are not normally distributed.

ii) The volatilities of crude oil and oil & gas equities increased significantly during 2015.

iii) Crude oil and oil & gas equities daily returns are more volatile than S&P 500 daily returns.

iv) ES clearly outperforms VaR, in terms of exceedances.

Each finding will be discussed in a separate section. Further illustrations and other relevant diagrams can be found in Appendices B.1 and B.2.

The analysed returns are not normally distributed

The analysed financial returns exhibit excess kurtosis and non-zero skewness values for all studied time periods. Furthermore, the conducted Jarque-Bera tests at the 95% confidence level indicate clearly that the analysed series are not normally distributed.

Thereby, it is noteworthy that the equally weighted oil & gas equity portfolio lost approximately 27% of its value between 2nd January 2014 and 1st January 2015. Looking at the time period between 2nd January 2014 to 31st December 2015, the portfolio shows a loss of approximately 40 % as visible in Appendix B.1. This indicates the presence of frequent and large losses among portfolio daily returns. The presence of 4 negative 3-Sigma returns over the period from 3rd January 2014 to 31st December 2015 indicates the occurrence of extreme losses. Furthermore, the mean returns of the portfolio were slightly negative over all analysed time periods. Those losses were probably triggered by a grim outlook for the oil & gas sector, due to oversupply and slowing global economic growth [35].

Brent and WTI crude oil daily returns show high kurtosis values for the time period between the 3rd January 2014 and 1st January 2015. Together with clearly non-zero skewness values for both crude oil daily returns, these properties show that those returns are not normally distributed. This was also confirmed by Jarque-Bera tests, conducted at the 95% confidence level. Brent daily returns have 2 negative 3-Sigma returns, while WTI daily returns have 3 negative 3-Sigma returns during the time period between 3rd January 2014 and 1st January 2015. These values indicate the presence of extreme events, leading to losses and fat tails for both crude oil sorts. Indeed, the price of Brent crude oil tumbled from 109.07 USD per Barrel on 2nd January 2014 to 55.84 USD per Barrel on 1st January 2015, as shown by the analysed data. As with portfolio daily returns, the mean returns of Brent and WTI daily returns over all analysed time periods are slightly negative. This underpins the fact that these assets experienced a price decline during 2014.

These findings have very important implications. Firstly, a parametric approach, relying on Gaussian distributions, is not suitable for estimating VaR and ES for oil & gas related securities. This is justified by the non-normal properties of the distributions of the analysed financial returns.

Therefore, the use of historical data with non-Gaussian properties for VaR and ES estimations yields results which are closer to the real characteristics of the analysed financial returns. Relying on parametric assumptions for estimating VaR and ES for oil & gas related securities might lead to disastrous outcomes and is not recommended.

The Volatilities of crude oil and oil & gas equities increased significantly during 2015

The oil price slide started already in 2014, however, the decrease in crude oil prices and oil & gas equity prices continued in 2015, accompanied by increasing volatility dynamics. The 3-day rolling standard deviation analysis also shows that the volatility of crude oil increased significantly during 2015. As expected, oil & gas equities also followed this trend and exhibit increased volatilities during 2015. This phenomenon could be explained by rising uncertainty about global and Chinese growth, in addition to ongoing concerns over excessive supply of crude oil and speculation activities [43].

Appendix B.2 illustrates the 3-day rolling volatilities of the oil & gas equity portfolio and the S&P 500 daily returns. We can observe that the volatility of the portfolio shows a spike around March 2014, probably the result of speculation activities linked to the events in Ukraine and Russia [44]. This confirms that oil & gas related securities are sensitive to major geopolitical events. However, it was not until December 2014 where portfolio daily returns started to exhibit frequent and extreme volatility spikes, continuing throughout 2015.

These volatility spikes are probably caused by the oil price hitting 5-year lows, leading to a grim outlook for oil & gas equities [45]. The drop in oil prices was initiated by signs of a weakening global economy, observable in December 2014 [35]. Furthermore, as oil prices are strongly influenced by production and storage data, it seems plausible that very high crude oil inventories in Cushing (Oklahoma) and increasing oil production led the oil price to tumble [46], [47].

The volatility dynamics of portfolio daily returns were much stronger in 2015 because of a continuing oil price slide and an overall higher volatility in financial markets [48]. The increasing market volatility in 2015 could be justified by many factors, including the economic slowdown in emerging markets, illiquidity pockets in some security markets, bubble-like asset prices in Chinese markets and eroding confidence in policy makers [48]. Many experts, including El-Erian [48], think that strong volatility dynamics in financial markets are here to stay and that 2015 was just the beginning of a new era of market volatility structure.

Crude oil and oil & gas equities daily returns are more volatile than S&P 500 daily returns

Overall, oil & gas related securities are shown to be more volatile than a broad equity index, represented by the S&P 500. Similar findings have been reported in the literature, however, the data used in this analysis is more up to date and focuses on the oil price slide. It is justified to assume that the oil price slide and uncertainty in global oil markets reinforced the higher volatility in oil & gas related securities.

As higher volatility if often associated with extreme tail losses, it is reasonable to expect that a classic VaR approach will not offer the most reliable measure of risk. The higher volatility in oil & gas related securities results from various factors influencing oil & gas prices and commodities in general.

ES clearly outperforms VaR, in terms of exceedances

The analysis shows that for all analysed financial assets ES proved to be a more reliable measure of risk, in terms of exceedances. This is based on the fact that ES considers tail losses and therefore, the 95 % ES estimate is more conservative than its VaR counterpart. Strong fluctuations in prices during 2015, caused by increasing volatility dynamics, led to a higher exceedance rate for the VaR estimates of all analysed returns. Some reasons responsible for exceedances of VaR and ES estimates in 2015 are presented below.

Looking at S&P 500 daily returns, we observe that August 2015 shows clear exceedances of both, VaR and ES estimates, as illustrated in figure 5.1. This can be explained by the devaluation of the Chinese currency and concerns over global and Chinese growth. August 2015 was also one of the worst months for the S&P 500. [49]

As visible in figure 5.1, the beginning of September 2015 also witnesses a violation of both estimates of S&P 500 daily returns probably caused by weak Chinese and US manufacturing data [50]. During the last part of September 2015, we can see another violation of both estimates in figure 5.1, as a result of market turbulences caused by more pessimist views on Chinese growth, uncertainty about the Federal Reserve policy, the negative effects of Volkswagen's diesel scandal and disappointing news about corporate earnings [51]. One more noteworthy violation of both estimates happened in December 2015, as illustrated in figure 5.1, caused by fears of the Fed rate hike and a "risk-off" behaviour by traders [52].

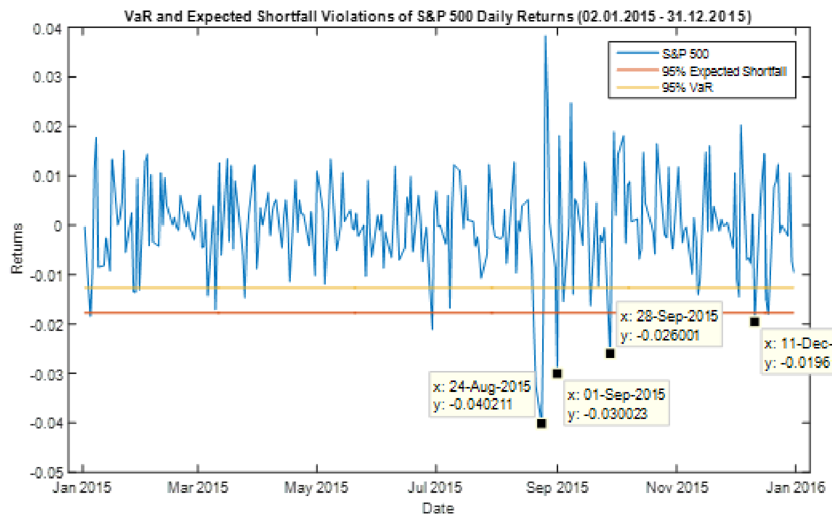

Figure 5.1: Violations of the 95% VaR (yellow) and 95% ES (red) estimates of S&P 500 daily returns. Source: Author's own analysis

As for WTI and Brent daily returns, we can see that violations of VaR and ES estimates are justified by bad news regarding oil markets, such as US oversupply and the oil price hitting low levels. As visible in figure 5.2, WTI daily returns violated their VaR and ES estimates in February 2015 significantly due to oversupply concerns in the US and a downward price correction [53]. Figure 5.2 shows that in April 2015 WTI daily returns exceeded both loss estimates caused by increasing US oil inventories and increasing Saudi Arabian oil production [54]. During the beginning of July, WTI daily returns recorded one more violation of their VaR and ES estimates as a result of concerns regarding the Greek debt crisis and expectations of a nuclear deal with Iran [55]. This is also visible in figure 5.2. WTI crude oil daily returns recorded one more significant exceedance of both risk estimates in September 2015, visible in figure 5.2, because of the market turbulences mentioned earlier [51], [50].

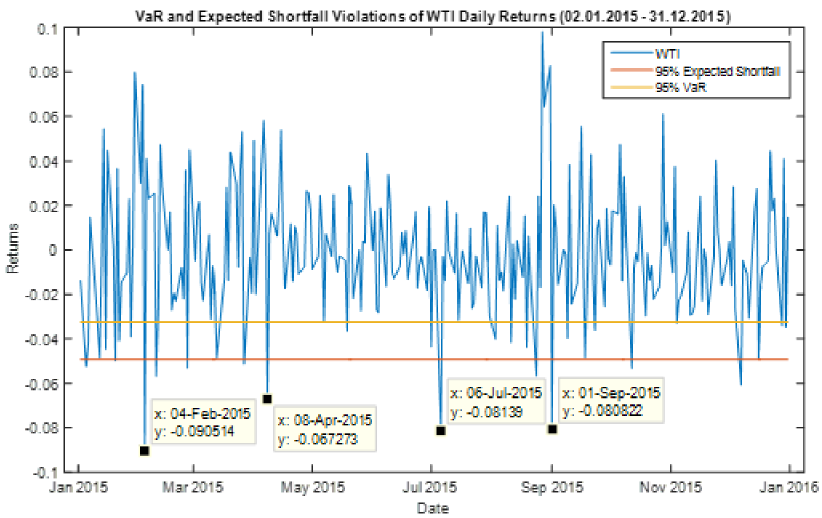

Figure 5.2: Violations of the 95% VaR (yellow) and 95% ES (red) estimates of WTI crude oil daily returns. Source: Author's own analysis.

During the first week of January 2015 Brent daily returns exceeded their VaR and ES estimates, as visible in figure 5.3. This led to a 5-year low in the price of Brent crude oil [56]. March 2015 also recorded a violation of both estimates, as visible in figure 5.3, probably due to a loss of confidence in oil stocks [57]. Further, Brent daily returns exceeded their VaR and ES estimates in July, August and September 2015 due to pressure coming from a slowing down Chinese market and rising oil production [58], [59]. Turbulences in financial markets during September 2015 also caused Brent daily returns to exceed their corresponding risk estimates [51]. December 2015 witnessed a violation of both risk estimates of Brent daily returns as a result of discouraging news from the December 2015 OPEC meeting [60]. These violations are all visible in figure 5.3. It is noteworthy that the VaR and ES estimates of Brent daily returns were violated more frequently than their WTI crude oil counterparts. However, the exceedances in Brent daily returns are not as heavy as those in WTI daily returns. This could be justified by the fact that WTI crude oil is traded more frequently [47], and thus more affected by financial speculation, leading to higher volatility and more extreme events.

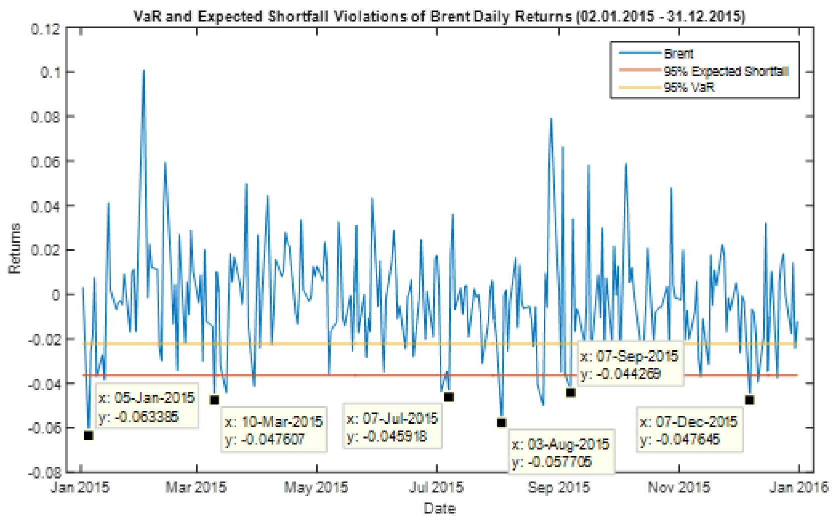

Figure 5.3: Violations of the 95% VaR (yellow) and 95% ES (red) estimates of Brent crude oil daily returns. Source: Author's own analysis.

Portfolio daily returns recorded the lowest exceedance rate for their ES estimate. The analysis shows few but significant exceedances of the ES estimate for Portfolio daily returns. The strongest exceedances are associated with the oil price hitting record lows in January 2015, a loss of confidence in oil stocks in March 2015 and the previously discussed turbulences in August and September 2015 [50], [57].One more noteworthy exceedance was recorded in December 2015 because of the disappointing outcome of the December 2015 OPEC meeting [60]. These exceedances are illustrated in figure 5.4.

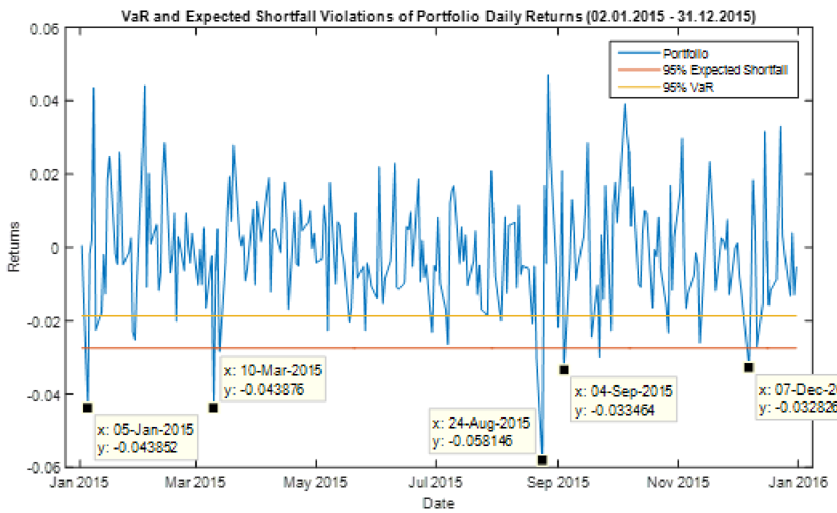

Figure 5.4: Violations of the 95% VaR (yellow) and 95% ES (red) estimates of WTI crude oil daily returns. Source: Author's own analysis.

These results show that portfolios with volatile assets, such as oil & gas related securities, are better served by applying ES as a risk measure. Furthermore, it is also interesting to see that oil & gas stocks are more volatile than the S&P500 but less volatile than crude oil. The increasing volatility dynamics experienced during 2015 might become the new norm of the market and therefore, ES is definitely a better alternative to classic VaR.

6. Discussion and further research

The presented findings could be complemented by further techniques and incorporated into various further research. This section suggests some ideas which could be applied, in order to provide more insight into the presented analysis or to look at the whole research question from a different point of view. These suggestions could be summarised as follows:

i) Backtesting VaR and ES estimates.

ii) Use more "stressed" data for VaR and ES estimation

iii) Using historical simulation and Extreme Value Theory (EVT) for VaR and ES estimation.

iv) Modelling volatility dynamics, using the Exponentially Weighted Moving Average (EWMA) approach.

Each suggestion is discussed in a following subsection.

Backtesting VaR and ES estimates

Although the exceedance rates already provide a good indication of the efficiency of ES compared to VaR, backtesting the estimates for all analysed financial returns will underpin the results statistically.

While there might be widely used and popular backtesting procedures for VaR, there is still an ongoing discussion regarding the backtesting of ES. However, VaR estimates could be backtested using the popular, two-tailed Kupiec test [61].

A possible technique for backtesting the ES estimate, based on a non-parametric approach, is presented by Emmer, Kratz and Tasche [62]. This is basically an approximation of the ES estimate, using 4 VaR estimates [62]. Thereby, the 95% ES is approximated by equally weighting the 95%, 96.25%, 97.5% and the 98.75% VaR estimates of the corresponding dataset, given these VaR estimates have been successfully backtested [62]. However, this might require a large dataset, in order to provide successfully backtested VaR estimates and higher accuracy for the approximated ES estimate [62].

The strength of this backtesting procedure lies within its simplicity and the fact that it does not require Monte Carlo simulations, as opposed to backtesting techniques suggested by Acerbi and Szekely [23], [62]. Although this test might seem as an inaccurate approximation, its simple implementation and empirical performance might make it the favoured approach by regulators and practitioners [17].

Future research might use a larger dataset than the one used in this analysis and apply this technique for backtesting ES estimates. More information about the backtesting procedure of Emmer, Kratz and Tasche can be found in [62].

Use more "stressed" data for VaR and ES estimation

Oil & gas related securities witnessed interesting price and volatility dynamics during specific events. One well-known event is the recent financial crisis of 2008-09 where the prices of oil & gas related securities skyrocketed before plummeting sharply. [34]

For example, historical data including events with a significant impact on the oil price and on oil & gas equities might be incorporated in future analysis. This could be implemented by using historical crude oil and oil & gas equities daily returns from the 2008-09 financial crisis.

Furthermore, a simulation-based approach might be carefully applied to produce return distributions representing sharp price declines as witnessed during the recent financial crisis, in order to estimate VaR and ES.

By looking at difficult periods for oil & gas related securities, this "stressed" VaR and ES estimation, could prepare investors for very bad scenarios. However, this approach might constantly lead to very conservative VaR and ES measures during calm times. Therefore, this approach could complement, rather than replace, the usual VaR and ES estimation. Hull discusses this procedure in [2].

Using historical simulation and EVT for VaR and ES estimation

Although historical simulation allows the data to "speak", VaR and ES estimates relying on historical data are very sensitive to sample sizes [1]. Therefore, we might need a way to produce more accurate VaR and ES estimates, especially when we have to estimate them at very high confidence levels, such as 99.9%. A small dataset is problematic, if combined with such a high confidence level, as there might be very few observations in the left tail (representing losses) of returns distribution. [1], [2]

EVT provides a way of fitting the left tail of the analysed historical financial returns, in order to allow for fatter tails and extreme events. It is smoothing the left tail of the used daily returns, allowing for larger losses to be represented by the “extended” left tail of the analysed financial returns. [2]

Estimating VaR and ES using this approach appears to be very attractive, as it seems to overcome sample size issues associated with historical simulation. We should be aware that EVT might still be inaccurate if relying on a very small dataset of historical returns [1]. Furthermore, EVT makes assumptions regarding the decay of the left tail of the analysed distribution, which could be problematic [1]. However, it might produce more accurate estimates than solely relying on “pure” historical simulation. More on EVT can be found in [1], [2] and [5].

Modelling volatility dynamics, using the EWMA approach

Despite its simplicity, the 3-day rolling window approach for volatility modelling has the shortcoming of weighting all observations equally [39]. However, the EWMA approach overcomes this weakness by modelling volatility with more weight attributed to recent observations and an exponentially declining weight given to older observations [1], [39]. This is useful as current volatility levels are more likely to be more influenced by recent observations, rather than older observations [1].

This might result in a better indicator for volatility dynamics over the analysed periods. Furthermore, the EWMA model does not assume that the modelled variance is mean-reverting, which is in accordance with today's increasing volatility dynamics which persist at high levels [48].

The widely praised GARCH(1,1) model may also be investigated as an alternative to model volatility, however, it assumes that the modelled variance is mean-reverting, which might be problematic, and it does not give an intuitive, model-free representation of volatility [2], [39].

Further research and empirical evidence, using contemporary data, are definitely required, in order to know which models fit best for modelling volatility dynamics. More information on the EWMA and GARCH can be found in [2].

7. Conclusion

Historical data covering the oil price slide in 2014-15 was used, in order to determine the suitability of VaR and ES as risk measures for oil & gas related securities. The idea of using non-modified historical data is to “let the data speak”, in order to see unbiased, pure empirical facts.

Descriptive statistics show that the analysed financial returns are not normally distributed. This should discourage the use of a parametric approach for VaR and ES estimation for oil & gas related securities.

In addition to this, the rolling standard deviation analysis shows that the volatility dynamics of oil & gas related securities increased tremendously during 2015. The conducted analysis also confirmed that oil & gas related securities are more volatile than a broad index, such as the S&P 500.

VaR and ES were estimated using data from 3rd January 2014 to 1st January 2015 and tested for exceedances using data from 2nd January 2015 to 31st December 2015. The exceedance rate analysis of both risk measures clearly shows that ES is a more conservative and reliable risk measure than VaR for all analysed financial securities.

However, these results could be complemented by appropriate backtesting of VaR and ES estimates and extended by a larger dataset and further methodologies. The findings presented in this work might be useful for portfolio managers, risk managers and investors exposed to the oil & gas sector.

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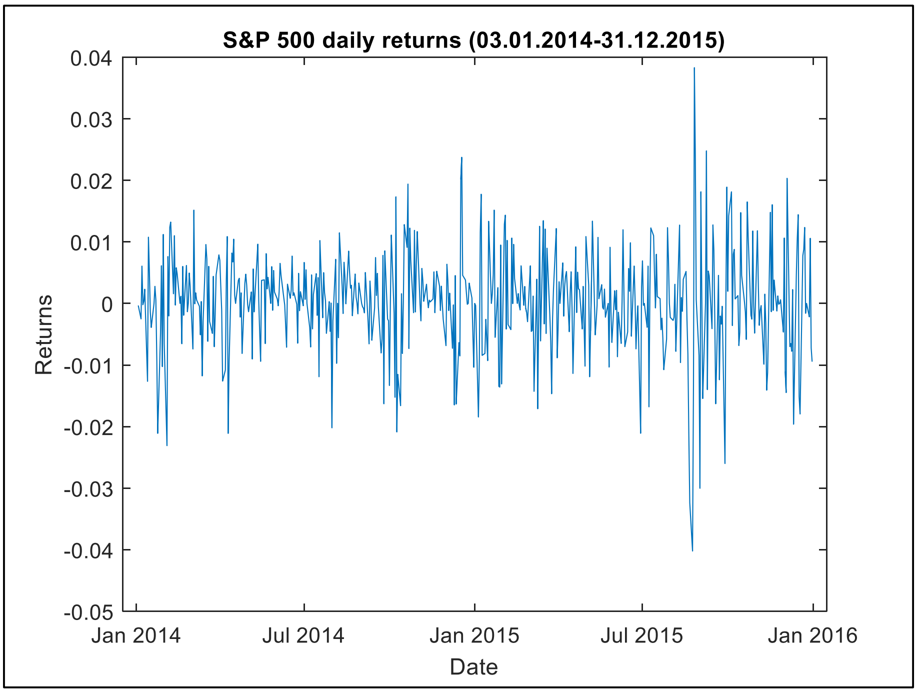
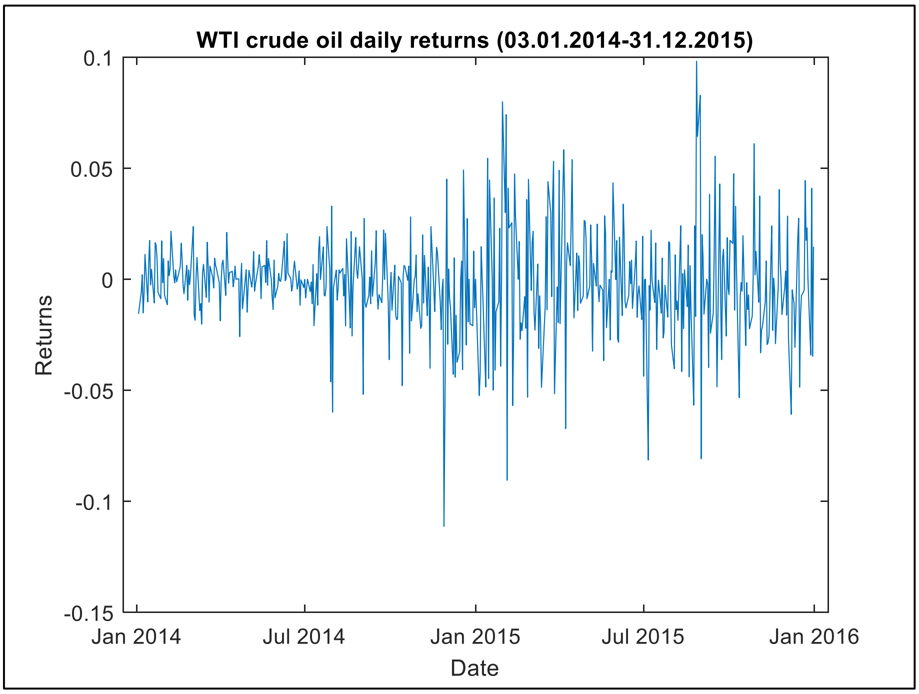
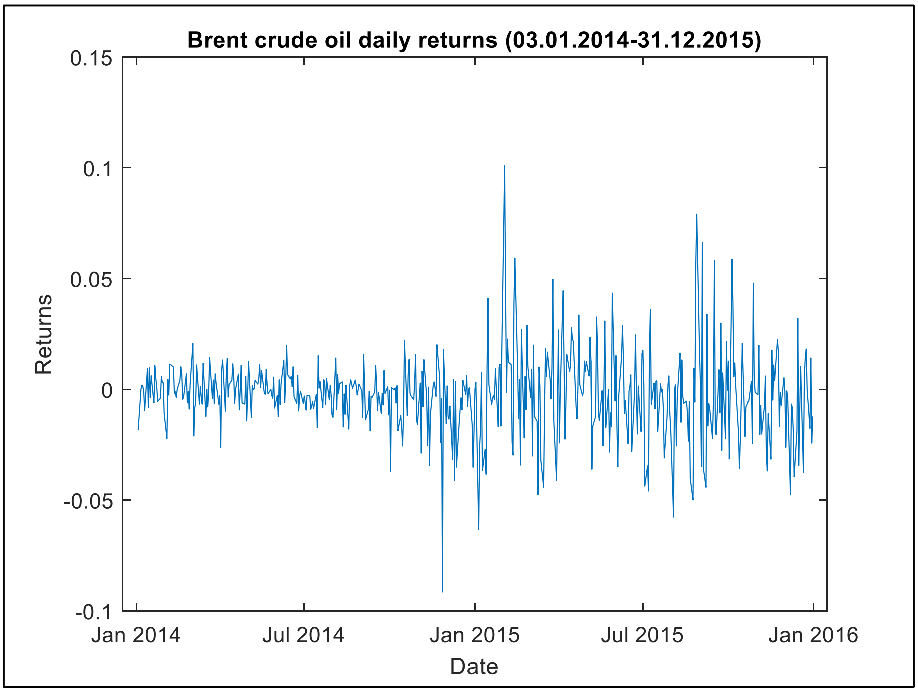
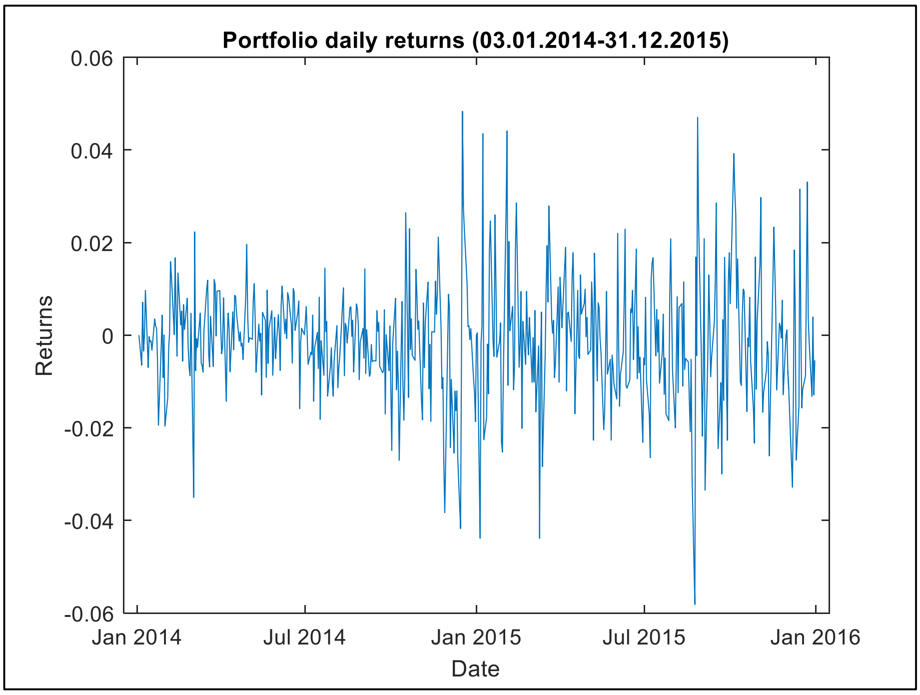
B. Appendix

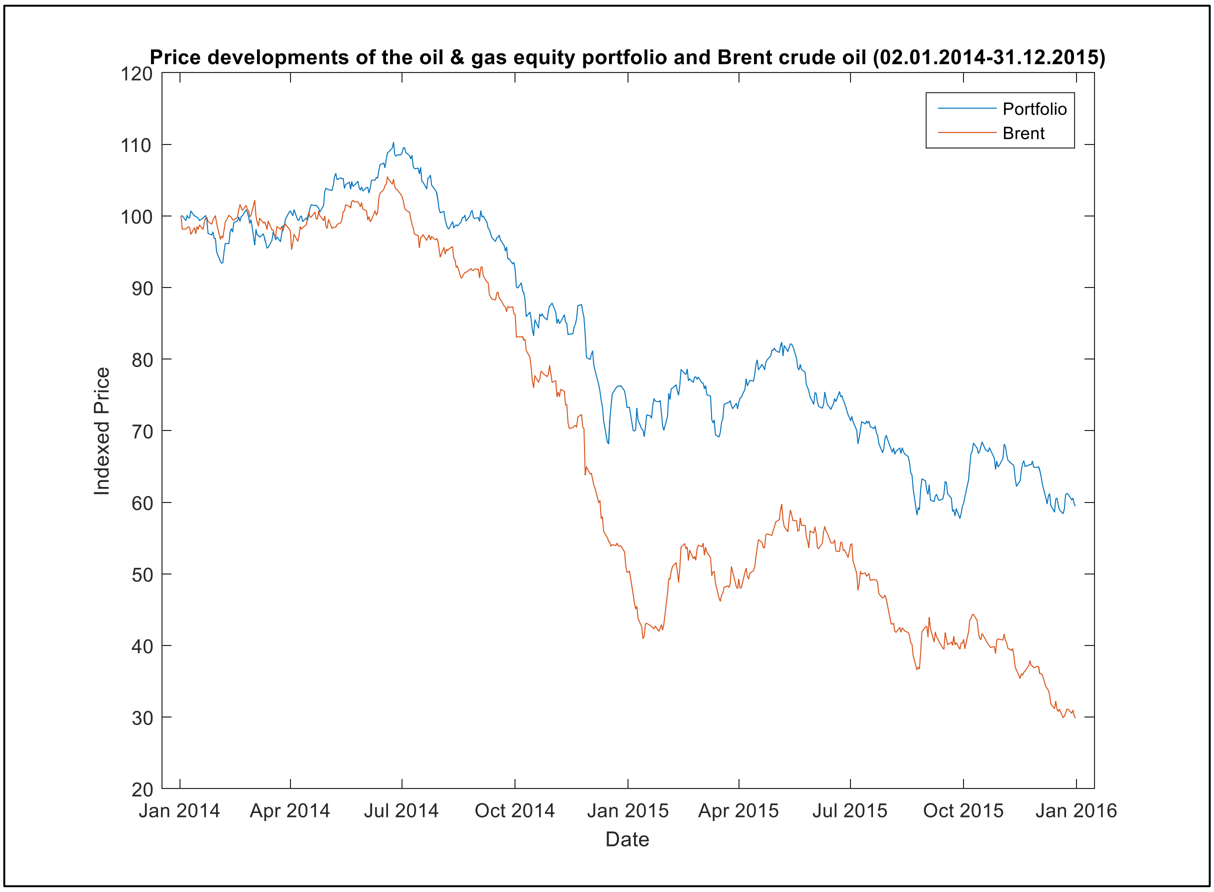
B.1 Daily returns, price developments and histograms

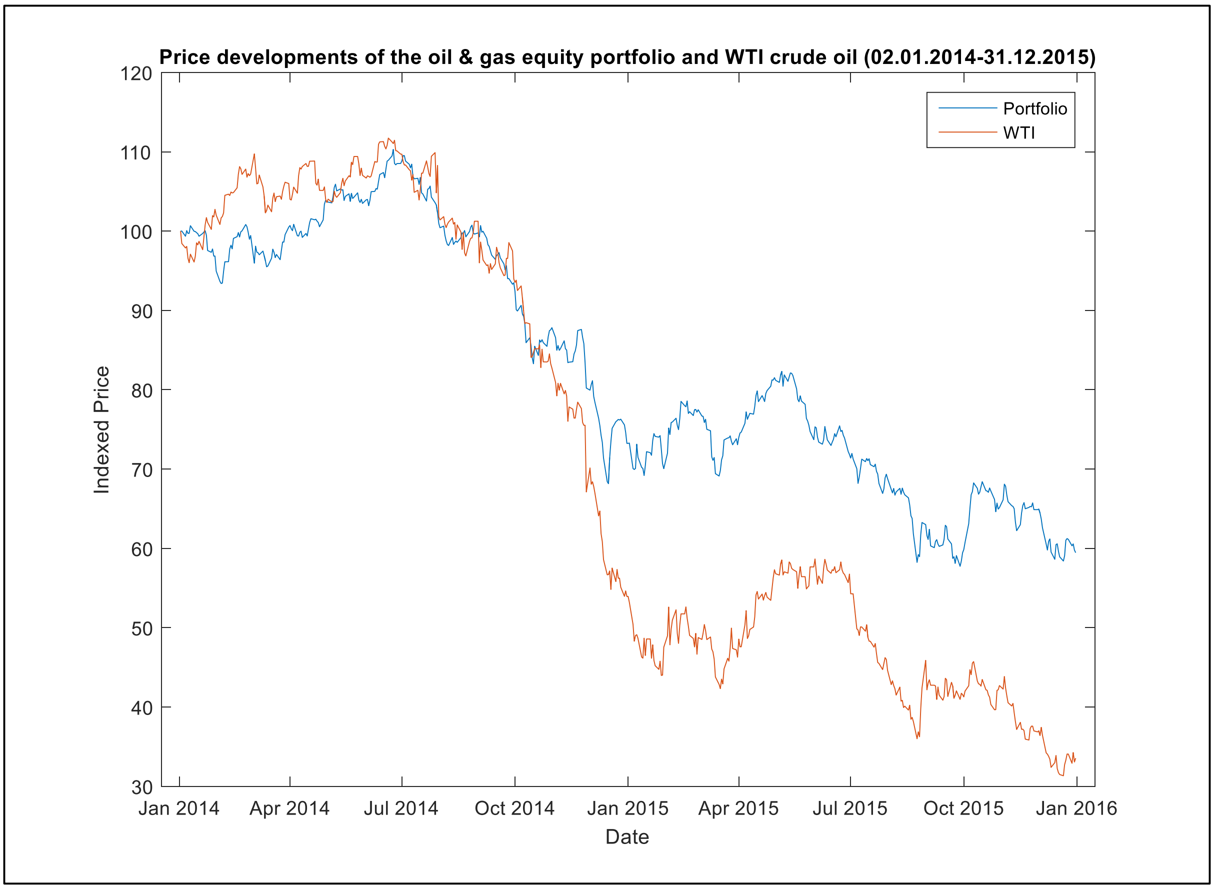


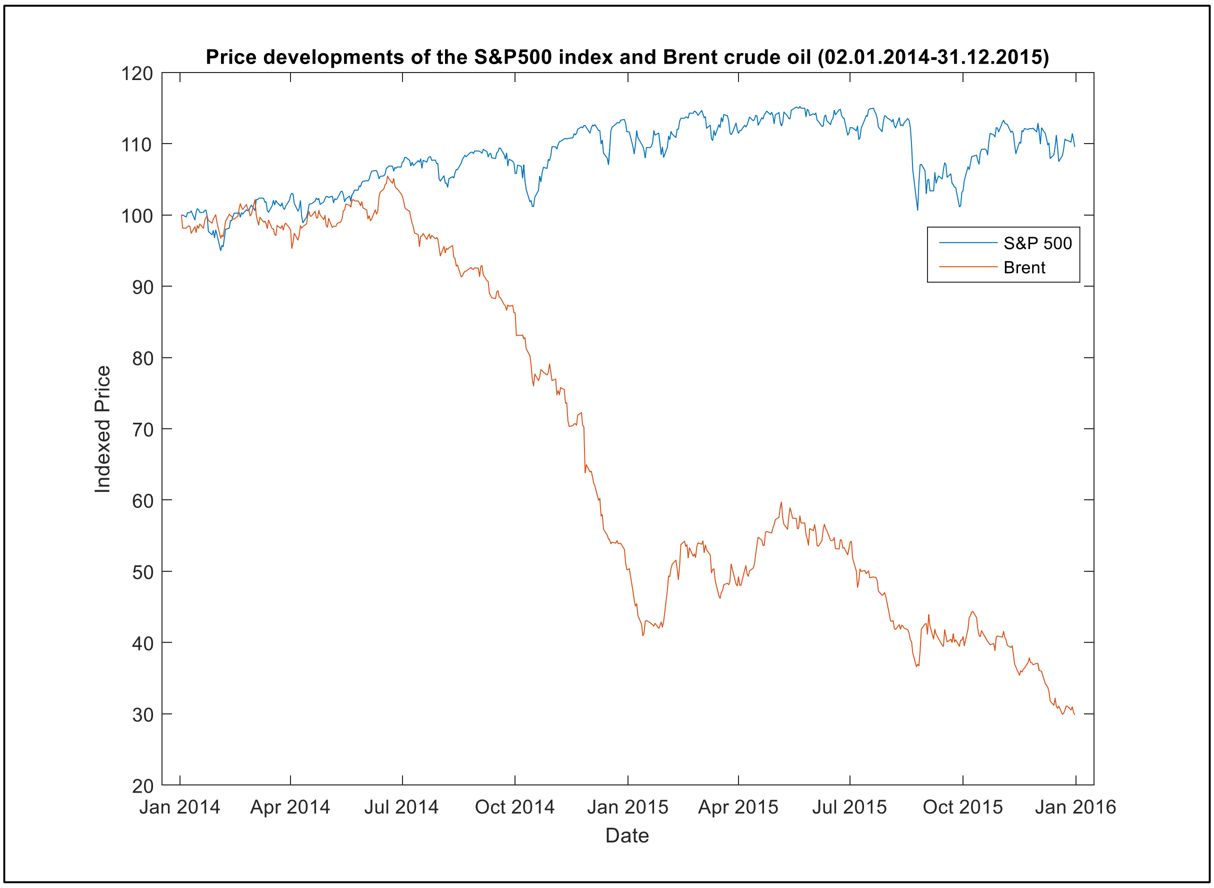


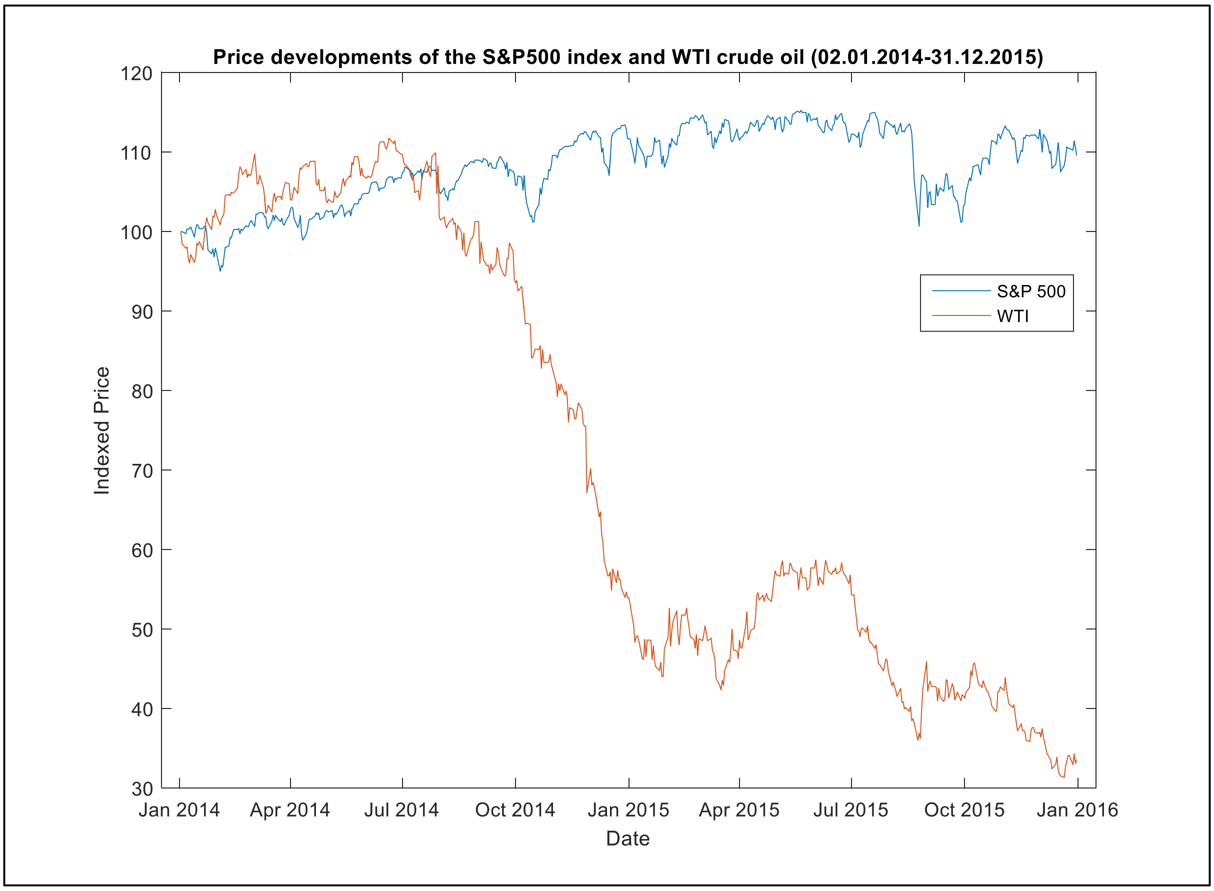

Brent crude oil daily returns (03.01.2014-31.12.2015)
0.15
0.1
0.05
0
-0.05
-0.1
Returns
Jan 2014
Jul 2014
Jan 2015
Jul 2015
Jan 2016
Date

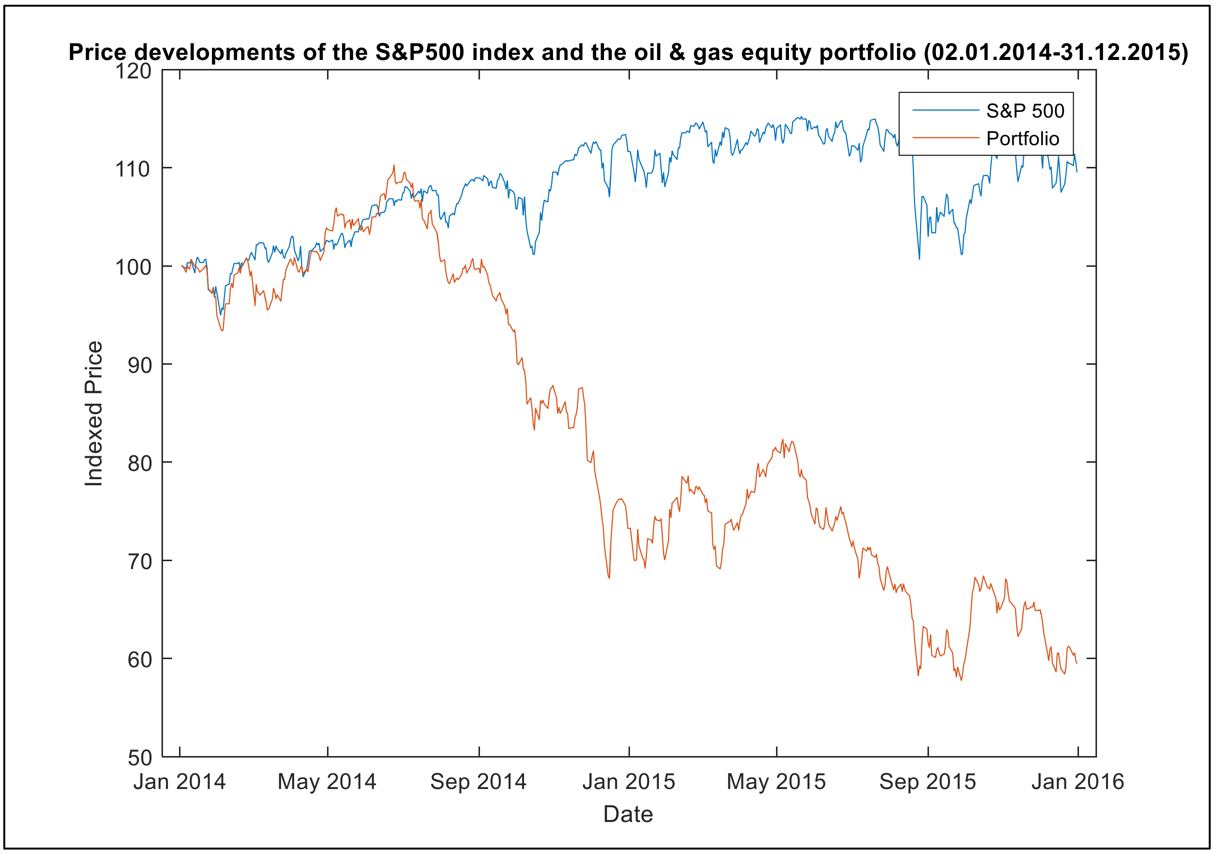

Portfolio daily returns (03.01.2014-31.12.2015)
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
Returns
Jan 2014
Jul 2014
Jan 2015
Jul 2015
Jan 2016
Date

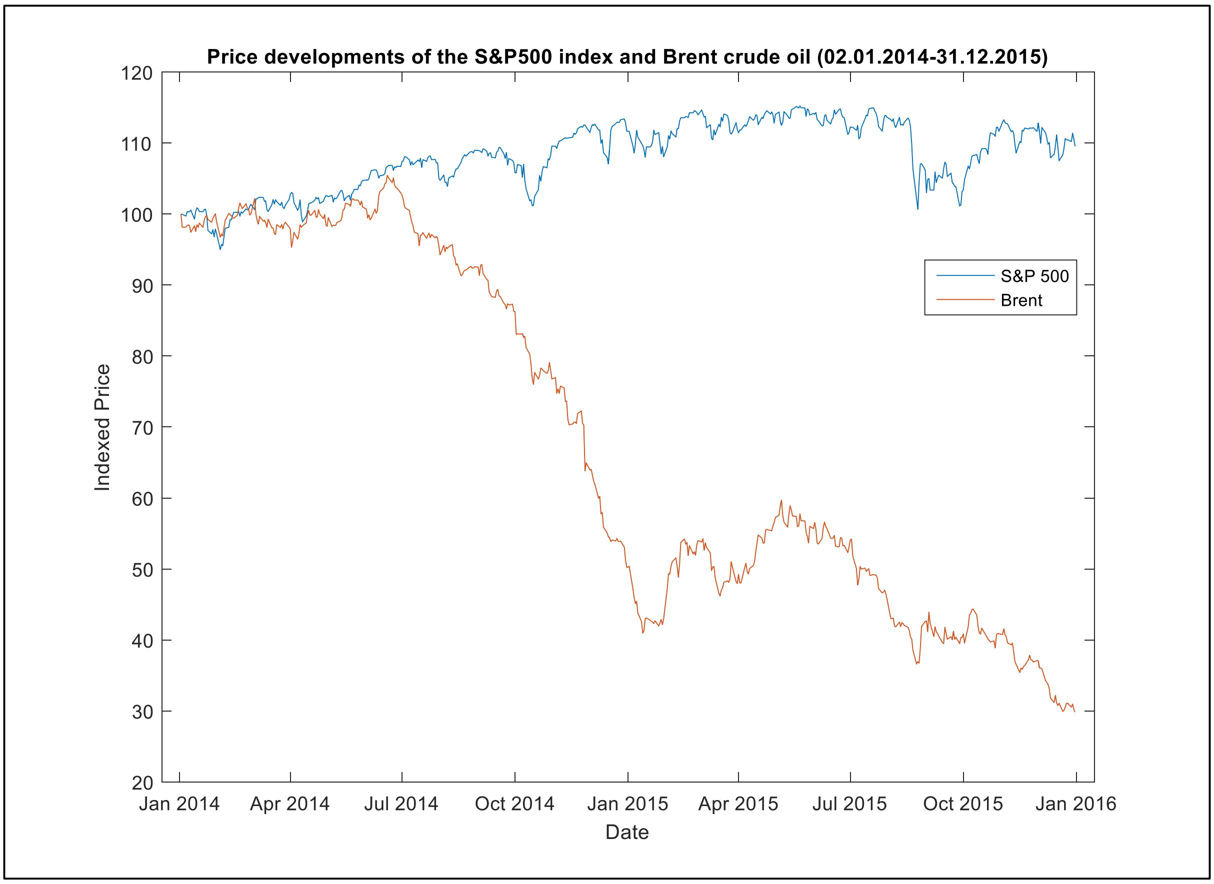

Price developments of the oil & gas equity portfolio and Brent crude oil (02.01.2014-31.12.2015)
Portfolio
Brent
Indexed Price
120
110
100
90
80
70
60
50
40
30
20
Jan 2014
Apr 2014
Jul 2014
Oct 2014
Jan 2015
Apr 2015
Jul 2015
Oct 2015
Jan 2016
Date

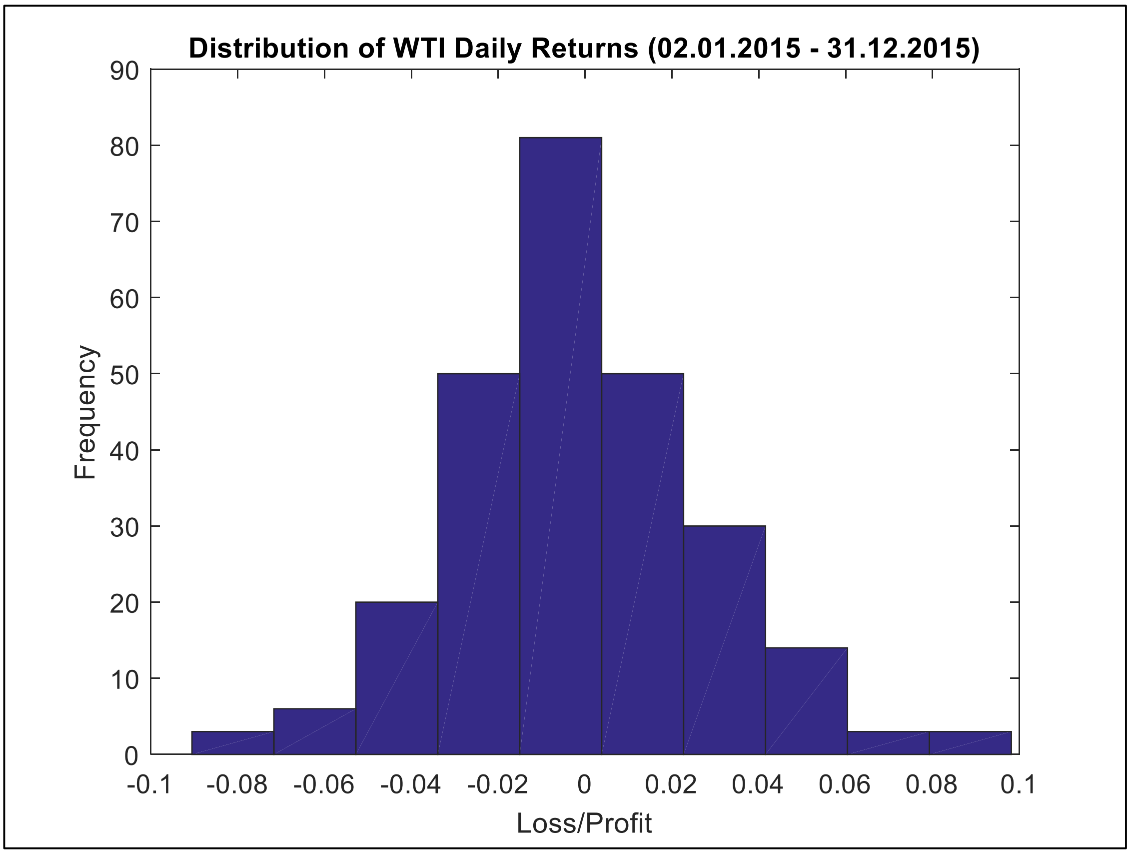

Price developments of the oil & gas equity portfolio and WTI crude oil (02.01.2014-31.12.2015)
Portfolio
WTI
Indexed Price
120
110
100
90
80
70
60
50
40
30
Jan 2014
Apr 2014
Jul 2014
Oct 2014
Jan 2015
Apr 2015
Jul 2015
Oct 2015
Jan 2016
Date

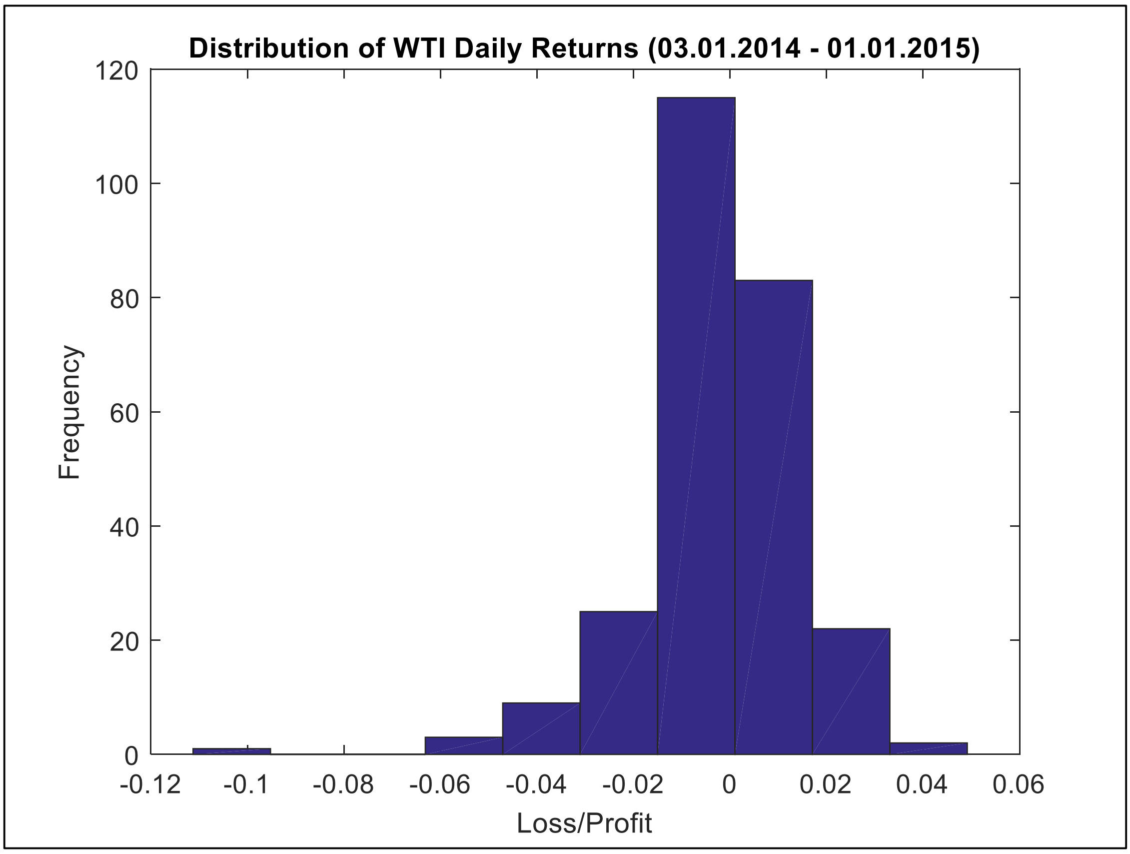

Price developments of the S&P500 index and Brent crude oil (02.01.2014-31.12.2015)
Indexed Price
Date
S&P 500
Brent
120
110
100
90
80
70
60
50
40
30
20
Jan 2014
Apr 2014
Jul 2014
Oct 2014
Jan 2015
Apr 2015
Jul 2015
Oct 2015
Jan 2016

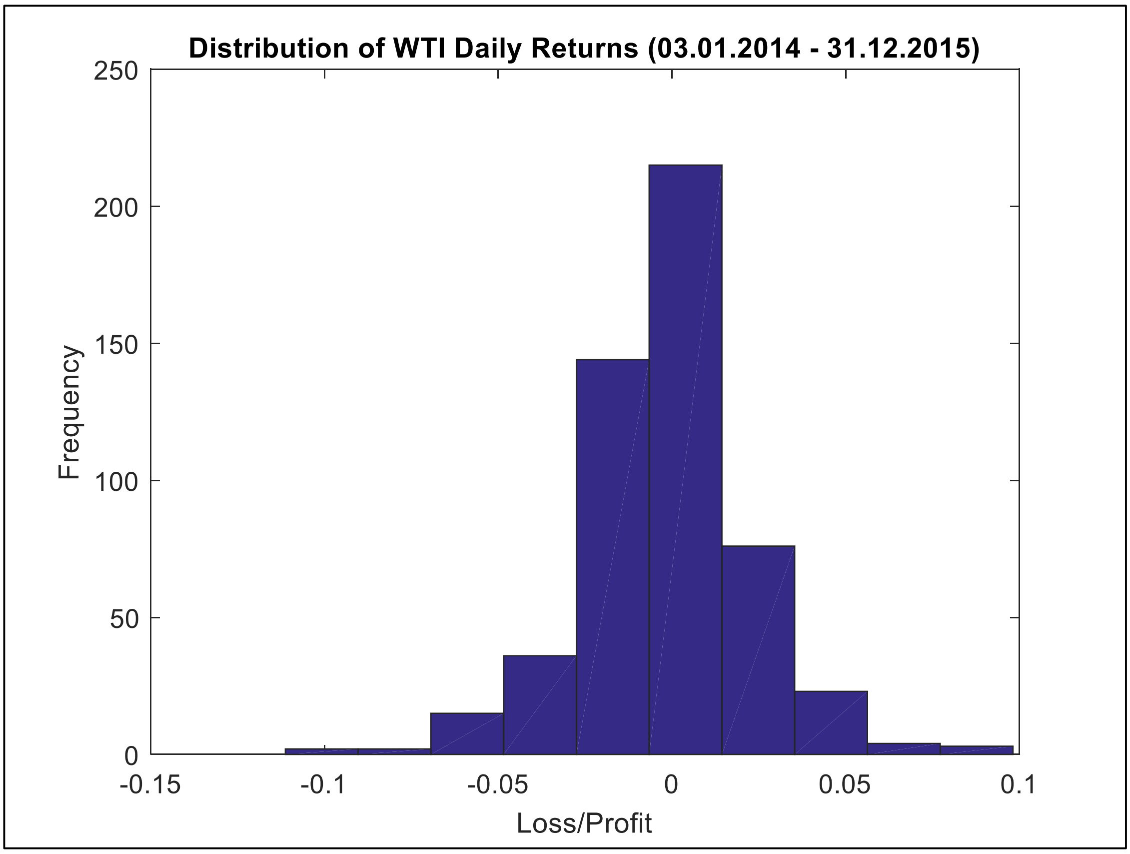

Price developments of the S&P500 index and WTI crude oil (02.01.2014-31.12.2015)
Indexed Price
Date
S&P 500
WTI
120
110
100
90
80
70
60
50
40
30
Jan 2014
Apr 2014
Jul 2014
Oct 2014
Jan 2015
Apr 2015
Jul 2015
Oct 2015
Jan 2016

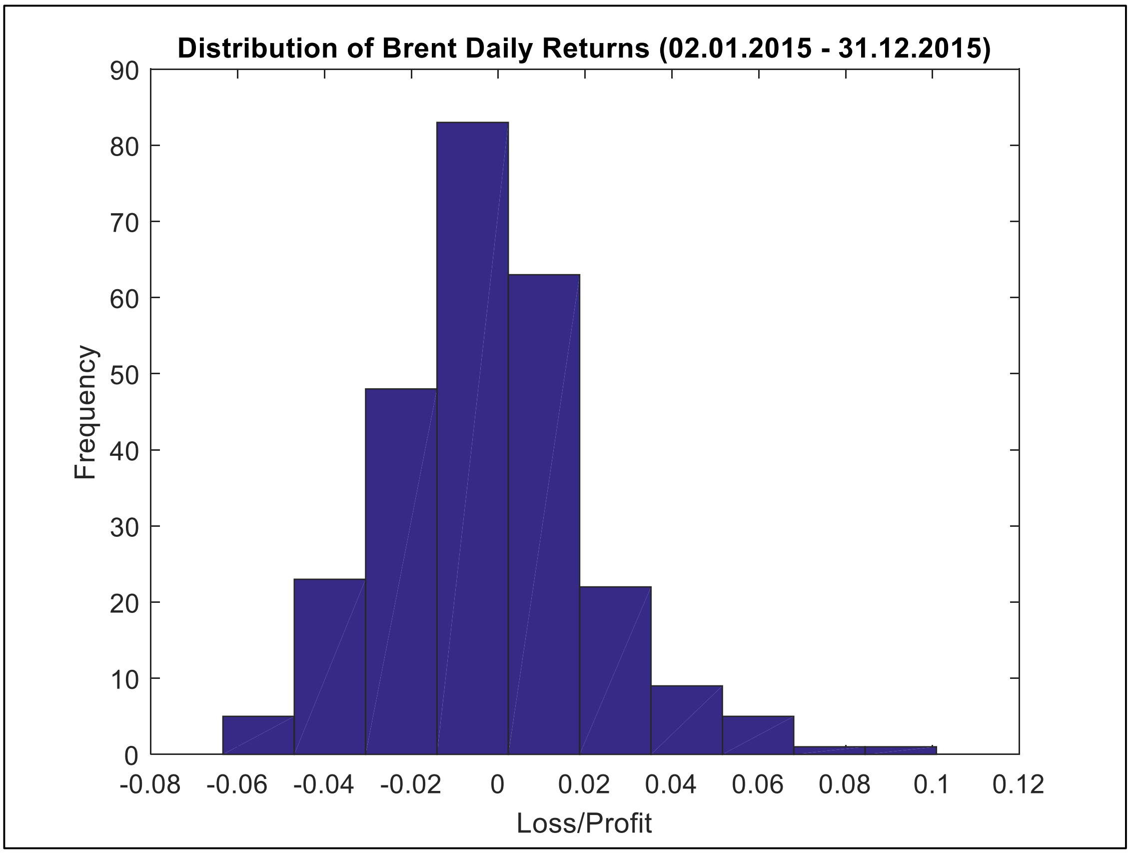

Price developments of the S&P500 index and the oil & gas equity portfolio (02.01.2014-31.12.2015)
Indexed Price
120
110
100
90
80
70
60
50
Jan 2014
May 2014
Sep 2014
Jan 2015
May 2015
Sep 2015
Jan 2016
Date
S&P 500
Portfolio

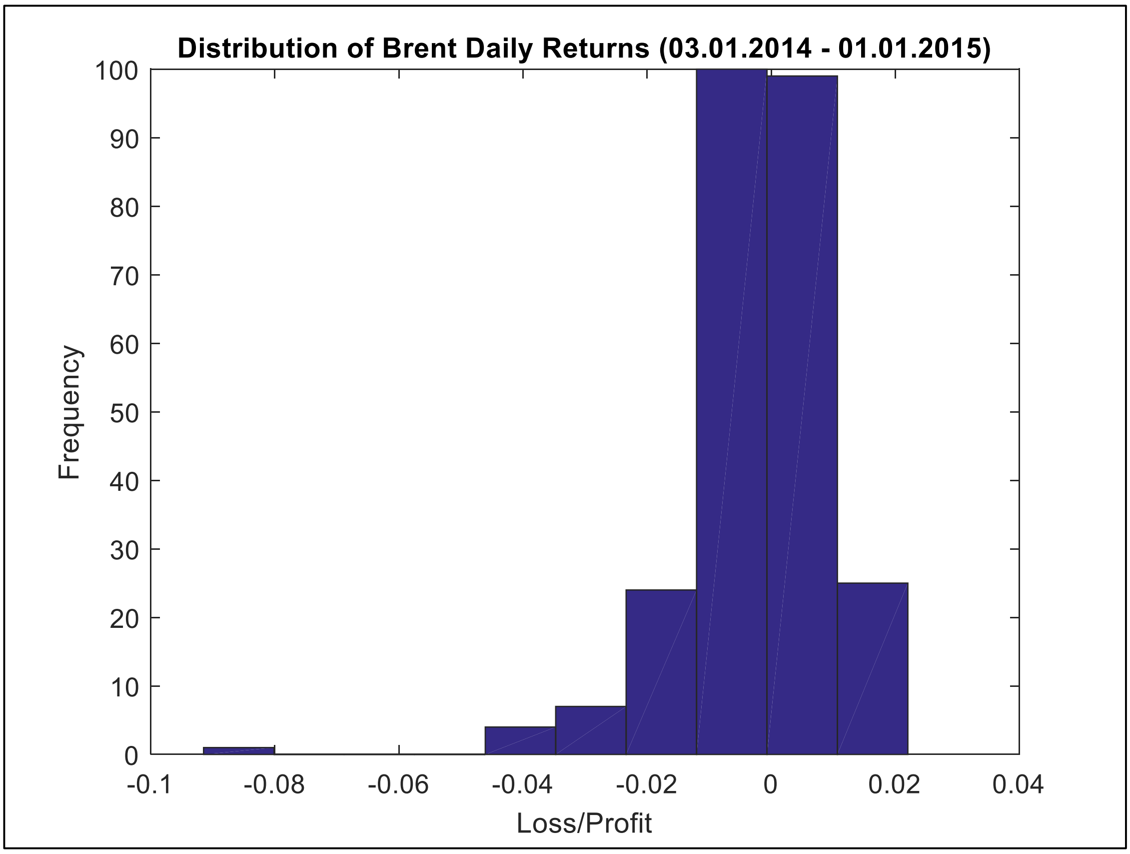

Price developments of the S&P500 index and Brent crude oil (02.01.2014-31.12.2015)
Indexed Price
120
110
100
90
80
70
60
50
40
30
20
Jan 2014
Apr 2014
Jul 2014
Oct 2014
Jan 2015
Apr 2015
Jul 2015
Oct 2015
Jan 2016
Date
S&P 500
Brent


Distribution of WTI Daily Returns (02.01.2015 - 31.12.2015)
Frequency
90
80
70
60
50
40
30
20
10
0
-0.1
-0.08
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
0.08
0.1
Loss/Profit

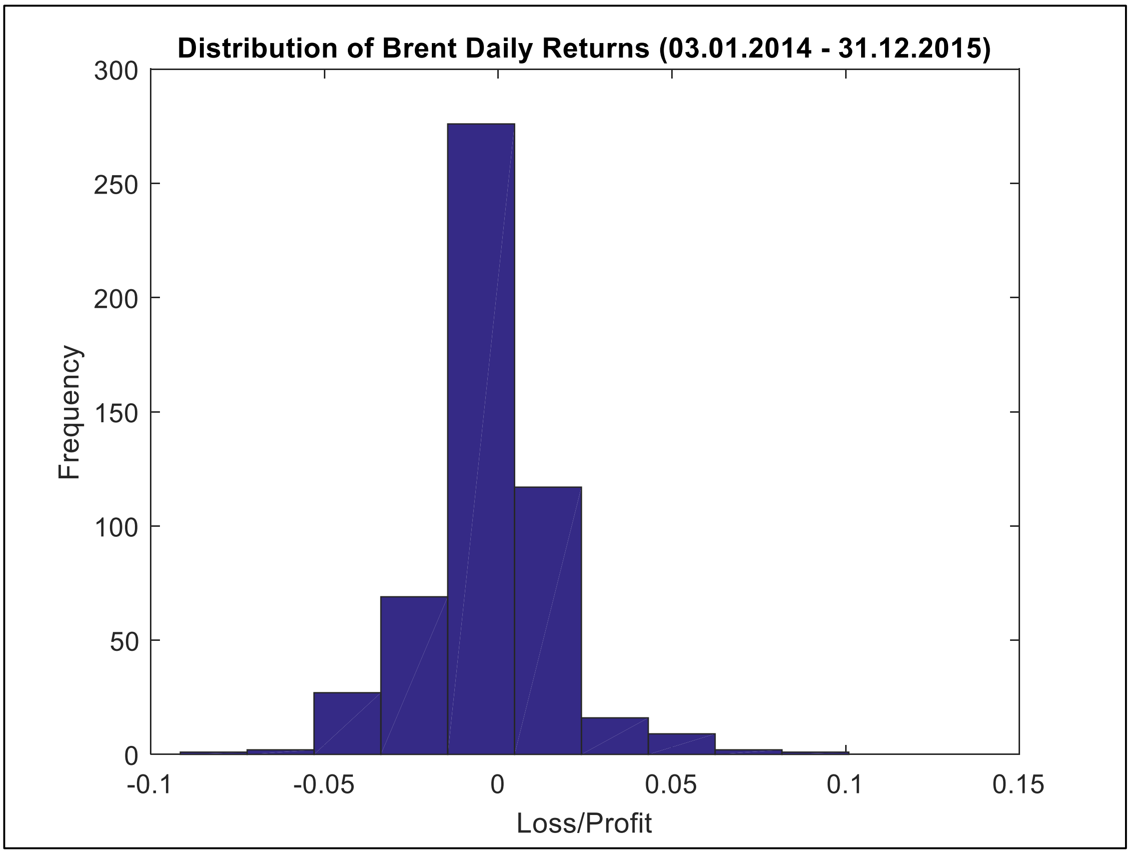

Distribution of WTI Daily Returns (03.01.2014 - 01.01.2015)
Frequency
120
100
80
60
40
20
0
-0.12
-0.1
-0.08
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
Loss/Profit


Distribution of WTI Daily Returns (03.01.2014 - 31.12.2015)
Frequency
250
200
150
100
50
0
-0.15
-0.1
-0.05
0
0.05
0.1
Loss/Profit

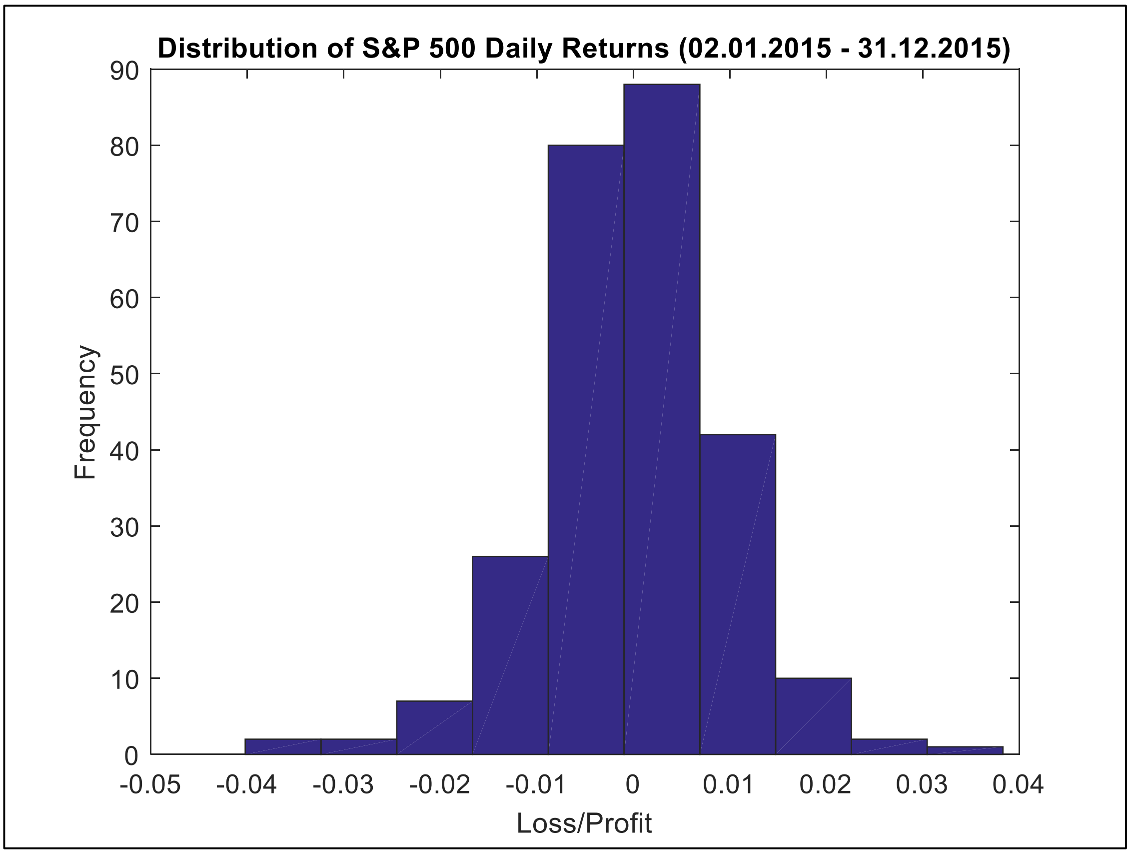

Distribution of Brent Daily Returns (02.01.2015 - 31.12.2015)
Frequency
90
80
70
60
50
40
30
20
10
0
-0.08
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
0.08
0.1
0.12
Loss/Profit



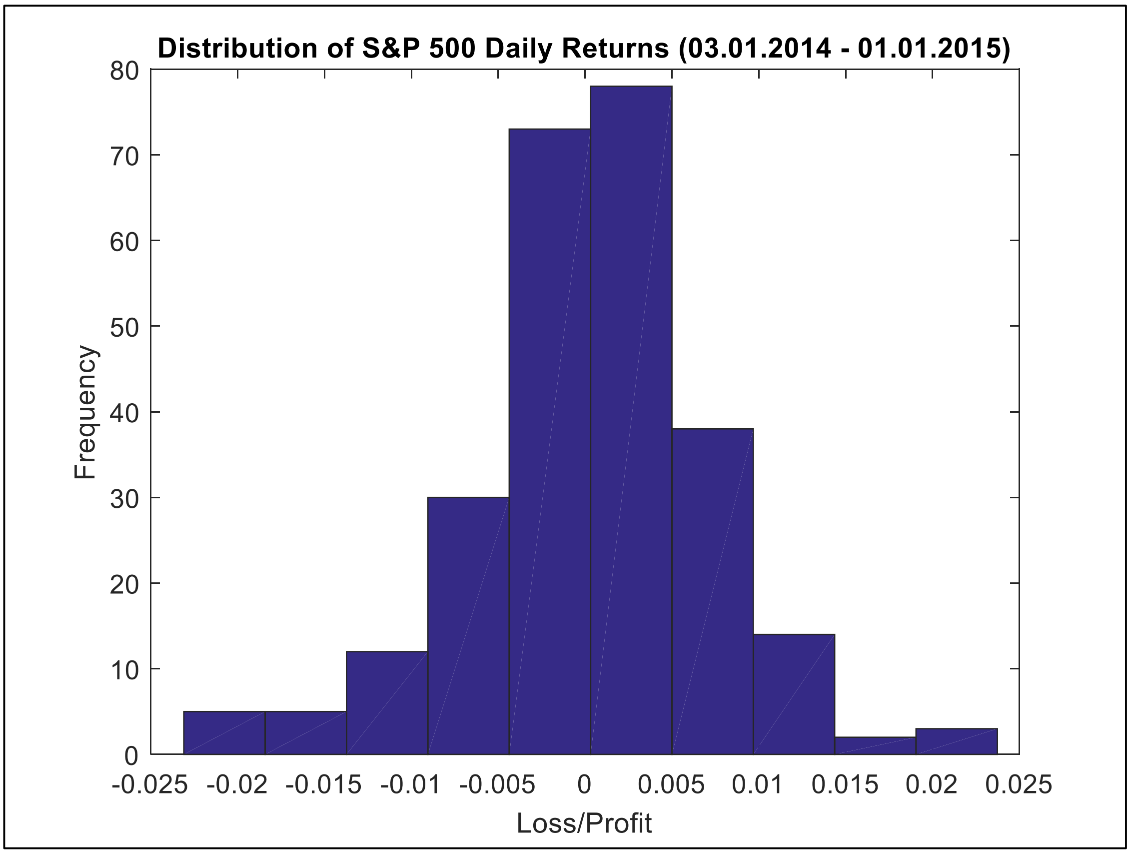
Distribution of Brent Daily Returns (03.01.2014 - 01.01.2015)
Frequency
Loss/Profit
100
90
80
70
60
50
40
30
20
10
0
-0.1
-0.08
-0.06
-0.04
-0.02
0
0.02
0.04



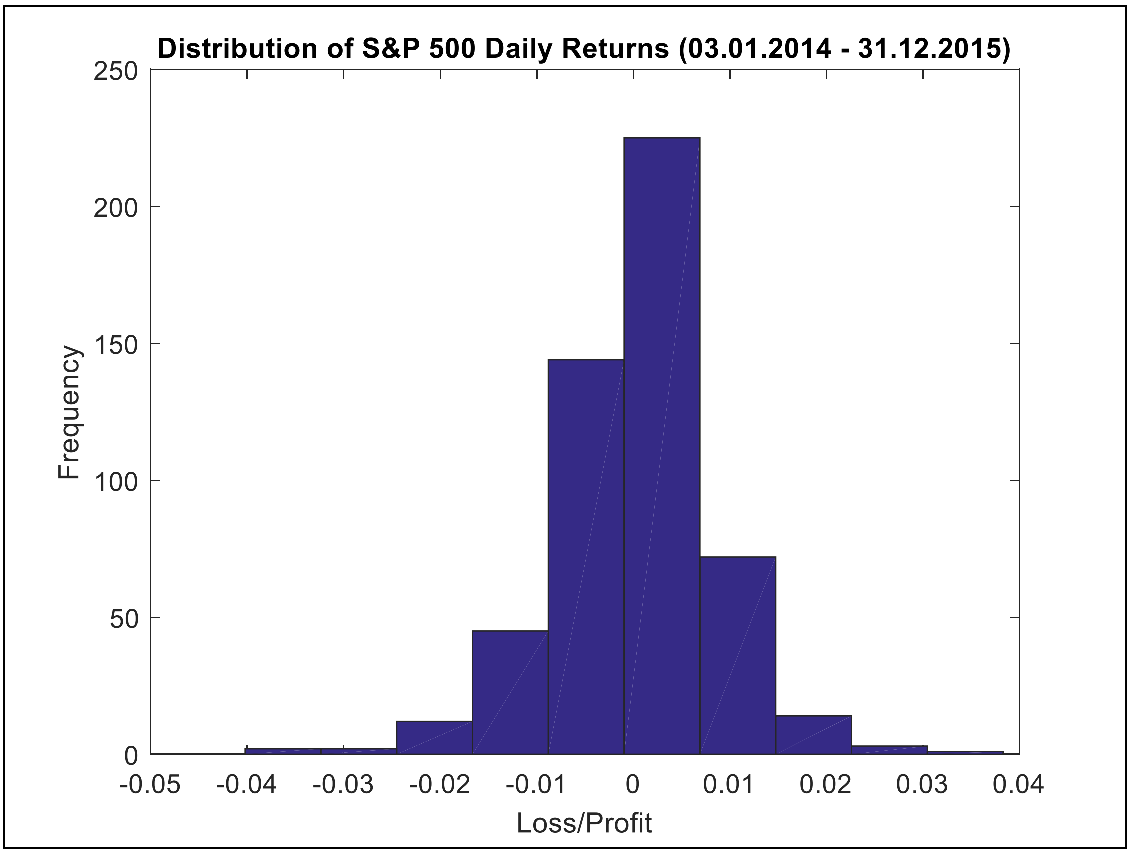
Distribution of Brent Daily Returns (03.01.2014 - 31.12.2015)
Frequency
Loss/Profit
300
250
200
150
100
50
0
-0.1
-0.05
0
0.05
0.1
0.15

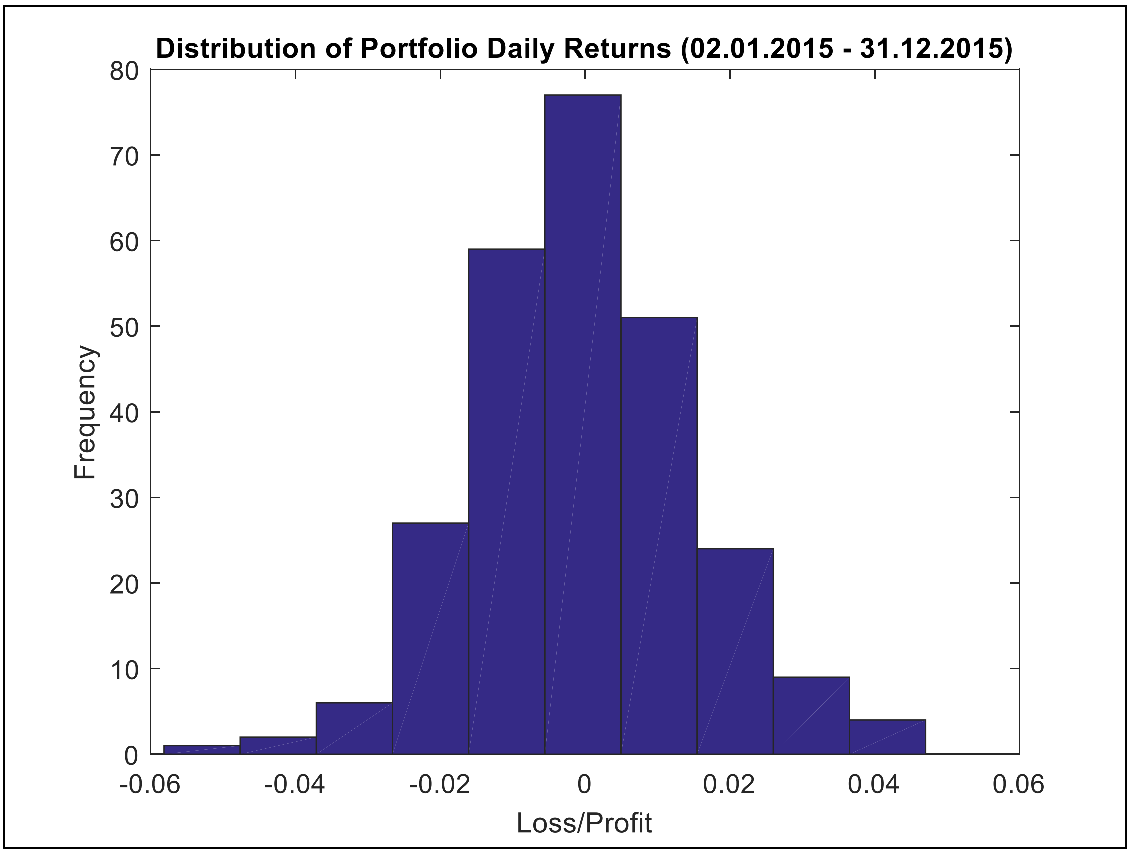


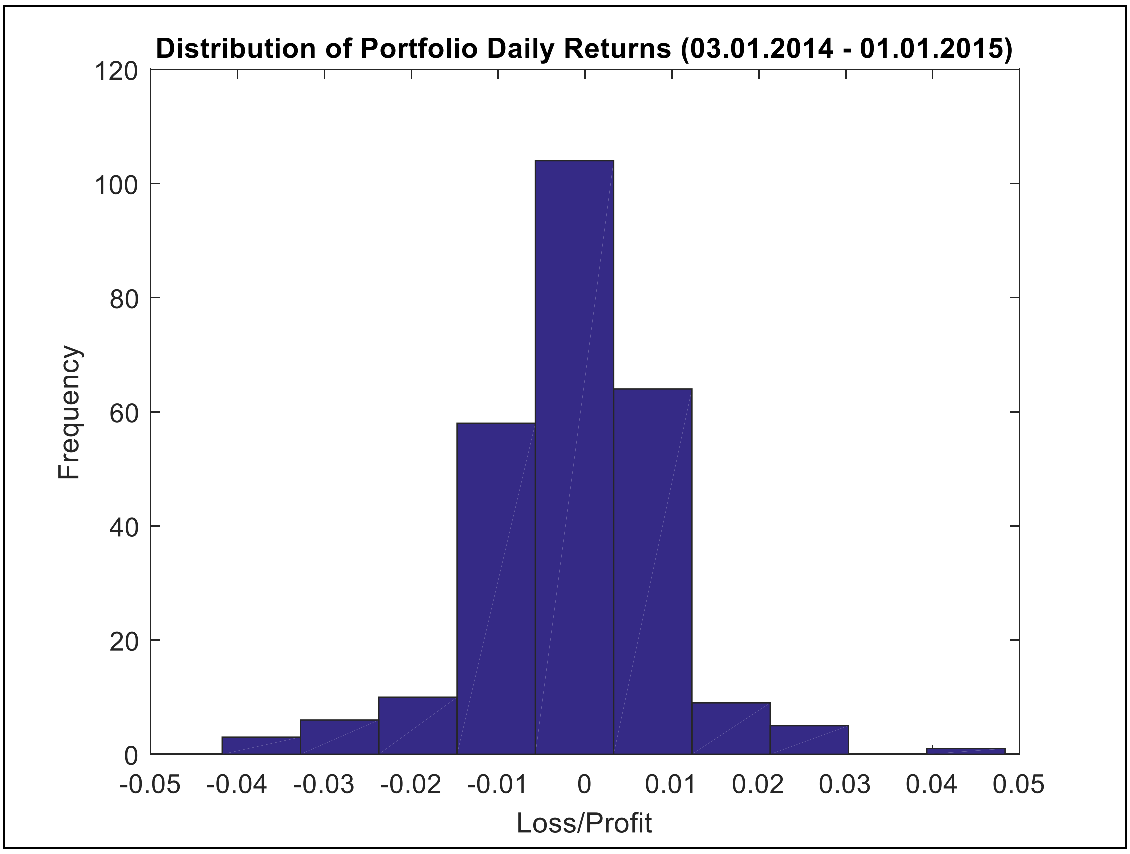
Distribution of S&P 500 Daily Returns (02.01.2015 - 31.12.2015)
Frequency
Loss/Profit
0
10
20
30
40
50
60
70
80
90
-0.05
-0.04
-0.03
-0.02
-0.01
0
0.01
0.02
0.03
0.04

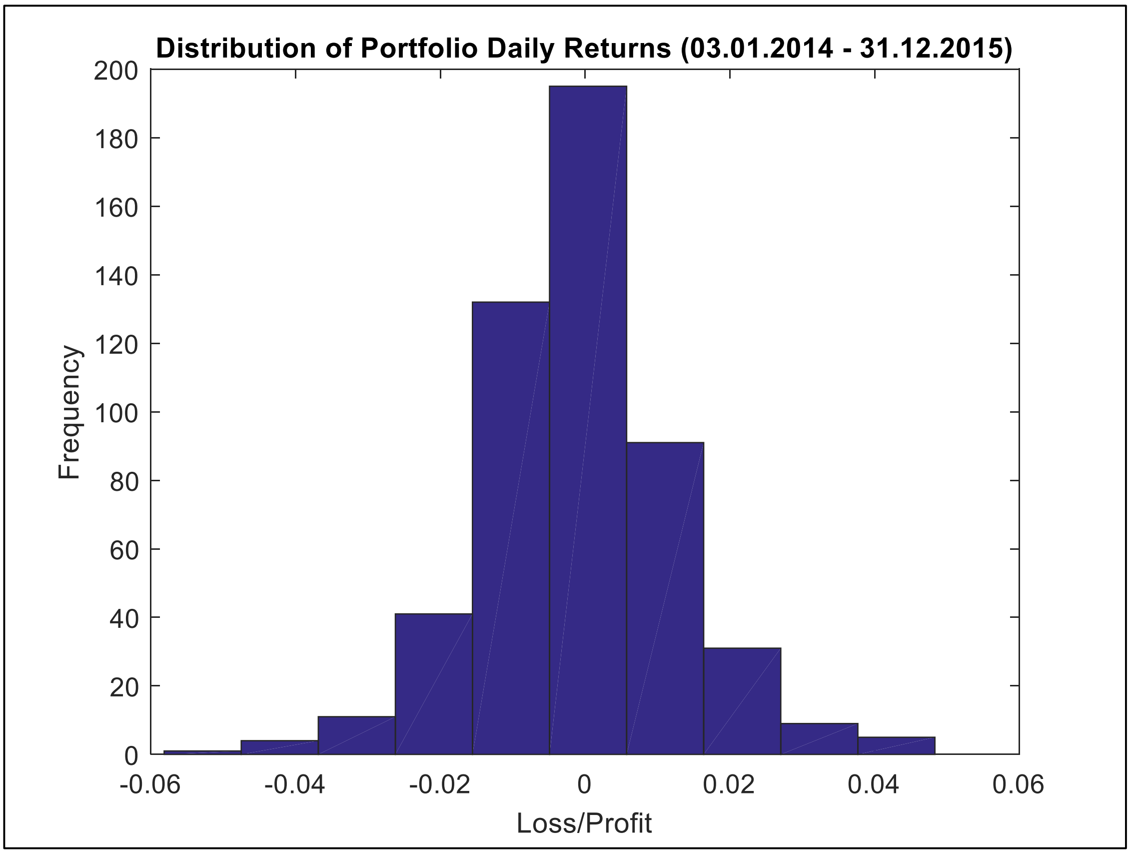


Distribution of S&P 500 Daily Returns (03.01.2014 - 01.01.2015)
Frequency
Loss/Profit
0
10
20
30
40
50
60
70
80
-0.025
-0.02
-0.015
-0.01
-0.005
0
0.005
0.01
0.015
0.02
0.025

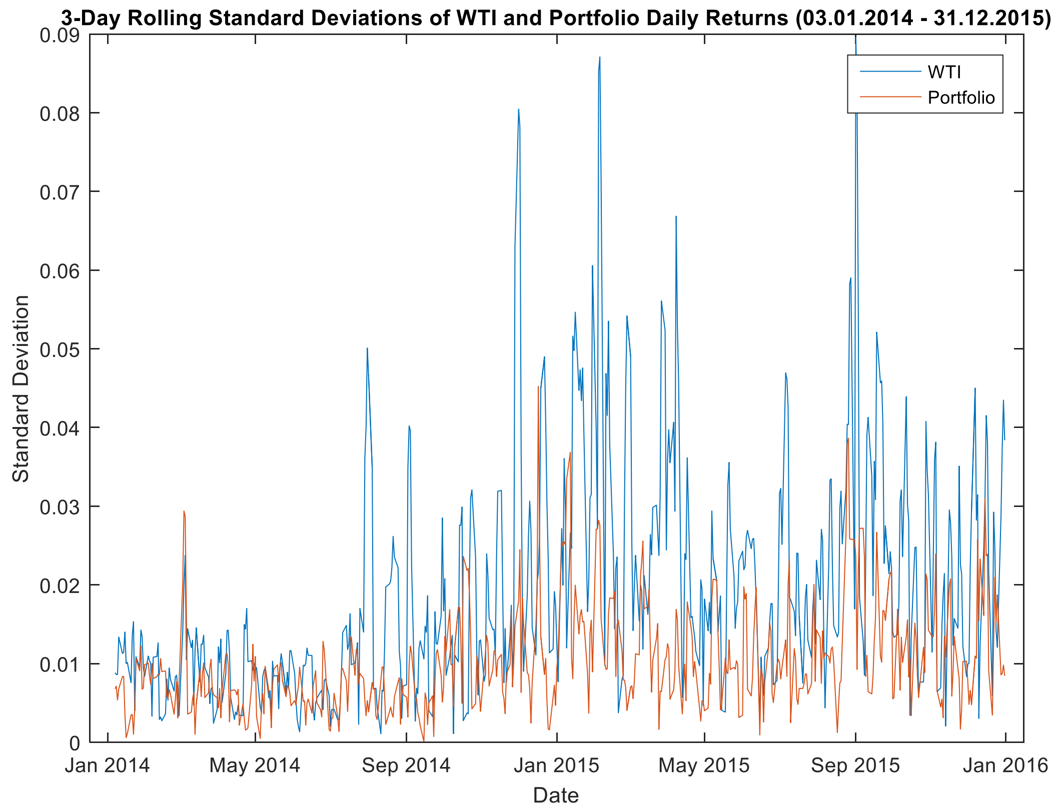

Distribution of S&P 500 Daily Returns (03.01.2014 - 31.12.2015)
Frequency
250
200
150
100
50
0
-0.05
-0.04
-0.03
-0.02
-0.01
0
0.01
0.02
0.03
0.04
Loss/Profit

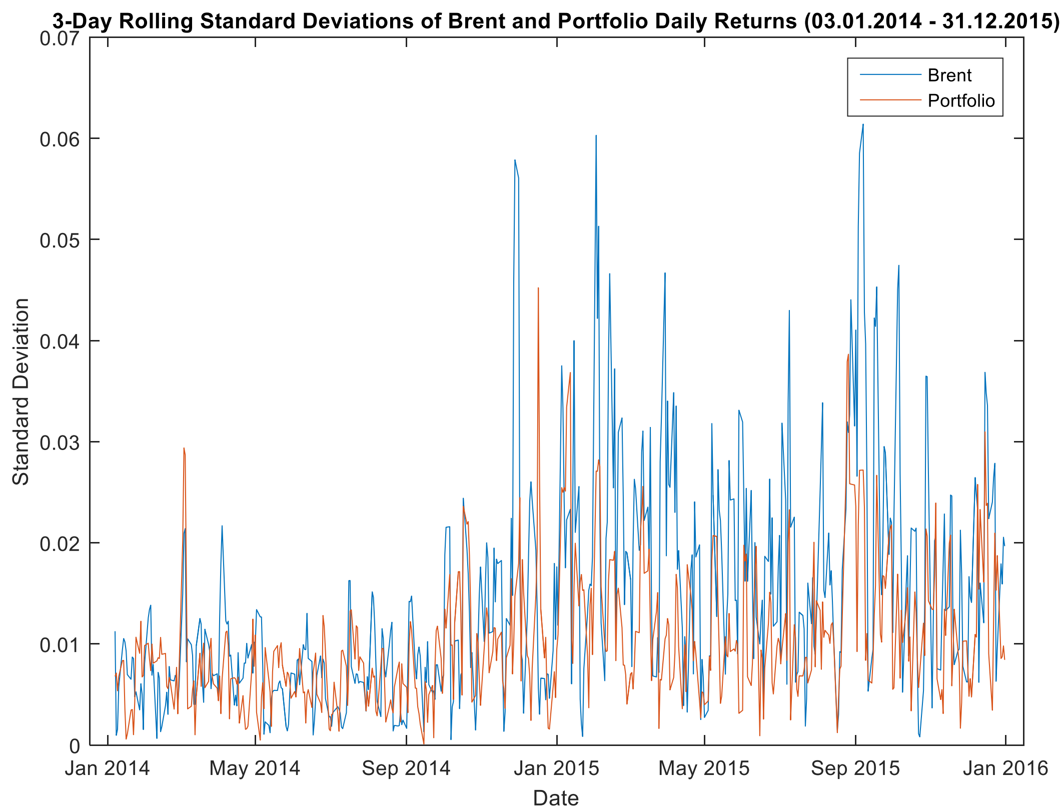

Distribution of Portfolio Daily Returns (02.01.2015 - 31.12.2015)
Frequency
80
70
60
50
40
30
20
10
0
-0.06
-0.04
-0.02
0
0.02
0.04
0.06
Loss/Profit

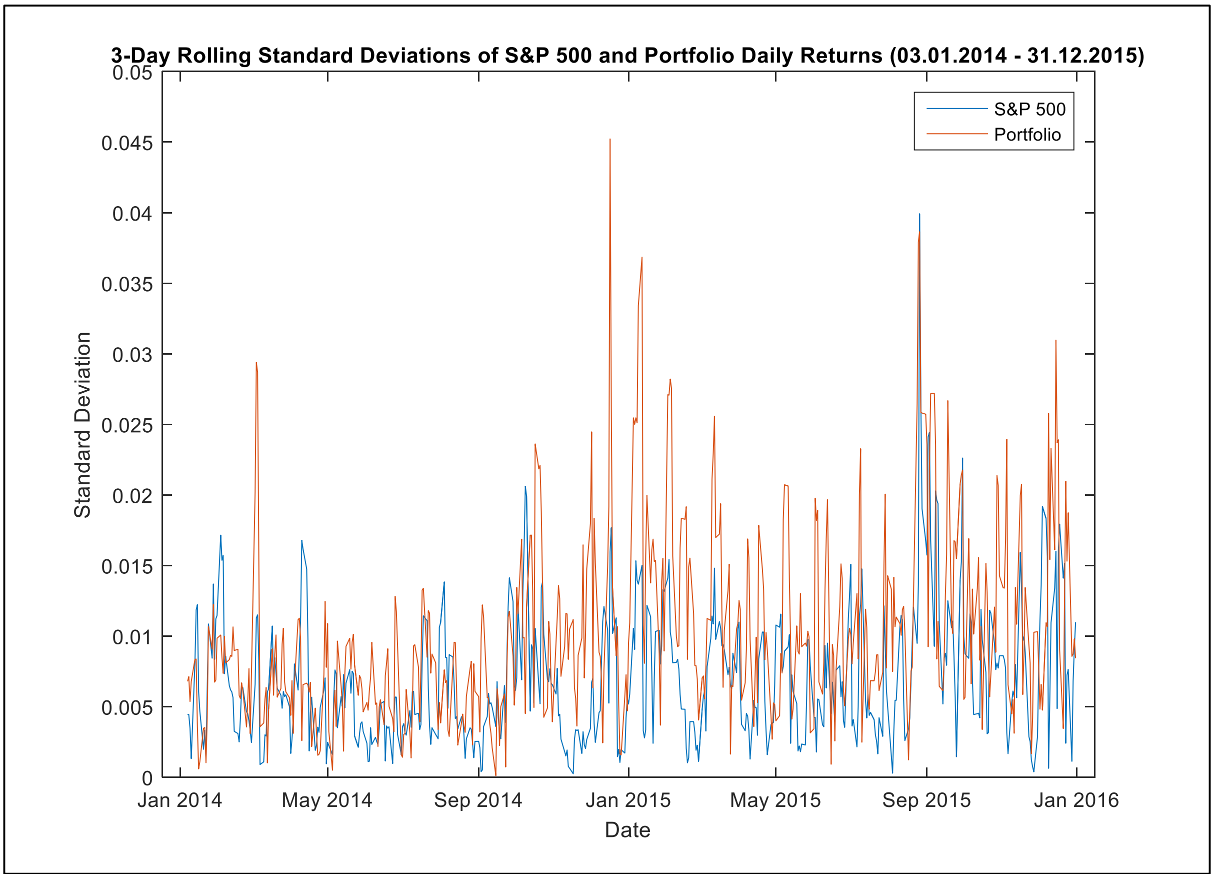

Distribution of Portfolio Daily Returns (03.01.2014 - 01.01.2015)
Frequency
Loss/Profit
120
100
80
60
40
20
0
-0.05
-0.04
-0.03
-0.02
-0.01
0
0.01
0.02
0.03
0.04
0.05

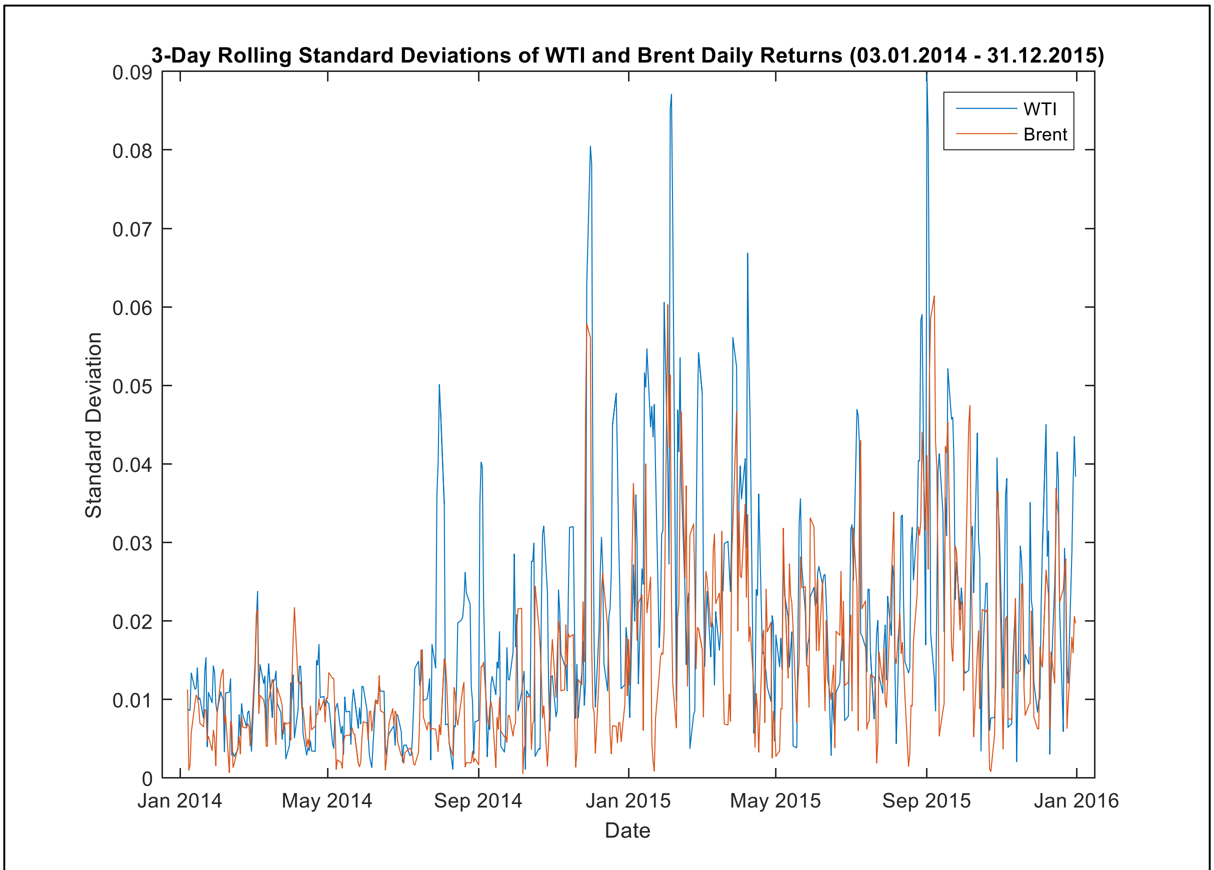

Distribution of Portfolio Daily Returns (03.01.2014 - 31.12.2015)
Frequency
Loss/Profit
200
180
160
140
120
100
80
60
40
20
0
-0.06
-0.04
-0.02
0
0.02
0.04
0.06

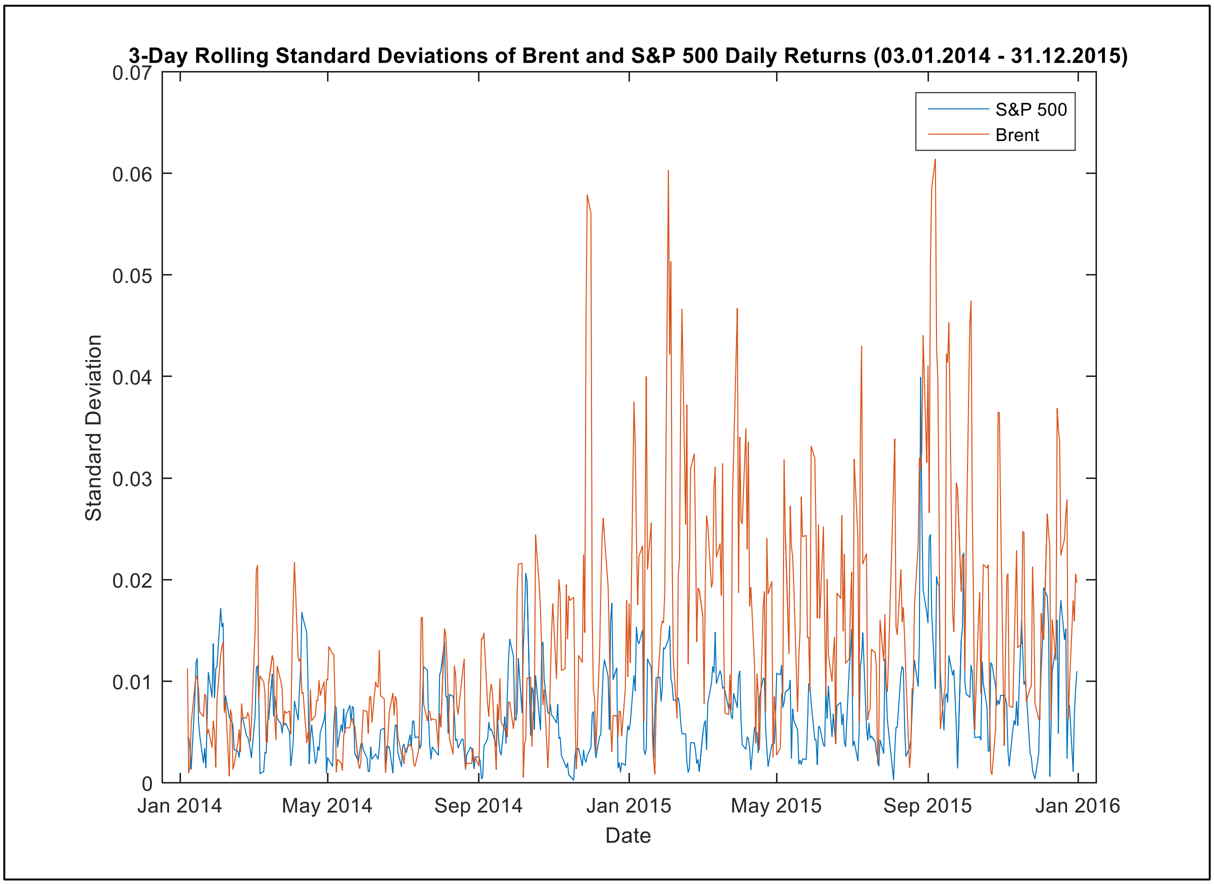
B.2 3-day rolling standard deviations






3-Day Rolling Standard Deviations of S&P 500 and Portfolio Daily Returns (03.01.2014 - 31.12.2015)
S&P 500
Portfolio
Standard Deviation
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
Jan 2014
May 2014
Sep 2014
Jan 2015
May 2015
Sep 2015
Jan 2016
Date


3-Day Rolling Standard Deviations of WTI and Brent Daily Returns (03.01.2014 - 31.12.2015)
WTI
Brent
Standard Deviation
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
Jan 2014
May 2014
Sep 2014
Jan 2015
May 2015
Sep 2015
Jan 2016
Date


3-Day Rolling Standard Deviations of Brent and S&P 500 Daily Returns (03.01.2014 - 31.12.2015)
S&P 500
Brent
Standard Deviation
0
0.01
0.02
0.03
0.04
0.05
0.06
0.07
Jan 2014
May 2014
Sep 2014
Jan 2015
May 2015
Sep 2015
Jan 2016
Date

B.3 Code

dataimport.m

```
%% Data import

close all
clear
clc

Shell = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx', 'SHELL
USD', 'B1051:B1571');
BP = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx', 'BP USD',
'B1051:B1571');
Exxon = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx', 'EXXON
USD', 'B1051:B1571');
Chevron = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx',
'CHEVRON USD', 'B1051:B1571');
OMV = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx', 'OMV
USD', 'B1051:B1571');
Total = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx', 'TOTAL
USD', 'B1051:B1571');
Eni = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx', 'ENI
USD', 'B1051:B1571');
Lukoil = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx',
'LUKOIL USD', 'B1051:B1571');
Gazprom = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx',
'GAZPROM USD', 'B1051:B1571');
Statoil = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx',
'STATOIL USD', 'B1051:B1571');

Brent = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx', 'BRENT
USD', 'B1051:B1571');
WTI = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx', 'WTI
USD', 'B1051:B1571');
SP500 = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx', 'S&P
500', 'B1051:B1571');

%% Date

[num, txt] = xlsread('data_rds_bp_exx_chev_wti_brent.xlsx',
'SHELL USD', 'A1051:A1571');

Date = datetime(txt);

%% Log returns

Shell_returns = price2ret(Shell);
BP_returns = price2ret(BP);
Exxon_returns = price2ret(Exxon);
Chevron_returns = price2ret(Chevron);
```

```
OMV_returns = price2ret(OMV);
Total_returns = price2ret(Total);
Eni_returns = price2ret(Eni);
Lukoil_returns = price2ret(Lukoil);
Gazprom_returns = price2ret(Gazprom);
Statoil_returns = price2ret(Statoil);

Brent_returns = price2ret(Brent);
WTI_returns = price2ret(WTI);
SP500_returns = price2ret(SP500);

%% Equally weighted Portfolio

Portfolio = (0.1*Shell_returns + 0.1*BP_returns +
0.1*Exxon_returns + 0.1*Chevron_returns + 0.1*OMV_returns +
0.1*Total_returns + 0.1*Eni_returns + 0.1*Lukoil_returns +
0.1*Gazprom_returns + 0.1*Statoil_returns);

% Equally weighted Portfolio 03.01.2014-01.01.2015

Portfolio14 = Portfolio(1:260);

% Equally weighted Portfolio 02.01.2015-31.12.2015

Portfolio15 = Portfolio(261:520);

%% All returns in one matrix 03.01.2014-31.12.2015

All_returns = [Brent_returns WTI_returns SP500_returns
Portfolio];

% Alle returns in one matrix 03.01.2014-01.01.2015

All_returns14 = All_returns(1:260,:);

% All returns in one matrix 02.01.2015-31.12.2015

All_returns15 = All_returns(261:520,:);
```

statistics.m

```
%% Some descriptive statistics

clear
close all
clc

load prices_and_returns.mat

%% Avergage returns of Brent oil, WTI oil, S&P500 and the
Portfolio

Mean_All_returns = mean(All_returns)'; %03.01.2014-31.12.2015
Mean_All_returns14 = mean(All_returns14)';%03.01.2014-
01.01.2015
Mean_All_returns15 = mean(All_returns15)';%02.01.2015-
31.12.2015

%% Standard deviation

STD_All_returns = std(All_returns)'; %03.01.2014-31.12.2015
STD_All_returns14 = std(All_returns14)';%03.01.2014-01.01.2015
STD_All_returns15 = std(All_returns15)';%02.01.2015-31.12.2015

%% Kurtosis

% Kurtosis of all returns 03.01.2014-31.12.2015

Kurt_All_returns = kurtosis(All_returns)';

% Kurtosis of all returns 03.01.2014-01.01.2015

Kurt14_All_returns14 = kurtosis(All_returns14)';

% Kurtosis of all returns 02.01.2015-31.12.2015

Kurt15_All_returns15 = kurtosis(All_returns15)';

%% Skewness of Brent oil, WTI oil, S&P500 and the Portfolio

Skew_All_returns = skewness(All_returns)'; %03.01.2014-
31.12.2015


Skew_All_returns14 = skewness(All_returns14)'; %03.01.2014-
01.01.2015
```

```
Skew_All_returns15 = skewness(All_returns15)'; %02.01.2015-
31.12.2015

%% Jarque-Bera test using a 95% confidence interval for Brent
oil returns, WTI oil returns and Portfolio returns


%03.01.2014-01.01.2015

JB14 = zeros(1,4);

for i = 1:4

    JB14(i) = jbtest(All_returns14(:,i));

end


%02.01.2015-31.12.2015

JB15 = zeros(1,4);

for i = 1:4

    JB15(i) = jbtest(All_returns15(:,i));

end


%03.01.2014-31.12.2015

JB = zeros(1,4);

for i = 1:4

   JB(i) = jbtest(All_returns(:,i));

end

% A JB value of 1 indicates that the null hypothesis of
normality is
% rejected at the 95% significance level.

JB
JB14
JB15

clear i

%% Negative-Sigma-3 returns
```

```
%03.01.2014-31.12.2015

NS31415 = zeros(4,1);

for i = 1:4

    NS31415(i,1) =
sum(All_returns(:,i)<(mean(All_returns(:,i))-
(3*std(All_returns(:,i)))));

end


%03.01.2014-01.01.2015

NS314 = zeros(4,1);

for i = 1:4

    NS314(i,1) =
sum(All_returns14(:,i)<(mean(All_returns14(:,i))-
(3*std(All_returns14(:,i)))));

end


%02.01.2015-31.12.2015

NS315 = zeros(4,1);

for i = 1:4

    NS315(i,1) =
sum(All_returns15(:,i)<(mean(All_returns15(:,i))-
(3*std(All_returns15(:,i)))));

end


%% 3-Day Rolling Standard Deviations (3-Day Rolling
Volatilities)

% Rolling volatility of the Portfolio 03.01.2014-31.12.2015

rvolp = zeros(1,518);

for i = 1:518
rvolp(1,i) = std(Portfolio(i:i+2,1));
end
```

```
% Rolling volatility of the S&P 500 03.01.2014-31.12.2015

rvolsp500 = zeros(1,518);

for i = 1:518
    rvolsp500(1,i) = std(SP500_returns(i:i+2,1));
end

% Rolling volatility of Brent oil price 03.01.2014-31.12.2015

rvolbrent = zeros(1,518);

for i = 1:518
    rvolbrent(1,i) = std(Brent_returns(i:i+2,1));
end

% Rolling volatility of WTI oil price 03.01.2014-31.12.2015

rvolwti = zeros(1,518);

for i = 1:518
    rvolwti(1,i) = std(WTI_returns(i:i+2));
end

clear i

figure(1)
plot(Date(4:end), rvolsp500, Date(4:end), rvolbrent);
hold on;
title('3-Day Rolling Standard Deviations of Brent and S&P 500
Daily Returns (03.01.2014 - 31.12.2015)');
xlabel('Date');
ylabel('Standard Deviation');
legend('S&P 500', 'Brent');

figure(2)
plot(Date(4:end), rvolwti, Date(4:end), rvolbrent);
hold on;
title('3-Day Rolling Standard Deviations of WTI and Brent
Daily Returns (03.01.2014 - 31.12.2015)');
xlabel('Date');
ylabel('Standard Deviation');
legend('WTI', 'Brent');

figure(3)
plot(Date(4:end), rvolsp500, Date(4:end), rvolp)
hold on;
title('3-Day Rolling Standard Deviations of S&P 500 and
Portfolio Daily Returns (03.01.2014 - 31.12.2015)');
xlabel('Date');
ylabel('Standard Deviation');
```

```
legend('S&P 500', 'Portfolio');

figure(4)
plot(Date(4:end), rvolbrent, Date(4:end), rvolp);
title('3-Day Rolling Standard Deviations of Brent and
Portfolio Daily Returns (03.01.2014 - 31.12.2015)');
xlabel('Date');
ylabel('Standard Deviation');
legend('Brent', 'Portfolio');

figure(5)
plot(Date(4:end), rvolwti, Date(4:end), rvolp);
title('3-Day Rolling Standard Deviations of WTI and Portfolio
Daily Returns (03.01.2014 - 31.12.2015)');
xlabel('Date');
ylabel('Standard Deviation');
legend('WTI', 'Portfolio');

%% Histograms

% Portfolio

figure(6)
hist(Portfolio);
hold on;
title('Distribution of Portfolio Daily Returns (03.01.2014 -
31.12.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');

figure(7)
hist(Portfolio(1:260));
hold on;
title('Distribution of Portfolio Daily Returns (03.01.2014 -
01.01.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');

figure(8)
hist(Portfolio(261:520));
hold on;
title('Distribution of Portfolio Daily Returns (02.01.2015 -
31.12.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');

% S&P 500

figure(9)
hist(SP500_returns);
hold on;
```

```
title('Distribution of S&P 500 Daily Returns (03.01.2014 -
31.12.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');

figure(10)
hist(SP500_returns(1:260));
hold on;
title('Distribution of S&P 500 Daily Returns (03.01.2014 -
01.01.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');

figure(11)
hist(SP500_returns(261:520));
hold on;
title('Distribution of S&P 500 Daily Returns (02.01.2015 -
31.12.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');

% Brent

figure(12)
hist(Brent_returns);
hold on;
title('Distribution of Brent Daily Returns (03.01.2014 -
31.12.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');

figure(13)
hist(Brent_returns(1:260));
hold on;
title('Distribution of Brent Daily Returns (03.01.2014 -
01.01.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');

figure(14)
hist(Brent_returns(261:520));
hold on;
title('Distribution of Brent Daily Returns (02.01.2015 -
31.12.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');

% WTI

figure(15)
hist(WTI_returns);
```

```
hold on;
title('Distribution of WTI Daily Returns (03.01.2014 -
31.12.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');

figure(16)
hist(WTI_returns(1:260));
hold on;
title('Distribution of WTI Daily Returns (03.01.2014 -
01.01.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');

figure(17)
hist(WTI_returns(261:520));
hold on;
title('Distribution of WTI Daily Returns (02.01.2015 -
31.12.2015)');
xlabel('Loss/Profit');
ylabel('Frequency');
```

indexing.m

```
clear
close all
clc

%% Loading prices and returns

load prices_and_returns.mat

%% Indexing Shell

Index_Shell = zeros(521,1);

Index_Shell(1,1) = 100;

for i = 2:521

    Index_Shell(i,1) = Index_Shell(i-1, 1).*(Shell_returns(i-
1,1)+1);

end

Index_SP500 = zeros(522,1);

%% Indexing BP

Index_BP = zeros(521,1);

Index_BP(1,1) = 100;

for i = 2:521

    Index_BP(i,1) = Index_BP(i-1, 1).* (BP_returns(i-1,1)+1);

end

%% Indexing Exxon

Index_Exxon = zeros(521,1);

Index_Exxon(1,1) = 100;

for i = 2:521

    Index_Exxon(i,1) = Index_Exxon(i-1, 1).* (Exxon_returns(i-
1,1)+1);

end
```

```
%% Indexing Chevron

Index_Chevron = zeros(521,1);

Index_Chevron(1,1) = 100;

for i = 2:521

    Index_Chevron(i,1) = Index_Chevron(i-1, 1).*
(Chevron_returns(i-1,1)+1);

end

%% Indexing OMV

Index_OMV = zeros(521,1);

Index_OMV(1,1) = 100;

for i = 2:521

    Index_OMV(i,1) = Index_OMV(i-1, 1).* (OMV_returns(i-
1,1)+1);

end

%% Indexing Total

Index_Total = zeros(521,1);

Index_Total(1,1) = 100;

for i = 2:521

    Index_Total(i,1) = Index_Total(i-1, 1).* (Total_returns(i-
1,1)+1);

end

%% Indexing Eni

Index_Eni = zeros(521,1);

Index_Eni(1,1) = 100;

for i = 2:521

    Index_Eni(i,1) = Index_Eni(i-1, 1).* (Eni_returns(i-
1,1)+1);

end
```

```
%% Indexing Lukoil

Index_Lukoil = zeros(521,1);

Index_Lukoil(1,1) = 100;

for i = 2:521

    Index_Lukoil(i,1) = Index_Lukoil(i-1, 1).*
(Lukoil_returns(i-1,1)+1);

end

%% Indexing Gazprom

Index_Gazprom = zeros(521,1);

Index_Gazprom(1,1) = 100;

for i = 2:521

    Index_Gazprom(i,1) = Index_Gazprom(i-1, 1).*
(Gazprom_returns(i-1,1)+1);

end

%% Indexing Statoil

Index_Statoil = zeros(521,1);

Index_Statoil(1,1) = 100;

for i = 2:521

    Index_Statoil(i,1) = Index_Statoil(i-1, 1).*
(Statoil_returns(i-1,1)+1);

end

%% Indexing Brent

Index_Brent = zeros(521,1);

Index_Brent(1,1) = 100;

for i = 2:521

    Index_Brent(i,1) = Index_Brent(i-1, 1).* (Brent_returns(i-
1,1)+1);
```

```
end

%% Indexing WTI

Index_WTI = zeros(521,1);

Index_WTI(1,1) = 100;

for i = 2:521

    Index_WTI(i,1) = Index_WTI(i-1, 1).* (WTI_returns(i-
1,1)+1);

end

%% Indexing SP500

Index_SP500 = zeros(521,1);

Index_SP500(1,1) = 100;

for i = 2:521

    Index_SP500(i,1) = Index_SP500(i-1, 1).* (SP500_returns(i-
1,1)+1);

end

%% Indexing Portfolio

Index_Portfolio = zeros(521,1);

Index_Portfolio(1,1) = 100;

for i = 2:521

    Index_Portfolio(i,1) = Index_Portfolio(i-1, 1).*
(Portfolio(i-1,1)+1);

end


%% Plot

figure(1)
plot(Date, Index_Portfolio, Date, Index_Brent)
hold on;
title('Price developments of the oil & gas equity portfolio
and Brent crude oil (02.01.2014-31.12.2015)')
xlabel('Date');
ylabel('Indexed Price');
```

```
legend('Portfolio', 'Brent');

figure(2)
plot(Date, Index_Portfolio, Date, Index_WTI)
hold on;
title('Price developments of the oil & gas equity portfolio
and WTI crude oil (02.01.2014-31.12.2015)')
xlabel('Date');
ylabel('Indexed Price');
legend('Portfolio', 'WTI');

figure(3)
plot(Date, Index_SP500, Date, Index_Brent)
hold on;
title('Price developments of the S&P500 index and Brent crude
oil (02.01.2014-31.12.2015)')
xlabel('Date');
ylabel('Indexed Price');
legend('S&P 500', 'Brent');

figure(4)
plot(Date, Index_SP500, Date, Index_WTI)
hold on;
title('Price developments of the S&P500 index and WTI crude
oil (02.01.2014-31.12.2015)')
xlabel('Date');
ylabel('Indexed Price');
legend('S&P 500', 'WTI');

figure(5)
plot(Date, Index_SP500, Date, Index_Portfolio)
hold on;
title('Price developments of the S&P500 index and the oil &
gas equity portfolio (02.01.2014-31.12.2015)')
xlabel('Date');
ylabel('Indexed Price');
legend('S&P 500', 'Portfolio');

figure(6)
plot(Date, Index_SP500, Date, Index_Brent)
hold on;
title('Price developments of the S&P500 index and Brent crude
oil (02.01.2014-31.12.2015)')
xlabel('Date');
ylabel('Indexed Price');
legend('S&P 500', 'Brent');

figure(7)
plot(Date(2:end), Portfolio)
hold on;
title('Portfolio daily returns (03.01.2014-31.12.2015)');
```

```
xlabel('Date');
ylabel('Returns')

figure(8)
plot(Date(2:end), Brent_returns)
hold on;
title('Brent crude oil daily returns (03.01.2014-
31.12.2015)');
xlabel('Date');
ylabel('Returns')

figure(9)
plot(Date(2:end), WTI_returns)
hold on;
title('WTI crude oil daily returns (03.01.2014-31.12.2015)');
xlabel('Date');
ylabel('Returns')

figure(10)
plot(Date(2:end), SP500_returns)
hold on;
title('S&P 500 daily returns (03.01.2014-31.12.2015)');
xlabel('Date');
ylabel('Returns')
```

VaRandES.m

```
%% VaR and Expected Shrotfall estimation, using daily returns
from 03.01.2014-31.12.2015

%% 95% Historical VaR and 95% Expected Shortfall for Portfolio

clear
close all
clc


load prices_and_returns.mat

MV = 1000000; % Market value Portfolio

sortr = sort(Portfolio(1:260)); % Sort returns 03.01.14-
01.01.15
q = 0.05*numel(sortr); % Determine percentile for 95% VaR

VAR95_Port = sortr(q)*MV*(-1); % VaR (13th value of ascending
returns)
L_Port = sortr(q); % 13th worst return

ES95_Port = mean(sortr(1:q-1))*MV*(-1); % Expected Shortfall
95%
L_ES_Port = mean(sortr(1:q-1));

Vio_VaR = sum(Portfolio(261:520)<L_Port) % Violations 95%
historical VaR
Vio_ES = sum(Portfolio(261:520)<L_ES_Port) % Violations 95%
Expected Shortfall

%% 95% Historical VaR and 95% Expected Shortfall for S&P 500

sortsp500 = sort(SP500_returns(1:260));
VAR95_SP500 = sortsp500(q)*MV*(-1);
L_SP500 = sortsp500(q);

ES95_SP500 = mean(sortsp500(1:q-1))*MV*(-1);
L_ESSP500 = mean(sortsp500(1:q-1));

Vio_VaR_SP500 = sum(SP500_returns(261:520)<L_SP500)
Vio_ES_SP500 = sum(SP500_returns(261:520)<L_ESSP500)

%% 95% Historical VaR and 95% Expected Shortfall for Brent

sortbrent = sort(Brent_returns(1:260));
VAR95_Brent = sortbrent(q)*MV*(-1);
L_brent = sortbrent(q);
```

```
ES95_Brent = mean(sortbrent(1:q-1))*MV*(-1);
L_ESBrent = mean(sortbrent(1:q-1));

Vio_VaR_Brent = sum(Brent_returns(261:520)<L_brent)
Vio_ES_Brent = sum(Brent_returns(261:520)<L_ESBrent)

%% 95% Historical VaR and 95% Expected Shortfall for WTI

sortwti = sort(WTI_returns(1:260));
VAR95_WTI = sortwti(q)*MV*(-1);
L_WTI = sortwti(q);

ES95_WTI = mean(sortwti(1:q-1))*MV*(-1);
L_ESWTI = mean(sortwti(1:q-1));

Vio_VaR_WTI = sum(WTI_returns(261:520)<L_WTI)
Vio_ES_WTI = sum(WTI_returns(261:520)<L_ESWTI)


%% Plots

ESPORT = repmat(L_ES_Port, 1, 260);
VARPORT = repmat(L_Port, 1, 260);

ESBRENT = repmat(L_ESBrent, 1, 260);
VARBRENT = repmat(L_brent, 1, 260);

ESWTI = repmat(L_ESWTI, 1, 260);
VARWTI = repmat(L_WTI, 1, 260);

ESSP500 = repmat(L_ESSP500, 1, 260);
VARSP500 = repmat(L_SP500, 1, 260);

% 95% VaR and 95% Expected Shortfall Violations for Portfolio
daily returns
figure(1)
plot(Date(262:end), Portfolio(261:520), Date(262:end), ESPORT,
Date(262:end), VARPORT);
hold on;
title('VaR and Expected Shortfall Violations of Portfolio
Daily Returns (02.01.2015 - 31.12.2015)');
xlabel('Date');
ylabel('Returns');
legend('Portfolio','95% Expected Shortfall', '95% VaR');

% 95% VaR and 95% Expected Shortfall Violations for Brent
daily returns
figure(2)
plot(Date(262:end), Brent_returns(261:520), Date(262:end),
ESBRENT, Date(262:end), VARBRENT);
```

```
hold on;
title('VaR and Expected Shortfall Violations of Brent Daily
Returns (02.01.2015 - 31.12.2015)');
xlabel('Date');
ylabel('Returns');
legend('Brent','95% Expected Shortfall', '95% VaR');

% 95% VaR and 95% Expected Shortfall Violations for WTI daily
returns
figure(3)
plot(Date(262:end), WTI_returns(261:520), Date(262:end),
ESWTI, Date(262:end), VARWTI);
hold on;
title('VaR and Expected Shortfall Violations of WTI Daily
Returns (02.01.2015 - 31.12.2015)');
xlabel('Date');
ylabel('Returns');
legend('WTI','95% Expected Shortfall', '95% VaR');

% 95% VaR and 95% Expected Shortfall Violations for S&P 500
daily returns
figure(4)
plot(Date(262:end), SP500_returns(261:520), Date(262:end),
ESSP500, Date(262:end), VARSP500);
hold on;
title('VaR and Expected Shortfall Violations of S&P 500 Daily
Returns (02.01.2015 - 31.12.2015)');
xlabel('Date');
ylabel('Returns');
legend('S&P 500','95% Expected Shortfall', '95% VaR');
```