Value-at-Risk:

Risk assessment for the portfolio of oil and gas producers

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Abstract

During the last decade, Value-at-Risk (VaR) has become the most common tool to measure the exposure to short term financial risk for companies in the oil industry, in common with most other sectors. However, VaR has been criticized after the financial crisis for providing too optimistic risk estimates and allowing portfolio managers with inflated credit lines. The crisis hit companies extracting natural resources hard, and the oil and gas industry experienced a severe fall in prices, with Brent oil dropping from $140 to below $40 in just 6 months. During events like the financial crisis, companies need to rely on precise risk estimates to adjust their positions. We show that when asset prices are highly correlated, a typical feature in the oil and gas industry, companies are vulnerable to inaccurate estimates. The findings are also compared to a theoretical study using Monte Carlo simulations and data provided with a student's t distribution at different correlation levels.

Keywords: Value-at-Risk (VaR), correlation, diversification, subadditivity, coherent risk measure, oil and gas industry.

JEL-classification: C.1, C.5, G.1, G.3

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1 Introduction

Prices for oil and gas are generally known to be highly volatile (Pindyck, 2001; Hamilton, 2009), and the recent price changes have caused several concerns for consumers, corporations and countries alike as they experience high dependency on oil and gas for transportation, electricity generation and industrial production. To better understand these price fluctuations, several authors including Cuaresma et al. (2009), Hamilton (2009), Alquist and Kilian (2010) and He et al. (2012), have studied forecasting models for the price of crude oil, with varying success. Recent developments have confirmed the difficulties of price forecasting, as the 2008 financial crisis reduced demand and saw prices drop from $147 per barrel to below $40 per barrel within months. The price of oil has since increased together with the increase in demand from emerging markets like China and India. On the supply side, oil production has been stable at around 80 million barrels per day since 2004 (BP Energy Review, 2012). And, although demand is steadily increasing and production is stable, supply disruptions from geopolitical events like the 2011 Arab-spring and extreme events like the 2011 Fukushima nuclear disaster in Japan, add supply and demand shocks, causing volatile prices. The price risk for companies in the oil and gas industry is further emphasized by the fact that most firms produce a portfolio of oil related products for which prices are all highly correlated (Girma and Paulson, 1999; Asche et al., 2003; Asche, Osmundsen and Sandsmark, 2006; Panagiotides and Ruthledge, 2007; Brown and Yucel, 2009), making diversification difficult.

A common method for companies to control market risk is Value-at-Risk (VaR), which allow companies to assess the downside risk of a portfolio of assets and adjust their positions with regards to a risk threshold. The method originates from the banking and financial industry where it was introduced in the Basel I Accord in 1992 as the standard market risk estimate. VaR is still the recommended method to estimate risk in the Basel III Accords (Basel, 2011), and has over the last twenty years been adopted by companies in a range of industries evaluating their portfolio risk (Alexander, 2008). Large industrial companies use VaR to assess market, credit and other risks of their portfolio and its individual positions for financial risk management, allowing them to optimize their portfolio. In addition, VaR is often used for regulatory and reporting purposes.

Oil companies, and particularly the companies with listed stocks, have to abide by similar requirements as other types of companies handling their financial risk. Simple performance indicators are often used, such as RoACE (Osmundsen et al., 2006), and similarly, Value-at-Risk (VaR) is commonly used to handle risk. However, there are significant differences when comparing a portfolio in the financial industry, which is diversified and multi-asset, with the oil and gas industry which is single-asset and combines highly correlated assets. This paper provides an evaluation of VaR as a risk estimate for a portfolio of petroleum assets with focus on the importance of the correlation between the assets.

VaR has been criticized during crisis for underestimating risk and providing too optimistic estimates (Taleb, 2008; Danielsson, 2008; FSA, 2009). There is a tendency that correlation levels are higher during crises (Ang and Bekaert, 2002; Longin and Solnik, 2001), and this is a potential cause for some of the problems with VaR. With its highly correlated assets, the oil and gas industry provides a stress test for VaR under such circumstances in addition to the direct evaluation of VaR that is of most relevance for the industry. Specifically, we test for a weakness discussed by Artzner et al. (1999), who show that VaR is vulnerable to produce incorrect/biased estimates as it cannot guarantee the diversification benefits seen in portfolio theory (Markowitz, 1952; Samuelson, 1969). While this weakness is generally known, it has only been studied with respect to volatility using financial data series (Garcia et al., 2007; Ibragimov and Walden, 2007; Ibragimov, 2009; Ibragimov et al., 2011; Danielsson et al., 2012). These studies conclude that VaR's problem only occurs if the underlying risk factors experience extreme volatility. However, the poorly diversified and highly correlated portfolio in the oil and gas industry demands further studies to investigate the impact of correlation to VaR's vulnerability.

The effect of correlation has not received much attention in previous papers, perhaps as a consequence of the diversified financial industry. In this paper, we consider a single-asset oil and gas portfolio where the underlying risk factors are highly correlated. In addition we perform a Monte Carlo simulation with varying degrees of correlation and volatility, to control for both when evaluating VaR's vulnerability to violate subadditivity.

2 Background

Exxon Mobile and Royal Dutch Shell are the two largest companies in the World ranked by revenue, and 10 of the 20 greatest companies by revenue have oil and gas as its primary industry (Financial Times, 2012). Although it's market share in energy consumption has declined for more than a decade, oil still remains the world's leading energy source with a market share of 33.1%, and the biggest and most important of the global industries. In 2011, oil consumption was 88 million b/d, with an average price of $111.26 per barrel, resulting in revenue of more than $3.5 trillion during the year (BP Energy Review, 2012). The industry itself is divided in an upstream sector consisting of activities such as exploration, drilling and refinery of oil and gas, and a downstream sector consisting of marketing and sales activities. In addition, the industry strongly influences the large oil services sector. These companies depend on the activities of oil companies and their investments in new projects. Both the oil industry and the oil service industry are highly dependent on the price of their common end products. Furthermore, Osmundsen et al. (2006) show that oil industry investments tend to be pro-cyclical following the oil price, and productivity in exploration can also vary over the cycle (Osmundsen et al., 2010; Guttormsen and Roll, 2011; Osmundsen et al., 2012). Although investments are pro-cyclical, Gronwald (2012) shows that it is difficult to base extraction paths and transmission to alternative technology on the oil price, as price signals are not reliable. Still, with volatile oil prices, oil related industries experience common boom and bust cycles.

Political risk is also an element in oil activity, as witnessed during the Arab embargo in 1973 and the Iranian revolution in 1979 (Hamilton, 1983). However, it is also an ongoing concern as exemplified in

2011 by two short term changes in demand and supply due to political events, both resulting in an increased price. First, the Arab Spring, with many oil exporting countries upset by social unrest and turmoil, provided a supply shock to the oil industry. Secondly, the earthquakes in Japan damaged several nuclear power stations and removed an important energy source, creating extra demand for alternatives like oil and gas.

Recent developments in China and the United States have also affected the traditional trade balances. Through its extreme growth the last two decades, China's demand for oil and gas has made the country more dependent on delivery of oil and gas from the Middle East and Russia. On the other side, the United States has become increasingly independent on import of gas, as the discovery and utilization of shale gas has made the country the biggest producer of gas (BP Energy Review, 2012). With the drilling for unconventional shale oil in the United States, the country may also become independent of oil import within a few decades. The shifts in demand and supply seen in superpowers like China and the US, has major impact on the trade balance between nations[2].

The price of oil and gas affect private households and consumption patterns, as well as a range of other industries like transportation and energy directly (Aggarwal, Akhigbe and Mohanty, 2012). With increasing prices of oil and gas, consumers, both domestic and industrial, have to prioritize the consumption of oil and gas over other commodities. Studies have shown that price elasticity for oil and gas are low (Hamilton, 2009; Killian and Murphy, 2011), indicating that consumers will continue to demand oil and gas with only minor adjustment to its price. This is especially true for the short-run price elasticity, as consumers have less opportunity to substitute in the short run. Therefore, an increase in price may reduce consumption of other goods. In addition, in a study of oil price impact on 38 industries Scholtens and Yurtseyer (2012) find that while an increase in oil price affect oil extracting and exploiting industries like mining and drilling positively, the increase have no significant effect on other industries. Opposite, a decrease in oil price have positive effect on more than half of

[2] Hamilton (2003) discusses the relationship between oil price shocks and macroeconomy.

the industries studied, especially for companies with oil and gas as an input, like airline, transport and forestry.

Historically, oil and natural gas have been highly correlated, and several papers conclude that the markets are integrated (Herbert and Serletis, 1999; Asche, Osmundsen and Sandsmark, 2006; Panagiotides and Ruthledge, 2007; Brown and Yucel, 2009; Neuman, 2009). An integrated market is a result of substitution between oil and gas in some uses. End buyers can choose between energy sources according to price efficiency. If natural gas becomes cheaper, there is an economic incentive for the buyer to switch from oil to natural gas, although there may be investment and time cost in committing to a substitution. Similarly, oil companies will respond to changes in demand for different products by adjusting their product mix (Girma and Paulson, 1999; Asche, Gjølberg and Völker, 2003). This is what creates the high correlation in risk for oil assets, making it crucial to apply precise risk metrics when considering oil and gas relevant activities and investments.

3 Value-at-Risk

Value-at-Risk (VaR) is a widely used measurement in order to control the underlying risk of a portfolio (Jorion, 2006). It defines the worst case scenario within a certain confidence level over a specified time horizon. This introduces the two parameters of a VaR: its confidence level and time horizon. The confidence level specifies at what rate the estimate should not be underrating the actual change in portfolio value. E.g. a confidence level of 95% means that the actual loss will not be greater than the estimated VaR in 95% of the time. Time horizon is often referred to as the holding period, the time which the assets in the portfolio are constant and thus the portfolio is unchanged. A regular time horizon is 1 day.

We use the definition for conditional VaR in Chavez-Demoulin et al. (2012), where X is a random variable, denoting the unknown future realization of a position, then

$$VaR_{\alpha}\left(X_{h,t}\right) = F_X^{-1}(\alpha) = \inf\{x \in \mathbb{R} : F_{X_{h,t|H_t}}(x) \geq 1 - \alpha\}.$$

F_X^{-1} is the inverse function of the unknown distribution F_X, which is conditioned on the history H_t at time t. α is the desired quantile for VaR. In practice, VaR is often simplified by asking how much it is possible to lose within a certain time period at a certain significance level, although this ignores several critical aspects as reviewed in McNeil et al. (2005). E.g.: For the next day (period) 1% (alpha or significance level) of losses will be bigger than 500k (VaR). Or: I am 99% (confidence level or 1 - alpha) certain that my losses will not be bigger than 500k (VaR) the next day (period).

There are 3 commonly used approaches to estimating VaR: the historical simulation, the variance-covariance method and the Monte Carlo simulation (Jorion, 2006). In general the method must consider the tail size of the underlying risk factors' distributions and find an acceptable balance between adjusting to recent data compared to a longer trend. The analytical approach with a variance-covariance method is often implemented assuming a normal distribution (RiskMetrics, 1997). Several refinements have been made, with the introduction of GARCH and EWMA, which both allow for a dynamic adjustment to time. In addition there have been several approaches in order to loosen the normality assumption, for instance in Hull and White (1998) by implementing a student's t distribution. The Monte Carlo simulation allows for even more complexity, as the method can include non-linearity and distributional characteristics such as fat tails. However, the complexity comes at a price, and a lot of research has been focused on making Monte Carlo simulations more efficient for VaR estimation (Glasserman et al., 2002; Broda, 2011).

While Monte Carlo simulation and the variance-covariance method are dependent on analyzing the underlying distributions in order to find good approximations for its necessary parameters, historical simulation uses the empirical distribution directly by using the historical scenarios as possible scenarios for the next holding period. This is one of the main advantages of historical simulation as it keeps the computational part simple. On the other hand this is also its main disadvantage as the estimate relies on history to repeat itself without any adjustments. Pritsker (2006) studies some of the pitfalls and show that VaR depends on the appropriate sample size as their results indicate that

VaR responds slowly to changes in conditional volatility. Still it is the preferred method because it is easy to implement and does not require any assumption on the underlying distribution (Perignon and Smith, 2010).

Artzner et al. (1999) defines a coherent risk measure as a risk measure which satisfies four conditions. It needs to be characterized by monotonicity, subadditivity, homogeneity and translation invariance. The four characteristics guarantee properties that are necessary for an adequate risk measure. Monotonicity assures that if the values of estimate A is under all scenarios higher compared with B, then this should be reflected in the risk estimate. Homogeneity provides a scaling feature, meaning that if you double your position you also double your risk. Translation invariance presents an insurance opportunity. If you have a combined portfolio of a risky asset A and a risk free asset r, the risk of the portfolio is reduced by the risk free amount compared to the risk incurred by A alone.

Subadditivity is a natural requirement in order to achieve the diversification bonus which is fundamental to portfolio theory (Markowitz, 1959) and a common part of risk assessments. The opposite would mean that a portfolio manager would reduce the risk of the portfolio by splitting the portfolio into its underlying risk factors as a result of a negative diversification bonus. Although diversification is intuitive, Artzner et al. (1999) proves that VaR violates subadditivity, and therefore cannot guarantee the diversification bonus. The paper concludes that VaR has severe aggregation problems as the sum of even independent risks does not behave nicely, and may prohibit diversification.

The lack of subadditivity gives concerns to the regulator, as the portfolio manager could create additional sub portfolios in order to reduce the required amount of capital reserve, but without the guarantee of reduced risk. In addition, a sound risk estimate is necessary for the investor’s decision and an incorrect estimate might stop the investor from taking necessary steps to reduce risk.

In this paper we want to study the likelihood of violating subadditivity for a portfolio of highly correlated assets such as an oil and gas portfolio. According to portfolio theory, diversification should ensure that a portfolio of two assets have lower risk, compared to the sum of the two individual asset's risk. If this is not true, the portfolio is experiencing a subadditivity violation. For VaR we define this by comparing an asset's individual VaR, called the position VaR, to its contribution to a portfolio, the contribution VaR. The contribution should always be smaller or equal to its position VaR; otherwise we would reduce risk by keeping the asset outside of the portfolio[3].

VaR estimates calculated with historical simulation are prone to subadditivity violations due to tail coarseness which occurs when using a relatively short historical period (Danielsson et al., 2012). The historical simulation does not assume any distribution and instead uses past returns to predict future returns directly. The estimate is therefore very sensitive to the historical period, as one need to consider a sensible balance between adjusting to the long trend with a lower variation, and adjusting to the short trend with a higher variation. It is recommended in Basel II to use 1 000 days as the historical period to avoid temporary variations, but shorter periods may give better results during periods with high volatility, as it will adjust and respond quicker to changes in the market. When estimating a 99% VaR with a historical period of 250 days, representing a year of trading, VaR will be decided by the 2nd and 3rd worst scenario. Consequently the estimate is vulnerable to big variations as a result of the tail coarseness, causing possible subadditivity violations.

4 Monte Carlo simulation

By using Monte Carlo simulations it is possible to compare the probability of experiencing subadditivity violations when using a controlled data set. In order to test the proposition, we simulate a portfolio of two assets with returns X_1 and X_2 which are Student's t distributed with v degrees of freedom. The portfolio invests equally in each asset by setting the value of each asset to 1 on each trading day. The test is run for 1 000 000 simulations, and we report the violation ratio as a

[3] McNeil, Frey and Embrechts (2005) use the term superadditive VaR when subadditivity is violated.

percentage of subadditivity violations. Sample size is tested at three levels with 250, 500 and 1 000 historical scenarios and degree of freedom is tested at $v = \{2, 3, 4, 20, 50\}$. VaR is estimated for both 99% and 95% VaR.

The simulation tries both independent assets (ρ = 0.0) and correlated assets (ρ = 0.5 and ρ = 0.75). The correlation is achieved by using the Cholesky decomposition of the correlation matrix ρ_X between two independent draws from a Student's t distribution ξ_1 and ξ_2.

$$X_1 = \xi_1$$

$$X_2 = \rho_X \xi_1 + \sqrt{(1 - \rho_X{}^2)}\xi_2$$

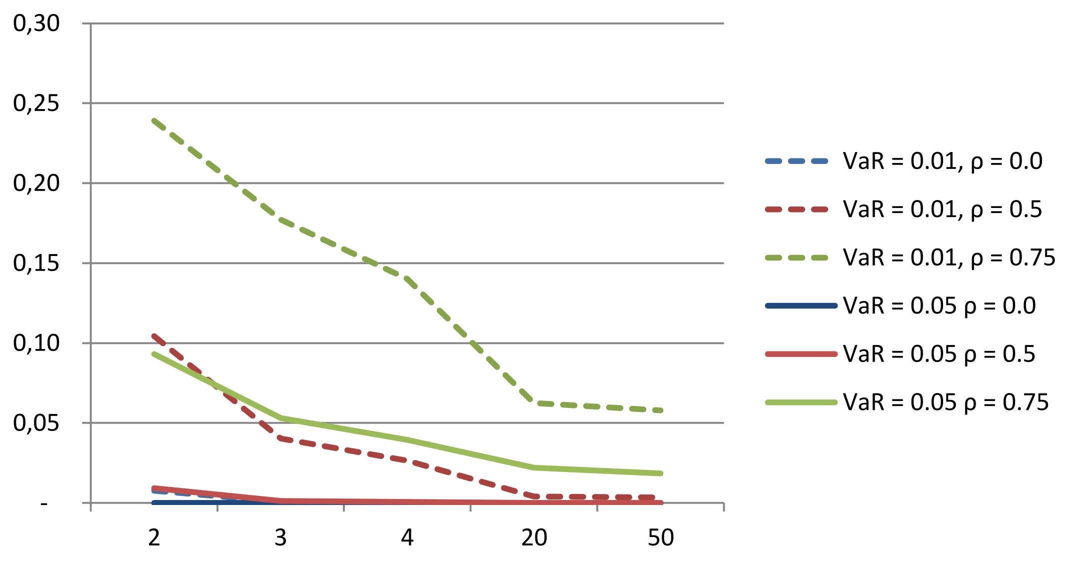

Figure 1 to

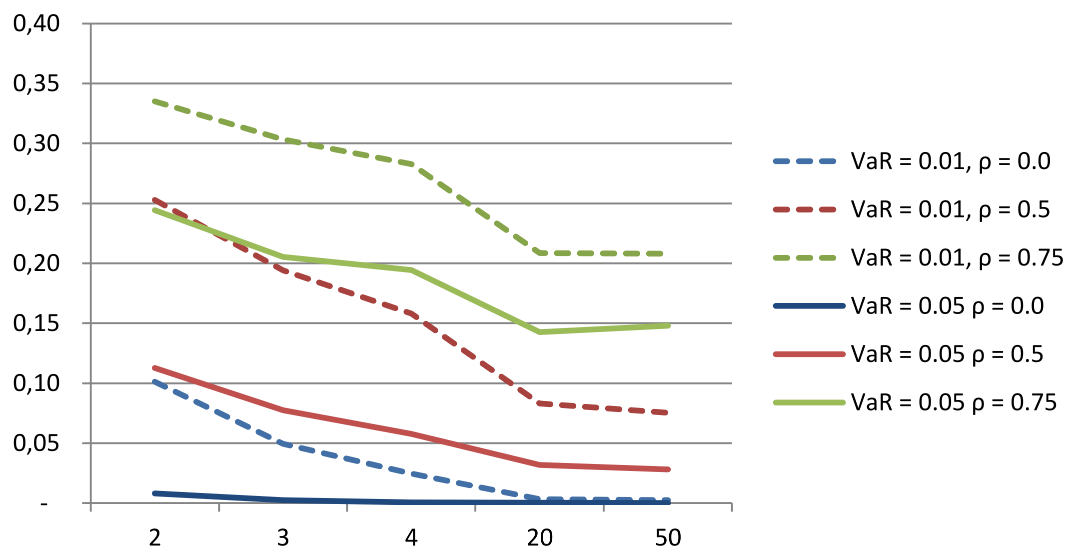

Figure 3 displays the results from the simulation test using data from a Student's t distribution, and it confirms that both tail coarseness and fat tails increase the vulnerability for subadditivity violation. First, independent of sample size, all figures show a linear dependence between tail size as measured by degree of freedom and the probability of subadditivity violations. Second, the figures indicate that a smaller sample size affects the possibility for violations, as using a sample size of only 250 has substantially higher violation ratio compared to a sample size of 1 000 observations. This confirms the tail coarseness problem and fat tail dependency when estimating VaR by historical simulation as observed by Danielsson et al. (2012).

However, when we compare the extreme level of correlation (ρ = 0.75), we find that the violations are high regardless of sample size and tail size. With a sample size of 1 000 observations, our results indicate that the violation ratio will converge to 5% when moving towards a normal distribution, if the correlation is extreme. By reducing the correlation to 0.5, convergence move towards 0% violation ratio, underlying the importance of correlation when considering the validity of VaR as a risk estimate. With 1 000 000 simulations, the test is statistically significant at every level, meaning that none of the findings can be attributed to randomness.

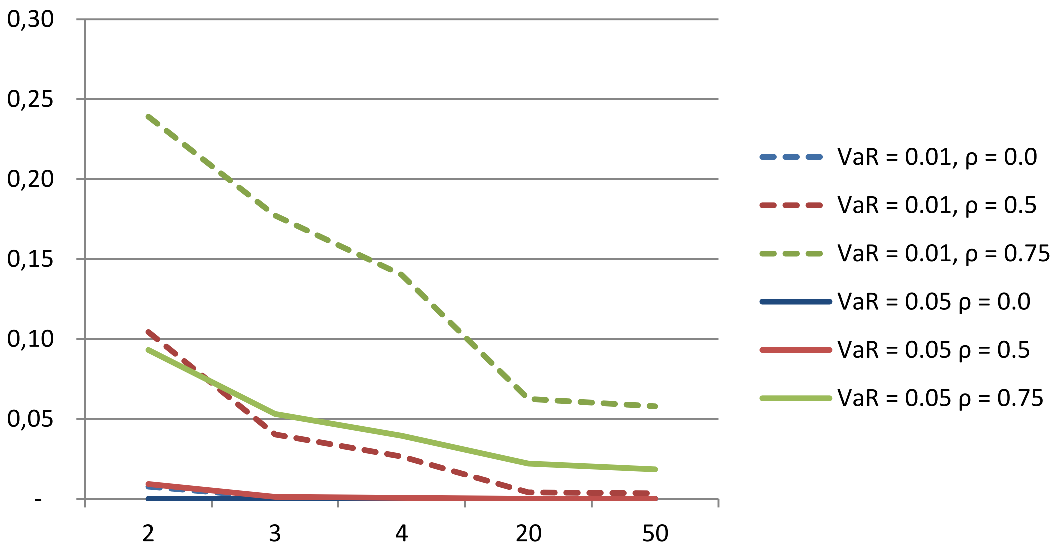

Figure 1 - Violation ratio from a Student's t with HS estimation of VaR. Sample size N = 1 000. Number of simulations = 1 000 000.

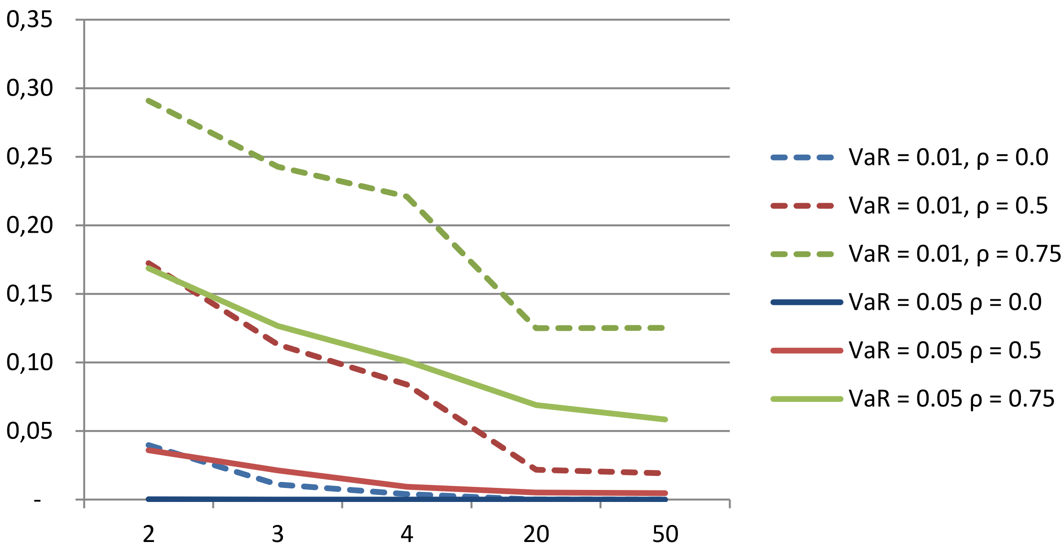

Figure 2 - Violation ratio from a Student's t with HS estimation of VaR. Sample size N = 500. Number of simulations = 1 000 000.

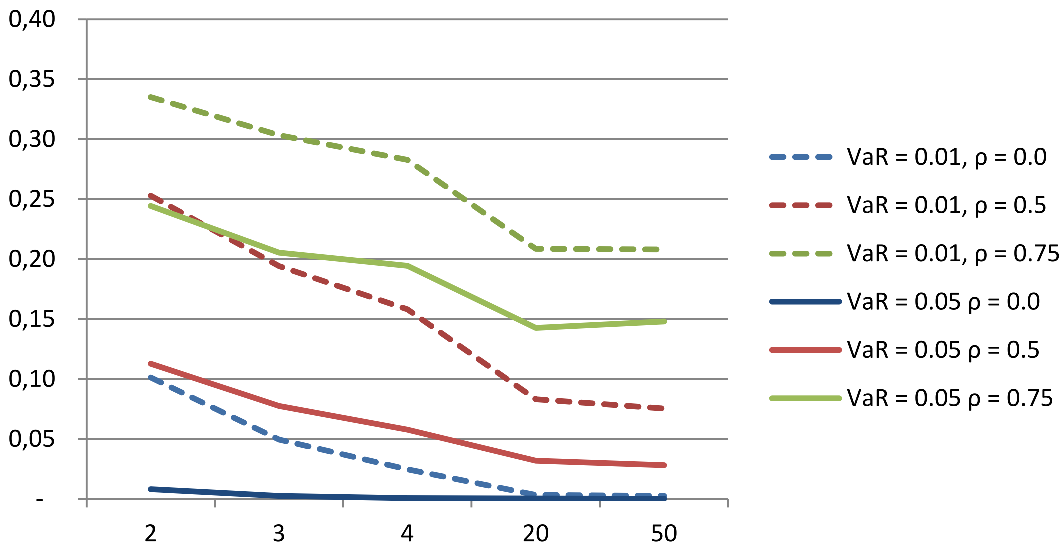

Figure 3 - Violation ratio from a Student's t with HS estimation of VaR. Sample size N = 250. Number of simulations = 1 000 000.

5 Oil and gas data

The study investigates the oil market portfolio with price data from October 1st 2002 to June 7th 2012 providing 2 455 observations. 10 products are included: Propane, Jet/Kerosene, HSFO 3.5%, No. 6 1%/LSFO, Naphtha, ULSD 10ppm, Henry Hub natural gas, Zeebrugge natural gas, NBP natural gas and Brent oil. Prices for oil products are quoted in US$:F/T and prices for gas are quoted in US$:F/MMBTU.

Table I summarizes the distributional characteristics of the daily log-return. The products experience a relatively high standard deviation, and all experience a positive excess kurtosis, indicating a high peak around mean and fat tails. As seen in part 4, assets with a high degree of freedom have a higher propensity to violate subadditivity, indicating that an oil portfolio may experience a high violation ratio.

The products used for the different oil portfolios experience high correlation as presented in Table II. The least correlated products are HSFO 3.5% and Propane (0.898), while ULSD 10ppm and Jet/Kerosene are the most correlated products (0.998). Only prices from Henry Hub Natural gas experience no correlation when considering data for the entire period. However,

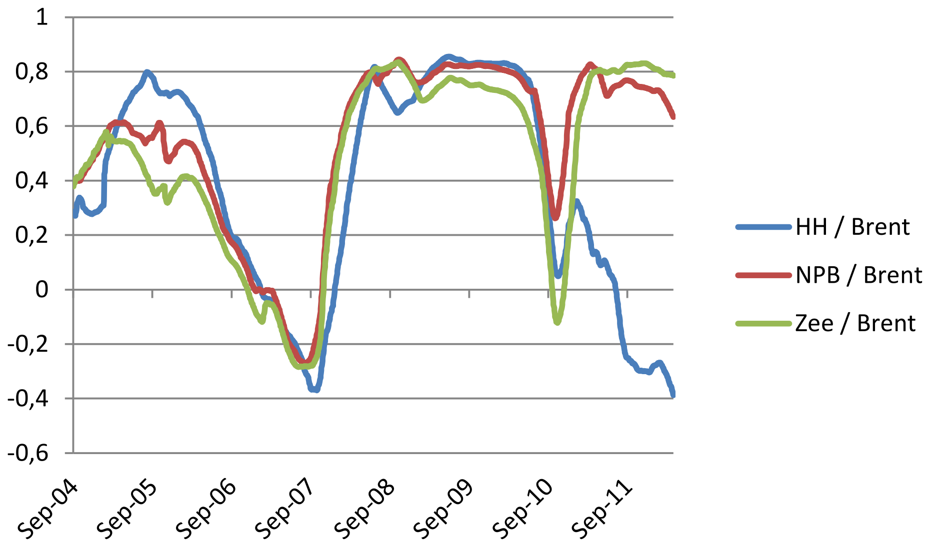

Figure 4 use a rolling period of correlation using a sample period of 500 days and show that natural gas traded at Henry Hub experienced high correlation for most of the period, except for two periods with negative correlation; the first period occurring before and at the beginning of the financial crisis, while the second period is taking place now, as a result of the increased supply of gas seen in the United States. Interestingly, natural gas traded at NBP and Zeebrugge experience the same shift in correlation before the financial crisis, but recovered quickly from the second shift seen for Henry Hub. This indicates a regional change in correlation between oil and gas. Still, in general, correlation is high between oil and gas products.

Table I - Distributional Characteristics for oil and gas portfolio assets, N = 2445

	Propane	Jet/ Kerosene	HSFO 3.5%	No.6 1%/LSFO	Naphtha	ULSD 10ppm	Henry Hub N. gas	NBP N. gas	Zee-brugge N. gas	Brent
Mean	0.03 %	0.05 %	0.05 %	0.05 %	0.05 %	0.05 %	-0.02 %	-0.06 %	0.06 %	0.05 %
Standard deviation	1.77 %	1.96 %	2.46 %	2.20 %	2.44 %	2.16 %	4.20 %	9.58 %	6.50 %	2.28 %
Skewness	0.37	0.09	0.39	0.10	-0.10	-0.35	0.84	-1.52	0.32	-0.22
Excess kurtosis	9.46	2.01	6.84	4.73	7.19	5.06	37.25	53.49	21.62	2.92

The diversification bonus appears as a result of the correlation between the underlying risk factors of a portfolio. By combining assets which are not perfectly correlated, the combined risk in a portfolio is lower than the sum of the individual risk. This is intuitive, since the probability of every asset to experience a negative shock is considerably smaller than the probability of any individual asset to experience this shock. However, the size of the diversification bonus is more difficult to estimate when considering extreme downside risk, since it is vulnerable to clustering in the tails as a result of the increased positive correlation often experienced in a regime shift, e.g. when a normal market shifts to a negative market (Ang and Bekaert, 2002; Longin and Solnik, 2001).

Figure 5 shows concurrent extreme events for the oil market portfolio. During the beginning of the financial crisis the oil market assets experienced several concurrent extreme events. The risk of simultaneous extreme events is high for the oil portfolio, with 33% (3 out of 9) of the assets experiencing a concurrent extreme event in 10.66% of the time. This is of course related to the high correlation in general, but also indicates higher tail correlation.

Table II - Correlation between underlying risk factors in oil portfolio.

Pearson Correlation Coefficients, N = 2445										
	Propane	Jet/ Kerosene	HSFO 3.5%	No.6 1%/LSFO	Naphtha	ULSD 10ppm	Henry Hub N. gas	NBP N. gas	Zee-brugge N. gas	Brent
Propane	1									
Jet/Kerosene	0.910	1								
HSFO 3.5%	0.898	0.927	1							
No.6 1%/LSFO	0.902	0.94	0.995	1						
Naphtha	0.947	0.967	0.958	0.958	1					
ULSD 10ppm	0.910	0.998	0.925	0.939	0.964	1				
Henry Hub Natural gas	0.011	0.091	-0.200	-0.157	-0.022	0.086	1			
NPB Natural gas	0.660	0.679	0.531	0.558	0.594	0.681	0.411	1		
Zeebrugge Natural gas	0.658	0.709	0.571	0.601	0.606	0.710	0.317	0.866	1	

Brent	0.892	0.975	0.948	0.956	0.956	0.973	0.002	0.637	0.686	1

Table III - Correlation summary for oil portfolio.

Pearson Correlation Coefficients Summary					
	Min	1st quartile	Median	3rd quartile	Max
Correlation	-0.200	0.571	0.710	0.947	0.998

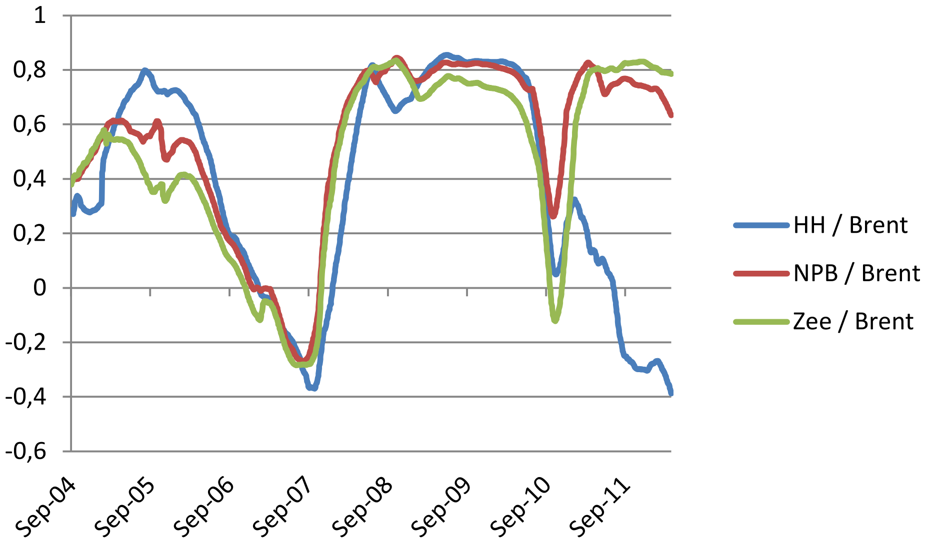

Figure 4 - 500 days running correlation between gas products and Brent oil (2004 – 2012)

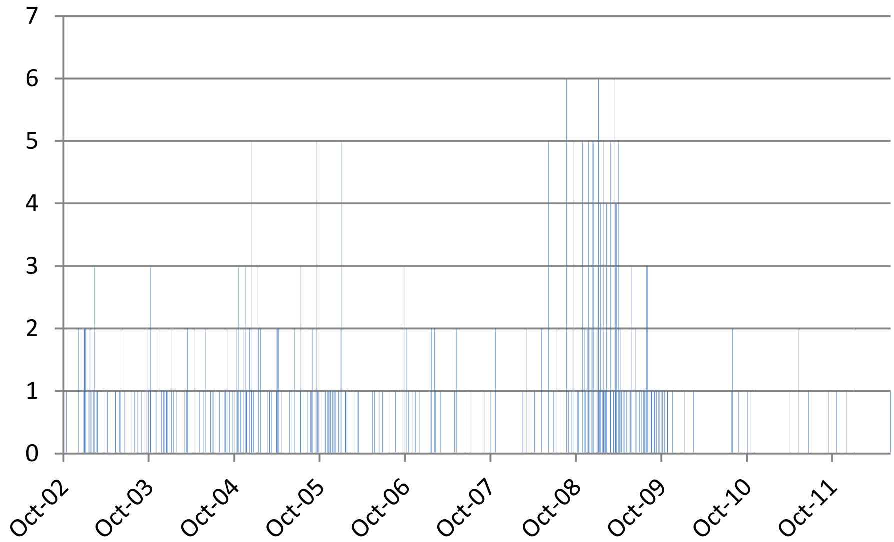

Figure 5 - Concurrent extreme events (2002 – 2012)
Extreme event defined as the 2% worst cases.

In addition, the oil portfolio experiences a shift in volatility as seen in

Figure 6. Until the peak in oil prices during the summer of 2008, the price had a relatively stable growth. The volatility experienced in the same period only small adjustments, until the rise in price took off in the fall of 2007. With the extreme fall in prices seen during the fall of 2008, volatility soared even more, creating high uncertainty about risk estimates. The increased volatility results in fatter tails for the implied distribution, increasing the risk for subadditivity violations as the degree of freedom is reduced.

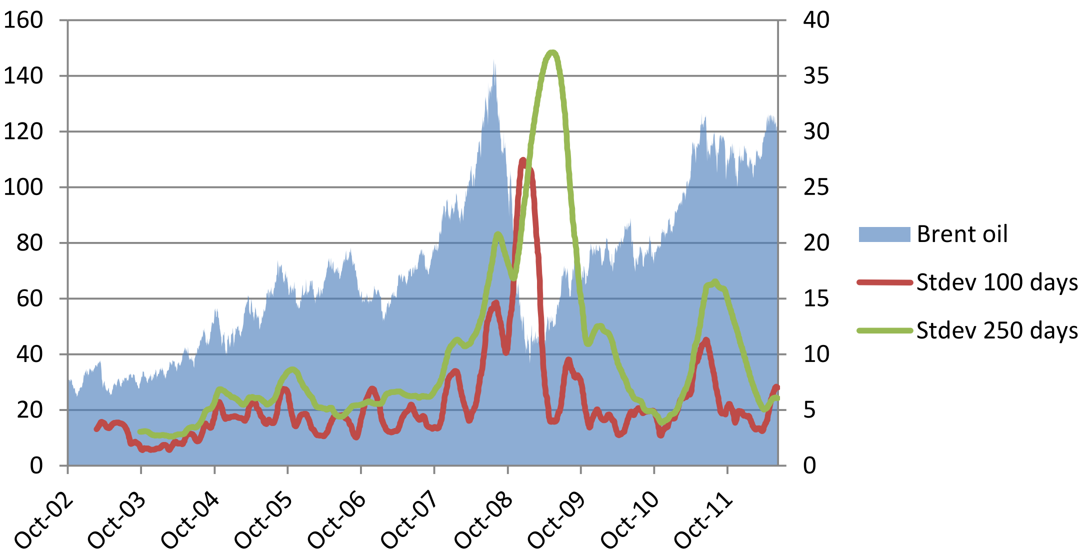

Figure 6 -Volatility for oil portfolio, calculated with both 100 and 250 days standard deviation. Brent oil price (USD/BBL) on first axis (2002 – 2012).

6 Empirical analysis of oil and gas portfolio

VaR is estimated on the petroleum assets using historical simulation and with varying running sample sizes of 250, 500 and 1000 days. The estimates are carried out on both 95% and 99% VaR level using the daily log returns of the assets. Every asset in a portfolio was given equal weight for each estimate and for a complete analysis all portfolios and subportfolios are tested, e.g. combining 3 assets gives 7 possible combinations (ABC = AB + C = AC + B = BC + A = A + B + C, AB = A + B, AC = A + C, BC = B + C). With 9 assets we test more than 15 000 possible portfolios.

Figure 7 and Figure 8 summarizes the findings and show how the oil and gas portfolios encounter violations during the entire period. The figures report the violation probability as the ratio of portfolios experiencing violations over the entire sample of portfolios. In both cases, a smaller sample period (N = 250), provides a higher violation ratio. This is in concordance with the findings in Danielsson et al. (2012) for financial data, and can be attributed to tail coarseness. It is also for the smaller sample we find the biggest increase in violation ratio during the financial crisis, and especially during the extreme events in fall 2008, when the violation ratio peaks at almost 20% at 95% VaR level. At the 99% VaR level the extremes are even more profound, and during the same period the violation ratio peaks just below 30%. Moreover, the uncertainty in the market have for the last 2 years produced high violation ratio at this level when using a small sample size.

For the larger sample sizes the deviations are smaller, although the medium sample size (N = 500) experiences peaks at the same time as the smallest sample size, the peaks are short lived. For the largest sample size (N = 1000), there are only small changes.

On average, VaR at 95% level violates subadditivity for ca. 8% of the portfolios, as seen in Figure 9. The results are convincing and indicate that violations are likely for a portfolio consisting of highly correlated risk factors. For both VaR-levels the violation ratio never drops to zero, meaning that some combination of assets in our test always produced a violation for the entire period. At 99% VaR level the violation ratio are more volatile. This is expected since we are considering the extreme tail end of the distribution. Moreover, our results indicate that VaR at the extreme levels are more vulnerable to subadditivity violations during extreme changes in the market, as seen in fall 2008.

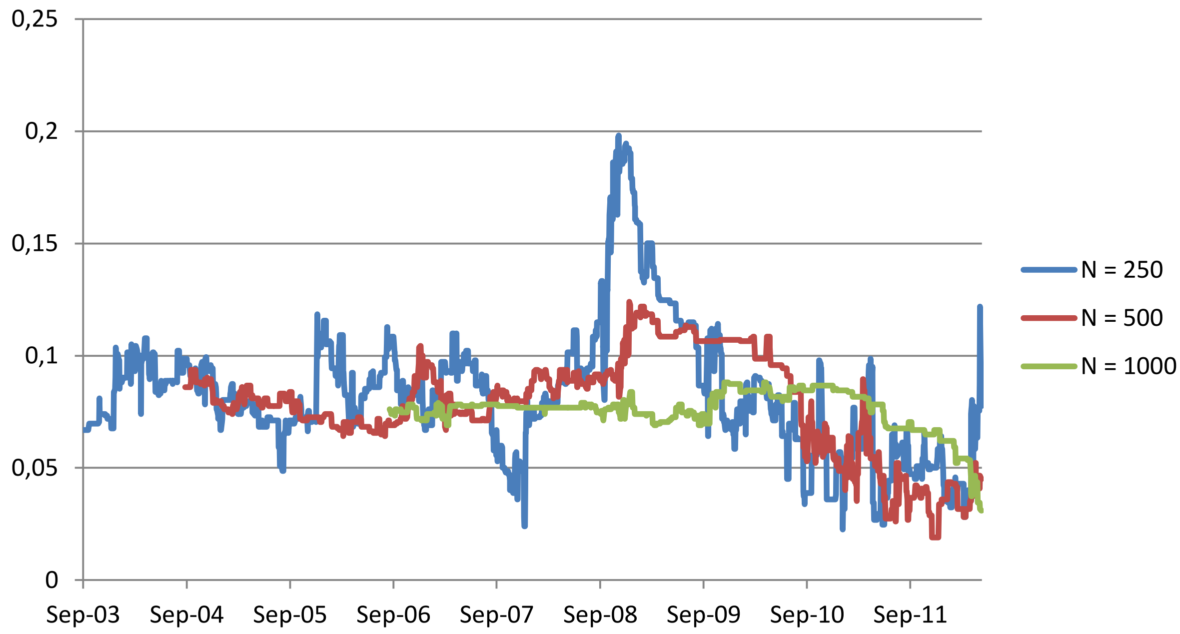

Figure 7 - Violation ratio for oil market portfolios (2003 – 2012). VaR = 0.05

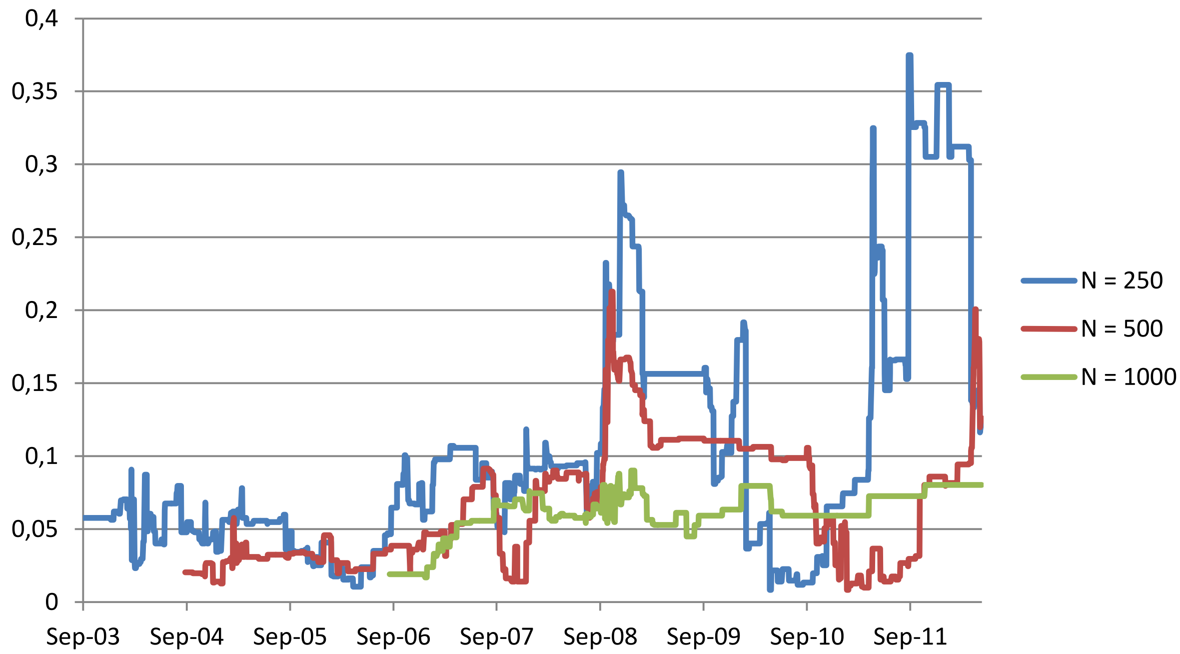

Figure 8 - Violation ratio for oil market portfolios (2003 – 2012). VaR = 0.01

For both VaR-levels, there seems to be a shift in the violation ratio in the fall of 2008, going from a around 5% to around 20% violation ratio on average for 99% VaR, and from 8% to 12% on average for 95% VaR. This coincides with the shift seen in standard deviation at the same time, both indicating a shift in volatility, and indicates that the effect of the financial crisis on both correlation and volatility increases the risk of overestimating risk when using VaR. For the last two years the 99% VaR have experienced significantly more violations compared to the 95% VaR, indicating that the extreme tail estimates are more prone to uncertainty in the market. According to Table III, the correlation level in the oil market has a median of 0.7, and comparing the violation ratio with the simulated results in part 4 using the extreme correlation at 0.75, the results indicate a change in the degree of freedom to extreme levels between 2 and 4 during the financial crisis.

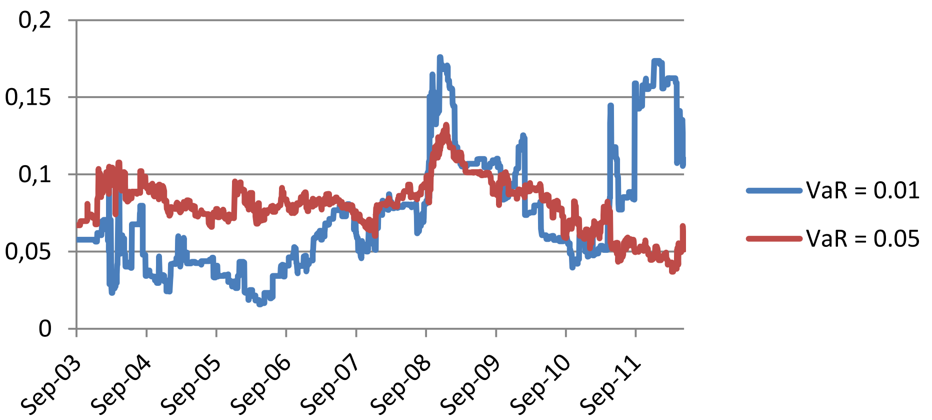

Figure 9 - Average violation ratio for oil market portfolios (2003 – 2012)

7 Conclusion

VaR has become a standard tool to estimate short-term market risk in most industries. In the oil and gas industry, a structure with highly correlated asset prices present particular challenges. In this paper we discuss the probability of violating subadditivity for such portfolios. The oil and gas industry is characterized by assets with high volatility and high correlation, and we show that both features increase the violation probability when using VaR. We first show the relationship with a Monte Carlo simulation, using a set of correlation and student's t distributed data over a range of tail sizes, and find that even normally distributed data may experience violations if the correlation between the underlying risk factors are extreme (ρ = 0.75). We then confirm the simulation results for an empirical analysis of oil and gas data from 2002 to 2012, and find that the oil market is particularly prone to violations, as VaR on average violates subadditivity for 10% of the portfolios. This can be partially attributed to a very high correlation (median $\rho = 0.7$) and a high volatility. On average, violation ratio is smaller when using a larger sample ($N = 1000$), but we still get more than 5% violations at both 95% and 99% VaR level.

For portfolio managers it may be difficult to identify a subadditivity violation, as a portfolio can consist of hundreds of assets and changing on a daily basis. Controlling for none-coherency is therefore a task which may be neglected. However, as seen by both the Monte Carlo simulated estimates and in the empirical analysis of the oil market, the violation ratio for correlated assets can be substantial. For a portfolio manager in the oil and gas industry this may result in inaccurate risk estimates. Furthermore, as indicated by both the increase in violation ratio during the financial crisis, and the clustering of extreme events in this period, a regime shift going from normal to recession will increase the probability of overestimating risk when using VaR with historical simulation. This is a period where risk estimates are at its most important, and the lack of coherency may prove a severe failure for portfolio managers in the oil and gas industry trying to adjust their positions according to an acceptable risk threshold.

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