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Risk and Sensitivity Analysis of U.S. Oil and Gas Company Stock Return - A Quantile Regression Approach

Empirisk Risiko-Analyse av Aksjeavkastninger i Olje- og Gassbransjen i Perioden 2000-2015

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This study marks the completion of my Master of Science in Business at the Norwegian University of Life Science (NMBU).

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II. Summary

The purpose of this study is to investigate and develop a risk model for oil and gas stocks. I focus on the US gas and oil stock return formation by studying how fundamental factors influence different quantiles of the return distribution. In this paper, I analyze the return distribution of 49 oil and gas stocks of NYSE, obtained from the five-factor model, using Quantile Regression method. Quantile regression offers an efficient alternative to ordinary least squares estimation. The model is more robust to outliers than ordinary least squares (OLS) and is semi-parametric, as it avoids assumptions about the parametric distribution of the error process. In order to obtain the Standard errors and confidence limits for the quantile regression coefficient estimates it us used bootstrapped standard error estimation.

Several interesting results emerge from this study analysis. First, this study not only shows that the factor models does not necessarily follow a linear relationship, but also shows that the traditional OLS becomes less effective when it comes to analyzing the extremes within a distribution, which is often a key interest for investors and risk managers. Generally speaking, the findings show that the median regression line is almost identical with the OLS regression line. However, as we move away from the median quantile toward estimates in the tails of the return distribution the coefficients changes notably. To further prove the difference between the coefficients across the quantiles, I use the Wald-test. The evidence suggests that the validity of the risk from different risk factors occurs in the upper and lower shoulders and tails, showing a significant difference from those derived from the median quantile.

Findings suggest that the sensitivity to important factors exhibit variation across the distribution. Investors in the oil and gas market will have substantially differences in the level of risk associated with their long/short position. For an investor with long position in an oil and gas stock, will be substantially greater risk associated with the position, in the comparison with an investor with a short position. Finally, as a demonstration of the practical use of the quantile regression method, I will propose a parametric one-week-ahead value at risk model (VaR) by using the 5th or 95th regression quantile. The model is easy to implement and it will let an investor with an idea about the futures price change of the risk factors be able to estimating/predicting expected shortfall.

Keywords: Factor models; Quantile regression; US oil and gas industry

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1. Introduction

The question regarding risk factors influence on stock price and stock return has always been a part of modern finance, where subject has been examined throughout the years with different result (See Ramos & Veiga, 2011 and Mohanty & Nandha, 2011) and Tjaaland, et al. (2016). The oil and gas industry is far the largest industry in the US. Together, they supply more than 60 percent of US energy and the production of both oil and natural gas were increasing rapidly as of early 2015. US natural gas and crude oil productions achieved new record highs for each year from 2011 through 2014, but have now faced a new reality when the global oil prices have been in free fall. Morgan Stanley analysts calculate that only nine large projects, out of more than 230 projects, are realistic to be profitable and $400bn in expected investment has been cancelled or delayed across the industry due to low prices (Ft.com, 2016). This investigation should be of interest to investors who are considering investing in oil and gas companies, and it provides a more comprehensive picture of the effects from the variables on the oil and gas industry in normal time and periods with extreme prices. In the present study I will examine in what extent variables, both financial and macroeconomic, will affect oil and gas companies stock returns by using weekly data observation in the period January 2000 to December 2015. The purpose and the aim of this study is three fold:

(1) First, explore the impact of a number of risk factors on the entire conditional distribution of oil and gas companies' stock returns by modeling a set of quantiles.
(2) Next, using two companies for a more comprehensive and profound analysis of the quantile regression and return distribution.
(3) Finally, I will perform a sensitivity analysis and show the practical use of quantile regression method for oil and gas stock market participants.

The quantile regression application has recently attracted an increasing amount of research attention in finance and financial risk management. See for example Taylor (1999) and Allen, Singh and Powell (2009). This paper aims to contribute to the quantile regression literature by applying this method on factor models in the oil and gas industry. In the analysis of oil and gas companies it is of great interest to examine how various risk factors affect stock prices returns, not only on average, but also at high and low values. By using quantile regression I can uncover potential differences in factor effects across quantiles of returns. Fundamental factors can be specified in the quantile, which may exhibit different coefficients according to the quantile levels. This feature offers greater predictive insight and accuracy (Bunn, et al. 2012). Looking at just the conditional mean of the stock price return series, it can 'hide' interesting risk-return characteristics.

Selecting the US oil and gas companies are based on the research of Tjaaland, et al. (2016), which builds on the study of Mohanty & Nandha (2011). To examine the distribution of the stock returns by using a quantile regression model, I had to choose appropriate risk factors that explain the fluctuation in oil and gas company stock return. Although estimating standard multifactor regression models is straightforward, identification of the most important risk factors to be included in the model is challenging and difficult. Relevant risk factors are selected from previous empirical studies who has identified various risk factors, which I believe is suitable for this study's purpose.

I will apply a standard five-factor model with the same risk factors for all the selected companies. After an overall quantile regression analysis of the selected companies, I will pull out two different companies with different characteristics, on which I will perform a more extensive analysis. Furthermore, I will use these two companies in a scenario and sensitivity analysis. In the scenario analysis, I will put different values on the most significant risk factors, taking this study's data periods minimum and maximum values into account, and see to what extent they affect the company's performance in the various quantile distributions. This will give us an opportunity to see the extent to which equity returns exposure to risk factors influence within the entire distribution. Quantile regression provides us useful information about the whole distribution and ability to investigate value at risk (VaR) models, since they naturally can be viewed as a conditional quantile function of a given return series. I will show the quantile method´s practical utilization by estimating a one-week-ahead VaR to risk measure of potential losses, and summarizing in a single number the maximum expected loss at a particular significance level.

In this paper I found that most firms in the oil and gas sector have significant market return and oil price risk exposures and many variables are found to have an asymmetric effect on the return distribution. Findings also suggest that the sensitivity to important factors exhibit variation across the distribution. Risk factors have strongest impact in the left tail and gradually decrease towards the right tail. This study is organized in the following parts: Part 2 reviews the literature; Part 3 gives a brief overview of the industry; Part 4 describes the data and the preliminary statistics; Part 5 presents the methodology; Part 6 reports the empirical results, and Part 7 concludes the study.

2. Literature review

In the review of the existing literature, I find to the best of my knowledge that only a small proportion examines the relationship between risk factors and oil and gas stock market using quantile regression. In a different manner, both the multifactor model and the quantile regression method have been separately used in many areas of applied economics and econometrics such as financial risk management. I want to fill the gap in the literature by performing risk analysis for US oil and gas companies using a multifactor quantile regression model. A factor model states a relationship between the return of an assets and the value of a number of factors or independent variables (Alexander & Ruppert, 2013). It is challenging to decide which risk factors that should be included in the model. However, there is some consensus among the researchers on which risk factors oil and gas companies are exposed to.

Oil is the major input in oil and gas companies and there have been broad research over the years directed towards the understanding of oil price movements and its impact on oil and gas stock returns in both the US and other countries. First Al-Mudhaf & Goodwin (1993) examined 29 oil companies listed in NYSE and how oil price shock in the period of 1973 influenced their stock return. Their results showed that oil prices had a significant positive impact on the stock return for companies in the refining and production sector. Boyer og Filion (2007) used a multifactor regression model to investigate the impact of oil shock in oil and gas companies stock return in the Canadian market. The conclusion is that Canadian oil and gas stocks returns were positively influenced by crude oil and natural gas prices. They also found that an increase in the CAD/USD exchange rate would hive a negative effect on the stock return. A more complex study by Ramos & Veiga (2011) found evidence to support oil as a globally priced factor for the oil industry in 34 countries. Additionally they found that the oil and gas industry react stronger on positive fluctuations in the oil price, than negative. Said in other words, the returns act asymmetrically to oil price changes. Mohanty & Nandha (2011) used a Fama-French-Carhart's four factor for measuring the oil price risk sensitivities of US oil and gas firms. Their results indicate that oil price is positive and significant for most of the oil and gas companies operating in the US. Companies exhibit substantial exposure to oil price shock from May 2003 to December 2008, when oil price rose from $27 per barrel to $144 per barrel. Similarly, Tjaaland, et al. (2016) did a continuation on the Mohanty & Nandha (2011) study by updating the time frame and expanding to include royalty trust. They used an augmented one-factor model, which include oil, gas, and interest rate. The results display that US oil and gas companies, and royalty trusts have statistically significant exposure to the market, oil price and natural gas price factors.

Quantile regression is now an important tool in modern risk management operations, and many studies have adopted this method for their research. Applications in quantile regression methods include Taylor (1991) who applies quantile regression approach to estimating the distribution of multi period returns. Bunn, et al. (2012) have analyzed a practical and validated multifactor quantile approach for predicting the electricity price distribution where market participants are able to analyze how various risk factors affect low/high prices. Their findings display effects such as mean reversion, spikes and time varying volatility by using a dynamic quantile regression model with fundamental factors and conditional volatility as explanatory variables. Allen, Singh and Powell (2009) showed that stock price return obtained large and sometimes significant differences between returns and these three factors, both across quantiles and through time. The picture that results from quantile regression analysis is far more complex than the assumptions inherent in OLS would lead us to believe, and Bao, Lee and Saltoglu (2006) consider that the main advantage of quantile regression is to provide better statistics by means of the empirical quantiles.

Quantile regression can help “complete the picture” when we intend to understand the relationship between variables for which the effects may vary with outcome levels. In addition, quantile regression is more accepting than ordinary least squares in that quantile regression is relatively insensitive to outliers and can avoid censoring problems (Conley & Galenson, 1998). Using the quantile regression approach, Tsai (2012) finds a significant relation between stock market indices and exchange rates for six Asian countries. The negative relation between these two markets is more obvious when exchange rates are extremely high or low. Mensi, et al. (2014) examine the conditional dependence of specific quantiles of the BRICS (Brazil, Russia, India, China and South Africa) stock returns with respect to the conditioning variables using a quantile regression. They found that the effects from the commodity markets (oil prices) display a symmetric independence with the BRICS markets. Barnes og Hughes (2002) establish that the quantile regression method is a statistically viable and appropriate way of analyzing the cross section of returns. Their study showed that quantile regression alleviates some of the statistical problems which plague CAPM studies: errors-in-variables; omitted variables bias; sensitivity to outliers; and non-normal error distributions. They also showed that the method allows modeling the performance of firms or portfolios that underperform or over-perform in the sense that the conditional mean under- or over predicts the firm’s return.

In the analysis it is also of particular interest to identify the risk factors associated with US oil and gas companies. Lately, some studies have analyzed the oil price movement's impact on stock return. A recent study by Sim & Zhou (2015) was the first to use a *quantile-on-quantile regression* (QQ) approach to estimate the effect of oil price shock quantiles on US stock return quantiles. They found that negative oil price shocks could improve the return of US equities when the US market is performing well, but the explanatory power of positive oil price shocks is always weak. A follow up is Roberedo & Ugolini`s (2015) study on Quantile dependence of oil price movements and stock returns. They found that the dependence significantly increased after the onset of the crisis. Furthermore, before the crisis, large upward or downward oil price changes had an asymmetric and limited impact on extreme upward or downward stock price changes, whereas interquantile positive or negative oil price movements had no impact at all. They also found that small positive and negative oil price movements had no effect on stock price movements.

Our approaches and findings contribute to two specific strands of the literature. Our first contribution is using a multifactor quantile regression model on US oil and gas companies. The practical relevance of my study is documented by use of sensitivity and scenario analysis and further, a Value at risk estimation (VaR).

3. The oil and gas industry characteristics

As mentioned in the introduction, US oil and gas industry have faced some challenges over the last year. Low commodity prices and new climate policies are rapidly transforming the American energy sector, while escalating wars in the Middle East and a nuclear deal with Iran are clouding the global oil picture (Yergin, 2016). The figure below shows the price index for S&P400 oil & gas companies. The most volatile fluctuations in the oil and gas companies are due to the Gulf war (1990), Finance crisis (2008), and oil price fall (2014). The oil and gas industry are characterized by being capital intensive. New projects and plants can cost up to billions of dollar, continuously searching for low cost natural resource because the oil and gas industry produce a product that is fairly homogeneous. Since product differentiation is not possible with raw oil and gas, the most sustainable companies are the lowest cost producers.

Figure 1 *weekly price for the S&P400oil and gas companies index*

Figure 1: The index value on the Y-axis, and date on the x-axis

The oil and gas industry has four distinct sub sectors, each with its own unique characteristics, and they don't necessarily fluctuating at the same time. In this study I have used following sectors; *Exploration & Production ("E&P")* own and operate the globe's valuable oil and natural gas reserves; *Integrated* companies explore for energy, produce it, transport it, refine it into fuels and chemicals, and then sell it to end users; *Equipment and Services* includes offshore drilling, deep offshore drilling, onshore drilling, equipment manufacturing and technical or support services. These companies tend to specialize in a niche and *Pipelines* transport natural gas and oil to refining facilities around the US.

The rapid growth of solar and wind, combined with energy-efficiency gains for automobiles, means low oil prices may not trigger a big oil demand rebound like we have seen in the past. With today's low oil and gas prices, companies with their bottom-line that are directly linked to energy prices will be negatively affected the most. Pure upstream exploration and production companies fall under this category and they have taken the worst losses among the energy sub sectors. With high leverage levels and negative cash flows, big numbers of bankruptcies has come to this sector and 35 percent of pure-play exploration and production companies listed worldwide, or about 175 companies, are high risk, as defined by the combination of high leverage and low debt service coverage ratios (England & Slaughter 2015). That is prompting some large energy companies to reconsider the viability of their expensive megaprojects that take a long time to build before they produce oil and gas. Companies with strong balance sheets are managing better than those that borrowed heavily from banks or that rely on private equity and hedge funds. Stronger companies will consolidate, accumulating better-producing assets, while weaker companies downsize or disappear. The sub sectors integrated and pipeline companies have more stability due to that fact that they are not directly impacted by the oil price. The trade off between risk and return is one of the central issues faced by individuals who trade equities, manage portfolios, or engage in capital budgeting. A falling demand off the big users of petroleum products have led to consequently lower oil prices. This, with the recent economic and financial crises is particularly relevant to the oil and gas industry because it has led investors to avoid risky investments and move money into more safe havens. In this study I will specifically look at whether an investor with a short position carries the same risk as an investor with long position in oil and gas market.

4. Description of data and preliminary tests

This section begins with a brief description of the data used, followed by descriptive statistics for the time series. The study consists of data from a total of 49 oil and gas companies listed on the American Stock Exchange NYSE. In each series, I use weekly closing prices of the period Jan.2000 to Dec.2015. The data have been obtained by DataStream[1] and denominated in US dollar. The data are adjusted prices, which takes stock splits and similar corporate actions into account, but it is not adjust for dividends. For all price ranges, p_t are calculated weekly compounded continuous returns:

$$r_t = 100\ln\left(\frac{p_t}{p_{t-1}}\right) \qquad (1)$$

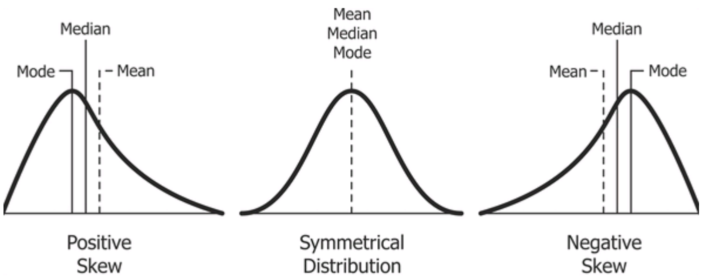
Jondeau, Poon & Rockinger (2006) describes the features of historical stock returns: 1) Fat tails: The distribution of returns exhibit larger tails than the normal distribution. This exposes investors to greater and more frequent losses than what is expected; 2) Asymmetry: the unconditional distribution of returns is often negatively screwed (skewed), i.e. that negative returns occur more than positive; 3) Aggregated normality: The distribution of returns is approaching a normal distribution when the frequency of returns becomes longer; 4) Serial correlation: Returns are not usually considered serial correlated. 4) Volatility clustering: Volatility of returns is serial correlated which means

[1] DataStream – A numeric database provided from Thomson Reuters: Plug-in function in Excel

that large movements in returns are most likely followed by new large movements. Note that the movements can go both ways, both negatively and positively.

In the basic descriptive statistics, it is important to notice the skewness and kurtosis in terms of the distribution estimation. Skewness describes asymmetry from the normal distribution in a set of statistical data and the data cab be skewed to the left (negative) or right (positive) of the mean. Kurtosis is a statistical measure used to describe the distribution of observed data around the mean. A high kurtosis portrays a chart with fat tails and a low even distribution, whereas a low kurtosis portrays a chart with skinny tails and a distribution concentrated toward the mean.

Figure 2 *Illustrations of Skewness (reference: Closure for Data Science)*



The figure above compares the shape of the probability density function for the standard normal distribution and two skewed distribution (Right: positive skew; Left: negative skew). The symmetrical distribution has a skewness of zero and it is a normal distribution.

4.1 US gas and oil companies (Dependent variable)

The descriptive statistics for the sample is calculated from 30^{rd} January 2000 to 30^{rd} December 2015 and it is divided into four subsectors: (1) Exploration & Production (30 firms), (2) Integrated Oil & Gas (8 firms), (3) Oil Equipment & Services (9 firms), and (4) Pipelines (4 firms). See the complete list of the selected companies in Appendix A. Financial returns rarely follow normal distribution, and often have fat tails and volatility clustering. To further prove this, I compute the descriptive statistics of the dataset and the results are as follows:

Table 1 *Descriptive statistics of the data (mean, st.dev, skewness and kurtosis), along with the Jarque-Bera test. The NYSE-ticker codes are described in Appendix A.*

Oil & Gas Producers							
Ticker	Mean	St. Dev	Min	Max	Skewness	E-kurt	JB (p-value)
APC	0,09 %	5,31 %	-41,25 %	21,62 %	-0,31	1,53	21,81
APA	0,10 %	5,01 %	-30,34 %	16,65 %	-0,01	0,54	2,32
COG	0,31 %	5,72 %	-30,78 %	20,85 %	-0,02	0,89	6,37
CPE	-0,08 %	9,80 %	-34,81 %	23,81 %	-1,49	10,50	948,20
CNQ	0,20 %	5,59 %	-34,81 %	23,81 %	-0,07	0,09	0,24
CHK	0,06 %	6,91 %	-56,00 %	25,29 %	0,08	1,72	23,65
SNP	0,16 %	5,04 %	-20,86 %	25,29 %	0,03	0,87	5,83
XEC	0,24 %	5,48 %	-26,42 %	25,29 %	1,04	-0,11	26,86
CWEI	0,06 %	8,75 %	-41,51 %	32,50 %	0,03	0,89	6,39
CRK	-0,11 %	8,67 %	-40,14 %	46,35 %	-0,32	4,81	187,65
DNR	0,04 %	7,06 %	-44,89 %	29,67 %	-0,06	3,12	89,13
DNV	0,04 %	4,95 %	-31,86 %	16,55 %	-0,06	1,64	32,97
ECA	-0,09 %	5,31 %	-34,80 %	20,43 %	-1,15	4,25	159,85
E	0,05 %	4,01 %	-25,29 %	20,18 %	-0,02	0,89	6,26
EOG	0,34 %	5,13 %	-29,38 %	22,13 %	0,07	1,42	16,18
GDP	-0,49 %	10,34 %	-103,31 %	31,22 %	-0,23	1,55	20,92
HES	0,10 %	5,19 %	-33,93 %	21,45 %	-0,08	1,30	13,68
MRO	0,02 %	4,79 %	-33,08 %	21,12 %	-0,57	1,87	38,41
NFX	0,08 %	5,97 %	-34,46 %	23,67 %	-0,50	0,82	13,43
NBL	0,21 %	5,15 %	-34,10 %	29,51 %	-0,08	1,22	12,03
OXY	0,23 %	4,34 %	-33,76 %	19,52 %	0,01	1,32	14,16
PHX	0,32 %	6,52 %	-37,01 %	43,08 %	-0,12	0,91	7,11
PVA	-0,49 %	9,63 %	-102,30 %	82,47 %	-1,83	8,54	688,61
PTR	0,16 %	4,78 %	-23,66 %	23,22 %	0,21	1,64	22,39
PQ	-0,18 %	9,59 %	-58,78 %	47,00 %	-0,01	1,50	18,28
PXD	0,31 %	5,96 %	-41,40 %	22,38 %	-0,94	4,98	225,77
RRC	0,31 %	6,27 %	-33,27 %	31,85 %	0,74	4,46	176,32
SM	0,09 %	6,48 %	-38,24 %	24,13 %	-0,45	1,69	29,28
STO	0,06 %	4,42 %	-19,82 %	19,37 %	-0,16	0,12	0,90
Integrated Oil and Gas							
Ticker	Mean	St. Dev	Min	Max	Skewness	E-kurt	JB (p-value)
CVX	0,09 %	3,37 %	-31,67 %	15,47 %	-0,001	0,65	3,34
COP	0,12 %	3,82 %	-31,58 %	12,80 %	-0,50	2,09	46,13
XOM	0,08 %	3,01 %	-22,30 %	9,50 %	0,16	1,06	9,88
SGY	-0,31 %	8,60 %	-78,29 %	52,88 %	-0,72	3,87	136,05
SU	0,25 %	5,92 %	-39,68 %	77,69 %	0,76	12,23	1208,74
SFY	-0,53 %	9,73 %	-80,18 %	61,30 %	-1,53	6,41	401,91
UPL	0,02 %	6,49 %	-29,17 %	23,19 %	-0,64	1,21	23,41
Oil equipment and services							
Ticker	Mean	St. Dev	Min	Max	Skewness	E-kurt	JB (p-value)
BHI	0,10 %	5,34 %	-40,81 %	17,22 %	-1,03	4,93	227,01

ESV	-0,05 %	6,00 %	-42,09 %	21,38 %	0,00	0,74	4,40
HAL	0,08 %	6,30 %	-57,99 %	35,45 %	-0,91	2,41	72,74
HP	0,22 %	6,04 %	-41,22 %	22,42 %	-0,13	0,61	3,52
NBR	-0,07 %	6,63 %	-41,49 %	30,97 %	-0,25	2,16	39,28
NE	-0,02 %	5,34 %	-39,96 %	24,92 %	-0,10	1,06	9,29
SLB	0,10 %	4,68 %	-26,11 %	16,00 %	-0,34	1,51	21,99
TDW	-0,17 %	5,25 %	-30,64 %	11,22 %	-0,31	0,74	7,61
WFT	0,04 %	6,54 %	-42,08 %	26,27 %	-0,17	1,17	11,95
Pipelines							
Ticker	Mean	St. Dev	Min	Max	Skewness	E-kurt	JB (p-value)
EEP	0,00 %	3,68 %	-35,77 %	21,82 %	-0,22	3,25	85,65
OGE	0,11 %	3,11 %	-32,82 %	11,95 %	-0,10	0,82	5,73
PAA	0,13 %	3,62 %	-28,85 %	27,35 %	-0,53	2,12	44,70
WMB	-0,05 %	9,77 %	-158,26 %	116,55 %	-1,49	9,84	841,67

It emerges from the table 1 that weekly mean return approximately is within the interval -0,53% to 0,34%, while COG, XEC, CNQ EOG, OXY, PHX, PXD, RRC, SU and HP stands out with higher average returns. On the other hand do GDP, PVA, PQ, SGY, SFY and TDW have significantly lower mean return. The selected companies have a total average return of 0.05%, compared with the reference index, the S&P 500 composite, which has a weekly return of 0.03% in the period 2000-2015. Next, I will examine the returns and volatility within the various sub sectors in the data sample. Volatility is a statistical measure of the dispersion of returns for a given security and can be measured by using the standard deviation. Within the various sub sectors the producers and explorations exhibit the highest weekly return in the period, but also the greatest volatility, respectively 0.07% and 6.28%. Not far behind, the companies in the sector pipelines have a weekly return of 0.05% and a volatility of 5.05%. The companies in this sector exhibit the lowest volatility of all sub sectors. Integrated is the only sector with a negative weekly return for the period at -0.04%, this sector also holds the second most volatility. Equipment and service sector has the third highest return (0.03%) and third lowest standard deviation (5.79%).

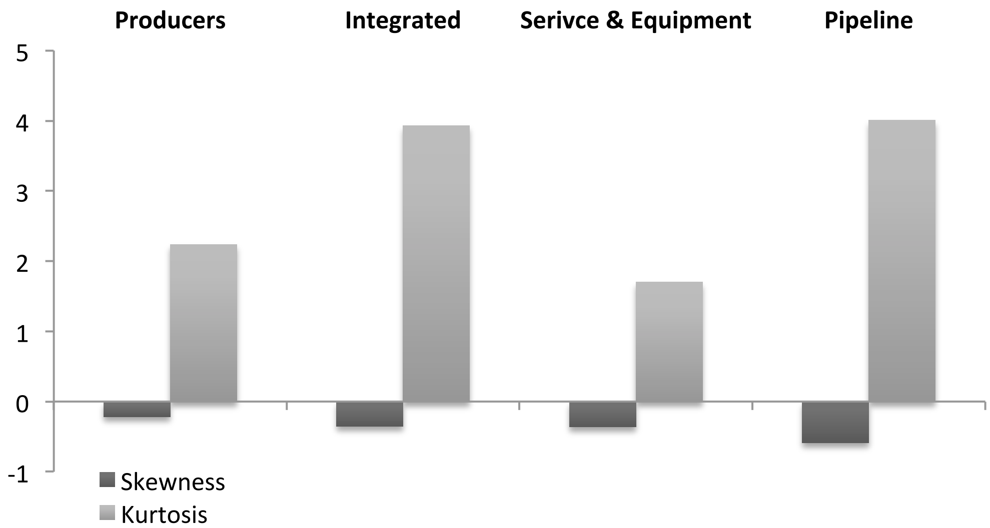
10 of the 59 selected companies exhibit positive skewness, while the other exhibit negative skewness. This suggests that extreme negative price falls are more likely than extreme price increases for the respective oil and gas companies. All of the exhibit kurtosis is far higher than for a Normal Law[2], conforming once again the fat tails of stock

[2] Sample from a normal distribution have an expected excess kurtosis and skewness of 0

returns. The Jarque–Bera normality test[3] is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. The result of the test shows that only 8 of the 49 companies follow a normal distribution. The result is presented in the last column of Table 1; the normality hypothesis is rejected at 5% level of significance.

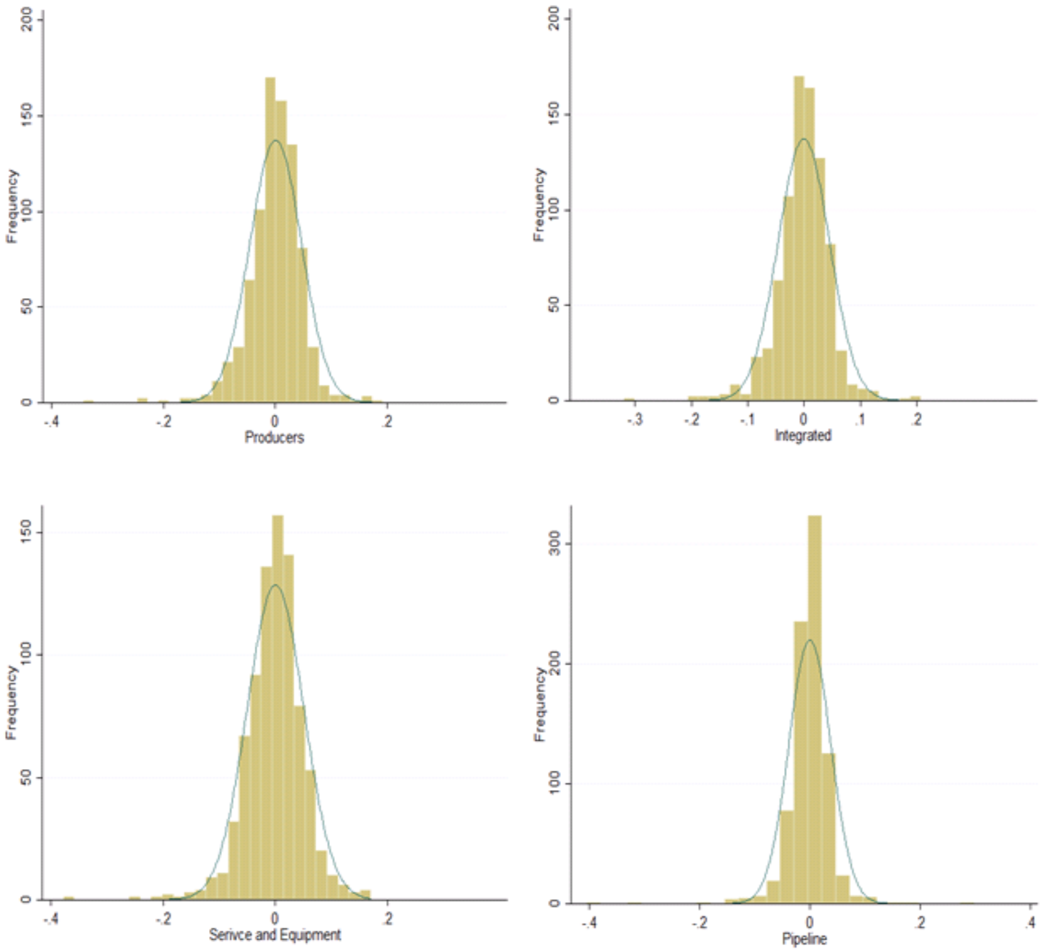
Previous studies find the Production sub sector to have the highest exposure, while Pipeline firms seem to have lower exposure towards both oil and gas price fluctuations. See Mohanty & Nandha (2011) and Tjaaland, et al. (2016). The reason for the differences in the return characteristics is that upstream (E&P) companies will be hit the hardest since the price at which they sell oil is regulated by the market, yet their costs of production are largely fixed. Downstream companies will not tend to be hit as hard, since they profit by purchasing crude and selling the refined products at a premium. The sub sector, Integrated, are hedged against oil and gas price fluctuations as they take part in both upstream (output) and downstream (input) operations. The impact on midstream (pipeline) is more indirect. This is because some midstream companies derive part or all of their revenues from long term and fee-based contracts. Another possible explanation may be their ability to pass on higher fuel costs to their customers. The companies' stock returns exhibit very different kurtosis within the segment and this can be explained by the leverage level, diversified business and how strong they are diversified and exposed against different risk factors.

Figure 3 *Aggregated skewness and kurtosis - A representative from each sub sector.*



[3] The Jarque–Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. We reject the null-hypothesis if p-value>critical value

Figure 4 *Aggregated Stock returns distribution. A representative from each sub sector: producers (top-left), Integrated (top-right), Equipment and service (bottom left) and pipelines (bottom right)*



When we look at the aggregated returns distribution for each sub sector in figure 4, there is no clear pattern within the sub sectors. Pipeline sector is the sector with the lowest skewness and kurtosis highest (See figure 3). This implies that the sector had higher probabilities of negative returns and extreme values of returns during the period. The four histograms look relatively similar, but within the sectors the return distributions vary greatly. As mentioned above, only eight of 49 companies follow normal distribution. For example, Penn Virginia and Cimarex Energy have skewness in each end of the scale, respectively, -1.83 and 1.06. Regarding kurtosis, Cimarex Energy has the lowest value at -0.11, while Suncor Energy has the largest value of 12.23. These relatively large differences between companies' distributions indicate very great uncertainty and risk for an investor who will enter the oil and gas industry, and it is these characteristics we want to further investigate by using quantile regression.

4.1 Oil and gas Risk factors (Independent variable)

This section presents the risk factors included as explanatory variable in this study. A discussion of each explanatory variable`s relevance for the US oil and gas companies and descriptive statistics is also given. The explanatory variables consists of time series for four different variables; 1) Returns in the stock market, 2) The oil price, 3) The natural gas price, 4) Volatility Index and 5) US Dollar index. All returns and rates used in this report are denominated in US dollars.

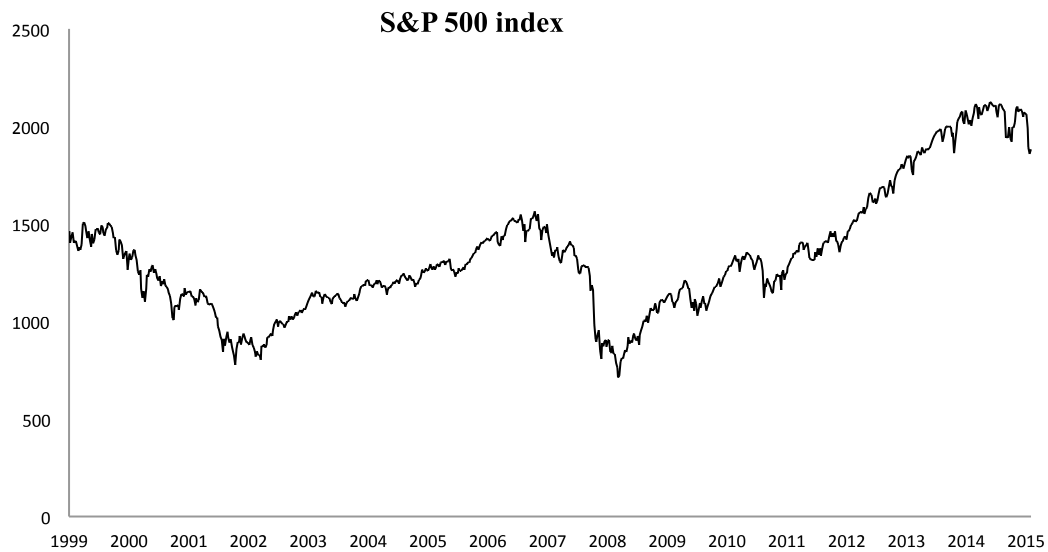
Based on the literature by Sharpe (1964), a prior expectation is that the market return, crude oil prices and natural gas prices should have a positive impact on oil and gas stock returns. Further on I expect that the level of interest rates should have a negative impact on stock price returns. I have chosen the S&P500 composite. The theoretical relationship between changes in oil prices and stock market pricing can best be explained by a discounted cash flow (DCF) model. In a DCF model, the value of shares in a company at any time equal to the expected present value of future cash flows (Huang , Masulis and Stoll, 1996). While the oil and gas industry shows exposure to the world market portfolio, local market indices have greater explanatory power (Ramos & Veiga, 2011).

With regards to commodity prices as a risk factor, I use the weekly returns on the West Texas Intermediate (WTI) and NYMEX Natural Gas. The reasons I use the prices of the West Texas Intermediate (WTI) and of the NYMEX Natural Gas is first, they are most widely used indices in North America and second, by using these two US dollar denominated prices I don’t need to consider exchanges complexity. Changes in oil prices will have impact on the future cash flows. For net oil producing companies, a rise in oil prices increase the cash flows, while the opposite will be the case for net oil consuming companies. Since the majority of companies belong to the first category, the expected net impact of higher oil prices on the stock market in theory is positive (Tjaaland, et al. 2016). Other research papers, such as Hamilton (2001), Mork (1989), Bernanke & Watson (1997) and Lee & Ni (2002) argue that both oil and gas price, and also the he exchange rate, have a significant impact on oil and gas companies’ return. Investors in the oil and gas sector follow oil price fluctuations because corporate managers and investors care about the exposures firms have to exchange (Ramos & Veiga, 2011).

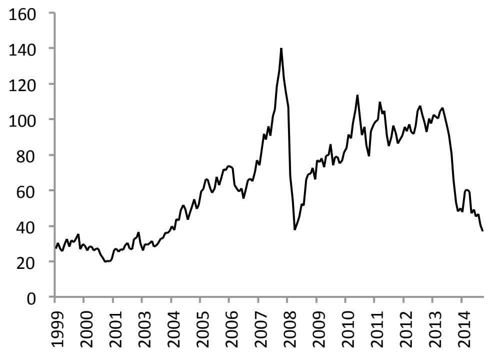
The US Dollar Index (DXY) is a measure of the value of the US dollar relative to majority of its most significant trading partners. The choice of the US dollar index (DXY) as a risk factor is justified by the fact that the oil price is determined in US dollar in the international oil industry. The USD is a relevant risk factor for those who primary have investments or are exposed to non-US dollar costs. Also, exchange rates can change oil prices via its effect on oil supply and oil demand, and via financial market (Buetzer, Habib and Stracca, 2012).

As mentioned earlier the CBOE Volatility Index (VIX) is a measure of the implied volatility of the S&P500 index options. Since its introduction in 1993, VIX has been considered by many to be the world's premier barometer of investor sentiment and market volatility, and it is often referred to as the fear index. Recent studies show that volatility risks significantly affect asset prices and the macro economy. See for example Bloom (2009), Bensal, et al. (2012) and Gurdip, Kapadia and Madan (2003). Alternatively, I can use the CBOE Crude Oil ETF Volatility Index (OVX) who measures the market's expectation of 30-day volatility of crude oil prices by applying the VIX methodology. The history of OVX only goes back to May 2007 and so is too short for this study´s purpose. Implied volatility (VIX) indices exhibit greater volatility than the other risk factor series in the sample because these indices are measures of policy risk of the economy and the stock market volatility. Another reason the VIX index should be used as an variable in the model, is because of volatility clustering as mentioned in chapter 4. As we can se in the figures below, the market index in general reacts negative to changes in the VIX index and fluctuating in different directions.

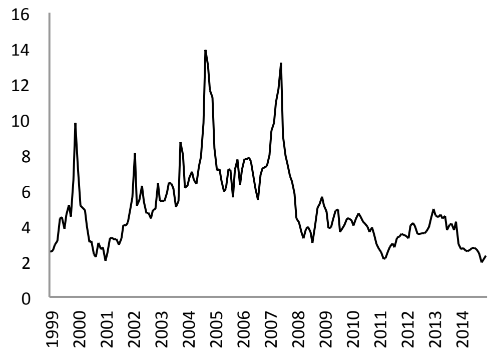
Figure 5 *Graph comparisons between historical prices of the risk factors.*



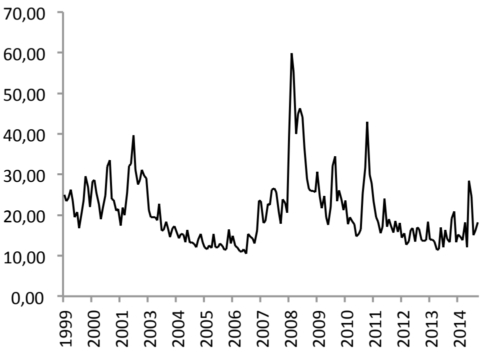
Crude oil



Natural gas



VIX index



DXY index

Table 2 *Descriptive statistics of the data for each explanatory variable.*

2000-2015	Mean	Std. Dev	Skewness	E-Kurt
S&P 500 index	0,0003	0,0242	-0,6108	7,7958
Crude Oil-WTI	0,0001	0,0499	-0,0723	6,3582
Natural Gas	-0,0002	0,0850	0,3328	5,8550
DXY index	-0,0000	0,0114	-0,3344	6,4165
VIX index	-0,0000	0,1192	0,5763	6,1736

Table 3 *Correlation matrix between the US oil and stock return divided into sub sectors and their respective risk factors in period 2000 to 2015.*

	Producers	Integrated	Service & Equipment	Pipeline
S&P 500 index	0,396	0,377	0,374	0,450
Crude Oil-WTI	0,350	0,317	0,275	0,195
Natural Gas	0,182	0,157	0,143	0,078
VIX index	-0,214	-0,184	-0,162	-0,114
DXY index	-0,294	-0,263	-0,288	-0,320

Descriptive statistics of the risk factors are presented in table 2. As we can see, the market index has the strongest positive average weekly returns over the last 15 years and the lowest kurtosis. The other risk factors, except oil price returns, had negative returns in the period. The CBOE volatility index (VIX) has the highest volatility and the lowest weekly return.

Table 3 shows the correlation between the US oil and stock return divided into sub sectors in period 2000 to 2015 and their respective risk factors. Signs of the pairwise correlations give an indication of the co-movement of the sub sectors with fundamentals. Generally, correlations support the expected effects of the fundamentals discussed earlier in this section. S&P500 index, gas price and oil price have positive correlation with the US oil and gas sub sectors. The US dollar index (DXY) and the volatility index (VIX) have negative correlation. Negative and low correlation with VIX index might imply that implied volatility is of little importance of the price formation in most quantiles. From the table we can see that the correlations are strongest with the S&P500 index for all the sub sectors, especially for the pipeline companies. Opposite for the gas price where all sub sectors have a weak correlation. The correlation between the oil and gas industry stocks and the different risk factors provides a motivation for modeling of these particular variables.

5. Methodology

Ordinary Least Squares (OLS) regression models describe the average relationship of stock returns with the set of risk factors. However, this approach might not be adequate due to the particular characteristics of stock returns. Recent research, for example, Jondeau, Poon and Rockinger (2006) has revealed that, due to their highly dynamic complex nature, stock price returns may exhibit a high degree of non-normality, fat tails, excess kurtosis and skewness. In the presence of these characteristics, the conditional mean approach may not capture the effect of risk factors to the entire distribution of returns, and may provide estimates that are not robust. The regression technique that can be used here is known as quantile regression and was developed by Koenker and Basset Jr (1978). The method develops explicit models for specific quartiles of the distribution of a dependent variable using exogenous variables with different coefficients for each quantile. The quantile regression method is the distribution independent and regression parameters are obtained by minimizing a function of the absolute deviation between observations y and regression estimates yˆ weighted by the quantile q. In this way, we can build up a much more complete picture of the conditional distribution of Y given X. The results of quantile regression for the full range of quantiles [0,1] allows for the identification of potential interactions between measured and unmeasured factors (Cade og Noon 2003).

I use quantiles to describe the distribution of the dependent variable. The q^{th} quantile linear regression model is given by:

$$Y_j = \alpha^q + \sum_{i=1}^{k} \beta_i{}^q X_i + \varepsilon_j \qquad (2)$$

Where Y_t is the stock return at time t, X_i, $i = 1, \dots, k,$ is the relative price changes of factor i at time t, α^q is the constant and $\beta_i{}^q$ is the loading of risk factor i. The distribution of the error term is an unspecified distribution function. The standard conditional quantile is specified to be linear:

$$Q_q(Y_j | \, X_i) = \, X_i \beta_q \qquad (3)$$

The conditional q^{th} quantile, 0 < q < 1, is defined as any solution to the minimization problem. We find the parameter β_q by following optimization problem (Koenker og Basset Jr 1978):

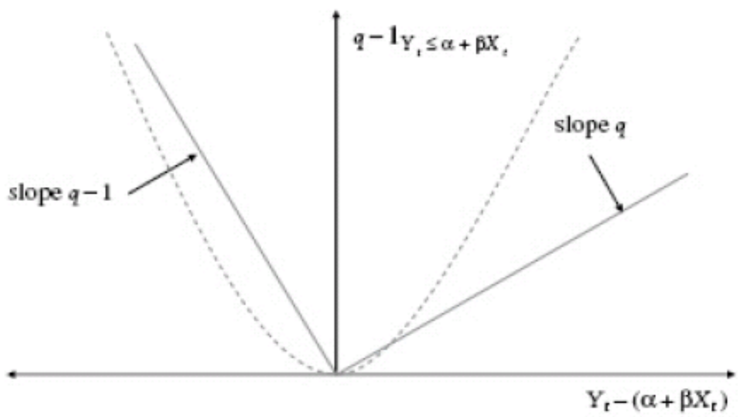
$$\min_{\beta_1, \beta_2} \sum_{t=1}^{T} (q - 1_{Y_t \leq \beta_1 X_{1,t}})(Y_j - \beta_1 X_{1,t}), \qquad (4)$$

Where $1_{Y_t \leq X_{1,t} \beta_1} \; = \;$ if $Y_j \; \leq \; \beta_1 X_{1,t} + \beta_2 X_{2,t}$, 0 otherwise. Solution $\hat{\alpha}_i^q$ and $\hat{\beta}_i^q$ are found by using numerical optimizations. For the i^{th} regressor, the marginal effect is the coefficient for the q^{th} quantile

$$\frac{\partial Q_t(y|x)}{\partial x_i} = \; \beta_{qi} \qquad (5)$$

A quantile regression parameter (β_{qi}) estimates the change in a specified quantile q of the dependent variable (y) produced by a one-unit change in the independent variable (X_i). There are two types of significance that is important for β_{qi}. First, coefficients can be significantly different from zero; Second, coefficients can be significantly different from OLS coefficients, showing different effects along the distribution.

Figure 6 *The Quantile regression ρ function*



The model from equation 4 can be extended by further factors. Quantile regression is more robust to outliers than OLS, and is semi parametric as it avoids assumptions about the parametric distribution of the error process. The estimator for the standard errors computed by Stata commando *qreg* assumes that the sample is independent and identically distributed (i.i.d.). This non-differentiable function is minimized via the simplex method, which is guaranteed to yield a solution in a finite number of iterations.
Standard errors and confidence limits for the quantile regression coefficient estimates can be obtained with asymptotic and bootstrapping methods. Both methods provide robust results (Koenger & Hallock 2001), with the bootstrap method preferred as more practical (Hao & Naiman 2007)

5.1 Bootstrap estimation

There are two ways to employ the bootstrap method proposed by Efron (1982), based on fundamentally different assumptions about the form of the asymptotic covariance matrix of $\beta_i{}^q$. Bootstrapping is a non-parametric method for inference. It involves repetitive computations to estimate the shape of the sampling distributions. Bootstrapping allows one to obtain standard errors for any statistic (Efron 1982). Let $y_t^*,\ x_t^*, i = 1, \dots, n.$, be a randomly drawn sample from the empirical distribution F_{nxy}. It follows from the model in (1) that $Y_t = \beta_i{}^q X_i + \varepsilon_j$, where $Y_t = y_1^*, \dots, y_n^*$ and $(x_i^*, \dots, x_n^*)$. Let $\hat{\beta}_i{}^q$ donate the bootstrap estimate obtained from a quantile regression of Y_t on X_i. This process can be repeated B times, to yield bootstrap estimates $\hat{\beta}_i{}^q, \dots, \hat{\beta}_{iB}{}^q$ the bootstrap estimation of Δ_q is given by:

$$\hat{\Delta}_q^{DMB} = \frac{n}{B}\sum_{j=1}^{B}(\hat{\beta}_i{}^q - \bar{\beta}_i{}^q)(\hat{\beta}_i{}^q - \bar{\beta}_i{}^q)`, \tag{6}$$

Where $\bar{\beta}_i{}^q = \frac{1}{B}\sum_{j=1}^{B}\hat{\beta}_i{}^q$ Specifies the number of bootstrap replications to be used to obtain an estimate of the variance–covariance matrix of the estimators (standard errors). The standard errors produced by the bootstrap technique are only approximations, and estimating the same model again will produce different estimates. The approach is preferable over the asymptotic approach, which is dependent on strong parametric assumptions like *i.i.d*. The accuracy of the approximation increases with the number of replications. The commands *bsqreg* and *sqreg* compute the standard errors of the quantile regression estimates using the pairs-bootstrap, a procedure recommended by Buchinsky (1995).

6. Empirical analysis

In the following analysis I develop a multi factor quantile regression model with a purpose to model the entire distribution of oil and gas companies returns, and to identify risk factors that affect each conditional quantiles of returns. Before doing any estimation and calculation I have made the following *a priori* expectations: First, I expect that all companies are significantly different from coefficient to market risk. This expectation is based on earlier studies that have confirmed this, see Ramos & Veiga (2011) and Sim & Zhou (2015); Second, that WTI gas price is only significant for companies that are directly exposed to gas price in their business; Third, the US Dollar Index (DXY) is only significantly affecting companies that are exposed and have costs in countries outside the US, and is thus exposed to other currencies; and last, the implied volatility (VIX) will have negative significant influence in the lower part of the distribution. The reason for this is that a high VIX reflects increased investor fear and a low VIX suggests complacency. During periods of market turbulence, the VIX spikes higher and during bullish periods, there is less fear and less impact in VIX.

6.1 Multi factor quantile estimates

Quantile regression methodology provides a way of understanding and testing how the relationship between returns and other conditioning variables or risk factors changes across the distribution of conditional returns. It is these changes that are our primary focus here. I perform in-sample analysis using all data from 30th January 2000 to 30th December 2015, which consist of 833 observations for the 49 oil and gas companies. I begin by modeling weekly returns, focusing on the 5%, 10%, 25%, 75%, 90% and 95% quantiles and the median since these are most interesting from an economic point of view. These estimates are derived from the methodology discussed in section 5 and on following linear quantile regression model:

$$r_i^q = \alpha_i^q + \beta_i^q X_{S\&P500} + \beta_i^q X_{oil\,price} + \beta_i^q X_{gas\,price} + \beta_i^q X_{DXY} + \beta_i^q X_{VIX} + \varepsilon_t^q \tag{7}$$

Where Y_r is the stock return of the selected companies; β_1^q the percentage change in market return; β_2^q the percentage change in the Crude oil price; β_3^q the percentage change in Natural gas price; β_4^q the percentage change in US Dollar index and β_5^q the percentage change in a volatility index. All calculations are performed in Stata (Bsqreg commando). The table in appendix B presents the estimated parameters of the quantile regression. I now highlighted particular and common characteristics from the above empirical results and provide some suggestions.

The adjusted R-squared value indicates how much the variation in oil and gas share price returns can be explained by market returns and oil price returns. The estimate from equation 4 are present in appendix B, has considerably higher explanatory power in the lower quantiles than in the higher quantiles.

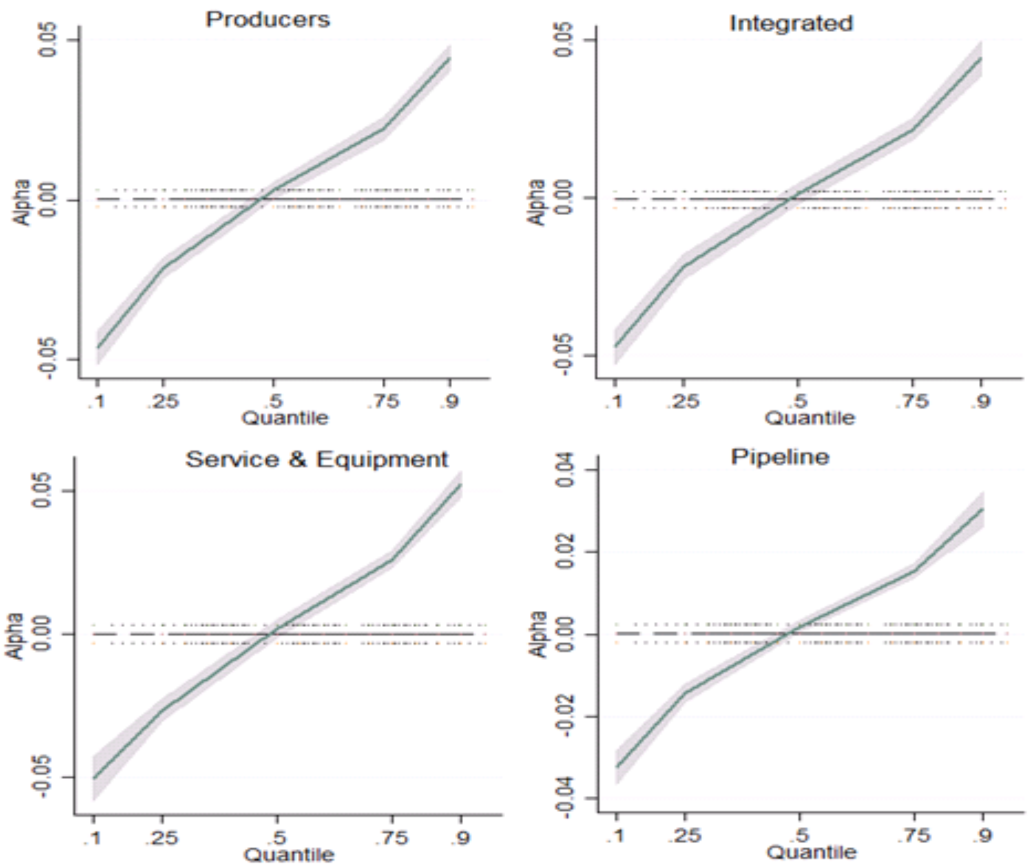
Table 4 shows the minimum and maximum values of the alpha estimates within each sub sector. As we can se, the producers have the largest alpha estimate ranging from -0,80 to -0,06 in the 5%-quantile. At the median quantile,

Table 4 *minimum and maximum alpha Estimate across the quantile in the sub sectors*

	Producers		Integrated		Service & Equipment		Pipeline	
	Min	Max	Min	Max	Min	Max	Min	Max
Quantile .5%	-0,80	-0,06	-0,10	-0,05	-0,10	-0,07	-0,10	-0,05
Quantile 10%	-0,06	-0,05	-0,10	-0,04	-0,07	-0,05	-0,06	-0,03
Quantile 25%	-0,02	-0,02	-0,04	-0,02	-0,04	-0,03	-0,03	-0,01
Quantile 50%	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Quantile 75%	0,03	0,02	0,03	0,04	0,03	0,04	0,02	0,03
Quantile 90%	0,05	0,05	0,03	0,08	0,05	0,07	0,03	0,06

In figures 7 are the results for the aggregated parameter estimates of α for each sub sectors. When considering these figures, it becomes noticeable that for all oil and gas stocks the α values increase continuance from the lowest quantile 0.05 to the 0.9 quantile. At the median, the alpha (α) estimates are very close to zero for all stocks. This is a clear sign for the asymmetric behavior of stock returns. This happens when negative market returns generally result in even more negative stock returns, as I referred as volatility clustering earlier. In this case the positive returns only have a small impact on the returns. This result corresponds to the descriptive statistics displayed in chapter 4.

Figure 7 *Alpha estimates for the sub-sectors. Alpha (a) estimates on Y axis and the quantile on X axis.*



For our purposes, we are most interested in whether or not the coefficient is significant over any portion of the conditional distribution. I also explore whether the coefficient changes significantly across quantiles. Table in appendix B shows that 48 out of 49 oil and gas companies have positive and significant oil price return coefficient across the quantiles, while only 24 firms have positive and significant gas price return coefficients during the sample period. I find that the gas price in central quantiles general tends to be significantly different from zero, while lower and upper quantiles tend not to be. It also reveals that median quantile oil coefficient of 46 firms are positive and highly significant at the 1% level with *parameter*-values from the lowest of 0,062 to the highest of 0,316. This result indicating that most energy firms experienced an increase in equity returns as the oil price continued to rise from the lowest. Most notably, our results indicate that oil price risk exposure is significant higher in the lower quantile for most energy firms. Generally speaking, investors are more pessimistic to bad news when the stock market stays under a worse performance. In other words, stock market participants should be concerned about the stock market performances and then judge if they should consider the impact of oil price shocks on stock returns with optimistic or pessimistic standpoints. These results link the findings in the energy and financial realms and offer relevant suggestions to market participants.

Unlike oil price return, the market return coefficients are significant at the 1% level for all companies and the entire distribution, from 10% quantile to 90% quantile. These findings support the argument that company earnings in the energy sector may have been driven by the US stock market cycle ($\beta_{i,m}^{q}$). This provides some support for the robustness of the market return coefficient. One interesting case that deserves noting is that VIX index coefficient commonly shows opposite sign at opposite ends of the distribution of conditional returns for almost all companies. Such cases are also discovered for other risk factors. Examples are the factor US dollar index (DXY) for Cimarex Energy (XEC) and China Petroleum (SNP) with coefficient equal to 0,456 and 0,104 in the 10th regression quantile and equal to -0,185 and -0,297 in the 90th regression quantile. In those cases the factor's coefficient formats a U-shape where the parameter becomes lowest around the 25% percentile of the distribution of conditional returns. Clearly, the quantile regression approach prevents us from drawing incorrect inferences with respect to the factors' effect on the distribution of returns.

In order to illustrate and further examine different impact of risk factors between the companies within all the sub sectors, I will look at the sectors that contain specific coefficient characteristics. I would emphasize that there is considerable variation in the different companies in sub sectors, but I will here present a larger picture from the various sub sectors. The Appendix figure C shows an aggregated mean return coefficient for five different quantile values (q=0.10, q=0.25, q=0.50, q=0.75, and q=0.90) of securities within the four sub sectors. The shaded areas represent estimators within 95% confidence band. This figure and analysis indicates that the coefficients across quantiles affect stock price returns in varying degrees in the different sub sectors. The figure shows that the regression line for q=0.50 is often almost identical and close to the OLS regression line. However, as we move away from the 50% quantile toward estimates in the tails of the return distribution, the impact of the risk factors changes markedly. I find that the market return parameters in a quantile regression in general follow a decreasing pattern over the quantiles of the conditional return distribution: high positive returns in the lower quantiles while lower returns in the upper quantiles. I also find such a pattern to hold when accounting for crude oil return. The size of the estimated natural gas coefficient for producing companies is almost unchanged in the lower quantiles of the conditional return distribution, while in the upper quantiles the parameter estimates are slightly more pronounced.

I present the four main findings: First, production companies show the highest oil exposure, in all parts of the distribution. Integrated companies have a slightly lower oil influence in the lower part of the distribution, but have a larger influence than production companies in the upper part of the tail. Pipeline companies have the lowest exposure to oil price return. Equipment and pipeline do not have as high significant coefficients as the other sub sectors. This is expected when producing and integrated companies have oil as a direct input-factor in their business area. It is also expected that integrated companies will have lower impact when they take part in both downstream and upstream operations. Surprisingly, integrated companies have higher impact in the upper quantile then producing companies;

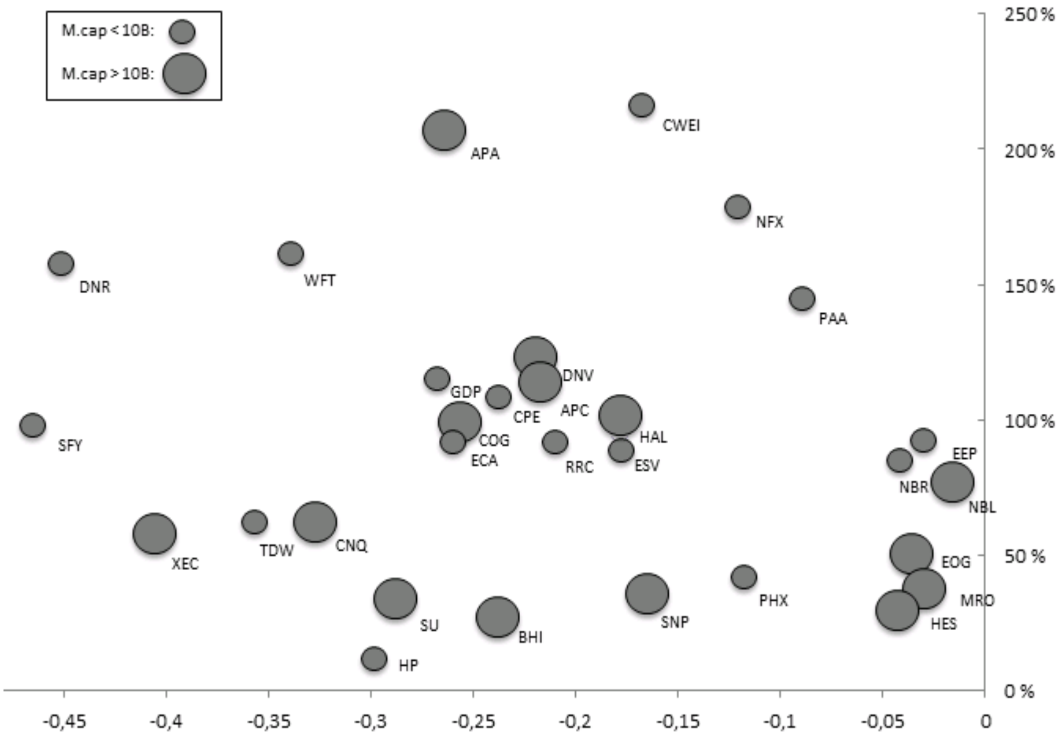
Secondly, the market coefficient has the highest influence on the integrated companies in all parts of the distribution. Next to highest, after integrated companies, are producing companies. The market coefficient has the lowest impact on pipeline companies. The coefficient of the market is highly significant across all quantiles, for all companies and in all sub sectors;

Thirdly, Gas prices have the highest impact on integrated companies in the low tail, while producing companies have the greatest impact to the upper tail. The companies in both sectors are very similar in patient's shoulder and median quantile;

Last, regarding the volatility index (VIX) impact on companies in the various sectors, the exposures are greatest in both ends (U-shape) of the distribution and lowest in median quantile for all companies. The biggest impact is for producing companies in the lower tail. The interesting thing is that both the integrated and equipment companies have relatively low exposure in the left tail, but increases sharply in the right tail (upper quantiles). DeLisle, Doran and Peterson (2011) documents in their study that sensitivity to VIX is negatively related to returns when volatility is increasing, but is unrelated when it is decreasing. The low average returns to stocks with high distinctive volatilities could arise because stocks with high volatilities may have high exposure to aggregate volatility risk, which lowers their average return.

One interesting thing related to the VIX index is to investigate if there is any “Leverage effect”. The “leverage effect” refers to the relationship between stock return and volatility. A standard explanation ties the phenomenon to the effect a change in market valuation of a firm`s equity has on the degree of leverage in its capital structure. It suggest that a negative return should make the firm more levered, hence riskier and therefore lead to higher volatility (Figlewski og Wang 2000). My hypothesis is that as larger the company gearing is, the larger the exposure from the VIX index. As we can see in figure 8, there is a pattern for companies debt-level and their exposure to the VIX index. However, the pattern is not apparent and further research has to be done to drawn a conclusion. The figure shows 30 of the companies and the D/E-ratio is shown in appendix A.

Figure 8 *Scatterplot of companies D/E ratio and VIX index 50% quantile coefficient. Debt-to-equity ratio on Y axis and the VIX coefficient on the X axis.*



To get a better understanding in which extent these risk factors influence the stock price return in different level of the distribution I will present an analysis of two selected companies in the next section.

6.2 Analysis of Chesapeake Energy & ENI s.p.a

In this section I will present an application of the model and a more detailed analysis and a comparison of the stock return of Chesapeake Energy (NYSE: CHK) and ENI s.p.a (NYSE: E). Further, I will use these two companies in the scenario and sensitivity analysis. The Chesapeake Energy is the second largest producer of natural gas and the 12th largest producer and oil. The natural gas comprises 71% of the company`s income, while oil generate 12%. ENI s.p.a on the other hand has around 40% of their business in exploration and producing, which means that their business is more diversified compared with Chesapeake Energy. In addition, ENI s.p.a is far less local compared with Chesapeake, because they operate in many different countries. In the sample period (2000-2015), both companies have positive weekly average stock return, respectively 0,06% and 0,05%. Chesapeake Energy exhibits more volatility than Eni s.p.a, where Chesapeake Energy has a return in interval from lowest -56% to highest 25% and Eni s.p.a -25% to 20%.

Table 5 *Estimate across the quantile regression and OLS estimate for Chesapeake*

Quantile	**Cons (α)**	**Market (β)**	**Oil Price (β)**	**Gas Price (β)**	**DXY index (β)**	**VIX index (β)**	**Adj. R^2**
.5%	-0,101	1,598***	0,518***	0,026	-0,735	0,185**	0,15
10%	-0,069	1,031***	0,463***	0,086	-0,327	0,082	0,11
25%	-0,032	0,708***	0,307***	0,162***	-0,099	-0,005	0,11
50%	0,002	0,529***	0,310***	0,104***	-0,184	-0,027	0,10
75%	0,033	0,449***	0,186***	0,134***	-0,364	-0,027	0,07
90%	0,066	0,378*	0,101	0,199***	-0,570*	-0,005	0,07
OLS	**0,0002**	**0,717*** **	**0,248*** **	**0,133*** **	**0,009**	**-0,394** **	**0,16**

Table 6 *Estimate across the quantile regression and OLS estimate for ENI s.p.a*

Quantile	**Cons (α)**	**Market (β)**	**Oil Price (β)**	**Gas Price (β)**	**DXY index (β)**	**VIX index (β)**	**Adj. R^2**
.5%	-0,062	0,629***	0,194**	0,051	-0,396	-0,001	0,14
10%	-0,044	0,599***	0,157***	0,016	-0,512**	0,001	0,11
25%	-0,020	0,520***	0,097***	-0,005	-0,661***	-0,014	0,10
50%	0,002	0,194**	0,091***	0,023	-0,522	-0,049	0,08
75%	0,022	0,150*	0,043	0,040**	-0,439***	-0,047***	0,07
90%	0,041	0,207**	0,016	0,057***	-0,619***	-0,035*	0,07
OLS	**0,0003**	**0,409*** **	**0,059** **	**0,023**	**-0,527*** **	**-0,028***	**0,16**

Table 5 and table 6 show the regression estimate from a standard OLS and quantile method. As we can see from the OLS, Chesapeake energy have significant coefficient at least in 5% levels for four of five variables, while ENI s.p.a have three out of five. As I have discussed earlier, it could well be that a variable can predict events in the left tail (i.e. losses) although it fails to predict the center (mean) of the return distribution and vice versa. To explore this possibility, I present a series of quantile regressions for the univariate specification. In the same table are the estimated coefficients of the independent variables with a range of quantiles from 0.05 to 0.90 for the five risk factors, which can be obtain by running the regression model in Equation (7). Only three of five variables for Chesapeake and two of five for ENI s.p.a have highly statistically significant coefficient for the median of stock returns. In comparison with the OLS method, it is differences in factor effects across quantiles of returns and the coefficient exhibit differently estimates according to the quantile levels.

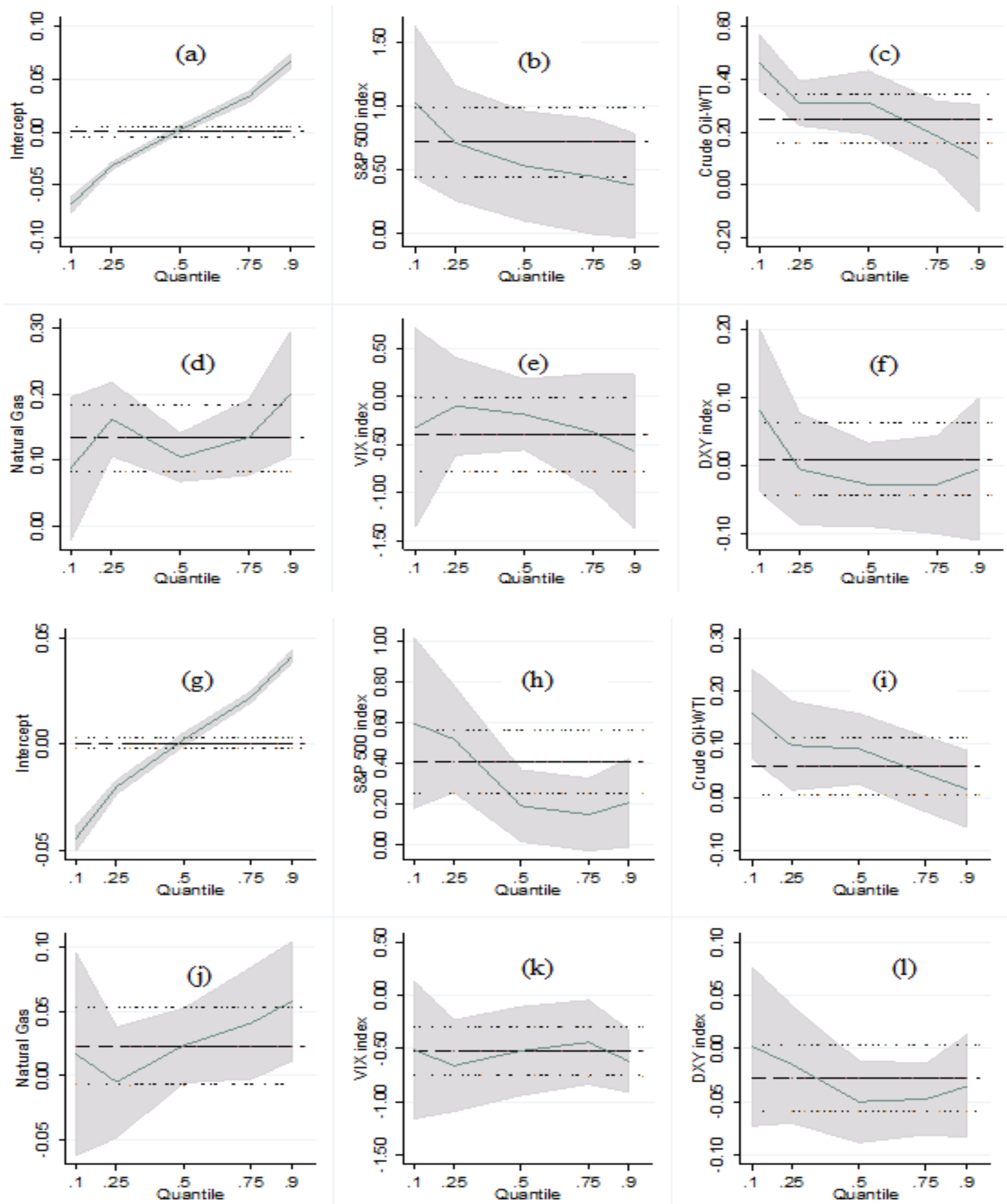
As shown in the table, the S&P 500 index coefficients are highly significant for all quantiles. In contrast, the coefficient on the relative change in the VIX displays insignificant for both companies. Estimates that are worth noting for Chesapeake energy is the coefficients gas price return, US dollar index (DXY) and volatility index (VIX). For the gas price factor the standard OLS shows an estimated coefficient at 0.133 and a significant level of 1%. From quantile regression method the coefficient emerges a very small impact on the lower quantile. Conversely, we see in coefficient of DXY where estimated OLS coefficient is insignificant in 0,009, while from quantile regression method estimates only show a significant and higher impact (-0,570 in 90th quantile) in the upper quantile. For the VIX Index, the OLS method display a higher impact (and significant) than all the quantiles and only the 5th quantile providing a significant estimate of 5% from the quantile regression.

Regarding the market price and oil price coefficient on ENI s.p.a, they significantly influence the stock return across the whole quantile distribution. For gas price, the coefficient only have influence in the upper quantile, respectively 0,040 (75th quantile) and 0,057 (90th quantile). For VIX the coefficients are significant only in the upper quantile, while OLS estimate shows a significant coefficient at 10% level. These results show a clear sign that the risk factors influence can be inconsistent in different parts of the distribution of the returns, and that OLS is not always able to show the risk of the entire distribution.

Chesapeake is more exposed to changes in the market, oil price and the gas price than ENI s.pa. As a supplier of oil and natural gas, Chesapeake's and ENI`s revenue rises and falls with commodity prices. The differences between the coefficients across the quantiles can be explained by the fact that ENI s.p.a has half of its production concentrated in North and West Africa and the Caspian Sea. The production outside of the US border does also explain why ENI s.p.a has relatively high exposure and highly significant coefficient against the US dollar index, and not as much exposure against the market risk as Chesapeake energy. Another explanation can be the “leverage effect” - with an increase in leverage producing an increase in stock volatility. With that said, Chesapeake has a much higher debt-level with 502% debt-to-equity, while ENI has a 53% ratio.

To visualize patterns of the quantile distributions, figure 8 provides an example of the values of the individual coefficients across different quantiles (10%, 25%, 50%, 75% and 90%) plotted against the values obtained from OLS (Horizontal black line).

Figure 9 *Quantile regression plot for the CHK and E coefficient estimates*



Quantile regression plot for the Chesapeake Energy stock return. Intercept is the stock return alpha, S&P 500 index the percentage change in Market return; Crude oil WTI is the percentage change in the Crude oil price;

Natural gas is the percentage change in Natural gas price; DXY index the percentage change in US Dollar index and VIX index the percentage change in a volatility index

The plots show that the return of a security is not linearly dependent on these factors around the whole distribution. The shaded areas represent estimators within 95% confidence bands. Figure 8 a-f show the coefficient estimate for Chesapeake energy and Figure 9 g-l show the estimates for ENI s.p.a. The alphas for various quantiles can be seen in Figure 9(a). As expected, the upward sloping indicates that the lower quantiles tend to be associated with negative alphas and the upper quantile generate positive alphas. Figures 9(b) - (d) plot the parameters of the selected five factors over various quantiles. The coefficient for Natural gas and US Dollar index curve display a u-shaped curve, suggesting that the Natural gas and DXY index at the tails of the return distribution have relatively more exposure to the market risk and size factors. On the other hand, the figure 9(e) shows that the stock return have higher exposure to VIX index in the median. The plots in figure 9(a) and (c) show the exposure to S&P500 and crude oil. The shape of this curve shows a downward sloping curve and that the left tail of the return distribution delivers higher coefficients. This suggesting that the stock returns have higher exposure to these risk factors. For ENI s.p.a the coefficient result exhibit much of the same as Chesapeake energy. In figure 9(d) we find a distinctive, s-shaped pattern across quantiles of the conditional stock return distribution. In particular, we find lower quantiles to exhibit positive dependence with past returns while upper quantiles are marked by negative dependence. Typically, we find no or only very weak dependence for central quantiles.

6.2.1 Robustness of Quantile Regression Coefficients

Although it seems obvious that the estimated coefficients vary with the quantile levels reported in Table 4 and 5, it would be more compelling if we conduct a formal test of the hypothesis of the equality of slopes. Since the median quantile is close to the mean value of the least squares estimation that has been conventionally used in testing, we shall address the equality test of various quantiles against the median quantile coefficient ($q^{0,5th}$). Specifically, we test:

$$\begin{cases} \beta_{i,q=0,10} = \beta_{i,q=0,5} \\ \beta_{i,q=0,25} = \beta_{i,q=0,5} \\ \beta_{i,q=0,75} = \beta_{i,q=0,5} \\ \beta_{i,q=0,90} = \beta_{i,q=0,5} \end{cases} \quad (8)$$

To estimate the difference between the coefficients across the quantiles, I use the Wald-test. The Wald statistics show that the null is uniformly rejected on the coefficients of the crude oil price variable, for both Chesapeake Energy and ENI s.p.a, at different quantile distributions, suggesting that the estimated coefficients for the quantiles of 0.10, 0.75, and 0.90 are significantly different from that of the median distribution. Similarly, the natural gas price coefficient reject the null hypothesis of 0,25, 0,75 and 0,9 quantiles, leaving those as well different from the median distribution. For S&P500 variable we reject the null hypothesis at 10% confidence level at only the 0,10 quantile for both, and for the VIX index we do not reject the null hypothesis across the quantiles at any confidence level. For the US dollar index, ENI s.p.a has significant value only in the 0,10 quantile. These testing shows us that the OLS or median quantile not always display the true picture of a company`s risk. The evidence suggests that the validity of the risk from different risk factors occurs in the upper and lower shoulders and tails, showing a significant difference from those derived from the median quantile. Specifically, the coefficients at quantiles 0,10, 0,75 and 0.90 are significantly different from those of the median. Nonetheless, for the coefficients of the US dollar index and VIX index, I cannot find strong evidence against the equality of the slopes between quantiles.

In addition to the evidence that the estimated coefficients deviate from the median quantile, we are also concerned about the symmetry of the risk-return relation for the quantiles that lie above the median versus those that lie below the median. In particular, I test the following restrictions:

$$\begin{cases} \beta_{i,q=0,10} + \beta_{i,q=0,90} = \beta_{i,q=0,5} \\ \beta_{i,q=0,25} + \beta_{i,q=0,75} = \beta_{i,q=0,5} \end{cases} \tag{9}$$

Test results are reported in Table 8, where we find very little evidence of a departure from symmetry for the market index, US dollar index and VIX index, and the hypothesis cannot be rejected. For the WTI crude oil and natural gas prices we can reject the hypothesis of symmetry for the (0.25, 0.75), and the pair of (0.05, 0.95).

An implication of this test is that variance or standard deviation is still a crucial factor in modeling stock return. However, to validate the risk-return trade-off hypothesis, risk factors should be restricted to certain appropriate ranges.

Table 7 *Wald-test result*

Table 6 A: S&P500index

Stock	$\beta_{i,q=0,10} = \beta_{i,q=0,5}$	$\beta_{i,q=0,25} = \beta_{i,q=0,5}$	$\beta_{i,q=0,75} = \beta_{i,q=0,5}$	$\beta_{i,q=0,90} = \beta_{i,q=0,5}$
CHK	3,34*	0,79	0,19	0,25
E	2,73*	1,38	0,20	0,33

Table 6 B: WTI Crude Oil

Stock	$\beta_{i,q=0,10} = \beta_{i,q=0,5}$	$\beta_{i,q=0,25} = \beta_{i,q=0,5}$	$\beta_{i,q=0,75} = \beta_{i,q=0,5}$	$\beta_{i,q=0,90} = \beta_{i,q=0,5}$
CHK	3,95**	0,01	6,35**	6,04**
E	3,75*	0,00	7,33***	5,74**

Table 6 C: Natural Gas

Stock	$\beta_{i,q=0,10} = \beta_{i,q=0,5}$	$\beta_{i,q=0,25} = \beta_{i,q=0,5}$	$\beta_{i,q=0,75} = \beta_{i,q=0,5}$	$\beta_{i,q=0,90} = \beta_{i,q=0,5}$
CHK	0,09	4,60**	3,30*	5,45**
E	0,09	3,47*	2,8*	8,39***

Table 6 D: US dollar index

Stock	$\beta_{i,q=0,10} = \beta_{i,q=0,5}$	$\beta_{i,q=0,25} = \beta_{i,q=0,5}$	$\beta_{i,q=0,75} = \beta_{i,q=0,5}$	$\beta_{i,q=0,90} = \beta_{i,q=0,5}$
CHK	2,65	0,66	0,00	0,17
E	5,35**	0,60	0,00	0,22

Table 6 E: VIX index

Stock	$\beta_{i,q=0,10} = \beta_{i,q=0,5}$	$\beta_{i,q=0,25} = \beta_{i,q=0,5}$	$\beta_{i,q=0,75} = \beta_{i,q=0,5}$	$\beta_{i,q=0,90} = \beta_{i,q=0,5}$
CHK	0,21	0,23	0,96	1,07
E	0,15	0,28	0,47	0,73

Table 8 *Wald-test result*

Table 7A: S&P500index

Stock	$\beta_{i,q=0,10} + \beta_{i,q=0,90} = \beta_{i,q=0,5}$	$\beta_{i,q=0,25} + \beta_{i,q=0,75} = \beta_{i,q=0,5}$
CHK	1,68	0,41
E	1,43	0,90

Table 7B: WTI Crude Oil

Stock	$\beta_{i,q=0,10} + \beta_{i,q=0,90} = \beta_{i,q=0,5}$	$\beta_{i,q=0,25} + \beta_{i,q=0,75} = \beta_{i,q=0,5}$
CHK	4,46**	6,82***
E	3,46**	3,75**

Table 7C: Natural Gas

Stock	$\beta_{i,q=0,10} + \beta_{i,q=0,90} = \beta_{i,q=0,5}$	$\beta_{i,q=0,25} + \beta_{i,q=0,75} = \beta_{i,q=0,5}$
CHK	3,28**	2,85*
E	4,24**	2,39*

Table 7D: US dollar index

Stock	$\beta_{i,q=0,10} + \beta_{i,q=0,90} = \beta_{i,q=0,5}$	$\beta_{i,q=0,25} + \beta_{i,q=0,75} = \beta_{i,q=0,5}$
CHK	1,53	0,28
E	2,89*	0,31

Table 7E: VIX index

Stock	$\beta_{i,q=0,10} + \beta_{i,q=0,90} = \beta_{i,q=0,5}$	$\beta_{i,q=0,25} + \beta_{i,q=0,75} = \beta_{i,q=0,5}$
CHK	1,07	0,28
E	0,41	0,32

6.3. Sensitivity analysis and VaR Simulation

Many variables are found to have an asymmetric effect on the return distribution, affecting lower, central and upper quantiles very differently. Finally, I will evaluate different quantiles through a scenario analysis of the quantile coefficient estimate based on a base scenario for each of the most important variables for Chesapeake Energy and

ENI s.p.a. I have made a distinction by referring to “important” parameters as those who uncertainty contributes substantially to the uncertainty in assessment results, and “sensitive” parameters as those that have a significant influence on assessment results. Moving the magnitude value (factor level) of one risk factor within the interval from minimum to maximum values in the sample period presented in table 9, while other risk factors are held constant at their baseline values. Sensitivity may then be measured by monitoring changes in the output by the quantile regression. This appears as a logical approach as any change observed in the output will unambiguously be due to the single variable changed. Furthermore, by changing one variable at a time, one can keep all other variables fixed to their central or baseline values. This increases the comparability of the results.

Table 9 *Risk factors minimum and maximum values from the data set (2000-2015)*

2000-2015	Min	Max
S&P 500 index	-0,164	0,101
Crude Oil-WTI	-0,235	0,321
Natural Gas	-0,320	0,419
DXY index	-0,084	0,039
VIX index	-0,427	0,687

To illustrate the results from the sensitivity analysis, I've put the results in the figures below. Figure 10 shows Chesapeake Energy´s exposure to market returns, figure 11 shows change in oil prices and in Figure 12 shows change in gas price. The first two figures show ENI s.p.a sensitivity to market returns and changes in oil prices. Figure 15 shows the change in the US dollar index (DXY). The X axis shows the change in magnitude level. The Y axis displayed stock return ($\hat{y}$). Below I present six figures each representing an important risk factor and their sensitivity within the lower and upper tail of the stock return (Lower tail: 1%, 5%, 10%; Upper tail: 90%, 95% and 99%).

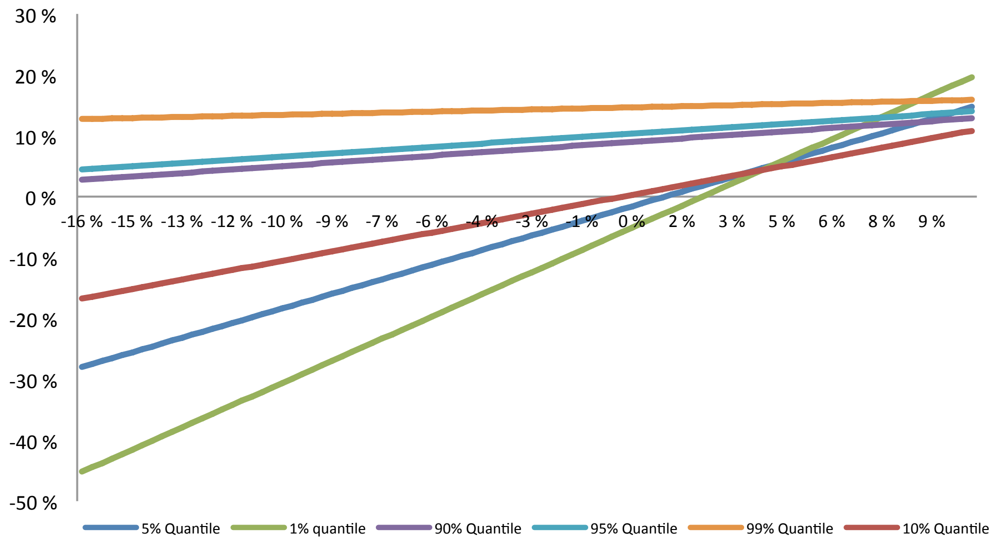


Figure 10: Sensitivity analysis result for S&P500 index on CHK. The Y axis shows the change in magnitude level. The X axis display stock return. The six graph shows the quantile1%, 5%, 10%, 90%, 95% and 99%.

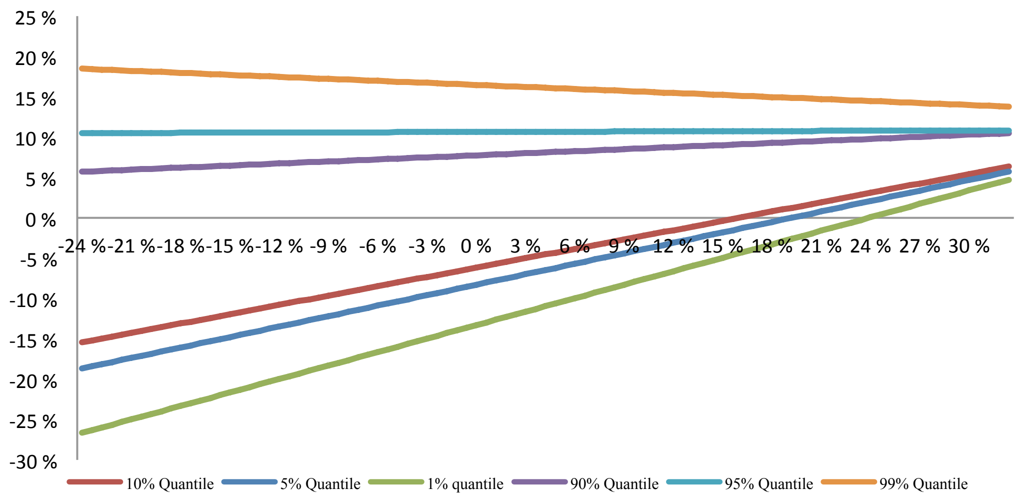


Figure 11: Sensitivity analysis result for WTI crude oilprice on CHK. The Y axis shows the change in magnitude level. The X axis display stock return. The six graph shows the quantile1%, 5%, 10%, 90%, 95% and 99%.

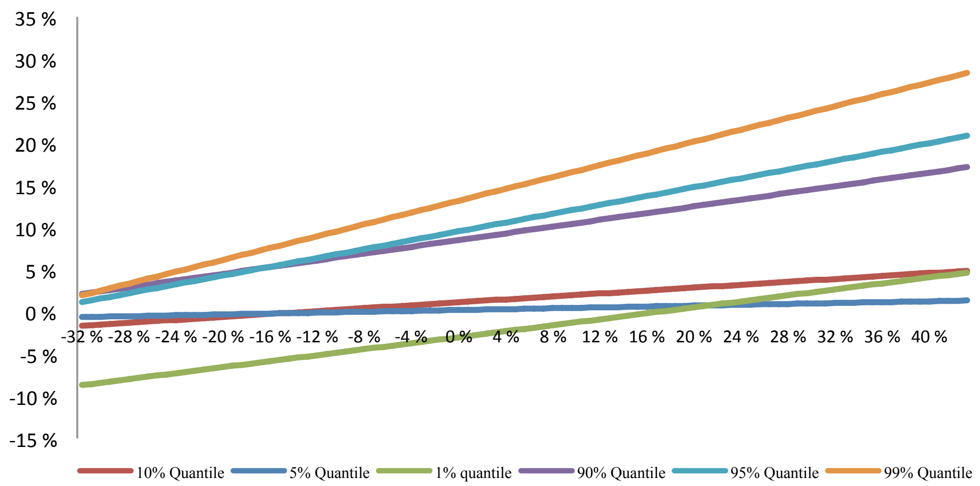


Figure 12: Sensitivity analysis result for WTI crude oilprice on CHK. The Y axis shows the change in magnitude level. The X axis display stock return. The six graph shows the quantile1%, 5%, 10%, 90%, 95% and 99%.

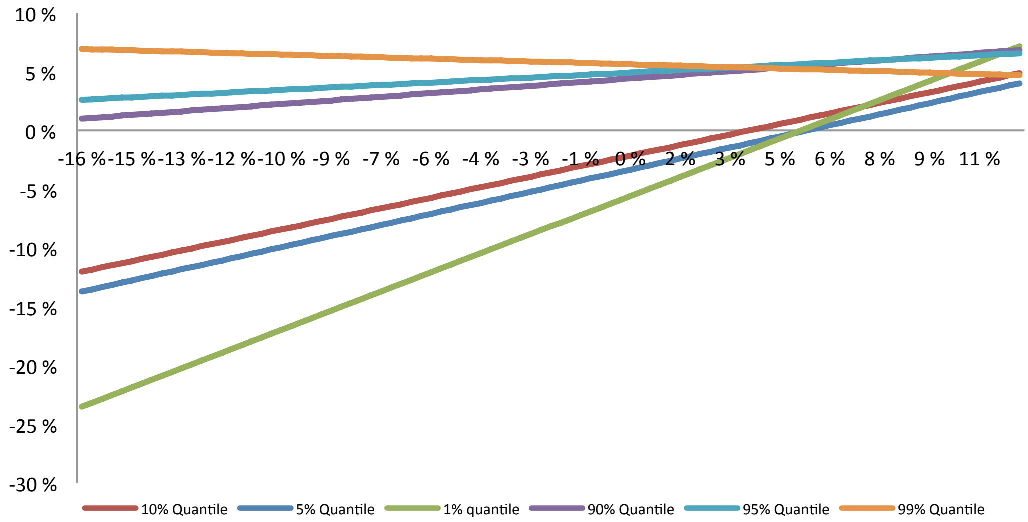


Figure 13: Sensitivity analysis result for S&P500 index on E. The Y axis shows the change in magnitude level. The X axis display stock return. The six graph shows the quantile1%, 5%, 10%, 90%, 95% and 99%.

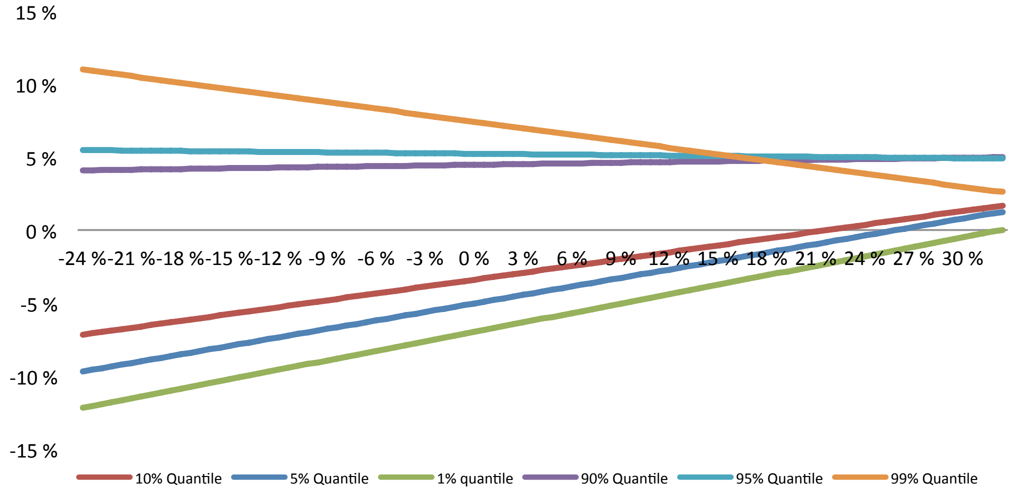


Figure 14: Sensitivity analysis result for WTI crude oil price on E. The Y axis shows the change in magnitude level. The X axis display stock return. The six graph shows the quantile1%, 5%, 10%, 90%, 95% and 99%.

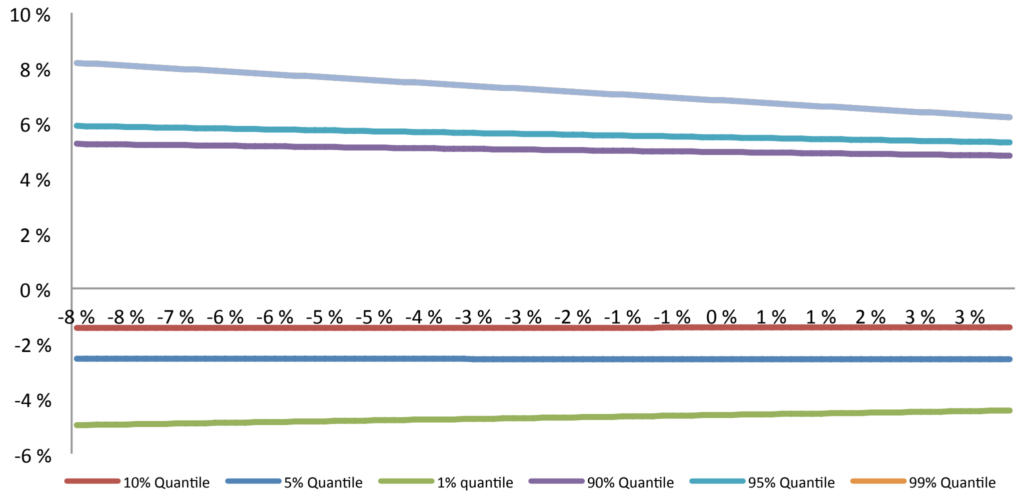


Figure 15: Sensitivity analysis result for US dollar index (DXY price on E. The Y axis shows the change in magnitude level. The X axis display stock return. The six graph shows the quantile1%, 5%, 10%, 90%, 95% and 99%.

A factorial analysis involves choosing a given number of samples for each parameter and running the model for all combinations of the samples. The results obtained in this fashion are then utilized to estimate parameter sensitivity. For example, a model has five parameters and it is determined, rather arbitrarily, that each parameter will be sampled at three specific locations, e.g. the 25th, 50th, and 75th quantiles. From the figures above, we see a clear pattern in the slope to the various risk factors. We see that the sensitivity is steepest in the left tail and gradually decreases towards the right tail. This is clearly evident in Figure 10 and 11, where Chesapeake Energy's exposure to both market factor and the oil price return gradually decreases when it reaches the upper part of the return distribution. In the case of natural gas prices (Figure 12) we see that the sensitivity and the risk is greatest both at the end of both tails (1% & 99%).

We see the same patterns for ENI s.p.a, however, in the upper part of the distribution (99%), the slope fluctuate in opposite direction as magnitude increases for that market factor (Figure 13) and oil price (Figure 14). The coefficient of US dollar index (Figure 15) indicates that the stock price moves very little in the lower quantile of changes in DXY index. In general, we see a steeper lower quantile, suggests that risk factor publishes a significantly higher risk in the lower part of the distribution. For an investor with long position in an oil and gas stock, it will be a substantially greater risk associated with the position of the comparison with an investor with a short position.

To get a better and more complete picture of the risk of price changes in risk factors, I will use the sensitivity index (SI). The sensitivity index was introduced by Krieger, Durston and Albright (1977). The model are utilizing each parameter's entire range of possible values in order to assess true parameter sensitivities, and it is calculated using:

$$SI = \frac{Y_{max} - Y_{min}}{Y_{max}} \tag{10}$$

Where Y_{min} and Y_{max} represent the minimum and maximum output values, resulting from varying the input over its entire range.

Table 10 *Sensitivity index For Chesapeake Energy (NYSE: CHK)*

	Lower			**Upper**		
Quantile	**1%**	**5%**	**10%**	**90%**	**95%**	**99%**
Market (β)	3,30	2,90	2,55	0,79	0,68	0,20
Oil Price (β)	7,54	4,58	3,62	0,45	0,03	-0,33
Gas Price (β)	3,05	1,47	1,35	0,87	0,94	0,93

Table 11 *Sensitivity index For ENI s.p.a (NYSE: E)*

	Lower			Upper		
Quantile	**1%**	**5%**	**10%**	**90%**	**95%**	**99%**
Market (β)	5,25	5,46	4,03	0,85	0,59	-0,44
Oil Price (β)	19,43	10,43	5,79	0,18	-0,12	-2,96
DXY index (β)	-0,12	0,00	-0,01	-0,09	-0,11	-0,32

Table 10 and 11 show results for the calculation of the sensitivity index. For Chesapeake Energy, we see a consistent pattern of coefficients. Exposure is as highest in the lower part of the distribution and gradually decreases towards the right tail. Oil prices have the highest sensitivity in the left tail (quantile 1%, 5% and 10%). The sensitivity decreases strong against the right tail and goes from positive to negative at the edge of the distribution (99% quantile). Interestingly, the gas price exhibit strongest sensitivity in the upper part with a value of 0.87 to 0.93 in the 95th to 99th quantile. As with Chesapeake Energy, also ENI s.p.a exhibit highest sensitivity to oil prices in the lower quantile. In the upper part of the distribution, the market index holds the highest sensitivity. My findings suggest that the sensitivity to important factors exhibit variation across the distribution. For example, during periods with low oil price changes, the stock price return is heavily influenced by oil. During high oil price changes, changes are marginal for the stock price return. For an investor who holds either a long or short position in a stock, for example Chesapeake Energy, does not necessary have the same risk exposure against important risk factors. The asymmetric price risk of an US oil and gas stock contains characteristics that standard OLS regression are not suitable to display.

6.3.1 Value at risk (VaR)

The quantile regression method`s ability to explore each quantile and the findings from the sensitivity analysis suggests that the sensitivity to important factors exhibit variation across the distribution. The risk for an investor with a long position in a stock is not necessarily equal to the risk for an investor with a short position in a stock. In this section I will focus on the asymmetric risk associated with the tails of the return distribution. For agents concerned with managing and assessing risk, price models which are accurate in forecasting tail risk is thus vital. Downside and upside risk is an estimation of a security's potential to suffer a decrease or increase in value if the market conditions change, or the amount of loss that could be sustained as a result of fluctuations.

VaR is a statistical risk measure of potential losses, and summarizes in a single number the maximum expected loss over a target horizon, at a particular significance level. Quantile regression can be used to construct VaR *(Value at risk)* without imposing a parametric distribution or the i.i.d assumption. Chen (2001) was among the first to consider the quantile regression for the VaR model. The study discusses a multi period VaR model based on quantile regression. Quantile regression provides a way of understanding how the relationship between US oil and gas stock return and risk factors changes across the distribution of conditional returns. The method provides useful information about the whole distribution and the ability to investigate VaR, since they can naturally be viewed as a conditional quantile function of a given return series.

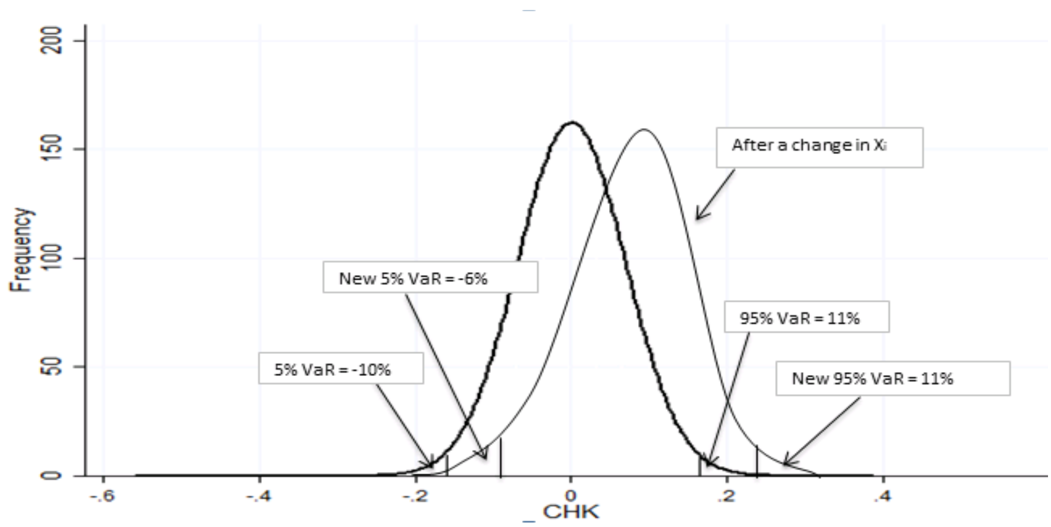
The linear quantile regression models developed by Koenker and Basset (1978) are briefly introduced in section 5. Quantile regression models can, hence, be directly translated into VaR models, which is yet another advantage of this methodology. According to equation (4), $VaR_t \equiv -g(x_t; \beta_i^q)$, the confidence level is chosen to be 95% and 5%, meaning that the respectively 5% and 95% significance level VaR is of interest. By modeling the 5% quantile in the left tail and the 95% quantile in the right tail of the price distribution, the 5% 1-week-ahead VaR for both long positions (the 5% quantile) and short positions (the 95% quantile) in the US oil and gas market are computed.

In this section I would like to illustrate how the model can be used by an investor with an idea about how the prices of risk factors will develop. If you can forecast the relative changes of the risk factors, you would be estimating/predicting expected shortfall.
To illustrate one-week-ahead value at risk, I have used the stock returns a week after the data period. The value used for the various risk factors where: S&P500: 0.01, WTI Crude oil: -0.05; NYMEX Natural gas: 0.05; VIX index 0.001; and DXY index 0.08. Table 11 Shows the VaR estimates from Chesapeake Energy and the 5%- and 95%-value at risk is respectively -10% and 11%.

Table 11 *Value at Risk (VaR) estimate*

	5% significance level	95% significance level
Value at Risk	-10%	11%

Figure 16 *distribution and Value at Risk (VaR)*



The figure above shows the distribution of Chesapeake Energy and one- week-ahead value at risk at specified rates by a base scenario. In case of events that change the assumptions, for example oil prices will change the expected VaR. The second graph in the figure above illustrates the change in expected shortfall, a change of -0.04 to 0.04 will increase the 5 % -VaR from -10% to -6 %. This model can be used to identify potential risks associated with downside risk (long position) and upside risk (short position) when you expect a change in the risk variables.

8. Conclusion

In this master thesis, I demonstrate how the return distribution of 49 US gas and oil companies stock are influenced by five risk factors (Market return, Oil price, Gas price, US dollar index and VIX index) from January 2000 to December 2015. Unlike the standard conditional mean regression method, which only examines how the risk factors affect the returns on average, this quantile regression approach is able to uncover how this dependence varies across quantiles of return. Thus, the approach provides useful insights into the distributional dependence of US oil and gas stock returns on risk factors.

Overall I find evidence of that most firms in the oil and gas sector have significant market return and oil price risk exposures. Results also suggest that oil exposure coefficients are not equal across the whole distribution. I show that with quantile regression models the whole underlying conditional distribution can be considered by examining any desired quantile, whereas the OLS based methods are restricted. General speaking, many variables are found to have an asymmetric effect on the return distribution, affecting lower, central and upper quantiles very differently. The median regression line is almost identical with the OLS regression line. However, as we move away from the median quantile toward estimates in the tails of the return distribution, the impact of coefficients changes markedly.

As a demonstration of the usefulness of the quantile regression framework, I present a more detailed analysis. I also perform various t-tests for each stock to test whether the estimated parameters in selected quantiles τ are different from those in the median. My findings specifically shows that the coefficients at quantiles 0,10, 0,75 and 0.90 are significantly different from those of the median, suggesting that quantile regression show hidden return distribution characteristics that are not suitable for OLS. This study not only shows that the factor models does not necessarily follow a linear relationship, but also shows that the traditional OLS becomes less effective when it comes to analyzing the extremes within a distribution, which is often a key interest for investors and risk managers. My findings suggest that the sensitivity to important factors exhibit variation across the distribution. The sensitivity of the coefficients where measured by a sensitivity index which monitor changes in the output by the quantile regression. The risk factors have the strongest impact in the left tail and gradually decrease towards the right tail. For an investor with long position in an oil and gas stock, will be substantially greater risk associated with the position, in the comparison with an investor with a short position.

Finally, I show the practical use of quantile regression method by estimating the value at risk (VaR). The method that is used is a relatively new way of performing Value at Risk and the advantage of this method is that it is easy to implement. This evidence on quantile dependence of important risk factors on stock returns have implications for investors who need to adopt risk management strategies that protect portfolios against price fluctuations in oil markets. I show that downside risk is greater than the upside risk of investments in US oil and gas stocks, suggesting that investors who held long position in US oil and gas stock is exposed to greater risk than participant with short position.

I believe that there exist several potential applications of this conditional quantile regression approach in the area of risk analysis. Several extensions to this study can be considered. It would be interesting to expand the study to analyzing other risk factors or to conduct assets (i.e. other stocks) to see if the conclusions drawn would be the same. Other assets can have characteristics that fit my model better leading to better results. Additionally, it would have been interesting to use non-linear quantile regression to examine if there are non-linear relationship between the dependent variable and the risk factors.

Appendix

Name	Ticker	Industry	M.cap($) (30.04.16)	D/E-ratio (30.04.16)
ANADARKO PETROLEUM	APC	Oil & Gas Producers	24,26B	111,88
APACHE	APA	Oil & Gas Producers	19,20B	207,59
CABOT OIL & GAS	COG	Oil & Gas Producers	11,32B	100,79
CALLON PETROLEUM	CPE	Oil & Gas Producers	1,23B	108,70
CANADIAN NATURAL RESOURCES	CNQ	Oil & Gas Producers	38,54B	60,07
CHESAPEAKE ENERGY	CHK	Oil & Gas Producers	3,79B	449,06
CHINA PETROLEUM & CHEM	SNP	Oil & Gas Producers	84,43B	31,95
CIMAREX ENERGY	XEC	Oil & Gas Producers	10,06B	53,10
CLAYTON WILLIAMS ENERGY	CWEI	Oil & Gas Producers	212,72M	216,18
COMSTOCK RESOURCE	CRK	Oil & Gas Producers	45,06M	550,97
DENBURY RESOURCES	DNR	Oil & Gas Producers	1,11B	157,16
DEVON ENERGY	DVN	Oil & Gas Producers	16,40B	119,53
ENCANA	ECA	Oil & Gas Producers	5,35B	92,69
ENI SPA	E	Oil & Gas Producers	5.4,00T	51,79
EOG RESOURCES	EOG	Oil & Gas Producers	43,63B	51.46
GOODRICH PETROLEUM	GDP	Oil & Gas Producers	3,59M	115,12
HESS Corporation	HES	Oil & Gas Producers	17,36B	32,50
MARATHON OIL	MRO	Oil & Gas Producers	10,32B	39.22
NEWFIELD EXPLORATION	NFX	Oil & Gas Producers	6.81B	178.90
NOBLE ENERGY	NBL	Oil & Gas Producers	15,32B	77.43
OCCIDENTAL PETROLEUM	OXY	Oil & Gas Producers	56.49B	34.22
PANHANDLE OIL & GAS	PHX	Oil & Gas Producers	269.07M	46.28
PENN VIRGINIA	PVA	Oil & Gas Producers	7.23M	214.99
PETROCHINA CO LTD	PTR	Oil & Gas Producers	123.71B	42,59
PETROQUEST ENERGY	PQ	Oil & Gas Producers	53,23M	146,05
PIONEER NATURAL RESOURCES	PXD	Oil & Gas Producers	26.32B	43,64
RANGE RESOURCES	RRC	Oil & Gas Producers	7.06B	96,07
SM ENERGY	SM	Oil & Gas Producers	2.05B	135,93
STATOIL ASA	STO	Oil & Gas Producers	53,77B	80,14
CHEVRON	CVX	Integrated oil and gas	189.58B	25,08
CONOCOPHILLIPS	COP	Integrated oil and gas	53.66B	62,07
EXXON MOBIL	XOM	Integrated oil and gas	364.97B	21,88
STONE ENERGY	SGY	Integrated oil and gas	44.91M	2666,01
SUNCOR ENERGY	SU	Integrated oil and gas	41,72B	39,20
SWIFT ENERGY	SFY	Integrated oil and gas	6,24M	91,97
ULTRA PETROLEUM	UPL	Integrated oil and gas	47,89M	1585,15
BAKER HUGHES	BHI	Equipment and services	19,70B	24,67
ENSCO	ESV	Equipment and services	3,23B	90,45
HALLIBURTON	HAL	Equipment and services	34,78B	99,04
HELMERICH & PAYNE	HP	Equipment and services	6.60B	11,01
NABORS INDUSTRIES	NBR	Equipment and services	2,39B	85,28
NOBLE CORP	NE	Equipment and services	2,44B	60,48
SCHLUMBERGER	SLB	Equipment and services	105.96B	52,98
TIDEWATER	TDW	Equipment and services	394,53M	61,10
WEATHERFORD INTL	WFT	Equipment and services	5,43B	170,93
ENBRIDGE ENERGY PRTNRS	EEP	Pipelines	7,78B	92,32
OGE ENERGY	OGE	Pipelines	6,02B	8285
PLAINS ALL AMER PIPELNE	PAA	Pipelines	8,95B	144,48
WILLIAMS COS	WMB	Pipelines	14,78B	129,86

Appendix B

	Cons (α)	Market (β)	Oil Price (β)	Gas Price (β)	DXY index (β)	VIX index (β)	Adj. R^2
APC							
.5%	-0,795	1.056***	0,294***	0,060	-0,730*	0,075	0,12
10%	-0,058	1,118***	0,305***	0,050	-0,020	0,100**	0.09
25%	-0,024	0,682***	0,357***	0,044	-0,115	0,009	0,08
50%	0,001	0,484***	0,170***	0,050**	-0,217	-0,009	0,06
75%	0,026	0,444***	0,143***	0,055**	-0,020	-0,024	0,05
90%	0,054	0,1621	0,137**	0,071*	-0,169	-0,048	0,05
APA							
.5%	-0,075	1,039***	0,224**	0,118**	-0,521	0,079	0,14
10%	-0,054	0,869***	0,306***	0,059	-0,172	0,042	0,12
25%	-0,023	0,579***	0,209***	0,044*	-0,086	-0,023	0,10
50%	0,002	0,391***	0,188***	0,402**	-0,264*	-0,049**	0,09
75%	0,027	0,269**	0,193***	0,064***	-0,230	-0,035	0,07
90%	0,067	0,230	0,232**	0,050	-0,165	0,007	0,06
COG							
.5%	-0,083	1,100***	0,341***	0,180***	-0,166	0,042	0,15
10%	-0,059	0,794***	0,208***	0,139***	-0,438	0,005	0,11
25%	-0,028	0,370**	0,229***	0,094***	-0,275	-0,024	0,07
50%	0,004	0,421***	0,165***	0,124***	-0,255	-0,019	0,07
75%	0,031	0,377***	0,181***	0,123***	-0,120	-0,004	0,06
90%	0,062	0,333	0,084	0,059	-0,174	0,028	0,02
CPE							
.5%	-0,132	1,460***	0,517***	0,156	-0,118	0,211**	0,11
10%	-0,091	1,535***	0,395***	0,095	-0,399	0,126	0,10
25%	-0,042	1,052***	0,288***	0,058	-0,180	0,021	0,07
50%	-0,002	0,584***	0,215***	0,076***	-0,239	-0,042	0,05
75%	0,039	0,513**	0,225***	0,078*	-0,465	-0,046	0,04
90%	0,092	1,101**	0,169	0,146*	-0,289	0,094	0,05
CNQ							
.5%	-0,080	0,418	0,342***	0,033	-0,618	-0,016	0,14
10%	-0,055	0,581**	0,451***	0,034	-0,043	-0,017	0,15
25%	-0,023	0,514***	0,370***	0,041*	-0,161	-0,022	0,14
50%	0,011	0,562***	0,300***	0,054**	-0,330**	0,005	0,10
75%	0,029	0,374***	0,206***	0,088***	-0,459**	-0,046*	0,08
90%	0,058	0,324*	0,246**	0,064*	-0,492**	-0,044	0,10
CHK							
.5%	-0,101	1,598***	0,518***	0,026	-0,735	0,185**	0,15
10%	-0,069	1,031***	0,463***	0,086	-0,327	0,082	0,11
25%	-0,032	0,708***	0,307***	0,162***	-0,099	-0,005	0,11
50%	0,002	0,529***	0,310***	0,104***	-0,184	-0,027	0,10
75%	0,033	0,449***	0,186***	0,134***	-0,364	-0,027	0,07
90%	0,066	0,378*	0,101	0,199***	-0,570*	-0,005	0,07
SNP							
.5%	-0,075	0,624*	0,106	0,034	0,104	-0,046	0,10
10%	-0,055	0,381*	0,079	0,021	0,006	-0,077*	0,08
25%	-0,026	0,289**	0,079	0,004	0,013	-0,059**	0,05
50%	0,002	0,270**	0,013	-0,014	-0,168	-0,047**	0,04
75%	0,032	0,235*	-0,080*	-0,017	-0,356*	-0,065***	0,04
90%	0,056	0,351**	-0,128**	-0,009	-0,297	-0,050	0,04
XEC							
.5%	-0,072	1,204***	0,334**	0,0869	0,456	0,090	0,18
10%	-0,055	1,14***	0,291***	0,109***	0,337	0,062	0,16
25%	-0,028	1,102***	0,293***	0,098***	0,098	0,055*	0,13
50%	0,003	0,744***	0,263***	0,047**	-0,411	0,002	0,11
75%	0,029	0,413**	0,174***	0,042	-0,290	-0,025	0,07
90%	0,061	0,090	0,160***	0,075*	-0,185	-0,052	0,04
CWEI							
.5%	-0,134	1,707**	0,269	-0,030	-1,36	0,132	0,12
10%	-0,93	1,121***	0,380***	-0,041	-0,595	-0,014	0,09
25%	-0,042	0,764***	0,299***	0,054	-0,222	-0,011	0,06

50%	0,003	0,482***	0,216***	0,131***	-0,168	-0,028	0,05
75%	0,046	0,625***	0,144**	0,175***	-0,628**	-0,052	0,06
90%	0,091	0,517*	0,191*	0,217***	-0,885**	-0,043	0,08
CRK							
.5%	-0,124	1,162*	0,628***	0,109	-0,657	0,043	0,14
10%	-0,088	1,320***	0,368***	0,104	-0,261	0,058	0,11
25%	.0,045	0,630***	0,380***	0,119***	-0,540*	-0,003	0,08
50%	-0,003	0,539***	0,279***	0,125***	-0,088	-0,025	0,06
75%	0,042	0,368*	0,024***	0,088**	-0,274	-0,011	0,04
90%	0,084	0,434	0,272***	0,130**	0,116	-0,068	0,03
DNR							
.5%	-0,103	1,446***	0,566***	0,035	0,244	0,120	0,17
10%	-0,071	0,973***	0,436***	0,069	-0,277	0,005	0,15
25%	-0,033	0,680***	0,400***	0,044	-0,434	-0,042	0,12
50%	0,001	0,570***	0,210***	0,045*	-0,451**	-0,032	0,08
75%	0,033	0,258*	0,266***	0,050*	-0,226	-0,043	0,07
90%	0,068	0,415*	0,322***	0,045	-0,123	-0,025	0,05
DNV							
.5%	-0,715	0,863**	0,187	0,145**	0,064	0,032	0,14
10%	-0,051	0,787***	0,277***	0,105**	-0,024	0,048	0,11
25%	-0,024	0,521***	0,319***	0,055**	-0,078	-0,004	0,11
50%	-0,001	0,419***	0,223***	0,085***	-0,221	-0,017	0,11
75%	0,026	0,416***	0,185***	0,078***	-0,309**	-0,017	0,08
90%	0,052	0,442***	0,200***	0,067**	-0,060	0,012	0,06
ECA							
.5%	-0,793	1,062***	0,481***	0,076	0,111	0,094	0,19
10%	-0,055	0,700***	0,374***	0,081*	-0,364	0,025	0,15
25%	-0,026	0,493***	0,292***	0,081***	-0,333	-0,003	0,12
50%	-0,010	0,430***	0,220***	0,079***	-0,261	-0,011	0,10
75%	0,026	0,459***	0,178***	0,096***	-0,112	-0,014	0,07
90%	0,050	0,380**	0,205***	0,110***	-0,266	-0,023	0,09
E							
.5%	-0,062	0,629***	0,194**	0,051	-0,396	-0,001	0,14
10%	-0,044	0,599***	0,157***	0,016	-0,512**	0,001	0,11
25%	-0,020	0,520***	0,097***	-0,005	-0,661***	-0,014	0,10
50%	0,002	0,194**	0,091***	0,023	-0,522	-0,049	0,08
75%	0,022	0,150*	0,043	0,040**	-0,439***	-0,047***	0,07
90%	0,041	0,207**	0,016	0,057***	-0,619***	-0,035*	0,07
EOG							
.5%	-0,074	1,128***	0,194*	0,105*	-0,139	0,128*	0,12
10%	-0,054	0,906***	0,216***	0,072*	0,059	0,019	0,10
25%	.0,024	0,501***	0,227***	0,0799***	0,118	-0,028	0,08
50%	0,002	0,237**	0,189***	0,090***	-0,031	-0,048**	0,07
75%	0,030	0,457***	0,115***	0,088***	-0,038	-0,020	0,05
90%	0,059	0,407**	0,128**	0,061	-0,086	0,010	0,05
GDP							
.5%	-0,141	1,880***	0,718***	-0,124	-1,564	0,258*	0,13
10%	-0,104	1,765***	0,674***	0,039	-1,025*	0,212***	0,11
25%	-0,052	0,851***	0,462***	0,108**	-1,159***	0,044	0,07
50%	-0,003	0,888***	0,316***	0,101***	-0,268	0,016	0,06
75%	0,046	0,703***	0,223***	0,135***	-0,043	-0,023	0,05
90%	0,095	0,763**	0,187	0,127*	-0,102	0,024	0,04
HES							
.5%	-0,078	0,818**	0,362***	0,110	0,190	0,018	0,10
10%	-0,049	0,633***	0,266***	0,064	-0,051	-0,032	0,10
25%	-0,023	0,533***	0,206***	0,039*	-0,060	-0,042	0,10
50%	0,001	0,261**	0,237***	0,018	-0,034	-0,067	0,08
75%	0,027	0,263**	0,179***	0,032	-0,356	-0,031	0,07
90%	0,058	0,585***	0,187***	0,035	-0,288	0,035	0,05
MRO							
.5%	-0,072	0,848***	0,331***	0,109*	0,430	0,006	0,17
10%	-0,056	0,966***	0,318***	0,753*	0,618*	0,014	0,12
25%	-0,022	0,526***	0,185***	0,004	-0,175	-0,032	0,08
50%	0,001	0,466***	0,126***	0,041**	-0,025	-0,031	0,08
75%	0,025	0,410***	0,128***	0,036*	-0,041	-0,019	0,06
90%	0,049	0,394**	0,074	0,071**	-0,251	-0,007	0,04

NFX							
.5%	-0,090	1,172***	0,440***	0,159**	-0,526	0,0347	0,13
10%	-0,064	0,678***	0,207***	0,104**	-0,438	-0,034	0,12
25%	-0,028	0,496***	0,263***	0,052*	0,004	-0,052	0,09
50%	0,002	0,363***	0,214***	0,044**	-0,121	-0,054**	0,08
75%	0,033	0,537***	0,172***	0,048	-0,039	-0,018	0,05
90%	0,062	0,331*	0,048	0,038	-0,408	-0,044	0,05
NBL							
.5%	-0,070	1,079***	0,267**	0,082	-0,581	0,095	0,12
10%	-0,049	1,052***	0,230***	0,040	-0,211	0,064	0,11
25%	-0,022	0,576***	0,214***	0,039*	-0,142	-0,019	0,10
50%	0,001	0,453***	0,194***	0,041**	-0,017	-0,028	0,08
75%	0,027	0,198*	0,165***	0,100***	-0,172	-0,061***	0,06
90%	0,054	0,110	0,159***	0,095***	-0,011	-0,057	0,05
OXY							
.5%	-0,062	0,974***	0,198**	0,087*	0,374	0,015	0,17
10%	-0,045	0,700***	0,224***	0,06**	0,272	-0,006	0,13
25%	-0,021	0,522***	0,135***	0,008	-0,212	-0,022	0,09
50%	0,003	0,256***	0,158***	0,010	-0,265	-0,035	0,08
75%	0,0244	0,314***	0,131***	0,026	-0,288	-0,024	0,05
90%	0,046	0,213	0,128***	0,035	-0,392*	-0,013	0,05
PHX							
.5%	-0,091	0,780**	0,404***	0,085	-0,470	0,011	0,15
10%	-0,066	0,682**	0,385***	0,111**	-0,192	0,004	0,10
25%	-0,027	0,433***	0,207***	0,064	-0,164	0,010	0,04
50%	0,001	0,306***	0,153***	0,040**	-0,120	-0,008	0,03
75%	0,034	0,263	0,193***	0,079**	-0,240	-0,000	0,03
90%	0,068	0,203	0,148*	0,164***	-0,485	-0,037	0,05
PVA							
.5%	-0,132	2,479***	0,482*	0,153	-1,055	0,308	0,13
10%	-0,088	1,577***	0,366***	0,154**	-0,643	0,125	0,11
25%	-0,041	-0,862***	0,259***	0,114***	-0,158	-0,028	0,08
50%	-0,001	-0,524***	0,270***	0,090***	-0,384	-0,032	0,06
75%	0,033	0,401**	0,248***	0,078**	-0,078	-0,026	0,05
90%	0,077	1,057***	0,155*	0,131***	-0,147	0,107**	0,05
PTR							
.5%	-0,062	0,583*	0,068	0,025	-0,455	-0,061	0,12
10%	-0,047	0,141***	0,141***	0,041	-0,428*	-0,061**	0,11
25%	-0,024	-0,393***	0,168***	0,018	-0,302**	-0,034*	0,10
50%	0,000	0,389***	0,149***	0,011	-0,194	-0,023	0,06
75%	0,025	0,349***	0,131***	0,001	-0,127	-0,018	0,05
90%	0,052	0,303	0,182***	0,051	-0,027	-0,057	0,07
PQ							
.5%	-0,139	1,347*	0,489*	-0,048	-1,241	0,039	0,08
10%	-0,102	1,475***	0,249*	0,014	-0,713	-0,713	0,07
25%	-0,047	1,032***	0,245***	0,122***	-0,719**	0,010	0,07
50%	0,001	0,616***	0,263***	0,111***	-0,903***	-0,066*	0,07
75%	0,045	0,352	0,296***	0,107***	-0,833***	-0,080*	0,06
90%	0,095	0,078	0,374***	0,112	-1,746***	-0,090	0,07
PXD							
.5%	-0,087	1,462***	0,520***	0,065	0,499	0,175**	0,18
10%	-0,058	1,222***	0,370***	0,112***	0,253	0,105**	0,15
25%	-0,028	0,786***	0,317***	0,085***	0,109	0,020	0,10
50%	0,001	0,685***	0,180***	0,093***	-0,113	0,015	0,08
75%	0,033	0,550***	0,240***	0,117***	-0,010	0,025	0,07
90%	0,065	0,460**	0,233***	0,089**	0,283	0,004	0,06
RRC							
.5%	-0,086	0,698**	0,307***	0,093*	-0,700*	0,039	0,13
10%	-0,066	0,775***	0,239***	0,113***	-0,287	0,037	0,11
25%	-0,030	0,366**	0,268***	0,108***	-0,423*	-0,040	0,07
50%	0,003	0,302**	0,258***	0,089***	-0,197	-0,070***	0,06
75%	0,034	0,264*	0,229***	0,094***	-0,202	-0,073**	0,06
90%	0,070	0,292	0,214***	0,100**	0,107	0,029	0,05
SM							
.5%	-0,089	1,304***	0,464***	0,098	-0,231	0,125	0,13
10%	-0,069	1,428***	0,351***	0,107**	-0,324	0,122***	0,12

25%	-0,022	0,686***	0,321***	0,071**	-0,209	0,021	0,10
50%	0,003	0,351***	0,264***	0,086***	-0,166	-0,031	0,07
75%	0,033	0,257	0,230***	0,130***	-0,409*	-0,042	0,06
90%	0,067	0,337	0,177**	0,140***	-0,688**	-0,012	0,06
STO							
.5%	-0,060	0,305	0,288***	0,007	-0,963***	-0,060	0,23
10%	-0,046	0,493***	0,304***	-0,004	-0,796***	-0,022	0,19
25%	-0,022	0,581***	0,239***	0,025	-0,637***	0,002	0,14
50%	0,000	0,442***	0,196***	0,029	-0,514***	-0,023	0,11
75%	0,024	0,319***	0,183***	0,002	-0,549***	-0,035	0,10
90%	0,047	0,348**'	0,180***	0,052*	-0,296	0,005	0,09
CVX							
.5%	-0,054	0,900***	0,124**	0,080**	0,293	0,059*	0,15
10%	-0,035	0,265***	0,107**	0,034	0,009	0,008	0,10
25%	-0,016	0,473***	0,072***	0,009	-0,157	-0,001	0,08
50%	0,002	0,331***	0,086***	0,008	-0,033	-0,019	0,07
75%	0,018	0,219***	0,058**	0,025*	-0,180	-0,028*	0,06
90%	0,035	0,213*	0,050	0,027	-0,325*	-0,013	0,04
XOM							
.5%	-0,048	0,471***	0,078	0,071**	0,309	-0,020	0,12
10%	-0,035	0,471***	0,113**	0,058**	0,270	-0,015	0,09
25%	-0,015	0,344***	0,092***	0,003	-0,081	.0,006	0,06
50%	0,001	0,268**	0,077***	0,010	-0,017*	-0,029	0,05
75%	0,017	0,067	0,037	0,028**	-0,161	-0,040***	0,04
90%	0,034	0,024	0,029	0,026	-0,390**	-0,035	0,03
SGY							
.5%	-0,129	1,833**	0,540**	0,202	1,086	0,147	0,13
10%	-0,080	1,058***	0,465***	0,174**	0,104	0,037	0,11
25%	-0,037	0,841***	0,339***	0,093**	-0,179	0,016	0,08
50%	-0,003	0,522***	0,266***	0,073***	-0,482**	-0,055**	0,08
75%	0,032	0,407***	0,257***	0,058**	-0,314	-0,079***	0,07
90%	0,074	0,855***	0,253**	0,044	-0,816*	0,074	0,06
SU							
.5%	-0,073	0,692**	0,294**	0,047	-0,010	-0,003	0,12
10%	-0,050	0,403**	0,338***	0,049	-0,410	-0,040	0,11
25%	-0,024	0,340***	0,252***	0,031	-0,419**	-0,013	0,10
50%	0,003	0,265***	0,232***	0,030	-0,500***	-0,041**	0,08
75%	0,028	0,285**	0,235***	0,048**	-0,463***	-0,039	0,08
90%	0,055	0,339*	0,256***	0,0579	-0,399	-0,016	0,06
SFY							
.5%	-0,149	2,130***	0,478**	0,174	-0,994	0,224	0,13
10%	-0,096	1,508***	0,623***	0,039	-0,420	0,102	0,09
25%	-0,043	0,790***	0,392***	0,096**	-0,226	-0,013	0,08
50%	-0,003	0,639***	0,299***	0,078***	-0,341	-0,059	0,07
75%	0,038	0,787***	0,259***	0,120***	-0,238	0,0142	0,06
90%	0,084	1,294***	0,239***	0,145***	-0,339	0,146***	0,06
UPL							
.5%	-0,096	0,933**	0,580***	0,126	-0,012	0,033	0,17
10%	-0,073	1,023***	0,496***	0,202*	0,401	0,025	0,16
25%	-0,034	0,746***	0,404***	0,121***	0,147	0,001	0,10
50%	-0,001	0,392***	0,259***	0,104***	0,015	-0,041	0,08
75%	0,034	0,386**	0,232***	0,073**	-0,278	-0,033	0,05
90%	0,072	0,386	0,133	0,096**	-0,266	0,040	0,03
BHI							
.5%	-0,078	1,027**	0,185	0,071	0,044	0,010	0,07
10%	-0,058	0,838***	0,264***	0,050	-0,134	0,041	0,08
25%	-0,024	0,583***	0,184***	0,035	-0,051	0,000	0,07
50%	0,001	0,452***	0,145***	0,043**	-0,088	-0,033*	0,07
75%	0,028	0,437***	0,067	0,074***	-0,112	-0,030	0,06
90%	0,059	0,386	0,113	0,067	-0,462	-0,024	0,04
ESV							
.5%	-0,091	1,129***	0,037***	0,087	0,157	0,046	0,11
10%	-0,067	1,023***	0,396***	-0,000	0,019	0,053	0,08
25%	-0,032	0,608***	0,292***	0,049	0,025	-0,022	0,07
50%	0,000	0,428***	0,226***	0,044*	-0,239	-0,07***	0,07
75%	0,031	0,364***	0,149***	0,055**	-0,398*	-0,031	0,06

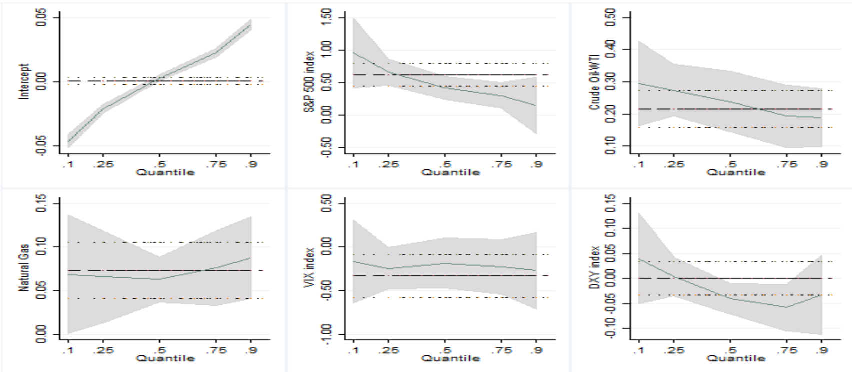
90%	0,064	0,449**	0,023	0,075	-0,454	-0,006	0,05
HAL							
.5%	-0,082	1,126**	0,374**	0,140	0,499	0,039	0,10
10%	-0,059	0,929***	0,238***	0,125***	0,285	0,017	0,10
25%	-0,028	0,658***	0,203***	0,054*	0,049	-0,010	0,07
50%	0,001	0,329***	0,106**	0,066***	-0,179	-0,072	0,07
75%	0,032	0,408***	0,081*	0,095***	-0,515**	-0,062**	0,06
90%	0,063	0,244	0,061	0,102**	-0,183	-0,080*	0,05
HP							
.5%	-0,096	1,016**	0,207	0,120	-0,509	0,067	0,11
10%	-0,062	0,549**	0,408***	0,063	-0,195	-0,006	0,08
25%	-0,027	0,646***	0,265***	0,062**	0,093	-0,010	0,08
50%	0,004	0,318***	0,209***	0,057**	0,056	-0,069***	0,07
75%	0,035	0,0357***	0,130***	0,103***	-0,179	-0,034	0,05
90%	0,064	0,155	0,072	0,112***	-0,652**	-0,039	0,04
NBR							
.5%	-0,099	1,844***	0,338**	0,119	-0,669	0,202**	0,14
10%	-0,069	1,127***	0,350***	0,117**	-0,354	0,059	0,12
25%	-0,036	0,694***	0,295***	0,096***	-0,299	-0,015	0,11
50%	0,001	0,358**	0,216***	0,083***	-0,300	-0,102***	0,09
75%	0,034	0,504***	0,154***	0,062**	-0,299	-0,070**	0,07
90%	0,066	0,695***	0,049	0,095**	-0,401	0,007	0,04
NE							
.5%	-0,081	0,873**	0,391***	0,008	0,048	0,052	0,13
10%	-0,064	0,754***	0,345***	0,013	-0,120	0,050	0,10
25%	-0,030	0,883***	0,260***	0,023	0,215	-0,002	0,10
50%	0,000	0,587***	0,215***	0,025	0,041	-0,044*	0,08
75%	0,029	0,339**	0,158***	0,018	-0,223	-0,041	0,06
90%	0,062	0,380*	0,074	-0,017	-0,370	-0,008	0,04
SLB							
.5%	-0,066	0,660**	0,213*	-0,028	-0,682	0,017	0,13
10%	-0,048	0,650***	0,150***	-0,0113	-0,224	-0,022	0,12
25%	-0,023	0,563***	0,185***	0,017	0,015	-0,016	0,10
50%	0,001	0,443***	0,148***	0,008	-0,061	-0,051**	0,09
75%	0,026	0,460***	0,098***	0,022	-0,286*	-0,043**	0,08
90%	0,053	0,622***	0,122**	0,0711**	-0,457*	0,003	0,08
TDW							
.5%	-0,085	0,837***	0,252***	0,045	-0,560	0,085	0,09
10%	-0,062	0,730***	0,153**	0,050	-0,808**	0,006	0,10
25%	-0,031	0,696***	0,141***	0,065**	-0,434**	-0,017	0,07
50%	0,001	0,629***	0,136***	0,070***	0,145	-0,024	0,08
75%	0,028	0,435***	0,135***	0,042*	-0,055	-0,026	0,07
90%	0,054	0,433**	0,016	0,028	-0,355	-0,006	0,06
WFT							
.5%	-0,975	1,260***	0,415***	0,105	0,041	0,075	0,17
10%	-0,071	0,919***	0,317***	0,091	-0,126	0,016	0,12
25%	-0,031	0,889***	0,043	0,043	-0,268	0,002	0,09
50%	0,001	0,660***	0,216***	0,047**	-0,360*	-0,046*	0,09
75%	0,034	0,630***	0,215***	0,022	-0,192	-0,053	0,08
90%	0,069	0,621***	0,139*	0,051	-0,139	-0,019	0,06
EEP							
.5%	-0,053	1,043***	0,192***	0,014	0,351	0,087**	0,13
10%	-0,037	0,832***	0,209***	0,011	0,374	0,066*	0,10
25%	-0,016	0,399***	0,120***	0,023*	0,088	0,003	0,07
50%	0,001	0,241***	0,097***	0,010	-0,031	-0,001	0,05
75%	0,016	0,243***	0,062**	0,003	0,034	-0,016	0,05
90%	0,033	0,403***	0,080*	0,005	0,249	-0,002	0,04
OGE							
.5%	-0,046	0,610**	-0,008	-0,025	-0,060	-0,016	0,08
10%	-0,029	0,528***	-0,020	-0,028	-0,269	0,007	0,08
25%	-0,013	0,269***	-0,022	0,000	-0,069	-0,030**	0,06
50%	0,002	0,258***	-0,021	0,019*	0,048	-0,031***	0,05
75%	0,017	0,230***	0,005	0,015	-0,009	-0,030**	0,05
90%	0,031	0,143	0,050	0,029	-0,078	-0,033	0,05
PAA							
.5%	-0,047	0,550**	0,144	-0,003	-0,358	0,014	0,11
10%	-0,031	0,341**	0,123**	0,031	-0,209	-0,018	0,08

25%	-0,015	0,151*	0,084***	0,000	-0,161	-0,043	0,06
50%	0,002	0,138*	0,056**	0,000	-0,089	-0,034*	0,04
75%	0,017	0,160**	0,073***	-0,007	0,080	-0,021	0,03
90%	0,033	0,200	0,026	0,018	-0,020	-0,023	0,02
WMB							
.5%	-0,100	1,080**	0,295*	-0,039	-0,440	-0,072	0,13
10%	-0,063	1,304***	0,213**	0,054	0,000	0,031	0,13
25%	-0,029	1,024***	0,180***	0,058**	0,165	-0,006	0,09
50%	0,001	0,824***	0,227***	0,077***	0,007	-0,0078	0,08
75%	0,027	0,680***	0,0166	0,080***	-0,220	-0,022	0,07
90%	0,059	0,072***	0,036	0,109**	-0,483	-0,006	0,05

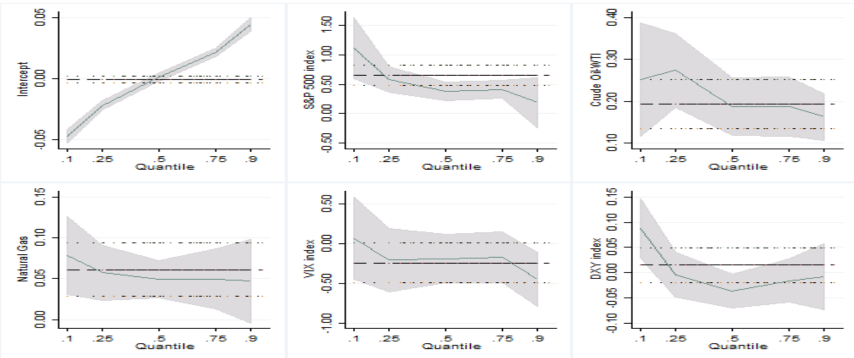
Table: Quantile regression result. The ***, ** and * indicates significance at the 1%, 5% and 10% level.

Appendix C Quantile regression plot for the different sub sectors. Intercept is the stock return alpha, S&P 500 index the percentage change in Market return; Crude oil WTI is the percentage change in the Crude oil price; Natural gas is the percentage change in Natural gas price; DXY index the percentage change in US Dollar index and VIX index the percentage change in a volatility index

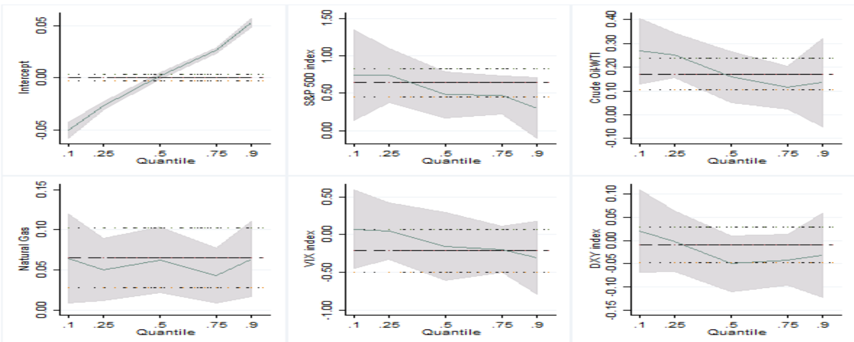
Producers



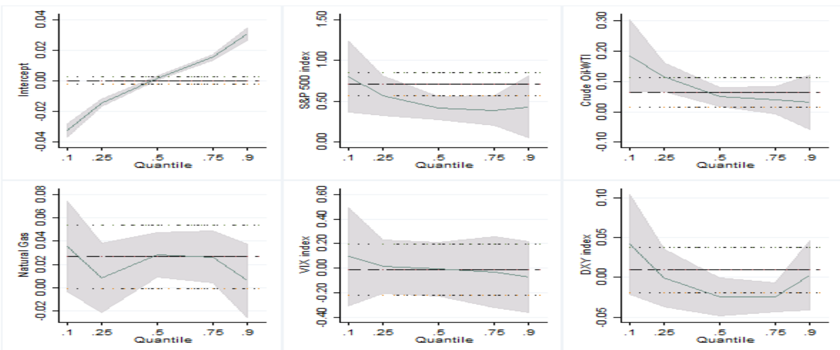
Integrated



Service and Equipment



Pipeline



Appendix D - Stata Commando

I present the Stata features to conduct a complete data analysis. Throughout the appendix, Stata commands are shown in bold font and comments using regular font. The variables stored in the file will be denoted as follows:

y: Dependent variable
x1, x2, x3, x4, x5: Explanatory variables

```
// the import excel command allows to directly read
// file to use to read the first sheet of the workbook
// whereas there are not column names on the first row
import excel y x1 x2 x3 x4 x5 example.xls, clear

// specified summary statistics for a single variable
tabstat y, stats(mean sd skewness kurtosis)

// displays the correlation matrix for a group of variables
Correlate y x1 x2 x3 x4 x5


// the width option allows to specify the width of the bins
histogram y, frequency

// OLS, multiple regression estimation
regress y x1 x2 x3 x4 x5

// QR estimation for more quantiles
qreg y x, q(.10 .25 .5 .75 .9)

// to compute Bootstrap500 replicates of 25-th quantile
// regression coefficients.
bootstrap, qreg y x1 x2 x3 x4 x5, q(.25) _b, reps(500)

// In order to obtain a graphical representation of the QR //
coefficients - install the grqreg module
ssc install grqreg
// after the installation, the grqreg command allows
// to plot the QR coefficients
// it works after the commands: qreg, bsqreg, sqreg
qreg y x1 x2 x3 x4 x5
// Quantile Regression coefficient plot for the slope
// by default the graph for all the estimated
// coefficients except.
grqreg
// to set the minimum and maximum values, and the
// steps for the quantiles (min = .10 and max = .90)
gqreg y x1 x2 x3 x4 x5, qmin = .01 qmax=.99 qstep=.01
// to draw the Quantile Regression confidence intervals
gqreg, ci level=0.05
// to plot the OLS regression-line
gqreg, ols olsci ci level=0.05

// test whether the effect of weight is the same at the
// 25th and 75th percentiles
qui sqreg y x1 x2 x3 x4 x5, nolog q(.1 .25 .5 .75 .9)
test [q10=q50]: Xi
test [q25=q50]: Xi
test [q75=q50]: Xi
test [q90=q50]: Xi
```

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