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ORIGINAL RESEARCH

Risk factors in stock returns of U.S. oil and gas companies: evidence from quantile regression analysis

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Abstract
The boom and bust in oil prices during the last two decades have attracted many investors to oil and gas companies in search of returns and risk diversification benefits. This study analyzes the impact of several risk factors, including oil and gas prices, overall stock market returns, stock market volatility index, and the trade-weighted U.S. Dollar Index (DXY) on stock returns of U.S. oil and gas companies, using a quantile regression (QR) method. The findings suggest that most firms in the U.S. oil and gas sector have significant risk exposures to changes in market portfolio returns and oil prices. The analysis also reveals that risk factor sensitivities are not equal across quantiles, indicating asymmetric responses of oil and gas stock returns to various systematic risk factors. Changes in oil prices, in general, are likely to have the strongest impact in the left tail, and this impact gradually decreases toward the right tail. This implies that an investor with a long position in an oil and gas stock will be exposed to a substantially greater risk than an investor with a short position.

Keywords Stock returns · Crude oil · Value at Risk (VaR) · Oil and gas industry · Quantile regression

JEL Classification G12 · C3 · C22 · C58

1 Introduction

Boom and bust in oil prices during the past two decades have been a concern for investors and portfolio managers in the oil and gas industry because changes in oil and gas prices are likely to have a significant impact on the revenues, profits, investments, cashflows, and stock returns of oil and gas firms (Boyer and Filion 2007; Mohanty and Nandha 2011). Prior studies provide evidence that changes in the crude oil prices are likely to have a positive effect on oil and gas industry returns (Al-Mudhaf and Goodwin 1993; Boyer and Filion 2007; Mohanty and Nandha 2011). With growing interest in the relationship between

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systematic risk factors and the return-generating process in oil and gas stocks, a number of studies investigate drivers of oil and gas sector returns, including aggregate market returns, interest rates, exchange rates, natural gas prices, and stock market implied volatility (VIX)[1] in addition to changes in crude oil prices (e.g., Mohanty and Nandha 2011; Ramos and Veiga 2011; Mensi et al. 2014; Tjaaland et al. 2016; Kang et al. 2017; Liu and Kemp 2019). Guesmi et al. (2018) utilize multifactor models to disentangle contagion from fundamental factors in Europe, Asia and North America. They find that oil price risk is equally important as contagion. They define contagion as excess correlation between markets not explained by fundamental factors. They also find that oil price volatility can increase contagion in markets linked to the USA. Bedoui et al. (2018) use copula based GARCH models to analyze the dependence among oil, gold and USD exchange rate and find stronger correlation in financial crisis periods than in calm periods.

Most of these studies, however, assume a linear relationship between independent and dependent variables and use ordinary least squares (OLS) regression models,[2] while ignoring the non-normal, skewed, fat-tailed distribution of return data and the possible non-linear relationship between dependent and independent variables (e.g., Zhu et al. 2016; You et al. 2017; Zhang et al. 2022).

To address the heterogeneity in return distributions and the non-linear relationship between dependent and independent variables, a few studies have analyzed the effects of oil price shocks on aggregate stock market returns using quantile regression (QR) models (e.g., Tsai 2012, for Asian stock markets; Mensi et al. 2014, for the U.S. and emerging stock markets; Nusair and Al-Khasawneh 2017, for stock markets in Gulf Council Countries; You et al. 2017; Zhu et al. 2016; Xiao et al. 2018, for Chinese stock markets; Das and Kannadhasan 2020, for emerging stock markets). The overall findings of the above studies suggest that the coefficient of a risk parameter is not constant throughout the distribution of stock returns.[3] Other studies based on QR analysis provide evidence that stock market responses to oil price shocks may differ significantly when the stock market is bearish than when it is bullish (e.g., Sim and Zhou 2015; Reboredo and Ugolin 2016; Zhu et al. 2016).

Galvao et al. (2020) suggest that QR models represent an important class of non-linear data and are robust in terms of capturing some stylized facts such as outliers and asymmetric dependence when the assumption of linearity may not be appropriate (Guo et al. 2018;

[1] The Chicago Board of Options Exchange (CBOE) Volatility Index (VIX), a measure of investors' attitude toward risk, has been found to be negatively related to stock returns (e.g., Bollerslev et al. 2009; Ready 2018). Tjaaland et al. (2016) find a negative association between VIX and stock returns of oil and gas companies.

[2] For example, Elyasiani et al. (2011) investigate the impact of macroeconomic forces such as changes in oil prices and stock market risk factors on return-generating processes of 13 U.S. industry sectors. El-Sharif et al. (2005) use a multifactor model to examine the impact of oil price risk on stock returns of the U.K. oil and gas industry. Similarly, Sadorsky (2001) uses a multifactor risk model to study the effects of oil price risk on stock returns of Canadian oil and gas firms.

[3] Badshah (2013) examines the nexus between stock index returns and changes in VIX using a QR method and finds evidence of a significant negative and asymmetric return-volatility relationship in which the asymmetry increases from the 0.5 quantile to the 0.95 quantile. The study also provides evidence that the OLS regression underestimates this relationship in the upper quantiles. Using QR analysis, Chiang and Li (2012) examine the risk-return relationship between daily volatility and stock index returns in the U.S. stock markets. They find that the risk-return relationship seems to evolve from negative to positive as the quantile increases. For quantiles below the median, excess return is negatively related to risk and vice versa. These finding suggests that, during optimistic market conditions, investors anticipate that increased volatility will be compensated by a higher return, whereas for pessimistic market conditions, stock prices are likely to fall when volatility increases due to increased uncertainty.

Geraci 2018). Unlike OLS analysis, QR analysis allows the coefficient estimates to vary throughout the distribution of the dependent variable, providing a complete picture of the relationship between the explanatory variables and dependent variable. QR analysis also enables market participants to study how the impact of any macroeconomic risk variable might vary throughout the distribution of stock returns of a given firm. As indicated earlier, QR analysis overcomes two major limitations associated with OLS models. First, the OLS method minimizes the sum of squared deviations. The QR approach, unlike the OLS method, minimizes the sum of weighted absolute deviation. Therefore, estimates based on OLS models in comparison to those of QR models are likely to be more biased if there are outliers in data with a non-normal distribution. Second, OLS models are not suitable to capture variations in return sensitivities of stock returns in response to a change in the individual risk variable. In contrast, QR analysis captures estimates of return sensitivities that might vary throughout the distribution in response to a change in individual risk exposure. For example, stock returns of an oil and gas company may react differently to oil price shocks when the stock market is bearish than when it is bullish. Similarly, an energy stock also may react differently (asymmetrically) to a positive oil price change than to a negative oil price change.

This study investigates the relationship between stock returns for U.S. oil and gas firms and changes in oil prices and other macro-risk variables using a QR model. The QR methodology is designed to explore the impact of various risk variables on oil and gas stock returns related to extreme downside (upside) risk under adverse (favorable) market conditions. Further, the study examines whether the dependence between energy stock returns and macroeconomic risk variables is symmetric or asymmetric. To the best of our knowledge, this is the first study to analyze the impact of macroeconomic risk factors on stock returns of oil and gas companies in the U.S. using QR analysis. The current study builds on prior research that examines the impact of oil price shocks on stock markets using QR analysis (e.g., Roberedo and Ugolini 2016; Zhu et al. 2016; You et al. 2017; Xiao et al. 2018; Du Plooy 2019; Nusair and Olson 2019; Das and Kannadhasan 2020).[4] The study uses weekly equity returns for 49 listed U.S. oil and gas companies from 2000 to 2015. Sample firms are grouped into categories that reflect four major subsectors in which they operate, including exploration and production, integrated oil and gas, oil equipment and services, and pipelines. The findings suggest that, relative to benchmark OLS results, QR results provide a more comprehensive picture of the risk-return relationship. Further, QR analysis identifies nuances that would not have been uncovered by standard OLS analysis.

The results based on OLS analysis as well as QR analysis show that most firms in the oil and gas sector have significant risk exposures to changes in market portfolio returns and oil prices. QR analysis also reveals that risk-actor sensitivities are not equal across quantiles, indicating asymmetric responses of oil and gas stock returns to various risk factors. We test whether the estimated parameters in selected quantiles are different from those in the median. The QR results show that the coefficients at quantiles 0.10, 0.75, and 0.90 are significantly different from those of the median and that the sensitivity to key risk factors varies across the distribution. The results also provide a comprehensive picture of the effects of all risk variables on oil and gas companies' returns during normal times as well as during periods with extreme market volatility. The results show that changes in oil prices are

[4] Sim and Zhou (2015) use QR analysis and find that U.S. stock returns react differently to oil price shocks in the bear market than in the bull market, indicating that there is an asymmetric dependence between oil prices and returns on the stock market.

likely to have the strongest impact in the left tail and that this impact gradually decreases toward the right tail. This implies that an investor with a long position in an oil and gas stock will be exposed to substantially greater risk when the oil price is high than will an investor with a short position when the oil price is low.

The study contributes to the literature in several ways. First, we use QR analysis to determine risk factor sensitivities in U.S. oil and gas stock returns. Second, we uncover asymmetric dependence between stock returns and macroeconomic risk factors under extreme market conditions. Third, consistent with previous studies (Engle and Manganelli 2004; Rubia and Sanchis-Marco 2013), we apply a QR model and estimate Value at Risk (VaR)[5] for two selected energy stocks (i.e., Chesapeake Energy and ENI SPA). These results present more accurate tail risk distributions of stock returns at the firm level. The risk management analysis is conducted at the individual firm level and reveals that it would be inappropriate for a single firm to use the industry average when the return sensitivity of a firm in response to a particular risk differs significantly from one firm to another.

The remainder of the paper is organized as follows. Section 2 provides the data and methodology. Section 3 presents the empirical results for risk factor sensitivities in U.S. oil and gas stock returns based on quantile estimates using the QR approach and includes a comparison of these results with those of traditional estimates based on the OLS method. Section 4, which contains implications for investors and portfolio managers who invest in oil and gas companies, concludes.

2 Methodology and data

2.1 Methodology

There are various theories that describe the relationship between return and risk. The mean–variance equilibrium model, developed by Sharpe (1964), and Lintner (1964), is one of the leading models that describes the relationship between return and risk. According to the model, the expected return for any asset can be expressed by a linear risk model that states that expected rate of return on any asset is the sum of a risk-free rate of return and a risk premium.

Previous studies use multi-factor linear risk models based on an OLS approach to examine the impact of systematic risk factors on stock returns (e.g., Al-Mudhaf and Goodwin 1993; Fama and French 1993; Jin and Jorion 2006; Nandha and Faff 2008; Mohanty and Nandha 2011; Ramos and Viega 2011). These studies use a multivariate regression model to describe the average relationship of stock returns with a set of risk factors.

As an alternative to the mean–variance equilibrium model, Ross (1976) developed the arbitrage pricing theory (APT) of capital assets. In APT, expected return and risk are expressed as a linear function of expected returns and a number of macroeconomic risk factors. The model can be expressed as follows:

[5] Value at Risk (VaR) or expected shortfall can be established based on systematic and unsystematic risk components. In ordinary least squares (OLS) models, one has to make a simple parametric form of the error variance (e.g., normal distribution). It is well known that distributions of stock returns have fat tails and are often skewed. Thus, the assumption of normality of data does not hold, which leads to an underestimation of risk. Hence, using QR analysis, one could precisely estimate the risk. In addition, the impact of the risk factors on VaR (e.g., the 1% VaR) can be estimated as well.

$$R_i = \alpha_i + \beta_{i,1} * F_1 + \beta_{i,2} * F_2 + \cdots + \beta_{i,K} * F_K + \varepsilon_i \quad (1)$$

The error term ε_{in} is expected to be 0. Investors assume a perfect and frictionless capital market. The factors must be risk factors that are tradeable so that their position can be replicated. In contrast to the mean–variance equilibrium model, APT posits that the market corrects for arbitrage possibilities because the model assumes a number of investors who buy and sell large volumes of securities, which, in turn, leads to equilibrium prices. APT is recognized as a more robust test compared to the mean–variance equilibrium model. Nevertheless, this model is not optimal, as it does not tell how many variables to use and which risk factors are relevant. The risk sensitivities of each factor is estimated from a multiple-linear regression model based on an OLS method.

We argue, however, that the estimation of sensitivities of risk factors based on OLS might not be entirely satisfactory due to particular stylized characteristics of stock returns. Jondeau et al. (2006) show that stock price returns 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 effects of risk factors on the entire distribution of returns and may provide estimates that are not robust. The QR method developed by Koenker and Basset (1978) explicitly models specific quantiles of the distribution of a dependent variable using exogenous variables with different coefficients for each quantile.

The QR analysis overcomes some of the limitations associated with OLS estimates. First, QR captures all of the information about the dependence structure and allows for an analysis beyond linear correlation (e.g., Galvao et al. 2020). Second, the QR approach is a more effective tool than is OLS in terms of analyzing extreme movements in risk variables and risk management (e.g., Du Plooy 2019). The behavior of tails of a distribution is more efficiently described by the QR approach than by the OLS method. Third, QR provides a more comprehensive picture of the effects of the predictors on the response variable by modeling the relationship between a set of predictor variables and specific percentiles (or quantiles) of the response variable (e.g., Xiao et al. 2018; Nusair and Olson 2019). Fourth, the QR parameter estimates the change in a specified quantile of the independent variable produced by a one-unit change in the dependent variable. This allows researchers to compare how some percentiles may be more affected by certain predictor variables than others and, thus, provides a complete picture of the joint distribution of the data (e.g., Koenker 2004; Mensi et al. 2014). Fifth, the increasing volatility of the price of oil has made companies and investors wary of a potentially negative cash flow and financial stress and more concerned with potential lower quantiles. Thus, the relationship between risk and return in addition to the asymmetric valuation response to oil price changes is better analyzed by applying a QR method (e.g., Mohn and Osmundsen 2011; Xiao et al. 2018). In sum, when the return distributions are skewed and non-normal, quantiles of distribution can succinctly describe the asymmetry and fat tail of a skewed distribution. Finally, QR analysis has also been employed to measure VaR, a widely used quantitative measure of extreme downside market risk (e.g., Engle and Manganelli 2004; Rubia and Sanchis-Marco 2013).

The QR method is distribution-independent, and regression parameters are obtained by minimizing a function of the absolute deviation between observations *y* and regression estimates $y\hat{}$, weighted by the quantile q. In this way, we can build a more comprehensive picture of the conditional distribution of *Y*, given *X*. The results of QR for the full range of quantiles [0.1] by Cade and Noon (2003) allow for the identification of potential interactions between measured and unmeasured factors.

The *qth* quantile linear regression model is given by:

$$Y_t = \alpha^q + \sum_{i=1}^{k} \beta_i^q X_{ti} + \varepsilon_j, \tag{2}$$

where Y_t is the stock return at time t, X_i, $i = 1, \ldots, k$, is the relative 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:

$$Q_q(Y_j|X_i) = X_i\beta_q + Q(e) \tag{3}$$

The conditional qth quantile, $0 < q < 1$, is defined as any solution to the minimization problem. We find the parameter β_q by the following optimization problem (e.g., Koenker and Basset 1978):

$$\min_{\beta_1,\beta_2} \sum_{t=1}^{T} \left(q - 1_{Y_t \le \beta_1 X_{1,t}}\right)(Y_j - \beta_1 X_{1,t}), \tag{4}$$

where $1_{Y_t \le X_{1,t}\beta_1} = 1$ if $Y_j \le \beta_1 X_{1,t} + \beta_2 X_{2,t}$, or 0 otherwise. The solution, $\hat{\alpha}_i^q$ and $\hat{\beta}_i^q$, is found by using numerical optimizations. For the i^{th} regressor, the marginal effect is the coefficient for the q^{th} quantile:

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

A QR parameter $\left(\beta_{qi}\right)$ 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 are important for β_{qi}. First, coefficients can be significantly different from zero; and, second, coefficients can be significantly different from OLS coefficients, revealing varying effects along the distribution.

The model in Eq. (4) can be extended by additional factors. QR is more robust to outliers than is 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 QR coefficient estimates can be obtained with asymptotic and bootstrapping methods. Both methods provide robust results (Koenger and Hallock 2001), with the bootstrap method preferred as being more practical (Hao and Naiman 2007).

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 that involves repetitive computations to estimate the shape of the sampling distributions. Bootstrapping is a step toward the true population parameters and effects, which we continue to seek. It alleviates measurement errors in the relatively few observations that we have. Bootstrapping allows one to obtain standard errors for any statistic (Efron 1982). Let $y_t^*, x_t^*, i = 1, \ldots, n$ be a randomly drawn sample from the empirical distribution F_{nxy}. It follows from Eq. (2) that $Y_t = \beta_i{}^q X_i + \varepsilon_j$, where $Y_t = y_1^*, \ldots, y_n^*$ and $(x_i^*, \ldots, x_n^*)$. Let $\hat{\beta}_i^q$ denote the bootstrap estimate obtained from a QR analysis of Y_t on X_i. This process can be repeated B times to yield bootstrap estimates $\widehat{\beta}_i^q, \ldots, \widehat{\beta}_{iB}^q$. The bootstrap estimation of Δ_q is given by:

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

where $\overline{\beta}_i^{\,q} = \frac{1}{B} \sum_{j=1}^{B} \widehat{\beta}_i^q$ 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, such as 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 QR estimates using the pairs-bootstrap, a procedure recommended by Buchinsky (1995).[6] We use the bootstrap techniques because there are relatively few observations in the tail, and we do not know the parameter distribution in the tail.

2.2 Data and variables

The study includes a sample of 49 publicly traded oil and gas companies listed on the New York Stock Exchange (NYSE) and the American Stock Exchange. For each company, we use weekly closing prices of the stock over a period of January 1, 2000, to December 31, 2015. The weekly return data are obtained from DataStream[7] and are denominated in U.S. dollars, with the data adjusted for stock splits. The trade-weighted DXY is a weighted average of the foreign exchange value of the U.S. dollar against major currencies, including those of the Euro area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. The Chicago Board Options Exchange (CBOE) Volatility Index (VIX) is the proxy for investors' attitude toward risk, which expected to be negatively related to stock returns of oil and gas companies (e.g., Bollerslev 2009; Ready 2018). Data for DXY and VIX are obtained from the DataStream database. The weekly returns on the West Texas Intermediate (WTI) crude oil price and weekly returns on the New York Mercantile Exchange (NYMEX) natural gas price are used in the study. AppendixA provides a list of the sample of 49 oil and gas firms and their respective ticker symbol, industry sector, and market capitalization in U.S. dollars. Our sample is further divided into four subsectors: (1) Oil and Gas producers (29 firms), (2) Integrated Oil and Gas (7 firms), (3) Equipment and Service (9 firms), and (4) Pipelines (4 firms). Table 1 provides the descriptive statistics and correlation coefficients among the variables.

[6] We checked our QR results using *bsqreg*, but the statistical significance of major variables is then reduced slightly, and the use of a bootstrap method does not result in our discarding the findings. We also find that risk factors such as overall stock market returns, oil price, gas price, and VIX are still significant under the bootstrap estimation procedure described here.

[7] DataStream is a numeric database provided by Thomson Reuters.

Table 1 Descriptive statistics and correlation matrix for variables used in the study

Variable	Obs	Mean	SD	Min	Max
avgreturns	831	0.0027	0.0435	−2.883	0.1880
sp500indexret	833	0.0004	0.0243	−0.1645	0.1018
crudeoilwtiret	833	0.0001	0.0499	−0.2359	0.3211
naturalgasret	833	−0.0002	0.0850	−0.3204	0.4195
usdollarindexret	833	0..0000	0.0115	−0.0840	0.0397
vixindexret	833	0.0001	0.1193	−0.4276	0.6872

	avgreturns	sp500indexret	crudeoilwtiret	naturalgasret	usdollarinsexret	vixindexret
usavgreturns	1					
sp500indexret	0.3930	1				
crudeoilwtiret	0.3265	0.2293	1			
naturalgasret	0.1744	0.0108	0.1535	1		
usdollarindexret	−0.1984	−0.1929	−0.2376	−0.1021	1	
vixindexret	−0.2949	−0.7365	−0.2007	−0.0129	0.1075	1

3 Empirical results

In the analysis presented here, we develop a multifactor QR model to model the entire distribution of oil and gas companies returns and to identify risk factors that affect each conditional quantile of returns. Before doing any estimation or calculation, we make the following a priori hypotheses. First, the market beta differs significantly across firms within the oil and gas industry. Our hypothesis is based on earlier studies that have confirmed this hypothesis (e.g., Ramos and Veiga 2011; Sim and Zhou 2015). Second, the WTI gas price is significant only for companies exposed directly to gas prices. Third, DXY significantly affects firms that have operations in countries outside the United States and are exposed to other currencies. VIX is likely to have a significantly negative influence on the tail of the distribution when the market is bearish. This is consistent with our expectation that a high VIX reflects increased investor fear, whereas a low VIX suggests complacency. During periods of market turbulence, the VIX spikes higher, whereas during bullish periods, there is less fear and less impact on VIX. These hypotheses, which are contingent on the state of the markets, can be tested using multifactor QR.

3.1 Multifactor quantile estimates

A QR 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. Those changes are our primary focus here. We perform an in-sample analysis using all data from January 30, 2000, to December 30, 2015, which comprises 833 observations for a sample of 49 oil and gas companies. We begin by modeling weekly returns, focusing on the 5, 10, 25, 50, 75, and 90% quantiles. These estimates are derived from the methodology discussed in Sect. 4 based on the linear QR model:

$$Y_i^q = \alpha_i^q + \beta_{1i}^q X_{S\&P500} + \beta_{2i}^q X_{oilprice} + \beta_{3i}^q X_{gasprice} + \beta_{4i}^q X_{DXY} + \beta_{5i}^q X_{VIX} + \varepsilon_t^q, \tag{7}$$

where Y_i^q is the stock return of the selected companies; β_{1i}^q, the percentage change in market return; β_{2i}^q, the percentage change in the crude oil price; β_{3i}^q, the percentage change in the natural gas price; β_{4i}^q, the percentage change in DXY, and β_{5i}^q, the percentage change in VIX.

The estimated parameters of the QR for each firm, based on Eq. (4), are presented in Appendix B. We report the coefficient values of six quantiles as the regression output for each firm: $\tau = (5, 10, 25, 50, 75, \text{and } 90\%)$. The low quantiles (5, 10, and 25%) designate the bullish, the median quantile (0.50) denotes the normal, and, finally, the higher quantiles (75 and 90%) signify the bearish market condition. In general, estimates in lower quantiles (5, 10, and 25%) have better explanatory power than do those of estimates in higher quantiles, indicating that oil and gas stock returns react more strongly when oil prices are rising than when they are falling.

We are most interested in whether the coefficient is significant over any portion of the conditional distribution. We explore whether regression coefficients change significantly across quantiles. The results reported in AppendixB show that 48 out of 49 oil and gas companies have positive and significant coefficients for oil price variables, whereas only 24 firms have positive and significant coefficients for gas prices during the same period. We find that the gas price coefficient in central quantiles (50%) tends to be significantly different from zero, whereas in lower and upper quantiles, the gas price coefficients are not significant. The results show that oil price coefficients of 46 firms for median quantile are positive and significant at the 1% level, with regression coefficients that range from 0.062 to 0.316. These results indicate that most energy firms experience an increase in stock returns as the price of oil rises from high quantiles to low quantiles. Notably, our results indicate that oil price risk exposure is significantly higher in the lower quantile observation for most energy firms. In general, investors are more pessimistic about bad news when oil prices fall in a bearish stock market. In other words, market participants should be concerned about the general stock market condition when evaluating the impact of oil price shocks on stock returns. Overall, these results have significant implications for market participants.

Unlike oil price returns, the market return coefficients are significant at the 1% level for all companies and the entire distribution, from the 10% quantile to the 90% quantile. These findings support the argument that company earnings in the energy sector may have been driven by the U.S. economic cycle ($\beta_{i,m}^q$). One notable case is that the VIX coefficient exhibits opposite signs at opposite ends of the distribution of conditional returns for almost all oil and gas companies, with similar findings observed for other risk factors. For example, the DXY for Cimarex Energy (XEC) and China Petroleum (SNP) have coefficients equal to 0.456 and 0.104, respectively, in the 10th quantile, and the same coefficients are −0.185 and −0.297, respectively, in the 90th regression quantile. In these cases, the risk factors' coefficients form a U-shape, in which the estimate becomes lowest around the 25% percentile of the distribution of conditional returns. Clearly, the QR approach prevents us from drawing incorrect inferences with respect to the impact of risk factors on the distribution of returns.

We further examine the different impacts of risk factors between the companies within all of the subsectors. We notice that there is a considerable variation between companies in each subsector, but we present a larger picture of the various subsectors. AppendixC presents an aggregated mean return coefficient for five different quantile values ($q = 10\%$,

$q=25\%$, $q=50\%$, $q=75\%$, and $q=90\%$) of portfolio returns of oil and gas stocks within the four subsectors. The shaded areas represent estimators within a 95% confidence band. Our analysis indicates that coefficients across quantiles affect stock price returns to varying degrees in the different subsectors.

Figures in AppendixC show that the regression line for $q=50\%$ is often almost identical and close to the OLS regression line. As we move away from the 50% quantile toward estimates in the tails of the return distribution, however, the impact of the risk factors changes markedly. We find that estimates of market portfolio returns in a QR essentially follow a decreasing pattern over the quantiles of the conditional return distribution, thereby indicating higher positive returns in the lower quantiles, with lower positive returns in the upper quantiles. We also find that the pattern holds when accounting for crude oil returns. The size of the estimated natural gas coefficient for gas producers is almost unchanged in the lower quantiles of the conditional return distribution, while in the upper quantile, parameter estimates are slightly more pronounced. These findings suggest asymmetric dependence between risk factors and stock returns of oil and gas companies.

Overall, there are four main findings. First, in general, oil and gas producers 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 a larger influence than do production companies in the upper part of the tail. Pipeline companies have the lowest exposure to oil price returns. Service, equipment, and pipeline subsectors do not have significant coefficients that are as large as those of the other two subsectors (oil and gas producers and integrated companies).This is expected because oil and gas producers and integrated companies have oil as a direct input factor in their business area. It is also expected that integrated companies will have a lower impact when they take part in both downstream and upstream operations. Surprisingly, an integrated subsector has a higher impact in the upper quantile than do oil producers.

Second, the market coefficient has the highest influence on the integrated companies in all parts of the distribution. After integrated companies, the next highest are oil and gas producers. The market coefficient has the lowest impact on pipeline companies. Exposure to the market risk factor is highly significant across all quantiles for all companies and for all subsectors.

Third, gas prices have the highest impact on integrated companies in the low tail, whereas oil producers have the greatest impact in the upper tail. The market risk exposure of both oil and gas producers and integrated companies is very similar in the median quantile.

Fourth, the risk exposures of VIX are greatest in both ends (U-shape) of the distribution and lowest in the median quantile for all four subsectors, with the greatest impact on oil and gas producers in the lower tail in a bearish market. One interesting observation is that both the integrated and the equipment and services companies have relatively low exposures in the left tail, though the risk exposure increases sharply in the right tail (upper quantiles). DeLisle et al. (2011) document that sensitivity to VIX is negatively related to returns when volatility is increasing but is unrelated when it is decreasing. The low average returns on stocks with high distinctive volatility could arise because stocks with high volatility may have a high exposure to aggregate volatility risk, which lowers their average return.

To gain a better understanding to what extent these risk factors influence the stock price return in different levels of the distribution, in the next section, we present an in-depth analysis of two selected companies.

Table 2 Estimate across the quantile regression and OLS estimate for Chesapeake Energy Corp.

Quantile	5%	10%	25%	50%	75%	90%	OLS
Cons	−0.101	−0.069	−0.032	0.002	0.033	0.066	0.0002
Market	1.598***	1.031***	0.708***	0.529***	0.449***	0.378*	0.717***
Oil Price	0.518***	0.463***	0.307***	0.310***	0.186***	0.101	0.248***
Gas Price	0.026	0.086	0.162***	0.104***	0.134***	0.199***	0.133***
DXY Index	−0.735	−0.327	−0.099	−0.184	−0.364	−0.570*	0.009
VIX Index	0.185**	0.082	−0.005	−0.027	−0.027	−0.005	−0.394**
Adj.R^2	0.15	0.11	0.11	0.10	0.07	0.07	0.16

Table 3 Estimate across the quantile regression and OLS estimate for ENI S.p.A

Quantile	5%	10%	25%	50%	75%	90%	OLS
Cons	−0.062	−0.044	−0.02	0.002	0.022	0.041	0.0003
Market	0.629***	0.599***	0.520***	0.194**	0.150*	0.207**	0.409***
Oil Price	0.194**	0.157***	0.097***	0.091***	0.043	0.016	0.059**
Gas Price	0.051	0.016	−0.005	0.023	0.040**	0.057***	0.023
DXY Index	−0.396	−0.512**	0.661***	−0.522	0.439***	0.619***	0.527***
VIX Index	−0.001	0.001	−0.014	−0.049	0.047***	−0.035*	−0.028*
Adj.R^2	0.14	0.11	0.10	0.08	0.07	0.07	0.16

3.2 Analysis of Chesapeake Energy and ENI S.p.A.: an example

In this section, we present an application of the model as well as a more detailed analysis and comparison of the stock returns of Chesapeake Energy (NYSE: CHK) and ENI S.p.A. (NYSE: E) through a scenario and sensitivity analysis. We have chosen these two companies for several reasons. Chesapeake Energy is the second largest producer of natural gas and the 12 largest producer of oil in the United States. Natural gas comprises 71% of the company's revenue, and oil, 12%. In contrast, ENI S.p.A. earns only 40% of its revenue from oil-related business, indicating that ENI S.p.A. is more diversified than is Chesapeake Energy. In addition, ENI S.p.A. is a more international company, operating in a number of different countries, as compared with Chesapeake. In our sample period (2000–2015), both Chesapeake Energy and ENI S.p.A. have positive weekly average stock returns (0.06 and 0.05%, respectively). Chesapeake Energy exhibits more volatility than does ENI S.p.A., and Chesapeake Energy has weekly returns that range from 38 to 56%, while those of ENI S.p.A. range from 20 to 25%. Regression estimates based on OL, as well as the QR approach for Chesapeake Energy and ENI S.p.A., are reported in Tables 2 and 3, respectively.

As can be seen from results reported in Tables 2 and 3, for Chesapeake Energy, four out of five variables have coefficients that are significant at the 5% level or better, whereas, for ENI S.p.A., three out of five variables have coefficients that are significant at the 5% level or better. As 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 further, we present a series of QRs for the univariate specification. Estimated coefficients of the five independent risk variables with quantiles that range from 5 to 90% are obtained by running the regression model based on Eq. (7). Only three of the five variables for Chesapeake and two of the five variables for ENI S.p.A. have statistically significant coefficients for the median of stock returns. Estimates of various risk factors across quantiles of returns vary across quantile levels.

As shown in Tables 2 and 3, regression coefficients of the market risk factor are highly significant for all quantiles. In contrast, coefficients of the relative change in VIX are statistically insignificant for both companies. In the case of Chesapeake Energy, our findings related to the effects of gas prices, DXY, and VIX are as follows. For the gas price factor, the standard OLS estimated coefficient is 0.133, which is significant at the 1% level. In contrast, the coefficient based on the QR method shows that gas prices have an insignificant impact on the lower quantile. Conversely, the estimated coefficient of DXY based on OLS (0.009) is insignificant, whereas the same based on the QR method exhibits a significant impact only in the upper quantile (0.570 in the 90th quantile). In the case of VIX, the coefficient based on the OLS method is significant, and its impact is greater than coefficients based on QR across all quantiles, except the 5% quantile.

In the case of ENI S.p.A., market and oil price risk factors significantly influence stock returns across the entire quantile distribution. In contrast, the gas price risk factor has a significant influence on stock returns in the upper quantiles (0.040 for the 75th quantile and 0.057 for the 90th quantile). In the case of VIX, the coefficients are significant only in the upper quantile, whereas the OLS estimate shows that VIX has a significant coefficient at the 10% level. These results demonstrate that the influence of risk factors on stock returns are inconsistent in different parts of the distribution of the returns and that the OLS estimate is not always able to identify the influence of each risk factor on the entire return distribution.

Chesapeake Energy appears to be more exposed to changes in the market, oil prices, and gas prices than is ENI S.p.A. As a supplier of oil and natural gas, both Chesapeake Energy's and ENI S.p.A.'s revenues rise and fall 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. In addition, the production outside the U.S. border explains why ENI S.p.A. has high exposure and a highly significant coefficient against the DXY and is less exposed to the market risk in comparison to Chesapeake Energy. Another explanation could be the "leverage effect," whereby an increase in the financial leverage of a firm can lead to an increase in stock volatility. Chesapeake Energy has a significantly higher debt-to-equity ratio (5X) in comparison to the debt-to- equity ratio (0.5X) of ENI S.p.A.

An illustration of the patterns of the quantile distributions are provided in Fig. 1A and B. The estimated values of the individual coefficients for Chesapeake Energy (Fig. 1A) and ENI S.p.A. (Fig. 1B) across different quantiles (10, 25, 50, 75, and 90%) are plotted against the values obtained from OLS.

The plots show that the return of a security is not linearly dependent on these factors around the entire distribution. The shaded areas represent estimates within 95% confidence bands. Figure 1A(a)–(f) show coefficient estimates for Chesapeake Energy, and Fig. 1B(g)–(l) show the coefficient estimates for ENI S.p.A. The alphas for various quantiles can be seen in Fig. 1A(a). As expected, the upward sloping indicates that the lower quantiles tend to be associated with negative alphas, and the upper quantile, with positive alphas. Figure 1A(b)–(d) provide a plot of the parameters of the selected five factors over various quantiles. The coefficient for natural gas and DXY indicates a U-shaped curve,

Table 4 Wald test results

Stock	$\beta_{i,q=0.10} = \beta_{i,q=0.5}$	$\beta_{i,q=0.25} = \beta_{i,q=0,5}$	$\beta_{i,q=0.75} = \beta_{i,q=0.5}$	$\beta_{i,q=0.90} = \beta_{i,q=0.5}$
A: S&P500 index				
CHK	3.34*	0.79	0.19	0.25
E	2.73*	1.38	0.20	0.33
B: WTI crude oil				
CHK	3.95**	0.01	6.35**	6.04**
E	3.75*	0.00	7.33***	5.74**
C: Natural gas				
CHK	0.09	4.60**	3.30*	5.45**
E	0.09	3.47*	2.8*	8.39***
D: U.S. Dollar index				
CHK	2.65	0.66	0.00	0.17
E	5.35**	0.60	0.00	0.22
E: VIX index				
CHK	0.21	0.23	0.96	1.07
E	0.15	0.28	0.47	0.73

suggesting that natural gas and DXY at the tails of the return distribution have more exposure to market risk and size factors, whereas Fig. 1A(e) shows that stock returns have a higher exposure to VIX in the median. The plots in Fig. 1A(b) show the exposure to the S&P 500 and crude oil. The shape of this curve shows a downward sloping and that the left tail of the return distribution delivers higher coefficients. This indicates that stock returns have a higher exposure to these risk factors. For ENI S.p.A., the coefficients (Fig. 1B(g)–(l) exhibit much of the same results as do those for Chesapeake Energy. In Fig. 1A(d), there is a distinctive S-shape pattern across quantiles of the conditional stock return distribution. In particular, the lower quantiles exhibit a positive dependence with past returns, while the upper quantiles are marked by a negative dependence. We typically find little or only a very weak dependence for central quantiles.

3.3 Stability of quantile regression (QR) coefficients across quantiles

Although it seems clear that the estimated coefficients vary with the quantile levels reported in Table 1, this finding would be more compelling if we conduct a formal test of the hypothesis of the equality of slopes. Because the median quantile is close to the mean value of the OLS estimation, which is conventionally used in testing, we address the equality test of various quantiles against the median quantile coefficient ($q^{0,5th}$). Specifically, we test:

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

Table 5 Wald test results

Stock	$\beta_{i,q=0.10} + \beta_{i,q=0.90} = \beta_{i,q=0.5}$	$\beta_{i,q=0.25} + \beta_{i,q=0.75} = \beta_{i,q=0.5}$
A: S&P 500 index		
CHK	1.68	0.41
E	1.43	0.90
B: WTI Crude oil		
CHK	4.46**	6.82***
E	3.46**	3.75**
C: Natural Gas		
CHK	3.28**	2.85*
E	4.24**	2.39*
D: U.S. Dollar index		
CHK	1.53	0.28
E	2.89*	0.31
E: VIX index		
CHK	1.07	0.28
E	0.41	0.32

To help estimate the difference between the coefficients across the quantiles, we use a Wald test, whose statistics are reported in Table 4. 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, indicating that the estimated coefficients for the quantiles of 10, 75, and 90% are significantly different from those of the median distribution. Similarly, the natural gas price coefficient enables us to reject the null hypothesis of the 25, 75, and 90% quantiles, indicating that they are different from the median distribution. For the S&P 500, we reject the null hypothesis at a 10% confidence level at only the 10% quantile for both; for VIX, however, we do not reject the null hypothesis across the quantiles at any confidence level. For DXY, ENI S.p.A. has a significant value in only the 10% quantile. These tests show that the OLS or median quantile does not always display the true picture of a company's risk. Specifically, coefficients of oil and gas prices at quantiles 10, 75, and 90% are significantly different from those of the median. In the case of DXY and VIX, we 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 also are concerned about the symmetry of the risk-return relationship for the quantiles that lie above the median versus those that lie below the median. In particular, we test the following restrictions:

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

The results reported in Table 5 show very little evidence of a departure from symmetry for the market index, DXY, and VIX, and the hypothesis cannot be rejected. In contrast, we reject the hypothesis of symmetry for the pairs of (25%, 75%) and (10%, 90%) in the case of WTI crude oil and gas prices. These results are consistent with findings of Xiao

Table 6 OLS and quantile regression estimates for the oil and gas sector

Model	1	2	3	4	5	6	7	8
	avgretOLS	avgret5%	avgret10%	avgret25%	avgret50%	avgret75%	avgret90%	avgret95%
sp500ind	0.58***	1.15***	0.86***	0.59***	0.38***	0.31***	0.24	0.44
	7.04	5.31	5.02	5.98	4.24	−3.45	−1.68	−1.50
crudeoil	0.19***	0.30***	0.28***	0.25***	0.20***	0.17***	***	0.20***
	6.62	4.02	4.73	7.31	6.43	−5.31	−3.42	−1.96
naturalg	0.07***	0.09*	0.05	0.06***	0.06**	0.07****	0.09****	0.11*
	4.24	2.07	1.66	3.15	3.29	−4.11	−3.36	−1.97
usdollar	−0.27	−0.04	−0.18	−0.18	−0.15	−0.17	−0.36	−0.39
	−2.23	−0.14	−0.70	−1.22	−1.15	−1.24	−1.77	−0.92
vixindex^t	0.00	0.09	0.04	0.00	−0.05**	−0.05**	−0.02	0.01
	0.19	1.96	1.21	−0.10	−2.87	−3.00	−0.69	−0.10
_cons	0.002***	−0.06***	−0.04***	−0.02***	0.0003***	0.023***	0.044***	0.058***
	1.76	−16.5	−15.6	−11.9	2.15	15.41	19.49	12.49
AIC	−3065							
bic	−3037							
*r*2	0.236							
N	831	831	831	831	831	831	831	831

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Note: Model 1 is OLS regression of average returns for the companies on the independent variables stock market return, crudeoil price changes, naturalgas price changes, FX-variable and the VIX index. Model 2–8 are results from quantile regressions for the same variables as the OLS regression in model 1

et al. (2018) and Das and Kannadhasan (2020) that the impact of oil price shocks on stock returns of oil and gas companies is asymmetric.

The results presented in Table 6 show that returns on the overall stock market and changes in crude oil and natural gas prices have a significant positive impact on returns of oil and gas companies. The dependence on stock market return is higher in the low quantiles. The effect of the world market portfolio return, represented by the excess market return $\left(R_{Mt} - R_{Ft}\right)$, on oil and gas stock returns differs across quantiles. This result shows a tendency for increasing market return sensitivity, with higher market betas associated with low oil stock returns. This indicates a stronger tail dependence on the market factor and implies that OLS regression underestimates the sensitivity of market risk at the lower quantiles of the return distribution.

Overall, our results present evidence that the effect of oil price changes on oil and gas stock returns is positive. The positive relationship implies that the effect of oil is a proxy for the state of the world economy and the energy sector itself. The crude oil price changes, in contrast, show a steadier influence on the oil and gas stock returns across the quantiles than does the overall stock market return. The natural gas influence is higher in the tail of the return distribution, shown by higher natural gas betas for low and high quantiles. The impact of VIX on oil stock returns is significant for only the 50 and 75% quantile but not in the OLS regression, indicating that QR can detect sensitivities, while OLS cannot.

Table 7 Value-at-Risk (VaR) estimate

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

3.4 Value at risk (VaR)

The QR analysis suggests that the sensitivity to each risk factor exhibits 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 the same stock. In this section, we focus on the asymmetric risk associated with the tails of the return distribution. For investors or portfolio managers who are concerned with managing and assessing risk, the accuracy in forecasting tail risk is critical. The downside and upside risk is an estimation of an oil and gas stock's potential gain (loss) in value due to sudden increase (decrease) in the oil price due to exogeneous supply or demand shock. VaR is a statistical risk measure of a potential loss of value, which is summarized in a single number. It is the maximum expected loss over a target horizon at a particular significance level.

The QR framework provides a unique opportunity for investors to construct VaR without imposing a parametric distribution or the i.i.d. assumption. Chen was among the first to consider the QR for the VaR model. Chen presents a multi-period VaR model based on QR, which provides a way of understanding how the relationship between stock returns and risk factors changes across the distribution of conditional returns. The QR method provides useful information about the entire distribution and the ability to investigate VaR, as VaR can be viewed as a conditional quantile function of a given return series.

The linear QR models developed by Koenker and Basset (1978) can be directly translated into VaR models, which is yet another advantage of this methodology. The confidence level is chosen as 95 and 5%, meaning that the 5 and 95% significance level VaR, respectively, 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 long positions (5% quantile) and short positions (95% quantile) in the U.S. oil and gas market are computed.

In the following section, we illustrate how the model can be used by an investor with an idea about how the prices of risk factors will develop. If we can forecast the relative changes of the risk factors, we would be estimating/predicting an expected shortfall. To illustrate the 1-week-ahead VaR, we estimate the stock returns over 1 week after the data period. The value used for the various risk factors were the S&P 500: 0.01, WTI Crude oil: −0.05; NYMEX Natural gas: 0.05; VIX: 0.001; and DXY: 0.08. The results reported in Table 7 and the distribution of VaR seen in Fig. 2 show the VaR estimates from Chesapeake Energy, and the 5 and 95% VaR is −10 and 11%, respectively.

Figure 2 shows the distribution of Chesapeake Energy and the 1-week-ahead VaR at specified rates through a base scenario. For events that change the assumptions, e.g., oil prices, the expected VaR will change. The second graph in the figure shows that the change in expected shortfall, −0.04 to 0.04, will increase the 5% VaR from −10 to −6%. This model can be used to identify the potential risks associated with downside risk (long position) and upside risk (short position) when one expects a change in risk variables.

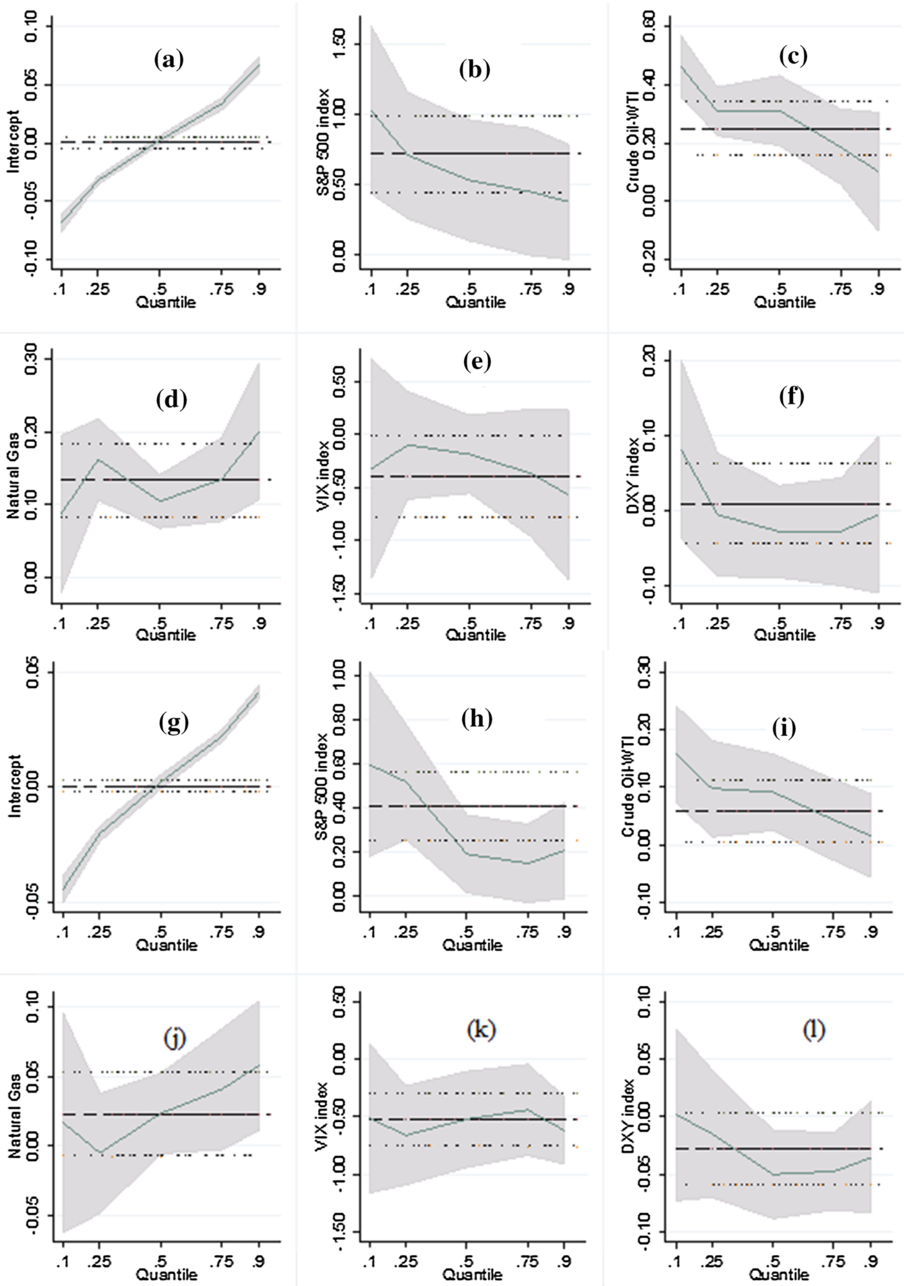


Fig. 1 **A** *Quantile regression plot for the* Chesapeake Energy *(CHK) coefficient estimates.* **B** *Quantile regression plot for the* ENI *coefficient estimates.*Note: Quantile regression plot shown above for the Chesapeake and ENI Energy stock returns. Intercept is the stock return alpha, S&P 500 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 the Natural gas price; the DXY Index is the percentage change in the U.S. Dollar Index and the VIX is the stock market volatility index

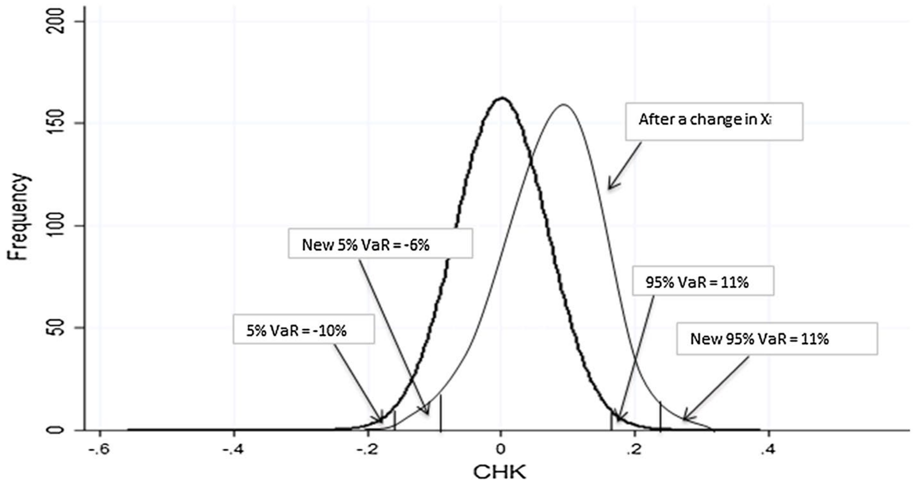


Fig. 2 Distribution and Value-at-Risk (VaR)

4 Conclusions

We use the QR method to analyze the risk factor sensitivities in U.S. oil and gas companies' stock returns. The QR method is a powerful mathematical tool for modeling the simultaneous interdependence between univariate time series of risk factors and stock returns. This method covers all of the information of the dependence structure and enables an analysis beyond linear correlation. Further, the QR approach allows us to model the tail dependence structure between risky assets that quantify the probability that the risky assets co-move as extreme events occur. For example, from the perspective of an investor, not only is the average impact of oil price changes on the stock returns important but also the impact of extreme price movements. Quantifying the upside and downside systemic risk is particularly important for investors to develop strategies for risk management because investors may have long or short positions in oil and gas-related stocks.

The study provides evidence that most firms in the oil and gas sector have significant market and oil price risk exposures. The results also show that oil exposure coefficients are not equal across the entire distribution. The study finds that coefficients at quantiles 0.10, 0.75, and 0.90 are significantly different from those of the median. These findings suggest that sensitivities to a particular risk factor differ across the quantile distributions, indicating that the sensitivity of oil and gas stock returns changes across the state of the market. The risk factors have the strongest impact in the left tail, and their impact gradually decreases toward the right tail, indicating asymmetric responses of oil and gas stock returns to risk factors. This implies that an investor with a long position in an oil and gas stock will be exposed to a substantially greater risk than will an investor with a short position. Finally, we estimate VaR for a specified oil and gas company and find that the downside risk is greater than the upside risk of investments, suggesting that investors who hold a long position in U.S. oil and gas stocks over the data period are likely to be exposed to greater risk than are investors with a short position.

Further, investors can perform scenario analysis and stress testing using a QR approach and can better understand how a specific risk factor (e.g., changes in natural gas prices, changes in market volatility) influences the left tail risk (long-only trader) or the right tail risk (short-only trader). Investors also can address scenarios such as falling natural gas prices and investigate their effect directly on risk exposure. Stress testing and scenario analysis can be done in such a way that would be of interest to investors and portfolio managers and useful to regulators and policymakers. An understanding of the asymmetry and extreme effect of a risk variable on stock returns is critical for market participants because they can measure VaR and make important portfolio allocation decisions (e.g., Mensi et al. 2014). Thus, the results of our study should be of interest to investors, portfolio managers, and policymakers.

Appendix A

List of sample firms with ticker symbol, industry subsector, and market capitalization

Name	Ticker	Industry	M.cap($) (30.04.16)
ANADARKO PETROLEUM	APC	Oil & Gas Producers	24.26B
APACHE	APA	Oil & Gas Producers	19.20B
CABOT OIL & GAS	COG	Oil & Gas Producers	11.32B
CALLON PETROLEUM	CPE	Oil & Gas Producers	1.23B
CANADIAN NATURAL RESOURCES	CNQ	Oil & Gas Producers	38.54B
CHESAPEAKE ENERGY	CHK	Oil & Gas Producers	3.79B
CHINA PETROLEUM & CHEM	SNP	Oil & Gas Producers	84.43B
CIMAREX ENERGY	XEC	Oil & Gas Producers	10.06B
CLAYTON WILLIAMS ENERGY	CWEI	Oil & Gas Producers	212.72 M
COMSTOCK RESOURCE	CRK	Oil & Gas Producers	45.06 M
DENBURY RESOURCES	DNR	Oil & Gas Producers	1.11B
DEVON ENERGY	DVN	Oil & Gas Producers	16.40B
ENCANA	ECA	Oil & Gas Producers	5.35B
ENI SPA	E	Oil & Gas Producers	5.400 T
EOG RESOURCES	EOG	Oil & Gas Producers	43.63B
GOODRICH PETROLEUM	GDP	Oil & Gas Producers	3.59 M
HESS Corporation	HES	Oil & Gas Producers	17.36B
MARATHON OIL	MRO	Oil & Gas Producers	10.32B
NEWFIELD EXPLORATION	NFX	Oil & Gas Producers	6.81B
NOBLE ENERGY	NBL	Oil & Gas Producers	15.32B
OCCIDENTAL PETROLEUM	OXY	Oil & Gas Producers	56.49B
PANHANDLE OIL & GAS	PHX	Oil & Gas Producers	269.07 M
PENN VIRGINIA	PVA	Oil & Gas Producers	7.23 M
PETROCHINA CO LTD	PTR	Oil & Gas Producers	123.71B
PETROQUEST ENERGY	PQ	Oil & Gas Producers	53.23 M
PIONEER NATURAL RESOURCES	PXD	Oil & Gas Producers	26.32B
RANGE RESOURCES	RRC	Oil & Gas Producers	7.06B
SM ENERGY	SM	Oil & Gas Producers	2.05B
STATOIL ASA	STO	Oil & Gas Producers	53.77B
CHEVRON	CVX	Integrated oil and gas	189.58B
CONOCOPHILLIPS	COP	Integrated oil and gas	53.66B

Name	Ticker	Industry	M.cap($) (30.04.16)
EXXON MOBIL	XOM	Integrated oil and gas	364.97B
STONE ENERGY	SGY	Integrated oil and gas	44.91 M
SUNCOR ENERGY	SU	Integrated oil and gas	41.72B
SWIFT ENERGY	SFY	Integrated oil and gas	6.24 M
ULTRA PETROLEUM	UPL	Integrated oil and gas	47.89 M
BAKER HUGHES	BHI	Equipment and services	19.70B
ENSCO	ESV	Equipment and services	3.23B
HALLIBURTON	HAL	Equipment and services	34.78B
HELMERICH & PAYNE	HP	Equipment and services	6.60B
NABORS INDUSTRIES	NBR	Equipment and services	2.39B
NOBLE CORP	NE	Equipment and services	2.44B
SCHLUMBERGER	SLB	Equipment and services	105.96B
TIDEWATER	TDW	Equipment and services	394.53 M
WEATHERFORD INTL	WFT	Equipment and services	5.43B
ENBRIDGE ENERGY PRTNRS	EEP	Pipelines	7.78B
OGE ENERGY	OGE	Pipelines	6.02B
PLAINS ALL AMER PIPELNE	PAA	Pipelines	8.95B
WILLIAMS COS	WMB	Pipelines	14.78B

Appendix B

Quantile regression results

	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

	Cons (α)	Market (β)	Oil Price (β)	Gas Price (β)	DXY Index (β)	VIX Index (β)	Adj.R^2
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

	Cons (α)	Market (β)	Oil Price (β)	Gas Price (β)	DXY Index (β)	VIX Index (β)	Adj.R^2
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

	Cons (α)	Market (β)	Oil Price (β)	Gas Price (β)	DXY Index (β)	VIX Index (β)	Adj.R^2
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

	Cons (α)	Market (β)	Oil Price (β)	Gas Price (β)	DXY Index (β)	VIX Index (β)	Adj.R^2
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

	Cons (α)	Market (β)	Oil Price (β)	Gas Price (β)	DXY Index (β)	VIX Index (β)	Adj.R^2
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

	Cons (α)	Market (β)	Oil Price (β)	Gas Price (β)	DXY Index (β)	VIX Index (β)	Adj.R^2
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

	Cons (α)	Market (β)	Oil Price (β)	Gas Price (β)	DXY Index (β)	VIX Index (β)	Adj.R^2
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

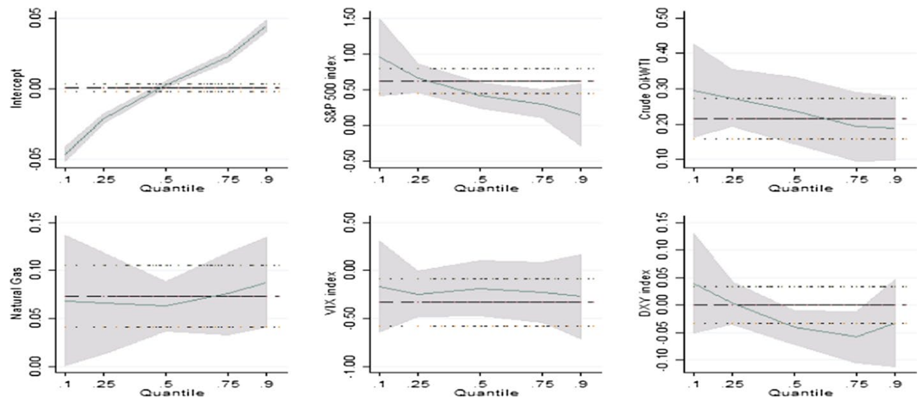
	Cons (α)	Market (β)	Oil Price (β)	Gas Price (β)	DXY Index (β)	VIX Index (β)	Adj.R^2
WMB							
5%	−0.100	1.080**	0.295*	−0.039	−0.440	−0.072	0.13
10%	−0.063	1.304***	0.213**	0.054	0.000	0.031	0.13
25%	−0.029	1.024***	0.180***	0.058**	0.165	−0.006	0.09
50%	0.001	0.824***	0.227***	0.077***	0.007	−0.0078	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

Note: ***, ** and * indicates significance at the 1, 5 and 10% level respectively

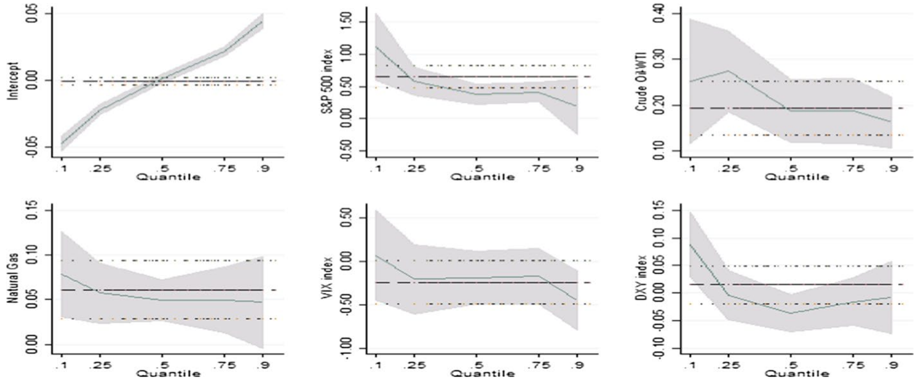
Appendix C

Quantile regression plot for the various subsectors. 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 the Natural gas price; the DXY Index is the percentage change in the U.S. Dollar Index and the VIX Index the percentage change in the Volatility Index.

Producers

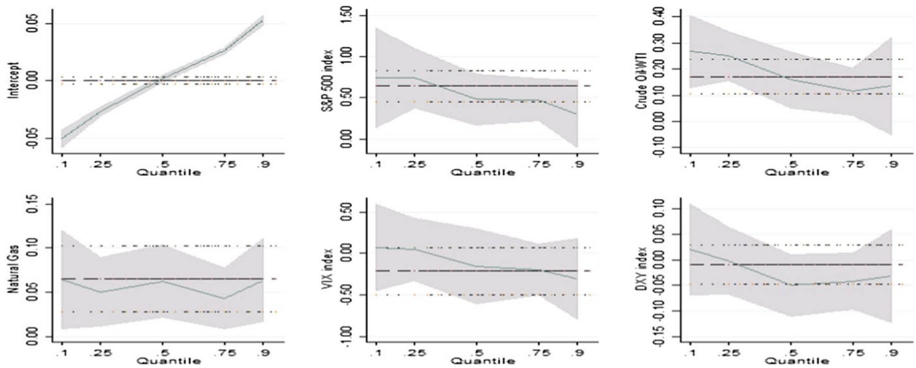


Integrated

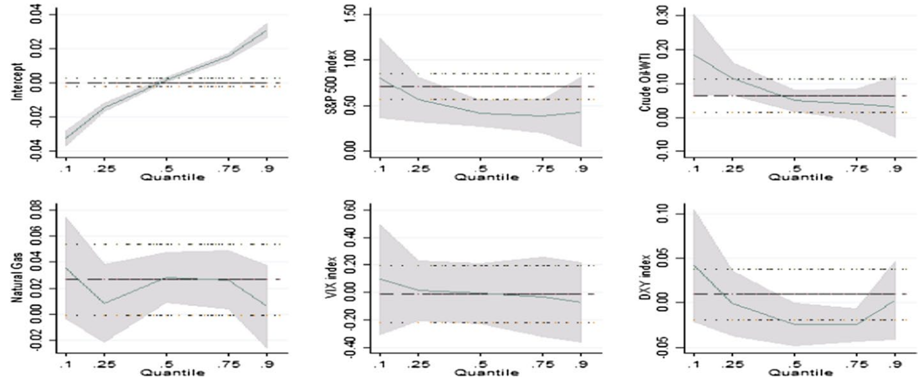


Quantile regression plot for the different subsectors. Intercept is the stock return alpha, S&P 500 Index the percentage change in market return; Crude oil WTI is the percentage change in the Crude oil price; Natural gas is the percentage change in the Natural gas price; the DXY Index the percentage change in the U.S. Dollar Index and the VIX Index the percentage change in the Volatility Index.

Service and Equipment



Pipeline



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