Quantile dependence of oil price movements and stock returns

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Abstract

This paper examines the impact of quantile and interquantile oil price movements on different stock return quantiles by testing the hypothesis of equality in conditional and unconditional quantile distribution functions of stock returns. We capture quantile dependence under different stock market conditions while taking into account different kinds of oil price movements by computing unconditional and conditional stock return quantiles through marginal models for stock returns and copula functions for oil-stock dependence. Taking data on stock return indices for three developed economies (the US, the UK and the European Monetary Union) and the five BRICS countries (Brazil, Russia, India, China and South Africa) since 2000 to 2014, our results indicate that: (1) the impact of extreme upward and downward oil price changes on the upper and lower stock price quantiles is much smaller before the crisis than after the crisis; (2) the downside spillover effects are larger than the upside spillover effects for most countries before the crisis and for all countries after the crisis; and (3) small positive and negative oil price movements have no impact on any stock return quantiles both before and after the crisis.

Keywords: Oil prices; Stock returns; Quantile; Copula.

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1. Introduction

The effect of crude oil price movements on equity returns has long been under the scrutiny by investors, policymakers and researchers alike. Theoretically, higher oil prices lead to higher inflation rates, lower real consumption and higher production costs, all of which ultimately impact stock prices. However, stock price reactions to oil price changes may be complex; the stock market may react asymmetrically to the size and the sign of oil prices shocks and market reaction may differ depending on whether it is bullish or bearish. In recent years, oil prices have swung up and down with different intensities over relatively brief periods of time, inducing different reactions from stock markets that have puzzled investors. Given that the effect of oil price shocks may differ according to stock market conditions and the size of the oil shock, we investigate how oil price changes influence equity returns by considering the effects of oil price upper and lower quantile and interquantile movements on stock price quantiles.

Although there is abundant empirical literature on the influence of oil on stock market returns, there is no empirical consensus as to whether an oil price shock has a positive, negative or insignificant impact on equity returns. One strand of the literature found that surging oil prices had a negative impact on returns for the aggregate or sectoral stock markets (see Kaul and Jones, 1996; Basher and Sadorsky, 2006; Hammoudeh and Choi, 2007; Nandha and Haff, 2008; Kilian and Park, 2009; Sadorsky, 1999; among others), whereas another strand of the literature found no significant relationship between oil prices and stock returns (see, e.g., Huang, et al., 1996; Henriques and Sadorsky, 2008; Apergis and Miller, 2009; Sukcharoen et al. 2014). Further studies reported that the oil-stock relationship was time-varying and nonlinear and could change to reflect specific events like the recent global financial crisis (see, e.g., Miller and Rati, 2009; Reboredo, 2010; Filips et al., 2011; Daskalaki and Skiadopoulos, 2011; Chang and Yu, 2013; Reboredo and Rivera-Castro, 2014; Zhang and Li, 2014). All these studies analyse the linear or nonlinear impact of oil price changes on stock returns, yet little is known as yet regarding how large positive or negative oil price movements or interquantile oil price movements may impact on different equity return quantiles. A recent study by Sim and Zhou (2015) was the first to use a quantile-on-quantile regression approach to estimate the effect oil price shock quantiles on US stock return quantiles. Our paper follows along these lines and adds to the current literature on the oil-stock return relationship along two axes.

First, we characterize the bivariate dependence structure between oil and stock returns through copulas. From these copulas we can compute the stock return quantile conditional on a large positive (high quantile) or negative (low quantile) oil price movement and then can assess whether the impact of a large oil price movement is significant by testing whether the conditional stock return quantile differs significantly from the unconditional stock return quantile computed from the marginal distribution function of the stock returns. For this purpose we used the Kolmogorov-Smirnov (KS) bootstrapping test – as proposed by Abadie (2002) – to test for significant differences in quantile functions. Similarly, we assessed how oil price changes within a specific oil price range (interquantile oil price change) impact on stock returns by testing whether the stock return quantile conditional on an interquantile oil price change, as computed from the dependence structure, differed significantly from the unconditional stock return quantile.

Our proposed methodological approach is substantially different from that of Sim and Zhou (2015). To begin with, using copulas rather than quantile regression results in more modelling flexibility as copulas enable heterogeneity in characterizing marginal distributions and also account for specific features of the data such as conditional heteroskedasticity, volatility asymmetries and leverage effects. Moreover, our empirical setup allows for time-varying dependence, so the impact of oil price changes on stock returns are allowed to differ in different moments of time depending on the dependence and volatility features of both markets. Finally, our methodological approach allows to assess the impact of interquantile oil price movements, which is not possible in a quantile regression framework. On the other hand, our approach also differs from the copula quantile regression framework adopted by Bouyé and Salmon (2009) and by Jing et al. (2008) for the tail risk measurement in that we computed copula quantiles conditional on quantile and interquantile values of the conditioning variable. Likewise, in our analysis we considered time-varying copulas and tested for the equality in the conditional and unconditional quantiles, which has implications in terms of the effects of oil price movements on stock returns.

Second, our empirical study considers the dependence structure between oil prices and a broad set of global stock market indices (but excluding oil and gas stocks to avoid the direct effects) – those of three developed countries (US, UK and European Monetary Union (EMU)) and of the five BRICS countries (Brazil, Russia, India, China and South Africa) – before and after the onset of the global financial crisis. We check whether the dependence structure is static or time-varying and how it changes with the onset of the financial crisis. Furthermore, we test for downside and upside spillover effects of oil price movements on stock returns, for asymmetries in upside and downside oil price spillovers on extreme up and down stock return quantiles, and for the impact of interquantile positive and negative oil price movements on stock return quantiles. Our results, consistent with the fact that oil and equity prices were driven by certain common economic forces (e.g., aggregate demand), provide new evidence of asymmetries in the oil-stock relationship and of how this relationship has changed since the onset of the global financial crisis. Our evidence on quantile dependence of oil price movements with stock returns has implications for investors who need to adopt different risk management strategies to protect portfolios against price upturns and downturns in oil markets.

The remainder of the paper is laid out as follows: in Section 2 we describe the methodological approach used to account for the impact of quantile and interquantile oil price movements on different stock return quantiles; in Section 3 we describe our data; in Section 4 we discuss our results; and finally, Section 5 concludes the paper.

2. Methodology

2.1 Oil price quantile and interquantile effects on stock return quantiles

Let y_t denotes stock price returns. Hence, the α-quantile of the stock price return distribution at time t given by $P(y_t \le q_{\alpha,t}^{y_t}) = \alpha$ can be obtained as:

$$q_{\alpha,t}^{y_t} = F_{y_t}^{-1}(\alpha), \tag{1}$$

where $F_{y_t}^{-1}(\alpha)$ is the inverse of the distribution function of y_t. In the risk finance literature, this α-quantile, for low values of alpha (usually 0.05 or 0.01), is called value-at-risk (VaR). Similarly, letting x_t denote oil price returns, the β-quantile for oil price returns can be obtained as in Eq. (1) from the inverse of the distribution function of x_t, $F_{x_t}^{-1}(\beta)$.

We can assess the impact of oil price changes of different sizes on stock returns by considering how an oil price quantile change or how an oil price interquantile movement impacts on the stock return quantile. For this purpose, we need to have information on the conditional stock return quantile. The conditional α-quantile of the stock price return distribution at time t for a given β-quantile for the oil price return given by $P(y_t \le q_{\alpha,\beta,t}^{y_t|x_t} \mid x_t \le q_{\beta,t}^{x_t}) = \alpha$ can computed as:

$$q_{\alpha,\beta,t}^{y_t|x_t} = F_{y_t|x_t \le q_{\beta,t}^{x_t}}^{-1}(\alpha), \tag{2}$$

where $F_{y_t|x_t \le q_{\beta,t}^{x_t}}^{-1}(\alpha)$ is the inverse of the distribution of y_t conditional on the fact that $x_t \le q_{\beta,t}^{x_t}$. Furthermore, we can obtain the conditional α-quantile of the stock price return distribution at time t conditional on the fact that oil price changes take values between a low and up bound that correspond with the θ- and β-quantiles, respectively. It is given by $P(y_t \le q_{\alpha,(\theta,\beta),t}^{y_t|x_t} \mid q_{\theta,t}^{x_t} \le x_t \le q_{\beta,t}^{x_t}) = \alpha$ and can be computed as:

$$q_{\alpha,(\theta,\beta),t}^{y_t|x_t} = F_{y_t|q_{\theta,t}^{x_t} \le x_t \le q_{\beta,t}^{x_t}}^{-1}(\alpha), \tag{3}$$

where $F_{y_t|q_{\theta,t}^{x_t} \le x_t \le q_{\beta,t}^{x_t}}^{-1}(\alpha)$ is the inverse of the distribution of y_t conditional on the fact that $q_{\theta,t}^{x_t} \le x_t \le q_{\beta,t}^{x_t}$.

Now, we can assess the impact of quantile and interquantile oil price movements on stock return quantiles by testing the hypothesis of equality in the between conditional and unconditional stock return quantile. These hypothesis can be formally states as:

$$H_0: \; q_{\alpha,t}^{y_t} = q_{\alpha,\beta,t}^{y_t|x_t}, \tag{4}$$

$$H_0: \; q_{\alpha,t}^{y_t} = q_{\alpha,(\theta,\beta),t}^{y_t|x_t}. \tag{5}$$

Thus, by considering the α- and β-quantiles for stock and oil returns, respectively, if we do not reject the null hypothesis in Eq. (4), the conditional and unconditional stock return quantiles are indistinguishable, so changes in oil prices has no impact on stock returns (the opposite holds when we reject the null hypothesis in Eq. (4)). Similarly, if we do not reject the null hypothesis in Eq. (5), then interquantile oil price movements (given by θ and β) have no impact on stock return quantile. To test these hypothesis, we employed the KS bootstrapping test, introduced by Abadie (2002), which measures the difference between two cumulative quantile functions without considering any underlying distribution function given that it relies on the empirical distribution function. This test is given by:

$$KS_{mn} = \left(\frac{mn}{m+n} \right)^{\frac{1}{2}} \sup_x \left| F_m\left(x\right) - G_n\left(x\right) \right|, \tag{6}$$

where $F_m\left(x\right)$ and $G_n\left(x\right)$ are the cumulative conditional and unconditional quantile distribution functions for stock returns, respectively, and where n and m are the size of the two samples.

2.2 Quantile and conditional quantile estimation method

We estimated unconditional and conditional quantiles for the stock return distribution as follows.

We assumed that y_t has time-varying mean (μ_t) and variance such that

$$y_t = \mu_t + \varepsilon_t, \tag{7}$$

where $\mu_t = \phi_0 + \sum_{j=1}^{p} \phi_j y_{t-j} + \sum_{h=1}^{q} \varphi_j \varepsilon_{t-h}$, with ϕ_0, ϕ_j and φ_j denoting a constant parameter and the autoregressive (AR) and moving average (MA) parameters, respectively, whereas p and q are non-negative integers. $\varepsilon_t = \sigma_t z_t$ is a stochastic variable, with σ_t accounting for the conditional standard deviation and z_t for a stochastic variable with zero mean and unit variance. The variance of y_t is given by the variance of ε_t, which has a dynamics that is assumed to be given by a threshold generalized autoregressive conditional heteroskedasticity (TGARCH) model as proposed by Glosten et al. (1993):

$$\sigma_t^2 = \omega + \sum_{k=1}^{r} \beta_k \sigma_{t-k}^2 + \sum_{h=1}^{m} \alpha_h \varepsilon_{t-h}^2 + \sum_{h=1}^{m} \lambda_h 1_{t-h} \varepsilon_{t-h}^2, \tag{8}$$

where ω is a constant; β and α are the GARCH and autoregressive conditional heteroskedasticity (ARCH) parameters, respectively, $1_{t-h} = 1$ if $\varepsilon_{t-h} < 0$ and otherwise 0. λ captures asymmetric effects in such a way that a negative shock has more impact on variance than a positive shock provided that $\lambda > 0$. Note that when $\lambda = 0$ we have the GARCH model. In addition, the zero mean unit variance random variable z_t is assumed to follow a Hansen's (1994) skewed-t density distribution that captures fat tails and asymmetries in stock return distributions. This distribution is specified as:

$$f(z_t;\upsilon,\eta)=\begin{cases} bc\left(1+\frac{1}{\upsilon-2}\left(\frac{bz_t+a}{1-\eta}\right)^2\right)^{-(\upsilon+1)/2} & z_t<-a/b \\ bc\left(1+\frac{1}{\upsilon-2}\left(\frac{bz_t+a}{1+\eta}\right)^2\right)^{-(\upsilon+1)/2} & z_t\geq -a/b \end{cases}, \tag{9}$$

where υ is the degrees of freedom parameter ($2<\upsilon<\infty$), η is the symmetric parameter ($-1<\eta<1$) and where the constants a, b and c are given by $a=4\eta c\left(\frac{\upsilon-2}{\upsilon-1}\right)$, $b^2=1+3\eta^2-a^2$ and $c=\Gamma\left(\frac{\upsilon+1}{2}\right)\Big/\sqrt{\pi(\upsilon-2)}\Gamma\left(\frac{\upsilon}{2}\right)$. The skewed-t density distribution converges to the Gaussian density when $\eta=0$ and $\upsilon\to\infty$, and to the symmetric Student-t distribution when $\eta=0$ and υ is finite.

From the information on the mean and variance of y_t, we can compute the unconditional α-quantile of the stock price return distribution as:

$$q_{\alpha,t}^{y_t}=\mu_t+F_{\upsilon,\eta}^{-1}(\alpha)\sigma_t, \tag{10}$$

where $F_{\upsilon,\eta}^{-1}(\alpha)$ denotes the α-quantile of the skewed Student-t distribution in Eq. (9).

To compute the conditional quantiles for the stock return distribution, we used copula functions.[1] Note that $P(y_t\leq q_{\alpha,\beta,t}^{y_t|x_t}\mid x_t\leq q_{\beta,t}^{x_t})=\alpha$ can be written as:

$$\frac{F_{y_t x_t}(q_{\alpha,\beta,t}^{y_t|x_t},q_{\beta,t}^{x_t})}{F_{x_t}(q_{\beta,t}^{x_t})}=\alpha, \tag{11}$$

hence, the conditional quantiles for the stock return distribution requires information on the joint distribution function of y and x, $F_{yx}(\cdot)$. Bearing in mind that Sklar's (1959) theorem allows us to express the joint distribution function in terms of a copula function C, where $C\left(F_X(x),F_Y(y)\right)=F_{XY}(x,y)$, and that $F_{x_t}(q_{\beta,t}^{x_t})=\beta$, Eq. (11) can be written as:

$$C(F_{y_t}(q_{\alpha,\beta,t}^{y_t|x_t}),\beta)=\alpha\beta. \tag{12}$$

Hence, by inverting the copula function in Eq. (12) for a given values of α and β we can obtain the value of $F_{y_t}(q_{\alpha,\beta,t}^{y_t|x_t})$, which we denote as $\hat{F}_{y_t}(q_{\alpha,\beta,t}^{y_t|x_t})$.[2] Then, by inverting the marginal distribution function of y_t we obtain the conditional quantile as:

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[1] A detailed analysis of copula functions can be found in Joe (1997) and Nelsen (2006).

[2] Note that the bivariate copula relates two arguments, $F_x(x)$ and $F_y(y)$, through a copula function. Once we have the specific form of this copula function, the value of this copula function (given by $\alpha\beta$) and the value of $F_y(y)=\beta$, we have one equation with one unknown; so we can solve this equation in order to obtain the value of $F_y(y)$.

$$q_{\alpha,\beta,t}^{y_t|x_t} = F_{y_t}^{-1}(\hat{F}_{y_t}(q_{\alpha,\beta,t}^{y_t|x_t})). \tag{13}$$

Similarly, using copula functions we can also compute the conditional α-quantile of the stock price return distribution at time t conditional on the fact that oil price changes take values between a lower and upper boundary. Note that $P(y_t \le q_{\alpha,(\theta,\beta),t}^{y_t|x_t} \mid q_{\theta,t}^{x_t} \le x_t \le q_{\beta,t}^{x_t}) = \alpha$ can be written as:

$$\frac{P(y_t \le q_{\alpha,(\theta,\beta),t}^{y_t|x_t}, q_{\theta,t}^{x_t} \le x_t \le q_{\beta,t}^{x_t})}{P(q_{\theta,t}^{x_t} \le x_t \le q_{\beta,t}^{x_t})} = \alpha. \tag{14}$$

Given that $P(q_{\theta,t}^{x_t} \le x_t \le q_{\beta,t}^{x_t}) = (\beta - \theta)$ and $P(y_t \le q_{\alpha,(\theta,\beta),t}^{y_t|x_t}, q_{\theta,t}^{x_t} \le x_t \le q_{\beta,t}^{x_t})$ can be expressed in terms of the distribution function as $F_{y_t x_t}(q_{\alpha,(\theta,\beta),t}^{y_t|x_t}, q_{\beta,t}^{x_t}) - F_{y_t x_t}(q_{\alpha,(\theta,\beta),t}^{y_t|x_t}, q_{\theta,t}^{x_t})$, we can rewrite Eq. (14) in terms of the copula function as:

$$C(F_{y_t}(q_{\alpha,(\theta,\beta),t}^{y_t|x_t}), \beta) - C(F_{y_t}(q_{\alpha,(\theta,\beta),t}^{y_t|x_t}), \theta) = (\beta - \theta)\alpha. \tag{15}$$

Hence, by inverting the copula function in Eq. (15) we can obtain the value of $F_{y_t}(q_{\alpha,(\theta,\beta),t}^{y_t|x_t})$ (denoted by $\hat{F}_{y_t}(q_{\alpha,(\theta,\beta),t}^{y_t|x_t})$) for a given values of α, θ and β; then by inverting the marginal distribution function of y_t we obtain the conditional quantile as:

$$q_{\alpha,(\theta,\beta),t}^{y_t|x_t} = F_{y_t}^{-1}(\hat{F}_{y_t}(q_{\alpha,(\theta,\beta),t}^{y_t|x_t})). \tag{16}$$

Computing conditional quantiles through copula functions has several advantages. First, copulas offer modelling flexibility by allowing separate modelling of the marginals and dependence structures. This is crucially important when upper and lower quantile dependence differs (for example, when the impact of upper or lower oil price changes on stock returns has a different size), when the joint distribution function is not elliptical or when data has special characteristics (such as conditional heteroskedasticity, leverage or time-varying conditional dependence). Second, computing conditional quantiles from copulas is computationally easy as we only need information on the copula, on the marginal distribution of stock returns and on the cumulative probability of oil price quantiles (see Reboredo, 2015; Reboredo and Ugolini, 2015).

In our empirical study, we used different static and time-varying copula specifications in order to capture different dependence characteristics: tail independence (Gaussian), symmetric tail dependence (Student-t) and asymmetric tail dependence (Gumbel, Rotated Gumbel and BB7). Their main features are summarized in Table 1.

[Insert Table 1 here]

Using the inference function for margins (Joe and Xu, 1996), we firstly estimated the parameters of the marginal models using maximum likelihood and then estimated the copula parameters using copula pseudo-sample observations given by the probability integral transformation of the standardized residuals from the marginals. The number of lags in the mean and variance equations for each series was selected according to the Akaike information criteria (AIC) and the different copula models were evaluated using the AIC adjusted for small-sample bias, as in Breymann et al. (2003) and Reboredo (2011).

3. Data

We empirically studied the impact of quantile and interquantile oil price changes on stock return quantiles using weekly data for the period 7 January 2000 to 19 December 2014.[3] Our database covered the period of the dot-com crisis, subprime/global financial crisis and European debt crisis, so we could better assess how dependence between quantiles of the stock and oil prices changed as a result of these crises. We used Brent crude oil prices, sourced from the US Energy Information Agency (http://www.eia.doe.gov) and expressed in USD per barrel, as it is a benchmark for determining the price of light crudes and is closely related to other crude oil benchmark such as those for West Texas Intermediate (WTI), Maya, Dubai, etc (see Reboredo, 2011). To account for the effects of oil prices on stock returns, we considered stock price indices for several developed and emerging economies, including the USA, the UK, the EMU and the five BRICS countries, Brazil, Russia, India, China and South Africa. Stock price indices were sourced from the Datastream database, which provides information on global equity indices at six different levels, where level 1 is the total market index and level 2 divides the market into ten sectors: oil and gas; basic materials; industrial materials; consumer goods; consumer services; healthcare; telecommunications; utilities; financials; and technology. As in Sukcharoen et al. (2014), we used the level 2 stock price indices and their corresponding market values to build up a new aggregate stock market index, but excluding the oil and gas sectors in order to eliminate the direct effects of oil prices on stock returns. The new aggregate index was built by weighting industry price indices with the corresponding total market value shares, with weights updated every six months. Also, to account for the effects of exchange rates on the oil-stock returns relationship, each computed aggregated index was expressed in USD using the USD exchange rate against the home currency.

Figure 1 depicts the temporal dynamics of stock price return (computed as the first difference of log prices) for all the stock markets analysed, showing differences in the size and timing of stock price movements in different markets and sharing high volatility episodes around the onset of the global financial crisis. The size and dynamics of price volatility also differed significantly across countries. Table 2 provides descriptive statistics for all the stock return indices and oil price returns for the whole sample and for the periods before and after the onset of the global financial crisis (taking 15 September 2008 as the breakpoint[4]). As is common in

[3] Due to data availability, the sample extends to 31 January 2014 for China.

[4] There is no real consensus on the date of onset of the global financial crisis. The date 15 September 2008, coinciding with the collapse of Lehman Brothers that almost brought down

financial returns, weekly returns had average values close to zero, were negatively skewed and exhibited significant kurtosis (mainly in the period after the onset of the crisis). Nevertheless, the Jarque-Bera (JB) test indicated that all series had no normal distributions. The standard deviation differed across indices, with oil returns and emerging market indices having the highest values; this is also confirmed by the maximum and minimum values of the return series. Furthermore, the Ljung-Box (LB) statistic confirmed the presence of serial correlation, except for oil, whereas the autoregressive conditional heteroskedasticity Lagrange multiplier (ARCH-LM) statistic unambiguously indicated the presence of ARCH effects in all series. Finally, the unconditional linear Pearson correlation evidence indicated that stock returns were positively correlated with oil price returns for the overall sample period; however, considering linear dependence in the periods before and after the onset of the global financial crisis, the Pearson correlation coefficients indicated that there was no dependence before the crisis and that dependence considerably increased with the onset of the crisis, a fact that could have implications in terms of quantile dependence that will be analysed below.

[Insert Figure 1 and Table 2 here]

4. Results

We discuss results for the impact of quantile and interquantile oil price changes on stock return quantiles by firstly presenting results for the marginal models for stock returns from which we computed the stock return quantiles. We then present the copula model estimations from which we computed the conditional quantiles. We finally present quantile estimation results and tests for differences between unconditional and conditional stock return quantiles and discuss the implications of the results.

4.1 Empirical results for marginal models

Table 3 displays parameter estimates and goodness-of-fit test for the marginal models in Eqs. (7)-(9) for stock and oil returns.[5] The appropriate lags in mean and variance were selected using values between 0 and 2, taking the values that minimized the AIC value as the suitable lag structure. Parameter estimates for the mean show that no AR or MA coefficients were significant in any series, providing evidence of no serial dependence. As for volatility, volatility parameter estimates indicated that GARCH components were significant in all series, whereas ARCH components were significant only in the Chinese and US stock markets and for crude oil returns. Volatility was also persistent across all markets, with leverage effects

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the world's financial system, is typically used, even though the foundations of the crisis were forged prior to this date. Our results were not sensitive to this choice of breakpoint.

[5] We also estimated marginal models in the pre- and post-onset crisis. Results, available on request, were similar to those reported here.

observed for all series except for China and Brent; hence, returns responded asymmetrically to information shocks. Furthermore, estimated values for asymmetry and the degrees-of-freedom parameter confirmed that error terms were not normal and were well characterized by a distribution with asymmetries and fat tails; the exceptions were Russia and China, where a symmetric Student-t provided a better fit than an asymmetric distribution function.

[Insert Table 3 here]

The last rows of Table 3 provide information on the goodness-of-fit-tests for the estimated marginal models. They can be summarized as follows. Neither serial correlation nor GARCH effects remained in the model residuals according to the LB and ARCH statistics. We also found no evidence of any structural change after testing the model residuals using the cumulative sum test. In addition, we assessed the adequacy of the skewed-t distribution by inspecting whether the distribution of the standardized model residuals was uniform (0,1). We used the well-known KS, Cramér-von Mises (CvM) and Anderson-Darling (AD) tests to compare the empirical and theoretical distribution functions, obtaining p values for these tests that provide evidence in favour of the null hypothesis of correct specification of the distribution model for the overall sample. Furthermore, provided that linear dependence between oil and stock returns changed with the onset of the global financial crisis (see Table 2), we checked whether the adequacy of the skewed distribution held in the pre- and post-onset crisis periods; p values for these two subsamples provide evidence in favour of the null hypothesis of correct specification. Overall, our goodness-of-fit tests conclude that there was no mis-specification errors in our marginal distribution models. Hence, stock return quantiles could be computed from the information provided by the marginal models using Eq. (10); furthermore, the copula model was able to capture dependence between oil and stock returns and provide information on the conditional stock return quantiles, as given by Eqs (12)-(13) and (15)-(16).

4.2 Empirical estimates for copula models

We estimated different copula models (see Table 1), taking as pseudo-sample observations the probability integral transform of the standardized residuals for each of the marginal models. For each oil-stock return pair, we considered dependence in the pre- and post-onset crisis period by estimating copula functions for both periods delimited by 15 September 2008 data (see footnote 2).

Table 4 reports evidence from both static and time-varying (TVP) copulas for the pre-onset period. The empirical evidence indicates that oil and stock returns weakly co-moved and that there was weak evidence of upper or lower tail dependence. Elliptical copulas offered evidence of low positive correlation between oil and stock returns and of low negative dependence for the UK and the USA. According to the AIC values, Brazil, Russia, India and China displayed static dependence, with low values for both average and tail dependence. In contrast, South Africa, the UK, the USA and the EMU exhibited time-varying dependence – characterized by the TVP Gaussian and Student-t copulas -- displaying evidence of relatively high periods of negative dependence interspersed with other periods of positive and near-zero correlations.

[Insert and Table 4]

Regarding the post-onset period, copula results reported in Table 5 indicate that the shape of oil-stock dependence dramatically changed. Oil and stock markets coupled and moved in the same direction, exhibiting some kind of tail dependence. In fact, elliptical copulas provide evidence of a high correlation coefficient. The best copula fit, according to the AIC, provided evidence of lower tail dependence for all stock markets and upper tail dependence only in Brazil, the UK, Russia and EMU. Also, in the post-onset period we found more evidence of static dependence, observing time-varying dependence only in Russia, India and South Africa. Obviously, the changes in the dependence structure we observed in post-crisis period has implications for the conditional stock return quantiles and thus for the impact of oil price changes on stock return quantiles (to be assessed below).

[Insert Table 5 here]

To sum up, the evidence on the bivariate dependence structure between oil and stock returns across different countries indicates that: (a) in the pre-onset period, average dependence was low in all markets and there was upper and lower tail independence; (b) in the post-onset period, average dependence was positive and relatively high, with evidence of lower tail dependence and mixed evidence of upper tail dependence; (c) there was no distinctive patterns in the behaviour or dependence between oil and stock returns across the sample period regarding developed and emerging markets. In the next section we use the best copula fit to obtain the conditional stock return quantiles as given by Eqs (12)-(13) and (15)-(16).

4.3 Unconditional and conditional quantile results

Using the information from the marginal and copula models, we estimated unconditional and conditional stock returns as given by Eq. (10) and Eqs. (12)-(13) and (15)-(16), respectively. For the sake of brevity, we only present results for upward and downward stock return quantiles, considering two values for α; namely $\alpha = 0.05$ and $\alpha = 0.95$, as they are crucial for investors in terms of downside and upside risk management (note that for $\alpha = 0.95$ we have $P(y_t \geq q^{y_t}_{0.95,t}) = 0.05$). Although our reported evidence accounts for the effect of large and small oil price movements on extreme stock returns, we can also consider the impact of oil price movements of diverse sizes on different stock return quantiles. Figure 2 shows different combinations of stock and oil return quantiles, where points A and B indicate the quantiles for which we report conditional dependence throughout the sample periods before and after the onset of the financial crisis. We can also consider the impact of oil price movements of specific sizes on different stock return quantiles; for example, point C in Figure 2 accounts for the effect of an oil price movement with a size below its 0.4 quantile on the 0.6 quantile of stock returns; similarly, point D accounts for the effect of an oil price movement with a size below its 0.6 quantile on the 0.05 quantile of stock returns. We also computed the conditional stock return quantiles for different oil-stock quantile combinations as the one represented in Figure 2.[6]

[Insert Figure 2 here]

Regarding the impact of the interquantile oil price variations, we considered: (a) $\beta = 0.05$ and $\beta = 0.95$ for oil price quantile variations, and (b) either $(\theta, \beta) = (0.2, 0.4)$ for negative oil price movements that correspond with weekly oil price changes between -3.2% and -0.6% or $(\theta, \beta) = (0.6, 0.8)$ for positive oil price movements that correspond with weekly oil price changes between 1.4% and 3.9%.

Figure 3 reports graphical evidence on the size and dynamics of both unconditional and conditional stock return quantiles in the periods before and after the outbreak of the global financial crisis (delimited by a vertical line). Descriptive statistics and hypothesis test results for quantiles are reported in Table 6. Considering the period before the crisis, we found that lower conditional stock return quantiles were systematically below the conditional quantiles for BRICS countries with the exception of China; for the three developed countries we found some periods when this did not happen, mainly in the USA and the UK. This result is consistent with the results for the copula functions: some evidence of lower tail dependence was found for emerging economies (excepting China), but not for developing countries. The graphical evidence is also confirmed by the descriptive statistics reported in Table 6; in contrast, the results of the KS bootstrapping test (see Eq. (6)) indicated that differences between unconditional and conditional stock returns at the 0.05 level were significant for emerging countries (excepting China) and not significant for developed countries. Hence, extreme downward oil price movements did have spillover effects on stock markets in emerging economies to the extent that stock return quantiles were significantly impacted by downward oil price movement, whereas no evidence of those spillovers was found for developed economies. Figure 3, which depicts the impact of oil price upward movement on stock returns, shows that the 0.95 conditional and unconditional stock return quantiles were very close in the period before the onset of the global financial crisis, with Brazil, Russia, South Africa and the USA as exceptions, a result corroborated by the descriptive statistics. Also, the KS test evidence reported in Table 6 indicates that upward oil price movements had upward spillover effects on oil prices in all the countries except for India, China, the UK and the EMU. Furthermore, graphical evidence in Figure 3 and descriptive statistics in Table 6 show that upside spillover effects were much smaller than the downside spillover effects. We formally test for asymmetries in the downside and spillovers effects by testing for the significant differences between the conditional

[6] Results for different quantiles are available on request. These results are summarized graphically below.

upside quantile (normalized by the unconditional upside quantile) and conditional downside quantile (normalized by the unconditional downside quantile); that is

$$H_0 : \; q^{y|x}_{0.05,0.05} \Big/ q^{y}_{0.05} = q^{y|x}_{0.95,0.95} \Big/ q^{y}_{0.95} \,, \tag{17}$$

using the KS statistic in Eq. (6). The last column of Table 6 reports the results for this hypothesis, showing that downside spillover effects are larger than the upside spillover effects for most countries before the crisis. Hence, our results on the impact of oil prices on stock return quantiles provide evidence of symmetric effects for developed economies like the UK and the EMU and of asymmetric effects for the USA and for emerging economies like India and China.

[Insert Figure 3 and Table 6 here]

The graphical evidence in Figure 3 regarding the size and dynamics of unconditional and conditional stock return quantiles for the period after the onset of the financial crisis shows that the impact of oil price movements on stock returns changed with respect to the pre-onset crisis period. We found that lower conditional stock return quantiles were systematically below the unconditional quantiles for all countries and, furthermore, displayed abrupt downward movements in the months after crisis outbreak, even though subsequent dynamics differed across countries. This graphical evidence was corroborated by the descriptive statistics and the KS statistics in Table 6. It is therefore possible to conclude that extreme downward oil price movements did have spillover effects on stock markets, as long as the stock return quantile was significantly impacted by this downward movement. Regarding the effects of extreme upward oil price movements, Figure 3 also confirms that oil prices impacted stock prices, even though the size of the impact differed across countries, as confirmed by the descriptive statistics and the KS statistics reported in Table 6. These results on the spillover effects of extreme oil price movements on upside and downside stock price movements are consistent with the fact that oil and stock markets coupled after the onset of the financial crisis, increasing tail dependence (mainly lower tail dependence). Hence, not surprisingly, differences between unconditional and conditional stock return quantiles are greater for lower quantiles than for upper quantiles. In fact, the results of the KS statistic in the last column of Table 6 for the hypothesis in Eq. (17) indicate that downside spillover effects are larger than the upside spillover effects for all countries after the crisis.

Figure 4 summarizes the impact of oil price movements of specific sizes on different stock return quantiles, as represented in Figure 2. Each plot represents the average value of the conditional over the corresponding unconditional stock return quantile: values differing from 1 indicate that oil price movements impacted on stock returns in the corresponding quantiles. The graphical evidence provide by Figure 5 confirms that the impact of oil price movements on stock returns was more prominent in the period after the onset of the crisis and that moderate positive or negative oil price movements had a limited impact on stock returns.

[Insert Figures 4 here]

Figure 5 plots the dynamics of the unconditional and conditional stock returns for each country by considering the impact of moderate negative ($(\theta, \beta) = (0.2, 0.4)$) and positive ($(\theta, \beta) = (0.6, 0.8)$) oil price movements in the periods before and after the onset of the global financial crisis (delimited by a vertical line). Descriptive statistics and hypothesis test results for quantiles are reported in Table 7. Regarding the period before the crisis, we found that both lower and upper conditional stock return quantiles closely evolved with the corresponding unconditional quantiles. In fact, descriptive statistics and KS statistic results reported in Table 7 indicate that there were no significant differences between unconditional and conditional stock return quantiles, whether upper or lower. Hence, moderate oil price movements had no spillover effects on extreme movements in stock returns. As for the period after crisis onset, our results in Figure 5 also shows that, like in the pre-crisis period, conditional and unconditional stock returns in the upper and lower quantiles were so close as to be almost indistinguishable. This graphical evidence was also corroborated by the descriptive statistics and KS statistic results reported in Table 7. Hence, independently of the time period, moderate positive or negative oil price movements had no spillover effect on upward or downward stock price movements. In addition, we tested for asymmetries of the impact of the effect of moderate positive or negative oil price movements using the KS statistics. The results of this test, reported in the last column of Table 7, indicate that the hypothesis of symmetry holds for most countries.

[Insert Figure 5 and Table 7 here]

Our results have implications for stock return dynamics and for investors. First, extreme oil price changes did have spillover effects on stock markets, mainly after the onset of the financial crisis, meaning that abrupt changes in oil prices exacerbate extreme movements in stock markets, whereas moderate positive or negative oil price changes have no significant impact on stock price movements. The existence of oil price spillovers effects and the fact that the effects are asymmetric in size have implications for portfolio risk management. More specifically, asymmetric co-movement between oil and stock prices and differences in spillover size would imply that investors who wish to protect their portfolios should take into account long and short positions in bearish and bullish stock markets, given that long positions are less (more) vulnerable to oil in bullish (bearish) markets; whereas the opposite holds for short positions.

5. Conclusions

We examined how quantile and interquantile oil price movements impact different stock return quantiles in the periods before and after the onset of the global financial crisis for three developed economies (the US, the UK and the EMU) and the five BRICS countries (Brazil, Russia, India, China and South Africa). We described a methodological approach that consisted of testing for the existence of significant differences between unconditional and conditional stock return quantiles, where the unconditional quantile was computed from the marginal stock return distribution and where the conditional stock return quantile (given an oil price movement of specific size or inside a specific range) was obtained from a copula function that characterizes bivariate dependence between oil and stock prices. This approach allowed us to capture dependence between oil and stock returns under different stock market conditions and also took into account different kinds of oil price movements --- of interest for investors in terms of downside or upside portfolio risk management decisions.

Using weekly prices for the period January 2000 to December 2014, our empirical results indicate that oil and stock prices weakly co-moved in the period before the onset of the global financial crisis, whereas 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. However, after the crisis broke, large upward (downward) oil price changes significantly impacted on large upward (downward) stock price quantiles, with a more sizeable impact observable in the lower than in the upper quantiles. We also found that small positive and negative oil price movements had no effect on stock price movements. Our results provide new evidence on asymmetries in oil price spillovers to stock returns and on how the oil-stock relationship has changed in recent years with the outbreak of the global financial crisis. Our evidence also have implications for investors, who need to apply risk management strategies to protect against upturns or downturns in oil prices.

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Table 1. Copula specifications.

Name	Copula	Parameter	Structure of dependence
Gaussian	$C_N(u,v;\rho)=\Phi\left(\Phi^{-1}(u),\Phi^{-1}(v)\right)$	ρ	No tail dependence: $\lambda_U=\lambda_L=0$
Student-T	$C_{ST}(u,v;\rho,\upsilon)=T(t_\upsilon^{-1}(u),t_\upsilon^{-1}(v))$	ρ,υ	Symmetric tail dependence: $\lambda_U=\lambda_L=2t_{\upsilon+1}\left(-\sqrt{\upsilon+1}\sqrt{1-\rho}/\sqrt{1+\rho}\right)$
Gumbel	$C_G(u,v;\delta)=\exp\left(-\left((-\log u)^{\delta}+(-\log v)^{\delta}\right)^{1/\delta}\right)$	$\delta\geq 1$	$\lambda_L=0,\ \lambda_U=2-2^{1/\delta}$
Rotated Gumbel	$C_{RG}(u,v;\delta)=u+v-1+C_G(1-u,1-v;\delta)$	$\delta\geq 1$	$\lambda_L=2-2^{1/\delta},\ \lambda_U=0$
BB7	$C_{BB7}(u,v;\delta,\theta)=1-\left(1-\left[\left(1-(1-u)^{\theta}\right)^{-\delta}+\left(1-(1-v)^{\theta}\right)^{-\delta}-1\right]^{-1/\delta}\right)^{1/\theta}$	$\theta\geq 1,\ \delta>0$	$\lambda_L=2^{-1/\delta},\lambda_U=2-2^{1/\theta}$

Note. λ_U (λ_U) denotes upper (lower) tail dependence. We captured time-varying parameter (TVP) dependence by assuming that copula parameters change over time. For the Gaussian and the Student-t copulas, we adopted an ARMA(1,q)-type process (Patton, 2006) for the linear dependence parameter ρ_t: $\rho_t=\Lambda_1\left(\psi_0+\psi_1\rho_{t-1}+\psi_2\frac{1}{q}\Sigma_{j=1}^{q}\Phi^{-1}(u_{t-i})\cdot\Phi^{-1}(v_{t-i})\right)$, where $\Lambda_1(x)=\left(1-e^{-x}\right)\left(1+e^{-x}\right)^{-1}$ is the modified logistic transformation that keeps the value of ρ_t in (-1,1). For the Student-t copula, $\Phi^{-1}(x)$ is replaced by $t_\upsilon^{-1}(x)$. We considered the TVP for the Gumbel copula, the rotated Gumbel copula and the BB7 copula by assuming that the parameters follow the dynamics given by the following equation: $\delta_t=\bar{\omega}+\bar{\beta}\delta_{t-1}+\bar{\alpha}\frac{1}{q}\Sigma_{j=1}^{q}\left|u_{t-i}-v_{t-i}\right|$ and $\theta_t=\omega+\beta\theta_{t-1}+\alpha\frac{1}{q}\sum_{j=1}^{q}\left|u_{t-j}-v_{t-j}\right|$.

Table 2. Descriptive statistics.

	Brazil	Russia	India	China	S.Africa	UK	US	EMU	Brent
Panel A: Overall sample									
Mean	0.001	0.002	0.003	0.001	0.001	0.000	0.000	0.000	0.001
Maximum	0.208	0.118	0.120	0.159	0.165	0.148	0.125	0.147	0.239
Minimum	-0.292	-0.165	-0.135	-0.150	-0.204	-0.143	-0.186	-0.250	-0.251
Std. Dev.	0.044	0.039	0.038	0.035	0.038	0.028	0.027	0.035	0.051
Skewness	-0.992	-0.481	-0.133	-0.141	-0.527	-0.457	-0.762	-0.868	-0.521
Kurtosis	8.681	4.575	3.389	4.825	5.570	6.781	9.150	7.400	5.374
J-B	1176.64*	110.67*	7.24*	104.34*	250.77*	491.72*	1304.82*	726.99*	218.41*
ARCH	15.026	5.143	3.867	4.556	27.505	13.063	11.483	5.191	6.858
	[0.000]	[0.000]	[0.000]	[0.000]	[0.122]	[0.000]	[0.000]	[0.000]	[0.000]
Q(20)	51.503	64.570	36.508	56.816	11.805	63.980	35.919	35.395	15.655
	[0.000]	[0.000]	[0.013]	[0.000]	[0.000]	[0.000]	[0.016]	[0.018]	[0.738]
Corr. oil	0.22	0.21	0.19	0.06	0.22	0.21	0.18	0.22	
Panel B: Before the onset of the financial crisis									
Mean	0.003	0.004	0.003	0.000	0.001	-0.001	0.000	0.000	0.004
Maximum	0.117	0.118	0.120	0.128	0.086	0.113	0.087	0.147	0.180
Minimum	-0.198	-0.165	-0.112	-0.147	-0.117	-0.112	-0.134	-0.114	-0.220
Std. Dev.	0.042	0.037	0.039	0.034	0.036	0.025	0.024	0.034	0.054
Skewness	-0.719	-0.374	-0.073	-0.074	-0.555	-0.412	-0.626	-0.318	-0.508
Kurtosis	4.887	4.907	3.200	4.766	3.619	5.599	6.966	4.511	4.166
J-B	105.78*	78.85*	1.15*	59.02*	30.35*	139.75*	324.99*	50.47*	44.95*
ARCH	1.294	4.632	1.698	0.031	1.125	3.284	1.914	4.322	3.306
	[0.178]	[0.000]	[0.031]	[0.001]	[0.321]	[0.000]	[0.011]	[0.000]	[0.000]
Q(20)	33.323	31.969	23.586	46.388	14.853	27.251	35.775	15.393	21.669
	[0.031]	[0.044]	[0.261]	[0.001]	[0.785]	[0.128]	[0.016]	[0.753]	[0.359]
Corr. oil	0.02	0.04	0.05	0.03	0.04	-0.02	-0.07	0.03	
Panel C: After the onset of the financial crisis									
Mean	-0.001	0.001	0.002	0.002	0.001	0.001	0.001	0.000	-0.002
Maximum	0.208	0.118	0.103	0.159	0.165	0.148	0.125	0.108	0.239
Minimum	-0.292	-0.156	-0.135	-0.150	-0.204	-0.143	-0.186	-0.250	-0.251
Std. Dev.	0.046	0.043	0.036	0.037	0.041	0.032	0.030	0.037	0.046
Skewness	-1.258	-0.533	-0.243	-0.241	-0.490	-0.511	-0.875	-1.417	-0.625
Kurtosis	12.141	4.100	3.683	4.863	6.936	6.995	9.832	9.894	8.225
J-B	1232.1*	32.14*	9.62*	43.67*	225.55*	233.12*	681.85*	761.51*	395.64*
ARCH	4.023	1.710	2.472	3.526	4.657	4.278	7.199	3.662	1.078
	[0.000]	[0.031]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.372]
Q(20)	25.660	32.459	28.309	14.969	30.203	46.100	25.676	36.067	33.323
	[0.177]	[0.039]	[0.102]	[0.778]	[0.067]	[0.000]	[0.177]	[0.015]	[0.031]
Corr. oil	0.51	0.44	0.45	0.11	0.47	0.52	0.51	0.51	

Notes: Weekly data for the period 7 January 2000 to 19 December 2014 (7 January 2000 to 31 January 2014 for China). JB, LB and ARCH denote the Jarque-Bera statistic for normality, the Ljung-Box statistics for serial correlation in returns computed with 20 lags, and Engle's LM test for heteroskedasticity computed using 20 lags; respectively. An asterisk (*) indicates rejection of the null hypothesis at the 5% level. Numbers in square brackets are p values. 'Corr. oil' denotes Pearson correlation between oil and stock returns.

Table 3. Estimates for marginal distribution models.

	Brazil	Russia	India	China	S.Africa	UK	US	EMU	Brent
Mean									
ϕ_0	0.002	0.004*	0.003*	-0.001	0.002	0.000	0.001	0.001	0.000
	(1.629)	(3.567)	(2.113)	(-0.794)	(1.266)	(0.579)	(1.419)	(0.747)	(-0.023)
ϕ_1		-0.898*	-0.529*				-0.109*		
		(-14.00)	(-2.590)				(-2.407)		
θ_1		0.897*	0.547*						
		(13.67)	(3.052)						
Variance									
ω	0.722*	0.529*	0.131	0.372	0.812	0.192*	0.117*	0.218	0.206
	(2.093)	(2.514)	(1.530)	(1.763)	(1.777)	(2.776)	(2.438)	(1.775)	(0.941)
α_1	0.028	0.055	0.006	0.106*	0.000	-0.014	-0.082*	0.005	0.050*
	(1.184)	(1.629)	(0.373)	(3.019)	(-0.020)	(-0.829)	(-2.677)	(0.257)	(2.478)
β_1	0.873*	0.873*	0.949*	0.874*	0.879*	0.924*	0.948*	0.920*	0.918*
	(25.630)	(25.520)	(55.260)	(27.760)	(15.190)	(39.140)	(20.940)	(29.240)	(30.890)
λ	0.101*	0.071*	0.068*		0.103*	0.105*	0.197*	0.090*	
	(2.599)	(2.061)	(3.764)		(2.627)	(4.013)	(5.463)	(2.393)	
Asymetry	-0.248*	-0.052	-0.145*	-0.114	-0.177*	-0.203*	-0.256*	-0.224*	-0.234*
	(-4.349)	(-0.991)	(-3.132)	(-1.950)	(-3.845)	(-3.465)	(-4.521)	(-4.144)	(-4.744)
Tail	12.797*	7.893*	100.000*	5.718*	15.171*	8.711*	9.694*	9.378*	9.823*
	(2.697)	(4.075)	(19.200)	(5.338)	(2.104)	(3.874)	(3.240)	(3.458)	(3.363)
LogLik	1442.66	1486.83	1492.62	1470.57	1515.60	1799.66	1889.73	1628.63	1294.59
LJ	27.261	8.396	31.863	31.658	19.314	30.069	22.410	22.503	11.775
	[0.13]	[0.59]	[0.06]	[0.07]	[0.50]	[0.07]	[0.32]	[0.31]	[0.92]
LJ 2	15.298	12.308	5.652	9.865	12.341	12.559	10.452	18.781	24.197
	[0.64]	[0.83]	[0.99]	[0.94]	[0.83]	[0.82]	[0.92]	[0.41]	[0.15]
ARCH	0.771	0.690	0.244	0.502	0.685	0.645	1.485	1.044	1.257
	[0.75]	[0.84]	[0.99]	[0.97]	[0.84]	[0.88]	[0.08]	[0.41]	[0.20]
K-S (1)^t	[0.27]	[0.93]	[0.88]	[0.45]	[0.26]	[0.34]	[0.11]	[0.70]	[0.43]
C-vM (1)^t	[0.56]	[0.92]	[0.88]	[0.64]	[0.39]	[0.34]	[0.08]	[0.55]	[0.22]
A-D (1)	[0.46]	[0.95]	[0.84]	[0.66]	[0.41]	[0.45]	[0.11]	[0.63]	[0.16]
K-S (2)	[0.18]	[0.28]	[0.84]	[0.28]	[0.25]	[0.77]	[0.52]	[0.86]	[0.43]
C-vM (2)	[0.14]	[0.35]	[0.84]	[0.20]	[0.47]	[0.69]	[0.25]	[0.82]	[0.37]
A-D (2)	[0.16]	[0.36]	[0.86]	[0.25]	[0.57]	[0.73]	[0.21]	[0.76]	[0.31]
K-S (O)	[0.64]	[0.78]	[0.86]	[0.61]	[0.35]	[0.88]	[0.70]	[0.87]	[0.84]
C-vM (O)	[0.68]	[0.74]	[0.96]	[0.48]	[0.44]	[0.86]	[0.70]	[0.88]	[0.91]
A-D (O)	[0.76]	[0.87]	[0.98]	[0.59]	[0.53]	[0.89]	[0.70]	[0.93]	[0.96]

Notes. The table provides information on maximum likelihood parameter estimates and z-statistics (in brackets) for the marginal models described in Eqs. (7)-(9). LogLik, LJ, LJ2 denote the log-likelihood value and the Ljung-Box statistic for serial correlation in the residual model and in the squared residual model calculated with 20 lags, respectively. ARCH denotes Engle's LM test for the ARCH effect in residuals up to 20th order. KS, CvM and AD denote the Kolmogorov-Smirnov, Cramér-von Mises and Anderson-Darling statistics for the overall sample (O), first subsample from 2000-2008 (1) and second subsample from 2008-2014 (2); p values (in square brackets) below 0.05 indicate rejection of the null hypothesis of correct specification. An asterisk (*) indicates significance at 5%.

Table 4. Copula model estimates for oil and stock returns for the period 2000-2008.

Panel A: Parameter estimates for time-invariant copulas.

	Brazil	Russia	India	China	S.Africa	UK	USA	EMU
Gaussian copula								
ρ	0.032	0.055	0.061	0.016	0.056	-0.002	-0.115*	0.049
	(0.02)	(0.03)	(0.04)	(0.10)	(0.04)	(0.06)	(0.02)	(0.03)
AIC	1.463	0.597	**0.290**	1.887	0.553	2.004	-4.437	0.991
Student-T copula								
ρ	0.036	0.059	0.057	0.016	0.045	-0.011	-0.123*	0.043
	(0.05)	(0.05)	(0.04)	(0.48)	(0.05)	(0.05)	(0.05)	(0.04)
υ	9.740*	13.648	100.0*	500.0	10.170*	14.587*	30.310	42.182
	(4.28)	(10.42)	(3.51)	(1706.25)	(4.44)	(4.17)	(39.30)	(47.96)
AIC	**-1.814**	0.203	2.270	3.970	-2.442	1.665	-3.244	2.727
Gumbel copula								
δ	1.030*	1.024*	1.019*	1.009*	1.035*	1.006*	1.000*	1.020*
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.05)	(0.02)
AIC	0.145	1.131	1.451	**1.731**	-0.403	1.930	2.009	1.116
Rotated Gumbel copula								
δ	1.022*	1.045*	1.027*	1.000*	1.037*	1.014*	1.006*	1.019*
	(0.03)	(0.03)	(0.03)	(0.05)	(0.03)	(0.02)	(0.01)	(0.03)
AIC	1.371	**-0.951**	0.859	2.009	-1.036	1.183	1.071	1.553
BB7 copula								
θ	1.038*	1.001*	1.004*	1.011	1.033*	1.009*	1.001*	1.015*
	(0.03)	(0.04)	(0.04)	(0.72)	(0.03)	(0.03)	(0.40)	(0.03)
δ	0.011	0.077	0.044	0.001	0.052	0.010	0.001	0.041
	(0.05)	(0.06)	(0.05)	(0.96)	(0.05)	(0.05)	(0.94)	(0.05)
AIC	2.072	1.772	3.035	3.721	0.517	3.823	4.202	2.739

Panel B: Parameter estimates for time-varying copulas.

	Brazil	Russia	India	China	S.Africa	UK	USA	EMU
TVP-Gaussian								
ψ_0	0.024	0.212	0.129	0.062	0.127	-0.004	-0.046	0.010
	(0.06)	(0.15)	(0.26)	(0.13)	(0.15)	(0.02)	(0.04)	(0.03)
ψ_1	0.039	-0.515*	0.056	-0.195	-0.362	0.135	0.240	0.215*
	(0.10)	(0.24)	(0.19)	(0.23)	(0.21)	(0.07)	(0.13)	(0.09)
ψ_2	1.130	-1.342*	-0.063	-0.603	-1.408*	1.583*	1.367*	1.339*
	(1.33)	(0.43)	(3.62)	(1.50)	(0.40)	(0.25)	(0.38)	(0.30)
AIC	5.305	-0.909	4.239	5.155	1.558	**-0.669**	**-9.768**	**-7.176**
TVP-Student-T								
ψ_0	0.083	0.215	0.539*	0.179*	0.119	-0.079	-0.028	0.064
	(0.15)	(0.16)	(0.10)	(0.04)	(0.12)	(0.14)	(0.10)	(0.17)
ψ_1	-0.087	-0.169	0.034*	0.009*	-0.335*	-0.143	0.178	0.215*
	(0.13)	(0.12)	(0.01)	(0.00)	(0.10)	(0.15)	(0.59)	(0.09)
ψ_2	-1.202	-1.611*	-2.076*	-2.043*	-1.415*	-1.078	1.624*	-1.924*
	(0.86)	(0.31)	(0.02)	(0.03)	(0.30)	(0.68)	(0.28)	(0.05)
υ	9.614*	12.821*	43.216*	45.000	11.401*	14.780*	42.055	45.000
	(2.54)	(1.90)	(5.10)	(30.64)	(2.01)	(5.97)	(80.07)	(56.16)
AIC	1.691	1.568	3.445	7.909	**-5.368**	4.672	-8.883	0.671
TVP-Gumbel								
$\bar{\omega}$	2.626*	2.118	3.044*	-0.420	-2.319	-1.248	0.000	-1.500*
	(1.16)	(27.20)	(0.93)	(0.89)	(1.65)	(8.58)	(1.00)	(0.67)
$\bar{\beta}$	-2.507*	-2.174	-2.637*	0.759	2.284	1.505	0.000	1.718*
	(1.19)	(35.01)	(1.02)	(0.83)	(1.18)	(6.91)	(1.00)	(0.59)
$\bar{\alpha}$	0.355	-0.136	-0.329	-1.021*	-0.538	-0.448	0.000	-0.334
	(0.43)	(38.39)	(0.19)	(0.39)	(1.51)	(4.84)	(1.00)	(0.26)
AIC	3.870	2.782	3.205	3.184	2.729	0.766	6.073	1.882
TVP-Rotated Gumbel								
$\bar{\omega}$	-1.121*	-0.106	2.882*	0.000	1.788*	0.991	3.139	-0.952*
	(0.41)	(2.36)	(0.73)	(1.00)	(0.56)	(1.48)	(2.59)	(0.36)
$\bar{\beta}$	1.446*	0.356	-2.431*	0.000	-2.031*	-1.345*	-3.304	1.269*
	(0.27)	(2.24)	(0.84)	(1.00)	(0.47)	(0.63)	(2.50)	(0.29)
$\bar{\alpha}$	-0.835	-0.180	-0.477	0.000	1.302*	0.947	0.518*	-0.551*
	(0.72)	(0.48)	(0.25)	(1.00)	(0.35)	(5.51)	(0.23)	(0.27)
AIC	2.209	2.930	2.807	6.055	-1.756	0.617	4.208	-0.659
TVP-BB7								
$\bar{\omega}_\theta$	2.327	8.440	3.068*	-0.252	0.363	1.098	0.710	0.669*
	(1.46)	(663.11)	(1.50)	(2.91)	(0.21)	(8.26)	(1.55)	(0.30)
$\bar{\beta}_\theta$	0.529	0.300	-0.335	-1.184*	0.153	0.564	-0.001	-0.006
	(0.54)	(35.64)	(0.32)	(0.58)	(0.57)	(3.17)	(2.44)	(0.39)
$\bar{\alpha}_\theta$	-2.272	-8.464	-2.662	0.645	-0.527*	-1.390	-0.710*	-0.665*
	(1.46)	(655.70)	(1.60)	(2.68)	(0.13)	(6.77)	(0.33)	(0.14)
$\bar{\omega}_\delta$	-0.436*	-0.314	-0.435*	0.003	0.382*	0.488*	-0.001	-0.465*
	(0.03)	(2.56)	(0.21)	(2.27)	(0.16)	(0.24)	(1.98)	(0.16)
$\bar{\beta}_\delta$	1.140*	0.359	0.652	-0.008	-1.888*	-1.370*	0.001	0.824
	(0.20)	(6.07)	(0.49)	(6.09)	(0.45)	(0.47)	(4.25)	(0.42)
$\bar{\alpha}_\delta$	-1.086*	-0.890	1.259	1.872	1.435*	1.002	0.028	-0.875*
	(0.04)	(15.94)	(0.97)	(2.80)	(0.30)	(0.64)	(1.77)	(0.24)
AIC	6.647	9.012	9.206	9.234	3.104	4.881	12.207	4.042

Notes. The table reports parameter estimates for different copula models and their standard errors (in brackets) for several stock and oil price returns. Minimum AIC value (in bold), adjusted for small-sample bias, indicates the best copula fit. For the time-varying parameter (TVP) copulas, q was set to 10. An asterisk (*) indicates significance of the parameter at 5%.

Table 5. Copula model estimates for oil and stock returns for the period 2008-2014.

Panel A: Parameter estimates for time-invariant copulas.

	Brazil	Russia	India	China	S.Africa	UK	USA	EMU
Gaussian copula								
ρ	0.435*	0.332*	0.369*	0.102*	0.382*	0.446*	0.417*	0.416*
	(0.03)	(0.05)	(0.04)	(0.04)	(0.08)	(0.05))	(0.04)	(0.06)
AIC	-68.002	-36.849	-46.012	-0.912	-49.800	-69.576	-58.069	-60.699
Student-T copula								
ρ	0.477*	0.347*	0.403*	0.119	0.398*	0.462*	0.413*	0.433*
	(0.04)	(0.06)	(0.04)	(0.07)	(0.07)	(0.04)	(0.05)	(0.05)
υ	14.759	8.400*	7.743*	16.584*	28.413	8.689*	8.716*	11.851
	(12.24)	(2.44)	(3.51)	(1.99)	(433.23)	(4.32)	(4.02)	(6.14)
AIC	**-68.968**	-38.161	-47.880	0.536	-48.301	**-73.396**	-61.517	-61.464
Gumbel copula								
δ	1.411*	1.272*	1.328*	1.051*	1.287*	1.405*	1.330*	1.369*
	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)
AIC	-56.144	-29.555	-41.051	0.841	-33.966	-59.868	-47.558	-49.207
Rotated Gumbel copula								
δ	1.399*	1.258*	1.331*	1.087*	1.314*	1.387*	1.333*	1.336*
	(0.06)	(0.05)	(0.06)	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)
AIC	-68.370	-43.010	-50.461	**-3.448**	-53.082	-71.155	**-62.274**	-60.597
BB7 copula								
θ	1.216*	1.091*	1.200*	1.001	1.059*	1.220*	1.160*	1.213*
	(0.11)	(0.10)	(0.10)	(0.61)	(0.09)	(0.11)	(0.09)	(0.10)
δ	0.572*	0.419*	0.459*	0.160	0.539*	0.524*	0.480*	0.469*
	(0.11)	(0.09)	(0.10)	(0.28)	(0.10)	(0.10)	(0.10)	(0.10)
AIC	-67.179	-39.891	-48.623	-0.906	-52.116	-70.177	-59.677	**-61.834**

Panel B: Parameter estimates for time-varying copulas.

	Brazil	Russia	India	China	S.Africa	UK	USA	EMU
TVP-Gaussian								
ψ_0	-0.122	0.029	0.818*	0.338	-0.030	1.749*	0.222	0.197
	(0.08)	(0.02)	(0.35)	(0.25)	(0.03)	(0.34)	(0.23)	(0.53)
ψ_1	0.028	0.183	-0.305	0.451*	0.070	-0.167	0.189	0.093
	(0.03)	(0.09)	(0.35)	(0.20)	(0.06)	(0.20)	(0.14)	(0.13)
ψ_2	2.418*	1.887*	0.304	-1.958*	2.146*	-1.574*	1.383*	1.609
	(0.20)	(0.14)	(0.71)	(0.07)	(0.13)	(0.62)	(0.67)	(1.31)
AIC	-67.145	-44.040	-43.747	-1.771	-53.282	-66.339	-57.970	-58.330
TVP-Student								
ψ_0	2.199*	0.023	1.557*	0.184	1.611*	2.192*	1.634*	1.764*
	(0.22)	(0.02)	(0.41)	(0.13)	(0.39)	(0.27)	(0.33)	(0.31)
ψ_1	0.062	0.141*	-0.208	0.394	-0.176	0.011	-0.149	-0.236
	(0.10)	(0.07)	(0.23)	(0.25)	(0.30)	(0.03)	(0.14)	(0.18)
ψ_2	-2.473*	1.920*	-1.524	0.253	-1.721*	-2.567*	-1.635*	-1.644*
	(0.17)	(0.12)	(0.94)	(0.78)	(0.57)	(0.11)	(0.56)	(0.57)
υ	14.845	7.705*	7.948*	22.755	27.190	9.070*	8.550*	8.517
	(23.51)	(2.67)	(3.49)	(29.77)	(19.21)	(4.20)	(1.72)	(14.13)
AIC	-65.569	-47.046	-44.689	0.561	-45.148	-70.902	-58.504	-59.895
TVP-Gumbel								
$\bar{\omega}$	-0.131	0.234	0.796	1.367	0.526	0.875*	-0.093	0.669
	(0.31)	(0.47)	(0.73)	(0.81)	(0.38)	(0.43)	(0.36)	(0.60)
$\bar{\beta}$	0.593*	0.379	-0.356	-0.590	-0.380	-0.272	0.536*	-0.123
	(0.16)	(0.30)	(0.54)	(0.77)	(0.26)	(0.29)	(0.25)	(0.44)
$\bar{\alpha}$	-0.306	-0.838	1.059*	-2.007*	1.961*	0.618	-0.193	0.413
	(0.36)	(0.65)	(0.54)	(0.48)	(0.76)	(0.51)	(0.24)	(0.49)
AIC	-55.154	-30.390	-40.734	-0.030	-38.575	-57.255	-44.370	-45.844
TVP-Rotated Gumbel								
$\bar{\omega}$	-0.341*	0.034	0.808*	-0.718	0.846*	-0.291*	-0.075	0.891
	(0.17)	(0.35)	(0.38)	(0.50)	(0.37)	(0.14)	(0.40)	(0.51)
$\bar{\beta}$	0.708*	0.510*	-0.410	1.069*	-0.496*	0.681*	0.547*	-0.320
	(0.10)	(0.21)	(0.24)	(0.35)	(0.22)	(0.08)	(0.26)	(0.36)
$\bar{\alpha}$	-0.084	-0.718	1.393*	-0.704	1.518*	-0.135	-0.316	0.493
	(0.14)	(0.42)	(0.49)	(0.72)	(0.66)	(0.15)	(0.28)	(0.54)
AIC	-65.504	-46.690	**-54.102**	-2.185	**-56.641**	-69.029	-60.589	-57.396
TVP-BB7								
$\bar{\omega}_\theta$	1.854*	1.407*	1.306*	1.285	-0.422	2.009*	2.134*	1.859*
	(0.01)	(0.43)	(0.32)	(0.75)	(0.75)	(0.13)	(0.47)	(0.54)
$\bar{\beta}_\theta$	-0.168*	-2.387*	1.512*	-1.803*	-2.916*	-0.661*	-1.911*	-0.465
	(0.03)	(1.03)	(0.67)	(0.82)	(1.24)	(0.24)	(0.69)	(2.45)
$\bar{\alpha}_\theta$	-1.073*	-0.689*	-1.079*	-0.610	0.727	-1.142*	-1.177*	-1.084*
	(0.01)	(0.17)	(0.34)	(0.89)	(0.43)	(0.22)	(0.50)	(0.40)
$\bar{\omega}_\delta$	1.208*	0.736*	0.384	0.407*	0.902*	0.996*	0.981*	0.970*
	(0.08)	(0.14)	(0.22)	(0.16)	(0.16)	(0.11)	(0.10)	(0.10)
$\bar{\beta}_\delta$	-0.360	-1.111*	1.827*	-0.727	0.698	0.415	0.315	0.260
	(0.33)	(0.52)	(0.67)	(0.55)	(0.62)	(0.27)	(0.26)	(0.31)
$\bar{\alpha}_\delta$	-0.624*	0.384*	-0.210	0.891*	-0.625*	-0.680*	-0.703*	-0.705*
	(0.05)	(0.11)	(0.26)	(0.26)	(0.10)	(0.06)	(0.06)	(0.07)
AIC	-63.072	**-51.253**	-51.008	2.780	-55.047	-68.143	-55.500	-54.488

Notes. See notes for Table 4.

Table 6. Statistics and hypothesis test for the impact of extreme oil price movements on unconditional and conditional quantile stock return.

		$q^{y}_{0.05}$	$q^{y\|x}_{0.05,0.05}$	H_0: $q^{y}_{0.05}=q^{y\|x}_{0.05,0.05}$ H_1: $q^{y}_{0.05}>q^{y\|x}_{0.05,0.05}$	$q^{y}_{0.95}$	$q^{y\|x}_{0.95,0.95}$	H_0: $q^{y}_{0.95}=q^{y\|x}_{0.95,0.95}$ H_1: $q^{y}_{0.95}<q^{y\|x}_{0.95,0.95}$	H_0: $\bar{q}^{y\|x}_{0.05,0.05}=\bar{q}^{y\|x}_{0.95,0.9}$ H_1: $\bar{q}^{y\|x}_{0.05,0.05}>\bar{q}^{y\|x}_{0.95,0.9}$
Brazil	Before	-0.069	-0.089	0.488	0.062	0.074	0.404	1.000
		(0.02)	(0.02)	[0.00]	(0.02)	(0.02)	[0.00]	[0.00]
	After	-0.070	-0.125	0.815	0.062	0.096	0.699	1.000
		(0.04)	(0.06)	[0.00]	(0.03)	(0.05)	[0.00]	[0.00]
Russia	Before	-0.054	-0.075	0.557	0.060	0.064	0.151	1.000
		(0.02)	(0.02)	[0.00]	(0.02)	(0.02)	[0.00]	[0.00]
	After	-0.063	-0.116	0.663	0.069	0.089	0.389	0.903
		(0.02)	(0.05)	[0.00]	(0.02)	(0.03)	[0.00]	[0.00]
India	Before	-0.062	-0.067	0.155	0.061	0.057	0.000	1.000
		(0.01)	(0.01)	[0.00]	(0.01)	(0.01)	[0.99]	[0.00]
	After	-0.059	-0.101	0.714	0.058	0.074	0.438	0.997
		(0.02)	(0.03)	[0.00]	(0.02)	(0.02)	[0.00]	[0.00]
China	Before	-0.057	-0.058	0.042	0.050	0.054	0.364	0.000
		(0.01)	(0.01)	[0.44]	(0.01)	(0.01)	[0.46]	[0.99]
	After	-0.062	-0.102	0.724	0.054	0.061	0.254	1.000
		(0.02)	(0.03)	[0.00]	(0.02)	(0.02)	[0.00]	[0.00]
S.Africa	Before	-0.060	-0.072	0.386	0.056	0.065	0.357	0.188
		(0.01)	(0.02)	[0.00]	(0.01)	(0.01)	[0.00]	[0.00]
	After	-0.061	-0.111	0.888	0.057	0.072	0.669	0.979
		(0.02)	(0.04)	[0.00]	(0.02)	(0.02)	[0.00]	[0.00]
UK	Before	-0.043	-0.042	0.044	0.037	0.037	0.071	0.102
		(0.01)	(0.01)	[0.41]	(0.01)	(0.01)	[0.10]	[0.01]
	After	-0.046	-0.086	0.766	0.040	0.067	0.723	1.000
		(0.02)	(0.03)	[0.00]	(0.02)	(0.03)	[0.00]	[0.00]
USA	Before	-0.040	-0.034	0.011	0.035	0.039	0.188	0.000
		(0.01)	(0.02)	[0.95]	(0.01)	(0.01)	[0.00]	[0.99]
	After	-0.041	-0.083	0.696	0.036	0.046	0.362	1.000
		(0.02)	(0.05)	[0.00]	(0.02)	(0.03)	[0.00]	[0.00]
EMU	Before	-0.054	-0.057	0.091	0.047	0.045	0.022	0.242
		(0.02)	(0.02)	[0.12]	(0.02)	(0.02)	[0.80]	[0.00]
	After	-0.058	-0.113	0.745	0.050	0.081	0.611	1.000
		(0.03)	(0.05)	[0.00]	(0.02)	(0.04)	[0.00]	[0.00]

Notes. The table reports average and standard deviation (in parenthesis) values for conditional and unconditional 0.05 and 0.9 quantile stock returns in the periods before and after the onset of the global financial crisis. Conditional quantiles are computed usin the best copula fit in Tables 4-5 and considering extreme upwards (0.95) and downwards (0.05) oil price changes. The last colum reports the results for the test in Eq. (17) for differences between the conditional downside quantile (normalized by the unconditiona downside quantile) and the conditional upside quantile (normalized by the unconditional upside quantile). P values for th Kolmogorov-Smirnov (KS) statistic are in squared brackets.

Table 7. Statistics and hypothesis tests for the impact of moderate positive and negative oil price movements on unconditional and conditional quantile stock returns.

	Crisis	$q^{y}_{0.05}$	$q^{y\|x}_{0.05,(0.2,0.4)}$	H_0: $q^{y}_{0.05} = q^{y\|x}_{0.05,(0.2,0.4)}$ H_1: $q^{y}_{0.05} > q^{y\|x}_{0.05,(0.2,0.4)}$	$q^{y}_{0.95}$	$q^{y\|x}_{0.95,(0.6,0.8)}$	H_0: $q^{y}_{0.95} = q^{y\|x}_{0.95,(0.6,0.8)}$ H_1: $q^{y}_{0.95} < q^{y\|x}_{0.95,(0.6,0.8)}$	H_0: $\bar{q}^{y\|x}_{0.05(0.2,0.4)} = \bar{q}^{y\|x}_{0.95,(0.6,0.8)}$ H_1: $\bar{q}^{y\|x}_{0.05(0.2,0.4)} > \bar{q}^{y\|x}_{0.95,(0.6,0.8)}$
Brazil	Before	-0.069	-0.067	0.000	0.062	0.060	0.000	0.843
		(0.02)	(0.02)	[0.99]	(0.02)	(0.02)	[0.99]	[0.00]
	After	-0.070	-0.071	0.040	0.062	0.059	0.000	1.000
		(0.04)	(0.04)	[0.59]	(0.03)	(0.03)	[0.99]	[0.00]
Russia	Before	-0.054	-0.054	0.000	0.060	0.061	0.042	0.000
		(0.02)	(0.02)	[0.99]	(0.02)	(0.02)	[0.44]	[0.95]
	After	-0.063	-0.060	0.000	0.069	0.070	0.036	0.024
		(0.02)	(0.02)	[0.99]	(0.02)	(0.02)	[0.64]	[0.82]
India	Before	-0.062	-0.063	0.049	0.061	0.060	0.000	1.000
		(0.01)	(0.01)	[0.34]	(0.01)	(0.01)	[0.99]	[0.00]
	After	-0.059	-0.055	0.000	0.058	0.059	0.027	0.000
		(0.02)	(0.02)	[0.99]	(0.02)	(0.02)	[0.78]	[0.95]
China	Before	-0.057	-0.058	0.020	0.050	0.050	0.000	1.000
		(0.01)	(0.01)	[0.83]	(0.01)	(0.01)	[0.99]	[0.00]
	After	-0.062	-0.061	0.000	0.054	0.055	0.053	0.000
		(0.02)	(0.02)	[0.99]	(0.02)	(0.02)	[0.44]	[0.98]
S.Africa	Before	-0.060	-0.057	0.000	0.056	0.053	0.000	0.406
		(0.01)	(0.01)	[0.99]	(0.01)	(0.01)	[0.99]	[0.00]
	After	-0.061	-0.057	0.000	0.057	0.057	0.049	0.000
		(0.02)	(0.02)	[0.99]	(0.02)	(0.02)	[0.45]	[0.99]
UK	Before	-0.043	-0.042	0.024	0.037	0.037	0.009	0.395
		(0.01)	(0.01)	[0.76]	(0.01)	(0.01)	[0.96]	[0.00]
	After	-0.046	-0.042	0.000	0.040	0.037	0.000	1.000
		(0.02)	(0.02)	[0.99]	(0.02)	(0.01)	[0.99]	[0.00]
USA	Before	-0.040	-0.038	0.007	0.035	0.035	0.031	0.164
		(0.01)	(0.01)	[0.98]	(0.01)	(0.01)	[0.64]	[0.00]
	After	-0.041	-0.038	0.000	0.036	0.036	0.036	0.000
		(0.02)	(0.02)	[0.99]	(0.02)	(0.02)	[0.64]	[0.97]
EMU	Before	-0.054	-0.054	0.024	0.047	0.046	0.004	0.514
		(0.02)	(0.02)	[0.76]	(0.02)	(0.02)	[0.99]	[0.00]
	After	-0.058	-0.057	0.000	0.050	0.048	0.000	1.000
		(0.03)	(0.03)	[0.99]	(0.02)	(0.02)	[0.99]	[0.00]

Notes. The table reports average and standard deviation (in parenthesis) values for conditional and unconditional 0.05 and 0.95 quantile stock returns in the periods before and after the onset of the global financial crisis. Conditional quantiles are computed using the best copula fit in Tables 4-5 and considering moderate negative (between quantiles 0.2 and 0.4) and positive (between quantiles 0.6 and 0.8) oil price movements. P values for the Kolmogorov-Smirnov (KS) statistic are in squared brackets. The last column reports the results of the test for differences between the impact of moderate negative (normalized by the unconditional downside quantile) and moderate positive (normalized by the unconditional upside quantile) oil price movements. P values for the Kolmogorov-Smirnov (KS) statistic are in squared brackets.

Figure 1. Time series plots for weekly stock returns for the period January 2000 to December 2014.

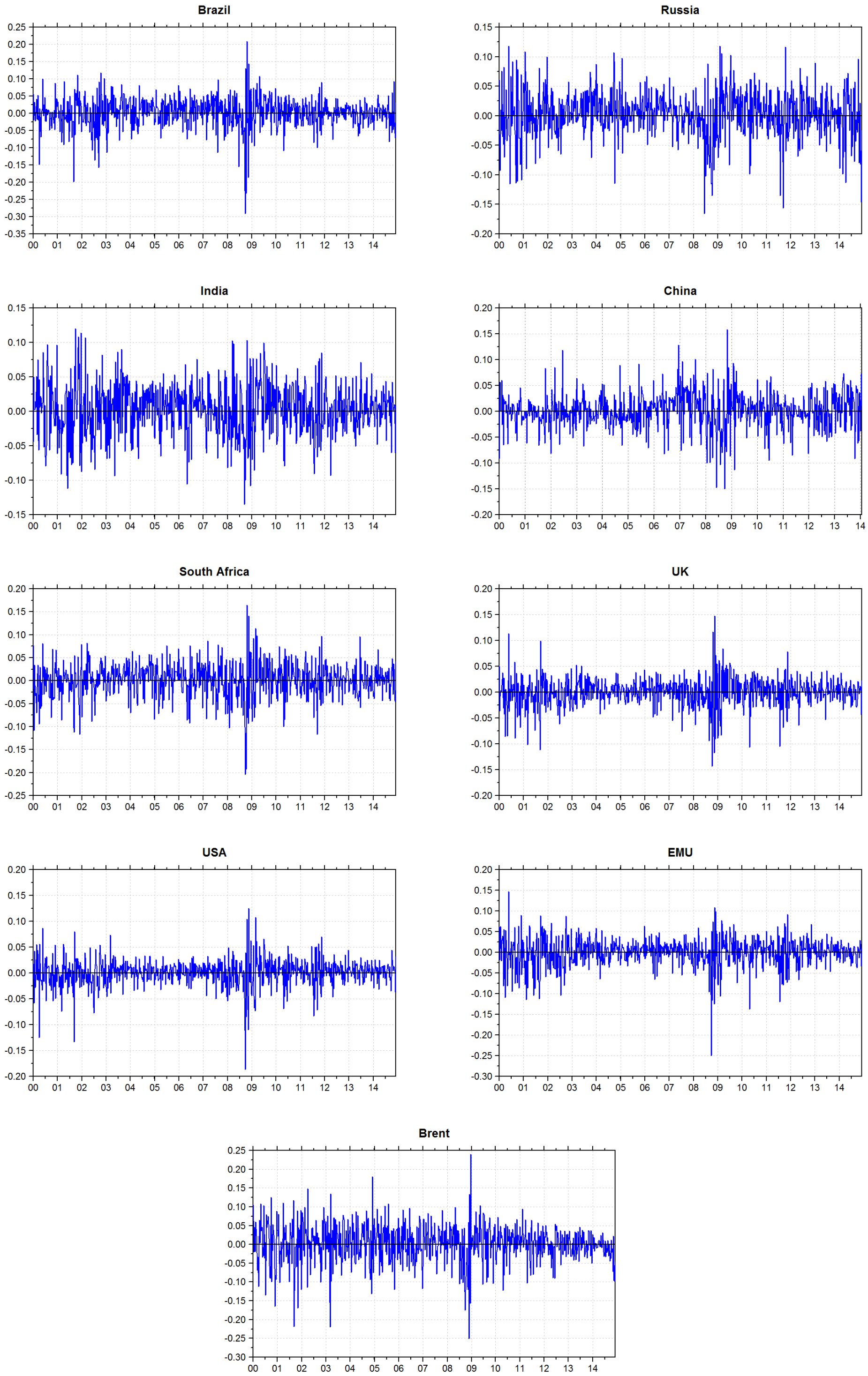


Figure 2. Oil and stock return quantiles.

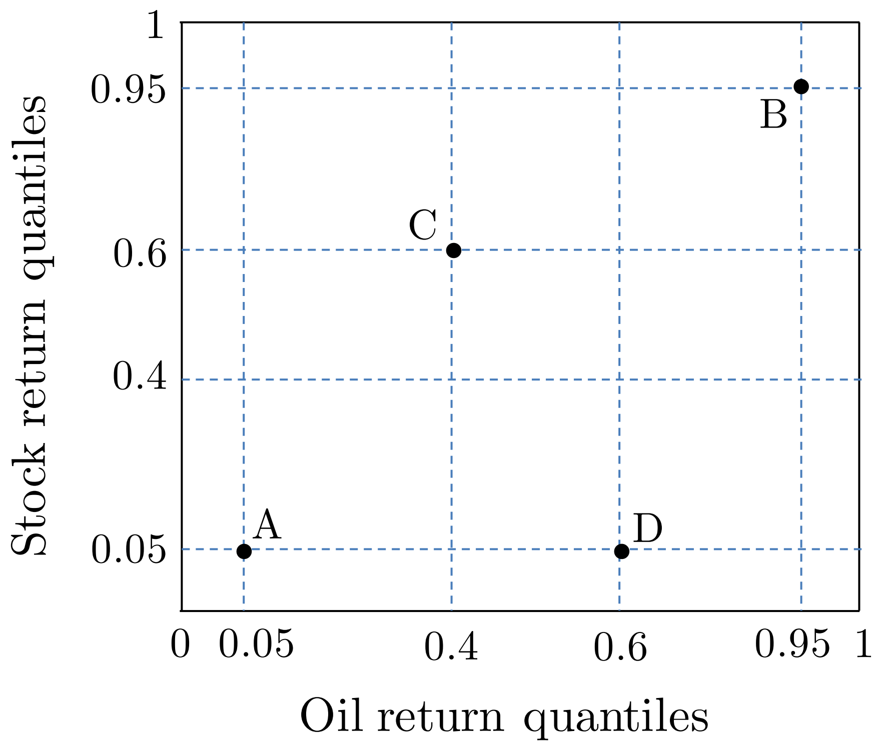


Figure 3. Time series plots for the impact of extreme oil price movements on unconditional and conditional quantile stock returns.

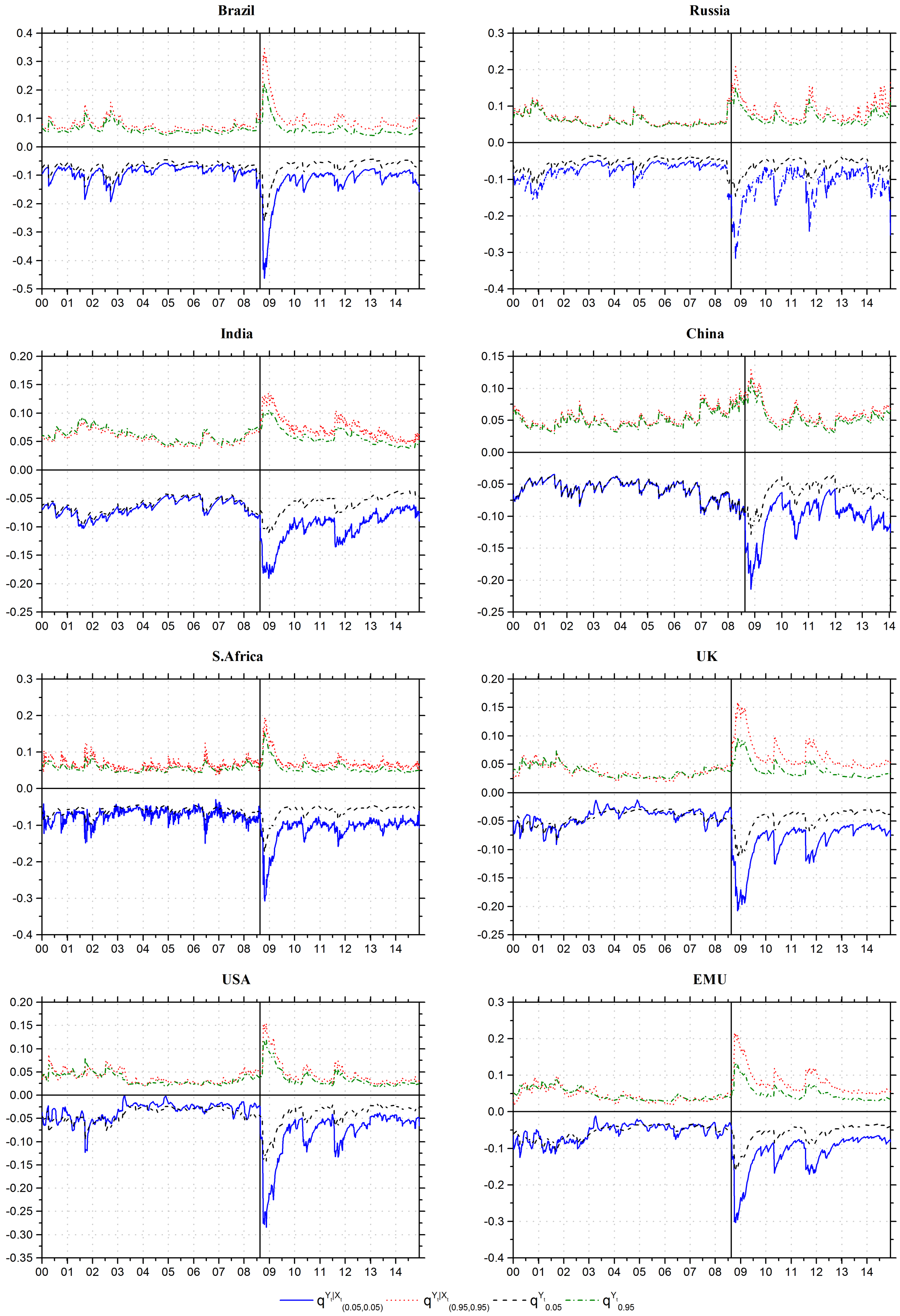
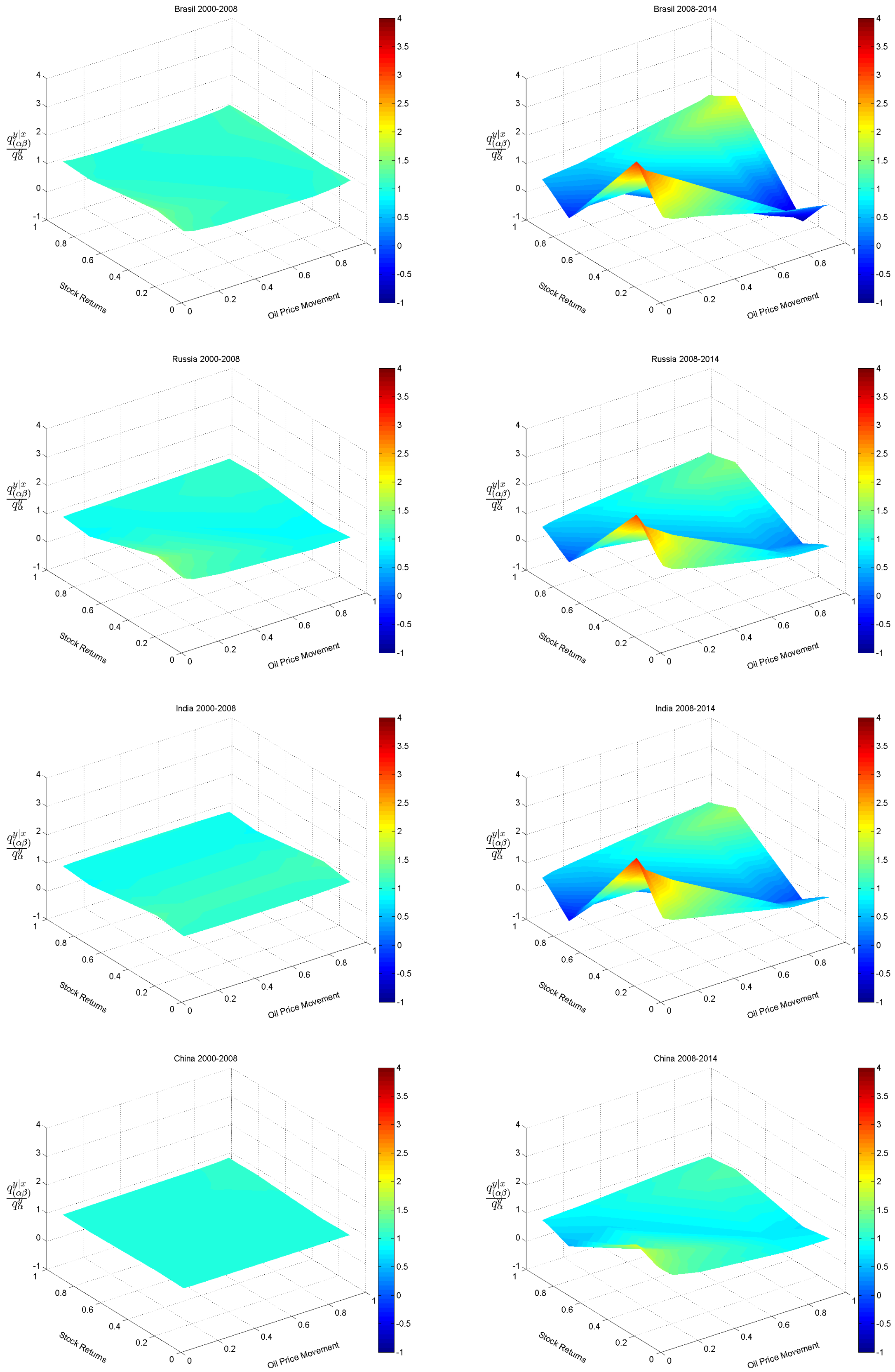
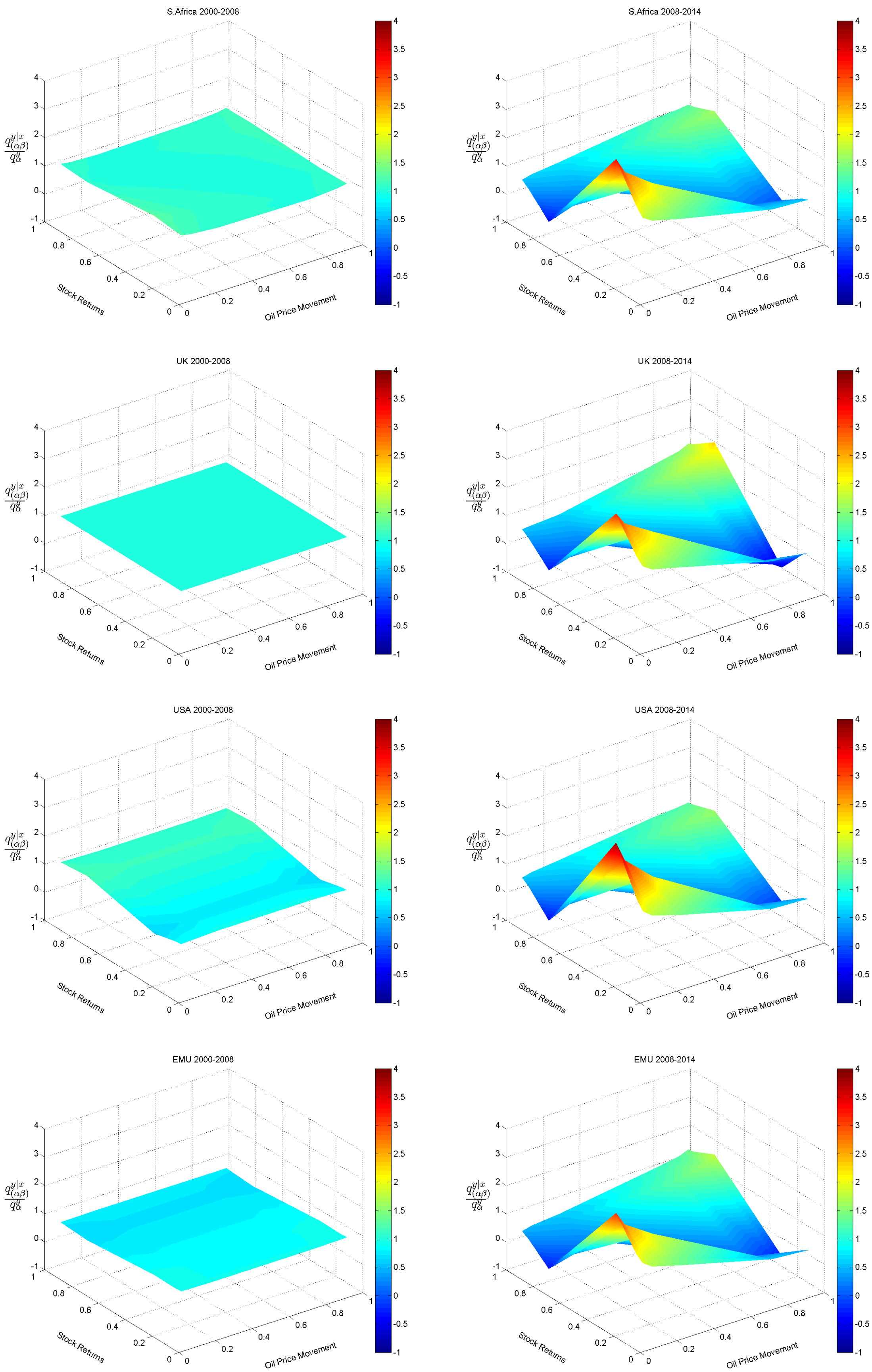


Figure 4. Average conditional versus unconditional quantile estimates for stock returns for the periods 2000-2008 and 2008-2014.





S.Africa 2000-2008
S.Africa 2008-2014
UK 2000-2008
UK 2008-2014
USA 2000-2008
USA 2008-2014
EMU 2000-2008
EMU 2008-2014
$\frac{q^{y|x}_{(\alpha\beta)}}{q^{y}_{\alpha}}$
Stock Returns
Oil Price Movement

Figure 5. Time series plots for the impact of moderate positive and negative oil price movements on unconditional and conditional quantile stock return.