The Impact of Oil Price Uncertainty on GCC Stock Markets

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Abstract

This paper investigates the dynamics of the co-movement of GCC stock market returns with global oil market uncertainty, using an ARMA-DCC-EGARCH and time varying Student-t copula models. Empirical results demonstrate that oil uncertainty has significant and time varying impacts on the GCC stock returns. The GCC stock returns are found to be negatively affected by oil market uncertainty for almost the entire period under examination. More interestingly, we find that the impact of oil price uncertainty differs across GCC member states and allow for grouping. The results also show that the stock markets of Oman and Bahrain are relatively less sensitive to the oil uncertainty factor, thus offering investors and portfolio managers different investment options and portfolio diversification opportunities across GCC members.

Keywords: Time-varying copulas, Dynamic conditional correlations, Crude oil, Stock index, Uncertainty

JEL classification: C58; F37; G17; Q43

1. Introduction and literature review

During the first decade of the twenty-first century, the Gulf Cooperation Council (GCC) countries—Saudi Arabia, UAE, Qatar, Kuwait, Oman and Bahrain—experienced rapid economic growth supported by high oil prices and revenues. The GDP growth in the GCC, over the same period, averaged 6.2% annually making this region one of the fastest growing economic areas in the world. Driven by proper incentives and regulatory liberalisation, stock markets in GCC countries grew astonishingly in tandem with rapidly

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evolving economies. For example, in less than seven years, total GCC market capitalization increased fivefold, from $117 billion at the end of 2000 to $716 billion in the second quarter of 2007. The massive growth in market capitalization attracted increasing numbers of national and foreign investors in search of higher profits. Over the same period, the number of companies listed on GCC stock markets increased by 90%, from 333 to 631. Listed companies, however, tend to be concentrated in a few sectors, especially financial services and basic industries leading to unbalanced sectoral structure and a narrow range of investment options.

Being largely oil dependent and less diversified, GCC countries benefited financially from the rising oil prices between 2000 and 2007, while the drop observed during 2008-2009 and 2014-2016 greatly affected their budget deficits and economic growth. The higher volatility in oil prices coupled with fragility of the domestic financial system expose GCC countries to economic uncertainty from demand, supply, and price disruptions that are beyond the control of individual governments. Further, political and geo-strategic risks may significantly influence the growth dynamics of financial markets in GCC countries. For example, the social unrest in North Africa and the Middle East in 2011 and the Yemen war in 2015 were important factors affecting oil price volatility and adding more uncertainty to the political and economic environment in the Gulf region. Since the prediction of future events is essential to current decision making and asset allocation strategies, it is important to measure the level of uncertainty and its consequent impact on all stock market participants.

A large strand of the recent literature has been devoted to analysing the impact of uncertainty on financial markets. Connolly et al. (2007) find that stock and bond market returns for the U.S. and Europe are negatively affected by stock market uncertainty as measured by the VIX index. Using a vector auto-regression analysis, Sum (2012b) shows that variations of economic policy uncertainty in Europe negatively affect all stock market returns in the Eurozone, Croatia, Norway, Russia, Switzerland, Turkey and Ukraine. Mensi et al. (2014) provide evidence that BRICS stock markets exhibit asymmetric dependence with the VIX. On the other hand, the authors show that there is no correlation between U.S. economic policy uncertainty and the stock markets of the BRICS countries. Li et al. (2015) find negative correlation between the change in economic policy uncertainty and co-movement of the U.S. stock and bond markets. Antonakakis et al. (2015) show that the dynamic conditional correlation between economic policy uncertainty (EPU) and real housing market returns is negative and not constant over time. Degiannakis & Filis (2019) show that global EPU is the main driver for local uncertainty, in particular for Europe. Bouri et al. (2018a) highlights the impact of global VIX indices on BRICS stock markets, where the its combined impact is shared with local implied volatilities.

Focusing on implied volatilites of crude oil and interconnectedness to other markets, research is manifold. Maghyereh et al. (2016) identifies strong directional spillover from oil implied volatilities to equity markets where the strongest transmission is recorded in the years after the financial crises. Degiannakis & Filis (2017) show that information channels of other asset classes are useful for forecasting oil volatilities. High-frequency is also useful for forecasting (Degiannakis & Filis, 2018). Dutta et al. (2017) find the OVX of significant explanatory power for Middle East and African stock indix volatilites, where anticipation of jumps is present. Bouri et al. (2018b) finds that implied volatility of oil has directional predictability for implied stock market volatilities of developed and emerging markets. Bouri et al. (2018b) provide evidence that implied volatility of oil markets provides directional predictability for implied volatilities of stock markets of developed and emerging markets. This holds in particular for oil importing countries as demonstrated in Bouri et al. (2017). Ji et al. (2018) highlights that information transmission between strategic commodities such as oil and emerging markets equities is unstable and prone to change with certain key events. Spillovers between different oil futures markets are identified in Klein (2018) and the WTI is found to be leading while Brent and other markets show a lagging behaviour in significant price changes. Wegener et al. (2016) find that oil price shocks that lead to higher oil prices improve fiscal stability of oil producing countries.

The primary purpose of this paper is to investigate time varying dependencies between crude oil uncertainty as measured by the OVX index and six GCC countries stock indices.

More specifically, we address the following questions. Does dependence exist between the GCC stock returns and the implied crude oil volatility index (OVX)? Does the degree of dependence change over time? Are all GCC stock markets affected in the same manner by oil price uncertainty?

In order to explore possible time-varying correlations, we implement the Dynamic Conditional Correlations (DCC) model of Engle (2002). The DCC dynamically models correlations of k assets while implementing a GARCH structure on both the idionsyncratic volatility of these assets as well as in the time-varying, conditional structure of the of standardized, multivariate residuals. This symmetric nature has been subject to extensions. Celik (2012) uses a heavy-tailed distribution to account for a more realistic leptocurtic distribution of returns. Mensi et al. (2017) extends the standard DCC to account for long memory and asymmetry by implementing the FIAPARCH (Tse, 1998) as idiosyncratic volatility. Klein (2017) outlines a flexible DCC framework in which the idiosyncratic variances might vary across assets. The DCC of Engle (2002) is widely adapted and competes with the BEKK framework Engle & Kroner (1995) that models volatility spillovers and news effects directly. Due to the flexibility in the underlying volatility for each asset, we adapt the DCC. Given the asymmetric shape of the data, we choose to implement the EGARCH (Nelson, 1991) to account for different effects of *good* and *bad* news on volatility. This asymmetry is well documented in literature (Cont, 2001) and commonly connected to the financial leverage effect while this term cannot be used for commodity markets in the narrower sense.

The impact of implied volatility of oil on stock markets of the GCC deserves a closer study for several reasons. From an investors or portfolio managers perspective, making the right investment decision, such as asset allocation and diversification, is highly dependent on the reaction of stock markets to oil price shocks. From an economists and policy makers point of view, an accurate reading of the dependence between oil price volatility and stock market returns can serve as the basis for adequate policy design, planning, and action. To the best of our knowledge, no studies yet have dealt with the joint impact of oil price uncertainty on all GCC stock markets in a time varying context. Until recently, the CBOE Crude Oil Volatility Index (OVX) has received less attention in the literature than other uncertainty measures which is surprising given the relevant information this index contains for both crude oil spot price returns and future realized volatility (Haugom et al., 2014). As a result, the OVX has received much academic attention in very recent years, as outlined above.

The study builds on the application of different correlation and dependency measures. Firstly, we extend the standard DCC model of Engle (2002) to an ARMA-DCC-EGARCH model which allows for non-constant correlations, asymmetries in idiosyncratic volatilities, and volatility clustering in financial time series. We then compare the results of this DCC variant with results obtained from a Student-t copula. The copula based methodology is less restrictive and allows to model possible dependencies in a flexible and realistic way. Using weekly data comprising of six equity markets of Saudi Arabia, UAE, Qatar, Kuwait, Oman, and Bahrain and the CBOE Crude Oil Volatility Index (OVX) from May 2007 to February 2018, our empirical results show that: a) the dependence between GCC stock returns and the implied crude oil volatility index is significant for all countries; b) the impact of global oil uncertainty on GCC stock markets is time varying and; c) that this impact differs from one country to another while grouping these countries based on their OVX sensitivity provides evidence for differing policy effectiveness.

The rest of the paper is organized as follows. Section 2 discusses the econometric methodologies employed throughout the paper. Section 3 presents the data and some preliminary statistics while Subsection 3.1 gives a brief overview of the GCC stock markets and their growth. Section 4 presents empirical findings correlations and implications thereof. Section 5 concludes the paper.

2. Empirical Methodology

2.1. Dynamic Conditional Correlation (DCC) model

Multivariate GARCH (MGARCH) models have proven to be highly successful in finance applications. Among the various specifications of MGARCH models, the most popular are often considered to be the Constant Conditional Correlations (CCC) model introduced by Bollerslev (1990) and extended by He and Terasvirta (2002b) and the Dynamic Conditional Correlations (DCC) model proposed by Engle (2002). A similar model is proposed by Tse & Tsui (2002). The DCC-GARCH model is a generalization of the CCC-GARCH model, which allows one to model important stylized facts of financial markets such as time varying correlation, fat tailed distributions of returns, and volatility clustering.

Suppose that r_t denotes a k-dimensional vector of returns on day $t = 1, \ldots, n$ from k assets that are conditionally multivariate normally distributed with mean μ_t and covariance matrix H_t. Then, the DCC-GARCH is defined as

$$\begin{aligned} r_t &= \mu_t + \varepsilon_t, \\ \varepsilon_t &= H_t^{1/2} z_t, \\ H_t &= D_t R_t D_t, \\ D_t &= \operatorname{diag}\left(\sqrt{h_{11,t}}, \ldots, \sqrt{h_{11,t}}\right), \end{aligned} \tag{1}$$

where z_t denotes a k-dimensional Gaussian i.i.d. error term and the $k \times k$-dimensional variance-covariance matrix H_t is decomposed to a matrix product of D_t, that describes the idiosyncratic conditional volatilities on its main diagonal and R_t, which is the time-varying dynamic correlation matrix.

Diagonal elements of the matrix D_t can be expressed as any univariate GARCH model with normally distributed errors that meet the requirements for suitable stationary and non-negative conditions. Engle (2002) chooses a symmetric GARCH model. The GARCH(p, q) of Bollerslev (1986) reads

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_t - j, \tag{2}$$

while we surpress the indices for the diagonal elements. Note that the univariate GARCH model can have different orders p and q. The estimation of the DCC-GARCH model is carried out in two steps. In the first step, the univariate GARCH model are estimated for each idiosyncratic return series; and in the second step, the parameters of the dynamic correlation are estimated using the estimated parameters from step one. The second stage quasi-likelihood function is given by

$$LL(\theta) = -\frac{1}{2}\sum_{t=1}^{n}\left(k\log 2\pi + 2\log|D_t| + \log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t\right). \tag{3}$$

Note that when using other error distributions, step one and two might not be separable (Klein, 2017). The dynamic correlation matrix R_t is then decomposed to

$$R_t = (\text{diag } Q_t)^{-1/2}\, Q_t\, (\text{diag } Q_t)^{-1/2}. \tag{4}$$

The matrix Q_t is the covariance matrix of the standardized residuals $\xi_t = (\xi_{1,t}, \ldots, \xi_{k,t})$ with $\xi_{i,t} = \varepsilon_{i,t}/\sqrt{h_{ii,t}}$. Engle (2002) models a GARCH(1,1)-like structure on the elements of Q_t which reads in matrix notation

$$Q_t = (1-a-b)\overline{Q} + a\xi_{t-1}'\xi_{t-1} + bQ_{t-1}, \tag{5}$$

where $\overline{Q}$ denotes the unconditional covariance matrix of the standardized errors. In this paper, the implementation of the DCC-GARCH and the asymmetric DCC-GARCH models are be considered using Gaussian and Student-t distributed errors. For a detailed discussion of DCC models under different distributions we refer the reader to Engle (2002), Celik (2012), and Klein (2017) and references therein.

For modelling idiosyncratic variances, Engle (2002) utilizes a GARCH(1,1) as outlined in Eq. 2. We extend the DCC to not only model symmetric volatility of k assets but to also cover asymmetric models as in Mensi et al. (2017) and Klein (2017). Asymmetry in variance is a common occurrence (Ding et al., 1993) and is related to a different reaction of asset prices to positive or negative news in terms of the sign of the residual returns. This asymmetry is asset-specific, however. For most stocks and indices, *bad news* have a greater impact on volatility and cause a higher increase than *positive* news, which is commonly referred to as *leverage effect*. Some commodities on the other hand, react in an opposite way.[1] We cover the stylized fact of asymmetry by including a second class of asymmetric GARCH models as idiosyncratic volatility model and use the EGARCH of Nelson (1991) which reads[2]

$$h_t = a_0 + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \beta_j h_{t-j}, \tag{6}$$

where $h_t = \log \sigma_t^2$. We note here that *bad news* (ε_{t-i} is negative) can have a different, possibly larger, impact on volatility than *good news* (ε_{t-i} is positive), which is measured by the sign and magnitude of γ_i. An alternative formulation of an exponential GARCH model is outlined in Engle & Ng (1993). Other asymmetric GARCH models exist such as APARCH (Ding et al., 1993) and the FIAPARCH (Tse, 1998), but are not taken into consideration in this paper.[3]

Regarding the time-varying mean structure μ_t in Eq. (1), we use the Box-Jenkins approach to define its autoregressive moving average ARMA(p, q) structure. Within the DCC-EGARCH, we find the ARMA(1,2) to yield the best BIC and AIC. We hence fix this lag structure for all countries and the OVX.

2.2. Copulas

The notion of copulas, introduced in Sklar (1959), gained traction in modern finance in the beginning of this millennium. It allowed for a relatively simple way to implement joint distributions of different assets (Embrechts et al., 2001, Patton, 2001a,b, Cherubini & Luciano, 2001, Cherubini et al., 2004). Over the last two decades, the number of papers and books using copula methodologies in quantitative finance has grown enormously while the practical adaption became widespread. The role of using Gaussian copulas to price collateralized debt obligations has been connected with mispricing of complex assets due to misinterpretation and wrong application. Some research and popular media go as far

[1] See for example: Hammoudeh et al. (2010), Arouri et al. (2012), Chkili et al. (2014), Bouri (2015), Chkili (2016), Klein & Walther (2016), and Nguyen & Walther (2019) for an analysis of precious and non-ferrous metals, energy commodities, and agricultural commodities in spot and futures markets.

[2] Note that the sign of γ has been changed to align with the implementation in R, which is used for estimations.

[3] For a comparison of calculation speed and efficiency of estimating long memory models, see Klein & Walther (2017).

as linking the outbreak and self-acceleration of the Financial Crises of 2008 to the misuse of copulas in asset pricing (MacKenzie & Spears, 2014).

A copula is a function that links marginal distributions to their multivariate distribution. The most fundamental theorem about copula functions, used in basically all practical applications of copulas, is Sklar's theorem (Sklar, 1959). Sklar's theorem can be summarized as follows.

Theorem *Let X and Y be two random variables with marginal distributions F and G and joint distribution H, then there exists a copula $C : [0,1]^2 \to [0,1]$ such that*

$$H(x,y) = C\left(F(x), G(y)\right).$$

If G and G are continuous, then C is unique. Otherwise, C is uniquely determined by range $F\times$ range G. If C is a copula and F and G are distribution functions, then the function H defined above is a joint distribution with margins F and G.

From Sklar's theorem, it is clear that margins can be modelled separately from the dependence structure. Bivariate distributions, as well as distributions in higher dimensions are possible and can be easily implemented.

The most common copula models used in finance literature are Elliptical and Archimedean copulas. Elliptical copulas are tractable due to the ease with which they can be implemented. The normal and the Student-t copulas fall into this family since they are based on an elliptically contoured distribution. The Gaussian copula is symmetric and has no tail dependence while the Student-t copulas can capture dependency in the tail of the distribution. Evidence from a number of papers suggests that the empirical fit of the Student-t copula is superior to that of the Gaussian copula (see Mashal et al., 2003, Aloui et al., 2013).In this paper, the implementation of the Student-t copula is considered in a time varying context. The bivariate copula is defined as

$$C(u,v) = \int_{-\infty}^{t_\nu^{-1}(u)} \int_{-\infty}^{t_\nu^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta^2}} \left(1 + \frac{s^2 - 2\theta st + t^2}{\nu\left(1-\theta^2\right)}\right)^{\frac{\nu+2}{2}} \mathrm{d}s\mathrm{d}t$$

where θ_t is the dependence parameter, which can be constant or time-varying, and $t_\nu^{-1}(u)$

denotes the inverse distribution function of a univariate Student-t distribution with ν degrees of freedom.

Following Patton (2001b) we allow the dependence parameter of the Student-t copula to change over time as a function of lagged information. This parameter θ is specified by

$$\theta_t = \Lambda\left(a + b\theta_{t-1} + c\sum_{i=1}^{q}\frac{t^{-1}\left(u_{t-i}\right)t^{-1}\left(v_{t-i}\right)}{q}\right),$$

where $\Lambda(x)$ is the modified logistic transformation and t^{-1} is the quantile transformation of the Student-t distribution.

3. Data

3.1. GCC stock markets

GCC stock markets have a short history relative to the world's major stock markets. During the last decade, the growth of the financial sector in the GCC countries was supported by higher economic growth, monetary stability, and stock markets reforms, all of which bode well for the future of these economies.

As reported in Table 1, the number of listed companies in the GCC countries in 2005 reached 473, with a market capitalization of all GCC markets equivalent to $US1012 billion. By 2017, the number of listed companies at the GCC level rose by about 40%. The Saudi equity market recorded the largest increase in listings (81) followed by Kuwait at 46 companies. During the same period, its market capitalization decreased to reach $US700.9 billion. The Saudi stock market has the largest share of the region's market capitalization, (53%) followed by Qatar (18%), while Bahrain and Oman are the smallest markets with a combined share of about 5% of the whole market capitalization. The GCC stock markets witnessed a decrease in trading activity, with the volume of shares traded decreasing from $US 1,372 billion in 2005 to less than $US 600 billion in 2017.

3.2. Data sets and preliminary analysis

The data set covers the stock markets of GCC countries for the period of May 2007 to February 2018 on a weekly frequency. Founded in 1981, the GCC is an organization of

Table 1: GCC stock market indicators for the years 2005 and 2017. Source: World Bank Development Indicators, 2017.

		Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE	Total
No of listed companies	2005	47	143	96	31	77	79	473
	2017	43	189	124	42	158	102	658
Market cap. ($m)	2005	17 364	130 080	15 268	87 315	646 104	115 952	1 012 083
	2017	16 064	97 091	20 107	126 371	373380	67 950	700 963
Market cap. (% of GDP)	2005	129.00	160.99	49.40	202.87	196.70	64.19	149.43
	2017	55.30	60.33	28.73	73.69	52.51	18.56	46.47
Stocks traded ($m)	2005	711	94 010	3 212	28 055	1 103 500	143 127	1 372 615
	2017	308	22 997	2 647	15 319	514 423	17644	573338
Stocks traded (% of GDP)	2005	5.28	116.35	10.39	65.18	335.96	97.24	202.66
	2017	1.06	14.29	3.78	8.93	72.34	4.82	38

six oil-exporting countries Bahrain, Oman, Kuwait, Qatar, Saudi Arabia, and the United Arab Emirates (UAE). Together, these countries possess at least 47% of the world's proven oil reserves and accounted for about 25% of crude oil exports in 2003. Due to their heavy reliance on oil to drive the growth of their non-oil sector, oil revenue fluctuations largely affect the current accounts and government's budgets balances in most GCC countries.

The implied volatility crude oil index (OVX), a new volatility derivative published by the CBOE (Chicago Board Options Exchange), is used in this study as a measure of oil market uncertainty. The OVX is a forward-looking measure of uncertainty calculated by applying the well-known VIX index methodology to the United States Oil Fund LP options spanning a wide range of strike prices.

The summary statistics for the log-return series are reported in Table 2. For each series, we noticed that the mean values are close to zero. Over the full period, standard deviations for GCC markets range from 1.4% (Bahrain) to 3.3% (Saudia and Qatar). The lower variability (e.g., the standard deviations of Bahrain and Kuwait) could provide great opportunities for global investors to benefit from diversification advantages there. The measures for skewness and kurtosis show that GCC stock returns are negatively skewed and highly leptokurtic with respect to the normal distribution, whereas the volatility implied indices are positively skewed and leptokurtic. The Jarque-Bera statistic rejects the normality hypothesis for each of the series at the 1% level of significance. According to the ARCH LM test, ARCH effects are found in all the return series and therefore estimation of a GARCH model is appropriate. Each return series is tested for the presence of unit roots using the Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests. Assuming a regression with an intercept, both test statistics reject the null hypothesis of a unit root, indicating that the return series are stationary.

The unconditional correlation reported in Table 3 show that there is a negative correlation between the GCC stock market returns and the implied volatility indices. The results show also a strong positive correlation between GCC markets, ranging from 0.316 (Saudia-Bahrain) to 0.642 (UAE-Oman).

Table 2: Descriptive statistics and preliminary analysis of weekly log-returns over the study period from May 18, 2007 through February 28, 2018.

	OVX	Saudia	UAE	Kuwait	Qatar	Oman	Bahrain
Min	−0.552	−0.209	−0.210	−0.107	−0.230	−0.196	−0.071
Max	0.476	0.138	0.103	0.063	0.120	0.124	0.047
Mean ($\times 10^{-4}$)	0.37	0.16	6.28	−8.56	4.49	−2.8	−8.56
Std Dev.	0.100	0.033	0.027	0.019	0.033	0.026	0.014
Skewness	0.353	−1.096	−1.866	−1.215	−1.209	−1.733	−0.680
Kurtosis	3.351	7.221	12.282	4.897	8.503	13.544	3.390
$Q(12)$	40.836	24.491	15.121	130.87	19.336	53.459	111.82
	(0.000)***	(0.235)	(0.017)**	(0.000)***	(0.081)*	(0.000)***	(0.000)***
$Q^2(12)$	38.104	198.57	173.66	243.85	248.78	286.26	159.13
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
JB	268.23	1307.82	3788.45	686.80	1795.10	4492.93	305.80
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
ARCH(12)	40.621	89.10	108.11	138.59	128.12	134.53	88.71
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***

Note: JB, $Q(12)$, and $Q^2(12)$ are the empirical statistics of the Jarque-Bera test for normality and Ljung-Box test for serial correlation in returns and squared returns with 12 lags, respectively. ARCH(12) is the empirical statistic of the LM test for conditional heteroscedasticity applied to 12 lags. Asteriks *, ** and *** denote the rejection of the null hypothesis of no autocorrelation, normality, and homoscedasticity at the 10%, 5% and 1% levels, respectively.

Table 3: Unconditional correlations between weekly returns of OVX and GCC stock markets.

	OVX	SA	UAE	Kuwait	Qatar	Oman	Bahrain
OVX	1						
SA	−0.170	1					
UAE	−0.132	0.494	1				
Kuwait	−0.156	0.433	0.474	1			
Qatar	−0.196	0.569	0.625	0.512	1		
Oman	−0.110	0.479	0.642	0.484	0.572	1	
Bahrain	−0.085	0.316	0.360	0.468	0.344	0.337	1

4. Empirical results and discussion

In order to understand how stock markets of oil exporting countries—in this case the GCC—are linked to oil markets andt their volatilities, we apply two approaches. Firstly, we apply a ARMA(1,2)-DCC-EGARCH(1,1) which explicitly covers asymmetry in idiosyncratic volatilities of stock markets. Secondly, we apply a bivariate Student-t copula and compare our findings.

To estimate the ARMA(1,2)-DCC-EGARCH(1,1) model for OVX and GCC stock market returns, we first estimate an EGARCH model for each return series. Then the estimated parameters from the first step are used to estimate the parameters of the DCC-GARCH model in a second step. The estimation results of the two-step DCC model based on the univariate EGARCH with Student-t distribution for the error terms are reported in Table 4. We notice for all stock return series that the EGARCH parameter β is close to one with a highly significant t-statistic. Given this value, it appears evident that the volatility process is persistent, i.e. large changes in the EGARCH conditional variance are followed by other large changes and small changes are followed by other small changes.

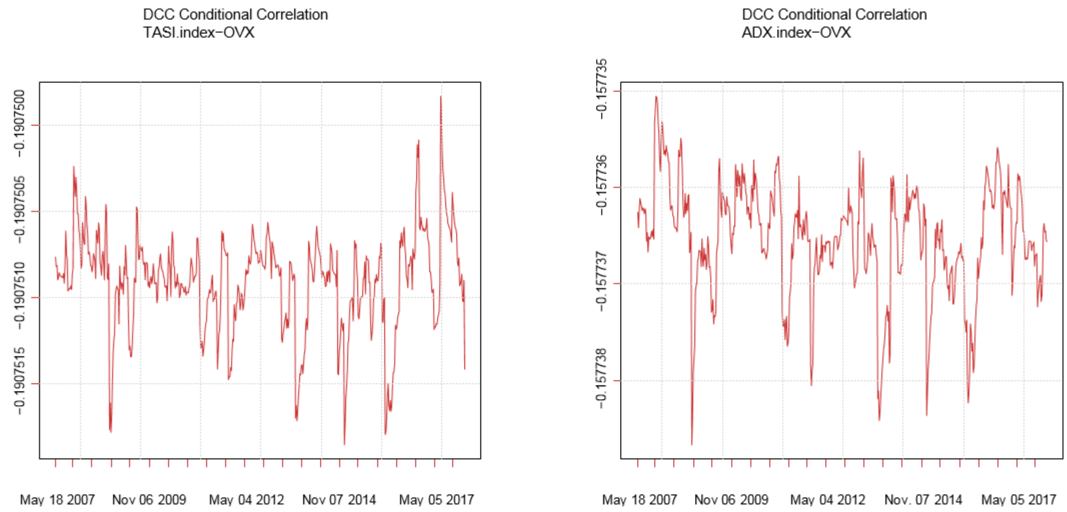
The estimated γ coefficients for the leverage term are significant for all series, which indicate the existence of an asymmetric response of volatility to shocks. We find γ to be positive for all return series. In our notation in Eq. (6) this translates to a higher impact of negative news on volatility, as expected for stock markets. Interestingly, Saudia Arabia and Kuwait have estimates of almost identical size whereas UAE, Qatar, Oman, and Bahrain form a second group of having similar leverage effects. Comparing the performance of EGARCH to a symmetric GARCH, which is unreported in detail here, shows an outperformance of asymmetric volatility models. Thus, the use of the asymmetric EGARCH model in the context of a Student-t driven DCC is justified and yields better fit.

The DCC parameter b, which links the variance-covariance matrix Q_t in Eq. (5) of the standardized residuals with its own past values, is highly significant for the relationship between OVX and the stock markets of Saudia Arabia, UAE, and Oman, while the parameter a is not statistically significant. This is a clear indication that the assumption of constant correlations is unsuitable for these markets. Indeed, we notice that the value of the parameter b is close to 1, indicating that the series of correlations are highly persistent. Kuwait shows different bahavior than these aforementioned markets. Albeit insignificant memory or persistance in the variance of the standardized residuals, Kuwait features a significant impact of lagged standardized residuals itself, translating to a dominant news effect. The hypothesis of constant correlation cannot be rejected in the cases of the Qatar and Bahrain stock markets.

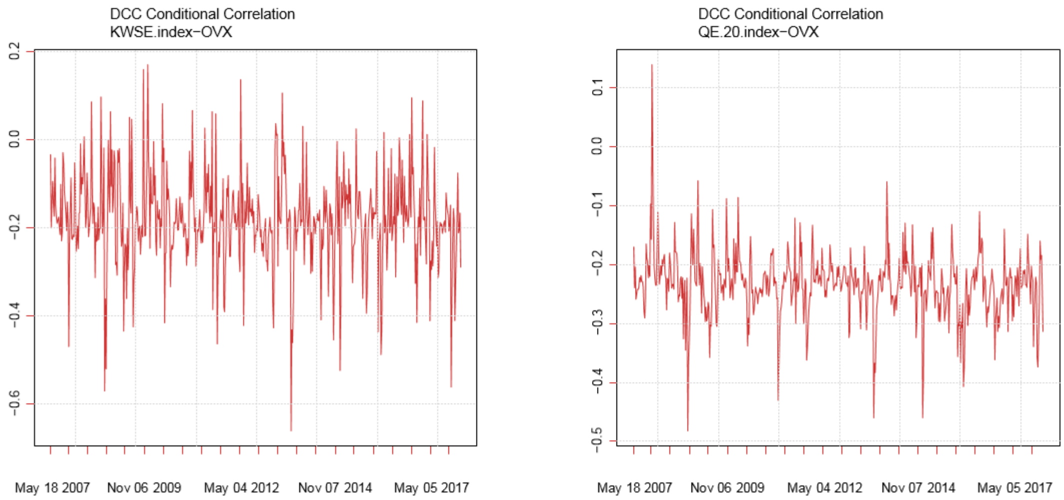
The conditional correlations between OVX and GCC stock markets returns are extracted from the fitted ARMA-DCC-EGARCH models and displayed in Figure 1. We notice that co-movement between the uncertainty index and the stock markets of Kuwait, Qatar, and Oman during the observed period is more volatile than that with the Saudia Arabia, UAE, and Bahrain stock markets. Further, the correlation between all return series is negative for almost the whole period under examination, indicating that greater uncertainty is associated with relatively lower stock returns in GCC countries. These findings are in line with research on other oil exporting countries (Maghyereh et al., 2016, Bouri et al., 2018a, Ji et al., 2018). During the last US financial crisis, GCC stock markets reacted sharply to uncertainty as evidenced by the drastic drop in the conditional correlation, which reached a trough in the fourth quarter of 2008. As highlighted above, marginal distributions are characterized by strong asymmetries and, as a consequence, the dependence structure cannot be detected by a simple linear correlation.

Table 5 reports the estimation results of the dynamic Student-t copula for the OVX index and GCC stock markets together with the AIC values for each model. As pointed out in Patton (2001b), the reported parameters are difficult to interpret because they are a subject to logistic transformations. Hence, we prefer to examine the dependence implied by the dynamic copula model instead. In Figure 2, dynamic dependencies based on the time varying Student-t copula for each OVX-country pair are visualized. The plots suggest that the uncertainty index and stock return fluctuations are likely to co-move over time. Further, we notice that the dependencies between return series are negative for almost the whole period under examination, ranging from $(-0.234; -0.103)$ for Saudia Arabia, $(-0.238; 0.08)$ for UAE, $(-0.54; 0.01)$ for Kuwait, $(-0.292; -0.137)$ for Qatar, $(-0.105; -0.035)$ for Oman, and $(-0.106; -0.045)$ for Bahrain stock markets.

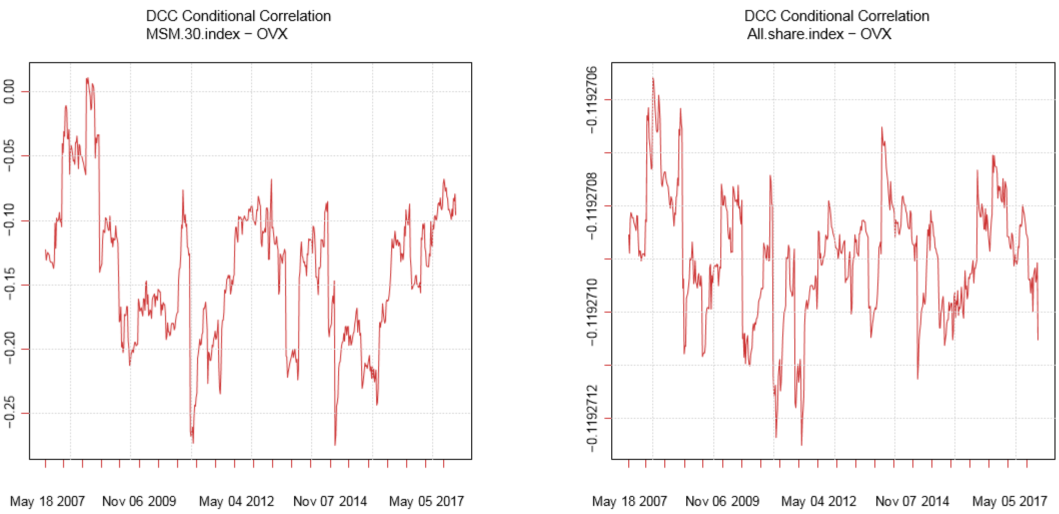
In order to simplify the overview and the interpretation, we transform the dependence parameters to Kendall's-τ and obtain the following intervals: $(-0.150; -0.066)$,



(a) (left) OVX - Saudi Arabia, (right) OVX - UAE



(b) (left) OVX - Kuwait, (right) OVX - Qatar



(c) (left) OVX - Oman, (right) OVX - Bahrain

Figure 1: Dynamic Conditional Correlations of the OVX and GCC countries from May 18, 2007 to February 28, 2018 based on weekly returns.

Table 4: Estimation results of the ARMA(1,2)-DCC-EGARCH(1,1).

	OVX	Saudia	UAE	Kuwait	Qatar	Oman	Bahrain
ARMA(1,2)							
μ	0.001	0.002	0.000	0.000	0.001	-0.003	0.000
	(0.001)	(0.001)	(0.002)	(0.00)	(0.001)	(0.004)	(0.000)
AR(1)	0.527***	-0.973***	0.986***	0.706***	0.125***	0.975***	0.934***
	(0.032)	(0.013)	(0.010)	(0.036)	(0.043)	(0.029)	(0.018)
MA(1)	-0.724***	1.108***	-0.905***	-0.517***	0.002	-0.760***	-0.875***
	(0.024)	(0.000)	(0.000)	(0.035)	(0.039)	(0.025)	(0.026)
MA(2)	0.059***	0.116***	-0.060***	0.054***	-0.061	-0.111***	0.025***
	(0.024)	(0.002)	(0.005)	(0.015)	(0.045)	(0.039)	(0.003)
EGARCH(1,1)							
ω	-2.256**	-0.834***	-0.299**	-1.351***	-0.294***	-0.327	-0.770***
	(1.005)	(0.296)	(0.116)	(0.351)	(0.114)	(0.201)	(0.283)
α	0.143**	-0.119**	-0.091**	-0.122***	-0.039	-0.182***	0.048
	(0.068)	(0.063)	(0.037)	(0.041)	(0.036)	(0.062)	(0.044)
β	0.514**	0.881***	0.959***	0.835***	0.957***	0.957***	0.911***
	(0.214)	(0.041)	(0.015)	(0.041)	(0.016)	(0.025)	(0.032)
γ	0.196*	0.431***	0.267***	0.436***	0.305***	0.310***	0.275***
	(0.113)	(0.088)	(0.059)	(0.084)	(0.065)	(0.060)	(0.065)
DCC (OVX -)							
a	—	0.000	0.000	0.127**	0.052	0.014	0.000
	—	(0.000)	(0.000)	(0.055)	(0.049)	(0.012)	(0.010)
b	—	0.892***	0.908***	0.261	0.476	0.951***	0.929
	—	(0.141)	(0.312)	(0.232)	(0.513)	(0.016)	(1.324)
Distribution							
ν	—	5.297***	6.619***	5.987***	6.166***	6.041***	6.272***
	—	(0.545)	(0.972)	(0.732)	(0.787)	(0.729)	(0.817)

Note: Estimation results for the ARMA(1,2)-DCC-EGARCH(1,1) model in pairwise specification (OVX - country) with Student-t distributed errors and shape parameter ν with respect to Eq. (5) and Eq. (6). Robust standard errors are given in parentheses. Asteriks ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

$(-0.153; 0.051)$, $(-0.363; 0.006)$, $(-0.189; -0.087)$, $(-0.067; 0.022)$, and $(-0.068; -0.029)$. Based on the obtained results, we can divide the GCC stock markets into three groups with regard to the level of dependence with uncertainty. The first group consists of the Kuwait and Qatar stock exchange markets which exhibit the strongest negative dependence with OVX. The second group is composed of Saudi Arabia and UAE and show similar and relatively medium levels of dependence with uncertainty, while the lowest degree of dependence is obtained for the last group composed of Oman and Bahrain. These findings are generally in line with the correlations produced by the ARMA-DCC-EGARCH. Being able to identify differing groups within the rather homogeneous GCC as oil exporting countries offers several implications.

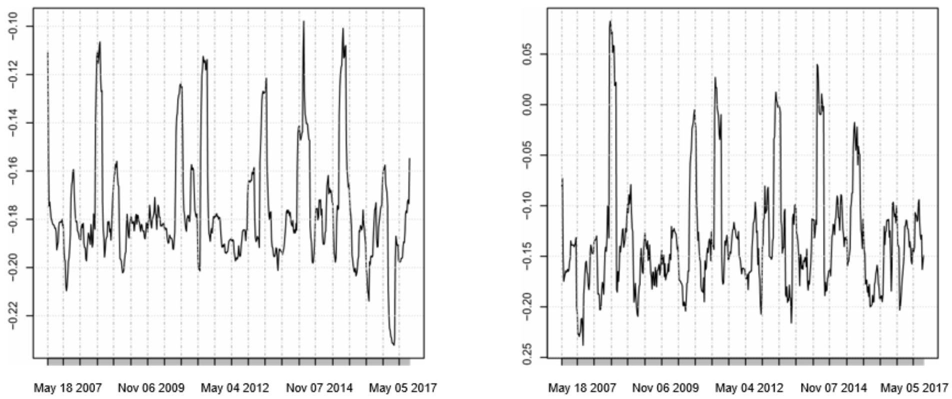
Firstly, it shows that GCC members have a varying diversification of listed companies. We observe strong dependencies of Kuwait and Qatar whose economy is focused on extraction and production of oil and natural gas as well as related products. Naturally, growing uncertainties of future oil prices impact these companies to a high degree. Oman and Bahrain, and to a certain extend Saudi Arabia and UAE feature a more diversified economy and hence, the stock market is less sensitive to oil price movements and uncertainty thereof.

Secondly and in view of implications for diversification opportunities, even within the oil exporting GCC group, there exist opportunities to diversify the impact of uncertainty of oil prices across these three identified groups. On the other hand, we do not identify any hedging opportunities within the GCC, as Table 3 only shows positive unconditional correlations between the GCC members.

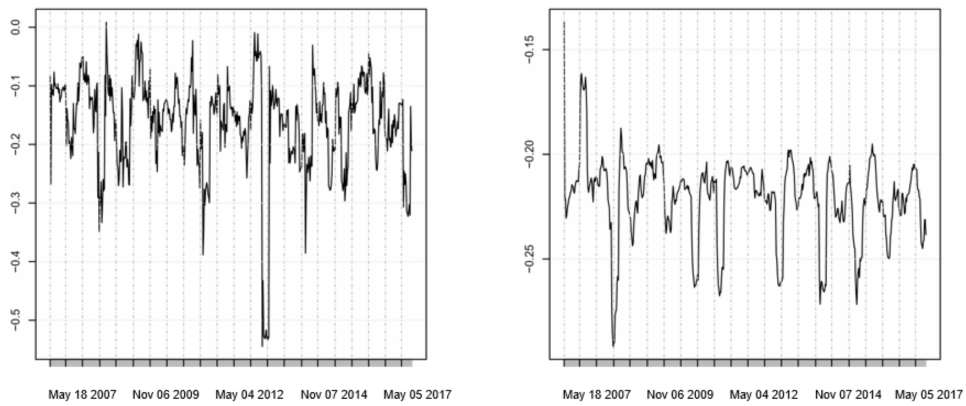
We can thus conclude that the relationship between the considered return series is not linear and varies over time. In addition, the use of copula models with time varying coefficients contribute better to understanding the non-linear association between crude oil uncertainty and stock market returns for GCC countries.

Table 5: Estimations results for the bivariate Student-t Copula for OVX - country.

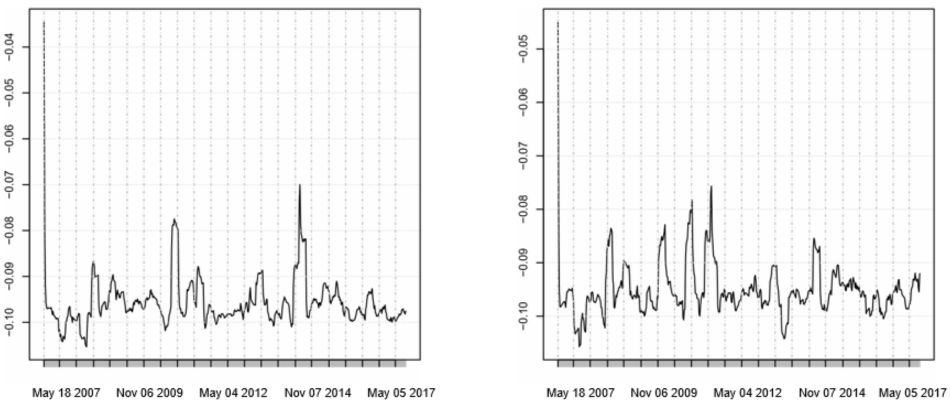
	OVX - Saudia	UAE	Kuwait	Qatar	Oman	Bahrain
a	−0.279	−0.309	0.348	−0.314	−0.148	−0.163
	(0.411)	(0.502)	(0.117)	(0.471)	(1.133)	(0.231)
b	0.543	0.068	−0.812	0.534	0.491	0.317
	(2.322)	(3.347)	(0.632)	(2.362)	(12.024)	(0.201)
c	−0.070	−0.237	0.494	0.058	−0.012	−0.015
	(0.132)	(0.294)	(0.223)	(0.206)	(0.112)	(0.135)
ν	13.522	15.336	16.084	12.555	12.293	12.491
	(3.626)	(4.779)	(6.301)	(3.399)	(3.902)	(3.982)
AIC	−10.910	−5.725	−9.963	−20.842	−6.270	−2.724



(a) (left) OVX - Saudi Arabia, (right) OVX - UAE



(b) (left) OVX - Kuwait, (right) OVX - Qatar



(c) (left) OVX - Oman, (right) OVX - Bahrain

Figure 2: Student-t copula of the OVX and GCC countries from May 18, 2007 to February 28, 2018 based on weekly returns.

5. Conclusions

Motivated by the paramount importance of the GCC stock markets and the ongoing process of economic and financial integration in the region, this study investigates the effect of global oil market uncertainty on stock market performance in Saudi Arabia, UAE, Kuwait, Qatar, Oman, and Bahrain. GCC countries are surrounded by different sources of economic and political uncertainties (such as the EU and US crisis, Arab spring, Iran and Israel conflict, etc.) which lead to a greater instability in oil export revenues and stock market performance. The economic reforms undertaken by GCC countries to develop the non-oil private sector and provide the necessary environment to foster healthy stock markets differ in their levels of success which is supported by our findings in terms of grouping of markets. Thus, reforms and policy changes have different impacts on the decisions taken by domestic and international investors in this markets caused by differing diversification of the GCC economies.

Empirically, the ARMA-DCC-EGARCH model and the time varying Student-t copula provide several important findings. We find evidence of significant links between oil market uncertainty and GCC stock market returns. These links are negative for almost the whole period under examination and are time varying, as expected. Stock markets of GCC member states react with negative returns as the OVX increases, which translates to an increase in uncertainty about future oil prices. We further report that GCC stock markets can be classified on the basis of the Kendall's-τ determined from copula dependence coefficient estimates into: a) markets that are highly affected by the variation in oil price volatility (led by Kuwait and Qatar); b) markets with medium levels of dependencies on oil volatility (i.e., Saudi Arabia and UAE); and c) markets with relatively low levels of dependencies on crude oil uncertainty (i.e., Oman and Bahrain), which is due to differing focus on the countries' economies on the extraction and production of crude oil and natural gas products. This grouping offers diversification benefits for portfolios that span investments across GCC members, but no hedging opportunities as stock markets within the GCC group unanimously feature positive correlations. This implies that market participants must pay more attention to global oil market uncertainty in order to properly forecast returns and volatilities in GCC stock markets.

Our findings provide evidence that the efforts of GCC countries to become less dependent on their oil exports has differing success across GCC members. Future research could explore how policy implementations differ across these countries and why different groups with regard to connectedness with the OVX have formed. It is important to address how these dependencies on oil price uncertainty can be further reduced.

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