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INSTABILITY AND DEPENDENCE STRUCTURE BETWEEN OIL PRICES AND GCC STOCK MARKETS

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This paper investigates the dependence structure between daily oil price changes and stock market returns in six GCC countries (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates) during the period from June 1, 2005 to February 11, 2013. For that, we apply copula functions that capture several dependence structures. The empirical results provide evidence of positive and asymmetric dependence between oil price changes and stock market returns. All countries (except Oman) exhibit left tail dependence while Oman shows right tail dependence. Moreover, we check whether the dependence structure is constant over time using change point testing method. The empirical results indicate significant change in the dependence structure. For all countries, the copula parameters and tail dependence coefficients are greater during financial period than tranquil implying a presence of contagion effect.

Keywords
oil price changes, stock market returns, copulas, change point testing method, contagion effect

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1. INTRODUCTION

There is a considerable interest in modeling the dependence structure between oil prices and stock market indices in developed and emerging countries due to its important implications for portfolio diversification and energy management. Theoretically, the value of a stock is equal to the discounted sum of expected futures cash flows. Consequently, oil prices can affect stock prices directly by impacting futures cash flows or indirectely through an impact on the interest rate used to discount the futures cash flows.

For the case of the Gulf Cooperation Council (GCC) region[1], numerous empirical studies have been developed to study the relationship between oil prices and stock market indices. Some authors investigate the short-term influence of oil price changes on stock market returns using VAR models. Abu Zarour (2006) finds that oil price changes affect stock market returns in Saudi Arabia and Oman. Bashar and Sadorsky (2006) find also that only the Saudi and Omani stock markets have predictive power of oil prices. Arouri et al. (2011) estimate a VAR-GARCH for six GCC countries. They find that oil price changes affect positively the stock market returns in Bahrain, Oman and Qatar. In particular, they show that this effect is more pronounced during crisis period than normal one. Few authors like Lescaroux and Mignon (2008) find that oil prices do not cause share prices in sense of Granger in Oman, Qatar, Saudi Arabia and UAE. A similar result is found by Akoum et al. (2012) for six GCC countries. Wang et al. (2013) find that the response of stock market returns to oil demand shocks is significant in Saudi Arabia and Kuwait. Other authors test the presence of long-term relationship between oil prices and stock market indices using cointegration techniques. Hammoudeh and Aleisa (2004) find that oil prices and stock market indices are positively cointegrated in Saudi Arabia. For Bahrain, Kuwait, Oman and UAE, there is no significant cointegration relationship. Similarly, Hammoudeh and Choi (2006) examine the long-term relationship between stock market indices, US oil price, SP500 index and US Treasury bill rate. They find that US Treasury bill rate has a direct effect on these markets while oil prices and SP500 index have indirect effects. Using bootstrap panel cointegration tests and seemingly unrelated regression method, Arouri and Rault (2011) find that positive oil price shocks have positive impact on the stock market.

Although there are numerous studies, there is no consensus on the nature of the relationship between oil price changes and stock market returns. The absence of consensus seems to be related to the linear models used which are based on the assumption that the parameters are constant over time. However, this assumption is restrictive due to presence of structural breaks (Arouri et al. (2010)) or regime change (Aloui and Jammazi (2009)[2]). The parameters are rather time-varying and the relationship between oil price changes and stock market returns seems to be nonlinear. In such context, Maghyereh and Al-Kandari (2007) provide evidence of nonlinearity on the relationship between oil price changes and stock market returns. Using nonparamteric method, Arouri and Fouquau (2009) find also evidence of nonlinearity in Qatar, Oman and UAE.

Recent studies find evidence of asymmetric effects of oil price changes on GCC stock markets returns. In particular, the GCC stock markets are more sensitive to negative oil shocks than to positive oil shocks. To reproduce this asymmetric effects, Mohanty et al. (2011) introduce dummy variable[3] in the linear model. They show that the decreases in oil prices have a significant negative impact in GCC stock market returns whereas the increases in oil prices affect positively the stock

[1]The Gulf Cooperation Council (GCC) region includes six countries, namely, Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates (UAE).

[2]These authors consider the case of France, UK and Japan.

[3]The dummy variable takes the value of 1 if the oil price changes are positive and 0 otherwise.

market returns in Saudi Arabia and UAE only. Awartani and Maghyereh (2013) employ DCC-GARCH model and find that the correlation between stock market returns and oil price changes varies over time. The main limitation of this model is that it cannot reproduce asymmetric dependence and do not give information about tail dependence. The tail dependence correspond to the possibility of joint events such as low or high extreme event occurrence. To overcome this shortcoming, we propose an alternative approach based on copula theory. The advantage of the copulas lies in separating the dependence structure from the marginal distributions without making any assumptions about the distribution of the marginals.

The objective of this paper is two fold. First, we examine the dependence structure between oil price changes and stock market returns in six GCC countries, namely, Bahrain, Kuwait, Qatar, Oman, Saudi Arabia and UAE during the recent period from June 1, 2005 to February 11, 2013 using copulas functions. Second, we check whether this dependence structure is constant over time or it is affected by financial crisis.

The copulas functions have been applied by few authors to study the dependence structure between oil price changes and stock market returns in several countries. For the case of Vietnam and China, Nguyen and Bhatti (2012) employ several copula families to examine the relationship between oil price changes and stock market returns. They argue left tail dependence for the case of Vietnam while there is no evidence of any tail dependence for the case of China. Using time-varying copulas, Wen et al. (2012) provide evidence of symmetric lower and upper tail dependence between oil price changes and US/Chinese stock market returns. For the case of six CEE countries (Bulgaria, Czech Republic, Hungary, Poland, Romania and Solvenia), Aloui et al. (2013) examine the dependence structure between oil price changes and stock market returns using copulas. For all countries, they find evidence of lower tail dependence. For the case of six GCC countries, Naifar and Al Dohaiman (2013) analyse the dependence structure between oil price changes and macroeconomic variables (stock market return, short term interest rate and inflation rate) using three Archimedean copulas (Gumbel, Clayton and Frank). They find that the dependence structures between the series differ in each country. In addition, they divide the period into two subperiods: a tranquil period (before financial crisis) and a crisis period (after financial crisis) to check whether the dependence structure is affected by financial crisis. They find different dependence structures: before financial crisis they provide evidence of symmetric dependence but after financial crisis they provide evidence of asymmetric dependence.

Although Naifar and Al Dohaiman (2013) provide evidence of change point in dependence structure between oil price change and stock markets returns, they suppose that the change point exists and that the date of change point is known a priori. In this paper, we assume no prior knowledge of the existence and the localisation of change point. We contribute to the literature methodologically in using a change point testing method, as advanced by Dias and Embrechets (2004) to test the existence of change point in dependence structure between the series and to determine the date of its localisation that are consistent with market events during the study period.

Understanding the interaction between oil price changes and stock market returns is of great interest to both investors and policymakers. For the investors, the presence of significant dependence between the series imply that the benefits from diversification will diminsh and that the investors should rebalance their portfolios: they should not be combined in diversified portfolios to reduce systemic risk. For policymakers, they should include the fluctuations of the stock market indices of the major oil producers when they determine and predict the oil price.

Testing the presence of change point in the dependence structure is also important. Indeed, if a change point exists and if the copula parameters and the tail dependence coefficients are larger after financial crisis than before, a contagion effect will exist. Here, we consider the contagion in sense of

Forbes and Rigobon (2002) and defined as a significant increase in cross-market linkages after a shock to one market or group of markets.

The remainder of this paper is organized as follows. Section 2 presents the main concepts of Archimedean copula functions. Section 3 describes the data and provides the empirical results. Section 4 concludes.

2. MAIN CONCEPTS OF COPULAS

In this section, we present the copula functions used to study the dependence structure between oil price changes and stock market returns, the estimation method and the goodness of fit test applied to select the best copula.

2.1. Presentation of copulas functions

A copula is a function that allows to joint different univariate distributions to form a valid multivariate distribution without losing any information from the orignial multivariate distribution[4]. According to Sklar's (1959) theorem, any joint distribution function F of two continuous random variables (x_1 and x_2) can be decomposed into two marginal distributions (F_1 and F_2) and a copula C that describes the dependence structure between the components.

Formally, let $x=(x_1,x_2)$ be a two-dimensional random vector with joint distribution function $F(x_1,x_2)$ and marginal distributions F_i, $i=1,2$. There exists a copula $C(u_1,u_2)$ such that:

$$F(x_1,x_2)=C(F_1(x_1),F_2(x_2)). \tag{1}$$

The theorem also states that if F_i are continuous then the copula $C(u_1,u_2)$ is unique.An important property of copula is that it can capture the tail dependence: the upper (right) tail dependence (λ_U) exists when there is a positive probability of positive outliers occuring jointly while the lower (left) tail dependence (λ_L) is a negative probability of negative outliers occuring jointly. Formally, λ_U and λ_L are defined respectively as:

$$\begin{aligned}\lambda_U &= \lim_{u\to 1} P\left(x_1 \geq F_1^{-1}(u) \mid x_2 \geq F_2^{-1}(u)\right),\\ &= \lim_{u\to 1}\frac{1-2u+C(u,u)}{1-u}.\end{aligned} \tag{2}$$

$$\begin{aligned}\lambda_L &= \lim_{u\to 0} P\left(x_1 \leq F_1^{-1}(u) \mid x_2 \leq F_2^{-1}(u)\right),\\ &= \lim_{u\to 0}\frac{C(u,u)}{u}.\end{aligned} \tag{3}$$

Where $F_1^{-1}(u)$ and $F_2^{-1}(u)$ are the marginal quantile functions.

[4]For an introduction to copulas, see Joe (1997) and Nelsen (2006).

In this paper, we consider several copula functions (Normal, Student-t, Gumbel, Clayton and Frank). In addition, we use Survival copulas.

2.1.1. Normal copula

The Normal copula is the copula of the multivariate normal distribution and is defined by:

$$C_N(u_1,u_2) = \int_{-\infty}^{\phi^{-1}(u_1)} \int_{-\infty}^{\phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{(1-2\theta^2)}} \exp\left(-\frac{s^2-2\theta st+t^2}{2(1-\theta^2)}\right) dsdt. \quad (4)$$

Where $-1 \le \theta \le 1$ is the linear correlation coefficient. φ^{-1} is the inverse of the univariate standard normal distribution function. The Normal copula has zero tail dependence: $\lambda_{L_N} = \lambda_{U_N} = 0$.

2.1.2. Student-t copula

The Student-t copula is defined by:

$$C_t(u_1,u_2) = \int_{-\infty}^{t_v^{-1}(u_1)} \int_{-\infty}^{t_v^{-1}(u_2)} \frac{1}{2\pi\sqrt{(1-2\theta^2)}} \exp\left(1+\frac{s^2-2\theta st+t^2}{v(1-\theta^2)}\right)^{-\frac{v+2}{2}} dsdt. \quad (5)$$

Where $-1 \le \theta \le 1$ is the linear correlation coefficient. t_v^{-1} is the inverse of the univariate standard Student-t distribution function with $v > 2$. The Student-t copula has also symmetric tail dependence:

$$\lambda_{L_t} = \lambda_{U_t} = -2t_{v+1}\left(\sqrt{v+1}\frac{\sqrt{1-\theta}}{\sqrt{1+\theta}}\right).$$

2.1.3. Gumbel copula

The Gumbel copula (Gumbel, 1960) is an extreme value copula. It is an asymmetric Archimedean copula exhibiting greater dependence in the upper tail than in the lower tail. This copula is given by:

$$C_G(u_1,u_2) = \exp\left(-\left[(-\ln(u_1))^\theta + (-\ln(u_2))^\theta\right]^{\theta^{-1}}\right). \quad (6)$$

Where $\theta \in [1,+\infty[$, the lower tail dependence is $\lambda_{L_G} = 0$ and the upper tail dependence is $\lambda_{U_G} = 2-2^{-\theta}$.

2.1.4. Clayton copula

The Clayton copula (Clayton, 1978) is also an asymmetric Archimedean copula but exhibiting greater dependence in the lower tail than in the upper tail. This copula is given by:

$$C_C(u_1,u_2) = \max\left\{\left(u_1^{-\theta} + u_2^{-\theta} - 1\right)^{-\theta^{-1}}, 0\right\}. \quad (7)$$

Where $\theta \in [-1,+\infty[\setminus \{0\}$, the lower tail dependence is $\lambda_{L_C} = 2^{-\theta^{-1}}$ and the upper tail dependence is $\lambda_{U_C} = 0$.

2.1.5. Frank copula

The Frank copula (Frank, 1979) is a symmetric Archimedean copula. This copula is given by:

$$C_F(u_1,u_2) = -\theta^{-1}\ln\left(1 + \frac{\left(\exp(-\theta u_1)-1\right)\left(\exp(-\theta u_2)-1\right)}{\exp(-\theta)-1}\right). \quad (8)$$

Where $\theta \in]-\infty,+\infty[\setminus \{0\}$, the lower tail dependence is $\lambda_{L_F} = 0$ and the upper tail dependence is $\lambda_{U_F} = 0$.

2.1.6. Survival copulas

Survival or Rotated copulas are the copula of $(1-u_1)$ and $(1-u_2)$ instead of u_1 and u_2 respectively. Its function measures the asymmetric dependence on the opposite side of the distribution as compared to the original function. Survival Gumbel copula measures left tail dependence instead of right tail dependence as compared to Gumbel while Survival Clayton copula measures right tail dependence instead of left tail dependence as compared to Clayton copula.

Survival Clayton copula

The Survival Clayton copula is derived from the Clayton copula. This copula is given by:

$$C_{SC}(u_1,u_2) = u_1 + u_2 - 1 + \left((1-u_1)^{-\theta} + (1-u_2)^{-\theta} - 1\right)^{-\theta^{-1}}. \quad (9)$$

Where $\theta \in [0,+\infty[\setminus \{0\}$.

Survival Gumbel copula

The Survival Gumbel copula is derived from the Gumbel copula. This copula is given by:

$$C_{SG}(u_1,u_2) = u_1 + u_2 - 1 + \exp\left(-\left[\left(-\ln(1-u_1)\right)^{\theta} + \left(-\ln(1-u_2)\right)^{\theta}\right]^{\theta^{-1}}\right). \quad (10)$$

Where $\theta \in [0,+\infty[\setminus \{0\}$.

2.2. Estimation of copula parameter

To estimate the parameters of the copula, several methods are proposed in the literature including the exact maximum likelihood method, the canonical maximum likelihood (CML) method, the inference functions for margins (IFM) method, the moments method and the empirical copula. In this paper, we adopt the canonical maximum likelihood (CML) method proposed by Genest et al. (1995). This method is semiparametric and we have chosen it because there are no assumptions on the parametric form of marginal distributions. Indeed, an incorrect specification of the marginal distribution can influence estimation of the copula parameters. More precisely, the CML method leaves the marginal densities unspecified and uses *the empirical probability integral transform* in order to obtain the uniform marginals $[0,1]$ needed to estimate the copula parameters. The estimation process is performed in two steps. In a first step, the dataset $(x_{1t}, x_{2t}),\ t = 1,...,T$ are transformed into uniform variates $(\hat{u}_{1t}, \hat{u}_{2t})$ using the empirical Cumulative Distribution Function (CDF) distribution $\hat{F}_i(\bullet)$ defined as follows:

$$\hat{F}_i(\bullet) = \frac{1}{T+1}\sum_{t=1}^{T} 1_{[X_{it} \leq \bullet]}, \forall i = 1,2. \tag{11}$$

Where $1_{[X_{it} \leq \bullet]}$ represents the indicator function.

In a second step, the copula parameters θ are estimated as follows:

$$\hat{\theta} = \underset{\theta}{argmax} \sum_{t=1}^{T} \ln\left(c\left(\hat{u}_{1t}, \hat{u}_{2t}\right); \theta\right). \tag{12}$$

Where $\hat{u}_{1t} = \hat{F}_1(x_{1t})$ and $\hat{u}_{2t} = \hat{F}_2(x_{2t})$ are pseudo-sample observations from the copula.

After estimating the parameters of the copula, a typical problem that arises is how to choose the best copula, i.e., the copula that provides the best fit with the data set at hand. To this purpose, we consider the information criterion, namely, the log-likelihood (LL), the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). In addition, we employ the goodness of fit test.

2.3. Goodness of fit test

To check if the dependence structure of a multivariate distribution is appropriately modeled by a specific copula C_0, we employ the goodness-of-fit test of Genest et al. (2009) which is based on a comparison of the distance between the estimated and the empirical copulas. The null hypothesis of this test is $H_0 : C \in C_0$ for same class C_0 of copulas and the statistic of this test S_T is based on the distance of Cramér-von Mises given by:

$$S_T = \int_0^1 \left|\tilde{K}(t)\right|^2 k_{\hat{\theta}}(t)\, dt. \tag{13}$$

Where $k_{\hat{\theta}}(t)$ is the density function associated with $K_\theta(t)$, $\hat{\theta}$ is the estimator of θ and $\tilde{K}(t)$ is Kendall's process given by:

$$\tilde{K}(t) = \sqrt{T}\left(\hat{K}(t) - K(t)\right), \forall 0 \leq t \leq 1. \tag{14}$$

Where $K(t)$ denotes the univariate distribution function and $\hat{K}(t)$ is the empirical distribution function given by:

$$\hat{K}(t) = \frac{1}{T}\sum_{i=1}^{T} 1_{\left[U_i \le t\right]}. \tag{15}$$

Where $U_i = 1/(T-1)\sum_{j=1}^{T} 1_{\left[X_{1j} \le X_{1i},\, X_{2j} \le X_{2i}\right]}$ for each $i = 1,\ldots,T$.

We reject the null hypothesis when the observed value of S_T is greater than the $(1-\alpha)th$ percentile of its distribution. To determine the p-values of the test, we use a multiplier approach as described in Kojadinovic and Yan (2011).

2.4. Change point testing method

To validate the selected copula, an assumption of stability of the estimated copula parameter is needed. To test the stability of the copula parameter, that is to verify that the selected copula parameter is constant over time, we apply the change point testing method advanced by Dias and Embrechts (2004).

Let T denote the sample size and let $(x_{11}, x_{21}),\ldots,(x_{1T}, x_{2T})$ denote the observed date. We are interested in testing the null hypothesis of no change point: $H_0 : \theta_1 = \cdots = \theta_T$ against the alternative of one change point $H_1 : \theta_1 = \cdots = \theta_{k^*} \ne \theta_{k^*+1} = \cdots = \theta_T$, where k^* is the location of the unknown single change point. All parameters are assumed to be unknown under both null and alternative hypotheses. If $k^* = k$ is known, the likelihood ratio statistic to test H_0 can be constructed as follows:

$$\begin{aligned} -2\log\Lambda_k = 2\Bigg[&\sum_{i=1}^{k} \log C\left(\hat{\theta}_k; F_1(x_{1i}), F_2(x_{2i})\right) \\ &+ \sum_{i=k+1}^{T} \log C\left(\hat{\theta}_{k^*}; F_1(x_{1i}), F_2(x_{2i})\right) \\ &- \sum_{i=1}^{T} \log C\left(\hat{\theta}_T; F_1(x_{1i}), F_2(x_{2i})\right)\Bigg]. \end{aligned} \tag{16}$$

Where $\hat{\theta}_k$, $\hat{\theta}_{k^*}$ and $\hat{\theta}_T$ are estimated from data using Maximum Likelihood Estimation (MLE).

However, if k^* is unknown, the null hypothesis of no change point will be rejected with a large value for Z_T:

$$Z_T = \max_{1 \le k \le T}\left(-2\log\Lambda_k\right). \tag{17}$$

The critical values under different levels of statistical significance are discussed in details on Dias and Embrechts (2004).

3. EMPIRICAL RESULTS

3.1. Data description

Our database consists of daily crude oil prices and stock market indices in six GCC countries over the period June 1, 2005 until February 11, 2013, yielding a total of 1939 observations[5]. The countries include Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates (UAE). Oman, Qatar, Saudi Arabia and UAE are also members of OPEC (Organization of the Petroleum Exporting Countries). As advanced by Naifar and Al Dohaiman (2013), daily data are more adequately to capture the interaction of oil and stock prices in the region than low-frequency data.

As a proxy for oil price, we use Brent crude oil price collected from the Energy Information Administration. As a proxy for stock market, we use major stock market index for each of countries extracted from MSCI (Morgan Stanley Capital International). All data are expressed in US dollars.

These data are transformed in logarithm form and are considered in first difference, so the series obtained correspond to stock market returns and oil price changes. The application of standard unit root tests and unit root tests with structural breaks show evidence of stationarity[6] for all return series. The descriptive statistics for return series are presented in Table 1.

Table 1. Descriptive statistics of return series

Countries	Mean (%)	Std Dev (%)	Skw	Kurt	JB Stat
Bahrain	-0.100	1.335	-3.359	62.223	286863.900***
Kuwait	-0.012	1.533	-1.288	17.317	17088.790***
Oman	-0.020	1.396	-1.612	29.721	58495.570***
Qatar	-1.6×10^{-4}	1.677	-1.018	16.958	16067.660***
Saudi Arabia	-0.027	1.840	-2.108	29.805	59453.300***
UAE	-0.048	2.095	-0.908	15.728	13348.670***
Brent	0.044	2.226	-0.010	9.051	2956.279***

Note: Skw is Skewness. Kurt is Kurtosis. JB Stat is the Jarque and Bera statistic for normality. *** indicates a rejection of null hypothesis of normality at the 1% level.

We see that the average return is negative for all the series except for Qatari stock market return and oil price changes where it is positive. The highest average daily stock market return is for Qatar (-0.0001%) while the lowest average daily stock market return is for Bahrain (-0.100%). Furthermore, we observe that UAE exhibits the highest risk degree as measured by the standard deviation (2.095%) followed by Saudi Arabia (1.840%) while Bahrain shows the least risk degree (1.335%) followed by Oman (1.396%).

Compared to stock market returns, the oil price changes exhibit higher average daily return (0.044%) and higher standard deviation (2.226%). This may be due to the fact that oil prices doubled

[5] We note that we have eliminated the observations when a stock or energy market was closed or during holidays.

[6] The results of the unit root tests are not reported here. These are available upon request.

during the study period from US$50.46 per barrel in 01/06/2005 to US$118.29 per barrel in 11/02/2013.

All series exhibit negative skewness and show excess kurtosis. Moreover, the Jarque-Bera test strongly rejects the null hypothesis of normality for all series, which justifies the choice of copula theory.

3.2. Marginal distributions

We adopt the two-step estimation method. In the first step, we model the marginal distributions. In the second step, we focus on the dependence structure.

A preliminary analysis of the autocorrelation function and the autocorrelation function of squared series show that these functions decrease hyperbolically to zero as lags increase. In addition, the associated spectral densities seem not to be bounded, which may indicate the presence of long memory behaviour in both mean and variance[7]. To address this, we estimate an ARFIMA-FIAPARCH (Autoregressive Fractionally Integrated Moving Average-Fractionally Intergrated Asymmetric Power AutoRegressive Conditionally Heteroskedastic) model proposed by Tse (1998). Compared to ARFIMA-FIGARCH model, the ARFIMA-FIAPARCH model presents the advantage to capture, in addition to the long range dependence, some important stylized features of oil price changes and stock market returns such as fat tails and leverage effects. Specifically, in the conditional mean equation, we fit an ARFIMA $\left(p, d_m, q\right)$ process given by:

$$\begin{gathered}\phi(L)(1-L)^{d_m}(u_t-\mu)=\theta(L)\varepsilon_t,\\ \varepsilon_t\,|I_{t-1}: \;\; N(0,h_t).\end{gathered} \tag{18}$$

Where $\mu > 0$ is a constant, $0 \le d_m < 1/2$ is the fractional integration parameter, L is the lag operator, $\phi(L) = 1 + \phi_1 L + \ldots + \phi_p L^p$ and $\theta(L) = 1 + \theta_1 L + \ldots + \theta_q L^q$ are polynomials of order p and q respectively whose roots are distinct and lie outside the unit circle. I_{t-1} is the information set available at time $t-1$. The innovations of the ARFIMA process are assumed to be normally distributed.

The conditional variance equation is modeled by a FIAPARCH (P, d_v, Q) process given by:

$$h_t^{\delta/2} = w + \left(1-\left(1-\beta\left(L\right)\right)^{-1}\varpi\left(L\right)\left(1-L\right)^{d_v}\right)\left(\left|\varepsilon_t\right|-\gamma\varepsilon_t\right)^{\delta}. \tag{19}$$

Where $w > 0$ is a constant, $0 \le d_v < 1$ is the fractional integration parameter, $\beta(L) = 1 + \beta_1 L + \ldots + \beta_P L^P$ and $\varpi(L) = 1 + \varpi_1 L + \ldots + \varpi_Q L^Q$ are polynomials of order P and Q respectively whose roots are distinct and lie outside the unit circle. $\delta > 0$ is the power term that plays the role of a Box-Cox transformation of the conditional standard deviation $h_t^{\delta/2}$. $-1 < \gamma < 1$ is the leverage coefficient that accounts for asymmetric effect. When $\gamma > 0$, negative shocks give rise to higher volatility than positive shocks. When $\gamma < 0$, the magnitude of the shocks is captured by the term $\left(\left|\varepsilon_t\right| - \gamma\varepsilon_t\right)$. When $\gamma = 0$ and $\delta = 2$, the process in equation (19) reduces to FIGARCH (P, d_v, Q) process.

[7]We do not report autocorrelation functions and spectral densities. These are available on request.

The estimation results of the ARFIMA-FIAPARCH model, using the method of quasi-maximum likelihood, are displayed in Table 2.

Table 2. Estimates of ARFIMA-FIAPARCH model

	Stock market returns						Oil price changes
	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE	
(p,d_m,q)	$(0,d_m,0)$	$(0,d_m,0)$	$(1,d_m,1)$	$(1,d_m,1)$	$(0,0,0)$	$(1,d_m,0)$	$(1,0,1)$
(P,d_v,Q)	$(1,d_v,1)$	$(1,d_v,1)$	$(1,d_v,1)$	$(1,d_v,1)$	$(1,d_v,1)$	$(1,d_v,1)$	$(1,d_v,1)$
μ							
d_m	0.068^{***}	0.042^{***}	0.144^{***}	0.091^{***}		0.209^{***}	
	(2.709)	(2.031)	(3.973)	(2.484)		(3.674)	
ϕ_1			-0.756^{***}	-0.659^{***}		-0.128^{**}	-0.756^{***}
			(-6.588)	(-3.276)		(-2.302)	(-9.365)
θ_1			0.720^{***}	0.612^{***}			0.771^{***}
			(5.837)	(2.782)			(9.511)
$\omega\times10^4$		0.042^{***}					
		(2.031)					
d_v	0.467^{***}	0.403^{***}	0.710^{***}	0.650^{***}	0.482^{**}	0.528^{***}	0.332^{***}
	(3.616)	(3.623)	(7.938)	(8.724)	(2.310)	(5.863)	(6.736)
γ	0.278^{**}	0.395^{***}	0.242^{***}			0.260^{***}	0.637^{***}
	(2.079)	(2.295)	(2.618)			(2.504)	(3.040)
δ	1.640^{***}	1.830^{***}	2.136^{***}			2.104^{***}	1.370^{***}
	(8.117)	(10.600)	(15.180)			(15.790)	(8.942)
β_1	0.465^{***}	0.701^{***}	0.750^{***}	0.771^{***}	0.741^{***}	0.603^{***}	0.518^{***}
	(3.044)	(10.960)	(10.720)	(11.320)	(6.763)	(5.653)	(3.548)
ϖ_1	0.191^{***}	0.336^{***}	0.096^{***}	0.171^{***}	0.278^{**}	0.171^{***}	0.240^{***}
	(3.040)	(4.646)	(3.819)	(4.027)	(2.462)	(3.577)	(2.778)
Skw	0.387	-0.508	-0.957	-1.053	3.400	-0.957	-0.160
Ex. Kurt	2.635	5.849	7.992	12.558	1.870	8.694	0.939
$Q(20)$	10.968	27.979	23.201	18.278	16.161	16.244	21.982
$Q^2(20)$	10.830	98.839	33.140	41.610	1.223	34.268	20.414

Note: The values in parenthesis are the t-Student. Skw is Skewness. Ex. Kurt is Excess of Kurtosis. $Q(20)$ is the Ljung-Box statistic for serial correlation in returns for order 20. $Q^2(20)$ is the Ljung-Box statistic for serial correlation in squared returns for order 20. ** and *** denote significance at the 5% and 1% levels respectively.

We see that the fractional integration parameter d_m is significant in all series (except Saudi stock market return and oil price changes) indicating presence of long range dependence in the mean of five GCC stock market returns. This could be explained by the fact that Saudi stock market is efficient and liquid. The fractional integration parameter d_v is significant in all series implying existence of long range dependence in the volatility of six GCC stock market returns and oil price changes. In particular, we observe that the degrees of d_m and d_v in OPEC stock market returns are higher than those of non-OPEC stock market returns and oil price changes implying more persistence in return and volatility in OPEC stock market returns. The power term δ is different from 2 in stock market returns of Oman and UAE. The leverage coefficient γ is positive and significant in stock market returns of Bahrain, Kuwait, Oman and oil price changes. Evidence regarding leverage effects implies that news in stock and oil markets have an asymmetric impact on volatility. In particular, bad news (negative shocks) give rise than good news (positive shocks).

The Ljung-Box statistic of order 20 suggests the absence of serial correlation for all returns series.

3.3. Dependence structure over the whole period

In this subsection, we study, for each country, the dependence structure between filtered oil price changes and filtered stock market returns over the whole period $[1,T]$[8] using the copula functions described in Section 2.1. We retain the best copula which presents the smallest LL[9], AIC and BIC. The choice of the selected copula is also confirmed by the goodness of fit test presented in Section 2.3[10]. According to the empirical results, we retain the copulas to fit the data at the 1% significance. Table 3 reports the selected copula, the corresponding copula parameter and the tail dependence coefficients.

Table 3. Copula parameters and tail dependence coefficients over the whole period

Countries	Selected Copula	$\hat{\theta}$	$\hat{\lambda}_L$	$\hat{\lambda}_U$	LL	AIC	BIC	$\hat{S}_T$ [p-values]
Bahrain	Clayton	0.044	0.000	0	-2.237	-4.474	-4.471	0.028 [0.423]
Kuwait	Clayton	0.098	0.000	0	-8.295	-16.591	-16.588	0.014 [0.232]
Oman	Gumbel	1.134	0	0.157	-16.440	-32.878	-32.876	0.024 [0.346]
Qatar	Survival Gumbel	1.126	0.149	0	-12.791	-25.581	-25.578	0.019 [0.309]
Saudi Arabia	Survival Gumbel	1.132	0.157	0	-26.674	-53.347	-53.345	0.021 [0.372]
UAE	Survival Gumbel	1.163	0.185	0	-29.232	-58.462	-58.459	0.031 [0.241]

Notes: $\hat{S}_T$ is the Cramér-von Mises statistic given by equation (13).

[8] T is the sample size, here $T = 1939$.

[9] We note that the retained copula in terms of LL is one with lowest LL, since we minimize in our estimation $(-\text{LL})$ rather maximize (LL).

[10] In practice, we estimate for each country the three Archimedean copulas. Here, we do not report the results. These results are available upon request.

According to the results, we see that the values of the copula parameters are positive in all countries which implies that increases in oil price coincide with an appreciation of stock price. This positive dependence may be related to positive shocks to the global demand for industrial commodities that cause higher oil prices and higher stock market prices or may be explained by the fact that both oil prices and stock market prices are positively related to the global business (Aloui et al., 2013).

Moreover, we observe that the Survival Gumbel copula gives a better fit of the dependence structure between oil price changes and stock market returns for Qatar, Saudi Arabia and UAE which are the largest oil-producters and exporters in GCC region. The Clayton copula fits the data for Bahrain and Kuwait. For Oman, we retain the Gumbel copula. So, we can conclude that the dependence structure between oil price changes and stock market returns is rather asymmetric in all countries. Indeed, Survival Gumbel copula and Clayton copula are able to capture lower tail dependence while Gumbel copula can mesure the upper tail dependence. This result suggests that the oil price changes and the stock market returns crash together in all countries except Oman where the series boom together. This may be explained by the fact that all GCC countries show an increase in oil production during study period except Oman which experiences a decline in oil production in recent years[11].

These findings are in line with that of Mohanty et al. (2011) and Awartani and Maghyereh (2013) who find that increases and decreases in oil prices have asymetric effect on six GCC stock market returns and to that of Naifar and Al Dohaiman (2013) who document asymmetric tail dependence between oil price changes and six GCC stock market returns.

As we announced in introduction these findings have important implications for both investors and policymakers. For investors who are interested in GCC stock markets. When oil prices are expected to increase, they can invest in all GCC countries except Oman, to benefit from diversification and to reduce expose to risk, because the returns series are not expected to boom together in these countries. In contrary, when oil prices are expected to decrease, they can invest in Oman because the returns series are expected to boom together in this country.

3.4. Testing the change point

Now, we test the null hypothesis that there is no change point in the selected copulas againt the alternative hypothesis of one change point. The empirical results[12] show that the maximum values of $-2\log\Lambda_k$ given by equation (16) are greater than the critical values[13]. So, the null hypothesis can be rejected in favor of one change. The dates of change points are summarized in Table 4.

Table 4. Dates of change points

Countries	$\hat{T}_1$
Bahrain	29/08/2008
Kuwait	28/08/2008
Oman	25/07/2008
Qatar	04/11/2008
Saudi Arabia	22/09/2008
UAE	29/08/2008

11For more details, see US Energy Information Administration website.

12Here, we do not report the empirical results of $-2\log\Lambda_k$. These are available up on request.

13The critical values are chosen from Dias and Embrechts (2004).

We see that all dates of change points are in 2008 with same differences across countries depending on their responses to shocks . These dates can be associated to recent global financial crisis 2008.

3.5. Dependence structure over subperiods

Now, we reexamine the dependence structure between filtered oil price changes and filtered stock market returns for each country over two subperiods: tranquil period (before financial crisis) $\left[1,\hat{T}_1\right[$ and crisis period (after financial crisis) $\left[\hat{T}_1,T\right]$. For each subperiod, we find the same copula that selected for the whole period[14]. The obtained results are reported in Table 5.

Table 5. Copula parameter and tail dependence coefficients over subperiods

Countries	Tranquil period			Crisis period		
	$\hat{\theta}_1$	$\hat{\lambda}_{L,1}$	$\hat{\lambda}_{U,1}$	$\hat{\theta}_2$	$\hat{\lambda}_{L,2}$	$\hat{\lambda}_{U,2}$
Bahrain	0.000	0.000	0	0.203	0.033	0
Kuwait	0.069	0.000	0	0.107	0.002	0
Oman	1.123	0	0.146	1.108	0	0.131
Qatar	1.112	0.135	0	1.130	0.153	0
Saudi Arabia	1.121	0.144	0	1.159	0.182	0
UAE	1.147	0.170	0	1.252	0.260	0

We observe that for all countries, the copula parameters and the tail dependence coefficients are greater during crisis period than tranquil one, indicating that the dependence structure between oil price changes and stock market returns is more intensified during the crisis period and implying the existence of contagion effect. This result is in line with Arouri et al. (2011) and who found that the sensitivity of GCC stock market returns to oil price changes has jumped following the global financial crisis. It is also similar to the one obtained by Wen et al. (2012) who find evidence of contagion effect between oil and US/Chinese markets and Naifar and Al Dohaiman (2013) who show that the dependence structure between stock market returns and oil price changes in tranquil period is different from the one in crisis period.

In addition, we see that UAE and Saudi Arabia, which are the largest oil-producers and exporters, and which have the most risky stock markets, exhibit the biggest increase in Survival Gumbel copula parameter (1.252 and 1.159 respectively) and lower tail dependence coefficient (0.260 and 0.182 respectively) during crisis period indicating a severe impact of financial crisis on these markets.

These results suggest some important implications for investors. Indeed, the existence of the contagion effect means that the benefits of diversification related to investing in crude oil will diminish during financial crisis.

4. CONCLUSION

In this paper, we examine the dependence structure between daily oil price changes and six stock market returns, namely, Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and UAE during the recent period from June 1, 2005 to February 11, 2013. For that, we apply several copula functions, namely, Normal, Student-t, Gumbel, Clayton and Franck that present different tail dependence structures.

[14]In practice, we re-estimate the several copulas presented above and we apply the goodness of fit test to select the best copula. We find the same copulas presented in Table 4. Here, we do not report the results. These are available on request.

The econometric approach adopted consists on two steps. First, we model the marginal distributions of stock market returns and oil price changes using ARFIMA-FIAPARCH model which is able to capture the asymmetric effect in addition to long memory behaviour in mean and variance. We find evidence of peristence and asymmetric in return and volatility of the series. Second, we focus on the dependence structure between oil price changes and stock market returns using copula functions. We find evidence of asymmetric tail dependence in all countries. More precisely, we find evidence of lower tail dependence in all countries (except Oman) which means that the stock market returns and oil price changes crash at same time. Contrary, in Oman we provide evidence of upper tail dependence which indicates that the stock market returns and oil price changes boom at same time. Consequently, investors should may attention when they invest in GCC stock markets taking into account the sign of changes in oil prices in selecting their porfolios.

Furthermore, we test the stability of the copula parameter estimated using change point testing method advanced by Dias and Embrechts (2004). The empirical results show evidence of one change point for all countries. In particular, we find that the copula parameters and the tail dependence coefficients are greater in financial period than normal implying a presence of contagion effect.

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