Crude Oil Price Uncertainty and Stock Markets in Gulf Corporation Countries: A Var-Garch Copula Model

By Jaghoubi Salma

Al Majmaah University, Saudi Arabia

Abstract: The main objectives of this study are twofold. The first objective is to examine the volatility spillover between the GCC stock markets and Oil prices, over the period 2005-2012, in a multivariate setting, using the VAR (1)-GARCH (1,1) model which allows for transmission in returns and volatility. The second is to investigate the dependence structure and to test the degree of the dependence between financial returns using copula functions. Five candidates, the Gaussian, the Student’s t, the Frank, the Clayton and the Gumbel copulas, are compared. Our empirical results for the first objective suggest that there exist moderate cross market volatility transmission and shocks between the markets, indicating that the past innovation in stock market have great effect on future volatility in oil market and vice versa.

Keywords: subprime financial crisis, return spillover, volatility spillover; oil market, var-garch (1,1)-copula model.

GJMBR - C Classification : JEL Code: B13

Strictly as per the compliance and regulations of:

© 2015. Jaghoubi Salma. This is a research/review paper, distributed under the terms of the Creative Commons Attribution-Noncommercial 3.0 Unported License http://creativecommons.org/licenses/by-nc/3.0/), permitting all non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.
Crude Oil Price Uncertainty and Stock Markets in Gulf Corporation Countries: A Var-Garch Copula Model

Jaghoubbi Salma

Abstract- The main objectives of this study are twofold. The first objective is to examine the volatility spillover between the GCC stock markets and Oil prices, over the period 2005-2012, in a multivariate setting, using the VAR (1)-GARCH (1,1) model which allows for transmission in returns and volatility. The second is to investigate the dependence structure and to test the degree of the dependence between financial returns using copula functions. Five candidates, the Gaussian, the Student’s t, the Frank, the Clayton and the Gumbel copulas, are compared. Our empirical results for the first objective suggest that there exist moderate cross market volatility transmission and shocks between the markets, indicating that the past innovation in stock market have great effect on future volatility in oil market and vice versa.

Moreover, the result on the second objective implies that, during the pre-crisis period, the dependence structure is asymmetric with asymmetric upper and lower tail dependence. However, the degree of the dependence becomes stronger when the financial crisis occurs. Moreover, both of the degree of the dependence and the dependence structure vary when the financial crisis occurs. Our findings have important implications for global investment risk management by taking into account joint tail risk.

Keywords: subprime financial crisis, return spillover, volatility spillover; oil market, var-garch (1,1)-copula model.

I. Introduction

Today, crude oil is the most important commodities and is regarded as one of the single most important driving forces of the global economy. Changes in the oil prices have significant effects on economic growth and welfare around the world; hence, crude oil prices have received considerable attention from both finance practitioners and market participants.

Several researches on crude oil price dynamics found that crude oil prices experienced very large fluctuations and could suffer increasingly drastic fluctuations in the future.

Shocks in oil price have continuously augmented in size and frequency. First, the greater instability in the oil prices initially appeared during the world oil crises of 1973 and 1979. Then, after 2003, oil prices began to increase very sharply, hitting a record high of 147 USD$/barrel in July 2008. Affected by the global financial crisis in late 2008, oil prices plummeted to 34 USD$/barrel in February 2009, which have recently started to rise again. During June 2014, the world market price of crude oil declined from $115 per barrel to its low point of approximately $43pb in January 2015.

In this context, understanding the possibly shock transmission and the relationship between oil prices and stock market of the emerging countries is of crucial importance for policy making and risk management.

In recent decades, numerous researches have been devoted to the study of the relationship between oil prices and economic activity. Essentially, these studies have established that shocks in oil prices have significant effects on macroeconomic variables in most developed and emerging countries [Cunado and Perez Garcia de (2005), Balaz and Londarev (2006), Gronwald (2008), Cologni and Manera (2008), Kilian (2008) and Lardic et Mignon (2006, 2008)]. However, relatively little attention has been given to the relationship between oil prices and stock markets. In particular, previous empirical investigations of the relationship between crude oil and stock returns are mainly devoted to developed markets, and sometimes to Pacific Basin countries and very few studies have focused on the stock markets in some emerging markets of the GCC countries. These studies have mainly examined the interaction between short-term impact of oil prices and stock returns.

Giving the increasing role of the GCC countries in the global oil market, studying the effects of oil prices on the stock markets of the GCC is interesting for several reasons. First, the GCC countries are major participants in the global oil market, their stock markets may be impacted by changes in oil prices. Second, the GCC markets differ from markets often covered by previous empirical studies by the fact that they are relatively poorly integrated into the global financial market and are extremely sensitive to regional political events. Finally, GCC markets are very promising for international portfolio diversification. Thus, studying the influence of oil price shocks on the returns of financial assets in the GCC allows both investors and authorities to understand the evolution of stock markets in response to changing oil prices.

The purpose of this paper is to examine the dynamic correlation and volatility transmission between...
the GCC and the crude oil returns and to explore the
dependence structure between each pair of market
indexes (OIL/GCC). We combine two models which are
the VAR- GARCH model and the Copula approach to
have a joint VAR- GARCH-Copula model with possibly
skewed, fat tailed return innovations and non-linear
property. The Vector Autoregressive–Generalized
Autoregressive Conditional Heteroskedasticity model
(VAR-GARCH) was introduced by Ling and McAleer
(2003) and later used by Arouri et al. (2011, 2012). One
of the main advantages of this model is that it is allows us
to investigate the shocks transmission, the dynamics of
conditional volatility and the volatility spillovers between
series. It also provides meaningful estimates of the
unknown parameters with less computational
complication than several other multivariate
specifications. The specific aspect of this model allows
us to observe the impact of crude oil events or news in the
GCC equity index returns and vice versa. Besides, to
take into account the stylized facts observed on financial
markets such as non-linear dependency, asymmetry and
heavy tails, the multivariate dependence structure between
markets is modeled by several copulas which are
perfectly suitable for non-normal distributions and
nonlinear dependencies.

The paper is organized as follow. Section 2
reviews the relationship between the crude oil and stock
markets. Section 3 outlines the methodology used.
Section 4 presents the data and discusses the empirical
results. The final section concludes.

II. Literature Review

The literature on the subject is quite rich in the
developed countries. One of the first studies to
investigate the exposure of stock returns to oil price
movements was Chen et al. (1986), who find that oil
price have no significant effect on US stock returns for

Recent research by Aloui and Jammazi (2009)
applied a univariate regime-switching EGARCH model
to examine the relationship between crude oil shocks and
UK, French and Japanese stock markets. They
concluded that there exist some nonlinearity in the
relationship between oil prices and the stock market
financial returns. In the same line, Odusami (2009)
defines that unexpected shocks in oil prices have
nonlinear and asymmetric effects on stock returns.

Miller and Ratti (2009) investigate the existence
of different regimes in the long term relationship
between oil and the stock market in OECD countries
over the past four decades.

Kilian and Park (2009) employ a structural VAR
to decompose the oil price shocks into aggregate
demand shocks and supply shocks. In their model, the
response of the stock market to these two types of
shocks is very different, with the aggregate demand
shock leading to a reduction in stock returns, while the
aggregate supply shock (representing better global
economic conditions) leads to an increase in returns.

More recently, Jammazi and Aloui (2010)
combine wavelet analysis and models change regime
Markov-type (MS-VAR) and find that the reaction of the
stock markets of these three countries to shocks in oil
prices is rather asymmetric.

Chang et al. (2010) employ a symmetric DCC-
GARCH model to investigate the conditional correlations
and volatility spillovers between crude oil (WTI and Brent
markets) and FTSE100, NYSE, Dow Jones and S&P500
stock indices.

Some recent studies have focused on the case of
European, Asian and Latin American emerging stock
markets. The results of these studies suggest a
significant link between short-term changes in oil prices
and returns in emerging equity markets.

Using a VAR model, Papapetrou (2001)
established the existence of a significant relationship
between changes in oil prices and stock markets in
Greece.

Basher and Sadorsky (2006) use a multifactorial
asset pricing model and find the same results for other
emerging stock markets.

In contrast to the work done on developed
markets, relatively little attention has been given to
smaller emerging markets, particularly in the GCC
countries, where the creation of stock markets is
relatively recent. Recent work in this area includes
Hamoudah et Eleisa (2004), Zarour (2006) and Onour
(2008).

Hamoudah et Eleisa (2004) estimate a vector
autoregression model to study the relationship between
oil prices and stock prices for five members (Bahrain,
Kuwait, Oman, Saudi Arabia, and the United Arab
Emirates) of the Gulf Cooperation Council (GCC). They
find that there is bidirectional causality between the
Saudi stock market and oil prices. Their results suggest
also that the other GCC markets are not directly affected
by oil prices.

In the same line, Zarour (2006) uses a VAR
model to study the relationship between
Oil prices and GCC stock markets and suggests that
only the Saudi and Omani markets have
predictive power of the increase in oil prices.

More recently, onour (2008) use more recent
data and shows that long-term oil prices significantly
affect stock prices in the GCC countries.

This paper concentrates on modeling the joint
evolution of conditional returns, volatility and correlation
between crude oil and GCC countries.

III. Methodology

It is often argued that the information flow
across markets through returns (correlation in first
moment) might not be significant and visible; however they may have strong effect through volatility (correlation in second moment). Volatility has been argued to be a better proxy of information by Clark (1973), Tauchen and Pitts (1983) and Ross (1983). The ARCH model developed by Engle (1982), and later generalized by Bollerslev (1986), is one of the most popular method used for modeling volatility of high-frequency financial time series data (See Engle (2002) for a detailed recent survey). Multivariate GARCH (MGARCH) models such as BEEK (full parameterization), CCC (constant conditional correlation) or DCC (dynamic conditional correlation) models with dynamic covariances and conditional correlation have been found to be very useful in studying volatility spillover effects than univariate models. These models are subject to a major delinquent that their estimation becomes extremely difficult, especially when the number of variables considered is important owing to the rapid proliferation of parameters to be estimated (see McAleer (2005) for more details). The other failure of these models is that they do not allow for cross market volatility spillovers effect, while the latter are likely to occur with the increasing integration between financial markets. The VAR(1)-GARCH(1,1) model introduced by Ling and McAleer (2003) and later applied by several authors such as Chan et al. (2005), Hammoudeh et al. (2009) and Arouri et al. (2011, 2012), includes the multivariate CCC-GARCH of Bollerslev (1990) as a special case where correlations between system shocks are assumed to be constant to ease the estimation and inference procedure (see Engle (2002) and McAleer et al. (2008) for more details about the CCC model). In this paper, we use a bivariate VAR(1)-GARCH(1,1) copula model to explore the joint evolution of conditional returns, volatility and dependency among GCC and the crude oil markets simultaneously.

The conditional mean equation of the VAR(1)-GARCH(1,1) system is giving by:

\[
\begin{align*}
\{ y_t & = \mu + \Phi y_{t-1} + \epsilon_t \\
\epsilon_t & = h_t^{1/2} \eta_t 
\end{align*}
\]

Where
- \( y_t = (R_{t,GCC}^{GCC}, R_{t,WTI}^{WTT}) \); \( R_{t,GCC}^{GCC} \) and \( R_{t,WTI}^{WTT} \) are the returns on the GCC and WTI market indices at time t, respectively.
- \( \epsilon_t = (\epsilon_t^{GCC}, \epsilon_t^{WTT}) \); \( \epsilon_t^{GCC} \) and \( \epsilon_t^{WTT} \) are the residual of the mean equations for the GCC and WTI markets returns, respectively.
- \( \eta_t = (\eta_t^{GCC}, \eta_t^{WTT}) \), refers to the innovation and is an i.i.d distributed random vectors.
- \( h_t^{1/2} = diag (\sqrt{h_t^{GCC}}, \sqrt{h_t^{WTT}}) \); with \( h_t^{GCC} \) and \( h_t^{WTT} \) being the conditional variances of \( R_{t,GCC}^{GCC} \) and \( R_{t,WTI}^{WTT} \), respectively given by:

\[
\begin{align*}
h_t^{GCC} & = \sigma_{GCC}^2 + \alpha_{GCC} (\epsilon_{t-1}^{GCC})^2 + \beta_{GCC} h_{t-1}^{GCC} + \alpha_{FX} (\epsilon_{t-1}^{WTT})^2 + \beta_{WTT} h_{t-1}^{WTT} \\
h_t^{WTT} & = \sigma_{WTT}^2 + \alpha_{WTT} (\epsilon_{t-1}^{WTT})^2 + \beta_{WTT} h_{t-1}^{WTT} + \alpha_{GCC} (\epsilon_{t-1}^{GCC})^2 + \beta_{GCC} h_{t-1}^{GCC}
\end{align*}
\]

Copulas are multivariate distribution functions with standard uniform marginal distributions. An-dimensional copula is represented as follows:

\[
C(u) = C(u_1, \ldots, u_m)
\]

Where \( u_1, \ldots, u_m \) are standard uniform marginal distributions. In such a context, copulas can be used to link margins into a multivariate distribution function. The copula function extends the concept of multivariate distribution for random variables which are defined over \([0,1]\). This is possible due to the Sklar (1959) theorem which states that copulas may be constructed in conjunction with univariate distribution functions to build multivariate distribution functions.

**Sklar’s Theorem:** Let \( F_{xy} \) be a joint distribution function with margins \( F_X \) and \( F_Y \). Then there exists a copula \( C \) such that for all \( x, y \) in \( \mathbb{R} \),

\[
C(u_x, u_y) = C(F_X(x), F_Y(y)) = F(F_X^{-1}(u_x), F_Y^{-1}(u_y))
\]

\[
C(u_x, u_y) = F(x, y)
\]

If \( F_X \) and \( F_Y \) are continuous, then \( C \) is unique; otherwise, \( C \) is uniquely determined on \( \text{Ran } F_X \times \text{Ran } F_Y \) and \( C \) is invariant under strictly increasing transformations of the random variables.

Here we study five copulas with different dependence structure: the Gaussian copula, the Student-t copula, the Frank copula, the Clayton and the
Gumbel copula. From them, the Gaussian copula is the most popular in finance and used as the benchmark.

- **The Gaussian copula**

  The multivariate Gaussian copula applied to a joint distribution function with correlation matrix $R$, is defined by:

  \[
  C_R(u_1, \ldots, u_m) = \Phi_R(\theta^{-1}(u_1), \ldots, \theta^{-1}(u_m))
  \]

  Where $C_R$ is the distribution function of joint variables, these variables are normal, standardized and have a correlation matrix $R$.

- **The Student-\( t \) copula**

  The Student-\( t \) copula is defined by:

  \[
  C_{W}(u_1, \ldots, u_m) = W(v, m, \sum)(W^{-1}(u_1), \ldots, W^{-1}(u_m))
  \]

  Where $W(v, m, \sum)$ is the multivariate student distribution function with a degree of freedom $v$ and variance-covariance matrix $\sum$.

- **Archimedean copula**

  We present as follow the characteristics of the best known models. The variables $u$ and $v$ are

  - The Clayton Copula:

    \[
    C(u, v, \theta) = (u^{-\theta} + v^{-\theta} - 1)^{-1} \quad \text{where } \theta > 0
    \]

  - The Gumbel Copula:

    \[
    C(u, v, \theta) = \exp\left(-\left((-\ln(u))^\theta + (-\ln(v))^\theta\right)\right)^{1/\theta} \quad \text{where } \theta \geq 1
    \]

  - The Frank Copula:

    \[
    C(u, v, \theta) = -\frac{1}{\theta} \ln\left[1 + \frac{(\exp(-\theta u)^{-1})(\exp(-\theta v)^{-1})}{\exp(-\theta - 1)}\right] \quad \text{where } \theta \neq 0
    \]

  According to the VAR-GARCH-Copula model that we consider, return, volatility and dependence are jointly modeled to explore the possibly spillover effects and the dependence structure between each pair of indexes (oil/CCG). Thus, the past shock and volatility of one market are allowed to affect the future volatility not only of itself but also of all other markets in the system.

**IV. Empirical Results and Discussion**

**a) Data And Descriptive Statistics**

We use daily market data from sex equity indices for the GCC countries, for a sample period of January 1, 2005 to December 31, 2012. We choose this period to investigate the impact of the 2007 Subprime crisis on the six emerging countries of the GCC. The countries used in our sample are Bahrain (BHRALSH), United Arab Emirates (ABUGNRL), Kuwait (KWSEIDX), Oman (OMANMSN), Qatar (QTRMRKT) and Saudi Arabia (TDWTASI). The total number of observations is 2013 for the full sample. We briefly overview summary statistics, then discuss the correlation.

The descriptive statistics for daily returns shown in Table 1 suggest that the mean daily stock returns range between -0.003107 and 0.028438 and the standard deviation between 0.275243 and 1.133865. Jarque-Bera tests on log returns data indicate that the normality hypothesis cannot be accepted for these stocks. Furthermore, the GCC stock market returns and oil prices show the properties of asymmetry, leptokurtosis, and tail dependence; hence, the normality assumption has been severely challenged.

Panel B of Table 1 presents the obtained results of the ADF, PP, and KPSS stationary tests. Both ADF and PP tests reject hypothesis of unit root for all the daily returns. For the KPSS, the null hypothesis of stationarity cannot be rejected at the 1% level. Therefore, the investigation of ARCH behavior in crude oil market, indicated by Engl’s LM test, shows evidence of the presence of ARCH effect.
**Table 1 :** Summary descriptive statistics

**Panel A :** Basic descriptive statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>BAHRAIN</th>
<th>UNITED ARAB EMIRATES</th>
<th>KUWAIT</th>
<th>OMAN</th>
<th>QATAR</th>
<th>SAUDI ARABIA</th>
<th>WTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.010879</td>
<td>-0.004532</td>
<td>0.028438</td>
<td>0.010182</td>
<td>0.005668</td>
<td>0.003107</td>
<td>0.018158</td>
</tr>
<tr>
<td>Median</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.029395</td>
<td>0.000000</td>
<td>0.003921</td>
<td>0.026456</td>
<td>0.052244</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.569186</td>
<td>17.29288</td>
<td>2.191839</td>
<td>3.491220</td>
<td>4.091916</td>
<td>7.122213</td>
<td>6.468785</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.275243</td>
<td>0.790156</td>
<td>0.319612</td>
<td>0.515664</td>
<td>0.714071</td>
<td>0.805843</td>
<td>1.133865</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.428670</td>
<td>1.151009</td>
<td>0.353775</td>
<td>0.845992</td>
<td>0.366285</td>
<td>0.560769</td>
<td>-0.244939</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>3001.739</td>
<td>31952.22</td>
<td>4890.688</td>
<td>14732.01</td>
<td>2915.341</td>
<td>7743.414</td>
<td>2303.212</td>
</tr>
<tr>
<td>Probability</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
</tr>
<tr>
<td>Sum Sq. Dev.</td>
<td>152.3504</td>
<td>1255.560</td>
<td>534.7430</td>
<td>1025.403</td>
<td>1305.908</td>
<td>2486.449</td>
<td></td>
</tr>
</tbody>
</table>

**Panel B :** Unit root and stationarity tests

<table>
<thead>
<tr>
<th>Variables</th>
<th>BAHRAIN</th>
<th>UNITED ARAB EMIRATES</th>
<th>KUWAIT</th>
<th>OMAN</th>
<th>QATAR</th>
<th>SAUDI ARABIA</th>
<th>WTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>PP</td>
<td>-631.93*</td>
<td>-1008.406*</td>
<td>-369.65*</td>
<td>-427.04*</td>
<td>-405.46*</td>
<td>-470.48*</td>
<td>-655.09*</td>
</tr>
<tr>
<td>KPSS</td>
<td>0.2606</td>
<td>0.081</td>
<td>0.0311</td>
<td>0.0506</td>
<td>0.0346</td>
<td>0.0428</td>
<td>0.0598</td>
</tr>
</tbody>
</table>

**Panel C :** ARCH-LM test

<table>
<thead>
<tr>
<th>Variables</th>
<th>BAHRAIN</th>
<th>UNITED ARAB EMIRATES</th>
<th>KUWAIT</th>
<th>OMAN</th>
<th>QATAR</th>
<th>SAUDI ARABIA</th>
<th>WTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-statistic</td>
<td>0.312</td>
<td>0.319</td>
<td>13.134</td>
<td>0.98</td>
<td>6.159</td>
<td>0.088</td>
<td>5.014</td>
</tr>
<tr>
<td>LM-statistic</td>
<td>0.242</td>
<td>0.319</td>
<td>13.062</td>
<td>0.016</td>
<td>6.146</td>
<td>0.0885</td>
<td>5.006</td>
</tr>
</tbody>
</table>


* denotes the rejection of the null hypothesis of normality, unit root, stationarity, and homoscedasticity at 10% level.

**b) Return And Volatility Dependency**

Our objective is to examine both own conditional volatility and shocks and conditional cross-market volatility transmission and shocks between the GCC stock returns and the oil returns. We experiment on GARCH terms up to p=1 and q=1. The optimal lag order for the VAR model is selected using the AIC and SIC information criteria. The estimations of the bivariate VAR (1)-GARCH (1,1) for the two sub-period, are presented as follows.

**Table 2 :** Estimates of VAR(1)–GARCH(1.1) for BAHRAIN

<table>
<thead>
<tr>
<th>Variables</th>
<th>BHRLASH</th>
<th>WTI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meanequation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>0.0081</td>
<td>[0.5088]</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.1924</td>
<td>[0.0000]</td>
</tr>
<tr>
<td>Variance equation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>0.0065</td>
<td>[0.2066]</td>
</tr>
<tr>
<td>$\varepsilon^2_{BHRLASH}(t-1)$</td>
<td>0.2590</td>
<td>[0.0000]</td>
</tr>
<tr>
<td>$\varepsilon^2_{WTI}(t-1)$</td>
<td>0.0032</td>
<td>[0.2015]</td>
</tr>
<tr>
<td>$h_{BHRLASH}(t-1)$</td>
<td>0.4250</td>
<td>[0.0000]</td>
</tr>
<tr>
<td>$h_{WTI}(t-1)$</td>
<td>0.0201</td>
<td>[0.0008]</td>
</tr>
</tbody>
</table>

Notes: $\varepsilon^2(t-1)$ represents the past unconditional shocks of the jth market in the short run, or news.$h_{j}(t-1)$ denotes the past conditional volatility dependency. J = BHRLASH, WTI. *, **, *** indicate statistical significance level at the 1%, 5% and 10%.
### Table 3: Estimates of VAR(1)–GARCH1.1 for UNITED ARAB EMIRATES

<table>
<thead>
<tr>
<th>Variables</th>
<th>ABUGNRL</th>
<th>WTI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Meanequation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>0.0028[0.9354]</td>
<td>-0.014[0.1961]</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.1790*[0.0005]</td>
<td>0.241*[0.0000]</td>
</tr>
<tr>
<td><strong>Variance equation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>0.2572*[0.0000]</td>
<td>-0.002*[0.0003]</td>
</tr>
<tr>
<td>$\varepsilon^2_{ABUGNRL}(t-1)$</td>
<td>0.2666*[0.0000]</td>
<td>0.296*[0.0000]</td>
</tr>
<tr>
<td>$\varepsilon^2_{WTI}(t-1)$</td>
<td>0.0746*[0.0005]</td>
<td>0.002*[0.0000]</td>
</tr>
<tr>
<td>$h_{ABUGNRL}(t-1)$</td>
<td>0.3833*[0.0000]</td>
<td>0.76*[0.0000]</td>
</tr>
<tr>
<td>$h_{WTI}(t-1)$</td>
<td>-0.055*[0.0000]</td>
<td>0.009*[0.0000]</td>
</tr>
</tbody>
</table>

**Notes:** $\varepsilon^2_t(t-1)$ represents the past unconditional shocks of the $j$th market in the short run, or news. $h_j(t-1)$ denotes the past conditional volatility dependency. $J=ABUGNRL$, WTI. *, **, ***indicate statistical significance level at the 1%, 5% and 10%.

### Table 4: Estimates of VAR(1)–GARCH(1.1) for KUWAIT

<table>
<thead>
<tr>
<th>Variables</th>
<th>KWSEIDX</th>
<th>WTI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Meanequation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>0.0731*[0.0000]</td>
<td>0.026*[0.0000]</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.1842*[0.0000]</td>
<td>0.234*[0.0000]</td>
</tr>
<tr>
<td><strong>Variance equation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>0.0044*[0.0227]</td>
<td>0.012*[0.0000]</td>
</tr>
<tr>
<td>$\varepsilon^2_{KWSEIDX}(t-1)$</td>
<td>0.2231*[0.0000]</td>
<td>0.49*[0.0000]</td>
</tr>
<tr>
<td>$\varepsilon^2_{WTI}(t-1)$</td>
<td>0.0026*[0.2253]</td>
<td>-0.0005[0.6308]</td>
</tr>
<tr>
<td>$h_{KWSEIDX}(t-1)$</td>
<td>0.7757*0.0000</td>
<td>0.209*[0.0000]</td>
</tr>
<tr>
<td>$h_{WTI}(t-1)$</td>
<td>-0.0013[0.2778]</td>
<td>0.006*[0.0000]</td>
</tr>
</tbody>
</table>

**Notes:** $\varepsilon^2_t(t-1)$ represents the past unconditional shocks of the $j$th market in the short run, or news. $h_j(t-1)$ denotes the past conditional volatility dependency. $J=KWSEIDX$, WTI. *, **, ***indicate statistical significance level at the 1%, 5% and 10%.

### Table 5: Estimates of VAR(1)–GARCH (1.1) for OMAN

<table>
<thead>
<tr>
<th>Variables</th>
<th>OMANMSN</th>
<th>WTI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Meanequation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>0.0284***[0.0767]</td>
<td>0.008[0.4123]</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.1480*[0.0003]</td>
<td>0.265*[0.0000]</td>
</tr>
<tr>
<td><strong>Variance equation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>0.006*[0.0002]</td>
<td>0.001***[0.0542]</td>
</tr>
<tr>
<td>$\varepsilon^2_{OMANMSN}(t-1)$</td>
<td>0.0426*[0.0000]</td>
<td>0.228*[0.0000]</td>
</tr>
<tr>
<td>$\varepsilon^2_{WTI}(t-1)$</td>
<td>0.0026[0.1794]</td>
<td>-0.0006[0.5239]</td>
</tr>
<tr>
<td>$h_{OMANMSN}(t-1)$</td>
<td>0.9351*[0.0000]</td>
<td>0.801*[0.0000]</td>
</tr>
<tr>
<td>$h_{WTI}(t-1)$</td>
<td>-0.0032*[0.0039]</td>
<td>0.0014**[0.0102]</td>
</tr>
</tbody>
</table>

**Notes:** $\varepsilon^2_t(t-1)$ represents the past unconditional shocks of the $j$th market in the short run, or news. $h_j(t-1)$ denotes the past conditional volatility dependency. $J=OMANMSN$, WTI. *, **, ***indicate statistical significance level at the 1%, 5% and 10%.
Table 6: Estimates of VAR(1)–GARCH (1.1) for QATAR

<table>
<thead>
<tr>
<th>Variables</th>
<th>QTRMRKT Pre-crisis</th>
<th>QTRMRKT Post-crisis</th>
<th>WTI Pre-crisis</th>
<th>WTI Post-crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meanequation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>0.0198 [0.4867]</td>
<td>0.016 [0.2538]</td>
<td>0.073** [0.0190]</td>
<td>0.024 [0.2905]</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.307* [0.0000]</td>
<td>0.149* [0.0000]</td>
<td>-0.085** [0.0465]</td>
<td>-0.087 [0.0049]</td>
</tr>
<tr>
<td>Variance equation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>-0.004 [0.7211]</td>
<td>0.004* [0.0001]</td>
<td>0.128 [0.0081]</td>
<td>0.024 [0.0030]</td>
</tr>
<tr>
<td>$\varepsilon_{QTRMRKT}^2(t-1)$</td>
<td>0.4959* [0.0000]</td>
<td>0.154* [0.0000]</td>
<td>-0.057 [0.1059]</td>
<td>0.009 [0.6717]</td>
</tr>
<tr>
<td>$\varepsilon_{WTI}^2(t-1)$</td>
<td>-0.008 [0.2697]</td>
<td>0.001 [0.4534]</td>
<td>0.099 [0.0001]</td>
<td>0.104 [0.0000]</td>
</tr>
<tr>
<td>$h_{QTRMRKT}(t-1)$</td>
<td>0.527* [0.0000]</td>
<td>0.849* [0.0000]</td>
<td>-0.0009 [0.6914]</td>
<td>0.015 [0.1241]</td>
</tr>
<tr>
<td>$h_{WTI}(t-1)$</td>
<td>0.045* [0.0021]</td>
<td>0.001 [0.1531]</td>
<td>0.757 [0.0000]</td>
<td>0.867 [0.0000]</td>
</tr>
</tbody>
</table>

Notes: $\varepsilon_j^2(t-1)$ represents the past unconditional shocks of the $j^{th}$ market in the short run, or news. $h_j(t-1)$ denotes the past conditional volatility dependency. J= QTRMRKT, WTI. *, **, *** indicate statistical significance level at the 1%, 5% and 10%.

Table 7: Estimates of VAR(1)–GARCH (1.1) for SAUDI ARABIA

<table>
<thead>
<tr>
<th>Variables</th>
<th>TDWTASI Pre-crisis</th>
<th>TDWTASI Post-crisis</th>
<th>WTI Pre-crisis</th>
<th>WTI Post-crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meanequation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>0.091* [0.0012]</td>
<td>0.036** [0.0278]</td>
<td>0.074** [0.0183]</td>
<td>0.024 [0.2842]</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.065 [0.1397]</td>
<td>0.089** [0.0161]</td>
<td>-0.089** [0.0332]</td>
<td>-0.089 [0.0040]</td>
</tr>
<tr>
<td>Variance equation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td>-0.014 [0.1046]</td>
<td>0.005* [0.0000]</td>
<td>0.087* [0.0108]</td>
<td>0.025* [0.0008]</td>
</tr>
<tr>
<td>$\varepsilon_{TDWTASI}^2(t-1)$</td>
<td>0.119* [0.0000]</td>
<td>0.104* [0.0000]</td>
<td>0.034** [0.0269]</td>
<td>-0.028 [0.1423]</td>
</tr>
<tr>
<td>$\varepsilon_{WTI}^2(t-1)$</td>
<td>0.016*** [0.0564]</td>
<td>-0.002 [0.2999]</td>
<td>0.095* [0.0000]</td>
<td>0.102* [0.0000]</td>
</tr>
<tr>
<td>$h_{TDWTASI}(t-1)$</td>
<td>0.870* [0.0000]</td>
<td>0.877* [0.0000]</td>
<td>-0.007 [0.1933]</td>
<td>-0.005 [0.6246]</td>
</tr>
<tr>
<td>$h_{WTI}(t-1)$</td>
<td>0.029* [0.0054]</td>
<td>0.003* [0.0022]</td>
<td>0.816* [0.0000]</td>
<td>0.879* [0.0000]</td>
</tr>
</tbody>
</table>

Notes: $\varepsilon_j^2(t-1)$ represents the past unconditional shocks of the $j^{th}$ market in the short run, or news. $h_j(t-1)$ denotes the past conditional volatility dependency. J= TDWTASI, WTI. *, **, *** indicate statistical significance level at the 1%, 5% and 10%.

We will discuss the empirical results of bivariate VAR(1)-GARCH(1,1) models in terms of own volatility and shock dependence, cross market volatility and shock spillover for the GCC stock returns and the Oil index, both for the pre-crisis and the post-crisis.

During the pre-crisis period and for the Bahrain, the sensitivity to past own conditional volatility and cross market volatility transmission are significant at the level of 1%, showing that future volatility can be predicted by both past own conditional volatility in the long run and the cross market volatility spillover. We found the same result for the rest of the GCC returns (United Arab Emirates, Oman, Qatar and Saudi Arabia) with exception for Kuwait. In addition, only own shocks or news are significant for these returns, exception for the United Arab Emirates and the Saudi Arabia which the impact of the past shocks is significant indicating a short run persistence.

Considering now the WTI return, only the past own volatility and the past own news are significant, exception for the Oman and the Saudi Arabia, displaying that cross market volatility transmission and shocks cannot be used to predict either the future volatility in the long run and the short run persistence.

After the occurrence of the Subprime crisis, the behavior of these markets changes considerably. Indeed, both the own past volatility and shocks remain significant but their persistence diverge. Moreover, own volatility and shock dependence and cross market volatility and shock spillover for the United Arab Emirates remain significant at level of 1% however the effect of past volatility is bigger than the effect of past shocks. This implies that fundamentals matter more than news.

For the oil market, cross shocks (or spillover) are more widespread inter-markets after the crisis.
For the oil market, cross shocks (or spillover) are more widespread inter-markets after the crisis. Indeed, cross market volatility and shock transmission become significant after the crisis, for the Bahrain stock market return with the oil market. This implies that past own shocks and volatility and cross market volatility and shock dependence can be used to predicting future volatility and news.

We show the same results for the Emirates Arab Unis/oil market returns which indicates significant cross volatility. Besides, the WTI stock market becomes more sensitive to past volatility of the Emirates Arab Unis than past shocks related to changes in news or noise. However, the shock spillover of the Saudi Arabia becomes non-significant after the crisis. For the rest of the GCC-OIL market returns, the past own volatility and news remain significant.

c) Estimates Copula Parameters

We now present results from our copula estimation. We consider five bivariate copulas, the bivariate normal, bivariate Student-t, bivariate Gumbel, bivariate Clayton and the bivariate Frank. We will examine the relationship between each pair of stock-oil return separately, for the two sub period. Table 8.A bellow, reports parameters estimates of bivariate copulas for each pair, before the occurrence of the financial subprime crisis. We note that the parameters ρ and ρ measure the degree of dependence between returns and DoF is the degree of freedom in the Student-t copula.

Table 8.A : Estimation of copula parameters for the pre-crisis period

<table>
<thead>
<tr>
<th>Pairs</th>
<th>Copula models</th>
<th>Parameters</th>
<th>Information criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>ρ</td>
<td>DoF</td>
</tr>
<tr>
<td>BHRALSH/WTI</td>
<td>Student</td>
<td>-0.021</td>
<td>40</td>
</tr>
<tr>
<td>ABUGNRL/WTI</td>
<td>Student</td>
<td>-0.020</td>
<td>40</td>
</tr>
<tr>
<td>KWSEIDX/WTI</td>
<td>Clayton</td>
<td>0.05</td>
<td>-13.32</td>
</tr>
<tr>
<td>OMANMSN/WTI</td>
<td>Gumbel</td>
<td>1.01</td>
<td>-13.46</td>
</tr>
<tr>
<td>QTRMRKT/WTI</td>
<td>Frank</td>
<td>0.31</td>
<td>-11.27</td>
</tr>
<tr>
<td>TDWTASI/WTI</td>
<td>Student</td>
<td>-0.043</td>
<td>40</td>
</tr>
</tbody>
</table>

The correlation coefficient ρ in Student-t copulas are negative for these pairs: BHRALSH/WTI, ABUGNRL/WTI and KWSEIDX/WTI. The DoF of the Student-t copulas are 40, indicating the presence of strongly extreme co-movements and tail dependence. These market returns have elliptical symmetric dependence structure (the case of the Student-t copulas) with the oil return.

However, we observe asymmetric tail dependence for the rest of the GCC-Oil market returns.

Indeed, the asymmetric dependence parameter θ in the Clayton, Gumbel and Frank copulas are positive. The Oman-WTI pair has the highest tail dependence, followed by the Qatar-WTI pair and the Kuwait-WTI pair.

In order to appreciate both, the dependence structure and the degree of this dependence, after the Subprime crisis; we estimate the copula parameters in the post-crisis period.

Table 8.B : Estimation of copula parameters for the post-crisis period

<table>
<thead>
<tr>
<th>Pairs</th>
<th>Copula models</th>
<th>Parameters</th>
<th>Information criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>ρ</td>
<td>DoF</td>
</tr>
<tr>
<td>BHRALSH/WTI</td>
<td>Gumbel</td>
<td>1.01</td>
<td>-14.24</td>
</tr>
<tr>
<td>ABUGNRL/WTI</td>
<td>Student</td>
<td>0.012</td>
<td>6</td>
</tr>
<tr>
<td>KWSEIDX/WTI</td>
<td>Frank</td>
<td>0.189</td>
<td>-12.95</td>
</tr>
<tr>
<td>OMANMSN/WTI</td>
<td>Student</td>
<td>0.052</td>
<td>6</td>
</tr>
<tr>
<td>QTRMRKT/WTI</td>
<td>Student</td>
<td>0.062</td>
<td>9</td>
</tr>
<tr>
<td>TDWTASI/WTI</td>
<td>Student</td>
<td>0.011</td>
<td>9</td>
</tr>
</tbody>
</table>

For all pairs, the dependence parameters; the correlation coefficient ρ in both Gaussian and Student-t copulas, the degree of freedom DoF in the Student-t copula and the asymmetric dependence parameter θ in the Clayton, Gumbel and Frank copulas are positive. The Qatar / WTI pair returns has the highest correlation coefficient with ρ = 0.062. The DoF of the Student-t copulas are 6, indicating the presence of extreme co-movements and tail dependence. The tail dependence parameter θ for post crisis period, are from...
1.01 to 0.189. The Bahrain / WTI pair has the highest tail dependence after the crisis, followed by the Kuwait pair. Moreover, the dependence structure between each stock index returns and exchange rate returns is largely changed from a symmetric structure with or not symmetric tail dependence to an asymmetric structure with non-zero and asymmetric upper and lower tail dependence.

From our results, we find The Gumbel copula which is limited to the description of a positive dependence structure. Thus, it allows only positive dependence structures or upper tail dependence, for which the parameter belongs to the interval $[1, +\infty)$. We find also the Frank copula. Consequently, the degree of the dependence varies when the financial Subprime crisis occurs. Indeed, as we see in tables above, it increased after the crisis, expect of ABUGNRL/WTI and TDWTAS1/WTI pairs which remain symmetric, with zero tail dependence. The degree of the dependence becomes stronger and moves from a negative to a positive one.

Our findings may have important implications in the risk management. First, symmetric dependence structure with zero tail dependence can specify different levels of correlation between the marginal; however, it must possess radial symmetry which doesn’t allow to extreme values correlation. Thus, in this case, the dependence has the linear correlation coefficient as measure of dependence. Second, asymmetric dependence structure can have upper tail dependence, lower tail dependence, or both; as such, they can better describe the reality of the behavior of financial markets. Additionally, it indicates the potential of simultaneous extreme events in both the stock and foreign exchange market. This property of dependence structure is important to international investors who invest in foreign stock markets.

V. Conclusion

This paper examines the dynamics relationship between the GCC and the oil stock market returns after the occurrence of the financial subprime crisis, using daily data from January 2005 to December 2012. Based on the VAR(1)-GARCH(1,1) model, the results show that there exist moderate cross market volatility transmission and shocks between the markets, indicating that the past innovation in stock market have great effect on future volatility in oil market and vice versa.

Copula models are used to specify the dependence structure and to examine the degree of the dependence between these two financial markets when the Subprime crisis takes place. We employ five bivariate copulas; the bivariate normal, bivariate Student-t, bivariate Gumbel, bivariate Clayton and the bivariate Frank to directly model the underlying dependence structure. We find that, during the pre-crisis period, the major of stock-oil market returns have asymmetric dependence structure with asymmetric upper and lower tail dependence. However, the degree of the dependence become stronger and moves from a negative to a positive one when the financial crisis occurs.

References Références Referencias


34. Sklar, A., (1959) : « Fonctions de répartition à n dimensions et leurs marges ». Publications de l'Institut de Statistique de l'Université de Paris 8, 229-231.
