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Volatility spillovers between crude oil futures returns and oil company stock returns

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Abstract: The purpose of this paper is to investigate volatility spillovers between crude oil futures returns and oil company stock returns by using the recent multivariate GARCH model, namely the CCC of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003) and VARMA-AGARCH model of McAleer, et al. (2008). This paper investigates the WTI crude oil futures returns and stock returns of ten oil companies; which are composed of the "supermajor" group of oil companies, namely Exxon Mobil (XOM), Royal Dutch Shell (RDS), Chevron Corporation (CVX), ConocoPhillips (COP), BP (BP) and Total S.A. (TOT), and other large oil and gas companies in the world, namely Petrobras (PBRA), Lukoil (LKOH), Surgutneftegas (SNGS), and Eni S.p.A. (ENI). The empirical results present conditional correlation between WTI crude oil futures returns and very low returns in stock of the CCC model oil company. Surprisingly, for the VARMA-GARCH and VARMA-AGARCH models, no volatility spillover effects are observed in every pairs of return series. The paper also presents the evidence of asymmetric effect of negative and positive shock on conditional variance in every pairs of return series.

Keywords: *Multivariate GARCH, Asymmetries, Volatility spillovers, Crude oil futures returns, Oil company stock returns*

1. Introduction

Crude oil is arguably the most influential physical commodity in the world and plays a prominent role in an economy. Therefore, oil prices fluctuation clearly affects the world economy in many different ways. Rising crude oil prices raises the cost of production of goods and services, transportation and heating cost. As a result, it provokes concerns about inflation and restricted discretionary spending of consumer and produces a negative effect to financial markets, consumer confidence, and the macroeconomy (see for example, Mork (1994), Sadorsky (1999), Lee et al. (2001), Hooker (2002), Hamilton and Herrera (2004), Cunado and Perez de Garcia (2005), Jimenez-Rodriguez and Senchez (2005), Kilian (2008), Cologni and Manera (2008) and Park and Ratti (2008)).

The value of stock prices in an equity pricing model theoretically equals the discounted earning expectation of companies or future cash flows. Therefore, oil price shocks influence stock prices through expected cash flow and discount rate. Since oil is one of the crucial inputs for goods and services production, a rise in oil prices without substitute inputs increases production costs; which in turns decrease cash flows and stock prices. In addition, rising oil prices affects the discount rate by influencing the inflation pressures which also leads to the decision making by the central bank to raise interest rate. Therefore, the corporate investment decision can be affected directly by change in the discount rate and change in stock price relative to book value. However the direction of stock price change depends on whether a stock is a producer or consumer of oil and oil related products. Since most companies in the world market are oil consumer, it is logical to see that the performance of oil prices and stock market might be negatively correlated.

A number of previous papers have observed and provided explanation of the oil price and stock market relationship and the negative impact of oil price on stock markets (see for example, Jones and Kaul (1996), Faff and Brailsford (1999), Hammoudeh and Aleisa (2002) and (2004), Nandha and Faff (2008), Sadorsky (2008)). However, Maghyereh (2004) does not find the significant impact on stock index returns in 22 emerging economy employing VAR model. This implies that the stock market returns in these economies do not rationally signal shocks in the crude oil market. Surprisingly up to this period, there is a very limited amount of literature work based on the relationship between oil price and oil company stock price. There is a positive relationship between the oil price and stock price of the oil company (see for example, Faff and Brailsford (1999), Sadorsky (2001), Boyer and Filion (2004), El-Sharif et al. (2005), Basher and Sadorsky (2006), Nandha and Faff (2008) and Henriques and Sadorsky (2008)).

As volatility (or risk) is unobservable but at the same time important in finance, there appears to be volatility spillover patterns that is widespread in the financial markets (Milunovich and Thorp (2006)), energy markets, and stock market (Sadorsky (2004)). Consequently, a volatility spillover occurs when changes in price or return volatility in one market produce a lagged impact on volatility in other markets or each other. However, there seems to be a small amount of research study in volatility spillovers between the oil market and stock market. Ågren (2006) investigates volatility spillovers from oil prices to stock markets using asymmetric BEKK model, and presents strong evidence of volatility spillovers in Japan, Norway, U.K. and the U.S. stock markets; but quite weak in Swedish.

The assessment of the volatility of oil company stock price returns and the linkage between oil price volatility and oil company stock price volatility are crucially important for investment decisions and policy makers to implement appropriate policies for managing stock markets and also financial hedgers, portfolio management, asset allocator, or other financial analysis. With the Oil & Gas industry sector being one of the largest industries in the world, they have different companies and business involved in the different chains of production, distillation and distribution. Surprisingly, none of these papers have looked at the relationship between crude oil futures returns volatility and oil company stock price volatility. To model volatility spillovers, there are several conditional volatility models which specify the risk on one asset as depending dynamically on its own past risk and on the past risk of the other assets, see McAleer (2005). de Veiga and McAleer (2004) presented that the multivariate VARMA-GARCH model of Ling and McAleer (2003) and VARMA-AGARCH model of McAleer et al. (2008) provided better volatility than the nested univariate model, namely GARCH of Bollerslev (1986) and GJR of Glosten, Jagannathan and Runkle (1992), respectively. Even though these models assume constant conditional correlation, they do not suffer form the curse of dimensionality when they are compared to VECH and BEKK models. On the other hand, in order to capture the dynamics of time-varying conditional correlation, recently development model is generalized autoregressive conditional correlation (GARCC) of McAleer et al. (2008).

The aim of this study is to examine the volatility spillovers between crude oil futures returns and oil company stock returns in many major oil companies. This issue is studied empirically with in a bivariate VARMA-GARCH and VARMA-AGARCH models. The results of the paper may shed on the importance of the crude oil on oil company stock. The remainders of the paper are organized as follows. The multivariate conditional volatility models are discussed in Section 2. The data are described in Section 3, and the empirical results are analyzed in Section 4. Some concluding remarks are given in Section 5.

2. Methodology

The purpose of this section is to brief multivariate conditional volatility model including spillover effect, in which the conditional variance of return *i* is specified to depend dynamically on past squared unconditional shocks and past conditional variance of each asset in the portfolio. The VARMA-GARCH model of Ling and McAleer (2003), assumes symmetry in the effect of positive and negative shocks on the conditional volatility, is given by

$$Y_t = E\left(Y_t \middle| F_{t-1}\right) + \varepsilon_t \tag{1}$$

$$\Phi(L)(Y_t - \mu) = \Psi(L)\varepsilon_t \tag{2}$$

$$\varepsilon_t = D_t \eta_t \tag{3}$$

$$H_t = W_t + \sum_{l=1}^{r} A_l \vec{\varepsilon}_{t-l} + \sum_{l=1}^{s} B_l H_{i,t-j} \tag{4}$$

where $Y_t = \left(y_{1t},...,y_{mt}\right)'$, F_{t-1} is the past information available up to time *t*, *m* is the total of returns to be analyzed and $t = 1,...,m$. L is the lag operator. $\Phi(L) = I_m - \Phi_1 L - ... - \Phi_p L^p$ and $\Psi(L) = I_m - \Psi_1 L - ... - \Psi_q L^q$ are polynomials in L. $D_t = \text{diag}\left(h_{i,t}^{1/2}\right)$, $\eta_t = \left(\eta_{1t},...,\eta_{mt}\right)'$ is a sequence of independently and identically (iid) random vectors. $H_t = \left(h_{1t},...,h_{mt}\right)'$, $W_t = \left(\omega_{1t},...,\omega_{mt}\right)'$, $\vec{\varepsilon}_t = \left(\varepsilon_{it}^2,...,\varepsilon_{mt}^2\right)'$, A_l and B_l are $m \times m$ matrices with typical elements α_{ij} and β_{ij}, respectively, for $i, j = 1,...,m$. A_l and β_l represent the ARCH effect and GARCH effect, respectively. Spillover effects or the independence of the conditional variance between WTI crude oil futures returns and oil company stock returns are given in conditional volatility for each return in the portfolio. Based on equation (3), the VARMA-GARCH model also assumes that the matrix of conditional correlations is given by $E\left(\eta_t \eta_t'\right) = \Gamma$. If $m = 1$, equation (4) reduces to the univariate GARCH model of Bollerslev (1986):

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}^2 \tag{5}$$

An extension of the VARMA-GARCH model to accommodate asymmetric impacts of the positive and negative shocks, is the VARMA-AGARCH model of McAleer et al. (2008), captures asymmetric spillover effects from each of the other returns. An extension of (4) to accommodate asymmetries with respect to ε_{it} is given by

$$H_t = W + \sum_{l=1}^{r} A_l \vec{\varepsilon}_{t-l} + \sum_{l=1}^{r} C_l I\left(\eta_{t-l}\right) \vec{\varepsilon}_{t-l} + \sum_{l=1}^{s} B_l H_{t-l} \tag{6}$$

in which $\varepsilon_{it} = \eta \sqrt{h_{it}}$ for all *i* and *t*, C_l are $m \times m$ matrices and $I\left(\eta_{t-l}\right)$ is an indicator variable, and $I\left(\eta_t\right) = diag\left(I\left(\eta_{it}\right)\right)$ is an $m \times m$ matrix, such that, such that

$$I\left(\eta_{it}\right) = \begin{cases} 0, & \varepsilon_{it} > 0 \\ 1, & \varepsilon_{it} \le 0 \end{cases} \tag{7}$$

If $m = 1$, equation (4) reduces to the asymmetric univariate GARCH, or GJR model of Glosten et al. (1992):

$$h_t = \omega + \sum_{j=1}^{r} \left(\alpha_j + \gamma_j I\left(\eta_{t-j}\right)\right) \varepsilon_{t-j}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \tag{8}$$

If $C_l = 0$ with A_l and B_l being diagonal matrices for all *l* then VARMA-AGARCH reduces to:

$$h_{it} = \omega_i + \sum_{l=1}^{r} \alpha_l \varepsilon_{i,t-l} + \sum_{l=1}^{s} \beta_l h_{i,t-l} \tag{9}$$

which is the constant conditional correlation (CCC) model of Bollerslev (1990). As given in equation (7), the CCC model does not have asymmetric effects of positive and negative shocks on conditional volatility and volatility spillover effects across different financial assets, so it is intrinsically univariate in nature. From (2), the conditional correlation is $\varepsilon_t \varepsilon_t' = D_t \eta_t \eta_t' D_t$, the conditional covariance matrix is

$$E\left(\varepsilon_t \varepsilon_t' \middle| F_{t-1}\right) = \Omega_t = D_t \Gamma D_t . \tag{10}$$

Therefore, the conditional correlation matrix is defined as $\Gamma = D_t^{-1} \Omega_t D_t^{-1}$. The parameters in model (1), (4), (6) and (9) can be obtained by maximum likelihood estimation (MLE) using a joint normal density: namely

$$\hat{\theta} = \arg\min_{\theta} \frac{1}{2} \sum_{t=1}^{n} \left(\log|Q_t| + \varepsilon_t' Q_t^{-1} \varepsilon_t \right) \tag{11}$$

where θ denotes the vector of parameters to be estimated on the conditional log-likelihood function, and $|Q_t|$ denotes the determinant of Q_t, the conditional covariance matrix. When η_t does not follow a joint multivariate normal distribution, the appropriate estimators are defined as the Quasi-MLE (QMLE).

3. Data

In this paper we focus on volatility spillover modeling between crude oil futures return in WTI market and the 10 oil company stock returns. Six of them are called "supermajor", six largest non state-owned energy companies, which are composed of Exxon Mobil (XOM, US), Royal Dutch Shell (RDS, The Netherlands), Chevron Corporation (CVX, US), ConocoPhillips (COP, US), BP (BP, UK) and Total S.A. (TOT, French). The rest of them are Petrobras (PBRA:Brasil), Lukoil (LKOH, Russia), Surgutneftegas (SNGS, Russia), and Eni S.p.A. (ENI, Italy). All 3,202 price observations are starting from 14 November 1996 to 20 February 2009 and are obtained from the DataStream database services and expressed in local currencies with the only exception of WTI crude futures prices, which are denominated in USD per barrel.

The empirical results of the unit root tests for WTI crude oil futures return and 10 oil company stock price returns are available from the authors upon request. The Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) test are used to explore the existence of unit roots in the individual series. Under the null hypothesis of a unit root, both tests provide large negative values for all cases presenting that all of the individual return series reject the null hypothesis at the 1% significant level, which means all returns series are stationary.

4. Empirical results

Since the univariate ARMA-GARCH nested to VARMA-GARCH and ARMA-GJR nested to VARMA-AGARCH with conditional variance specified in (5) and (8), univariate ARMA-GARCH and ARMA-GJR models will be estimated. It also makes sense to extend univariate to multivariate if the properties of univariate models are satisfied. The coefficients in the conditional variance equation resulted from ARMA(1,1)-GARCH(1,1) are significant both in the short and long run. However, the coefficient in the conditional variance resulted from the ARMA(1,1)-GJR(1,1) are all significant, but with PBRA only in long run. In addition, at the univariate level, the most estimates of the asymmetric effect in which negative shocks are a greater impact on volatility than positive shocks are significant except for TOT, LKOH and SNGS. The detail of the univariate estimates of conditional volatilities and structural properties of both univarite models, namely second moment and log-moment, based on WTI crude futures returns and oil company stock returns are available from the authors upon request.

The estimates of constant conditional correlations between WTI crude oil futures returns and oil company stock returns and Bollerslev-Wooldridge (1992) robust *t*-ratios using CCC model based on estimating univariate GARCH(1,1) models are presented in Table 1. For the 10 oil company stock returns, there are 10 conditional correlation, with the highest estimated constant conditional correlation being 0.334 between the standardized shocks to the volatilities in the WTI crude oil futures and COP returns and the lowest being 0.065 between the standardized shocks to the volatilities in the WTI crude oil futures and SNGS returns. The calculated constant conditional correlations are very low. This can be interpreted as the behavior of those standardized shocks to the volatilities which are possibly determined by other variables.

Table 2 Conditional correlation from CCC model between WTI crude oil futures return and oil company stock returns

	BP	COP	CVX	ENI	LKOH	PBRA	RDS	SNGS	TOTAL	XOM
WTI	**0.172**	**0.334**	**0.314**	**0.115**	**0.102**	**0.164**	**0.119**	**0.065**	**0.149**	**0.255**
	(9.051)	**(19.693)**	**(18.651)**	**(6.151)**	**(5.684)**	**(9.292)**	**(5.858)**	**(3.578)**	**(7.683)**	**(14.867)**

Notes: (1) The two entries for each parameter are their respective parameter estimates and Bollerslev and Wooldridge (1992) robust *t*- ratios. (2) Entries in bold are significant at the 95% level.

Table 3 VARMA-GARCH

Panel 3a. VARMA-GARCH: WTI_BP

	ϖ	α_{WTI}	α_{BP}	β_{WTI}	β_{BP}
WTI	**0.046**	**0.070**	0.001	**0.920**	-0.003
BP	**0.136**	0.032	**0.058**	-0.017	**0.912**

Panel 3b. VARMA-GARCH: WTI_COP

	ϖ	α_{WTI}	α_{COP}	β_{WTI}	β_{COP}
WTI	**0.046**	**0.061**	-0.004	**0.928**	0.003
COP	**0.134**	0.016	**0.058**	0.004	**0.908**

Panel 3c. VARMA-GARCH: WTI_CVX

	ϖ	α_{WTI}	α_{CVX}	β_{WTI}	β_{CVX}
WTI	**0.053**	**0.069**	0.002	**0.913**	-0.003
CVX	**0.143**	0.012	**0.063**	0.003	**0.907**

Panel 3d. VARMA-GARCH: WTI_ENI

	ϖ	α_{WTI}	α_{ENI}	β_{WTI}	β_{ENI}
WTI	0.024	**0.076**	-0.004	**0.916**	0.005
ENI	**0.141**	0.034	**0.055**	-0.007	**0.908**

Panel 3e. VARMA-GARCH: WTI_LKOH

	ϖ	α_{WTI}	α_{LKOH}	β_{WTI}	β_{LKOH}
WTI	0.252	**0.147**	0.005	**0.830**	0.007
LKOH	**0.176**	**0.008**	**0.062**	-0.007	**0.906**

Panel 3f. VARMA-GARCH: WTI_PBRA

	ϖ	α_{WTI}	α_{PBRA}	β_{WTI}	β_{PBRA}
WTI	**0.155**	**0.066**	0.001	**0.909**	-0.001
PBRA	0.228	0.005	**0.110**	-0.009	**0.860**

Panel 3g. VARMA-GARCH: WTI_RDS

	ϖ	α_{WTI}	α_{RDS}	β_{WTI}	β_{RDS}
WTI	**0.132**	**0.058**	0.021	**0.916**	-0.012
RDS	0.087	-0.003	**0.100**	0.006	**0.864**

Panel 3h. VARMA-GARCH: WTI_SNGS

	ϖ	α_{WTI}	α_{SNGS}	β_{WTI}	β_{SNGS}
WTI	**0.154**	**0.062**	0.003	**0.907**	-0.002
SNGS	0.101	-0.024	**0.079**	0.040	**0.911**

Panel 3i. VARMA-GARCH: WTI_TOTAL

	ϖ	α_{WTI}	α_{TOTAL}	β_{WTI}	β_{TOTAL}
WTI	**0.108**	**0.052**	0.020	**0.924**	-0.008
TOTAL	**0.039**	1.82E-05	**0.071**	-0.004	**0.927**

Panel 3j. VARMA-GARCH: WTI_XOM

	ϖ	α_{WTI}	α_{XOM}	β_{WTI}	β_{XOM}
WTI	**0.155**	**0.064**	0.014	**0.908**	-0.008
XOM	**0.048**	-0.001	**0.071**	0.001	**0.909**

Notes: (1) The two entries for each parameter are their respective parameter estimates and Bollerslev and Wooldridge (1992) robust *t*-ratios. (2) Entries in bold are significant at the 95% level

Corresponding multivariate estimates for the VARMA(1,1)-GARCH(1,1) and VARMA(1,1)-AGARCH(1,1) models using BHHH (Berndt, Hall, Hall and Hausman) algorithm and Bollerslev-Wooldridge (1992) robust *t*-ratio are reported in Table 2 and 3 respectively. The estimates of conditional mean for VARMA-GARCH are available upon request. In Panel 2a-2j, the ARCH and GARCH effects for WTI futures return and oil company stock returns are statistically significant in the conditional volatilities for the WTI futures return and oil company stock returns. Interestingly, there is also clear from table 2 that no evidence of volatility spillovers is observed both one direction and two directions (interdependence). It means that the pair of WTI futures returns and oil company stock returns are affected only by its own returns short run (α) and long run (β) shocks.

The results of the VARMA-AGARCH in Panel 3a-3j mirror those in Panel 2a-2j. Like the previous Panel, the estimates of conditional mean for VARMA-AGARCH are available upon request. Surprisingly, in Panel 3a-3j, the coefficients of volatility spillovers are all statistically insignificant. Therefore, each pair of returns in portfolio are only affected by their own previous short run (ARCH effect) and long run (GARCH effect) shocks, but with WTI of pair of WTI_ENI, PBRA of pair of WTI_PBRA and SNGS of pair of WTI_SNGS only in long run. The estimates of the conditional variance also show that asymmetric effects are evident in all cases, suggesting that VARMA-GARCH is superior to VARMA-AGARCH.

Table 4 VARMA-AGARCH

Panel 4a. VARMA-AGARCH: WTI_BP

	ϖ	α_{WTI}	α_{BP}	γ	β_{WTI}	β_{BP}
WTI	**0.137**	**0.036**	0.031	**0.037**	**0.915**	-0.017
BP	**0.049**	0.001	**0.044**	**0.047**	-0.003	**0.921**

Panel 4b. VARMA-AGARCH: WTI_COP

	ϖ	α_{WTI}	α_{COP}	γ	β_{WTI}	β_{COP}
WTI	0.135	**0.038**	0.016	0.032	**0.912**	0.002
COP	**0.060**	-0.004	**0.033**	**0.048**	0.002	**0.927**

Panel 4c. VARMA-AGARCH: WTI_CVX

	ϖ	α_{WTI}	α_{CVX}	γ	β_{WTI}	β_{CVX}
WTI	**0.144**	**0.039**	0.014	0.037	**0.912**	-0.002
CVX	**0.057**	0.001	**0.034**	**0.060**	-0.002	**0.914**

Panel 4d. VARMA-AGARCH: WTI_ENI

	ϖ	α_{WTI}	α_{ENI}	γ	β_{WTI}	β_{ENI}
WTI	**0.116**	0.029	0.033	**0.033**	**0.923**	-0.012
ENI	0.024	-0.005	**0.051**	**0.051**	0.008	**0.910**

Panel 4e. VARMA-AGARCH: WTI_LKOH

	ϖ	α_{WTI}	α_{LKOH}	γ	β_{WTI}	β_{LKOH}
WTI	**0.174**	**0.040**	0.008	**0.035**	**0.912**	-0.007
LKOH	0.252	0.003	**0.100**	**0.090**	0.012	**0.828**

Panel 4f. VARMA-AGARCH: WTI_PBRA

	ϖ	α_{WTI}	α_{PBRA}	γ	β_{WTI}	β_{PBRA}
WTI	**0.161**	**0.043**	0.001	**0.039**	**0.911**	-0.001
PBRA	**0.266**	0.004	0.022	**0.155**	-0.003	**0.857**

Panel 4g. VARMA-AGARCH: WTI_RDS

	ϖ	α_{WTI}	α_{RDS}	γ	β_{WTI}	β_{RDS}
WTI	**0.148**	**0.039**	0.020	0.036	**0.913**	-0.011
RDS	**0.036**	-0.005	**0.056**	**0.060**	0.005	**0.903**

Panel 4h. VARMA-AGARCH: WTI_SNGS

	ϖ	α_{WTI}	α_{SNGS}	γ	β_{WTI}	β_{SNGS}
WTI	**0.175**	**0.045**	0.003	0.035	**0.903**	-0.002
SNGS	5.326	**-0.115**	0.059	**0.156**	0.295	**0.751**

Panel 4i. VARMA-AGARCH: WTI_TOTAL

	ϖ	α_{WTI}	α_{TOTAL}	γ	β_{WTI}	β_{TOTAL}
WTI	**0.114**	**0.033**	0.019	0.033	**0.925**	-0.008
TOTAL	**0.037**	-0.001	**0.061**	0.014	-0.003	**0.930**

Panel 4j. VARMA-AGARCH: WTI_XOM

	ϖ	α_{WTI}	α_{XOM}	γ	β_{WTI}	β_{XOM}
WTI	**0.158**	**0.040**	0.014	**0.039**	**0.911**	-0.011
XOM	**0.057**	-0.001	**0.037**	**0.063**	0.003	**0.905**

Notes: (1) The two entries for each parameter are their respective parameter estimates and Bollerslev and Wooldridge (1992) robust *t*-ratios. (2) Entries in bold are significant at the 95% level

5. Conclusion

The empirical analysis in this paper examined the volatility spillovers between crude oil futures returns and oil company stock returns by using recently multivariate GARCH model, namely the CCC, VARMA-GARCH and VARMA-AGARCH model. This paper investigates the WTI crude oil futures returns and stock returns of ten oil companies, composing of the group of "supermajor" oil companies, namely Exxon Mobil, Royal Dutch Shell, Chevron Corporation, ConocoPhillips, BP and Total S.A., and other large oil and gas companies of the world, namely Petrobras, Lukoil, Surgutneftegas, and Eni S.p.A. The empirical results present that the conditional correlation between WTI crude oil futures returns and oil company stock returns of CCC model are very low. Surprisingly, the VARMA-GARCH and VARMA-AGARCH results show that there were no spillover effects between pair of returns series. The evidence of asymmetric effects of negative and positive shocks on conditional variance suggests that VARMA-AGARCH is superior to VARMA-GARCH models.

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