Chapter 5

Volatility Spillovers Between Crude Oil Futures Returns and Oil Company Stock Returns

Crude oil is the world's most influential physical commodity, and plays a prominent role in all economies, so that oil prices fluctuations affect the world economy in many different and significant ways. In financial market, the assessment of the volatility of oil company stock price returns, and the linkage between oil price volatility and oil company stock price volatility, is crucial for making investment decisions, for policy makers to implement appropriate policies for managing stock markets, and also for financial hedgers, portfolio management, asset allocators, and other financial analyses. Therefore, the objective of this chapter is to examine the volatility spillovers between crude oil futures returns and oil company stock returns for the major oil companies, which reveal the importance of the crude oil volatility on oil company stock volatility.

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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 the volatility spillovers between the returns on crude oil futures and oil company stocks using alternative multivariate GARCH models, namely the CCC model of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003), and VARMA-AGARCH model of McAleer et al. (2008). The paper investigates WTI crude oil futures returns and the stock returns of ten oil companies, which comprise 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 four other large oil and gas companies, namely Petrobras (PBRA), Lukoil (LKOH), Surgutneftegas (SNGS), and Eni S.p.A. (ENI). Estimates of the conditional correlations between the WTI crude oil futures returns and oil company stock returns are found to be quite low using the CCC model, while the VARMA-GARCH and VARMA-AGARCH models suggest no significant volatility spillover effects in any pairs of returns. The paper also presents evidence of the asymmetric effects of negative and positive shocks of equal magnitude on the conditional variances in all pairs of returns.

1 Introduction

Crude oil is arguably the world’s most influential physical commodity, and plays a prominent role in all economies, so that oil prices fluctuations affect the world economy in many different and significant ways. Rising crude oil prices raise the cost of production of goods and services, transportation and heating cost, among others. 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 earnings expectation of companies, or future cash flows. Therefore, oil price shocks influence stock prices through expected cash flow and the discount rate. Since oil is a crucial input for goods and services production, a rise in oil prices without substitute inputs increases production costs, which, in turn, decrease cash flows and stock prices. In addition, rising oil prices affects the discount rate by influencing inflationary pressures, which can also lead central banks to raise interest rates. Thus, corporate investment decision can be affected directly by changes in the discount rate and changes in stock prices relative to book value. However the direction of the 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, the performance of oil prices and the stock market may well be negatively correlated.

Several papers have provided an explanation of the oil price and stock market relationship, and the negative impact of oil prices on stock markets (see, for example, Jones and Kaul (1996), Hammoudeh and Aleisa (2002 and 2004), Sadorsky (2008)). However, Maghyereh (2004) does not find a significant impact on stock index returns in 22 emerging economies using a VAR model. This suggests that the stock market returns in these economies do not signal shocks in crude oil markets. Surprisingly, there is a very limited literature based on the relationship between oil prices and oil company stock prices. 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)).

There appears to be volatility spillover patterns that are widespread in financial markets (Milunovich and Thorp (2006)), energy markets, and stock markets (Sadorsky (2004)). A volatility spillover occurs when changes in price or returns volatility in one market produce a lagged impact on volatility in one or more other markets. However, there seems to have been little research of volatility spillovers between the oil and stock markets. Ågren (2006) investigated volatility spillovers from oil prices to stock markets using asymmetric BEKK model, and presented strong evidence of volatility spillovers in Japan, Norway, U.K. and the U.S. stock markets; but quite weak in evidence 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, is crucial for making investment decisions, for policy makers to implement appropriate policies for managing stock markets, and also financial hedgers, portfolio management, asset allocators, and other financial analysis. With oil and gas being one of the largest industries in the world, different companies and business are involved in different chains of production, distillation and distribution. It is surprisingly that none of these papers has yet examined the relationship between crude oil futures returns volatility and oil company stock price volatility.

In order to model volatility spillovers, there are several conditional volatility models which specify the risk of one asset as depending dynamically on its own past risk and on the past risk of the other assets (see, for example, McAleer (2005)). Even though the multivariate VARMA-GARCH model of Ling and McAleer (2003) and VARMA-AGARCH model of McAleer et al. (2009) assume constant conditional correlations, they do not suffer from the "the curse of dimensionality" when compared with the VECH and BEKK models (see, for example, Caporin and McAleer (2009)). On the other hand, in order to capture the dynamics of time-varying conditional correlations, a recently development model is generalized autoregressive conditional correlation (GARCC) of McAleer et al. (2008).

The purpose of this study is to examine the volatility spillovers between crude oil futures returns and oil company stock returns for the major oil companies. This issue is examined empirically using the VARMA-GARCH and VARMA-AGARCH models. The empirical results of the paper may shed light on the importance of the crude oil returns on oil company stock returns.

The remainder of the paper is organized as follows. Various multivariate conditional volatility models are discussed in Section 2. The data sources and sample evidence are described in Section 3, and the empirical results are analyzed in Section 4. Some concluding remarks are given in Section 5.

2 Econometric Models

The purpose of this section is to present alternative multivariate conditional volatility models, including a discussion of spillover effects, in which the conditional variance of returns depends dynamically on past unconditional shocks and the past conditional variance of each asset in the portfolio. The VARMA-GARCH model of Ling and McAleer (2003) assumes symmetry in the effects of positive and negative shocks of equal magnitude on the conditional volatility, and 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 $Y_t = (y_{1t},...,y_{mt})'$, F_{t-1} is the past information available to time *t*, *m* is the number of returns to be analyzed, $t = 1,...,n$, 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*, $D_t = \operatorname{diag}\left(h_{i,t}^{1/2}\right)$, $\eta_t = (\eta_{1t},...,\eta_{mt})'$ is a sequence of independently and identically (iid) random vectors. $H_t = (h_{1t},...,h_{mt})'$, $W_t = (\omega_{1t},...,\omega_{mt})'$, $\vec{\varepsilon}_t = \left(\varepsilon_{it}^2,...,\varepsilon_{mt}^2\right)'$, A_l and B_l are $m \times m$ matrices with typical elements α_{ij} and β_{ij}, respectively, for $i, j = 1,...,m$ and A_l and β_l represent the ARCH and GARCH effect, respectively.

Spillover effects, or the dependence of the conditional variance between WTI crude oil futures returns and oil company stock returns, are given in the 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), namely:

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

An extension of the VARMA-GARCH model to accommodate asymmetric impacts of the positive and negative shocks is given by the VARMA-AGARCH model of McAleer et al. (2009), which captures asymmetric spillover effects from each return. 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, $I\left(\eta_{t-l}\right)$ 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,

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

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 or volatility spillover effects across different financial assets, so it is intrinsically univariate in nature. From (2), the conditional correlation is $\varepsilon_t\varepsilon_t' = D_t\eta_t\eta_t' D_t$, and the conditional covariance matrix is given by

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

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

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

where θ denotes the vector of parameters to be estimated via the conditional log-likelihood function, and $\left| Q_t \right|$ 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).

The conditional correlations may be made dynamic, as given in the extension of the above models to multivariate conditional and stochastic volatility models, for which see McAleer et al (2008), and Asia and McAleer (2009), respectively.

3 Data

In this paper, we focus on modelling volatility spillovers between crude oil futures return in WTI market and the ten oil company stock returns. Six of them are called "Supermajor", namely the six largest non state-owned energy companies, which comprise 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), with the next four being 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. The data obtained from the DataStream database services, and are expressed in local currencies with the exception of WTI crude futures prices, which are denominated in USD per barrel. The returns of the daily futures prices for WTI, and for ten oil company stock price, are given in Figures 1 and 2, respectively. As the

Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test provide large negative values in all cases, all the individual return series are stationary. The empirical results of the unit root tests for WTI crude oil futures returns and ten company stock price returns are available from the authors on request.

4 Empirical results

As the univariate ARMA-GARCH model is nested in the VARMA-GARCH model and ARMA-GJR is nested in VARMA-AGARCH, with conditional variance specified in (5) and (8), univariate ARMA-GARCH and ARMA-GJR models are estimated. It will be appropriate to extend the univariate models to their multivariate counterparts if the properties of univariate models are satisfied. The coefficients in the conditional variance equation from the ARMA(1,1)-GARCH(1,1) are significant, both in the short and long run. However, the coefficient in the conditional variance of ARMA(1,1)-GJR(1,1) are all significant, but with PBRA, only in long run. In addition, at the univariate level, most of the estimates of the asymmetric effects, in which negative shocks have a greater impact on volatility than positive shocks of similar magnitude, are significant, except for TOT, LKOH and SNGS. The univariate estimates of the conditional volatilities, and the structural properties of both univarite models, namely second moment and log-moment conditions, based on WTI crude futures returns and oil company stock returns, are satisfied empirically, so that statistical inference is valid.

The estimates of constant conditional correlations between WTI crude oil futures returns and oil company stock returns, and the Bollerslev-Wooldridge (1992) robust *t*-ratios usping CCC model based on estimating univariate GARCH(1,1) models are presented in Table 1. For the ten oil company stock returns, there are ten conditional correlations. The highest estimated constant conditional correlation is 0.334 between the standardized shocks to the volatilities in the WTI crude oil futures and COP returns, and the lowest is 0.065 between the standardized shocks to the volatilities in WTI crude oil futures and SNGS returns. These estimated constant conditional correlations are reasonably low.

The 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 3 and 4, respectively. The estimates of conditional mean for VARMA-GARCH are available from the authors 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 both the WTI futures returns and oil company stock returns. Interestingly, Table 3 shows there is no evidence of volatility spillovers is either one direction or two directions (namely, interdependence). Thus, all pairs of WTI futures returns and oil company stock returns are affected only by the short run (α) and long run (β) shocks on their own returns.

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

5 Conclusion

The empirical analysis in this paper examined the volatility spillovers between the returns to crude oil futures and oil company stocks using alternative multivariate GARCH model, namely CCC, VARMA-GARCH and VARMA-AGARCH. This paper investigated the WTI crude oil futures returns and stock returns of ten oil companies, comprising the group of "supermajor" oil companies, namely Exxon Mobil, Royal Dutch Shell, Chevron Corporation, ConocoPhillips, BP and Total S.A., and four large oil and gas companies, namely Petrobras, Lukoil, Surgutneftegas, and Eni S.p.A.

The empirical results showed that the conditional correlations between WTI crude oil futures returns and oil company stock returns of CCC model were very low. The VARMA-GARCH and VARMA-AGARCH results show that there were no spillover effects between any pair of returns series. The evidence of asymmetric effects of negative and positive shocks of equal magnitude on the conditional variances suggested that VARMA-AGARCH was superior to VARMA-GARCH, and that both were superior to CCC.

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Table 1 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 5%.

Table 2. VARMA-GARCH

Panel 2a. 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 2b. 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 2c. 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 2d. 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 2e. 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 2f. 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 2g. 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**

Table 2. VARMA-GARCH (*continued*)

Panel 2h. 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 2i. 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 2j. 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 5% level

Table 3. VARMA-AGARCH

Panel 3a. 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 3b. 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 3c. 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 3d. 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 3e. 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 3f. 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 3g. 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**

Table 3. VARMA-AGARCH (*continued*)

Panel 3h. 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 3i. 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 3j. 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 5% level

Figure 1. Returns of daily futures prices of WTI

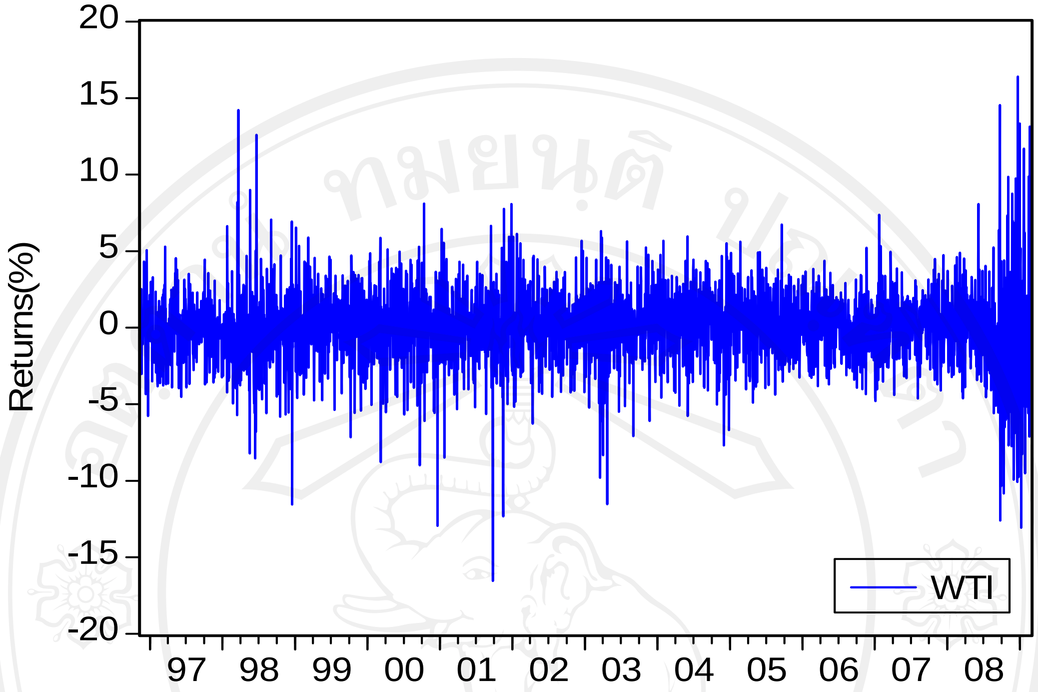

Figure 2. Returns of daily oil company stock prices

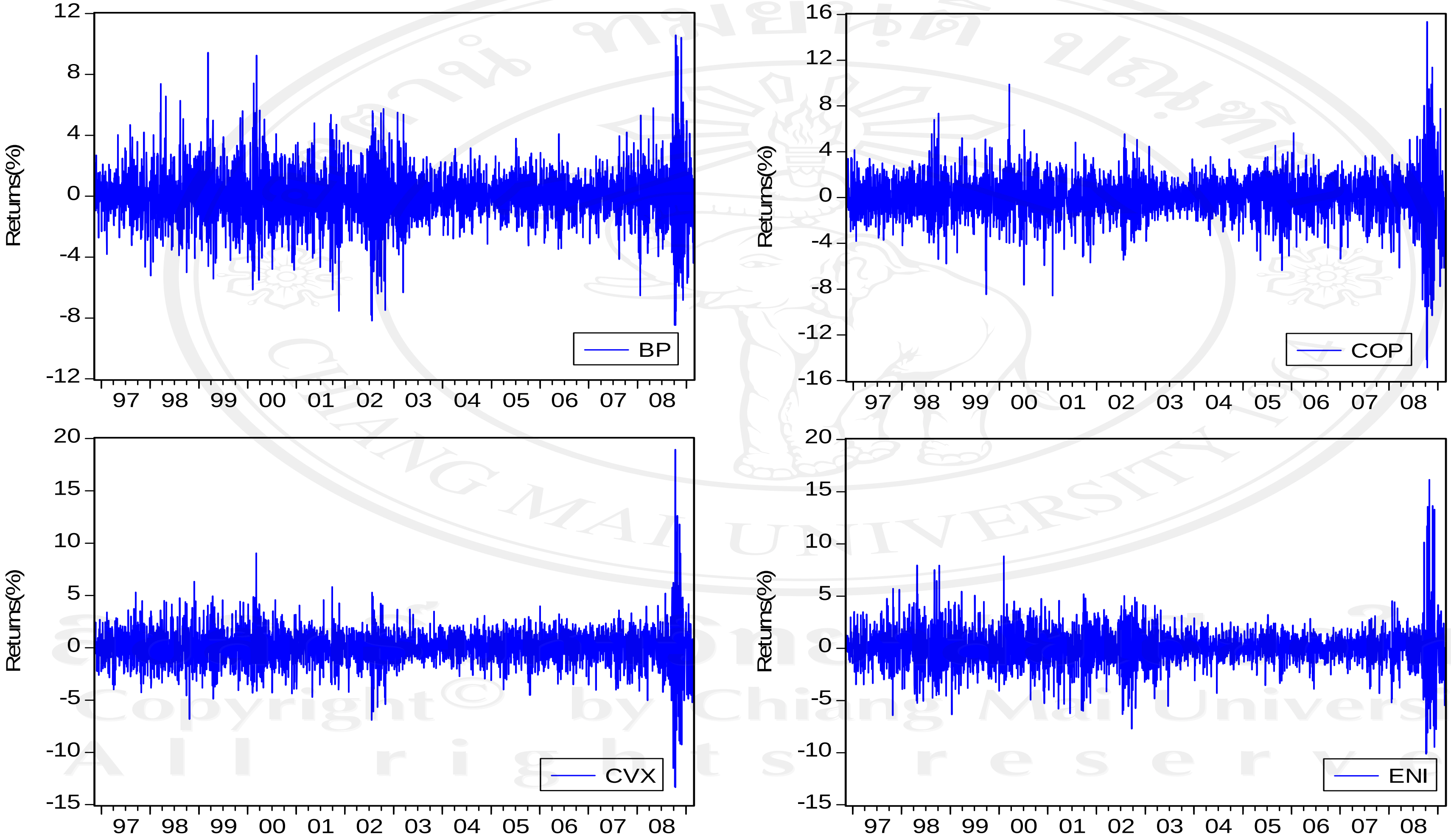

Figure 2 Returns of daily oil company stock prices (*continued*)

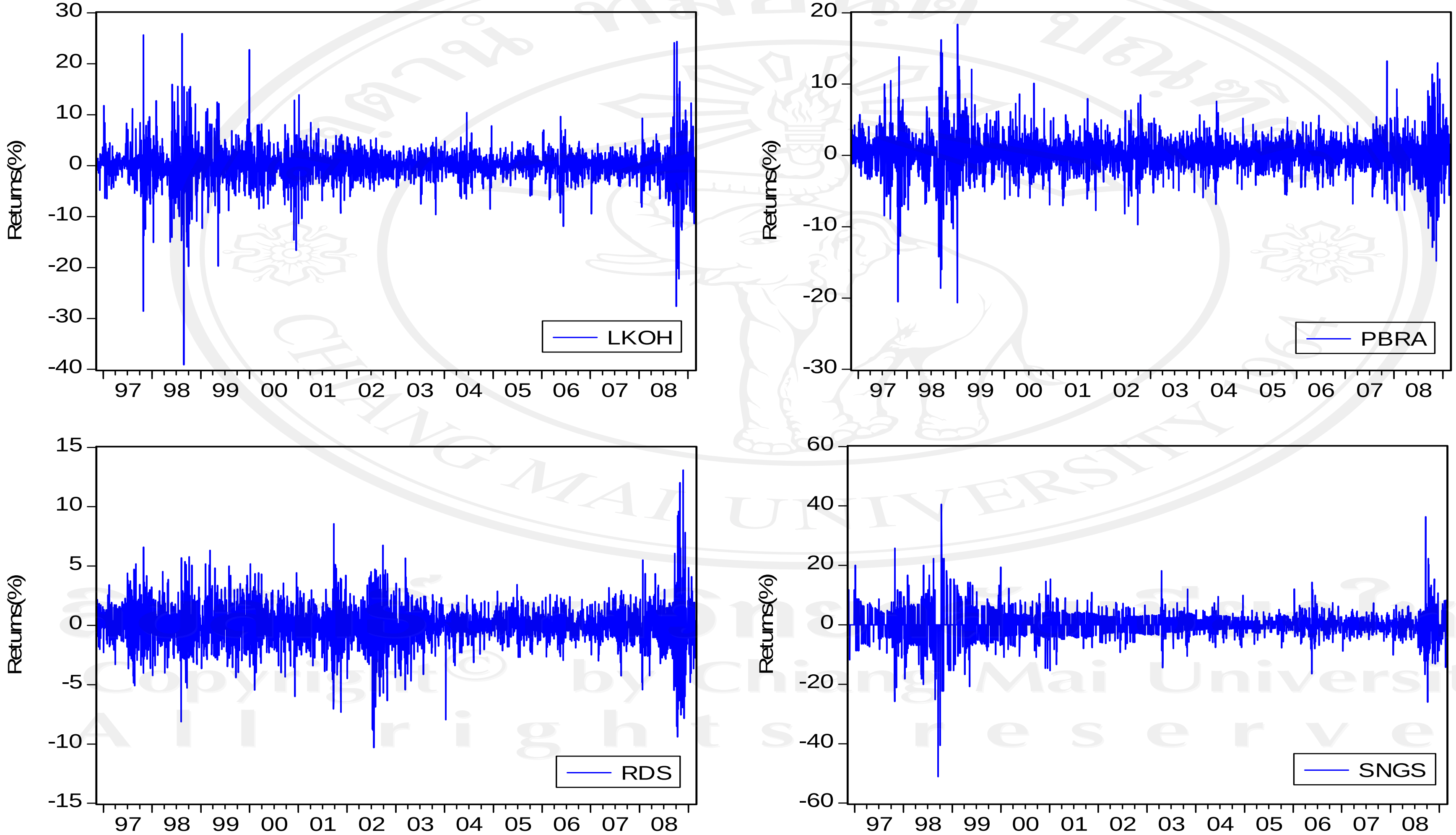

Figure 2 Returns of daily oil company stock prices (*continued*)