Chapter 4

Modelling Spillover Effects and Forecasting Volatility in Crude Oil Spot, Forward and Futures Markets

Nowadays, the four major benchmarks in the world of international crude oil trading are: (1) West Texas Intermediate (WTI), (2) Brent, (3) Dubai and (4) Tapis. Crude oil prices are usually quoted in three different kinds of financial transactions, namely spot, forward and futures prices. Thus crude oil is a part of commodity finance. Since volatility is crucially important on finance and volatility spillovers that appears to be widespread in the financial markets, including energy market. The purpose of this chapter is to investigate the importance of volatility spillover effects and asymmetric effects of negative and positive shocks on the conditional variance when modelling crude oil volatility in returns on spot, forward and futures prices in Brent, WTI, Dubai and Tapis markets and across these markets.

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Modelling spillover effects and forecasting volatility in crude oil spot, forward and futures markets

Roengchai Tansuchat[a,*], Michael McAleer[b,c] and Chia-Lin Chang[b]

[a] Faculty of Economics, Maejo University, Thailand; and Faculty of Economics, Chiang Mai University, Thailand

[b] Department of Applied Economics, National Chung Hsing University, Taichung, Taiwan

[c] Econometric Institute, Erasmus University Rotterdam, The Netherlands

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A B S T R A C T

Crude oil price volatility has been extensively analyzed for organized spot, forward and futures markets for over a decade and is crucial for forecasting volatility and Value-at-Risk (VaR). There are 4 major benchmarks in the international oil market, namely West Texas Intermediate (USA), Brent (North Sea), Dubai/Oman (Middle East) and Tapis (Asia-Pacific), all of which are likely to be highly correlated. This paper analyses the volatility spillover effects across and within the four markets using three multivariate GARCH models, namely the CCC model, VARMA-GARCH model and VARMA-AGARCH model. A rolling window approach is used to forecast 1-day ahead conditional correlations. The paper presents the evidence of volatility spillovers and asymmetric effect on the conditional variance in most pair of series. In addition, the forecasted conditional correlation between the pair of crude oil returns have both positive and negative trend.

1. Introduction

Over the past 20-30 years, oil has become the biggest traded commodity in the world. In the crude oil market, oil is sold under a variety of contract arrangements and in spot transactions, is also traded in futures markets which set the spot, forward and futures prices. Crude oil is usually sold close to the point of production, and is transferred as the oil flows from the loading terminal to the ship FOB (free on board). Thus, spot prices are quoted for immediate delivery of crude oil as FOB prices. Forward prices are the agreed upon price of crude oil in forward contracts. Futures price are prices quoted for delivering in a specified quantity of crude oil at a specific time and place in the future in a particular trading center.

* Correspondence author,
E-mail address: roengchaitan@gmail.com

The four major benchmarks in the world of international trading today are: 1) West Texas Intermediate (WTI), the reference crude for USA, (2) Brent, the reference crude oil for the North Sea, (3) Dubai, the benchmark crude oil for the Middle East and Far East, and (4) Tapis, the benchmark crude oil for the Asia-Pacific region. Volatility (or risk) is crucially important in finance and is typically unobservable, and volatility spillovers appear to be widespread in the financial markets (Milunovich and Thorp, 2006), including energy futures markets (Lin and Tamvakis, 2001). Consequently, a volatility spillover occurs when changes in volatility in one market produce a lagged impact on volatility in other markets, over and above local effects.

Accurate modelling of volatility is crucial in finance and for commodity.

Shocks to returns can be divided into predictable and unpredictable components. The most frequently analyzed predictable component in shocks to returns is the volatility in the time-varying conditional variance. The success of Generalized Autoregressive Conditional Heteroske-casticity (GARCH) model of Engle (1982) and Bollerslev (1986) have subsequently led to a family of univariate and multivariate GARCH models which can capture different behavior in financial returns, including time-varying volatility, persistence and clustering of volatility, and the asymmetric effects of positive and negative shocks of equal magnitude. In modelling multivariate returns, such as spot, forward and futures returns, shocks to returns not only have dynamic interdependence in risks, but also in the conditional correlations which are key elements in portfolio construction and the testing of unbiasedness and the efficient market hypothesis. The hypothesis of efficient markets is essential for understanding optimal decision making, especially for hedging and speculation.

Substantial research has been conducted on spillover effects in energy futures markets. Lin and Tamvakis (2001) investigated volatility spillover effects between NYMEX and IPE crude oil contracts in both non-overlapping and simultaneous trading hours. They found that substantial spillover effects exist when both markets are trading simultaneously, although IPE morning prices seem to be affected considerably by the close of the previous day on NYMEX. Ewing et al (2002) examined the transmission of volatility between the oil and natural gas markets using daily returns data, and found that changes in volatility in one market may have spillovers to the other market. Sola et al (2002) analyzed volatility links between different markets based on a bivariate Markov switching model, and discovered that it enables identification of the probabilistic structure, timing and the duration of the volatility transmission mechanism from one country to another.

Hammoudeh et al. (2003) examined the time series properties of daily spot and futures prices for three petroleum types traded at five commodity centers within and outside the USA by using multivariate vector error-correction models, causality models and the GARCH models. They found that WTI crude oil NYMEX 1-month futures prices involves causality and volatility spillovers, NYMEX gasoline has bi-directional causality relationships among all the gasoline spot and futures prices, spot prices produce the greatest spillovers, and NYMEX heating oil for 1- and 3-month futures are particularly strong and significant. Hammoudeh et al. (2009) examined the dynamic volatility and volatility transmission in a multivariate setting for four Golf Cooperation Council economies, and analyzed the optimal weights and hedge ratios for sectoral portfolio holdings.

Of four major crude oil markets, only the most well known oil market, namely WTI and Brent, have spot, forward and futures prices, while the Dubai and Tapis markets have only spot and forward prices. It would seem that no research has yet tested the spillover effects, for each of spot, forward and futures crude oil prices in and across all markets.

Several multivariate GARCH models specify risk on one asset as depending dynamically on its own past and on the past of the other assets (see McAleer, 2005). da Veiga, Chan and McAleer (2008) analysed the multivariate VARMA-GARCH model of Ling and McAleer (2003) and VARMA-AGARCH model of McAleer, Hoti and Chan (2009), and found that they were to superior to the GARCH of Bollerslev (1986) and GJR of Glosten, Jagannathan and Runkle (1992).

In this paper we investigate the importance of volatility spillover effects and asymmetric effects of negative and positive conditional shocks on the conditional variance when modelling crude oil volatility in returns on spot, forward and futures prices in Brent, WTI, Dubai and Tapis markets and across these markets by using multivariate conditional volatility models. The spillover effects between returns in the markets and across markets are also estimated. A rolling window is used to forecast 1-day ahead conditional correlations and to explain the conditional correlations movements, which are important for portfolio construction and hedging.

The plan of the paper is as followed. Section 2 discusses the univariate and multivariate GARCH models to be estimated. Section 3 explains the data, descriptive statistics and unit root tests. Section 4 describes the empirical estimates and some diagnostic tests of the univariate and multivariate models, and forecast 1-day ahead conditional correlations. Section 5 provides some concluding remarks.

2. Econometric models

This section presents the CCC model of Bollerslev (1990), the VARMA-GARCH model of Ling and McAleer (2003) and VARMA-AGARCH model of McAleer, Hoti and Chan (2009). These models assume constant conditional correlations, and do not suffer from the problem of dimentionality, as compare with the VECH and BEKK models (see McAleer et al. (2008) and Carporin and McAleer (2009)). The VARMA-GARCH model of Ling and McAleer (2003), assumes symmetry in the effect of positive and negative shocks of equal magnitude on the conditional volatility, and is given by

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

$$\Phi(L)\left(Y_t - \mu\right) = \Psi(L)\varepsilon_t \qquad (2)$$

$$\varepsilon_t = D_t \eta_t \qquad (3)$$

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

where $D_t = \text{diag}\left(h_{i,t}^{1/2}\right)$, $H_t = \left(h_{1t},...,h_{mt}\right)'$, $W_t = \left(\omega_{1t},...,\omega_{mt}\right)'$, $\eta_t = \left(\eta_{1t},...,\eta_{mt}\right)'$ is a sequence of independently and identically (iid) random vectors, $\vec{\varepsilon}_t = \left(\varepsilon_{it}^2,...,\varepsilon_{mt}^2\right)'$, A_l and B_l are $m \times m$ matrices with typical elements α_{ij} and β_{ij}, respectively, for $i, j = 1,...,m$, $I(\eta_t) = diag\left(I(\eta_{it})\right)$ is an $m \times m$ matrix. $\Phi(L) = I_m - \Phi_1 L - ... - \Phi_p L^p$ and $\Psi(L) = I_m - \Psi_1 L - ... - \Psi_q L^q$ are polynomials in *L*, the lag operator, and F_t is the past information available to time *t*. α_l represents the ARCH effect, and β_l represents the GARCH effect. Spillover effects or the independence of conditional variance across crude oil returns are given in the conditional volatility for each asset in the portfolio. Based on equation (3), the VARMA-GARCH model also assumes that the matrix of conditional correlations is given by $E(\eta_t \eta_t') = \Gamma$. If $m = 1$, equation (4.4) reduces to the univariate GARCH model of Bollerslev (1986):

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

The VARMA-GARCH model assumes that negative and positive shocks of equal magnitude have identical impacts on the conditional variance. An extension of the VARMA-GARCH model to accommodate asymmetric impacts of the positive and negative shocks is the VARMA-AGARCH model of McAleer, Hoti and Chan (2009), which captures asymmetric spillover effects from other crude oil returns. An extension of (4) to accommodate asymmetries with respect to ε_{it} is given by

$$H_t = W + \sum_{l=1}^{r} A_l \vec{\varepsilon}_{t-l} + \sum_{l=1}^{r} C_l I_{t-l} \vec{\varepsilon}_{t-l} + \sum_{l=1}^{s} B_l H_{t-l} \qquad (6)$$

in which $\varepsilon_{it} = \eta \sqrt{h_{it}}$ for all *i* and *t*, C_l are $m \times m$ matrices and $I(\eta_{it})$ is an indicator variable distinguishing between the effects of positive and negative shocks of equal magnitude on conditional volatility, such that

$$I\left(\eta_{it}\right)=\begin{cases}0, & \varepsilon_{it}>0\\ 1, & \varepsilon_{it}\leq 0\end{cases} \quad (4)$$

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

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

For the underlying asymptotic theory, see McAleer et al. (2007) and, for an alternative asymmetric GARCH model, namely EGARCH, see Nelson (1991).

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

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

which is the constant conditional correlation (CCC) model of Bollerslev (1990). As given in equation (7), the CCC model does not have volatility spillover effects across different financial assets, and hence is intrinsically univariate in nature. In addition, CCC also does not capture the asymmetric effects of positive and negative shocks on conditional volatility.

The parameters in model (1), (4), (6) and (9) can be obtained by maximum likelihood estimation (MLE) using a joint normal density, namely

$$\hat{\theta}=\arg\min_{\theta}\frac{1}{2}\sum_{t=1}^{n}\left(\log\left|Q_t\right|+\varepsilon_t' Q_t^{-1}\varepsilon_t\right) \quad (10)$$

where θ denotes the vector of parameters to be estimated on 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).

In order to forecast 1-day ahead conditional correlation, we use rolling windows technique and examine the time-varying nature of the conditional correlations using VARMA-GARCH and VARMA-AGARCH. Rolling windows are a recursive estimation procedure whereby the model is estimated for a restricted sample, then re-estimated by adding one observation at the end of the sample and deleting one observation from the beginning of the sample. The process is repeated until the end of the sample. In order to strike a balance between efficiency in estimation and a viable number of rolling regressions, the rolling window size is set at 2008 for all data sets.

3. Data

The univariate and multivariate GARCH models are estimated using 3,007 observations of daily data on crude oil spot, forward and futures prices in the Brent, WTI (West Texas Intermediate), Dubai and Tapis markets for the period 30 April 1997 to 10 November 2008. All prices are expressed in US dollars. In WTI market, prices are crude oil-WTI spot cushing price ($/BBL), crude oil-WTI one-month forward price ($/BBL) and NYMEX one-month futures prices, while the prices in the Brent market are crude oil-Brent spot price FOB ($/BBL), crude oil-Brent one-month forward price ($/BBL) and one-month futures prices. In the Dubai market, the prices are crude oil-Arab Gulf Dubai spot price FOB ($/BBL) and crude oil-Dubai one-month forward price ($/BBL), where as in the Tapis market, the prices are crude oil-Malaysia Tapis spot price FOB ($/BBL) and crude oil-Tapis one-month forward price ($/BBL). Three of them are obtained from DataStream database service, while the series for Tapis are collected from Reuters.

The synchronous price returns *i* for each market *j* are computed on a continuous compounding basis as the logarithm of closing price at the end of the period minus the logarithm of the closing price at the beginning of the period, which is defined as: $r_{ij,t}=\log\left(P_{ij,t}/P_{ij,t-1}\right)$.

Figure 1: Logarithm of daily spot, forward and futures of Brent, WTI, Dubai and Tapis

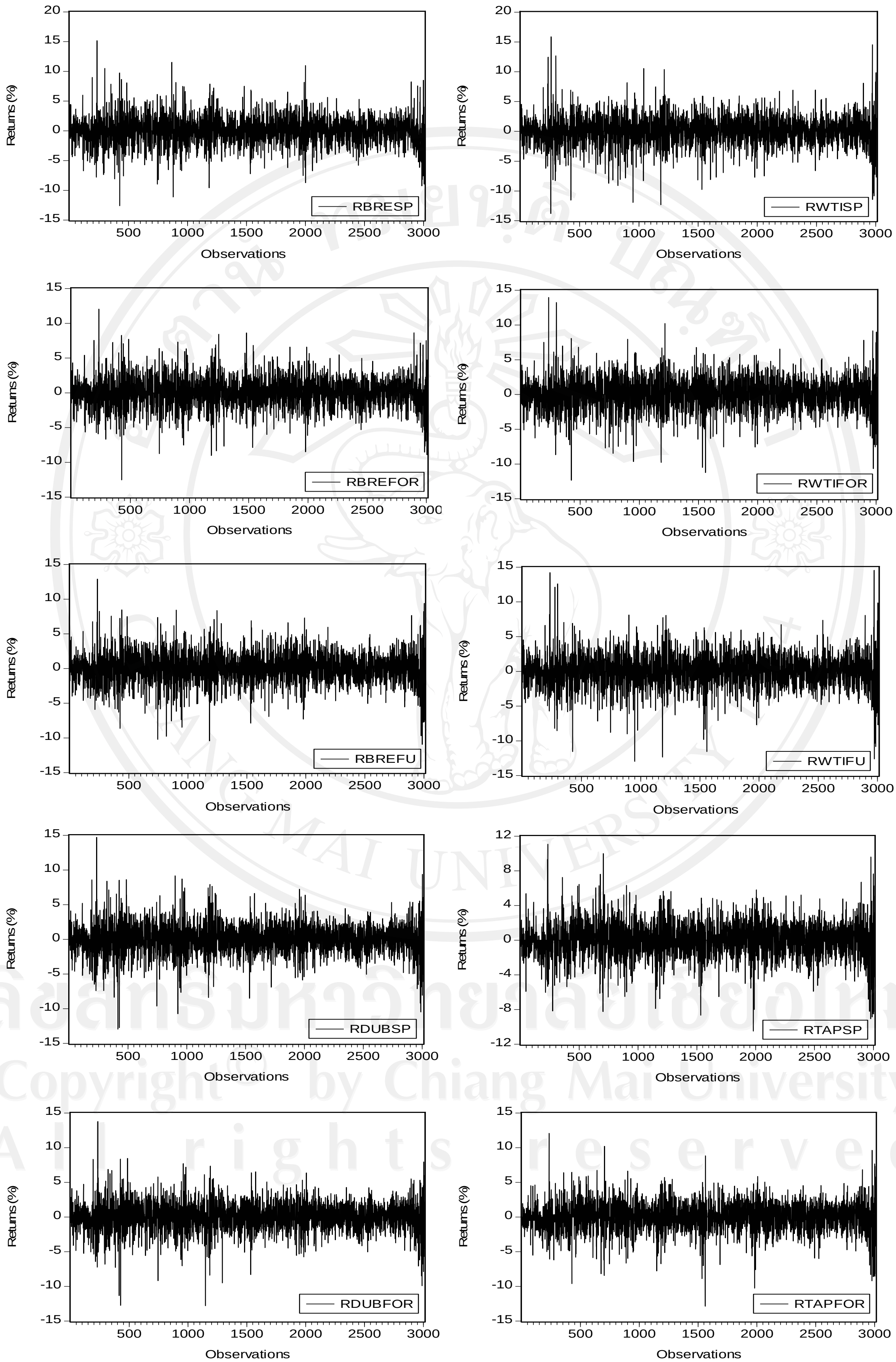


Table 1: Descriptive statistics for crude oil price returns

Returns	Mean	Max	Min	S.D.	Skewness	Kurtosis	Jarque-Bera
rbresp	0.043	15.164	-12.601	2.347	-0.0007	5.341	**686.6157**
rbrefor	0.043	12.044	-12.534	2.146	-0.141	4.939	**480.941**
rbrefu	0.043	12.898	-10.946	2.212	-0.124	4.934	**476.538**
rwtisp	0.043	15.873	-13.795	2.412	-0.129	6.479	**1524.764**
rwtifor	0.042	13.958	-12.329	2.316	-0.182	5.204	**625.414**
rwtifu	0.043	14.546	-12.939	2.349	-0.151	6.318	**1390.425**
rdubsp	0.043	14.705	-12.943	2.199	-0.179	5.844	**1029.861**
rdubfor	0.040	13.767	-12.801	2.115	-0.308	5.718	**973.0103**
rtapsp	0.038	11.081	-10.483	2.000	-0.183	5.373	**722.053**
rtapfor	0.038	12.071	-12.869	2.076	-0.289	5.567	**867.187**

Note: Entries in bold are significant at the 1% level.

Table 2: Unit Root test for sample returns

Returns	ADF test (t-statistic)			Phillips-Perron test		
	None	Constant	Constant and Trend	None	Constant	Constant and Trend
rbresp	**-54.264**	**-54.274**	**-54.265**	**-54.301**	**-54.298**	**-54.291**
rbrefor	**-57.076**	**-57.092**	**-57.083**	**-57.088**	**-57.100**	**-57.091**
rbrefu	**-57.944**	**-57.958**	**-57.949**	**-57.901**	**-57.919**	**-57.909**
rwtisp	**-41.065**	**-41.079**	**-41.073**	**-55.652**	**-55.677**	**-55.667**
rwtifor	**-56.618**	**-56.626**	**-56.617**	**-56.697**	**-56.715**	**-56.705**
rwtifu	**-55.872**	**-55.881**	**-55.872**	**-56.011**	**-56.030**	**-56.020**
rdubsp	**-59.130**	**-59.145**	**-59.135**	**-59.090**	**-59.129**	**-59.119**
rdubfor	**-59.664**	**-59.677**	**-59.667**	**-59.542**	**-59.573**	**-59.564**
rtapsp	**-59.059**	**-59.072**	**-59.062**	**-58.955**	**-58.956**	**-58.947**
rtapfor	**-59.949**	**-59.961**	**-59.951**	**-59.747**	**-59.775**	**-59.766**

Note: Entries in bold are significant at the 1% level.

Table 3: Univariate ARMA(1,1)-GARCH(1,1)

	Mean equation			Variance equation		
Returns	C	AR(1)	MA(1)	ω	$\hat{\alpha}$	$\hat{\beta}$
rbresp	**0.088**	**-0.981**	**0.988**	**0.069**	**0.039**	**0.949**
	2.179	**-95.091**	**119.046**	**2.585**	**4.292**	**83.066**
rbrefor	**0.084**	0.236	-0.277	**0.084**	**0.042**	**0.940**
	2.407	0.596	-0.707	**2.708**	**4.281**	**68.425**
rbrefu	**0.081**	0.092	-0.141	**0.062**	**0.042**	**0.946**
	2.281	0.259	-0.399	**2.396**	**4.451**	**77.153**
rwtisp	0.072	**-0.949**	**0.955**	**0.101**	**0.046**	**0.938**
	1.698	**-18.055**	**19.298**	**2.502**	**3.698**	**58.264**
rwtifor	0.078	0.350	-0.387	**0.144**	**0.055**	**0.919**
	2.063	0.888	-0.998	**2.731**	**4.448**	**48.541**
rwtifu	**0.085**	**-0.971**	**0.969**	**0.189**	**0.065**	**0.902**
	2.142	**-32.149**	**30.750**	**2.971**	**3.633**	**36.669**
rdubsp	**0.090**	0.019	-0.099	**0.048**	**0.049**	**0.942**
	2.771	0.083	-0.434	**2.303**	**5.355**	**85.548**
rdubfor	**0.086**	0.052	-0.134	**0.061**	**0.048**	**0.939**
	2.696	0.227	-0.593	**2.571**	**4.331**	**69.601**
rtapsp	**0.067**	0.153	-0.211	**0.076**	**0.047**	**0.935**
	2.217	0.493	-0.687	**2.419**	**3.818**	**53.855**
rtapfor	0.058	0.173	-0.246	**0.056**	**0.041**	**0.946**
	1.856	0.742	-1.072	**2.618**	**4.314**	**80.476**

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 1 presents the descriptive statistics for the returns series of crude oil prices. The average return of spot, forward and futures in Brent, WTI and Dubai are similar, while Tapis has the lowest average of returns. The normal distribution has a skewness statistic equal to zero and a kurtosis statistic of 3, but these crude oil returns series has high kurtosis, suggesting the presence of fat tails, and negative skewness statistics signifying the series has a longer left tail (extreme losses) than right tail (extreme gain). Jarque-Bera Lagrange multiplier statistics of crude oil returns in each market are statistically significant, thereby signifying that the distributions of these prices are not normal, which may be due to the presence of the extreme observations.

Figure 1 presents the plot of synchronous crude oil price returns. These indicate volatility clustering or period of high volatility followed by periods of tranquility, such that crude oil returns oscillate in a range smaller than the normal distribution. However, there are some circumstances where crude oil returns fluctuate in a much wider scale than is permitted under normality.

The unit root tests for all crude oil returns in each market are summarized in table 2. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test were used to test the null hypothesis of a unit root against the alternative hypothesis of stationarity. The test yield large negative values in all cases for level such that the individual return series reject the null hypothesis at the 1% significant level, so that all returns series are stationary.

Since the univariate ARMA-GARCH is nested to the VARMA-GARCH model, and ARMA-GJR is nested to VARMA-AGARCH with conditional variance specified in (5) and (8), the univariate ARMA-GARCH and ARMA-GJR models are estimated. It is sensible to extend univariate models to their multivariate counterpart if the properties of univariate models are satisfied. All estimation is conducted using the EViews 6 econometric software package.

Table 4: Univariate ARMA(1,1)-GJR (1,1)

Returns	Mean equation			Variance equation			
	C	AR(1)	MA(1)	ω	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\beta}$
rbresp	0.054	**-0.981**	**0.988**	**0.069**	0.0116	**0.042**	**0.955**
	1.367	**-91.730**	**114.293**	**2.5514**	0.974	**2.792**	**85.638**
rbrefor	0.063	0.178	-0.224	**0.086**	0.019	**0.035**	**0.944**
	1.814	0.454	-0.573	**2.687**	1.498	**2.419**	**68.125**
rbrefu	0.069	0.059	-0.111	**0.059**	**0.029**	0.017	**0.951**
	1.942	0.169	-0.318	**2.349**	**2.329**	1.252	**79.661**
rwtisp	0.059	**0.954**	**-0.963**	**0.597**	**0.064**	0.059	**0.802**
	1.730	**17.911**	**-19.727**	**3.814**	**2.104**	1.782	**18.291**
rwtifor	0.058	0.3439	-0.385	**0.137**	**0.029**	0.035	**0.927**
	1.560	0.9369	-1.068	**2.772**	**2.046**	2.069	**53.349**
rwtifu	0.060	**-0.9709**	**0.969**	**0.187**	0.039	**0.042**	**0.905**
	1.521	**-30.237**	**29.056**	**3.054**	1.812	**1.964**	**37.680**
rdubsp	**0.064**	0.034	-0.117	**0.052**	0.022	**0.036**	**0.949**
	1.970	0.154	-0.539	**2.579**	1.797	**2.445**	**89.095**
rdubfor	**0.065**	0.049	-0.135	**0.069**	0.023	**0.034**	**0.944**
	2.031	0.221	-0.616	**2.699**	1.566	**2.229**	**63.537**
rtapsp	0.052	0.1438	-0.199	**0.072**	**0.019**	**0.037**	**0.944**
	1.661	0.445	-0.628	**2.886**	**2.037**	**2.665**	**70.250**
rtapfor	0.043	0.169	-0.242	**0.055**	**0.017**	**0.032**	**0.953**
	1.372	0.724	-1.053	**3.132**	**2.045**	**2.457**	**107.102**

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 5: Log-moment and second moment condition for ARMA(1,1)-GARCH(1,1) and ARMA(1,1)-GJR(1,1)

Return	ARMA-GARCH		ARMA-GJR	
	Log-Moment	Second moment	Log-Moment	Second moment
rbresp	-0.0060	0.988	-0.0058	0.987
rbrefor	-0.0087	0.982	-0.0084	0.980
rbrefu	-0.0061	0.988	-0.0050	0.988
rwtisp	-0.0089	0.984	-0.0492	0.895
rwtifor	-0.0131	0.974	-0.0114	0.973
rwtifu	-0.0173	0.967	-0.0153	0.965
rdubsp	-0.0051	0.991	-0.0048	0.989
rdubfor	-0.0068	0.987	-0.0069	0.984
rtapsp	-0.0093	0.982	-0.0082	0.982
rtapfor	-0.0063	0.987	-0.0056	0.986

4. Empirical results

From Tables 3 and 4, the univariate ARMA(1,1)-GARCH(1,1) and ARMA (1,1)-GJR(1,1) models are estimated to check whether the conditional variance follows the GARCH process. In Table 3, not all the coefficients in mean equations of ARMA(1,1)-GARCH(1,1) are significant, whereas all the coefficients in the conditional variance equation are statistically significant. Table 4 shows that the long-run coefficients are all statistically significant in the variance equation, but rbrefu (brent futures return), rwtisp (WTI spot return), rwtifor (WTI forward return), rtapsp (Tapis spot return), and rtapfor (Tapis forward return) are only significant in the short run. In addition, the asymmetric effects of negative and positive shocks on conditional variance are generally statistically significant.

In order to check the sufficient condition for consistency and asymptotic normality of QMLE for GARCH and GJR model, the second moment conditions are $\alpha_1 + \beta_1 < 1$ and $\alpha_1 + (\gamma/2) + \beta_1 < 1$, respectively. Table 5 shows that all of the estimated second moment conditions are less than one. In order to derive the statistical properties of the QMLE, Lee and Hausen (1997) derived the log-moment condition for GARCH(1,1) as $E\left(\log\left(\alpha_1\eta_t^2 + \beta_1\right)\right) < 0$, while McAleer et al. (2007) established the log-moment condition for GJR(1,1) as $E\left(\log\left(\alpha_1 + \gamma_1 I(\eta_t)\eta_t^2 + \beta_1\right)\right) < 0$. Table 5 shows that the estimated log-moment condition for both models are satisfied for all returns.

For the spot, forward and futures returns of four crude oil markets, there are ten series of returns to be analyzed. Consequently, 45 bivariate models need to be estimated. The calculated constant conditional correlations between the volatility of two returns within markets and across markets using the CCC model and the Bollerslev and Wooldridge (1992) robust *t*- ratios are presented in Table 6. The highest estimated constant conditional correlation is 0.935 between, namely the standardized shocks in Brent spot returns (rbresp) and Brent forward returns (rbrefor).

Corresponding multivariate estimates of conditional variance from the VARMA(1,1)-GARCH(1,1) and VARMA (1,1)-AGARCH(1,1) models are also estimated. The estimates of volatility and asymmetric spillovers are presented in Table 7, which shows that the volatility spillovers for VARMA-GARCH and VARMA-AGARCH are evident in 32 and 31 of 45 cases, respectively. The significant interdependences in the conditional volatility among returns are both 3 of 45 cases for VARMA-GARCH and VARMA-AGARCH. In addition, asymmetric effects are evident in 27 of 45 cases. Consequently, the evidence of volatility spillovers and asymmetric effects

Table 6: Constant conditional correlation for CCC-GARCH(1-1) model

Returns	rbresp	rbrefor	rbrefu	rwtisp	rwtifor	rwtifu	rdubsp	rdubfor	rtapsp	rtapfor
rbresp	1.000	**0.935**	**0.762**	**0.696**	**0.756**	**0.713**	**0.576**	**0.586**	**0.259**	**0.254**
		(126.157)	**(74.699)**	**(57.939)**	**(87.222)**	**(61.139)**	**(45.118)**	**(57.787)**	**(13.994)**	**(14.047)**
rbrefor		1.000	**0.778**	**0.723**	**0.786**	**0.740**	**0.740**	**0.609**	**0.263**	**0.253**
			(75.679)	**(66.055)**	**(99.892)**	**(64.702)**	**(64.702)**	**(44.895)**	**(16.679)**	**(14.199)**
rbrefu			1.000	**0.824**	**0.839**	**0.843**	**0.430**	**0.443**	**0.187**	**0.176**
				(148.267)	**(90.429)**	**(104.926)**	**(37.236)**	**(22.395)**	**(11.102)**	**(10.188)**
rwtisp				1.000	**0.873**	**0.920**	**0.390**	**0.398**	**0.176**	**0.161**
					(108.318)	**(199.900)**	**(22.564)**	**(18.390)**	**(9.418)**	**(8.286)**
rwtifor					1.000	**0.902**	**0.421**	**0.437**	**0.126**	**0.115**
						(160.272)	**(20.303)**	**(24.507)**	**(6.294)**	**(6.329)**
rwtifu						1.000	**0.403**	**0.410**	**0.176**	**0.164**
							(19.881)	**(21.240)**	**(10.239)**	**(9.031)**
rdubsp							1.000	**0.958**	**0.466**	**0.455**
								(169.158)	**(19.442)**	**(20.383)**
rdubfor								1.000	**0.468**	**0.457**
									(22.445)	**(16.468)**
rtapsp									1.000	**0.930**
										(139.082)
rtapfor										1.000

Notes: (1) The two entries for each parameter are their respective estimated conditional correlation and Bollerslev and Wooldridge (1992) robust *t*-ratios.
(2) Entries in bold are significant at the 5% level.

Table 7: Summary of volatility spillovers and asymmetric effect of negative and positive shocks

No.	Returns	Number of volatility spillover		Number of Asymmetric effects
		VARMA-GARCH	VARMA-GJR	
1	rbresp_rbrefor	0	0	1
2	rbresp_rbrefu	1(←)	1(←)	0
3	rbrefor_rbrefu	1(←)	1(←)	0
4	rbresp_rwtisp	1(→)	1(→)	1
5	rbrefor_rwtisp	0	0	1
6	rbrefu_rwtisp	0	0	0
7	rbresp_rwtifor	0	0	1
8	rbrefor_rwtifor	0	0	1
9	rbrefu_rwtifor	0	0	0
10	rwtisp_rwtifor	0	0	0
11	rbresp_rwtifu	1(←)	1(←)	1
12	rbrefor_rwtifu	0	0	1
13	rbrefu_rwtifu	0	0	0
14	rwtisp_rwtifu	0	0	0
15	rwtifor_rwtifu	1(←)	0	0
16	rbresp_rdubsp	0	0	2
17	rbrefor_rdubsp	1(→)	1(→)	1
18	rbrefu_rdubsp	0	1(→)	0
19	rwtisp_rdubsp	2 (□)	2(□)	1
20	rwtifor_rdubsp	1(→)	1(→)	1
21	rwtifu_rdubsp	1(→)	1(→)	1
22	rbresp_rdubfor	1(→)	1(→)	0
23	rbrefor_rdubfor	1(→)	1(→)	0
24	rbrefu_rdubfor	1(→)	1(→)	0
25	rwtisp_rdubfor	1(←)	1(←)	1
26	rwtifor_rdubfor	1(→)	1(→)	0
27	rwtifu_rdubfor	1(→)	1(→)	0
28	rdubsp_rdubfor	1(→)	0	1
29	rbresp_rtapsp	1(→)	1(→)	2
30	rbrefor_rtapsp	1(→)	1(→)	2
31	rbrefu_rtapsp	1(→)	1(→)	1
32	rwtisp_rtapsp	2 (□)	2 (□)	1
33	rwtifor_rtapsp	1(→)	1(→)	1
34	rwtifu_rtapsp	1(→)	1(→)	1
35	rdubsp_rtapsp	1(→)	1(→)	2
36	rdubfor_rtapsp	1(→)	1(→)	2
37	rbresp_rtapfor	1(→)	1(→)	1
38	rbrefor_rtapfor	1(→)	1(→)	1
39	rbrefu_rtapfor	1(→)	1(→)	0
40	rwtisp_rtapfor	2 (□)	2 (□)	0
41	rwtifor_rtapfor	0	0	0
42	rwtifu_rtapfor	1(→)	1(→)	0
43	rdubsp_rtapfor	1(→)	1(→)	1
44	rdubfor_rtapfor	1(→)	1(→)	1
45	rtapsp_rtapfor	1(→)	1(→)	1

Notes: The symbols → (←) means the direction of volatility spillover from A returns to B return (B return to A return), □ means they are interdependence, and 0 means no volatility spillover effect between pair of returns.

Figure 2: The forecast of conditional correlations between pair of returns resulted form the VARMA-GARCH and VARMA-AGARCH models

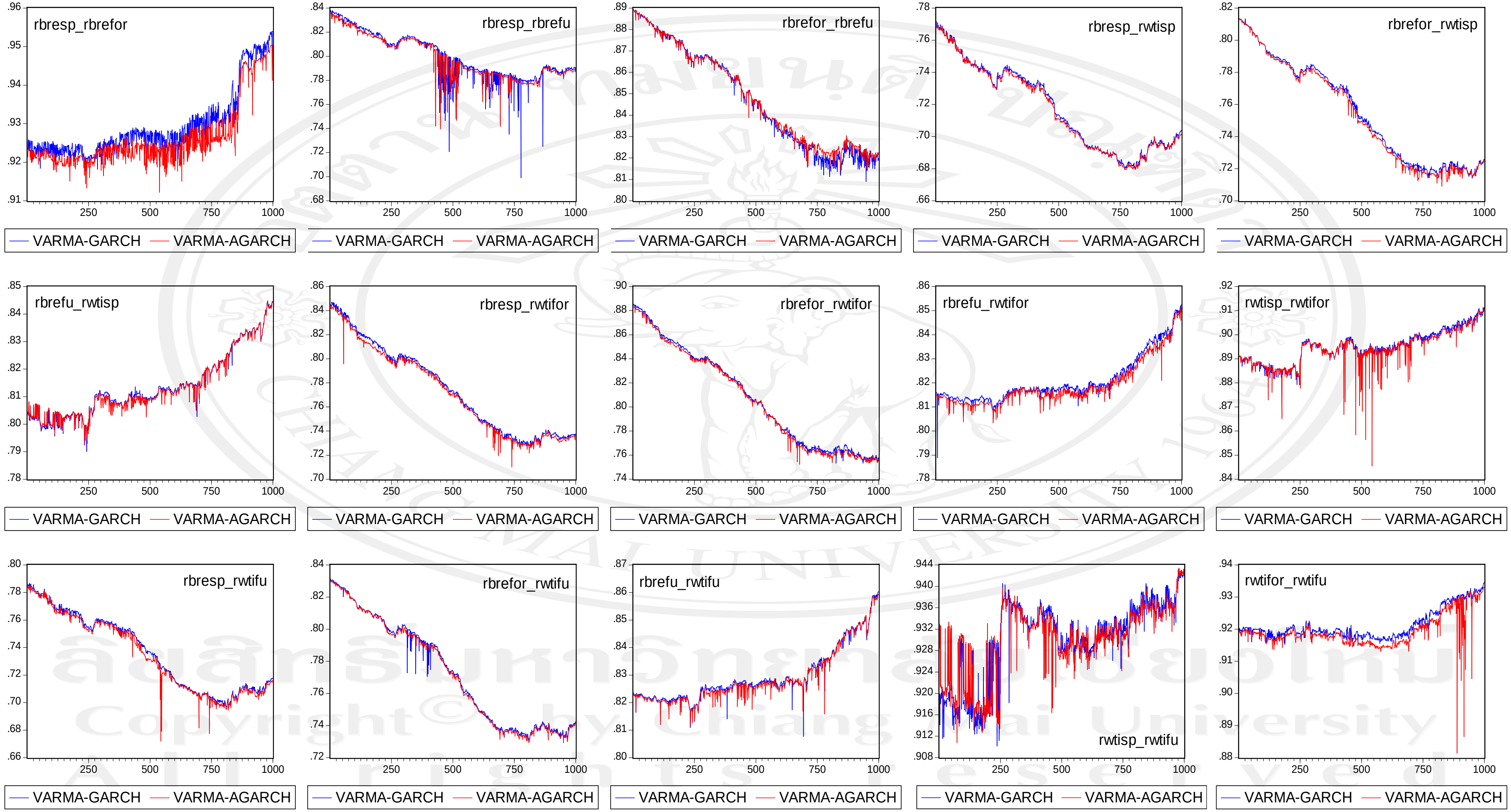


Figure 2: The forecast of conditional correlations between pair of returns resulted form the VARMA-GARCH and VARMA-AGARCH models (Continued)

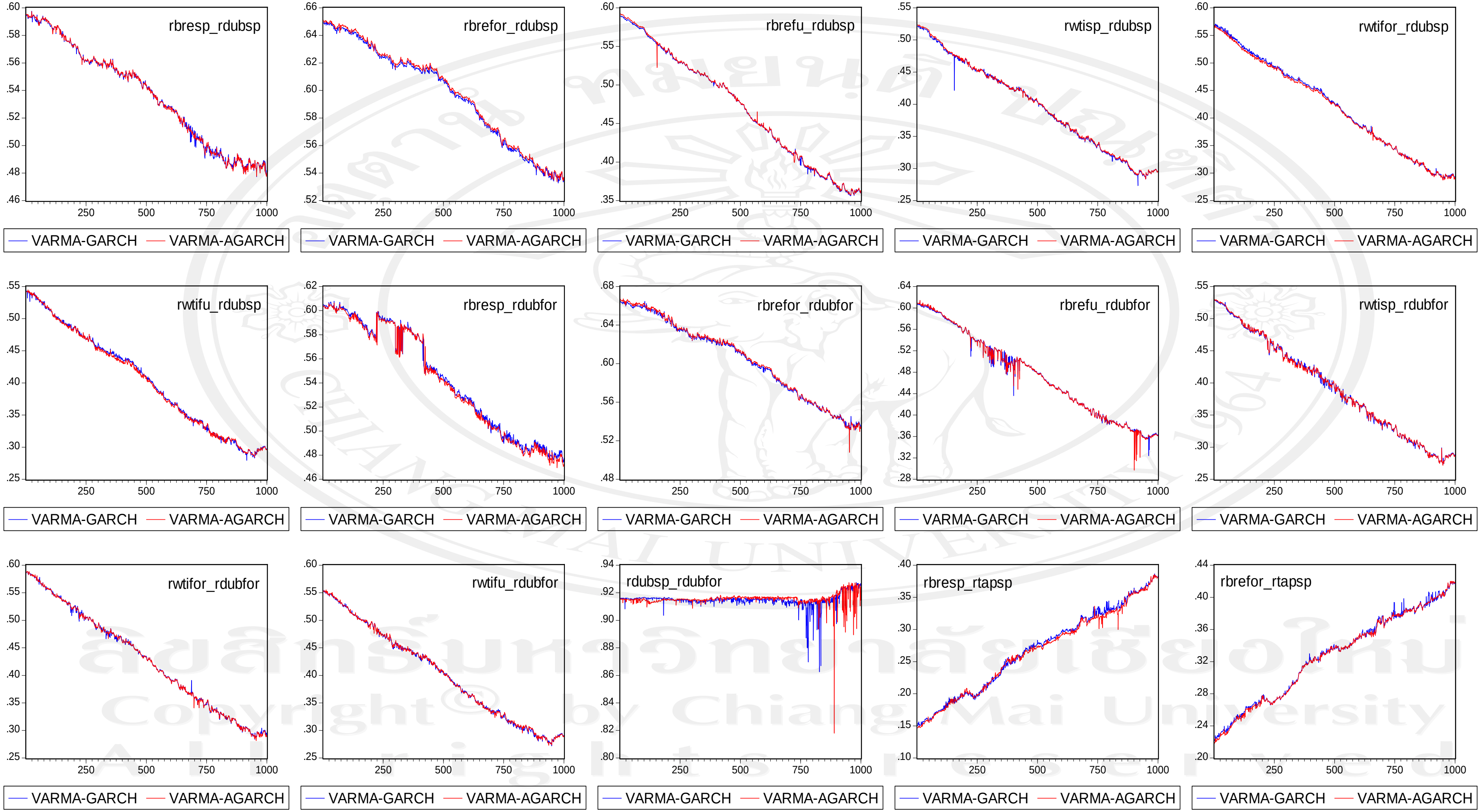
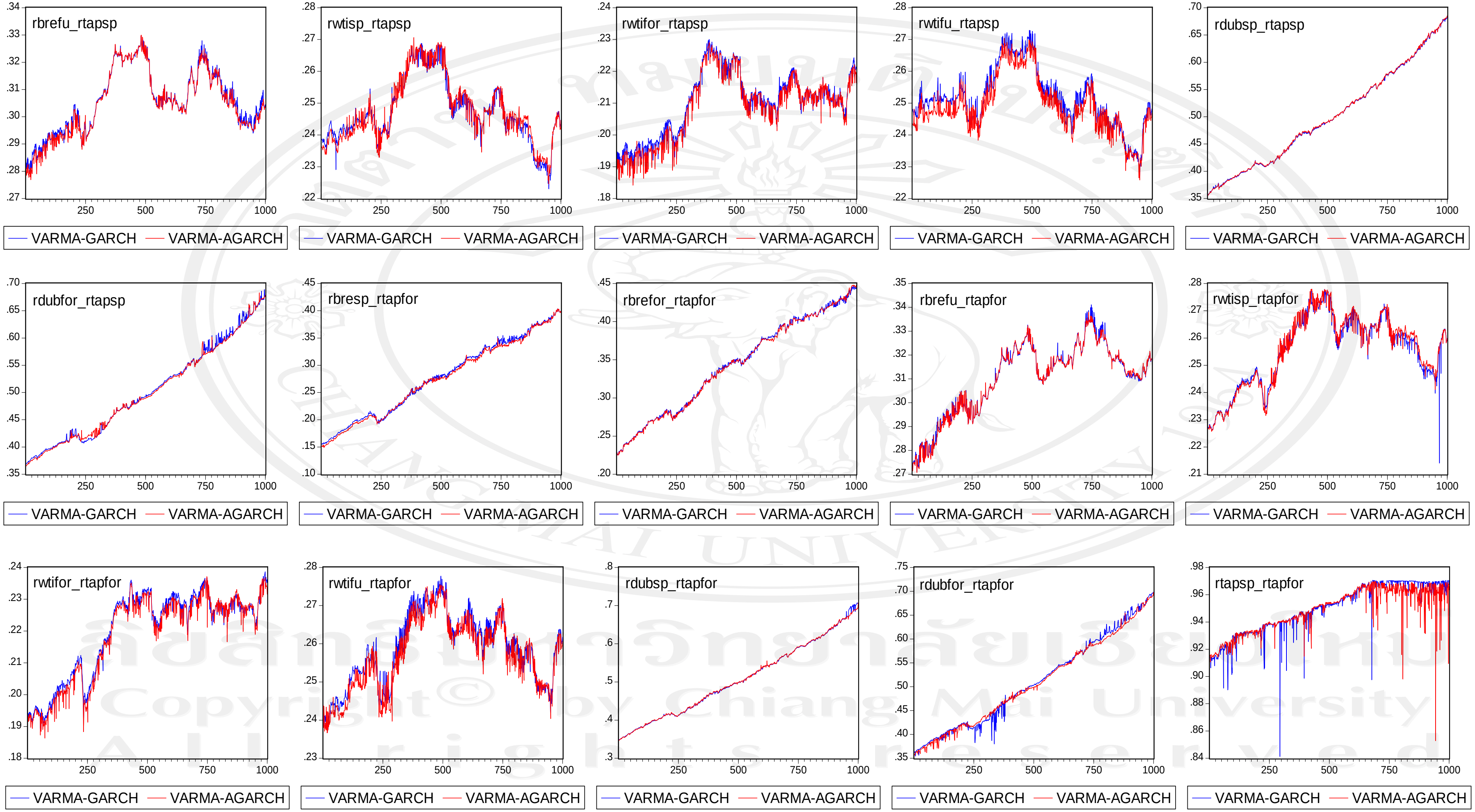


Figure 2: The forecast of conditional correlations between pair of returns resulted form the VARMA-GARCH and VARMA-AGARCH models (Continued)



of negative and positive shocks on conditional variance suggested that VARMA-AGARCH is superior to VARMA-GARCH and CCC models.

The estimated of the conditional variances based on the VARMA-GARCH and VARMA-AGARCH models reported in Table 7 suggest the presence of volatility spillovers between Brent and WTI returns, namely volatility spillovers from Brent futures returns to spot and Brent forward returns, from Brent spot returns to WTI spot returns, from WTI futures returns to Brent spot returns, and from WTI futures returns to Brent spot returns. In addition, the results show that most of the Dubai and Tapis returns have volatility spillover effects from Brent and WTI returns. These evidences are in agreement with the knowledge that the Brent and WTI markets are two "marker" crudes that set the crude oil prices and influence the other crude oil markets.

The conditional correlation forecasts are obtained from a rolling window technique. Figures 2 plots the dynamic paths of the conditional correlations from VARMA-GARCH and VARMA-AGARCH. All the conditional correlations display significant variability, which suggests that the correlation are positive for all pairs of crude oil returns, and rtapsp_rtapfor has the highest correlation, at 0.98. In addition, the conditional correlation forecasts of some pairs of crude oil returns exhibit an upward trend in 22 of 45 cases and a downward trend in 20 of 45 cases. These evidences should also be considered in diversifying a portfolio containing these assets.

5. Conclusion

The empirical analysis in the paper examined the spillover effect models in the returns on spot, forward and futures prices of four major benchmarks in the international oil market, namely West Texas Intermediate (USA), Brent (North Sea), Dubai/Oman (Middle East) and Tapis (Asia-Pacific) for the period 30 April 1997 to 10 November 2008. Alternative multivariate conditional volatility models were used, namely the CCC model of Bollerslev (1990), VARMA-GARCH of Ling and McAleer (2003) and VARMA-AGARCH of McAller et al (2009). Both the ARCH and GARCH estimates were significant for all returns in the ARMA(1,1)-GARCH(1,1) models. However, in case of the ARMA(1,1)-GJR(1,1) models, only GARCH estimates were statistically significant, and most of the estimates of the asymmetric effect are significant. Based on the asymptotic standard error, the VARMA(1,1)-GARCH(1,1) and VARMA-AGARCH models showed evidence of volatility spillovers and asymmetric effects of negative and positive shocks on conditional variance, which suggested that VARMA-AGARCH was superior to both VARMA-GARCH and CCC.

The paper also presented some volatility spillover effects from Brent and WTI returns, and from Brent and WTI crude oil markets to the Dubai and Tapis markets, which confirms that the Brent and WTI crude oil markets are the world reference for crude oil. The paper also compared 1-day ahead conditional correlation forecasts resulted from VARMA-GARCH and VARMA-AGARCH using rolling window approach, and showed that the conditional correlation forecast exhibited both upward trend and downward trend.

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