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Volatility Transmission in Crude Oil, Gold, Standard and Poor's 500 and US Dollar Index Futures using Vector Autoregressive-Multivariate Generalized Autoregressive Conditional Heteroskedasticity Model

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ABSTRACT

This paper examined volatility transmission in the crude oil, gold, S and P 500 and US Dollar Index futures. The data used in this study was the daily data from 2010 to 2015. The four vector autoregressive (VAR)-multivariate generalized autoregressive conditional heteroskedasticity models, namely the VAR (2)-diagonal VECH, the VAR (2)-diagonal Baba, Engle, Kraft and Kroner (BEKK), the VAR (2)-constant conditional correlations (CCC) and the VAR (2)-dynamic conditional correlation (DCC), were employed. The empirical results showed that the estimates of the VAR (2)-diagonal BEKK parameters were statistically significant in all cases. Later, the VAR (2)-diagonal VECH parameter were statistically significant in case of returns of crude oil (RCRUDE) with returns of gold futures (RGOLD), RGOLD with returns of Standard and Poor's 500 (S and P 500) futures (RSP) and RSP with returns of US Dollar Index (RUSD). At the same time the VAR (2)-CCC parameters were statistically significant in only case of RCRUDE with RGOLD. Finally, the VAR (2)-DCC were statistically significant in case of RCRUDE with RGOLD, RGOLD with RSP, RGOLD with RUSD and RSP with RUSD. In addition, we could conclude that the crude oil futures volatility was having an impact on the gold futures volatility, the gold futures volatility was having an impact on S and P 500 futures volatility, the gold futures volatility was having an impact on US Dollar Index futures volatility and S and P 500 futures volatility was having an impact on US Dollar Index futures volatility.

Keywords: Volatility Transmission, crude oil futures; gold futures; S&P 500 futures; US Dollar Index futures; VAR-MGARCH
JEL Classifications: C13, C32, G13

1. INTRODUCTION

Most investors pay attention and benefit from the relationships seen between the crude oil and other assets such as gold, Standard and Poor's 500 (S and P 500) and US Dollar. Mewati (2014) explain that crude oil, gold, stock prices and US Dollar are all asset prices with similar characteristics such as asset price inflation and momentum. They are significantly correlated with each other and with the business cycle. The price of all these assets as determined in the free markets is an important indicator of collective expectations of the future state of the world economy. Investors feel the future might be is reflected by the price of these assets. Let's look into the crude oil and gold in more detail.

The crude oil is the most important energy resource. An increase in the global oil prices affect the economy. The part of the crude oil futures is a contract between the buyer and seller in trading or exchange of crude oil by the price and quantity together today and pay the price in cash in the future. Later, gold is the most important store of value today and the most important components of the global economy since 1945. The value of gold remains fairly constant or increases overtime; it is hence used as an ideal hedge against inflation. People invest in gold because despite high inflation, its value does not depreciate. Increasing gold prices are a traditional indicator of a recession or a downturn in an economy. People run to the safety of gold when they think the value of other investments may go down in the future. The part of the gold futures is a tool that investors can make profit in both the price rise and the price down.

However, this paper we are interested in the relationship and volatility of the future prices of the assets. Due to the study in such matters is not much. And we understand quite a lot about crude oil and gold futures from above so we explain more S and P 500 and US Dollar Index futures as detailed below.

Investopedia (2014) explain that the S and P 500 contains many of the largest companies in the world, so it only makes sense that movement in the direction of the S and P 500 futures is one of the best indicators of overall short-term market direction. If S and P 500 futures are up, it is an indication that there is upward pressure on the market and the stock market will tend to rise. On the other hand, if S and P 500 futures are down, it is a sign that there is downward pressure on the market and it will likely trend lower. The main reason that S and P 500 futures are so popular for detecting strength is because this contract trades 24 h a day on financial exchanges around the world. It allows traders and brokers to gauge the futures level before the actual stock markets open for trading which gives a sense of where the market is likely trend at the start of trading. On the side of US Dollar Index is calculated by factoring in the exchange rates of six major world currencies: Euro, Japanese Yen, Canadian Dollar, British Pound, Swedish Krona and Swiss Franc. The changes in US Dollar Index affecting the crude oil, gold and S and P 500 futures prices.

From the above, it is the source of the study with the purpose is to analyze the volatility transmission in the crude oil, gold, S and P 500 and US Dollar Index futures by using vector autoregressive (VAR)-multivariate generalized autoregressive conditional heteroskedasticity (MGARCH), namely VAR-diagonal VECH, VAR-diagonal Baba, Engle, Kraft and Kroner (BEKK), VAR-constant conditional correlations (CCC) model and VAR-DCC and choose the best way for such analysis. In addition to see if the crude oil, gold, S and P 500 and US Dollar Index future returns do have an impact on each other, it could also be the case of the crude oil, gold, S and P 500 and US Dollar Index futures volatility having an impact on each other or not.

We can explain more in the next section, which is related to the literature reviews, research methodology and empirical results.

2. LITERATURE REVIEWS

In this section, we collect the research, which has been used VAR-MGARCH in detail below.

Ewing and Malik (2013) employ univariate and bivariate GARCH model to examine the volatility of gold and oil futures incorporating structural breaks using daily returns from July 1, 1993 to June 30, 2010. They find strong evidence of significant transmission of volatility between gold and oil returns when structural breaks in variance are accounted for in the model. Later Mensi et al. (2013) use a VAR-GARCH model to investigate the return links and volatility transmission between the S and P 500 and commodity prices indices for energy, food, gold and beverages over the turbulent period from 2000 to 2011. Understanding the price behavior of commodity prices and the volatility transmission mechanism between these markets and the stock exchanges are crucial for each participant, including governments, traders, portfolio managers, consumers and producers. For return and volatility spillovers, the results show significant transmission among the S and P 500 strongly influenced the oil and gold market. This study finds that the highest conditional correlations are between the S and P 500 and commodity markets. This study finds that the highest conditional correlations are between the S and P 500 and gold index and the S and P 500 and WTI index.

Look back to the conditional volatility of the oil price market. Selmi and Hachicha (2014) examine the role of oil prices, credit, financial and commercial linkages in the propagation of industrial market crisis during the period 2004-2012. They use VAR-DCC model and find that credit linkage played a significant role in the subprime, financial and global crises. As well as Bunnag (2015) examined comovements and spillovers in petroleum futures (crude oil, gasoline, heat oil and natural gas) using three MGARCH models, namely the VAR (1)-diagonal VECH, the VAR (1)-diagonal BEKK and the VAR (1)-CCC models. The empirical results overall showed that the estimates of the MGARCH parameters were statistically significant in almost all cases except in the case of gasoline with natural gas. This indicates that the short run persistence of shocks on the DCCs was greatest for crude oil with heat oil, while the largest long run persistence of shocks to the conditional correlations for crude oil with gasoline.

Finally, Bunnag (2015) examined the oil futures and the carbon emissions futures volatility comovements and spillovers for crude oil, gasoline and heat oil as well as carbon emissions. The data used in this study was the daily data from 2009 to 2014. The three MGARCH models, namely the VAR (3)-diagonal VECH, the VAR (3)-diagonal BEKK and the VAR (3)-CCC, were employed. The best model was the VAR (3)-diagonal BEKK model in volatility analysis of the oil futures and the carbon emissions futures returns. In addition, it could be concluded that oil futures volatility having an impact on carbon emissions futures volatility.

However, this study we use the VAR-MGARCH include VAR-diagonal VECH, VAR- diagonal BEKK, VAR-CCC and VAR-DCC model as detailed below.

3. RESEARCH METHODOLOGY

An important task is to model the conditional mean and conditional variances of the return series. The conditional mean comes from VAR which can display the source as follows:

3.1. VAR Model

Let $Y_t = (Y_{1t}, Y_{2t}, ..., Y_{nt})'$ denote a $k \times 1$ vector of crude oil, gold, S and P 500 and US Dollar Index futures return series variables. The basic VAR model of order p, VAR (p), is,

$$Y_t = c + \prod_t Y_{t-1} + \prod_2 Y_{t-2} + ... + \prod_p Y_{t-p} + \mu_t,\ t = 1, \ldots T \quad (1)$$

Where, Π_t are $k \times k$ matrices of coefficients, c is a $k \times 1$ vector of constants and μ_t is an $k \times 1$ unobservable zero mean white noise vector process with covariance matrix Σ.

As in the univariate case with AR processes, we can use the lag operator to represent VAR (p)

$\Pi(L)Y_t = c + \mu_t$,

Where, $\Pi(L) = I_n - \Pi_1 L - \ldots - \Pi_p L^p$

If we impose stationarity on Y_t in (1), the unconditional expected value is given by,

$\mu = (I_n - \Pi_1 - \ldots - \Pi_p)^{-1} c$

Lag length selection: A reasonable strategy how to determine the lag length of the VAR model is to fit VAR (p) models with different orders $p = 0,\ldots p_{max}$ and choose the value of p which minimizes some model selection criteria. Model selection criteria for VAR (p) could be base on Akaike information criteria (AIC), Schewarz-Bayesian information criteria (SIC) and Hannan-Quinn (HQ) information criteria (Kozhan, 2010).

And for the conditional variances come from MGARCH which can show the source, according to the following details:

3.2. MGARCH Models

The basic idea to extend univariate GARCH models to MGARCH models is that it is significant to predict the dependence in the comovement of the crude oil, gold, S and P 500 and US Dollar Index futures returns. To recognize this feature through a multivariate model would generate a more reliable model than separate univariate models.

In the first place, one should consider what specification of a MGARCH model should be imposed. On the one hand, it should be flexible enough to state the dynamics of the conditional variances and covariances. On the other hand, as the number of parameters in a MGARCH model increase rapidly along with the dimension of the model, the specification should be parsimonious to simplify the model estimation and also reach the purpose of easy interpretation of the model parameters. However, parsimony may reduce the number of parameters, in which situation the relevant dynamics in the covariance matrix cannot be captured. So it is important to get balance between the parsimony and the flexibility when designing the MGARCH model specification. Another feature that MGARCH models must satisfy is that the covariance matrix should be positive definite.

Several different MGARCH model formulations have been proposed in the literature, and the most popular of these are the diagonal VECH, the diagonal BEKK, CCC and DCC models. Each of these is discussed briefly in turn below; for a more detailed discussion, see Kroner and Ng (1998) as well as Engle (2002).

3.3. The Diagonal VECH Model

The first MGARCH model was introduced by Bollerslev et al. in 1988, which is called VECH model. It is much general compared to the subsequent formulations. In the VECH model, every conditional variance and covariance is a function of all lagged conditional variances and covariances, as well as lagged squared returns and cross-products of returns. The model can be expressed below:

$$VECH(H_t) = c + \sum_{j=1}^{q} A_j VECH(\varepsilon_{t-j}\varepsilon'_{t-j}) + \sum_{j=1}^{p} B_j VECH(H_{t-j}) \quad (2)$$

Where, $VECH(H_t)$ is an operator that stacks the columns of the lower triangular part of its argument square matrix, H_t is the covariance matrix of the residuals, N presents the number of variables, t is the index of the t^{th} observation, c is an $\frac{N(N+1)}{2} \times 1$ vector, A_j and B_j are $\frac{N(N+1)}{2} \times \frac{N(N+1)}{2}$ parameter matrices and ε is an $N \times 1$ vector.

The condition for H_t is to be positive definite for all t is not restrictive. In addition, the number of parameters equals to $(p+q) \times \left(\frac{N(N+1)}{2}\right)^2 + \frac{N(N+1)}{2}$, which is large. Furthermore, it demands a large quantity of computation.

The diagonal VECH model, the restricted version of VECH, was also proposed by Bollerslev, et al. (1988). It assumes the A_j and B_j in Equation (2) are diagonal matrices, which makes it possible for H_t to be positive definite for all t. Also, the estimation process proceeds much smoothly compared to the complete VECH model. However, the diagonal VECH model with $(p+q+1) \times N \times \frac{(N+1)}{2}$ parameters is too restrictive since it does not take into account the interaction between different conditional variances and covariances.

3.4. The Diagonal BEKK Model

To ensure positive definiteness, a new parameterization of the conditional variance matrix H_t was defined by Baba et al. (1990) and became known as the BEKK model, which is viewed as another restricted version of the VECH model. It achieves the positive definiteness of the conditional variance by formulating the model in a way that is property is implied by model structure.

The form of the BEKK model is as follows:

$$H_t = CC' + \sum_{j=1}^{q}\sum_{k=1}^{K} A'_{kj}\varepsilon_{t-j}\varepsilon'_{t-j}A_{kj} + \sum_{j=1}^{p}\sum_{k=1}^{K} B'_{kj}H_{t-j}B_{kj} \quad (3)$$

Where, A_{kj}, B_{kj} and C are $N \times N$ parameter matrices, and C is a lower triangular matrix. The purpose of decomposing the constant term into a product of two triangle matrices is to guarantee the positive semi-definiteness of H_t. Whenever $K > 1$, an identification problem would be generated for the reason that there are not only single parameterizations that can obtain the same representation of the model.

The first order BEKK model is,

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \quad (4)$$

The BEKK model also has its diagonal form by assuming A_{kj}, B_{kj} matrices are diagonal. It is a restricted version of the diagonal VECH model. The most restricted version of the diagonal BEKK model is the scalar BEKK one with $A = aI$ and $B = bI$ where a and b are scalars.

Estimation of a BEKK model still bears large computations due to several matrix transpositions. The number of parameters of the complete BEKK model is $(p+q)KN^2 + \frac{N(N+1)}{2}$. Even in the diagonal one, the number of parameters soon reduces to $(p+q)KN + \frac{N(N+1)}{2}$, but it is still large. The BEKK form is not linear in parameters, which makes the convergence of the model difficult. However, the strong point lies in that the model structure automatically guarantees the positive definiteness of H_t. Under the overall consideration, it is typically assumed that $p = q = K = 1$ in BEKK form's application.

3.5. The CCC Model

The CCC model was introduced by Bollerslev in 1990 to primarily model the condition covariance matrix indirectly by estimating the conditional correlation matrix. The conditional correlation is assumed to be constant while the conditional variances are varying.

Consider the CCC model of Bollerslev (1990):

$$y_t = E\langle y_t | F_{t-1}\rangle + \varepsilon_t \quad , \quad \varepsilon_t = D_t \eta_t \tag{5}$$

$$\text{var}\langle \varepsilon_t | F_{t-1}\rangle = D_t \Gamma D_t$$

Where, $y_t = \left(y_{1t,...,}y_{mt}\right)'$, $\eta_t = \left(\eta_{1t,...,}\eta_{mt}\right)'$ is a sequence of independently and identically distributed random vectors, F_t is the past information available at time t, $D_t = diag\left(h_t^{1/2},...,h_m^{1/2}\right)$, m is the number of returns, and $t=1,\ldots,n$. As $\Gamma = E\langle \eta_t \eta_t' | F_{t-1}\rangle = E\left(\eta_t \eta_t'\right)$, where $\Gamma = \left\{\rho_{ij}\right\}$ for $i, j = 1,\ldots m$ the CCC matrix of the unconditional shocks, η_t, is equivalent to the constant conditional covariance matrix of the conditional shocks, ε_t, from (5), $\varepsilon_t \varepsilon_t' = D_t \eta_t \eta_{t-1}' D_t$, $D_t = \left(diag\ Q_t\right)^{1/2}$, and $E\langle \varepsilon_t \varepsilon_{t-1}' | F_{t-1}\rangle = Q_t = D_t \Gamma D_t$ where Q_t is the conditional covariance matrix.

The CCC model assumes that the conditional variance for each return $h_{it}, i = 1,...,m$, follows a univariate GARCH process, that is,

$$h_t = \omega_t + \sum_{j=1}^{r} \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^{s} \beta_{ij} h_{i,t-j} \tag{6}$$

Where, α_{ij} represents the ARCH effect, or short run persistence of shocks to return i, β_{ij} represents the GARCH effect, and $\sum_{j=1}^{r}\alpha_{ij} + \sum_{j=1}^{s}\beta_{ij}$ denotes the long run persistence.

3.6. The DCC Model

DCC model was introduced by Engle (2002) as detailed below:

$$H_t = D_t R_t D_t \tag{7}$$

Where, R_t is the conditional correlation matrix of the return vector $r_t = (r_{1t},....r_{nt})'$. Otherwise, the correlation matrix R_t can be indicated as:

$$R_t = diag\,(Q_t)^{-1} Q_t diag\,(Q_t)^{-1} \tag{8}$$

Where, $$Q_t = (1-\theta_1-\theta_2)\bar{Q} + \theta_1(\eta_{t-1}\eta_{t-1}') + \theta_2 Q_{t-1} \tag{9}$$

In which θ_1 and θ_2 are scalar parameters to capture the effects of previous shocks and previous DCCs on the current DCC, and θ_1 and θ_2 are non-negative scalar parameters satisfying $\theta_1 + \theta_2 < 1$, which implies that $Q_t > 0$. When $\theta_1 = \theta_2 = 0$, Q_t in Equation (9) is equivalent to CCC. As Q_t is conditional on the vector of standardized residuals, Equation (9) $\bar{Q}_t$ is a conditional covariance matrix and is the $k \times k$ unconditional variance matrix of ηt. DCC is not linear, but may be estimated simply using a two-step method based on the likelihood function, the first step being a series of univariate GARCH estimates and the second step being the correlation estimates (Chang et al., 2011).

3.7. Model Estimation for MGARCH

Under the assumption of conditional normality, the parameters of the MGARCH models of any of the above specifications can be estimated by maximizing the log-likelihood function.

$$\ell(\theta) = -\frac{TN}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{T}(\log|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t) \tag{10}$$

Where, θ denotes all the unknown parameters to be estimated, N is the number of the crude oil, gold, S and P 500 and US Dollar Index futures prices and T is the number of observations and all other notation is as above. The maximum-likelihood estimates for θ is asymptotically normal, and thus traditional procedures for statistical inference are applicable. However, when the process is not normal or the conditional distribution is not perfectly known, one may still use Gaussian maximum likelihood methods due to the property of asymptotic parameter efficiency. Such estimates are known as quasi-maximum likelihood (QMLE). The QMLE is consistent and asymptotically normal if $E(\varepsilon_t^2) < \infty$. The QMLE estimates are in general less precise than those from the maximum-likelihood. We can see more details from Ling and McAleer (2003) as well as Fabozzi et al. (2007).

4. DATA

The data used in this study is the daily data from January 4, 2010 to April 16, 2015. We will get 1348 observations. The data is derived from www.investing.com which trade in Chicago Mercantile Exchange. Moreover, data analysis can be carried out using EVIEWS 8. The crude oil, gold, S and P 500 and US Dollar Index futures return is defined as:

$$R_t = \log\left(\frac{FP_t}{FP_{t-1}}\right) \tag{11}$$

Where, FP_t is the crude oil, gold, S and P 500 and US Dollar Index futures price at time t and FP_{t-1} is the crude oil, gold, S and P 500 and US Dollar Index futures price at time $t-1$. The R_t of Equation (11) will be used in observing the volatility of the crude oil, gold, S and P 500 and US Dollar Index futures over the period 2010 to 2015. We can create the variables of the return on the crude oil, gold, S and P 500 and US Dollar Index futures as follows:

The returns of crude oil futures = RCRUDE, the returns of gold futures = RGOLD, the returns of S and P 500 futures = RSP and the returns of US Dollar Index futures = RUSD

In addition, we can show the movement of the daily crude oil, gold, S and P 500 and US Dollar Index futures prices and returns according to Figures 1 and 2.

The descriptive statistics are given in Table 1. The daily future returns of crude oil (RCRUDE) display the greatest variability with the mean of −0.0269%, a maximum of 8.94%, and a minimum of −9.03%. Furthermore, the skewness, the kurtosis and the Jarque-Bera Lagrange multiplier statistics of crude oil, gold, S and P 500, US Dollar Index futures returns are statistically significant, thereby implying that the distribution is not normal.

Figure 1: The daily crude oil, gold, S and P 500 and US Dollar Index futures prices

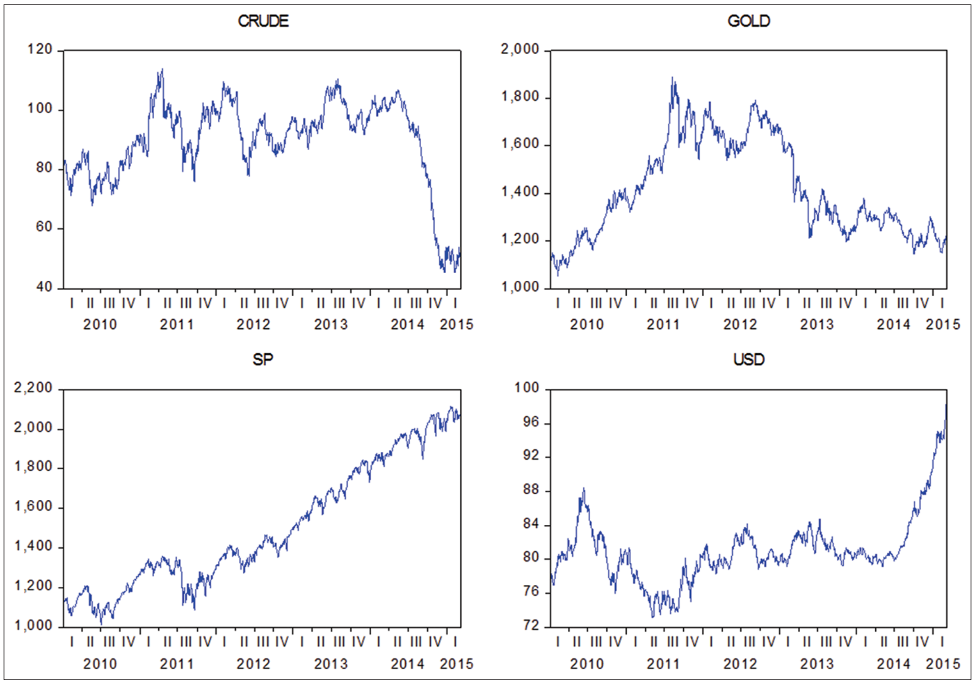
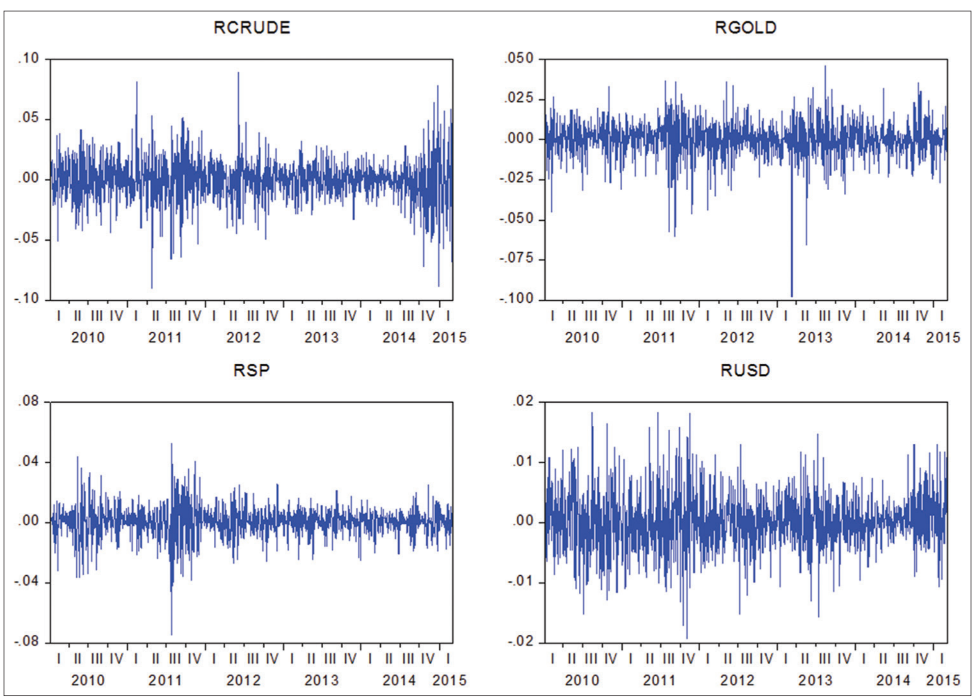


Figure 2: The daily crude oil, gold, S and P 500 and US Dollar Index futures returns



Beside, the return series will be used to construct the conditional mean and the conditional variances in next.

5. UNIT ROOT TESTS

Standard econometric practice in the analysis of financial time series data begins with an examination of unit roots. The augmented Dickey-Fuller and Phillips-Perron tests are used to test for crude oil, gold, S and P 500 and US Dollar Index futures returns under the null hypothesis of a unit root against the alternative hypothesis of stationarity. The results from unit root tests are presented in Table 2. The tests yield negative values in almost cases for levels, such that the individual returns series reject the null hypothesis at the 1% significance level, so that all returns are stationary.

6. EMPIRICAL RESULTS

Before we construct the conditional mean, the first thing to do is to find the right lag of VAR model as shown in Table 3. From the various criterions are found to be selected lag that 2 and 1. Most of them will choose lag 2. We therefore conclude that lag 2 should be suitable for the conditional mean.

Therefore, the appropriate multivariate conditional volatility model given as VAR (2)-diagonal VECH, VAR (2)-diagonal BEKK, VAR (2)-CCC and VAR (2)-DCC models is estimated.

After all multivariate conditional volatility models in this paper are already estimated. The next step, we will have to explain that the results of each model and select the best model.

The VAR (2)-diagonal VECH estimates of the conditional correlation between the volatilities of the crude oil, gold, S and P 500, US Dollar Index futures returns base on estimating the univariate GARCH (1,1) model for crude oil, gold, S and P 500 and US Dollar Index futures are given in Table 4. The estimates of the VAR (2)-diagonal VECH parameters that θ_1 and θ_2 are statistically significant in the case of $\rho_{(RCR.\_RSP.)}$, $\rho_{(RCR.\_RUS.)}$ and $\rho_{(RSP.\_RSP.)}$. except in the case of $\rho_{(RCR.\_RSP.)}$, $\rho_{(RCR.\_RUS.)}$ and $\rho_{(RCR.\_RUS.)}$. This indicates that the short run persistence of shocks on the DCCs is greatest for RCRUDE with returns of gold futures (RGOLD) at 0.045 (θ_1), while the largest long run persistence of shocks to the conditional correlations is 0.983 ($\theta_1 + \theta_2$) for RCRUDE with RGOLD also.

The VAR (2)-diagonal BEKK estimates of the conditional correlation between the volatilities of the crude oil, gold, S and P 500, US Dollar Index futures returns are given in Table 5.

The estimates of the diagonal BEKK parameters that θ_1 and θ_2 are statistically significant in all cases. This indicates that the short run persistence of shocks on the DCCs is greatest at 0.047 for returns of S and P 500 futures (RSP) with RUSD, while the largest long run persistence of shocks to the conditional correlations is 0.994 ($\theta_1 + \theta_2$) for RCRUDE with RUSD.

Later, in Table 6 presents the estimates for the VAR (2)-CCC model, with $p = q = r = s = 1$. The ARCH and GARCH estimates of the conditional variance between the crude oil, gold, S and P 500 and US Dollar Index futures returns are statistically significant in all cases. The ARCH (α) estimates are generally small (<0.2), and the GARCH (β) estimates are generally high (more than 0.7) and close to one. Therefore, the long run persistence (α + β), is generally to one, indicating a near long memory process. This indicates a near long memory process. In addition, since $\alpha + \beta < 1$, crude oil, gold, S and P 500 and US Dollar Index satisfies the second moment and log-moment condition, which is a sufficient condition for the QMLE to be consistent and asymptotically normal. The VAR (2)-CCC estimates of the CCC between RCRUDE and RGOLD with the highest in 0.274. This indicates that the standardized shock on the CCC for RCRUDE with RGOLD is 0.274.

Finally, in Table 7 presents the estimates for the VAR (2)-DCC model, with $p = q = r = s = 1$. The ARCH and GARCH estimates of the conditional variance between the crude oil, gold, S and P 500 futures and US Dollar Index returns are statistically significant in all cases. The ARCH (α) estimates are generally small (<0.2), and the GARCH (β) estimates are generally high (more than 0.8) and close to one. Therefore, the long run persistence (α + β), is

Table 1: Descriptive statistics

Returns	RCRUDE	RGOLD	RSP	RUSD
Mean	−0.000269	4.81E-05	0.000456	0.000186
Median	0.000110	0.000352	0.000728	0.000125
Maximum	0.0894	0.0460	0.0530	0.0184
Minimum	−0.0903	−0.0982	−0.0749	−0.0192
SD	0.0181	0.0113	0.0100	0.0047
Skewness	−0.1022	−0.9862	−0.4738	0.1804
Kurtosis	5.7067	9.7942	7.9447	4.2321
Jarque-Bera	413.8561	2811.3130	1423.7580	92.5953

RCRUDE: Returns of crude oil futures, RGOLD: Returns of gold futures, RSP: Returns of S and P 500 futures, RUSD: Returns of US Dollar index futures, SD: Standard deviation

Table 2: Unit root tests

Returns	ADF test				PP test			
	Constant		Constant and trend		Constant		Constant and trend	
	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)
RCRUDE	−38.334***	−19.200***	−38.373***	−19.193***	−38.335***	−810.341***	−38.370***	−1079.294
RGOLD	−38.086***	−24.238***	−38.146***	−24.229***	−38.100***	−474.610***	−38.187***	−474.869***
RSP	−39.425***	−16.679***	−39.416***	−16.674***	−40.069***	−568.228***	−40.070***	−567.724***
RUSD	−36.547***	−18.612***	−36.583***	−18.605***	−36.548***	−333.392***	−36.582***	−400.487***

***Denote significance at the 1% level. RCRUDE: Returns of crude oil futures, RGOLD: Returns of gold futures, RSP: Returns of S and P 500 futures, RUSD: Returns of US Dollar index futures, ADF: Augmented Dickey-Fuller, PP: Phillips-Perron generally to one, indicating a near long memory process. This indicates a near long memory process. In addition, since $\alpha + \beta < 1$, all cases satisfy the second moment and log-moment condition, which are a sufficient condition for the QMLE to be consistent and asymptotically normal. The estimates of the VAR (2)-DCC parameters that θ_1 and θ_2 are statistically significant in the case of $\rho_{(RCR.\_RGO.)}$, $\rho_{(RGO.\_RSP.)}$, $\rho_{(RGO.\_RUS.)}$ and $\rho_{(RCR.\_RSP.)}$ except in the case of $\rho_{(RCR.\_RSP.)}$ and $\rho_{(RCR.\_RUS.)}$. This indicates that the short run persistence of shocks on the DCCs is greatest for RCRUDE with RGOLD at 0.044 (θ_1), while the largest long run persistence of shocks to the DCCs is 0.980 ($\theta_1 + \theta_2$) for RGOLD with RUSD.

Furthermore, we will choose the best model next by considering the value of log-likelihood, AIC, SIC and HQ. From the Tables 4-7, we found that the VAR (2)-diagonal VECH model is highest log-likelihood and lowest AIC equal 17790.96 and −26.337, respectively. But the VAR (2)-DCC has SIC and HQ lowest is equal −26.201 and −26.272, respectively. Thus, it can be concluded that we should choose the VAR (2)-diagonal VECH and VAR (2)-DCC model in volatility analysis of the crude oil, gold, S and P 500 and US Dollar Index futures returns.

However, we can show the movement of the conditional covariance and the conditional correlation of the crude oil, gold, S and P 500 and US Dollar Index futures returns in each model according to Figures 3-8, respectively.

Table 3: Lag order selection

Lag	LR	FPE	AIC	SIC	HQ
0	NA	9.11e-17	−25.582	−25.567*	−25.576
1	111.151	8.59e-17	−25.642	−25.564	−25.613*
2	59.563*	8.41e-17*	−25.663*	−25.523	−25.610
3	18.688	8.49e-17	−25.653	−25.451	−25.577
4	25.718	8.53e-17	−25.648	−25.384	−25.549
5	18.068	8.62e-17	−25.638	−25.312	−25.516
6	15.459	8.72e-17	−25.626	−25.238	−25.481
7	15.402	8.83e-17	−25.614	−25.164	−25.445
8	19.819	8.91e-17	−25.605	−25.093	−25.413

*Indicates lag order selected. LR: Sequential modified LR test statistic, FPE: Final prediction error, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

Table 4: VAR (2) – diagonal VECH model estimates

VAR (2)	RCR.	RGO.	RSP.	RUS.	$\rho_{(RCR.\_RGO.)}$	$\rho_{(RCR.\_RSP.)}$	$\rho_{(RCR.\_RUS.)}$	$\rho_{(RGO.\_RSP.)}$	$\rho_{(RGO.\_RUS.)}$	$\rho_{(RSP.\_RUS.)}$
Constant	0.0001	0.0001	0.0008***	0.0002*	-	-	-	-	-	-
	(0.0004)	(0.0002)	(0.0002)	(0.0001)						
RCR. (−1)	−0.045	−0.012	0.057***	−0.004	-	-	-	-	-	-
	(0.028)	(0.017)	(0.011)	(0.006)						
RCR. (−2)	0.023	0.014	0.086***	−0.012*	-	-	-	-	-	-
	(0.029)	(0.016)	(0.011)	(0.006)						
RGO. (−1)	0.012	−0.023	0.030*	−0.013	-	-	-	-	-	-
	(0.040)	(0.032)	(0.018)	(0.010)						
RGO. (−2)	0.065*	−0.021	0.029*	0.007	-	-	-	-	-	-
	(0.036)	(0.030)	(0.015)	(0.010)						
RSP. (−1)	−0.001	0.014	−0.076**	−0.017	-	-	-	-	-	-
	(0.047)	(0.027)	(0.031)	(0.013)						
RSP. (−2)	−0.103*	0.007	0.001	−0.008	-	-	-	-	-	-
	(0.053)	(0.032)	(0.027)	(0.012)						
RUS. (−1)	−0.172*	0.050	−0.0003	−0.008	-	-	-	-	-	-
	(0.098)	(0.060)	(0.046)	(0.030)						
RUS. (−2)	−0.173*	−0.051	0.053	0.008	-	-	-	-	-	-
	(0.093)	(0.062)	(0.048)	(0.031)						
ω (constant)	2.20E-06***	2.58E-06***	4.15E-06***	9.48E-08**	-	-	-	-	-	-
	(8.69E-07)	(5.41E-07)	(8.44E-07)	(3.88E-08)						
α	0.057***	0.047***	0.160***	0.036***	-	-	-	-	-	-
	(0.008)	(0.004)	(0.006)	(0.007)						
β	0.938***	0.932***	0.796***	0.959***	-	-	-	-	-	-
	(0.008)	(0.005)	(0.023)	(0.007)						
α+β	0.995	0.979	0.956	0.995	-	-	-	-	-	-
θ_0 (constant)	-	-	-	-	8.26E-07**	−4.55E-08	1.20E-08	−1.17E-07	−1.02E-07	−4.93E-08
					(4.09E-07)	(1.21E-07)	(2.09E-08)	(1.37E-07)	(1.71E-07)	(1.27E-07)
θ_1	-	-	-	-	0.045***	0.010	0.003	0.026**	−0.008	−0.043**
					(0.007)	(0.009)	(0.004)	(0.013)	(0.012)	(0.019)
θ_2	-	-	-	-	0.938***	0.964***	0.989***	0.940***	0.909***	0.860***
					(0.010)	(0.027)	(0.011)	(0.025)	(0.109)	(0.096)
$\theta_1+\theta_2$	-	-	-	-	0.983	0.974	0.992	0.966	0.901	0.817
Log-likelihood	17790.96									
AIC	−26.337									
SIC	−26.082									
HQ	−26.241									

Note: Standard error in parenthesis, ***,**,*Denotes significance at the 1%, 5% and 10% respectively, RCR.: Returns of crude oil future, RGO.: Returns of gold future, RSP.: Returns of S and P 500 future, RUS.: Returns of US Dollar index future, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

Table 5: VAR (2) – diagonal BEKK model estimates

VAR (2)	RCR.	RGO.	RSP.	RUS.	$\rho_{(RCR.\_RGO.)}$	$\rho_{(RCR.\_RSP.)}$	$\rho_{(RCR.\_RUS.)}$	$\rho_{(RGO.\_RSP.)}$	$\rho_{(RGO.\_RUS.)}$	$\rho_{(RSP.\_RUS.)}$
Constant	0.0002	0.0001	0.0008***	0.0001	-	-	-	-	-	-
	(0.0004)	(0.0002)	(0.0002)	(0.0001)						
RCR. (−1)	−0.058**	−0.019	0.060***	−0.005	-	-	-	-	-	-
	(0.027)	(0.016)	(0.011)	(0.006)						
RCR. (−2)	0.023	0.015	0.085***	−0.010	-	-	-	-	-	-
	(0.027)	(0.016)	(0.011)	(0.006)						
RGO. (−1)	0.019	−0.022	0.028	−0.010	-	-	-	-	-	-
	(0.036)	(0.030)	(0.018)	(0.010)						
RGO. (−2)	0.070**	−0.015	0.025*	0.005	-	-	-	-	-	-
	(0.035)	(0.029)	(0.014)	(0.010)						
RSP. (−1)	0.005	0.021	−0.079***	−0.013	-	-	-	-	-	-
	(0.045)	(0.027)	(0.029)	(0.012)						
RSP. (−2)	−0.116**	0.006	−0.004	−0.009	-	-	-	-	-	-
	(0.049)	(0.030)	(0.025)	(0.011)						
RUS. (−1)	−0.168*	0.053	0.009	0.007	-	-	-	-	-	-
	(0.096)	(0.059)	(0.044)	(0.028)						
RUS. (−2)	−0.189**	−0.036	0.053	0.001	-	-	-	-	-	-
	(0.090)	(0.061)	(0.048)	(0.028)						
ω (constant)	1.77E-06***	4.15E-06***	4.12E-06***	8.83E-08***	-	-	-	-	-	-
	(4.76E-07)	(6.89E-07)	(7.37E-07)	(3.32E-08)						
α^2	0.042***	0.048***	0.115***	0.019***	-	-	-	-	-	-
β^2	0.955***	0.920***	0.840***	0.977***	-	-	-	-	-	-
$\alpha^2+\beta^2$	0.997	0.968	0.955	0.996	-	-	-	-	-	-
θ_0 (constant)					9.01E-07**	−5.14E-08	3.51E-08	8.74E-08	1.30E-08	−2.74E-08
					(2.81E-07)	(3.40E-07)	(6.07E-08)	(2.71E-07)	(6.59E-08)	(8.63E-08)
θ_1					0.045***	0.070***	0.028***	0.075***	0.030***	0.047***
θ_2					0.938***	0.895***	0.966***	0.879***	0.948***	0.906***
$\theta_1+\theta_2$					0.983	0.965	0.994	0.954	0.978	0.953
Log-likelihood	17724.76									
AIC	−26.256									
SIC	−26.047									
HQ	−26.178									

Note: Standard error in parenthesis, ***,**,*Denotes significance at the 1%, 5% and 10% respectively, RCR.: Returns of crude oil future, RGO.: Returns of gold future, RSP.: Returns of S and P 500 future, RUS.: Returns of US Dollar index future, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion, BEKK: Baba, Engle, Kraft and Kroner

Table 6: VAR (2) – CCC model estimates

VAR (2)	RCR.	RGO.	RSP.	RUS.	$\rho_{(RCR.\_RGO.)}$	$\rho_{(RCR.\_RSP.)}$	$\rho_{(RCR.\_RUS.)}$	$\rho_{(RGO.\_RSP.)}$	$\rho_{(RGO.\_RUS.)}$	$\rho_{(RSP.\_RUS.)}$
Constant	0.0001	0.0002	0.0008***	0.0001*	-	-	-	-	-	-
	(0.0004)	(0.0002)	(0.0002)	(0.0001)						
RCR. (−1)	−0.039	−0.008	0.061***	−0.003	-	-	-	-	-	-
	(0.030)	(0.017)	(0.011)	(0.006)						
RCR. (−2)	0.013	0.006	0.080***	−0.012*	-	-	-	-	-	-
	(0.028)	(0.017)	(0.011)	(0.006)						
RGO. (−1)	0.008	−0.013	0.025	−0.012	-	-	-	-	-	-
	(0.042)	(0.035)	(0.018)	(0.011)						
RGO. (−2)	0.079**	−0.018	0.028*	0.007	-	-	-	-	-	-
	(0.038)	(0.031)	(0.015)	(0.011)						
RSP. (−1)	−0.0002	0.030	−0.076**	−0.016	-	-	-	-	-	-
	(0.050)	(0.028)	(0.031)	(0.013)						
RSP. (−2)	−0.121**	−0.011	−0.005	−0.009	-	-	-	-	-	-
	(0.054)	(0.032)	(0.027)	(0.012)						
RUS. (−1)	−0.159	0.099*	0.003	−0.006	-	-	-	-	-	-
	(0.099)	(0.061)	(0.046)	(0.030)						
RUS. (−2)	−0.155*	−0.056	0.073	0.003	-	-	-	-	-	-
	(0.092)	(0.061)	(0.049)	(0.031)						
ω (constant)	2.21E-06**	3.85E-06***	4.19E-06***	8.95E-08**	-	-	-	-	-	-
	(8.87E-07)	(7.59E-07)	(8.53E-07)	(3.65E-08)						
α	0.061***	0.056***	0.162***	0.037***	-	-	-	-	-	-
	(0.010)	(0.005)	(0.020)	(0.015)						

(Cond...)

Table 6: *(Continued...)*

VAR (2)	RCR.	RGO.	RSP.	RUS.	$\rho_{(RCR.\_RGO.)}$	$\rho_{(RCR.\_RSP.)}$	$\rho_{(RCR.\_RUS.)}$	$\rho_{(RGO.\_RSP.)}$	$\rho_{(RGO.\_RUS.)}$	$\rho_{(RSP.\_RUS.)}$
β	0.935***	0.914***	0.795***	0.959***	-	-	-	-	-	-
	(0.010)	(0.008)	(0.022)	(0.007)						
α+β	0.996	0.970	0.957	0.996	-	-	-	-	-	-
Constant conditional	-	-	-	-	0.274***	0.041	−0.022	−0.009	−0.043	−0.028
correlation					(0.021)	(0.027)	(0.028)	(0.026)	(0.029)	(0.028)
Log-likelihood	17748.62									
AIC	−26.292									
SIC	−26.083									
HQ	−26.213									

Note: Standard error in parenthesis, ***,**,*Denotes significance at the 1%, 5% and 10% respectively, RCR.: Returns of crude oil future, RGO.: Returns of gold future, RSP.: Returns of S and P 500 future, RUS.: Returns of US Dollar index future, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQ: Hannan-Quinn information criterion, CCC: Constant conditional correlations

Table 7: VAR (2) – DCC model estimates

VAR (2)	RCR.	RGO.	RSP.	RUS.	$\rho_{(RCR.\_RGO.)}$	$\rho_{(RCR.\_RSP.)}$	$\rho_{(RCR.\_RUS.)}$	$\rho_{(RGO.\_RSP.)}$	$\rho_{(RGO.\_RUS.)}$	$\rho_{(RSP.\_RUS.)}$
Constant	−0.0003	1.86E-05	0.0005**	0.0001	-	-	-	-	-	-
	(0.0004)	(0.0003)	(0.0002)	(0.0001)						
RCR. (−1)	−0.049*	0.001	0.150***	−0.005	-	-	-	-	-	-
	(0.028)	(0.017)	(0.015)	(0.007)						
RCR. (−2)	−0.011	−0.007	0.092***	−0.0007	-	-	-	-	-	-
	(0.029)	(0.018)	(0.015)	(0.007)						
RGO. (−1)	−0.004	−0.036	−0.041*	−0.019*	-	-	-	-	-	-
	(0.044)	(0.028)	(0.023)	(0.011)						
RGO. (−2)	0.106**	−0.008	0.023	−0.023**	-	-	-	-	-	-
	(0.044)	(0.028)	(0.023)	(0.011)						
RSP. (−1)	0.018	0.035	−0.125***	−0.019	-	-	-	-	-	-
	(0.050)	(0.031)	(0.026)	(0.013)						
RSP. (−2)	−0.099**	0.004	0.032	−0.013	-	-	-	-	-	-
	(0.049)	(0.031)	(0.026)	(0.012)						
RUS. (−1)	−0.120	−0.066	0.081	0.006	-	-	-	-	-	-
	(0.105)	(0.066)	(0.056)	(0.027)						
RUS. (−2)	−0.068	0.070	−0.087	0.003	-	-	-	-	-	-
	(0.105)	(0.061)	(0.055)	(0.027)						
ω (constant)	1.40E-06	1.50E-06*	4.26E-06***	9.44E-08	-	-	-	-	-	-
	(1.02E-06)	(7.92E-07)	(1.33E-06)	(9.33E-08)						
α	0.051***	0.033***	0.159***	0.034***	-	-	-	-	-	-
	(0.011)	(0.009)	(0.031)	(0.009)						
β	0.947***	0.956***	0.803***	0.961***	-	-	-	-	-	-
	(0.012)	(0.012)	(0.033)	(0.011)						
α+β	0.998	0.989	0.962	0.995	-	-	-	-	-	-
θ_0 (constant)	-	-	-	-	0.0002	0.006	0.001	0.011	−0.0001	−0.066***
					(0.014)	(0.010)	(0.028)	(0.013)	(0.002)	(3.84E-07)
θ_1	-	-	-	-	0.044***	0.013	−0.011	0.026***	−0.010**	−0.028***
					(0.016)	(0.009)	(0.019)	(0.009)	(0.004)	(3.30E-07)
θ_2	-	-	-	-	0.913***	0.947***	0.745**	0.932***	0.990***	0.662***
					(0.031)	(0.037)	(0.330)	(0.032)	(0.008)	(1.33E-05)
$\theta_1+\theta_2$	-	-	-	-	0.957	0.960	0.734	0.958	0.980	0.634
Log-likelihood	17698.92									
AIC	−26.314									
SIC	−26.201									
HQ	−26.272									

Note: Standard error in parenthesis, ***,**,*Denotes significance at the 1%, 5% and 10% respectively, RCR.: Returns of crude oil future, RGO.: Returns of gold future, RSP.: Returns of S and P 500 future, RUS.: Returns of US Dollar index future, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion, DCC: Dynamic conditional correlation

7. MGARCH DIAGNOSTIC TESTS

The MGARCH models consist of the VAR (2)-diagonal VECH, the VAR (2)-diagonal BEKK and the VAR (2)-CCC model. We can diagnostic check on the system residuals to determine efficiency of estimator according to the Table 8. We found that system residuals have no autocorrelations up to lag 6 and are not normally distributed. And for the VAR (2) – DCC, we are unable

Figure 3: Conditional covariance (vector autoregressive (2) - diagonal VECH estimates)

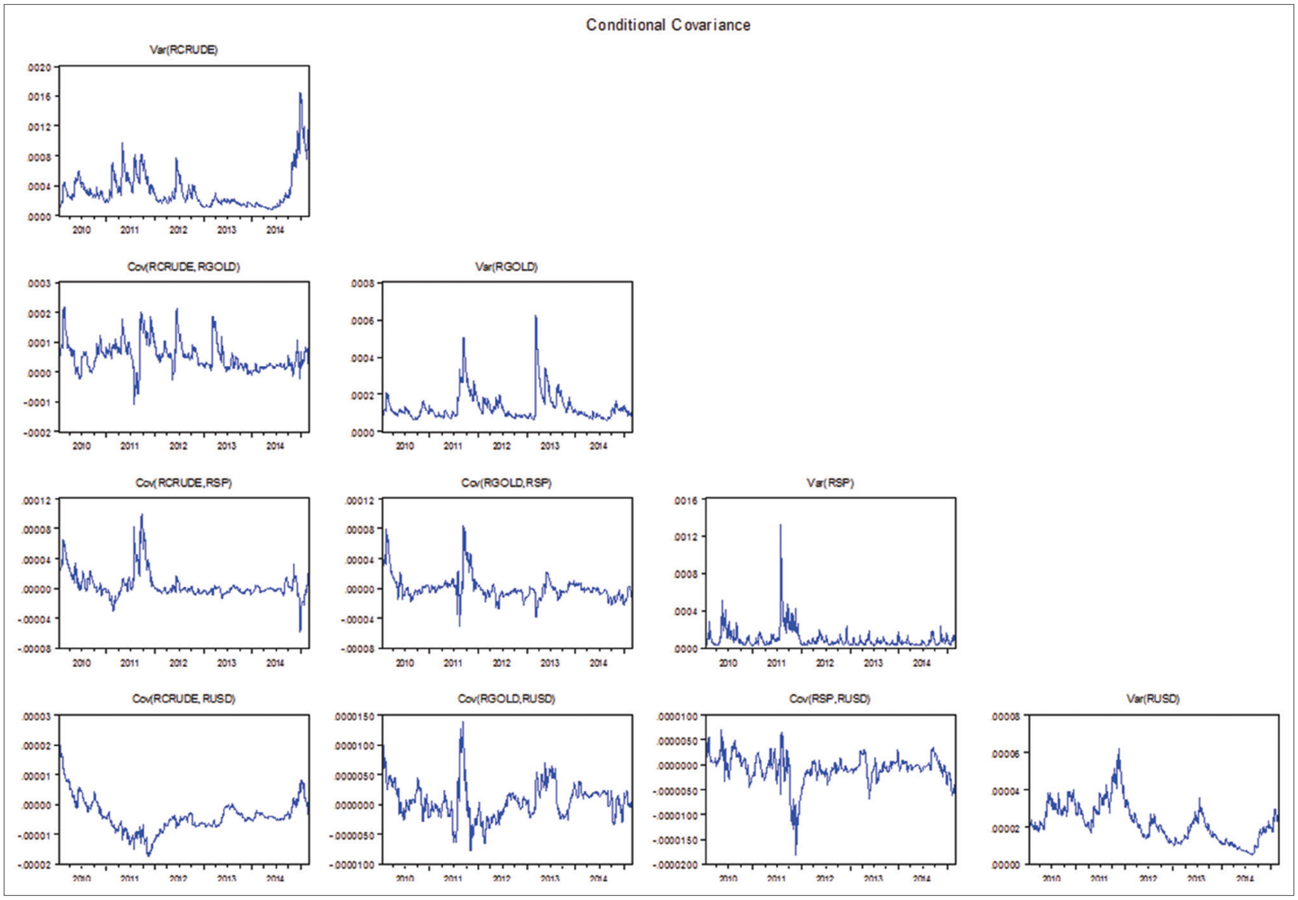


Figure 4: Conditional covariance (vector autoregressive (2) - diagonal Baba, Engle, Kraft and Kroner estimates)

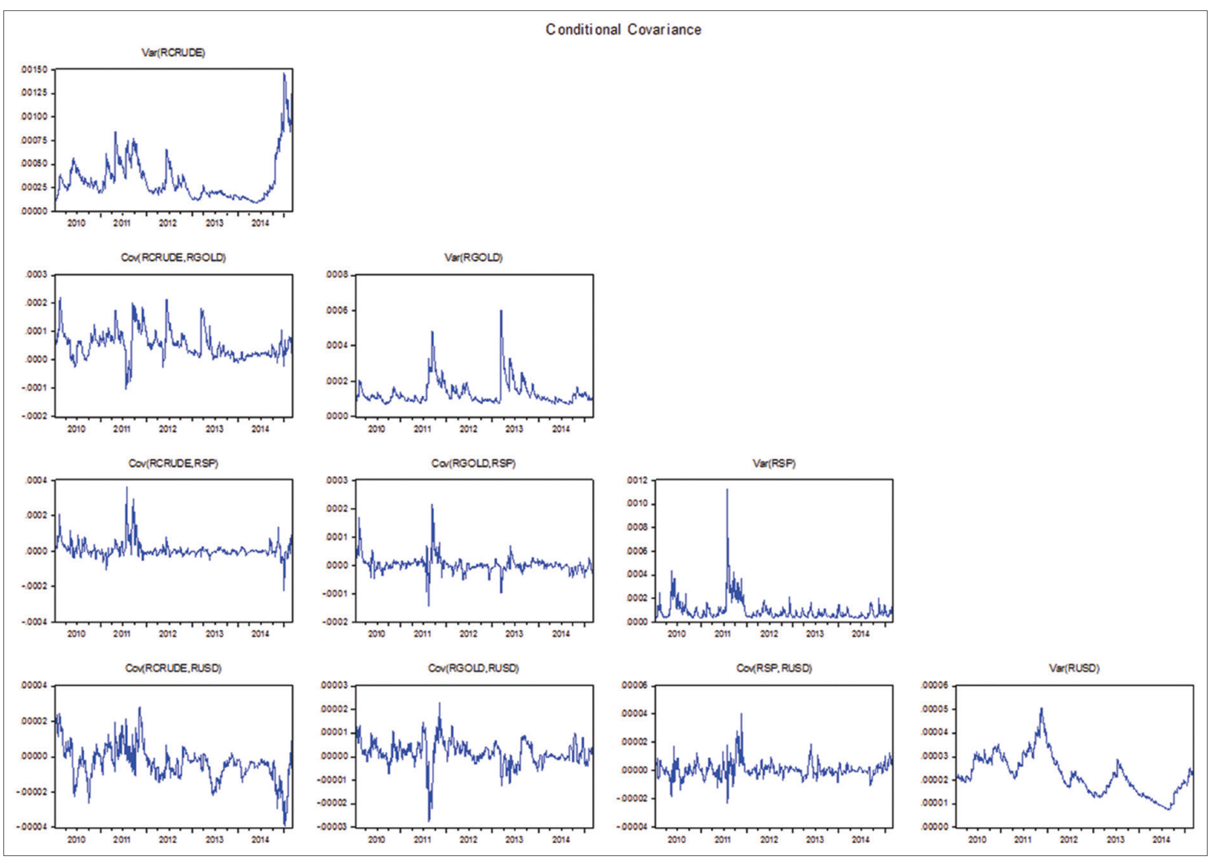


Figure 5: Conditional covariance (vector autoregressive (2) - constant conditional correlations estimates)

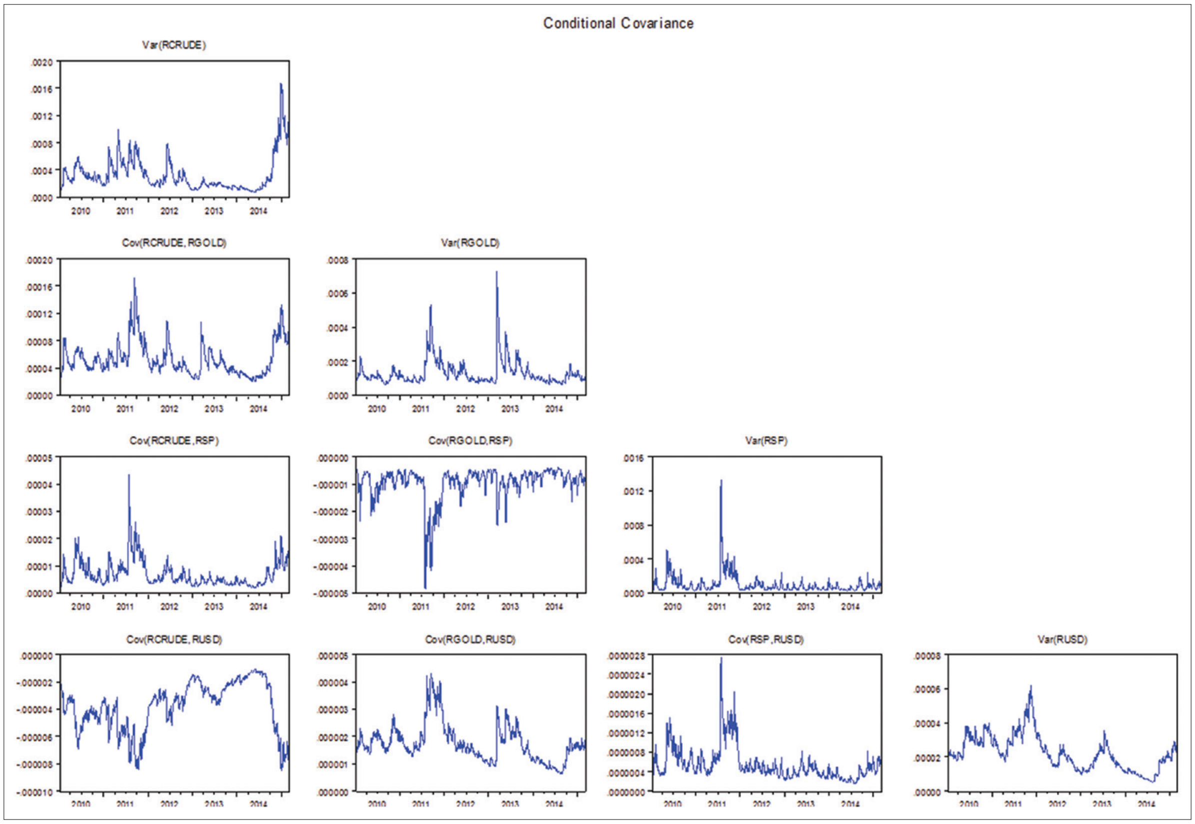


Figure 6: Conditional correlation (vector autoregressive (2) - diagonal VECH estimates)

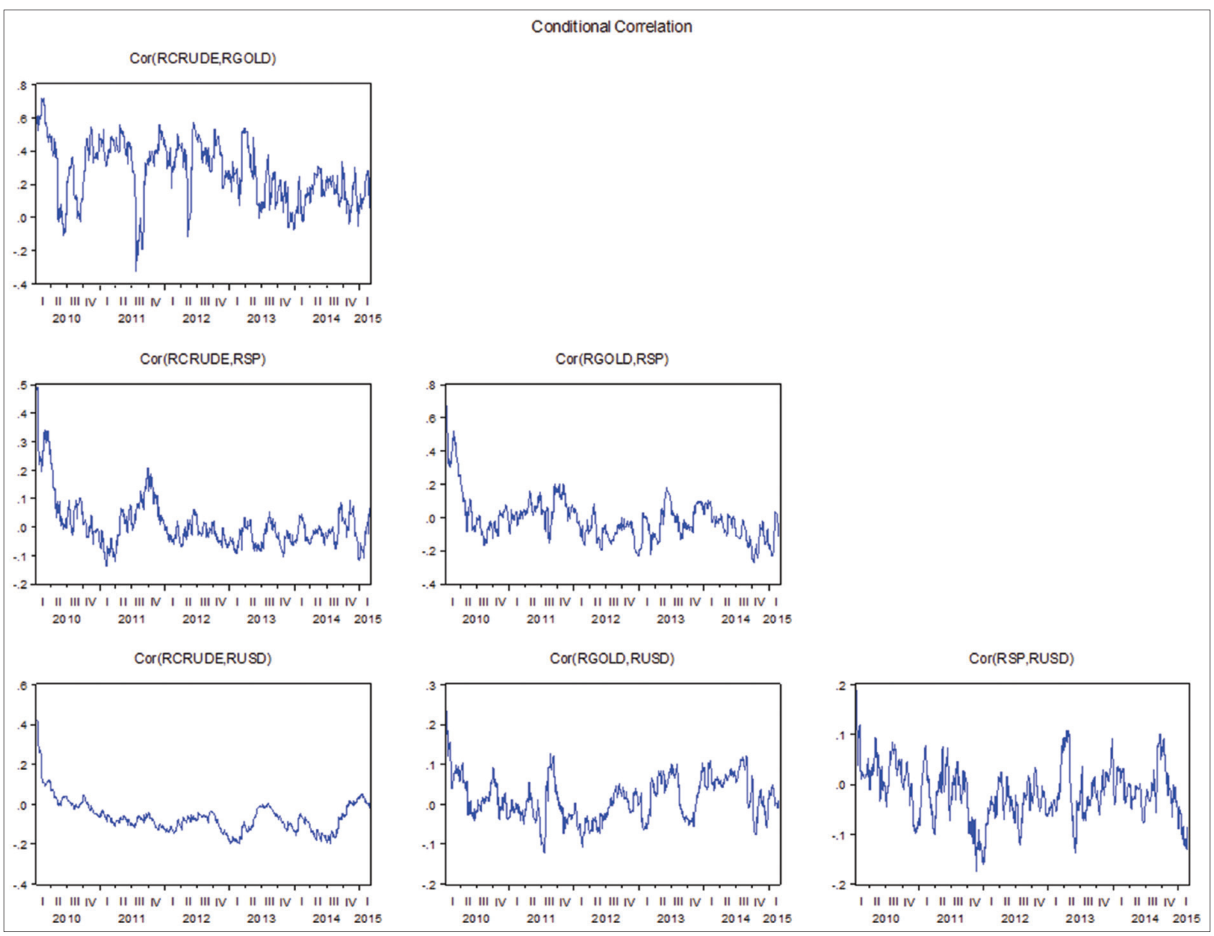


Figure 7: Conditional correlation (vector autoregressive (2) - diagonal Baba, Engle, Kraft and Kroner estimates)

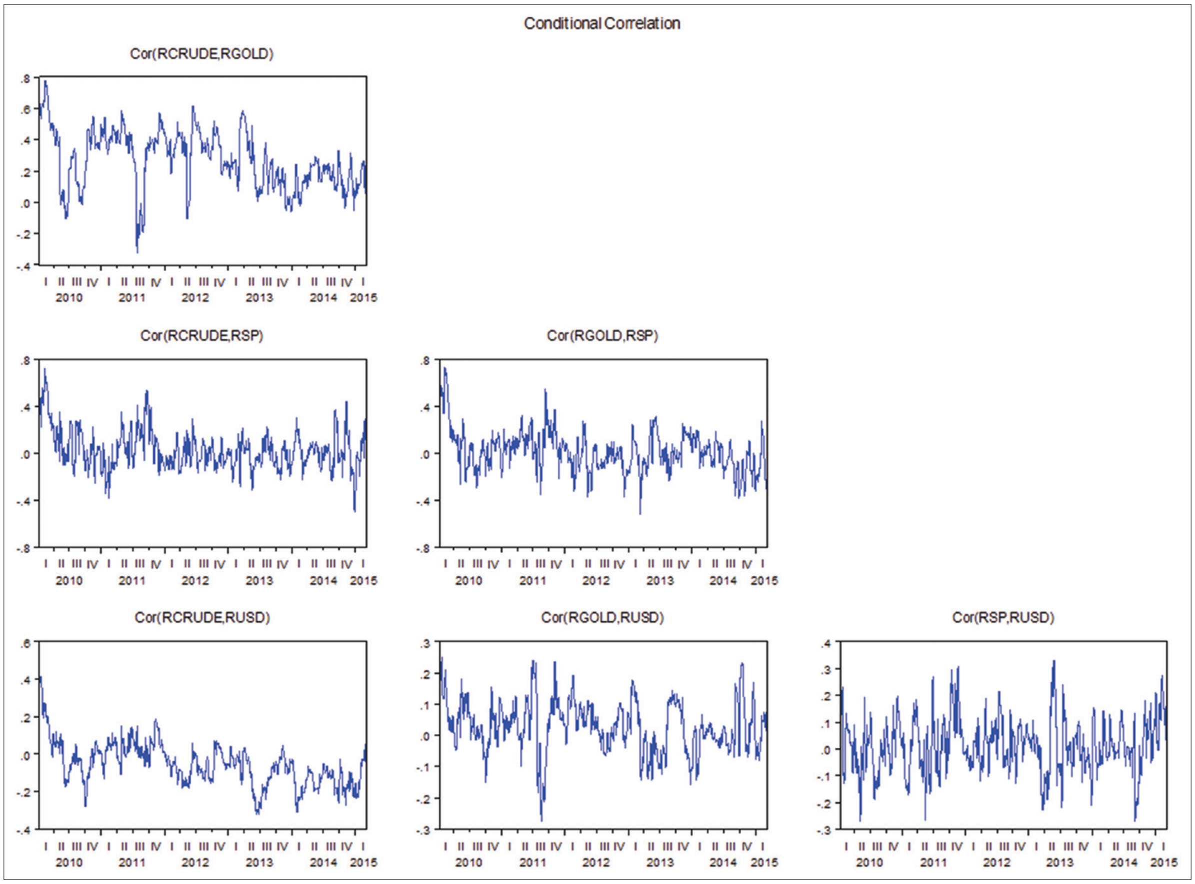


Figure 8: Conditional correlation (vector autoregressive (2) - dynamic conditional correlation estimates)

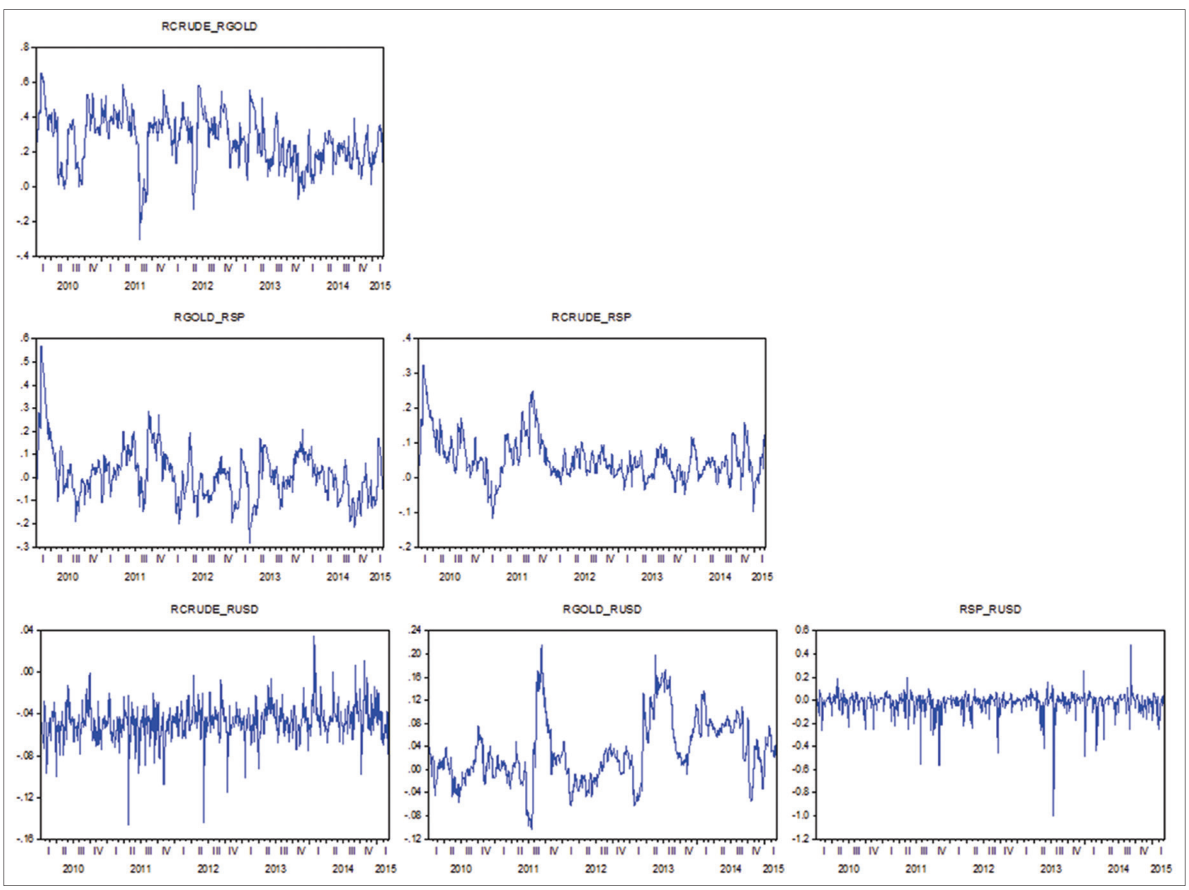


Table 8: Multivariate GARCH diagnostic tests

Test	Lags	Value	P	Test	Value	P
	VAR (2)-diagonal VECH					
	Lags	**Value**	**P**	**Test**	**Value**	**P**
System residual tests for autocorrelations	1	19.273	0.254	System residual normality tests		
H_0=No residual autocorrelation (Q-statistics)	2	27.300	0.703	H_0=Multivariate normal		
	3	33.656	0.942	-Skewness (Chi-square)	49.281	0.000
	4	49.420	0.910	-Kurtosis (Chi-square)	1174.560	0.000
	5	62.166	0.930	-Jarque-Bera	1223.841`	0.000
	6	82.134	0.842			
Test	**VAR (2)-diagonal BEKK**					
	Lags	**Value**	**P**	**Test**	**Value**	**P**
System residual tests for autocorrelations	1	27.306	0.038	System residual normality tests		
H_0=No residual autocorrelation (Q-statistics)	2	34.926	0.330	H_0=Multivariate normal		
	3	41.297	0.742	-Skewness (Chi-square)	54.618	0.000
	4	57.081	0.717	-Kurtosis (Chi-square)	1644.597	0.000
	5	67.964	0.829	-Jarque-Bera	1699.216	0.000
	6	88.761	0.687			
Test	**VAR (2)-CCC**					
	Lags	**Value**	**P**	**Test**	**Value**	**P**
System residual tests for autocorrelations	1	10.060	0.863	System residual normality tests		
H_0=No residual autocorrelation (Q-statistics)	2	14.645	0.996	H_0=Multivariate normal		
	3	19.088	0.999	-Skewness (Chi-square)	52.250	0.000
	4	30.385	0.999	-Kurtosis (Chi-square)	1476.766	0.000
	5	41.607	0.999	-Jarque-Bera	1529.017	0.000
	6	62.988	0.996			

Test	VAR (2)-DCC											
	GARCH (1,1) for RCRUDE			**GARCH (1,1) for RGOLD**			**GARCH (1,1) for RSP**			**GARCH (1,1) for RUSD**		
	Lags	**Value**	**P**	**Lags**	**Value**	**P**	**Lags**	**Value**	**P**	**Lags**	**Value**	**P**
Residual tests for auto-correlations	1	1.792	0.181	1	0.746	0.388	1	0.665	0.415	1	0.308	0.579
H_0=No residual autocorrelation (Q-statistics)	2	2.081	0.353	2	0.751	0.687	2	2.303	0.316	2	0.367	0.832
	3	2.419	0.490	3	0.754	0.860	3	2.480	0.479	3	0.435	0.933
	4	2.468	0.650	4	0.848	0.932	4	3.102	0.541	4	1.941	0.747
	5	2.927	0.711	5	1.300	0.935	5	5.667	0.340	5	4.073	0.539
	6	3.605	0.730	6	1.616	0.951	6	6.332	0.387	6	4.109	0.662
	Value	**P**		**Value**	**P**		**Value**	**P**		**Value**	**P**	
Residual normality tests												
H_0=Multivariate normal												
-Skewness (Chi-square)	−0.229	0.000		−0.819	0.000		−0.524	0.000		0.249	0.000	
-Kurtosis (Chi-square)	4.988	0.000		8.838	0.000		4.346	0.000		4.211	0.000	
-Jarque-Bera	232.943	0.000		2057.888	0.000		163.133	0.000		96.098	0.000	
	Value	**P F (15,1312)**		**Value**	**P F (15,1312)**		**Value**	**P F (15,1312)**		**Value**	**P F (15,1312)**	
Heteroskedasticity test: ARCH												
H_0=Homoskedasticity (F-statistic)	1.400	0.138		1.477	0.105		0.556	0.908		0.641	0.841	

ARCH: Autoregressive conditional heteroskedasticity, DCC: Dynamic conditional correlation, VAR: Vector autoregressive, CCC: Constant conditional correlations, RCRUDE: Returns of crude oil, RGOLD: Returns of gold futures, RSP: Returns of Standard and Poor's 500 future, RUSD: Returns of US Dollar Index, GARCH: Generalized autoregressive conditional heteroskedasticity, BEKK: Baba, Engle, Kraft and Kroner

to diagnose as there models above. We do by separate each the conditional volatility. We found that residuals of GARCH (1, 1) for RCRUDE, RGOLD, RSP and RUSD have no autocorrelations up to 6 and are not normally distributed also. Besides, from the ARCH test, we found that the residuals of GARCH (1, 1) for all cases have no heteroskedasticity. Therefore, it can be concluded that the estimators of MGARCH model are efficient.

8. CONCLUSION

This paper investigates volatility transmission in the crude oil, gold, S and P 500 and US Dollar Index futures. The empirical results showed that the estimates of the VAR (2)-diagonal BEKK parameters were statistically significant in all cases. Later, the VAR (2)-diagonal VECH parameter were statistically significant in case of RCRUDE with RGOLD, RGOLD with RSP and RSP with RUSD. This indicates that the short run persistence of shocks on the DCCs was greatest for RCRUDE with RGOLD, while the largest long run persistence of shocks to the conditional correlations for RCRUDE with RGOLD also. At the same time the VAR (2)-CCC parameters were statistically significant in only case of RCRUDE with RGOLD. Finally, the VAR (2)-DCC were statistically significant in case of RCRUDE with RGOLD, RGOLD with RSP, RGOLD with RUSD and RSP with RUSD. This indicates that the short run persistence of shocks on the DCCs is greatest for RCRUDE with RGOLD, while the largest long run persistence of shocks to the conditional correlations for RGOLD with RUSD.

Finally, we would choose the best model next by considering the value of log-likelihood, AIC, SIC and HQ. We found that the VAR (2)-diagonal VECH model is highest log-likelihood and lowest AIC equal 17790.96 and −26.337, respectively. But the VAR (2)-DCC has SIC and HQ lowest is equal −26.201 and −26.272, respectively. Thus, it can be concluded that we should choose the VAR (2)-diagonal VECH and the VAR (2)-DCC model in volatility analysis of the crude oil, gold, S and P 500 and US Dollar Index futures returns.

In addition, we could conclude that the crude oil futures volatility is having an impact on the gold futures volatility, the gold futures volatility is having an impact on S and P 500 futures volatility, the gold futures volatility is having an impact on US Dollar Index futures volatility and S and P 500 futures volatility is having an impact on US Dollar Index futures volatility. Such results can be useful as the management the volatility of the crude oil, gold, S and P 500 and US Dollar Index futures for investors.

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