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SPILLOVER EFFECTS OF THE FUTURES CONTRACT PRICES OF THE NYMEX CRUDE OIL: A MULTIVARIATE GARCH APPROACH

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Abstract
The main aim of this paper is to investigate spillover effects of the futures contracts prices of the Nymex Crude Oil. Tse and Tsui (2002) multivariate generalized autoregressive conditional heteroscedasticity model is used and a two-step MGARCH estimation of the two crude oil futures contracts prices of the New York Mercantile Exchange (NYMEX) is carried out. The results revealed of conditional volatility correlations between crude oil futures contract-3 and futures contract-4 of the NYMEX. The economic implication of this results is that a volatility of futures contract-4 could affect the volatility of futures contract-3 and vice-versa, which suggests that investment uncertainties associated with one of the contracts could foster investment uncertainties in the other contract which might raise the level of risks in the market and affect portfolio allocations of investors as well as firms' investment plans on the market. Therefore, the high level of volatility co-movements between the two series suggests that during the sample period there was high degree of volatility correlations between the two futures prices, which indicates that the forces driving the two futures prices of the NYMEX might be similar. Based on the finding of the study, the paper recommends that, authority concern should come up with appropriate policy that will reduce volatility correlations between crude oil future contracts.
***Key Words*:** Contracts, Crude Oil, Futures, Multivariate GARCH, Nymex, Volatility

I. Introduction

Oil prices have historically been variable since the large price increases that occurred in the 1970s and 1980s. Another round of wider fluctuations in the prices was observed in the periods 2007 and 2008 following the global financial and economic crisis. The figure gives a graphical depiction of fluctuations in the two oil futures prices of the NYMEX. It can be observed that the two series of the NYMEX crude oil futures contracts are not stationary and indicate presence of stochastic trend with drift[1].

Figure 1: NYMEX crude oil futures contract-3 and futures contract-4 prices

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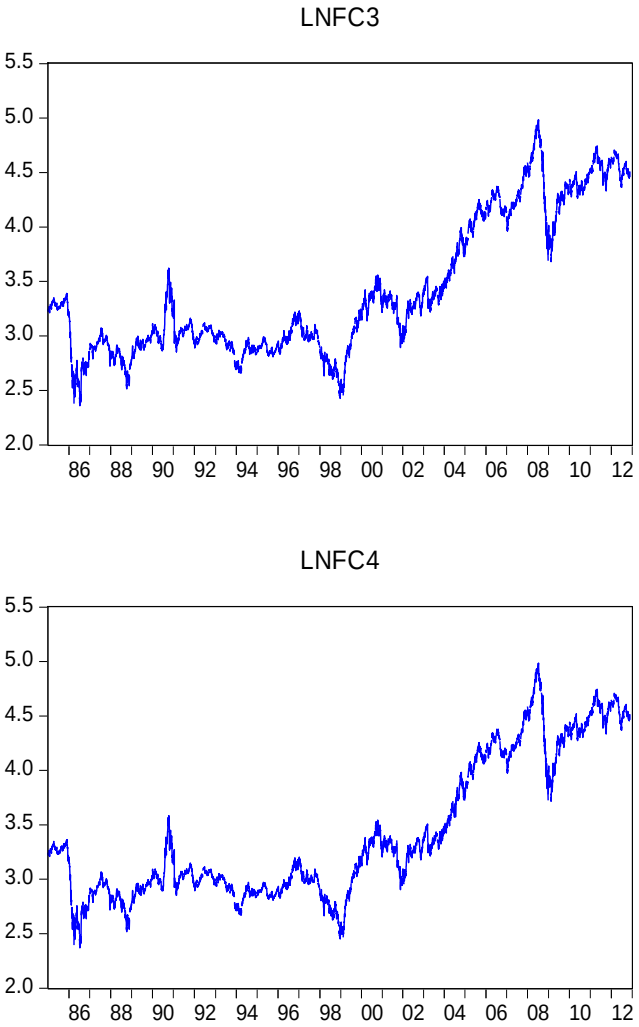


Figure: 1

Conventionally, the major forces triggering movements in oil prices are the supply and demand fundamentals. Oil futures markets such as the New York Mercantile Exchange (NYMEX) allow a buyer to accept (buy) and a seller to deliver (supply) a given quantity of a particular commodity at a specified place, price and time in the future. A standardized futures contract facilitates trading with market participants having only to negotiate the contract price as distinct from auction trading where products are sold one by one by the auctioneer to a large team of competitive buyers. The players on the futures market can be both buyers and sellers, and as such, the market is considered highly competitive. The futures market has often been used to provide projections of market prices, (UNCTAD, 2005). The New York Mercantile Exchange is a good example of a futures market that undertakes trading in futures contracts of crude oil. This paper takes a look at two out of the four futures contracts traded by the New York Mercantile Exchange oil futures market with a view to estimating the dynamic conditional volatility correlations in some of the futures contracts traded by the market.

Volatility and shock transmission among oil markets do entail practical implications for portfolio managers who seek to make optimal portfolio allocations. Nevertheless, the analysis of volatility transmission between and among different oil markets potentially implies that there could be a spillover of shocks from one market to another owing to financial interrelatedness and homogeneity in processing oil related information (Malik and Hammoudah, 2007). According to Chang, McAleer and Tansuchat (2009) a volatility spillover occurs when changes in volatility in one market produce a lagged impact on volatility in other markets. Therefore, investigating financial risks associated with the prices of financial assets is of paramount importance as doing so would mitigate the risks of trading on oil markets.

This paper as distinct from others uses the Tse and Tsui (2002) MGARCH in estimating the crude oil futures contract prices of the New York Mercantile Exchange (NYMEX). The primary aim of the paper is to investigate whether there exists evidence

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of contemporaneous volatility co-movements or spillovers in the futures prices of crude oil traded by the NYMEX. The paper is therefore organized into six sections. To the best of Authors' knowledge, this is the first to use the MGARCH model of Tse and Tsui in estimating the crude oil futures contract prices. The first section is introduction given in a non-technical form. The second section conducts a review of the literature related to oil price volatility and the third section presents the econometric models. The fourth section describes the data type used in this study, presents the descriptive statistics of the series and carries out time series stochastic analysis of the data. The fifth section presents the empirical results, and finally, the last section which is section six contains the conclusion.

II. Literature Review

The literature is replete with issues on volatility spillover, and a variety of markets have been considered by some studies. According to Enders (2010), while dealing with a data set containing several variables, it often makes sense to estimate the conditional volatilities simultaneously. However, Laurent (2009) contends that financial volatilities move together over time across assets and markets. The only econometric approach that is remarkably appropriate for the estimation of conditional volatilities while dealing with several variables is the multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) model. Modern developments in econometrics have led to the evolution of various classes of MGARCH models designed specifically for modelling and estimating conditional volatilities involving more than one variable.

Some studies have used different class of MGARCH models in estimating volatility spillovers among and across different financial markets that trade different assets. According to Malik and Hammoudah (2007), the autoregressive conditional heteroscedasticity (ARCH) model that was first developed by Engle (1982), and later generalized by Bollerslev (1986), is to a large extent the most popular and robust econometric method for modeling

Volatility of high frequency financial time series. However, the multivariate generalized autoregressive conditional heteroscedasticity (GARCH) models have been widely used in estimating volatility spillover among and across different markets. Ewing, Malik, and Ozfidan (2002), for example, used the MGARCH model to show that there exists significant volatility spillover between the oil and natural gas markets in the case of the United States.

Lanza, Manera and McAleer (2006) used the constant conditional correlation model of Bollerslev (1990), and the dynamic conditional correlation model of Engle (2002) for the West Texas Intermediate (WTI) oil forward and futures returns. Nonetheless, the CCC model they used is not without the methodological defect of assuming that the conditional correlations are constant over time (see Laurent, 2009). This according to Tse (2000) and Engle and Sheppard (2001) is plausibly unrealistic in many empirical applications. Manera, McAleer and Grasso (2006) employed the CCC, the VARMA-GARCH of Ling and

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McAleer (2003), the VARMA-Asymmetric GARCH Model of McAleer, Hoti and Chen (2009), and the Dynamic Conditional Correlation (DCC) model to estimate the spot and forward return in the Tapis oil market. Chang, McAleer and Tansuchat (2009a, 2009b) carried out the estimation of multivariate conditional volatility by investigating volatility spillovers for the returns on spot, forward and futures returns for Brent, WTI, Dubai and Tapis.Tansuchat, Chang and McAleer (2011), have comparatively examined the performance of some multivariate GARCH models, namely, the CCC, VARMA-GARCH, DCC and BEKK; for the crude oil spot and futures returns of two major bench mark international crude oil markets, namely; Brent and WTI.

However, none of these studies has sought to use the Tse and Tsui (2002) model to estimate the futures oil contract prices of the NYMEX and checked the statistical adequacy and robustness of the MGARCH models using the Hosking (1980) and Li and McLeod (1981) multivariate statistical diagnostic tests which are so far the only class of tests specifically designed for checking the statistical adequacy of the MGARCH class of models. Therefore, as distinct from other papers this paper seeks to carry out an MGARCH estimation of the crude oil futures contract-3 and contract-4, of the NYMEX and conducts the multivariate form of the tests on the residuals of the model.

III. The Theory

The economic theory or more specifically the price theory underlying trading in financial assets such as futures contracts postulates that the price of any specific good or service reflects the link between the market forces of supply and demand. The theory of price states that the point of which the benefit derived from those who buy the entity meets the seller's marginal costs is the most optimal market price for the good or the service.

IV. Econometric Model

According to Harris, Stoja and Tucker (2004) there are different class of multivariate GARCH models with each proposing the imposition of different set of restrictions on the dynamic process that governs the covariance matrix of economic and financial asset returns. Some of these models include: the Vech and Diagonal Vech models of Bollerslev, Engle and Wooldridge (1988), the BEKK model of Engle and Kroner (1995), the Constant Conditional Correlation (CCC) model of Bollerslev (1990), the Factor ARCH model of Engle, Ng and Rothschild (1990), the Dynamic Conditional Correlation (DCC) model of Engle and Sheppard (2001).

According to Laurent (2009) the multivariate GARCH models are widely used inthe study of the relations between the volatilities and co-volatilities of severalmarkets. These models have proved both adequate and robust in studying: (i) How the volatility of a market leads to the volatility of other markets; (ii) How the volatilityof an asset is transmitted to another asset directly (through its conditionalvariance) or indirectly (through its conditional covariances. (iii) How a shock on amarket increases the volatility on another market, and by how much? and; (iv) whether the correlations between asset returns change overtime.

A. The Tse and Tsui (2002) Model

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In the academic literature, multivariate GARCH models suffer from a number of problems in practice because the computational estimation of some group of this class of models particularly, the Vech and BEKK models is burdensome (Harris et al., 2004). This paper uses the dynamic conditional correlation model of Tse and Tsui (2002), as using the DCC models circumvents this problem.

The DCC model of Tse and Tsui (2002) is defined as:

$$y_t = \mu(\theta) + \varepsilon_t \quad (1)$$

$$H_t = D_t R_t D_t \quad (2)$$

where $D_t = diag(h_{11t}^{1/2} .....h_{NNt}^{1/2})$ .and h_t can be considered as any univariate GARCH model; and $R_t = (\rho_{ij})$ is a symmetric positive definite matrix with $\rho_{11} = 1, \forall i$, $R_t = (1-\theta_1-\theta_2)R + \theta_1 \psi_{t-1} + \theta_2 R_{t-1}$, θ_1 and θ_2 are non-negative parameters satisfying the condition $\theta_1 + \theta_2 < 1$, R as mentioned earlier is a symmetric $N \times N$ positive definite matrix with $\rho_{11} = 1$, and ψ_{t-i} is an $N \times N$ correlation matrix for ε_T with $T = t-M, t-M+1,..., t-1$. The i, j^{th} element is given by;

$$\psi_{ij,t-1} = \frac{\sum_{M=1}^{M} u_{i,t-M} u_{j,t-M}}{\sqrt{(\sum_{M=1}^{M} u_{i,t-M}^2)(\sum_{h=1}^{M} u_{j,t-M}^2)}} \quad (3)$$

Where $u_{1t} = \varepsilon_{1t}\sqrt{h_{iit}}$.

The matrix ψ_{t-1} can be expressed as:

$$\psi_{t-1} = \mathrm{B}_{t-1}^{-1} L_{t-1} L_{t-1}^{'} \mathrm{B}_{t-1}^{-1}, \quad (4)$$

Where B_{t-1} is an $N \times M$ diagonal matrix with i-*th* diagonal element given by $(\sum_{h=1}^{M} u_{i,t-h}^2)^{1/2}$ and $L_{t-1} = (u_{t-1}, ...u_{t-M})$ is an $N \times M$ matrix, with $u_t = (u_{1t}, u_{2t} .....u_{Nt})^{'}$.The necessary condition to ascertain the positivity of ψ_{t-1}, and the matrix (R_t) is that $M \geq N$.

The assumption that the conditional correlations are constant may seem unrealistic in many empirical applications. This paper adopts generalization of the Constant Conditional Correlation (CCC) model which is the dynamic conditional correlation (DCC) model developed by Tse and Tsui (2002). As highlighted earlier, the aim of this paper is to first make the conditional correlation matrix time dependent; and second, to investigate whether there is evidence of volatility correlations among the chosen oil futures contract prices of the NYMEX.

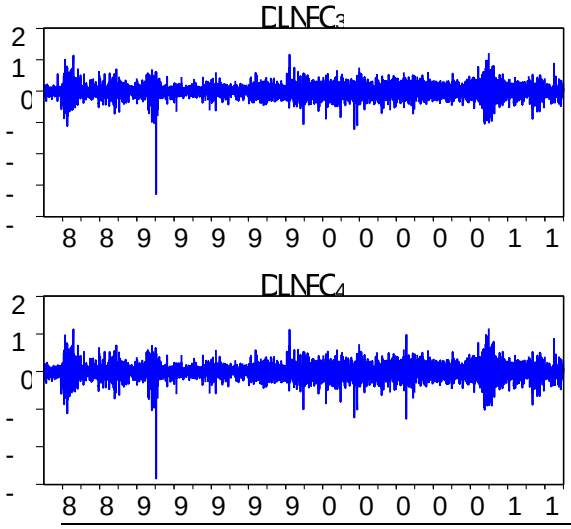
V. Data

The paper uses 8587 daily observations on the two futures contract prices of the NYMEX crude oil. The data used covers the period 1/03/1985 to 12/31/2018. All the data were obtained from the U.S. Energy Information Administration (EIA). The series were converted into their natural logarithms and appropriately tested for stationarity. The results from the unit root

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tests reported in Table 2 indicates that the two series are integrated of order one i.e. *I(1)*. Therefore, the natural log returns of the series were computed. The figure below depicts the natural log returns of the series.

Figure 2: Daily Returns of the NYMEX Crude oil futures contract-3 and futures contract- 4 prices



As can be observed from the above figure, the two series indicate volatility clustering, that is, periods of high volatility are accompanied by periods of high volatility and periods of low volatility are followed by another period of low volatility. Hence, according to Orskaug (2009), a GARCH model can be used to fit the data. A summary of descriptive statistics of the series is given in the table below:

Table 1: Series Summary Statistics

Statistics	Series	
	$lnFC_3$	$lnFC_4$
Mean	3.423	3.421
Standard Deviation	0.643	0.645
Skewness	0.698	0.716
Kurtosis	2.092	2.088
Jacque Bera Statistics	810.801^{***}	842.879^{***}

Note: *** indicates the rejection of hypothesis of normality at 1% level of significance**.**

From the results of the descriptive statistics of the series in Table 1 above, the mean which is an average value of the series is 3.4 for each of the two series. The standard deviation which is the measure of dispersion or spread in the series is 0.643 for futures contract-3, and 0.645 for futures contract-4 respectively. The skewness for futures contract 3 is 0.698 and for futures contract-4 is 0.716. These results indicate a non-zero and positive skewness in the two series which suggests that the series are not normally distributed but rather exhibit fat tails. This indeed is typical

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of most time series with high frequencies. The results for the Jacque-bera statistic for futures contract-3, and futures contract-4 are 810.801 and 842.879 respectively.[2] This further corroborates the fact that the series have fatter tails.

Table 2: Unit Root Tests

Tests at Level		
Series	Augmented Dickey Fuller	Phillips Perron
$lnFC_3$	-0.783	-0.677
$lnFC_4$	-0.684	-0.568
Tests at First Difference		
Variables	Augmented Dickey Fuller	Phillips Perron
$lnFC_3$	-83.617***	-83.762***
$lnFC_4$	-84.683***	-84.874***

Note: *** refers to 1% level of significance (Mackinnon critical value).

The results of the unit root tests reported in Table 2 above indicate that the series are non-stationary as such, the series were differenced once, and hence, can be referred to as *I(1)* processes. The asterisks indicate the rejection of the null hypothesis of the unit root at the 1%, 5% and 10% MacKinnon critical levels.

VI. Empirical Results

Most often, financial volatilities tend to move together over time across assets and markets. Therefore, it is necessary to take into account the dependence in the co-movements of asset returns (Orskaug, 2009). In this paper, an MGARCH estimation of the two out of the four crude oil futures contracts prices traded by the NYMEX is carried out. The estimation results are presented in Table 3 below:

Table: 3 Estimates of the DCC Tse & Tsui (2002) MGARCH Model

Step 1a: Univariate GARCH Model for dlnFC3				
Parameters	Coefficient	S.td Error	t-value	t-probability
Constant of the mean equation	0.028049	0.030875	0.9085	0.3637
MA(1)	-0.013984	0.028458	-0.4914	0.6232
MA(2)	-0.018192	0.025820	-0.7046	0.4811
MA(3)	-0.016475	0.025559	-0.6446	0.5193
MA(4)	-0.006304	0.024328	-0.2591	0.7956

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MA(5)	-0.043897	0.029694	-1.478	0.1395
Constant of the Variance equation	0.065537	0.034722	1.887	0.0592
ARCH-Term(α_1)	0.182112**	0.059757	3.048	0.0023
GARCH-Term(β_1)	0.820375**	0.052761	15.55	0.0000

Step 1b: Univariate GARCH Model for dlnFC4

Parameters	Coefficient	S.td Error	t-value	t-probability
Constant of the mean equation	0.022660	0.029349	0.7721	0.4401
MA(1)	0.004988	0.024404	0.2044	0.8381
MA(2)	-0.018820	0.025272	-0.7447	0.4565
MA(3)	-0.023580	0.024542	-0.9608	0.3368
MA(4)	-0.009587	0.024758	-0.3872	0.6986
MA(5)	-0.033169	0.026654	-1.244	0.2135
Constant of the Variance equation	0.050561	0.035359	1.430	0.1529
ARCH-Term(α_1)	0.147763**	0.058788	2.513	0.0120
GARCH-Term(β_1)	0.849424**	0.059851	14.19	0.0000

Multivariate GARCH Estimates

Parameters	Coefficient	S.td Error	t-value	t-probability
A	0.135031**	0.062267	2.169	0.0302
B	0.751069**	0.10380	7.236	0.0000
$\hat{\rho}_{34}$	0.9924**	0.0025	393.2	0.0000

Note: ** indicates rejection of null hypothesis of statistical insignificance at the 5% level.

Source: Authors' Computation using the G@RCH 8 Software Package

The results reported in the table above show two steps estimation output of the Tse and Tsui (2002) MGARCH model used in the paper. The first step of the estimation, which is the upper panel of the table, presents the univariate GARCH estimates of the two series. The Log Likelihood value for the univariate GARCH Model for $dlnFC_3$ is -3865.964, and the sum of the ARCH and GARCH terms i.e., Alpha [1] +Beta [1] is 1.00249. This suggests that the conditional variance of the univariate GARCH component of the Tse and Tsui (2002) model estimated in this paper is an IGARCH

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process. The sum of ARCH and GARCH terms i.e., Alpha [1] +Beta [1] is 0.99719. This suggests that there is evidence of high persistence of volatility shocks to the tune of 99.72% in the series. However, the asterisks indicate that all the coefficients of the ARCH and GARCH terms, as well as the coefficient of the volatility correlation targeting parameter (ρ), are statistically significant as the t-probabilities indicate the rejection of null hypothesis of insignificance at 5% level of significance. Nevertheless, the Log Likelihood for the univariate GARCH estimation step for futures contract-4 series of the NYMEX is (-3763.470).

Nonetheless, the results in the second panel of the table give estimates of the multivariate GARCH component of the model. It is noteworthy, however, that the second step uses the standardized residuals to estimate the conditional covariances from the covariance matrix of the model (see Enders, 2010). The numerical value of the coefficient of volatility correlation targeting parameter $\hat{\rho}_{21}$ from the multivariate GARCH estimation output reported in the lower panel of Table 4 above is 0.9924. This coefficient is statistically significant and indicates 98.81% level of daily volatility co-movements between the two series. In other words, the numerical value of 0.9924 suggests that there is evidence of high conditional volatility correlations of 99.24% between crude oil futures price contract-3, and futures contract-4 traded by the NYMEX over the sample period.[3] In other words, there is 99.24% spillover of volatility from futures contract price (4) to futures contract price (3). The log likelihood from the multivariate GARCH estimates is (-3289.70). The univariate GARCH tests on residuals of the model indicate no serial correlation in the series as the probability values are high which implies that the null hypothesis of no serial correlation cannot be rejected at all lag levels since the probabilities associated with the standardized residuals and squared standardized residuals tests are significantly high. The tests are reported in the tables below:

Table 4: Statistical Diagnostic Tests on dlnFC$_3$ Series

Q-Statistics Test on Standardized Residuals of dlnFC$_3$ Series		
Lag Order	Q-Statistic	Probability
5	8.7671	0.1187
10	10.9744	0.3595
20	24.2137	0.2332
50	50.5446	0.4519
Q-Statistics Test on Squared Standardized Residuals of dlnFC$_3$ Series		
Lag Order	Q-Statistic	Probability
5	2.1929	0.8219
10	2.4211	0.9919

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20	2.9669	0.9999
50	4.2349	1.0000

Source: Authors' Computation using E-Views

Table 5: Diagnostic Tests on dlnFC$_4$ Series

Q-Statistics Test on Standardized Residuals of dlnFC$_4$ Series		
Lag Order	Q-Statistic	Probability
5	8.0546	0.1533
10	11.4068	0.3267
20	14.3434	0.8127
50	35.8321	0.9345
Q-Statistics Test on Squared Standardized Residuals of dlnFC$_4$ Series		
Lag Order	Q-Statistic	Probability
5	0.0368	0.9999
10	0.8579	0.9999
20	2.5269	0.9999
50	7.4834	1.0000

Source: Authors' Computation using E-Views

However, results of the Hosking (1980) and Li and McLeod (1981) multivariate serial correlation tests reported in Tables 6 and 7 below indicate that the null hypothesis of no serial correlation in the errors can be rejected at 5% level of significance only for the squared standardized residuals not the standardized residuals indicating that the specification of the conditional variance of the model is correct and that the volatility information provided by the model could be deemed statistically reliable. However, the non-rejection of null for the standardized residuals implies that the conditional mean component of the model may have been misspecified. The Hosking's tests are given by:

$$HM(m) = T^2 \sum_{j=1}^{m} (T-j)^{-1} tr\{C_{yt}^{-1}(0)C_{yt}(j)C_{yt}^{-1}(0)C_{yt}^{'}(j)\}.$$

Where y_t is the vector of observed returns and $C_{yt}(j)$ is the sample auto covariance matrix of order j. Under null hypothesis of no serial correlation, the test is distributed asymptotically as a $\chi^2(N^2 m)$.

Table 6: Multivariate Diagnostic Tests on the Series using Hosking (1980) test

Hosking's Multivariate Portmanteau Statistics on Standardized Residuals		
Lag Order	H-Statistic	Probability

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5	59.7166	0.0000
10	84.0831	0.0000
20	123.8230	0.0003
50	234.0420	0.0293
Hosking's Multivariate Portmanteau Statistics on Squared Standardized Residuals		
Lag Order	H-Statistic	Probability
5	23.9940	0.1552
10	39.4602	0.4045
20	67.9249	0.7853
50	149.8560	0.9955

Source: Authors' Computation

Table: 7 Multivariate Diagnostic Tests on the Series using Li & McLeod (1981) Tests

Li & McLeod's Multivariate Portmanteau Statistics on Standardized Residuals		
Lag Order	L&M-Statistic	Probability
5	59.6957	0.0000
10	84.0379	0.0000
20	123.756	0.0003
50	234.127	0.0290
Li & McLeod's Multivariate Portmanteau Statistics on Squared Standardized Residuals		
Lag Order	L&M –Statistic	Probability
5	24.0031	0.1549
10	39.4890	0.4033
20	68.0793	0.7813
50	150.580	0.9949

Source: Authors' Computation using E-Views

VII. Conclusion

Studying how the volatility of a market spills over to other markets is of paramount importance in both economics and finance. This is because the volatility of an asset / price of a commodity could transmit to another asset / price of a commodity directly through its conditional variance. Volatility fosters risks for investments and portfolio management in financial markets. Conventionally, financial markets are structurally interrelated through trade and capital flows. Changes in the price or return of an asset traded on one market could affect prices of other assets traded on another market. This is because financial volatilities often tend to move together over time across assets and markets. This paper has carried out a two-step MGARCH estimation of the volatility spillover effects between two out of the four crude oil futures contracts prices

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traded by the New York Mercantile Exchange (NYMEX) using the Tse and Tsui (2002) model and 7026 daily observations of a data set from 1/03/1985 to 12/31/2018. The results revealed evidence of volatility spillover between the two futures price contracts of the NYMEX namely, price of the futures contract-3 and price of the futures contract-4. The univariate serial correlation tests on the errors revealed no evidence of serial correlation. However, multivariate tests revealed some evidence of serial correlation as indicated by the tests on standardized residuals which imply that the conditional mean may be misspecified. But, multivariate tests on the conditional variance matrix of the model revealed no evidence of serial correlation which suggests that the conditional specification is correct and that the multivariate volatility information provided by the model on the two series is statistically reliable.

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