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Multivariate Garch Analysis of Selected Nigerian Economic Data

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Abstract

Aims: The aim of this study is to examine multivariate GARCH modeling of selected Nigerian economic data.
Study Design: The study used monthly data of Nigerian crude oil prices (dollar Per Barrel), consumer price Index rural, maximum lending rate and prime lending rate.
Methodology: This work covers time series data on crude oil prices, consumer price Index rural, maximum lending rate and prime lending rate extracted from Central Bank of Nigeria (CBN) from 2000 to 2019. In attempt to achieve the aim of the study, quadrivariate VECH and DCC model were applied.
Results: The results confirmed that returns on economic data were correlated. Also, diagonal multivariate VECH model confirmed one of the properties that it must be 'positive semi-definite',
And the DCC confirmed also the positive-definite conditional-variance.
Conclusion: From the results obtained, it was confirmed that there exists a strong confirmation of a time-varying conditional covariance and interdependence among Nigeria economic data. As for cross-volatility effects, past innovations in crude oil price have utmost control on future volatility of returns on economic data. It was also confirmed that time varying covariance displays among these economic data and lower degree of persistence and based on Model selection criteria using the Akaike information criteria (AIC) has 17.485 for diagonal VECH while for DCC has 17.509 AIC which makes VECH model better fitted.

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1 Introduction

Planning is a very important part of any country's growth and development, good Economic Data is needed for this and it must be reliable to get accurate results. The use of statisticians and economists is the key to get reliable and authentic economic data for this purpose. It provides relevant and reliable information of any geographical region or continent like Nigeria. It reveals a true picture of the economic condition of a country. It also assists in determining the fruitfulness of financial plans and programs which has been adopted by a government.

With the boost in the difficulty of instrument in the risk administration field, high burden for different models can create and reveal the uniqueness of Economic data. One important feature of financial data is its volatility. This is because volatility is the assess of danger faced by policy makers, investors, individuals and monetary institution. It is known that volatility of Economic data varies over time and tends to cluster in periods. When analyzing the co-movements of returns on economic data, it is necessary to create, estimate, calculate and project the co-volatility.

One of the greatest challenges encountered by statisticians, econometricians, researchers, time series analysts and policymakers is the ability to capture the unsteady behavior of economic data. This implies that economic data series repeats itself after intervals and this makes planning with data that exhibit such behavior cumbersome. One of the key policies has been to use economic data to drive the economic growth and development of a country but reliable data has not been found which the Government of a country will use as information to develop different sectors of the economy. The frequency of repetition poses an obstacle that avoid a full knowledge of temporal stochastic processes of influenced to which the data can be used for planning and forecasting. Therefore, it becomes necessary to examine the time domain analysis of some Nigerian economic data. Consequently, there is need to examine an appropriate model to be used, this model fits the Multivariate GARCH model. This is because MGARCH has a great breakthrough for financial modeling [1].

Multivariate GARCH helps to examine the mean and volatility spillovers between emerging as well as developed markets. Worthington and Higgs [2] carried out an study of equity income and volatility between t six emerging markets and three developed markets, the results signify great and positive mean, volatility spillovers and higher own volatility spillovers than cross volatility spillovers. Also multivariate GARCH model was used to analize exchange rate volatility of Nigerian Naira against diverse key currencies in the world by Tasi'u [3]. One of the relative benefits of Multivariate GARCH is that it gives a non-constant estimate of the volatility of series. Worthington et al. [4] carried an analysis on conduction of spot electricity prices and price volatility was carried out on five regional electricity markets in Australian using a MGARCH model, the result reveals the existence of positive own mean spillovers in only a small number of markets.

Shamiri and Isa [5] investigate the Multivariate GARCH model with BEKK demonstration to test the transfer of volatility in the monetary crisis of 2007 to the stock markets of Southeast Asia and revealed a spillover effect of the volatility from US to Asia countries. An analysis was carried out by Bensafta and Semedo [6] using MGARCH, they introduced breaks in variance to evaluate contagion during crises, they emphasized that the bias adjustment allows saying that crises are not at all time infectious revealing results found by Forbes and Rigobon [7]. Afees and Kazeem [8] study the modeling of returns and shocks spillovers among stock market and financial market in Nigeria, their results show that shocks to shock returns tend to continue when they take place while shocks to money market returns tend to die out over time.

In recent years, most researchers study the spread of volatility in global stock markets using the MGARCH model extensively to examine and investigate the co-movements of stock markets and volatility spillovers. Grosvenor and Greenidge [9] investigate the co-movement of the regional stock markets of Barbaros, Jamaica, Trinidad and NYSE with a MGARCH model and revealed that important spillovers are present among each of the regional exchange beside NYSE. Similarly, [10] study the monetary co-movements among highly developed economies and arising markets throughout the subprime mortgage turmoil using MGARCH model and recommended that interlinkages among superior economies and EM monetary pointers have been extremely correlated and increased rapidly during the crisis period.

Li and Majerowwska [11] examines the linkages between the stock markets in Warsaw, Budapest, Frankfurt and the U.S. with the use of quadrivariate asymmetric GARCH-BEKK model. it was discovered that proof of return and volatility spillovers from the developed to the emerging markets shows that the magnitude of volatility linkages is small.

Sun and Zang [12] examined the spillovers of the United States to China and Hong Kong for the period 2005-2008. Two MGARCH models were used which is the univariate and multivariate GARCH models. It revealed that volatility spillovers from United state to china and Hong Kong with spillovers from U.S to Hong Kong being more persistent than those in china. The restricted connection among China and Hong Kong overweigh their restricted correlations with United States since the rising monetary integration among these two countries.

Also there exist studies that center on the co-movements of stock markets in rising countries. Fedorova and Saleem [13] used a bivariate BEKK GARCH model to discovered that proof of mean and volatility linkages among the Eastern European emerging equity markets (Hungary, Czech Republic and Russia). Similarly, [14] estimate trivariate GARCH (1,1) in –mean models for 41 emerging markets in Asia, Europe, Latin America and the Middle East. They confirm proof of mean spillovers in emerging markets in Asia and Latin America and spillovers in variance in emerging Europe. cross-market GARCH- in mean effects was also discovered. Bhar and Nikolovia [15] observe the level of integration of the BRIC equity markets (Russia, Brazil, India and China) using a bivariate EGARCH model. They detected that India shows the highest level of regional and international integration between the BRIC countries followed by China, Brazil, and Russia.

2 Materials and Methods

2.1 Model Specification

Multivariate GARCH models were adopted for this study. It shows the interaction of return volatilities of more than one variable in a constant period and also investigates the effectiveness of risk relationships, among different variables used in the study. MGARCH models are used in modeling and forecasting covariances and correlations. They are similar to univariate GARCH model, but the covariances as well as the variances are permitted to be time-varying. There are different classes of multivariate GARCH but in this study, two (2) main classes of multivariate GARCH was used which are the diagonal VECH, and CCC

2.2 The Diagonal VECH –GARCH Model

VECH means Vector Error Conditional Heteroskedasticity. It was introduced by Bollerslev et al. [16]. The model guarantees positive definiteness of variance and co-variance matrix. This model is the restricted version of the VECH model, because it assumes that A and B in the VECH model are diagonal matrices. Bunnag et al. [17] defined the VECH-GARCH Model as thus:

$$VECH\ (H_t) = C + AVECH(\varepsilon_{t-1}\varepsilon'_{t-1}) + BVECH(H_{t-1}) \tag{3.1}$$

H_t is an N x N conditional variance-covariance matrix.
C is an (N (N+1)/2) x 1 vector,
Ai and Bj are N (N+1)/2) x N (N+1)/2) parameter matrices.
N represents the number of variables,

Bollerslev et al. [16] denotes that VECH (.) is the column-stacking operator applied to the upper portion of the symmetric matrix. It stacks the element on and below the main diagonal of a square matrix. For example a 2x2 matrix:

$$\text{Vech} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} = \begin{bmatrix} \alpha_{11} \\ \alpha_{21} \\ \alpha_{22} \end{bmatrix} \tag{3.2}$$

2.3 The Constant Condition Correlation Model

CCC means Constant Conditional Correlation Model was introduced by Bollerslev [18] to basically model the conditional covariance matrix. The conditional correlation is assumed to be constant and the conditional variances are time varying. The model is defined by Modarres and Ouarda [19].

$$\sigma_{ijt} = D_t R D_t = \rho\sqrt{\sigma_{iit}\sigma_{jjt}}$$

Where

$$D_t = diag\left(\sigma_{11t}^{\frac{1}{2}} \dots \sigma_{kkt}^{\frac{1}{2}}\right)$$

R = n x n conditional correlation matrix.

Where σ_{iit} and σ_{jjt} can be defined by any univariate GARCH model and (ρ_{ij}) is the constant conditional correlation.

2.4 Multivariate GARCH model estimation

Following the theory of a conditional normal distribution, multi-variate GARCH models can be done using maximization of a Log-Likelihood function. It is given as:

$$L(\theta) = \frac{TN}{2} - \frac{1}{2}\sum_{t\neq 1}^{T}\left(\log/ H_t /+ \sum{}_t H_{t-1}^{-1} \sum{}_t\right) \tag{3.3}$$

where θ all the parameters to be estimated,

T represents number of observations and

N represents number of the series.

2.5 Diagnostics of MGARCH models

The check is used to identify a well specific MGARCH model that can achieve a reliable inference and estimates.

2.6 Sources of data

The data were collected from the Central Bank of Nigeria (CBN) website for 20yrs, (2000-2019). (www.cbn.gov. ng). The variables used are Crude Oil Price, Consumer Price Index, Maximum Lending Rate and Prime Lending Rate. Bichi [20] noted that the returns on the variables are fitted to conditionally compound monthly formula stated as thus:

$$RCOP = \log\left(\frac{COP_t}{COP_{t-1}}\right) x100. \tag{3.4}$$

$$\mathrm{RCPI} = \log\left(\frac{\mathrm{CPI_t}}{\mathrm{CPI_{t-1}}}\right) x100 \tag{3.5}$$

$$\mathrm{RMLR} = \log\left(\frac{\mathrm{MLR_t}}{\mathrm{MLR_{t-1}}}\right) x100 \tag{3.6}$$

$$\mathrm{RPLR} = \log\left(\frac{\mathrm{PLR}_t}{\mathrm{PLR}_{t-1}}\right)x100 \tag{3.7}$$

2.7 Estimation procedure

The estimation procedure for all models specified above starts with the following steps:

2.7.1 Time plot

The time series collection of the observation of the variables obtained through repeated measurements over time will be plotted on time graph in order to examine the trend in the movement of the variable along time line.

2.7.2 Descriptive test statistic for normality test

The test for normality is using the Jarque-Bera test statistics. Chinyere et al. [21] defined Jarque-Bera as combined test of skewness and kurtosis that examines if data sequence show normal distribution or not; and this test statistic was developed by Jarque and Bera [22] . It is defined as thus;

$$X^2_{\tilde{=}} \ \frac{N}{6}\left[S^2 + \frac{(K-3)^2}{4}\right]$$

S means Skewness,
K means Kurtosis
N means the size of the macroeconomic variables used.

Once a distribution does not observe the normality test, [23] suggested that the option inferential statistic was to use multivariate GARCH with its error distribution assumptions with fixed degree of freedom.

2.7.3 Unit root test

Unit root test is done to check for stationarity using Augmented Dickey -fuller test (ADF) to observe the order of time series.

2.7.4 Multivariate GARCH model estimation

This is done on the basis of the coefficients of the selected model. The news impact assessment and test for volatility persistence will be done under model parameter estimations.

2.7.5 Model selection

Model selection is done using Schwartz information criteria (SIC), Akaike information criteria (AIC). The (AIC) are defined thus:

$$\mathrm{AIC} = 2\mathrm{K} - 2\mathrm{In}\,(\mathrm{L}) = 2\mathrm{K} + \mathrm{In}\left(\frac{RSS}{n}\right) \tag{3.8}$$

K represents the number of variables used in the model and N represents the sample size
L represents maximized value of the likelihood .
RSS represents Residual Sum of Squares.

2.7.6 Model diagnostic check

For a test to be fitted and accurate, a confirmatory test shall be carried out by testing conditional heteroscedasticity. Two diverse tests are used for testing Conditional Heteroscedasticity, They are the ranked-based test and portmanteau test and both were used in this study.

3 Results and Discussion

Firstly, the series were analyzed using the Multivariate GARCH model. The time plot in Figs. 1-4 show the raw data. From visual examination, the crude oil price trend upward and downward (rise and fall which shows the presence of a trend).Consumer Price Index trends upward, Maximum lending rate and Price lending rate also trending upward and downward (rise and fall). The rise and fall in the trend indicates the presence of unit root which is capable of causing biasness in estimation. Therefore there is need for detrending or removal of the trends to enhance stationarity in the series. However, there are different ways of detrending a non stationary series but we will consider two ways which is the calculation of log returns of the series and the differencing. Using the Augmented Dickey- Fuller (ADF) test. It is used to examine the order of integration in time series and also to find the long term trend in the variables used in the study. If the series are stationary, it means their mean, variance and covariance are constant overtime and it implies that the results obtained from the analysis are reliable and can be useful in predicting future economic data [24].

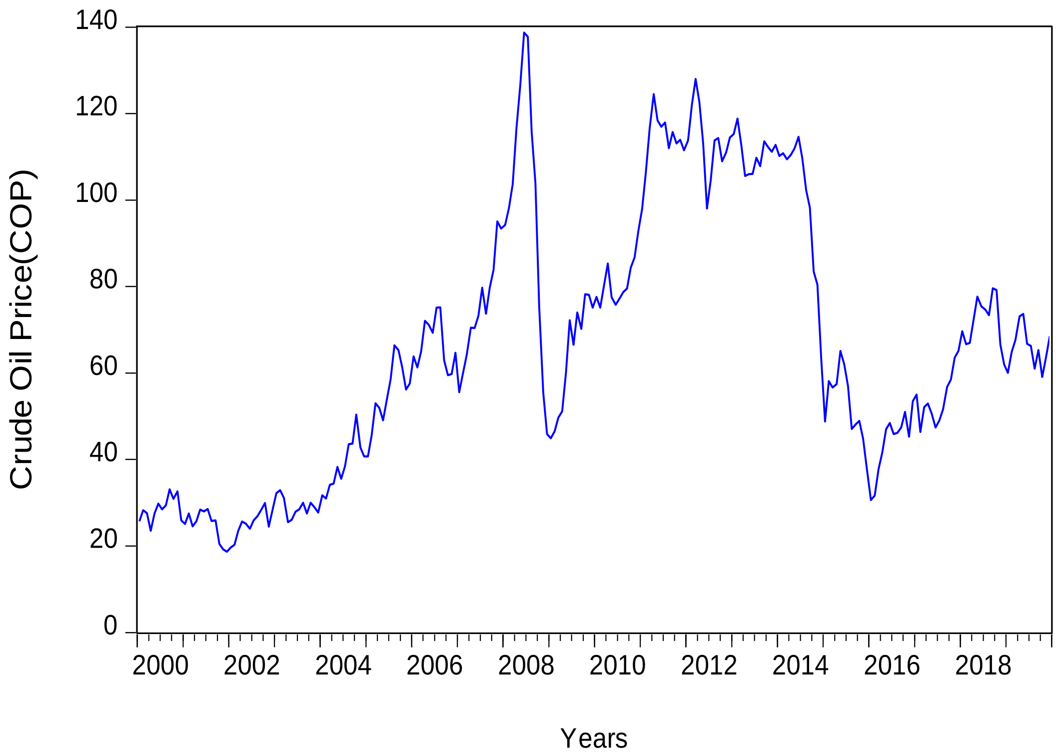

Fig. 1. Time Plot of Raw Data on Crude Oil Prices (COP)

Figs. 5 – 8 shows the time plot of the return series, they show volatility clustering (rise and fall follows another rise and fall around the origin zero). This simply means the series are stationary. Similarly, after differencing the raw data, the result obtained from the differenced series were used to do a time plot to check for stationarity this shows that it was stationary which revealed evidence of volatility clustering. The result obtained confirms [25] assertion in the investigation on return and volatility spillovers across equity markets in Mainland China, Hong Kong and the United States. In this study it was shown that the estimated returns on the series were stationary around zero.

Table 1 show descriptive statistics of the returns series, all the mean are positive, except crude oil price that shows negatively skewed statistics. This is an indication that the returns series are skewed to the left. The probability value of the series is less than 0.05 which shows that it violate the null hypothesis of normality. The null hypothesis of normality states that the probability value less than 0.05 is not normally distributed while the probability value greater than 0.5 is normally distributed. This was in line with [26] findings in their studied on volatility spillovers in emerging markets during the global financial crises: Diagonal BEKK Approach. In the study, all the series were not normally distributed.

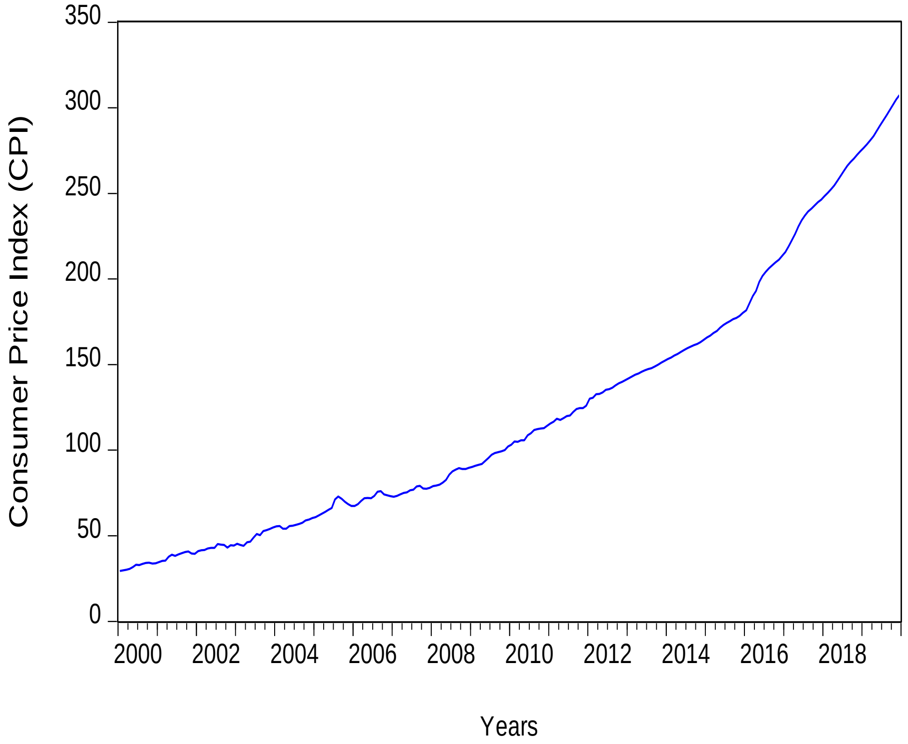

Fig. 2. Time Plot of Raw Data on Consumer Prices Index (CPI)

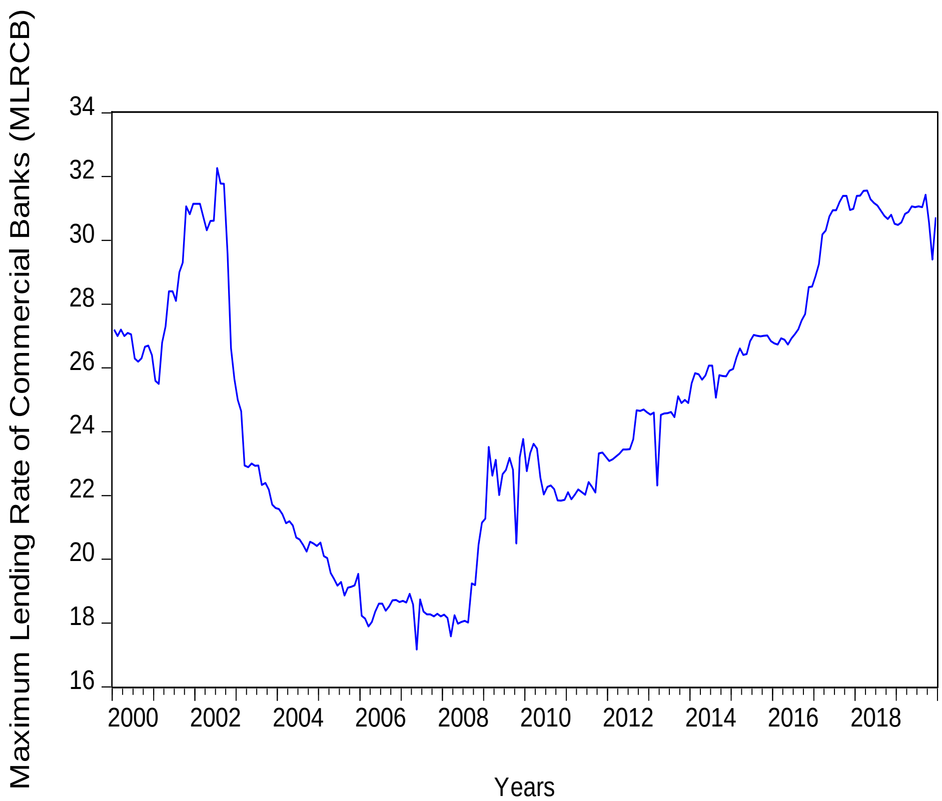

Fig. 3. Time Plot of raw Data on Maximum Lending Rate (MLR)

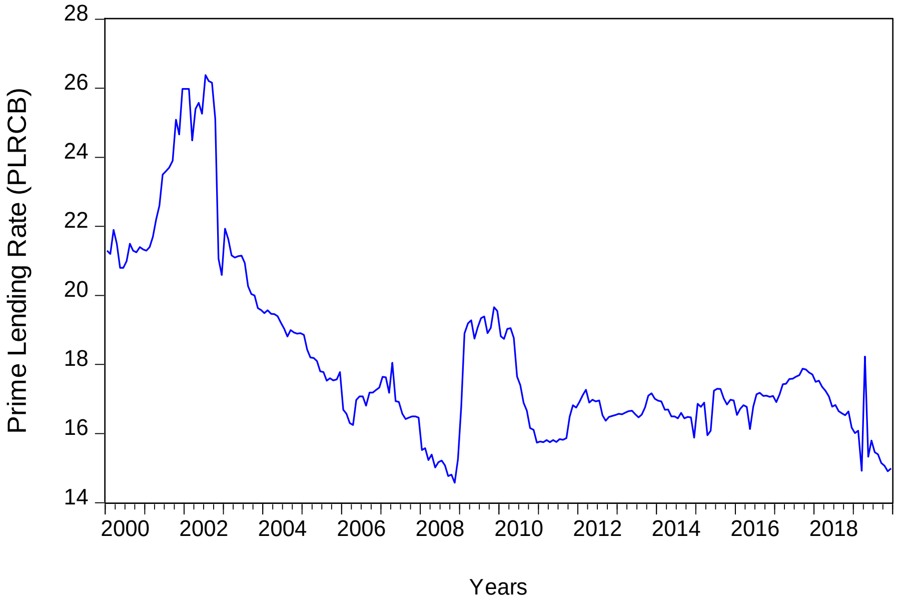

Fig. 4. Time plot of raw data on prime lending rate (PLR)

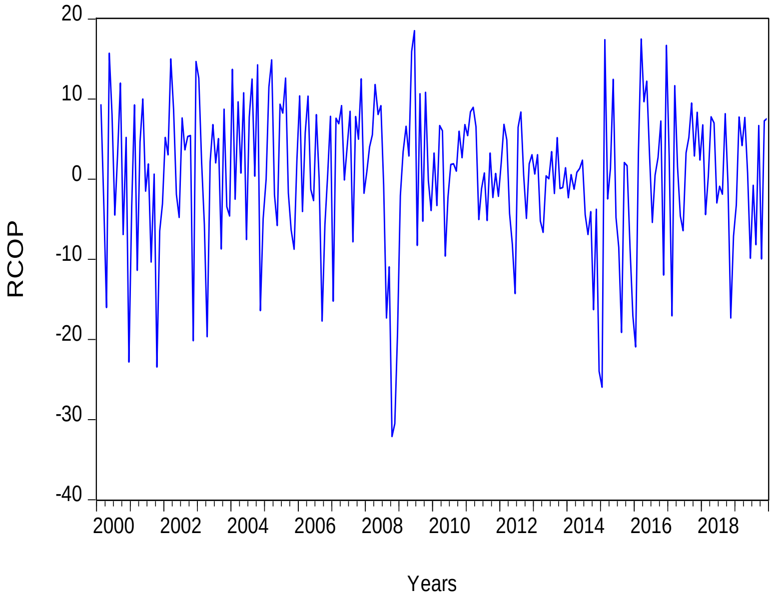

Fig. 5. Time Plot of the returns on crude oil prices (RCOP)

Table 1. Descriptive Statistics on the Returns Series

Text Statistics	RCOP	RCPI	RMLRCB	RPLRCB
Mean	0.409576	0.982453	0.050919	-0.146997
Median	1.340491	0.829724	0.031691	-0.111919
Maximum	18.53161	7.162548	12.37274	20.03660
Minimum	-32.10457	-3.489920	-10.67742	-17.58907
Std. Dev.	9.084101	1.324827	2.605758	3.039905
Skewness	-0.835426	0.527632	0.071632	0.052285
Kurtosis	3.976282	7.186879	9.587684	19.66538
Jarque-Bera	37.29268	185.6586	432.3719	2765.885
Probability	0.000000	0.000000	0.000000	0.000000

Source: Extract from E view software Analysis

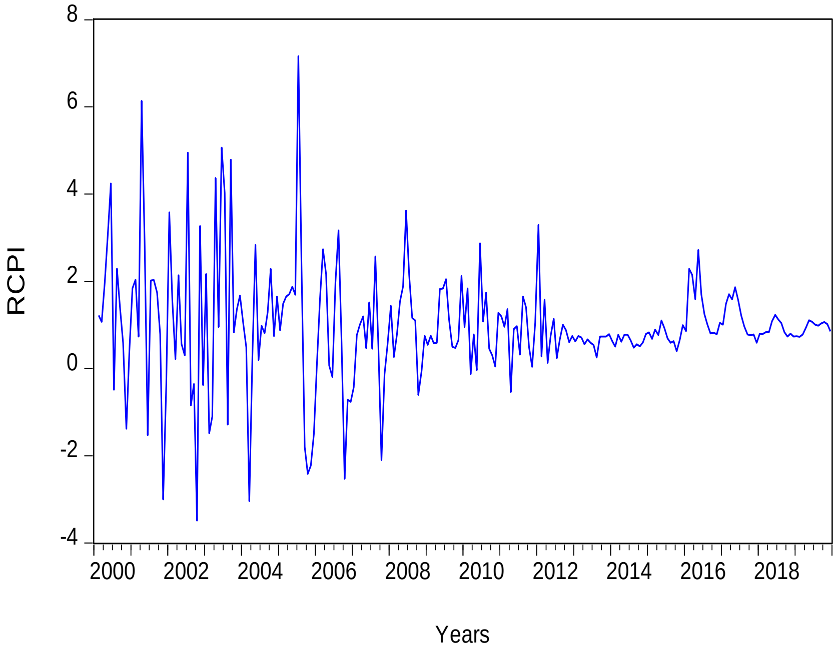

Fig. 6. Time plot of the Returns on Consumer Price Index (RCPI)

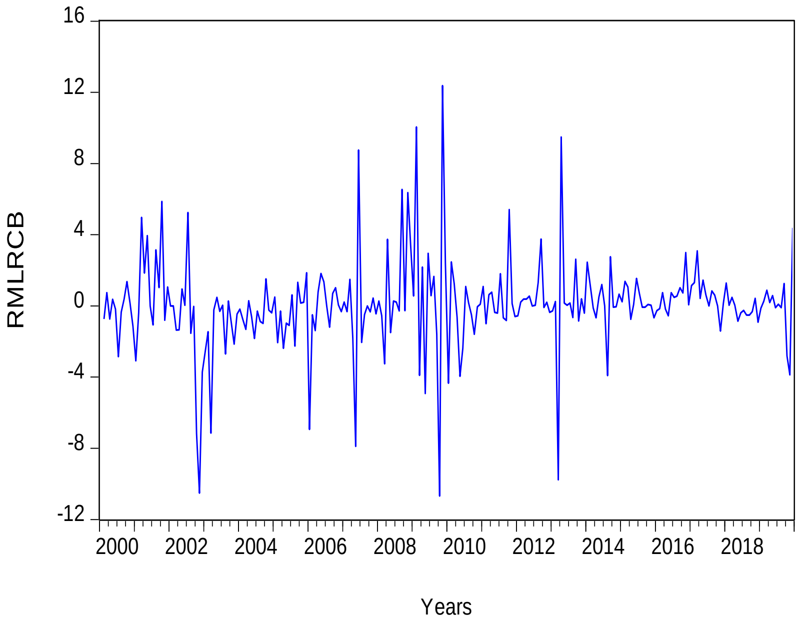

Fig. 7. Time Plot of the Returns on Maximum Lending Rate (RMLR)

Table 2. Extraction of Unit Root-Test for the Raw Series

Variable	ADF	
	1(0)	**1(1)**
Crude Oil Price	-2.182	-11.0715***
Consumer Price Index	6.465	-5.730***
Maximum Lending Rate	-0739	-15.929**
Prime Lending Rate	-1.694	-16.953**

***Source**: Extract from Eviews Software and *** represented 5% Level of Significance*

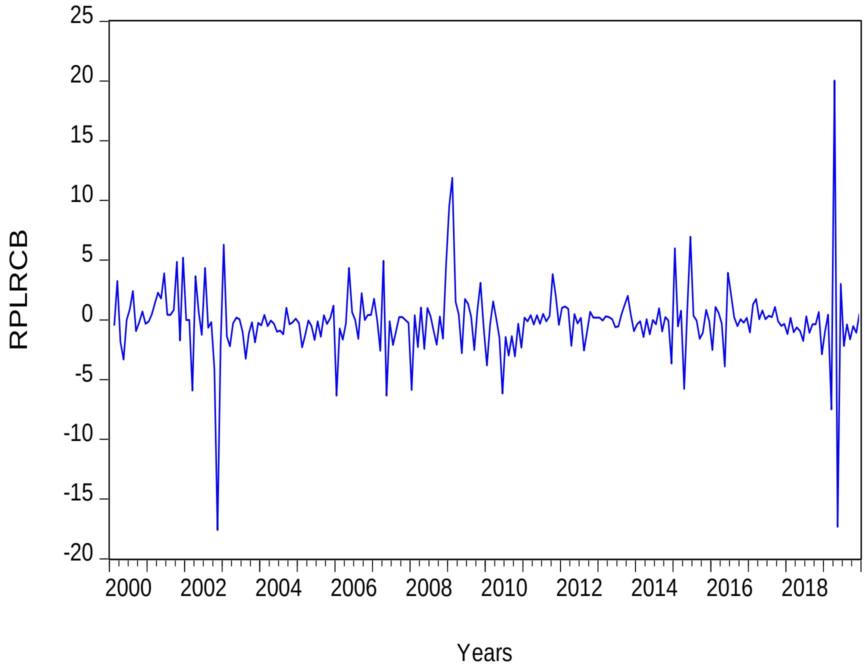

Fig. 8. Time plot of the Returns on Prime Lending Rate (RPLR)

Table 2 contains the result of unit root test for the raw data series. It shows that all the series were stationary at first difference order 1.

Table 3. Test for co integration using trace and maxeigen statistic

Hypothesized No of CE(S)	Eigen Value	Trace status	0.05 critical Value	Probability	Max Statistic	0.5 critical Value	Probability
None*	0.360	302.779	47.856	0.0001	105.376	27.584	0.0000
Almost 1*	0.303	197.403	29.797	0.0001	85.160	21.132	0.0000
Almost 2*	0.243	112.243	15.495	0.0001	65.794	14.265	0.0000
Almost 3%	0.179	46.449	3.841	0.0000	46.449	3.841	0.0000

Source: extract from e view Software

Table 4. Heteroskedaticity test

Joint test:					
Chi-sq	**Df**	**Prob.**			
375.9909	180	0.0000			
Individual components:					
Dependent	**R-squared**	**F(18,217)**	**Prob.**	**Chi-sq(18)**	**Prob.**
res1*res1	0.057762	0.739040	0.7685	13.63180	0.7528
res2*res2	0.296031	5.069575	0.0000	69.86339	0.0000
res3*res3	0.320037	5.674162	0.0000	75.52869	0.0000
res4*res4	0.201182	3.036180	0.0001	47.47886	0.0002
res2*res1	0.163208	2.351316	0.0020	38.51708	0.0033
res3*res1	0.078638	1.028944	0.4284	18.55866	0.4195
res3*res2	0.414085	8.520066	0.0000	97.72417	0.0000
res4*res1	0.205426	3.116800	0.0000	48.48059	0.0001
res4*res2	0.236654	3.737484	0.0000	55.85031	0.0000
res4*res3	0.179888	2.644331	0.0005	42.45354	0.0010

Table 3 contains the result for test of co-integration using trace and max Eigen test statistics. This is done to know whether there is a co-integrating relationship within the returns series and from the result obtained, there exist four co-integration equations because the probability is less than 0.05.

Table 4 above contains the Test for Heteroskedasticity, it states that residue obtained from a model must obey the assumption of a classical least square regression which says that the residual obtained from a linear regression must obey the assumption of homoskedaticity (zero mean and constant variance). The probability value in the table shows that its less 0.05% which violates the assumption of homoskedaticity.

In this study, a 4x4 MGARCH were examined in order to determine an appropriate form of MGARCH in modeling Economic data in Nigeria.

Table 5. VECH Residual Normality Tests

Component	**Skewness**	**Chi-sq**	**Df**	**Prob.***
1	-0.156571	0.964234	1	0.3261
2	-0.156718	0.966043	1	0.3257
3	-0.544151	11.64663	1	0.0006
4	0.430751	7.298146	1	0.0069
Joint		20.87505	4	0.0003
Component	**Kurtosis**	**Chi-sq**	**Df**	**Prob.**
1	3.133508	0.175274	1	0.6755
2	14.90759	1394.274	1	0.0000
3	6.649987	131.0037	1	0.0000
4	6.499635	120.4332	1	0.0000
Joint		1645.887	4	0.0000
Component	**Jarque-Bera**	**Df**	**Prob.**	
1	1.139508	2	0.5657	
2	1395.240	2	0.0000	
3	142.6503	2	0.0000	
4	127.7313	2	0.0000	
Joint	1666.762	8	0.0000	

Table 5 shows the Vector Error Correction Model (VECM) residual normality test. The result shows that the residual obtained is normally distributed.

Table 6 represents the results of the Quadrivariate Diagonal VECH-GARCH model. In the diagonal VECH Model, the leading diagonal in the indefinite matrix (A1) are positive and significant at 5% level of significance. The diagonal of the ARCH term confirms that there is short run persistence of shock in the return on maximum lending rate (RMLR) (0.691)(0.000) dynamics followed by RPLR (0.291)(0.000), RCOP (0.254)(0.005) and RCPI(0.103)(0.000) respectively. Similarly, the pattern and order of persistence confirm that the variables depend on their own lag innovations. In the GARCH term, the leading diagonal (0.706, 0.902, 0.326, and 0.555) are also positive and significant at 5% level of significance. The persistence of conditional variance are as thus: RCPI (0.902), RCOP (0.706), RPLR (0.555) and RMLR (0.326) respectively. This also shows that the changing pattern of dependence or influence of volatility of one macro –economic variables are in descending order of magnitude.

Table 7 represents the results of the Quadrivariate Diagonal CCC-GARCH model. In the case of diagonal constant correlation (DCC), the result shows that when the estimate of the ARCH and GARCH term are less than one, it means the conditional volatility of each of the series is finite otherwise it is infinite (which means it is greater than one). The GARCH parameter B1 (1), B1(2), B1(3) and B1(4) which is (0.739, 0.898, 0.269 and 0.605) are comparatively larger than the ARCH term. This simply means time vary correlation is persistence. The conditional correlation dynamics ranges between (-0.057 (RCOP and RPLR) and (0.086(RCPI and RMLR).

3.1 RCOP, RCPI, RMLRT $ RPLRT (VECH-GARCH)

Table 6. (VECK- GARCH) Model

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.252238	0.686505	0.367424	0.7133
C(2)	1.006754	0.034517	29.16703	0.0000
C(3)	16.95045	0.047046	360.2933	0.0000
C(4)	0.013990	0.157735	0.088696	0.9293
	Variance Equation Coefficients			
C(5)	5.535685	3.296715	1.679152	0.0931
C(6)	0.024004	0.152659	0.157239	0.8751
C(7)	0.004030	0.175755	0.022928	0.9817
C(8)	-0.639965	1.644445	-0.389168	0.6972
C(9)	-0.003080	0.001231	-2.501438	0.0124
C(10)	0.013482	0.021116	0.638452	0.5232
C(11)	-0.000168	0.009510	-0.017702	0.9859
C(12)	0.033391	0.018374	1.817309	0.0692
C(13)	0.099241	0.165201	0.600727	0.5480
C(14)	1.275797	0.273485	4.664961	0.0000
C(15)	0.253955	0.089917	2.824336	0.0047
C(16)	0.117007	0.080920	1.445961	0.1482
C(17)	0.148776	0.101284	1.468904	0.1419
C(18)	-0.244756	0.107977	-2.266732	0.0234
C(19)	0.102555	0.022530	4.551837	0.0000
C(20)	0.292853	0.086204	3.397196	0.0007
C(21)	0.031591	0.047633	0.663211	0.5072
C(22)	0.690517	0.196128	3.520743	0.0004
C(23)	0.083342	0.119326	0.698441	0.4849
C(24)	0.290647	0.082097	3.540287	0.0004
C(25)	0.706055	0.090720	7.782795	0.0000
C(26)	0.693338	0.226863	3.056200	0.0022
C(27)	0.443187	0.374018	1.184933	0.2360
C(28)	-0.387012	0.285280	-1.356604	0.1749
C(29)	0.901732	0.012469	72.31600	0.0000
C(30)	0.152764	0.235270	0.649314	0.5161
C(31)	0.925375	0.147219	6.285697	0.0000
C(32)	0.326254	0.098301	3.318938	0.0009
C(33)	-0.020848	1.186392	-0.017572	0.9860
C(34)	0.555430	0.073475	7.559474	0.0000
Log likelihood	-2055.479	Schwarz criterion		17.97974
Avg. log likelihood	-2.150083	Hannan-Quinn criter.		17.68447
Akaike info criterion	17.48518			
Equation: RCOP = C(1)				
R-squared	-0.000301	Mean dependent var		0.409576
Adjusted R-squared	-0.000301	S.D. dependent var		9.084101
S.E. of regression	9.085469	Sum squared resid		19645.89
Durbin-Watson stat	1.647971			
Equation: RCPI = C(2)				
R-squared	-0.000338	Mean dependent var		0.982453
Adjusted R-squared	-0.000338	S.D. dependent var		1.324827
S.E. of regression	1.325051	Sum squared resid		417.8707
Durbin-Watson stat	1.691589			
Equation: PLRCB = C(3)				

	Coefficient	Std. Error	z-Statistic	Prob.
R-squared	-0.203090	Mean dependent var		18.12109
Adjusted R-squared	-0.203090	S.D. dependent var		2.603088
S.E. of regression	2.855209	Sum squared resid		1940.228
Durbin-Watson stat	0.039720			
Equation: RMLRCB = C(4)				
R-squared	-0.000202	Mean dependent var		0.050919
Adjusted R-squared	-0.000202	S.D. dependent var		2.605758
S.E. of regression	2.606021	Sum squared resid		1616.340
Durbin-Watson stat	2.220019			
Covariance specification: Diagonal VECH				
GARCH = M + A1.*RESID(-1)*RESID(-1)' + B1.*GARCH(-1)				
M is an indefinite matrix*				
A1 is an indefinite matrix*				
B1 is an indefinite matrix*				
	Transformed Variance Coefficients			
	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
M(1,1)	5.535685	3.296715	1.679152	0.0931
M(1,2)	0.024004	0.152659	0.157239	0.8751
M(1,3)	0.004030	0.175755	0.022928	0.9817
M(1,4)	-0.639965	1.644445	-0.389168	0.6972
M(2,2)	-0.003080	0.001231	-2.501438	0.0124
M(2,3)	0.013482	0.021116	0.638452	0.5232
M(2,4)	-0.000168	0.009510	-0.017702	0.9859
M(3,3)	0.033391	0.018374	1.817309	0.0692
M(3,4)	0.099241	0.165201	0.600727	0.5480
M(4,4)	1.275797	0.273485	4.664961	0.0000
A1(1,1)	0.253955	0.089917	2.824336	0.0047
A1(1,2)	0.117007	0.080920	1.445961	0.1482
A1(1,3)	0.148776	0.101284	1.468904	0.1419
A1(1,4)	-0.244756	0.107977	-2.266732	0.0234
A1(2,2)	0.102555	0.022530	4.551837	0.0000
A1(2,3)	0.292853	0.086204	3.397196	0.0007
A1(2,4)	0.031591	0.047633	0.663211	0.5072
A1(3,3)	0.690517	0.196128	3.520743	0.0004
A1(3,4)	0.083342	0.119326	0.698441	0.4849
A1(4,4)	0.290647	0.082097	3.540287	0.0004
B1(1,1)	0.706055	0.090720	7.782795	0.0000
B1(1,2)	0.693338	0.226863	3.056200	0.0022
B1(1,3)	0.443187	0.374018	1.184933	0.2360
B1(1,4)	-0.387012	0.285280	-1.356604	0.1749
B1(2,2)	0.901732	0.012469	72.31600	0.0000
B1(2,3)	0.152764	0.235270	0.649314	0.5161
B1(2,4)	0.925375	0.147219	6.285697	0.0000
B1(3,3)	0.326254	0.098301	3.318938	0.0009
B1(3,4)	-0.020848	1.186392	-0.017572	0.9860
B1(4,4)	0.555430	0.073475	7.559474	0.0000

3.2 RCOP, RCPI, RMLR $ RPLR (DCC-GARCH)

Table 8 shows diagnostic test which is for autocorrelation using Ljung-Box Qstatistics. The result shows that there is no present of autocorrelation in the standard residuals obtained from the model using the return on the series of consumer price Index and maximum lending rate. Therefore, this shows that the conditional mean return equation are correctly specified with the bivariate BEKK-GARCH models.

Table 7. (DCC- GARCH) Model

	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
C(1)	0.531423	0.633751	0.838535	0.4017
C(2)	0.980826	0.022338	43.90780	0.0000
C(3)	16.85014	0.043428	388.0041	0.0000
C(4)	-0.007993	0.141035	-0.056672	0.9548
	Variance Equation Coefficients			
C(5)	7.767584	4.755545	1.633374	0.1024
C(6)	0.170242	0.064211	2.651292	0.0080
C(7)	0.739181	0.097268	7.599423	0.0000
C(8)	-0.002819	0.001454	-1.939222	0.0525
C(9)	0.110625	0.024830	4.455331	0.0000
C(10)	0.898115	0.013370	67.17346	0.0000
C(11)	0.052867	0.020012	2.641801	0.0082
C(12)	0.685777	0.225285	3.044033	0.0023
C(13)	0.269438	0.122111	2.206497	0.0273
C(14)	1.073914	0.206401	5.203049	0.0000
C(15)	0.275373	0.065713	4.190549	0.0000
C(16)	0.604653	0.055515	10.89175	0.0000
C(17)	0.147124	0.084308	1.745076	0.0810
C(18)	0.051798	0.075595	0.685196	0.4932
C(19)	-0.056720	0.064409	-0.880617	0.3785
C(20)	0.085516	0.077020	1.110310	0.2669
C(21)	0.056959	0.089566	0.635948	0.5248
C(22)	0.010686	0.076601	0.139504	0.8891
Log likelihood	-2070.372	Schwarz criterion		17.82939
Avg. log likelihood	-2.165661	Hannan-Quinn criter.		17.63834
Akaike info criterion	17.50939			
Equation: RCOP = C(1)				
R-squared	-0.000181	Mean dependent var		0.409576
Adjusted R-squared	-0.000181	S.D. dependent var		9.084101
S.E. of regression	9.084922	Sum squared resid		19643.52
Durbin-Watson stat	1.648169			
Equation: RCPI = C(2)				
R-squared	-0.000002	Mean dependent var		0.982453
Adjusted R-squared	-0.000002	S.D. dependent var		1.324827
S.E. of regression	1.324828	Sum squared resid		417.7302
Durbin-Watson stat	1.692158			
Equation: PLRCB = C(3)				
R-squared	-0.239386	Mean dependent var		18.12109
Adjusted R-squared	-0.239386	S.D. dependent var		2.603088
S.E. of regression	2.897959	Sum squared resid		1998.763
Durbin-Watson stat	0.038557			
Equation: RMLRCB = C(4)				
R-squared	-0.000513	Mean dependent var		0.050919
Adjusted R-squared	-0.000513	S.D. dependent var		2.605758
S.E. of regression	2.606427	Sum squared resid		1616.844
Durbin-Watson stat	2.219327			
Covariance specification: Constant Conditional Correlation				
GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)				
COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))				
	Transformed Variance Coefficients			
	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
M(1)	7.767584	4.755545	1.633374	0.1024
A1(1)	0.170242	0.064211	2.651292	0.0080

	Coefficient	Std. Error	z-Statistic	Prob.
B1(1)	0.739181	0.097268	7.599423	0.0000
M(2)	-0.002819	0.001454	-1.939222	0.0525
A1(2)	0.110625	0.024830	4.455331	0.0000
B1(2)	0.898115	0.013370	67.17346	0.0000
M(3)	0.052867	0.020012	2.641801	0.0082
A1(3)	0.685777	0.225285	3.044033	0.0023
B1(3)	0.269438	0.122111	2.206497	0.0273
M(4)	1.073914	0.206401	5.203049	0.0000
A1(4)	0.275373	0.065713	4.190549	0.0000
B1(4)	0.604653	0.055515	10.89175	0.0000
R(1,2)	0.147124	0.084308	1.745076	0.0810
R(1,3)	0.051798	0.075595	0.685196	0.4932
R(1,4)	-0.056720	0.064409	-0.880617	0.3785
R(2,3)	0.085516	0.077020	1.110310	0.2669
R(2,4)	0.056959	0.089566	0.635948	0.5248
R(3,4)	0.010686	0.076601	0.139504	0.8891

Table 8. Diagnostic check

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	Df
1	33.74407	0.0000	33.88585	1.0000	4
2	37.06766	0.0000	37.23749	0.0000	8
3	42.65781	0.0000	42.89870	0.0000	12
4	44.19141	0.0002	44.45840	0.0002	16
5	54.58444	0.0000	55.07351	0.0000	20
6	62.07002	0.0000	62.75185	0.0000	24
7	70.00408	0.0000	70.92530	0.0000	28
8	76.00991	0.0000	77.13912	0.0000	32
9	79.65480	0.0000	80.92664	0.0000	36
10	80.76680	0.0001	82.08720	0.0001	40
11	83.89948	0.0003	85.37101	0.0002	44
12	86.70155	0.0005	88.32121	0.0004	48

Table 9 test for residual normality using orthogonalization cholesky shows that the model is fitted.

Table 9. Normality

Component	Skewness	Chi-sq	Df	Prob.
1	-0.622799	15.45048	1	0.0001
2	-0.873715	30.40790	1	0.0000
Joint		45.85838	2	0.0000
Component	**Kurtosis**	**Chi-sq**	**Df**	**Prob.**
1	9.017608	360.6073	1	0.0000
2	7.082290	165.9565	1	0.0000
Joint		526.5638	2	0.0000
Component	**Jarque-Bera**	**Df**	**Prob.**	
1	376.0578	2	0.0000	
2	196.3644	2	0.0000	
Joint	572.4222	4	0.0000	

Table 10. Estimating Results for Model Selection

	QUADRIVARIABLE	AIC	SIC	LEAST AIC
VECH	RCOP, RCPI, RMLR & RPLR	17.485	17.980	VECH (17.485)
DCC	RCOP, RCPI, RMLR & RPLR	17.509	17.829	RCOP, RCPI, RMLR & RPLR

Table 10 contains estimation results for model selection for Quadruvariate MGARCH and it was found that based on Akaike information criteria diagonal VECH is better fitted than the DCC because it has the least Akaike information criteria in this study.

4 Conclusion

The study focused strictly on the application of Multivariate GARCH model to modeling Nigeria Economic Data (Crude oil price, Consumer price Index, Maximum lending rate and Prime lending rate). The result obtained shows that diagonal multivariate VECH model is better fitted than DCC model. it confirmed that it is positive definite and each micro economic variable depends on its own lag innovations. There exist a strong evidence of a time-varying conditional covariance and interdependence between Nigeria economic data. Time varying correlation displays between crude oil price and other economic data (consumer price index, maximum and prime lending rate) and high degree of persistence during these period under investigation. spillover effects also existed between crude oil and the other economic data.(consumer price index, maximum lending rate and prime lending rate). Based on Model selection criteria using the Akaike information criteria (AIC) diagonal VECH- GARCH model is better fitted than the other model.

Competing Interests

Authors have declared that no competing interests exist.

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