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TESTING THE PERFORMANCE OF CONDITIONAL VARIANCE-COVARIANCE IN DIAGONAL MGARCH MODELS USING EXCHANGE RATE AND NIGERIA COMMERCIAL BANKS INTEREST RATES

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Abstract: *The study examines the performance of conditional variance-covariance in Diagonal MGARCH models using exchange rate and Nigerian commercial Banks interest rate on time deposits maturing in a monthly order. The data for the study was on monthly Exchange rate (Excr), commercial banks interest rate on time deposits maturing in one month (CBIRTD1), commercial banks interest rate on time deposits maturing in three months (CBIRTD3), commercial banks interest rate on time deposits maturing in six months (CBIRTD6), commercial banks interest rate on time deposits maturing in twelve months (CBIRTD12).The monthly exchange rates (Naira/Dollars). These data were extracted from the Central Bank of Nigeria (CBN) statistical database website (www.cbn.gov.ng). The data spanned from January 1991 – December 2019 and they were fitted to monthly compound returns with the aid of STATA and Eviews Software version 15 and 10 respectively. Multivariate Diagonal VECH (DVECH) and BEKK-GARCH models were used to determine how variance- covariance interact over time and these models estimated conditional variance-covariance matrix of multiple of five time series data.The result obtained from the diagonal multivariate VECH GARCH model show that the covariance between these variables does not cluster overtime. It was also found that shocks arising from exchange rate have an effect on commercial banks interest rate on time deposits maturing whose estimates have the same positive conditional variance. The diagonal multivariate VECH model shows 'positive semi-definite' characteristic i.e variance-covariance matrix has positive estimates on its leading diagonal, and this shows that the entries are symmetrical about their leading diagonal. Also, the result obtained from the diagonal multivariate BEKK GARCH model shows that the estimated conditional variance depends on its own past historical innovations. This simply means volatility of exchange rate responds significantly to past squared shocks in its own sector, as well as in the commercial Banks interest rates operation.The result also confirmed that there exist a strong evidence of a time-varying conditional covariance and interdependence between exchange rate and indicators of Nigerian commercial banks interest rate. Similarly, evidence of cross-volatility effects was confirmed; past innovations in exchange rate have greatest influence on future volatility of Nigeria commercial banks interest rate returns. Based on Model selection criteria using the Akaike information criteria (AIC) diagonal VECH model is better fitted than the diagonal multivariate BEKK GARCH model.*

***Keywords**:* Exchange Rate, Commercial Banks Interest Rates and MGARCH

Introduction

1.1 Background to the study

The performance of Multivariate Generalized Autoregressive Conditional Heteroskedasticity models in finance had generated a lot of concerns for the past few years after the introduction of univariate Generalized Autoregressive Conditional Heteroskedasticity models by Engle in 1993 (Deebom and Tuaneh, 2019). According to Deebom and Tuaneh (2019), the use of Multivariate Generalized Autoregressive Conditional Heteroskedasticity models had been widely applied in several areas of studies especially in the modeling of the value at risk (VaR), portfolio optimization, pricing of assets and derivatives, futures hedging, volatility transmitting, and asset allocation, problems involving risk assessment, asset allocation, hedging in futures markets(Tse,2000). All of the above-mentioned problems require the application of variance and covariance in their estimation. According to (De Goeij*et al.* 2004), we use this because financial time series are always changing over time. They further explained that the tendency for financial time series to change over time are said to be risky if their returns are volatile. It is noted that in many financial econometric models conditional-variance equation plays a very significant role. For example, systematic risks are measured by beta which depends on the (conditional) second moments of the asset returns, and so does the minimum-variance hedge ratio. Reliable estimates and inference from these variables depend on well-specified conditional heteroscedasticity models (Deebom and Tuaneh, 2019). Therefore, this study deals with the linkage between the exchange rate and commercial Banks' interest rates of the financial sector. The financial sector remains a crucial issue for risk management and portfolio management.

In recent years, the dynamic relationship between exchange rate and indicators of commercial Banks interest rates risks has had important implications and has drawn the attention of numerous economists, both for theoretical and empirical reasons. This is because exchange rate and commercial banks interest rate risks play an important role in influencing the development of an economy. Besides, the liberalization of financial markets and hi-tech advancement has widened the nexus between exchange rate, interest rates, and price returns on the stock in the financial markets. The relationship between interest rates, exchange rate, and the price returns on the stock in the financial markets has given rise to a prolific research activity over the past few decades. To handle situation we use multivariate GARCH because they usually estimate the current value of a variable depends not only on its past values, but also combine the past and/or current values (conditional variance and covariance) of other variables (schmidth, 2005). It is against this background that this study examines the performance of conditional variance-covariance in Diagonal MGARCH models using exchange rate and Nigerian commercial banks interest rate.

2.1 Literature Review

Tai (2000), examine time-varying market, interest rate, and exchange rate risk premium in the US commercial bank stock returns. The study aimed to apply the multivariate GARCH in mean (MGARCH-M) method such that both conditional of first and second moments of the banks' portfolio returns and risk factors are estimated simultaneously. The data used in the study were three bank portfolios, namely: Money Center bank, large banks, and Regional bank. The results obtained from the estimation shows strong evidence of time-varying interest rate and exchange rate risk premium and weak evidence of time-varying world market risk premium for all the variables used in the study.

Deebom and Tuaneh(2019) revealed that there are three(3) main classes of multivariate GARCH formulation that are widely used: VECH, diagonal VECH, and BEKK. In the case of the VECH, the

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conditional variance and covariance depend upon lagged values of all of the variances and covariance and on lags of the squares of both error terms and their cross products. Similarly, in an attempt to examine Volatility and Macroeconomic Spillovers effects Scott (2015), investigates Oil-Price Volatility and Macroeconomic Spillovers in Central and Eastern Europe: Evidence from a Multivariate GARCH Model . The purpose of the study was to tests for spillovers among commodity-price and macroeconomic volatility using applying a VAR (1)-MGARCH model to monthly time series for eight CEE countries. The results show that oil prices do indeed have effects throughout the region, as do spillovers among exchange rates, inflation, interest rates, and output. However, the effect differs from country to country—particularly when different degrees of transition and integration are considered. Although oil prices have a limited impact on the currencies of Russia and Ukraine, they do make a much larger role to the two countries' macroeconomic unpredictability than do spillovers among the other macroeconomic variables

Material and methods

3.4 Sources of Data

The empirical work for this study was carried out using a monthly data on exchange rate (excr) , commercial banks interest rate on time deposits maturing in one month(CBIRTD1), commercial banks interest rate on time deposits maturing in three months(CBIRTD3), commercial banks interest rate on time deposits maturing in six months(CBIRTD6), commercial banks interest rate on time deposits maturing in twelve months(CBIRTD12).The monthly exchange rates (Naira/Dollars). These data were extracted from the Central Bank of Nigeria (CBN) statistical database website (www.cbn.gov. ng). The date was between January 1991 – December 2019 and they fitted to monthly compound return computed thus:

$$\mathrm{Re}\,xcr = \log\left(\frac{Excr}{Excr_{t-1}}\right)x100. \quad 3.1$$

$$\text{RCBIRTD1} = \log\left(\frac{\text{CBIRTD1}_t}{\text{CBIRTD1}_{t-1}}\right)x100 \quad 3.2$$

$$\text{RCBIRTD3} = \log\left(\frac{\text{CBIRTD3}_t}{\text{CBIRTD3}_{t-1}}\right)x100 \quad 3.3$$

$$\text{RCBIRTD6} = \log\left(\frac{\text{CBIRTD6}_t}{\text{CBIRTD6}_{t-1}}\right)x100 \quad 3.4$$

$$\text{RCBIRTD12} = \log\left(\frac{\text{CBIRTD12}_t}{\text{CBIRTD12}_{t-1}}\right)x100 \quad 3.5$$

For t = 1, 2, ….t-j where the data in "t" represents the data at the present time, while the data in "t-1" represents the data at the past period in time(lagged). The data were analyzed using STATA andEviews Software version 15 and 10 respectively.

Model Specification

In line with the objective of the study, the model adopted in this study wasdiagonal multivariate GARCH models. We applied the temporal dependence of the conditional variance (Ht) using two differentMultivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH) models.These models emphasize the interaction of return volatilities of more than one variable in a constant period. The model will also investigate the effectiveness of risk relationships, among different variables used in the study. The basic formulations of Multivariate GARCH models are similar to that of the univariate GARCH model, but where covariances as well as the variances are permitted to be time-varying.

Diagonal VECH-GARCH

A diagonal VECH (DVECH) model, developed byBollerslev*et al (*1988), presupposes that thematrices A and B in equation (2) are diagonal. Therefore, each conditional variance and covariance in the system has a single variable GARCH-type specification without allowing for feedbacks among volatilities and between volatilities and covariances; cited, for example, Bauwens*et al*.(2007) for a bivariate empirical application. Sufficient conditions to guarantee the positivity of the covariance matrices can be derived by diagonal VECH (DVECH) model parameters in terms of Hadamard products.According to Milan (2014), further opined that the derivative of a sufficient condition for diagonal VECH model for (Ht) to be positive definite can be written in matrix representation as follows **:**

$$VECH(H_t) = C + AVECH(\Xi_{t-1}\Xi_{t-1}^{1}) + BVECH(H_{t-1}) \quad , \ \Xi_t / \Psi_{t-1} \sim N(0, H_t) \qquad 3.16$$

The Diagonal VECH Constant with Indefinite Matrix modified presentation of the four variables models Of Variance and Covariance can written as thus

$$\sigma_t^2 = \mathrm{M} + \mathrm{A1.}{*}\varepsilon_{t-1} {*} \varepsilon_{t\text{-}1}^{1} + \mathrm{B1.}{*}\sigma_{t\text{-}1}^{2} \qquad 3.17$$

M is an indefinite matrix, A1 is an indefinite matrix and B1 is an indefinite matrix* The suitable way of decomposing each of the conditional variance into its ARCH and GARCH components. For example, the ARCH component is associated with the conditional variance and covariance of Excr ,CBIRTD1, CBIRTD3,CBIRTD6, and CBIRTD12 can be written as:

The decomposed conditional variance can be written as:

$$\left.\begin{aligned}
\sigma_1^2 &= M(1,1) + A1(1,1) * \varepsilon_{t-1}^2 + B1(1,1) * \sigma_{t-1}^2 \\
\sigma_2^2 &= M(2,2) + A1(2,2) * \varepsilon_{t-1}^2 + B1(2,2) * \sigma_{t-1}^2 \\
\sigma_3^2 &= M(3,3) + A1(3,3) * \varepsilon_{t-1}^2 + B1(3,3) * \sigma_{t-1}^2 \\
\sigma_4^2 &= M(4,4) + A1(4,4) \ * \varepsilon_{t-1}^2 + B1(4,4) * \sigma_{t-1}^2 \\
\sigma_5^2 &= M(5,5) + A1(5,5) * \varepsilon_{t-1}^2 + B1(5,5) * \sigma_{t-1}^2
\end{aligned}\right\} \quad 3.18$$

The decomposed covariance can also be written as:

$$\left.\begin{aligned}
\rho_{1,2} &= M(1,2) + A1(1,2) * \varepsilon_{1,t-1} * \varepsilon_{2,t-1} + B1(1,2) * \rho_{1,2t-1} \\
\rho_{1,3} &= M(1,3) + A1(1,3) * \varepsilon_{1,t-1} * \varepsilon_{3,t-1} + B1(1,3) * \rho_{1,3t-1} \\
\rho_{1,4} &= M(1,4) + A1(1,4) * \varepsilon_{1,t-1} * \varepsilon_{4,t-1} + B1(1,4) * \rho_{1,4t-1} \\
\rho_{1,5} &= M(1,5) + A1(1,5) * \varepsilon_{1,t-1} * \varepsilon_{5,t-1} + B1(1,5) * \rho_{1,5t-1} \\
\rho_{2,3} &= M(2,3) + A1(2,3)\varepsilon_{2,t-1} * \varepsilon_{3,t-1} + B1(2,3) * \rho_{2,3t-1} \\
\rho_{2,4} &= M(2,4) + A1(2,4) * \varepsilon_{2,t-1} * \varepsilon_{4,t-1} + B1(2,4) * \rho_{2,4t-1} \\
\rho_{2,5} &= M(2,5) + A1(2,5) * \varepsilon_{2,t-1} * \varepsilon_{5,t-1} + B1(2,5) * \rho_{2,5t-1} \\
\rho_{3,4} &= M(3,4) + A1(3,4)\varepsilon_{3,t-1} * \varepsilon_{4,t-1} + B1(3,4) * \rho_{3,4t-1} \\
\rho_{3,5} &= M(3,5) + A1(3,5) * \varepsilon_{3,t-1} * \varepsilon_{5,t-1} + B1(3,5) * \rho_{3,5t-1} \\
\rho_{4,5} &= M(4,5) + A1(4,5) * \varepsilon_{4,t-1} * \varepsilon_{5,t-1} + B1(4,5) * \rho_{3,5t-1}
\end{aligned}\right\} \quad 3.19$$

The DVECH model can be easily estimated using the G-QML estimation of the parameters than in the complete VECH model. It was further explained in Ledoit*et al*.(2003) argue that the DVECH model can be not easily computed for systems of dimension N >5. The model has too many parameters that interact in a complex way and so, there is tendency of having difficulties in obtaining convergence using existing optimization algorithms. Furthermore, during estimation the DVECH model does not necessarily give rise to positive semi-definite conditional covariance matrices. To overcome these issues, Ledoit*et al*.(2003) suggested that the DVECH model can be estimated using a flexible two-step procedure, hereafter refers to as Ledoit-Santa Clara-Wolf (LSW). In the first step, the volatilities are computed by fitting single variable GARCH models and the conditional covariance's by fitting bivariate GARCH models.These estimates do not necessarily yield positive conditional covariance matrices.Since it was noted that neither the VECH nor the diagonal VECH ensure a positive definite variance-covariance matrix, so this leads

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to the development of an alternative approach by Engle & Kroner in 1995 and this approach was called the BEKK model

Estimation of the VECH-GARCH

This is estimated using the Log-likelihood function and this is done in situation in whichthe distribution of errors of a multivariate normal is given, and then the log-likelihood function of (L) is given by :

$$\sum_{t=1}^{T} L_t(\theta) = C - \frac{1}{2}\sum_{t=1}^{T} In|H_t| - \frac{1}{2}\sum_{t=1}^{T} r_t^1 H_t^{-1} r_t \qquad 3.20$$

In estimating the log-likelihood function of (L) we have to reverse at every time H_t. This is computationally tedious when T and N are not small. Furthermore H_t is usually noninvertible.

MGARCH-BEKK

The MGARCH-BEKK stands for Multivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH)- Baba, Engle, Kraft and Kroner, which was named after its proponents in 1990. This gives a richer dynamic structure compared to both restricted processes as suggested in the VECH model.

$$H_t = A^1 A + \sum_{t=1}^{p} K_i^1 \varepsilon_{t-1} \varepsilon_{t-1}^1 K_i + \sum_{t=1}^{q} L_t^1 H_{t-1}^1 L_t \; 3.21$$

Where Kand *Li* are *N* × *N* matrices, but $A^1$is triangular and this equation ensures all positive definite diagonal representations. In the analysis that follows, we considered a situation, in which the data are set at lag length to one to ensure the results give a parsimonious specification of the BEKK model as,

$$H_t = A^1 A + K_t^1 \varepsilon_{t-1} \varepsilon_{t-1}^1 K_i + L_t^1 H_{t-1}^1 L_t$$

3.22

Although, for the purpose of convenient the study used the diagonal Multivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH)-BEKK which the econometric views software presentation of its conditional variance –covariance specification is given as thus

$$\mathrm{GARCH} = \mathrm{M} + \mathrm{A1} * \mathrm{RESID(-1)} * \mathrm{RESID(-1)'} * \mathrm{A1} + \mathrm{B1} * \mathrm{GARCH(-1)} * \mathrm{B1}$$

3.23

Where M represented an indefinite matrix, A1 and B1 are diagonal matrices of the parameters A1 and B1 to be estimated. The RESID and GARCH are the ARCH and GARCH components

Of the model and so this can be rewritten thus:

$$\sigma_1^2 = M + A1 * \varepsilon_{t-1} * \varepsilon_{t-1} A1 + B1 * \sigma_{t-1}^2 * B1 \qquad 3.24$$

The diagonal BEKK model provides a suitable way of decomposing each conditional variance into its ARCH and GARCH components. For example, the ARCH component associated with the conditional variance and covariance of Excr, CBIRTD1, CBIRTD3, CBIRTD6, and CBIRTD12can be written as:

$$\left.\begin{aligned}
\sigma_1^2 &= M(1,1) + A1(1,1)^2 * \varepsilon_{t-1}^2 + B1(1,1)^2 * \sigma_{t-1}^2 \\
\sigma_2^2 &= M(2,2) + A1(2,2)^2 * \varepsilon_{t-1}^2 + B1(2,2)^2 * \sigma_{t-1}^2 \\
\sigma_3^2 &= M(3,3) + A1(3,3)^2 * \varepsilon_{t-1}^2 + B1(3,3)^2 * \sigma_{t-1}^2 \\
\sigma_4^2 &= M(4,4) + A1(4,4)^2 * \varepsilon_{t-1}^2 + B1(4,4)^2 * \sigma_{t-1}^2 \\
\sigma_5^2 &= M(5,5) + A1(5,5)^2 * \varepsilon_{t-1}^2 + B1(5,5)^2 * \sigma_{t-1}^2
\end{aligned}\right\}$$

$$\left.\begin{aligned}
\rho_{1,2} &= M(1,2) + A1(1,1) * A1(2,2) * \varepsilon_{1,t-1} * \varepsilon_{2,t-1} + B1(1,1) * B1(2,2) * \rho_{1,2t-1} \\
\rho_{1,3} &= M(1,3) + A1(1,3) * A1(3,3) * \varepsilon_{1,t-1} * \varepsilon_{3,t-1} + B1(1,1) * B1(3,3) * \rho_{1,3t-1} \\
\rho_{1,4} &= M(1,4) + A1(1,4) * A1(4,4) * \varepsilon_{1,t-1} * \varepsilon_{4,t-1} + B1(1,1) * B1(4,4) * \rho_{1,4t-1} \\
\rho_{1,5} &= M(1,5) + A1(1,5) * A1(5,5) * \varepsilon_{1,t-1} * \varepsilon_{5,t-1} + B1(1,1) * B1(5,5) * \rho_{1,5t-1} \\
\rho_{2,3} &= M(2,3) + A1(2,2) * A1(3,3) * \varepsilon_{2,t-1} * \varepsilon_{3,t-1} + B1(2,2) * B1(3,3) * \rho_{2,3t-1} \\
\rho_{2,4} &= M(2,4) + A1(2,2) * A1(4,4) * \varepsilon_{2,t-1} * \varepsilon_{4,t-1} + B1(2,2) * B1(4,4) * \rho_{2,4t-1} \\
\rho_{2,5} &= M(2,5) + A1(2,2) * A1(5,5) * \varepsilon_{2,t-1} * \varepsilon_{5,t-1} + B1(2,2) * B1(5,5) * \rho_{2,5t-1} \\
\rho_{3,4} &= M(3,4) + A1(3,3) * A1(4,4) * \varepsilon_{3,t-1} * \varepsilon_{4,t-1} + B1(3,4) * B1(4,4) * \rho_{3,4t-1} \\
\rho_{3,5} &= M(3,5) + A1(3,3) * A1(5,5) * \varepsilon_{3,t-1} * \varepsilon_{5,t-1} + B1(3,3) * B1(5,5) * \rho_{3,5t-1} \\
\rho_{4,5} &= M(4,5) + A1(4,4) * A1(5,5) * \varepsilon_{4,t-1} * \varepsilon_{5,t-1} + B1(4,4) * B1(5,5) * \rho_{3,5t-1}
\end{aligned}\right\}$$

3.26

where the ARCH volatility in returns on Excr ,CBIRTD1, CBIRTD3,CBIRTD6, and CBIRTD12 in conditional variance and covariance , depends on the squares, as well as the cross-products of the previous period shocks associated with the five variables. Here, A1(1,1),A1(2,2), A1(3,3),A1(4,4) and A1(5,5) in the

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model captured the impacts of own past innovations on the current volatility in either exchange rate(excr) or indicators of commercial Banks interest rates. Similarly, the GARCH components of the model captured the influence of past conditional variances and covariances associated with each of the five variables. Also, if the co-efficients of B1(1,2),B1(2,1), B1(1,3),B1(3,1) , B1(1,4),B1(4,1), B1(1,5),B1(5,1) etc are significant across the off-diagonal ,it then means that there is presence of cross volatility spillover between exchange rate and commercial banks interest rate operations(Tsay,2005). In general, the co-efficients to be estimated in the variance-covariance model depends only on past values of the variables itself and past values of their interaction. This shows that the variance depends solely on the past squared residuals while the covariance dependents mainly on the interaction of the past squared residuals and interaction of the GARCH components across the diagonal.

Estimation Of Multivariate GARCH Models

According to Wenjing and Yiyu (2010) ,the most common way of estimating the conditional covariance matrix in the MGARCH model is by the use of quasi maximum likelihood method. Assuming Ht(θ) is a positive definite N×N conditional covariance matrix of some N×1 residual vector εt, parameterized by the vector θ. Denoting the available information at time t by f_t, we have : $\varepsilon_{t-1}\left[\varepsilon_t / f_{t-1}\right] = 0;$

$$\varepsilon_{t-1}\left[\varepsilon_t \varepsilon_t^1 / f_{t-1}\right] = H_t(\theta) \quad (3.27)$$

(3.28)

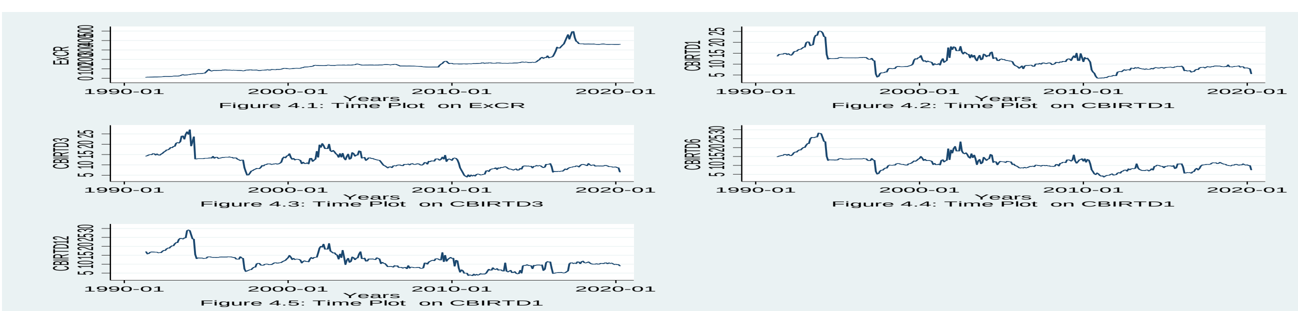
Generally the conditional covariance matrix *Ht*(*θ*) is well specified based on a certain MGARCH model. Suppose there is an underlying parameter vector *θ0* which one wants to estimate using a given sample of *T* observations. The quasi maximum likelihood (QML) approach estimates *θ0* by maximizing the Gaussian log likelihood

$$\log L_T(\theta) = \frac{-N.T}{2} Log(2\Pi) - \frac{1}{2}\sum_{t=1}^{T} Log / H_t / - \frac{1}{2}\sum_{t=1}^{T} \Xi_t^1 H_t^{-1} \Xi_t \quad (3.29)$$

One need to notice its assumption that the time series treated should be stationary and the distribution of its residual is pre-defined as a conditional Gaussian distribution. The latter assumption can meanwhile give us hints on how to check the adequacy of the established MGARCH model

Results

This was done in order to examine the trend in the movement of the variable over time.



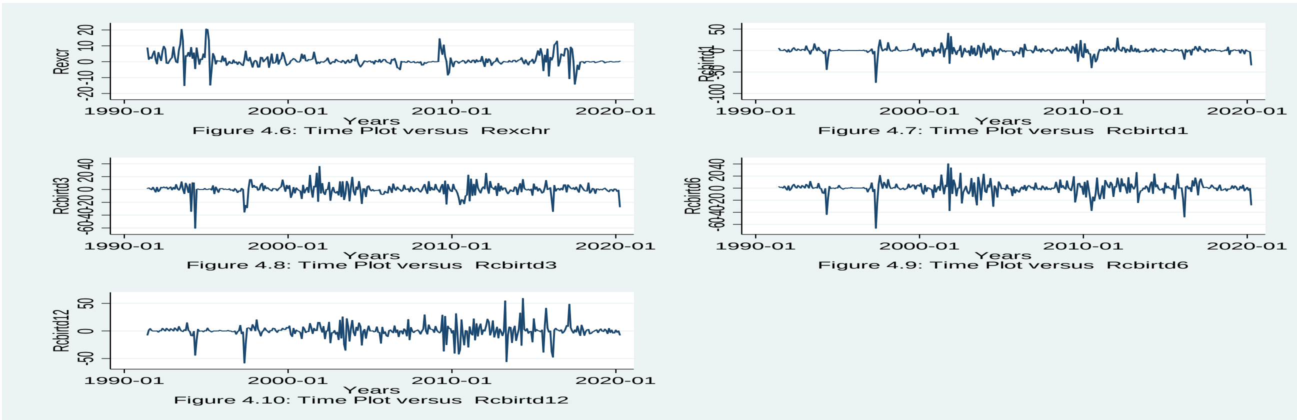


Figure 4.6: Time Plot versus Rexchr
Figure 4.7: Time Plot versus Rcbirtd1
Figure 4.8: Time Plot versus Rcbirtd3
Figure 4.9: Time Plot versus Rcbirtd6
Figure 4.10: Time Plot versus Rcbirtd12

Table 4.1: Descriptive Test for Normality Test

Test Statistic	EXCR	CBIRTD1	CBIRTD3	CBIRTD6	CBIRTD12
Mean	153.3662	10.87244	11.58049	11.74368	11.53787
Median	138.9200	10.20000	10.59000	10.92000	10.87500
Maximum	494.7000	25.16000	27.00000	28.13000	29.13000
Minimum	10.87000	3.490000	4.130000	3.500000	3.530000
Std. Dev.	100.0908	3.901446	3.943356	4.395481	4.688370
Skewness	1.301289	0.965120	0.990848	1.197774	0.960273
Kurtosis	4.297354	4.678636	4.603109	5.326967	4.528523
Jarque-Bera	122.6199	94.88281	94.20759	161.7247	87.36069
Probability	0.000000	0.000000	0.000000	0.000000	0.000000

Source: *Researcher's Estimation, 2020 using Eviews, Version 10. It was all tested with 1 and 5% level of Significant respectively.*

Table 4.2 : Estimated Result for Unit Root Test

Variables	ADF		Remark(s)
	1(0)	1(1)	
EXCR	-0.806	-7.096***	Stationary at First Difference
CBIRTD1	-2.735	-7.127***	Stationary at First Difference
CBIRTD3	-2.725	-6.649***	Stationary at First Difference
CBIRTD6	-2.710	-7.054***	Stationary at First Difference
CBIRTD12	-2.792	-8.416***	

Source :*Researcher's Computation Using Eview version 10*

Test for Correlation between Variable

Correlation analysis tells us about the strength and direction of the linear relationship that exit among variables. However, the dependability of the linear model also depends on how many observed data points are in the sample. The result of the test for Correlation between Variables are shown in table 4.3 below

Table 4.3 Correlation Matrix

	EXCR	CBIRTD1	CBIRTD3	CBIRTD6	CBIRTD12
EXCR	1.000000				
CBIRTD1	-0.473053	1.000000			
CBIRTD3	-0.480766	0.983027	1.000000		
CBIRTD6	-0.427843	0.967617	0.973627	1.000000	
CBIRTD12	-0.432703	0.951084	0.960473	0.978793	1.000000

Source :*Researcher's Computation Using Eview version 10*

Table 4.4 : Estimated Result for Lag length Criteria

Lag	LogL	LR	Df	FPE	AIC	HQIC	SBIC
0	-4298.23	NA	0.000	50483.9	25.0188	25.0188	25.0746
1	-2786.91	3022.6	0.000	8.91744	16.3774	16.5108*	16.7123*
2	-2744.29	85.238	0.000	8.04994	16.2749	16.5195	16.889
3	-2703.22	82.135*	0.000	7.33367*	16.1815*	16.5373	17.0747
4	-2685.33	35.789	0.000	7.64622	16.2228	16.6897	17.3951

Source :*Researcher's Computation Using Eview version 10*

The lag length selection criteria shows three lags, hence the model above is written as

Table 4.5 **Test for Co-integration between the variables**

Johansen tests for cointegration

Trend: constant Number of obs = 345
Sample: 1991-08 - 2020-04 Lags = 3

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	55	-2777.1666	.	136.2863	68.52
1	64	-2747.9089	0.15601	77.7707	47.21
2	71	-2725.4183	0.12224	32.7895	29.68
3	76	-2713.616	0.06613	9.1851*	15.41
4	79	-2709.1712	0.02544	0.2953	3.76
5	80	-2709.0235	0.00086		

HO: No cointegrating Equation Versus HoA: co-integrating Equation. Therefore, we reject the null hypothesis of no co-integrating Equation and accept the alternative , there is four co-integrating equations

Academic Journal of Current Research
Vol.7, No.8; August-2020;
ISSN (2343 – 403X);
p –ISSN 3244 - 5621
Impact factor: 6.37

Error Correction Model (ECM)

$$\Delta Excr_t = [1.00 y_{t-1} - 36.44\text{CBIRTD1}_{t-i} + 73.77\text{CBIRTD3}_{t-i} - 44.77\text{CBIRTD6}_{t-i} + 10.12\text{CBIRTD12}_{t-i} - 0.153 R_{t-1}]$$

The shows that a 36.44 percentage decrease in commercial banks interest rate on time deposits maturing in one month(CBIRTD1) is associated with exchange rate (excr) etc. The co-integrating equation result shows that the previous month's deviation in the long run equilibrium is corrected at an adjusted speed of 9.0008 percent. The error correction model estimation result was subjected to test for the present of heteroskedasticity and it was confirmed to be presence. This is what led to the test for the performance of conditional variance-covariance in a five variable diagonal VECH and BEKK GARCH Models.

DIAGONAL VECH-GARCH MODEL

Diagonal Variance

$$\sigma_1 = 1.04 + 0.449\varepsilon^2_{1t-1} + 0.617\sigma^2_{1t-1}$$

(0.000) (0.000) (0.000)

$$\sigma_2 = 15.161 + 0.330\varepsilon^2_{2t-1} + 0.608\sigma^2_{2t-1}$$

(**0.**000) (0.000) (0.000)

$$\sigma_3 = 17.543 + 0.523\varepsilon^2_{3t-1} + 0.352\sigma^2_{3t-1}$$

(0.000) (0.000) (0.000)

$$\sigma_4 = 8.883 + 0.140\varepsilon^2_{4t-1} + 0.809\sigma^2_{4t-1}$$

(0.000) (0.000) (0.000)

$$\sigma_5 = 25.193 + 0.160\varepsilon^2_{4t-1} + 0.542\sigma^2_{4t-1}$$

(0.000) (0.000) (0.000)

DIAGONAL COVARIANCE EQUATION

$$\rho_{1,2} = -0.103 + 0.262\varepsilon_{1t-1} * \varepsilon_{2t-2} + 0.469\rho_{1,2t-1}$$

(0.902) (0.010) (0.010)

$$\rho_{1,3} = 0.095 + 0.375\varepsilon_{1t-1} * \varepsilon_{3t-1} + 0.343\rho_{1,3t-1}$$

(0.895) (0.000) (0.006)

$$\rho_{1,4} = -0.06 + 0.178\varepsilon_{1t-1} * \varepsilon_{4t-1} + 0.634\rho_{1,4t-1}$$

(0.950) (0.062) (0.040)

$$\rho_{1,5} = 0.607 + 0.228\varepsilon_{1t-1} * \varepsilon_{4t-1} + 0.342\rho_{1,4t-1}$$

(0.950) (0.021) (0.297)

$$\rho_{2,3} = 14.833 + 0.406\varepsilon_{2t-1} * \varepsilon_{3t-1} + 0.380\rho_{2,3t-1}$$

(0.000) (0.000) (0.000)

$$\rho_{2,4} = 10.117 + 0.205\varepsilon_{2t-1} * \varepsilon_{4t-1} + 0.709\rho_{2,4t-1}$$

(0.00) (0.000) (0.000)

$$\rho_{2,5} = 15.934 + 0.226\varepsilon_{2t-1} * \varepsilon_{5t-1} + 0.709\rho_{2,5t-1}$$

(0.00) (0.000) (0.000)

$$\rho_{3,4} = 10.934 + 0.264\varepsilon_{3t-1} * \varepsilon_{4t-1} + 0.558\rho_{3,4t-1}$$

(0.000) (0.000) (0.000)

$$\rho_{3,5} = 19.334 + 0.282\varepsilon_{3t-1} * \varepsilon_{5t-1} + 0.431\rho_{3,5t-1}$$

(0.00) (0.000) (0.000)

$$\rho_{4,5} = 9.136 + 0.147\varepsilon_{4t-1} * \varepsilon_{5t-1} + 0.661\rho_{4,5t-1}$$

(0.000) (0.000) (0.000)

Log likelihood	-5337.095	Schwarz criterion	31.60420
Avg. log likelihood	-3.076135	Hannan-Quinn criter.	31.27038
Akaike info criterion	31.04954		

The matrix form of the model

Academic Journal of Current Research
Vol.7, No.8; August-2020;
ISSN (2343 – 403X);
p –ISSN 3244 - 5621
Impact factor: 6.37

$$M=\begin{bmatrix} 1.040^{***} & -0.103 & -0.085 & -0.061 & 0.007 \\ & 15.161^{***} & 14.833 & 10.118 & 15.934 \\ & & 17.543^{***} & 10.522^{***} & 19.339^{***} \\ & & & 8.833^{***} & 9.139^{***} \\ & & & & 25.193^{***} \end{bmatrix},$$

$$A=\begin{bmatrix} 0.446^{***} & 0.262 & 0.375 & 0.178 & 0.228 \\ & 0.330^{***} & 0.406 & 0.205 & 0.226 \\ & & 0.523^{***} & 0.264 & 0.282 \\ & & & 0.140^{***} & 0.147 \\ & & & & 0.159^{***} \end{bmatrix}$$

$$B=\begin{bmatrix} 0.617^{***} & 0.469^{***} & 0.405^{***} & 0.634^{*} & 0.380^{***} \\ & 0.608^{***} & 0.455^{***} & 0.709^{***} & 0.569 \\ & & 0.352^{***} & 0.558^{***} & 0.431^{***} \\ & & & 0.809^{***} & 0.661^{***} \\ & & & & 0.542^{***} \end{bmatrix}$$

The Diagonal MGARCH-BEKK model obtained from the results of the analysis of the five variables used in the study is given as thus:

Diagonal Variance

$$\sigma_1 = 0.823 + 0.817\varepsilon^2_{1t-1} + 0.340\sigma^2_{1t-1}$$
$$\mathbf{(0.000)} \quad \mathbf{(0.000)} \quad \mathbf{(0.000)}$$

$$\sigma_2 = 0.475 + 0.686\varepsilon^2_{2t-1} + 0.378\sigma^2_{2t-1}$$
$$(0.000) \quad (0.000) \quad (0.000)$$

$$\sigma_3 = 0.542 + 0.721\varepsilon^2_{3t-1} + 0.347\sigma^2_{3t-1}$$
$$(0.000) \quad (0.000) \quad (0.000)$$

$$\sigma_4 = 0.745 + 0.718\varepsilon^2_{4t-1} + 0.339\sigma^2_{4t-1}$$
$$(0.000) \quad (0.000) \quad (0.000)$$

$$\sigma_5 = 0.911 + 0.705\varepsilon^2_{4t-1} + 0.358\sigma^2_{4t-1}$$
$$(0.000) \quad (0.000) \quad (0.000)$$

DIAGONAL COVARIANCE EQUATION

$$\rho_{1,2} = 0.058 + 0.749\varepsilon_{1t-1} * \varepsilon_{2t-2} + 0.358\rho_{1,2t-1}$$
$$(0.977) \quad (0.000, 0.000) \quad (0.000,0.000)$$

$$\rho_{1,3} = 0.107 + 0.768\varepsilon_{1t-1} * \varepsilon_{3t-1} + 0.343\rho_{1,3t-1}$$
$$(0.753) \quad (0.000, 0.000) \quad (0.000, 0.000)$$

$$\rho_{1,4} = 0.015 + 0.766\varepsilon_{1t-1} * \varepsilon_{4t-1} + 0.339\rho_{1,4t-1}$$
$$(0.261) \quad (0.000,0.000) \quad (0.000,0.00)$$

$$\rho_{1,5} = 0.094 + 0.758\varepsilon_{1t-1} * \varepsilon_{4t-1} + 0.342\rho_{1,4t-1}$$
$$(0.261) \quad (0.000,0.000) \quad (0.000,0.00)$$

$$\rho_{2,3} = 0.472 + 0.703\varepsilon_{2t-1} * \varepsilon_{3t-1} + 0.362\rho_{2,3t-1}$$
$$(0.000) \quad (0.000, 0.00) \quad (0.000, 0.000)$$

$$\rho_{2,4} = 0.506 + 0.702\varepsilon_{2t-1} * \varepsilon_{4t-1} + 0.358\rho_{2,4t-1}$$
$$(0.448) \quad (0.000, 0.000) \quad (0.000, 000)$$

$$\rho_{2,5} = 0.519 + 0.695\varepsilon_{2t-1} * \varepsilon_{5t-1} + 0.361\rho_{2,5t-1}$$
$$(0.128) \quad (0.000,0.000) \quad (0.000,0.00)$$

$$\rho_{3,4} = 0.514 + 0.720\varepsilon_{3t-1} * \varepsilon_{4t-1} + 0.343\rho_{3,4t-1}$$
$$(0.128) \quad (0.000,0.000) \quad (0.000,0.00)$$

$$\rho_{3,5} = 0.537 + 0.713\varepsilon_{3t-1} * \varepsilon_{5t-1} + 0.346\rho_{3,5t-1}$$
$$(0.128) \quad (0.000,0.000) \quad (0.000,0.00)$$

$$\rho_{4,5} = 0.711 + 0.711\varepsilon_{4t-1} * \varepsilon_{5t-1} + 0.341\rho_{4,5t-1}$$
$$(0.128) \quad (0.000,0.000) \quad (0.000,0.00)$$

Log likelihood	-5352.787	Schwarz criterion	31.35750
Avg. log likelihood	-3.085180	Hannan-Quinn criter.	31.15722
Akaikeinfo criterion	31.02471		

Source :*Researcher's Computation Using Eview version 10*

Academic Journal of Current Research
Vol.7, No.8; August-2020;
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The results are further represented in matrix form as thus:

The matrix form of the model

$$M = \begin{bmatrix} 1.039^{***} & -0.280 & -0.527 & -0.187 & -529 \\ & 7.629^{***} & 10.627^{***} & 5.796^{***} & 8.419^{***} \\ & & 16.363^{***} & 9.529^{***} & 12.784^{***} \\ & & & 3.295^{***} & 6.835^{***} \\ & & & & 12.526^{***} \end{bmatrix}$$

$$A = \begin{bmatrix} 0.512^{***} & & & & \\ & 0.520^{***} & & & \\ & & 588^{***} & & \\ & & & 0.241^{***} & \\ & & & & 0.521^{***} \end{bmatrix}$$

$$B = \begin{bmatrix} 0.842^{****} & & & & \\ & 0.872^{****} & & & \\ & & 0.756^{****} & & \\ & & & 0.962^{****} & \\ & & & & 0.845^{****} \end{bmatrix}$$

The “***” represents 5 percent level of significance.

Table 4.6 contain the results of the Aike and least Schwartz information criterion obtained from each of the estimated MGARCH model

Table 4.6: Estimation Results for Model selection

Model Selection Criterion	**DVECH**	**DBEKK**(normal)	**Least AIC Across Error Dist**
Akaike info criterion	31.04954	31.02471	31.02471

Source: Researcher’s Calculation using Eviews Version 10

Table4.7 System Residual Portmanteau Tests for Autocorrelation

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	133.2303	0.0000	133.6154	0.0000	25
2	211.1718	0.0000	212.0087	0.0000	50
3	245.6152	0.0000	246.7525	0.0000	75
4	271.2146	0.0000	272.6504	0.0000	100
5	324.3702	0.0000	326.5831	0.0000	125
6	359.4369	0.0000	362.2668	0.0000	150
7	392.4693	0.0000	395.9793	0.0000	175
8	417.6705	0.0000	421.7753	0.0000	200
9	451.3355	0.0000	456.3366	0.0000	225
10	480.2703	0.0000	486.1300	0.0000	250
11	513.6864	0.0000	520.6402	0.0000	275
12	583.2122	0.0000	592.6564	0.0000	300

Source: Researcher’s Calculation using Eviews Version 1o

Table 4: 8 System Residual Normality Tests

Component	Skewness	Chi-sq	Df	Prob.
1	2.100124	255.0751	1	0.0000
2	-2.881576	480.2180	1	0.0000
3	-0.105468	0.643306	1	0.4225
4	0.384256	8.539261	1	0.0035
5	-0.180727	1.888976	1	0.1693
Joint		746.3646	5	0.0000
Component	Kurtosis	Chi-sq	Df	Prob.
1	12.48419	1300.524	1	0.0000
2	26.96849	8306.145	1	0.0000
3	7.278931	264.7212	1	0.0000
4	8.631053	458.4558	1	0.0000
5	9.996233	707.6960	1	0.0000
Joint		11037.54	5	0.0000
Component	Jarque-Bera	df	Prob.	
1	1555.599	2	0.0000	
2	8786.363	2	0.0000	
3	265.3645	2	0.0000	
4	466.9951	2	0.0000	
5	709.5850	2	0.0000	

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Vol.7, No.8; August-2020;
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Joint	11783.91	10	0.0000

Source: Researcher's Calculation using Eviews Version 10

5.1 Discussion of Results

This study focuses on five important variables such as data on Exchange rate (Excr) ,Commercial Banks Interest Rate on Time Deposits Maturing in 1 month(CBIRTD1), Commercial Banks Interest Rate on Time Deposits Maturing in 3 months(CBIRTD3), Commercial Banks Interest Rate on Time Deposits Maturing in 6 months(CBIRTD6), Commercial Banks Interest Rate on Time Deposits Maturing in 12 months(CBIRTD12). These made up about a total of 1364 observations started from 19th January, 1991 to 30th May, 2019.

First, we present time plot of the raw data as shown in Figure 4.1 -4.4. on the vertical axis of the time plot the raw data (data on Exchange rate (Excr) , Commercial Banks Interest Rate on Time Deposits Maturing in 1 month(CBIRTD1), Commercial Banks Interest Rate on Time Deposits Maturing in 3 months(CBIRTD3), Commercial Banks Interest Rate on Time Deposits Maturing in 6 months(CBIRTD6), Commercial Banks Interest Rate on Time Deposits Maturing in 12 months(CBIRTD12)) while on the horizontal axis we have time in Years(Monthly) format. This is done to portray the direction and moving trend of the variables under study. This is followed by Table 4.1 which contains the results of descriptive statistics of the returns on the transformed data under investigations. This is carried out in order to know whether the returns on the transformed data under investigations obey the normality assumption. Also, figures 4.5-4.8 illustrates the time plot or the data series on returns on prices of variables representing exchange rate and commercial banks interest rate on time deposits operations. From physical observation there exist clustering effects on the return series, a period of high volatility followed by period of tranquility, such that exchange rate and commercial banks interest rate on time deposits operations future returns fluctuate in a range smaller than the normal distribution. This conformed to Roengchai (2009) assertion these are some circumstances where certain commodity futures returns oscillate in a much wide scale that is allowed by a normal distribution. According to Mohammad and Saeid (2016) this process is important in order to recognize the distribution of the data as we prepare financial series for the process of modeling.

Table 4.1 presents the summary descriptive statistics which include, mean, median, maximum, minimum, standard deviation, skewed statistic, excess kurtosis and Jarque-Bera test statistic for individual data indicator. From the results obtained exchange rate and indicators of commercial banks interest rate. This simply means that exchange rate and indicators of commercial banks interest rate exhibit behavior that is positive mean reverting. Similarly, Excr(4.297), CBIRTD3(4.679) ,CBIRTD3(5.327), CBIRTD6(4.603109) and CBIRTD12(4.529) have positive skewed statistic This simply means that both exchange rate and indicators of commercial banks interest rate are skewed to right exhibiting the characteristics of financial data. This signifies that the series is skewed to the left (extreme loss) than right tail (extreme gain). Also, the kurtosis statistics are 4.297, 4.679, 4.603, 5.327 and4.529 respectively suggesting the presence of flat-tail. The Jarque-Bera (J-B) test statistic was 122.620, 94.883, 94.208, 161.725, and 87.361 respectively and they are all statistically significant theoretically indicating that the distribution for these indicators is not normally distributed. The causes of this could be attributed to the presence of extreme observations. Hence, the null hypothesis for normality test is rejected in all the cases while the alternative hypothesis that these indicators are not normally distributed is accepted. The results obtained here is in line with Roengchai (2009), attempt to model long memory volatility in Agricultural commodity futures returns. In Roengchai (2009), it was formed that the normal distributions of the indicators under investigations have a small skewed statistic and high kurtosis suggesting that the distributions for the returns in prices were not normal. However, in a situation like this, Deebom and Essi (2018) suggested that there is need to further use an alternative inferential statistic in order to eliminate the problems associated with non-normality distributions of the returns on prices of these commodities. This led us to test for the presence of unit root. Unit root test was conducted using the augmented dickey-fuller test statistics. The result of the Augmented Dickey-fuller (ADF) test revealed that P- value 95% confidence level were less than the standard probability value of 0.05, therefore , the null hypothesis was rejected and we concluded that the variable under considerable within the period of the study were not stationary at level but became stationary after first difference. This result was in line with Olokoyo (2011) studied on determinants of commercial banks' lending behavior in Nigeria. In Olokoyo (2011), it found that indicators of commercial banks' lending behavior in Nigeria were not stationary at first difference and it was made stationary after first difference.

Table 4.3 examine correlation matrix which has to do the strength and direction of the linear relationship that exit among variables. The results confirmed the present of negative relationship between exchange rate and indicators of commercial banks interest rate. Similarly, table 4.4 shows the estimated results for lag length criteria. It is generally believed that variables normally response in terms of interaction with a lagged of time and to selected appropriate time period for which these variables stay before reaction is what lead to lag length criteria. Therefore, table 4.4 shows the LR (sequential modified LR test statistic (each test at 5% level), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Information Criterion (HQ). However, this study was based on Akaike Information Criterion (AIC) since it penalized for lost of degree of freedom (Deebom&Essi, 2018). Similarly, test for co-integration was also carried out to check the existence of long-run relationship between the variables using the Johansen –Juselius (JJ) test based the results maximum eigenvalue test statistics.

Table 4.4 show estimated result for co-integration test and the results obtained, it was found that there exist four co-integrating equations at the 0.05 level using both maximumeigen-value and trace test statistics. Therefore, the null hypothesis of no co-integration is rejected while the alternative is accepted. The present result confirmed CEPDeR (2019) assertion, which opined that if the series under investigation are co-integrated: ie , they exhibit a long –run relationship , it implies that the series are related and can be combined in a linear fashion. This leads to the estimation of Vector Autoregressive Correction Model (VECM).The Vector Autoregressive Correction Model (VECM) is used to test the causal relationship between exchange rate and commercial banks interest rate on time in Nigeria after identifying the appropriate order of integration of each variable. The result of the estimation of Vector Autoregressive Correction Model (VECM) and this leads us to do Vector Autoregressive Correction Model (VECM) residual heteroscedaticity test.

Table 4.5 shows the estimated result for VECM residual heteroscedaticity test. The result confirmed the present of heteroskedasticity as the calculated probability value is less than the standard probability value of 5%. Therefore, the null hypothesis of the presence of homoscedasticity is rejected. This was in line with Deebom and Tuaneh (2018) findings in modeling exchange rate and Nigerian deposit money market dynamics using trivariate form of multivariate GARCH model. In Deebom and Tuaneh (2018) study, it was found that there exist the presence of heteroskedasticity in the cointegrating relationship between exchange rate and Nigerian deposit money market dynamics. However, Abdulkarem*et al*, (2017) opined that when such situation occur the alternative inferential statistic to be considered was multivariate GARCH with its error distribution assumptions with fixed degree of freedom. This leads to the application of multivariate GARCH models with its error distribution assumptions with fixed degree of freedom. Diagonal VECH Constant with Full Rank Matrix in normal was the first model considered in the study. The results have two components; the first was the variance and the second deal with covariance model. The co-efficient of the ARCH term (A1 (1,2)) was estimated to be 0.262 and the GARCH term(B1(1,2)) was 0.469 in the covariance model, though they were both positive but non-significant even at the one percent level of significance. This simply means that the covariance between the variables does not cluster overtime. Similarly, for the ARCH term (A1(1,2)) estimated to be 0.262 and it was positive, it means that shocks arising from exchange rate has an effect on indicators of commercial banks interest rate on time deposits maturing whose estimate has the same positive conditional variance positively. On the contrary, shocks of opposite signs and direction are expected to affect the forecasting covariance negatively. The ARCH term (A1(1,2)) are estimated to be 0.262 while the GARCH term(B1(1,2)) of 0.469 were non-significant where as others such A1(2,3) (0.406), A1(2,4)(0.205), A1(3,4) (0.264) , A1(3,5) (0.282) and A1(4,5) (0.147) were significant at 5% level of significance. For the ARCH term (A1(1,2)) estimated to be 0.262 and the GARCH term(B1(1,2)) (0.469) to be non-significant , it revealed that the causes of the correlation between exchange rate and indicators of commercial banks interest rate on time deposits maturing operation does not persist overtime. The results represented in variance--covariance or correlation matrix models confirmed the property associated with diagonal multivariate VECH model and according Brooks(2006), diagonal multivariate VECH model are always 'positive semi-definite'. He further explained that in the case where all the returns in a particular series are all the same such that their variance is zero is disregarded, then the matrix will be positive definite. This simply means that the variance--covariance matrix all positive numbers on the leading diagonal, and this shows that the entries are symmetrical about the leading diagonal. Brooks (2006), further explained that these properties are naturally interesting as well as important from a mathematical point of view, a situation in which an estimated variances can never be negative, and the covariance between exchange rate and deposit money bank lending operation series is the same irrespective of which of the five series is considered first, and positive definiteness ensures that the result is the same. This simply means that this property which ensures that, whatever the weight of each series in the asset portfolio, an estimated value-at-risk is always positive. This is one of the properties of time- invariant correlations. Similarly**,** the second model reported was the multivariate BEKK model. Accordingly, A1(i,j) and B1(i,j) are the resultant ARCH and GARCH parameters associated with both exchange rate and indicators of commercial Banks interest rates operation (i).The squared ARCH parameters $[A1(i,j)^2]$ capture the responses of exchange rate volatility and commercial Banks interest rates operation (i) to squared standardized innovations in each of the five variables. The ARCH effects show some unique behavior and firstly, all diagonal elements A1(1, 1)(0.512), A1(2, 2)(0.520), A1(3,3)(0.588), A1(4, 4) (3.295) and A1(5,5)(0.521) are statistically significant, this simply means that each conditional variance depends on its own squared lagged innovations. The commercial banks interest rate on time deposits maturing in three months (CBIRTD3)has the largest own ARCH effect with the coefficient value of A1(3, 3)(0.588), while commercial banks interest rate on time deposits maturing in six months(CBIRTD6) has the smallest own ARCH effect with the value of A1(4,4)(0.241). Since all the coefficients are virtually significance, it shows that the variances of both exchange rate and that of commercial Banks interest rates operation are more influenced by their own lagged values, rather than by "fresh news" which are shown by the lagged innovations. It also means that the volatility of exchange rate responds significantly to past squared shocks in its own market, as well as the commercial Banks interest rates operation. Secondly, the GARCH effects reveal the following patterns, firstly ,all the five conditional variances depend on their own past records; this is clearly shown in the estimated B1(1,1)(0.842), B1(2, 2)(0.872), B1(3, 3)(0.756) , B1(4, 4)(0.962) and B1(5,5)(0.845) of the GARCH parameters,which that all the estimates are statistically significant at the 5% level. The results also show that own spillovers are always much larger than the cross-sector spillovers. This phenomenon was synonymous to what we observed previously in Worthington and Higgs (2004) studied on transmission of equity returns and volatility in Asian developed and emerging markets: a multivariate GARCH analysis. Similarly, we found a unidirectional volatility spillover from exchange rate to indicators of commercial banks interest rate, from indicators of commercial banks interest rate to exchange rate respectively and vice-versa. In summary, there is strong evidence of volatility spillovers from the more Nigerian foreign exchange rate markets to commercial banks interest rate.All the estimated parameters in the interaction terms (cross –operations) in covariance equations are positive suggesting that shocks in both exchange rate and commercial Banks interest rates operation have positive affect in terms of their covariance.

Conclusion

This study mainly focused on modeling conditional variance-covariance between exchange rate and Nigerian commercial Banks Interest rate using Diagonal MGARCH models. In order to achieve the aim and objectives that were set as a guides for the study which include to;identify volatility transmission of both returns and the spillover effects between exchange rate and commercial Banks Interest rate, determine the changing pattern of the influence of volatility of returns on exchange rate to commercial Banks Interest rate, investigate time varying variance-covariance between exchange rate and commercial Banks Interest rate and the degree of their persistence in the operations between exchange rate and commercial Banks Interest rate and select the appropriate diagonal MGARCH model that best fit to the monthly returns on exchange rate and indicators of commercial Banks Interest rate. We utilized two diagonal multivariate GARCH approaches in modeling the conditional variance-covariance between exchange rate and commercial banks interest rate. The results obtained show that exchange rate and indicators of Nigerian commercial banks interest rate tends to move together, and appear to have been negatively correlated in recent years. An appreciation (depreciation) in Naira/Dollar exchange rate is typically associated with lower (higher) changes in the indicators of Nigerian commercial banks interest rate. It was also found that using diagonal multivariate VECH model one of the properties that the coefficients of the estimate must be 'positive semi-definite was confirmed. This simply means that the leading diagonal must be positive and significant at the 5% level of significance which is important from mathematical point of view. It is well noted that a situation in which estimated variances can never be negative, and the covariance between exchange rate and indicators of Nigerian commercial banks interest rate series are the same irrespective of which of the five series is considered first, and positive definiteness ensures that the result is the same. The result also confirmed that there exist a strong evidence of a time-varying conditional covariance and interdependence between exchange rate and indicators of Nigerian commercial banks interest rate. Similarly, it was found cross-volatility effects; past innovations in exchange rate have greatest influence on future volatility of indicators of Nigerian commercial banks interest rate returns. Based on Model selection criteria using the Akaike information criteria (AIC) diagonal VECH model are better fitted than the other. It was revealed that the volatility of the exchange rate and commercial banks interest rate on time deposits returns sometime has positive co-efficient and this shows to have positive impact on financial service sector of commercial banks. Moreover, we can state that the volatility of the exchange rate has an effect on commercial banks interest rate on time deposits returns. However, some of the indicators of Nigeria commercial banks interest rate on time deposits maturing in monthly order are positively affected by the volatility of the exchange rate market return spillovers. This is the few cases of the causes of financial sector crises in Nigeria. In this circumstance, this study has some policy implications. Regarding the characteristic behavior of the impact of exchange rate market rate risk as it affect Nigeria commercial banks interest rate on time deposits maturing in monthly order. This could provide valuable information for financial management purposes both domestically and internationally. The results suggest that Nigerian investors should follow local and international monetary policies more closely before considering the decisions to invest in commercial banks since the naira/dollar exchange rate has potential impact on the commercial banks interest rate on time deposits maturing in monthly order returns.

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