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Relationship between Nigeria Stock Exchange and Inflation to Dynamic Conditional Correlation Model

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Abstract: The paper studies the relationship between Nigeria Stock Exchange and inflation. Raw daily data between August 2010 to January, 2016 from cashcraft website and CBN. ADF was used to test the unit root of the data were the two variables were stationary all through by taking their first differences which make the series under study to be free from unit root. Presence of heteroscedastic was significant using Lagrange multiplier. The correlation matrix show that the result of the correlation value between NSE and INFL is negatively strong correlation which conclude that an increase in goods and services (Inflation) will effectually have negative impact on the Nigerian Stock Exchange. The model we used to fit the data in our paper is the bivariate DCC-GARCH (1, 1) model. The coefficients for all the parameters are positive while the correlation-Targeting is negative. We can conclude that both of coefficient and correlation- targeting values are very close to 1 and -1, indicating that high persistence in the conditional variances. Furthermore, both of them are between the confident interval (C.I) of 1 and -1, this means that conditional variance is finite and the series are strictly stationary. The forecast graph shows as goods and services increases; the Nigeria Stock Exchange will experience a non-steady shock in the stock market.

Keywords: Volatilities, GARCH model, Normality, Correlation, Dynamic Conditional Correlation (DCC).

1 Introduction

Multivariate volatilities have many important financial applications. About all, they play an important role in portfolio selection and asset allocation, and they can be used to compute the value at risk (VaR) of a financial position consisting of multiple assets (Tsay, 2005).

A topic high on the research agenda in financial econometrics is the construction of models that can summarize the dynamic properties of two or more asset returns, with a particular focus on volatility forecasting and portfolio selection (Christian and Philip, 2003). A class of models that addresses this topic is the multivariate GARCH model. By now, there are many variants available, see Bauwens *et al*. (2003) for a recent survey. The current benchmark models seem to be the Constant Conditional Correlation (CCC) model of Bollerslev (1990) and its extension, the Dynamic Conditional Correlation (DCC) model of Engle (2002). These models impose a useful structure on the many possible model parameters. By doing so, the model parameters can easily be estimated and the model can be evaluated and used in a rather straightforward way.

The class of multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models has been used to model the co-movements of volatilities in financial assets. The various model specifications can be categorized as follows: (i) diagonal GARCH model of Bollerslev, Engle and Wooldridge (1998) and Ding and Engle (2001); (ii) BEKK (Baba, Engle, Kraft and Kroner) model of Engle and Kroner (1995), which models the conditional covariances directly; (iii) constant conditional correlation (CCC) model of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003), and VARMA-AGARCH model of McAleer, Hoti and Chan (2007); (iv) Engle's (2002) dynamic conditional correlation (DCC) model, Tse and Tsui's (2002) varying conditional correlation (VCC) model, and Bauwens, Laurent and Rombouts's (2006) generalized DCC model, and McAleer et al.'s (2008) Generalized Autoregressive conditional correlation (GARCC) model, which relax the assumption of constant conditional correlations and model the dynamic conditional correlations and covariances; (v) generalized orthogonal GARCH model of van der Weide (2002); and (vi)

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the matrix-exponential GARCH model of Kawakatsu (2006). For further details of these models, see the review papers of McAleer (2005) and Bauwens, Laurent and

For multivariate models, Kroner and Ng (1998) proposed the asymmetric BEKK model, while McAleer, Hoti and Chan (2009) suggested the asymmetric VARMA-GARCH (or VARMA-AGARCH) model as a multivariate extension of the GJR model. Both of these models are multivariate generalizations of the univariate GJR model as they are based on threshold effects. Although the former is very flexible due to the BEKK specification, it suffers from the traditional large number of parameters associated with the BEKK specification. The latter model is an extension of the VARMA-GARCH model, and hence assumes constant conditional correlations. Recently, Kawakatsu (2006) suggested the matrix-exponential GARCH model, which is a multivariate extension of the EGARCH model.

2 Literature Review

From the ordinary linear regression in the estimation of the mean linear regression, researcher have to considered an in depth studies on the variance equation variation in a given regressed form which give birth to the study of heteroscedasticity model and the first model proposed by Engle (1984) give rebirth in others volatility model.

After the Generalized Autoregressive Conditional Heteroscedasticity model (GARCH model) was first introduced by Bollerslev (1986), it was concerned more and more by the application of those who use it as one of the powerful tools to analysis the financial return time series data. The financial return series with high frequency data display stylized facts such as volatility clustering, fat-tailness, high kurtosis and skewness. Modeling volatility in asset returns with such stylized facts is considered as a measure of risk, and investors want a premium for investing in risky assets.

Many researchers took quite a lot of in-depth studies and developed the univariate GARCH models and multivariate GARCH models. For instance, the Exponential GARCH model (EGARCH model) was pointed out by Nelson (1991). He pointed out that the volatilities aroused by negative news are larger than that by same level positive news. That is to say it is an asymmetry phenomenon. In order to solve this problem, he introduced a parameter “g” in the conditional variance part. Then it can reflect different volatilities when the random error takes negative or positive values.

Also the Threshold GARCH (TGARCH model) was mentioned by Zakoian (1990) and then by Glosten, Jaganathan and Runkle (1993) is an asymmetry GARCH models.

All the achievements above are the basis for the multivariate GARCH models like Constant Conditional Correlation (CCC) GARCH model by Bollerslev (1990) and is later extended by Jeantheau (1998). Then Engle (2000) introduced a Dynamic Conditional Correlation (DCC) GARCH model which the conditional correlation is not a constant term any more. And his main finding in his paper is that: The bivariate version of GARCH model provides a very good approximation to a variety of time varying correlation processes.

The comparison of the DCC-GARCH model with simple multivariate GARCH and several other estimators shows that the DCC is often the most accurate. This is true whether the criterion is mean absolute error, diagnostic tests or tests based on value at risk calculations.

In this study work of Constanza *et al.,* (2011) reviewed the models of volatility for a group of five Latin American countries, mainly motivated by the recent periods of financial turbulence by comparing the CCC and DCC models. Their results based on high frequency data suggest that Dynamic multivariate models are more powerful to study the volatilities of asset returns than Constant Conditional Correlation models. For the group of countries included, they identified that domestic volatilities of asset markets have been increasing; but the co-volatility of the region is still moderate.

Manabu and Micheal (2011) develop two Dynamic Conditional Correlation (DCC) models, namely the Wishart DCC (wDCC) model. The paper applies the wDCC approach to the exponential GARCH (EGARCH) and GJR models to propose asymmetric DCC models. They used the standardized multivariate t-distribution to accommodate heavy-tailed errors. The paper presents an empirical example using the trivariate data of the Nikkei 225, Hang Seng and Straits Times Indices for estimating and forecasting the wDCC-EGARCH and wDCC-GJR models, and compares the performance with the asymmetric BEKK model. The empirical results show that AIC and BIC favour the wDCC-EGARCH model to the wDCC-GJR, asymmetric BEKK and alternative conventional DCC models. Moreover, the empirical results indicate that the wDCC-EGARCH-t model produces reasonable VaR threshold forecasts, which are very close to the nominal 1% to 3% values. So in our study, we are going to uses the bivariate DCC GARCH to model the time varying volatility (conditional heteroscedasticity) in Nigeria stock Exchange and inflation.

3 Methodology

Multivariate GARCH models, composed by non-linear combinations of univariate GARCH, strongly depend on the definition of the matrix of conditional correlations. Under the assumption of correlations independent of time (R) the

models of Constant Conditional Correlations (CCC) allows a straightforward computation of the correlation matrix. But, if correlations vary over time(R_t), the models of Dynamic Conditional Correlations (DCC)
(Engle 2002, and Tse and Tsui 2002), are more appropriate to compute the returns variations. For high frequency data, DCC models are preferred over CCC since their structure allow an adequate estimation of the continuous changes in correlations, and also because DCC are more parsimonious than other multivariate GARCH models.
According to Engle (2002) the covariance matrix in a DCC model requires that

$$S_t = B_t R_t B_t \tag{1}$$

S and B both positive definite with probability of one, to avoid that linear dependencies on asset returns may produce variances negative or equal to zero. In equation (1) the matrix of variance is given by $B_t^2 = diag\{H_t\}$
DCC models are estimated in two stages. The first entails the selection of appropriate univariate GARCH models, in order to obtain the standard deviations $\left(\sqrt{h_{ii,t}}\right)$required to adjust the residuals $\left(U_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{ii,t}}}\right)$
This stage is characterized by its flexibility, since any univariate GARCH model can be used to estimate the individual volatility.
In the second stage the multivariate model is estimated based on the suitable dynamic quasi-correlation matrixP$_t$. For temporary stochastic processes with mean reverting changes in correlations (like those observed in asset returns) the matrix P$_t$ is defined by:

$$P_t = (1-\alpha-\beta)\overline{p} + \alpha u_{t-1}u_{t-1}^1 + \beta P_{t-1} \tag{2}$$

The $n \times n$covariance matrix of u_t is given by$\overline{P} = E\left[u_t u_t^1\right]$; and positive definiteness of the quasi-correlation matrix requires that the parameters α, β and (1-α-β) be all positive.
Expressing the correlation coefficient in a bivariate case, we have:

$$\rho_{12,t} = \frac{(1-\alpha-\beta)\bar{q}_{12} + \alpha\mu_{1,t-1}\mu_{2,t-1} + \beta q_{12.t-1}}{\sqrt{\left[(1=\alpha-\beta)\bar{q}_{11} + \alpha\mu_{1.t-1}^2 + \beta q_{11.t-1}\right]}\sqrt{\left[(1=\alpha-\beta)\bar{q}_{22} + \alpha\mu_{2.t-1}^2 + \beta q_{22.t-1}\right]}} \tag{3}$$

Lastly the Mean Reverting DCC approach requires the re-escalation of the matrix P$_t$ in order to guarantee that all the elements in the diagonal be equal to one. This stage finally leads us to the conditional correlation matrix, explained by the following equation:

$$R_t = diag\{P_t\}^{-\frac{1}{2}} P_t diag(P_t)^{-\frac{1}{2}} \tag{4}$$

Where $diag(P_t)^{-\frac{1}{2}} = diag\left(\frac{1}{\sqrt{p_{11,t}}},\ldots,\frac{1}{\sqrt{p_{nn,t}}}\right)$
Assuming that asset returns are multivariate normal, this approach permits the maximization of the log-likelihood function:

$$\begin{aligned}\ell(\theta,\phi) = &\left[-\tfrac{1}{2}\textstyle\sum_{t=1}^{T}\left(n\log(2\pi) + 2\log|B_t| + \varepsilon_t^1 B_t^{-2}\varepsilon_t\right] + \right.\\ &\left[-\tfrac{1}{2}\textstyle\sum_{t=1}^{T}\left(\log|R_t|\right) + u_t^1 R_t^{-1}u_t - u_t^1 u_t\right]\end{aligned} \tag{5}$$

In which the parameters in $B_t(\theta)$ and$R_t(\phi)$ are estimated simultaneously. The separate estimation of the volatility (first part of the equation) and the correlation component (the remaining part) is computationally easier than the simultaneous maximization. However, this separate estimation alternative represents limited information parameters that are not fully efficient. Besides, the maximization of the function requires of further assumptions on the data generating process, given that the multivariate density of returns usually differs from the Gaussian density. According to Bollerslev and Wooldridge (1992), consistent pseudo maximum likelihood estimators of equation (4) could be obtained under the correct specification of the conditional mean and variance equations.

4 Result Analysis

4.1 Empirical Result

An empirical analysis showed the results of the Nigeria Stock Exchange (NSE) and Inflation (INFL). From the mean value, the NSE incurred losses during the period of study and the percentage mean of inflation is very low.

From the table 4.2 shows the test for normality using the Jarque-Bera probability values also revealed and proved that the NSE and INFL don't follow a normally distribution with the p-value less than 5%.

Table 1: Empirical Result of Nigeria Stock Exchange and Inflation

Variable	*#obs*	*min*	*mean*	*max*	*std.dev*
DNSE	573	-2314.9	-5.9118	2635.3	499.75
DINFL	573	-15.4	0.0065096	17	2.4724

Table 2: Normality Test

DNSE	Skewness	Excess Kurtosis	Jarque-Bera
Statistic	0.40327	3.5581	317.79
P-Value	0.0001	0.0001	0.0001
DINFL			
Statistic	-0.11971	13.448	4319.3
P-Value	0.24082	0.0001	0.0001

Table 3: Augmented Dickey-Fuller Test.

	ADF Statistics	P-Value
DNSE	-12.1793	0.0001
DINFL	-15.0947	0.0001

1% 5% 10%
-2.56572, -1.94093, -1.61663

Table 4: Lagrange multiplier (LM) Test.

Series #1/2: NSE ---------	ARCH 1-2 test:	F(2,569)	=	39621. [0.0000]**
	ARCH 1-5 test:	F(5,563)	=	15743. [0.0000]**
	ARCH 1-10 test:	F(10,553)	=	7830.7 [0.0000]**
Series #2/2: INFL ---------	ARCH 1-2 test:	F(2,569)	=	612.21 [0.0000]**
	ARCH 1-5 test:	F(5,563)	=	258.34 [0.0000]**
	ARCH 1-10 test:	F(10,553)	=	153.83 [0.0000]**

4.2 *Analysis of the main result*

Stationarity test in Table 4.3 shows that the two variables were stationary all through with taking their first differences which make the series under study to be free from unit root. In testing the presence of heteroscedasticity Lagrange Multiplier was employed in Table 4.4 the F Statistic revealed that there was a presence of heteroscedasticity effect on two of the stocks with p-value greater than 1% highly significant level.
Table 4.4 shows the LM ARCH test for presence of heteroscedastic in the data. From the results, we can conclude that at different lags, ARCH effect is presence .i.e. there are presence of heteroscedastic in the data and it significant of 1%.
Table 4.5 illustrates the correlations of Nigeria Stock Exchange and Inflation.
Table 4.5 shows that the result of the correlation value between NSE and INFL =-0.04067. There correlation is negatively strong correlation. We can conclude that an increase in goods and services (Inflation) will effectually have negative impact on the Nigerian Stock Exchange. The literally explanation to investors is to monitor the rate of inflation in the country and decides when and when don't to invest on any particular stocks in Nigeria.

4.3 *Estimation of DCC-GARCH Model*

Conditional Variance: Dynamic Correlation Model (Engle) Multivariate Normal distribution.

Table 5: Correlation between NSE and INFL.

	NSE	*INFL*
NSE	1	
INFL	-0.04067	1

Table 6: Estimation of DCC-GARCH Model.

	Coefficient	Std.Error	t-value	t-prob
rho_21	-0.0044	0.05744	-0.0775	0.9383
alpha	0.3598	0.06308	5.7040	0.0000
beta	0.0001	0.2349	0.0000	1.0000

Log-likelihood = -5529.64

Table 4.6 shows the bivariate DCC-GARCH (1, 1) model of DNSE and DINFL. The results show estimated results for the DCC-GARCH (1, 1) model. The coefficients for all the parameters are positive while the correlation-Targeting is negative. In particular, alpha + beta = 0.359789 +0.0000 = 0.359789 $<$ 1 and rho_21 (Correlation-Targeting) =-0.04449 $<$ -1 , both of them are very close to 1 and -1, indicating that high persistence in the conditional variances. Furthermore, both of them are less than 1 and greater than -1, this means that conditional variance is finite and the series are strictly stationary for the parameter while is correlation-Targeting.

5 Conclusion

This study has correlated the major securities stock in Nigeria with the rate of the increase in goods and services in the nation. A bivariate DCC-GARCH (1, 1) model was fitted were the coefficients for all the parameters are positive while that of the correlation-Targeting is negative. However, both of parameter coefficient and correlation- targeting values are very close to 1 and -1, indicating that high persistence in the conditional variances. Furthermore, the model satisfied the properties of a good model of conditional mean and variance of the confident interval (C.I) of 1 and -1, i.e. the conditional variance is finite and the series are strictly stationary. The forecast graph also shows as goods and services increases; the Nigeria Stock Exchange will experience a non-steady shock in the stock market.

Appendix A: Graphical Plot of raw data and differences data

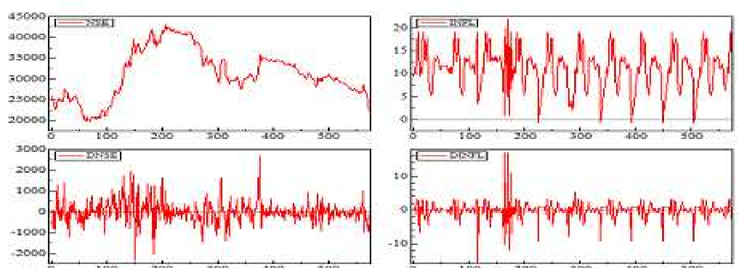

Fig. 1: shows the graph of raw data and differences data

Appendix B: Forecast Plot of Nigeria Stock Exchange and Inflation.

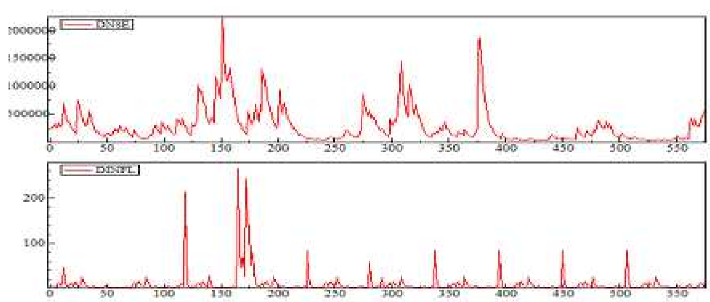

Fig. 2: forecast plot of DNSE and DINFL

References

[1] Asai, M. and M. McAleer (2008), "A Portfolio Index GARCH Model", *International Journal of Forecasting*, 24, 449-461.

[2] Asai, M. and M. McAleer (2009), "The Structure of Dynamic Correlations in Multivariate Stochastic Volatility Models", *Journal of Econometrics*, 150, 182-192.

[3] Asai, M., M. McAleer, and J. Yu (2006), "Multivariate Stochastic Volatility: A Review", *Econometric Reviews*, 25, 145-175.

[4] Bauwens L., S. Laurent and J.K.V. Rombouts (2006), "Multivariate GARCH Models: A Survey", *Journal of Applied Econometrics*, 21, 79-109.

[5] Bollerslev, T. (1990), "Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Approach", *Review of Economics and Statistics*, 72, 498-505.

[6] Bollerslev, T., R.F. Engle and J.M. Wooldridge (1988), "A Capital Asset Pricing Model with Time Varying Covariances", *Journal of Political Economy*, 96, 116-131.

[7] Bollerslev, T. and J.M. Wooldridge (1992), "Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances", *Econometric Reviews*, 11, 143–172.

[8] Christian M. Hafner1 Philip Hans Franses (2003) "A Generalized Dynamic Conditional Correlation Model for Many Asset Returns"

[9] Constanza Martnez and Manuel Ramrez (2011) "Dynamic Conditional Correlation In Latin-American Asset Markets" Serie Documentos De Trabajo No. 107

[10] Jejeebhoy,Chiu, T.Y.M, T. Leonard and K.-W. Tsui (1996), "The Matrix-Logarithmic Covariance Model", *Journal of the American Statistical Association*, 91, 198-210.

[11] Deb, P. (1996), "Finite Sample Properties of the Maximum Likelihood Estimator of EGARCH Models", *Econometric Reviews*, 15, 51-68.

[12] Ding, Z. and R.F. Engle (2001), "Large Scale Conditional Covariance Matrix Modeling, Estimation and Testing", *Academia Economic Papers*, 1, 83-106.

[13] Engle, R.F. (2002), "Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models", *Journal of Business and Economic Statistics*, 20, 339-350.

[14] Engle, R.F. and K.F. Kroner (1995), "Multivariate Simultaneous Generalized ARCH", *Econometric Theory*, 11, 122-150.

[15] Glosten, L., R. Jagannathan and D. Runkle (1992), "On the Relation Between the Expected Value and Volatility of Nominal Excess Returns on Stocks", *Journal of Finance*, 46, 1779-1801.

[16] Hentschel, L. (1995), "All in the Family: Nesting Symmetric and Asymmetric GARCH Models", *Journal of Financial Economics*, 39, 71-104.

[17] Kawakatsu, H., (2006), "Matrix Exponential GARCH", *Journal of Econometrics*, 134, Manabu Asai and Michael Mcaleer (2011) "Dynamic Conditional Correlations For Asymmetric Processes"

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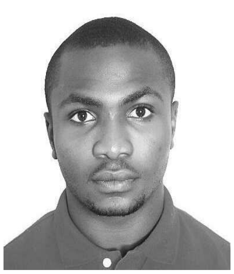

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