

Isenah, Godknows M.; Olubusoye, Olusanya E.

Article

Empirical model for forecasting exchange rate dynamics: The GO-GARCH approach

CBN Journal of Applied Statistics

Provided in Cooperation with:

The Central Bank of Nigeria, Abuja

Suggested Citation: Isenah, Godknows M.; Olubusoye, Olusanya E. (2016) : Empirical model for forecasting exchange rate dynamics: The GO-GARCH approach, CBN Journal of Applied Statistics, ISSN 2476-8472, The Central Bank of Nigeria, Abuja, Vol. 07, Iss. 1, pp. 179-208

This Version is available at:

<https://hdl.handle.net/10419/191680>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Empirical Model for Forecasting Exchange Rate Dynamics: the GO-GARCH Approach

Godknows M. Isenah¹ and Olusanya E. Olubusoye

The study aimed at determining a set of superior generalized orthogonal-GARCH (GO-GARCH) models for forecasting time-varying conditional correlations and variances of five foreign exchange rates vis-à-vis the Nigerian Naira. Daily data covering the period 02/01/2009 to 19/03/2015 was used, and four estimators of the GO-GARCH model were considered for fitting the models. Forecast performance tests were conducted using the Diebold-Mariano (DM) and the model confidence set (MCS) tests procedures. The DM test indicates preference for the GO-GARCH model estimated with nonlinear least squares (NLS) estimator – denoted as GOGARCH-NLS, while the MCS test determined a set of superior models (SSM) which comprised of GO-GARCH-NLS and GOGARCH model estimated by the method-of-moment, denoted as GO-GARCH-MM. These models were deemed best and adequate for forecasting of the five exchange rate dynamics.

Keywords: MGARCH, GO-GARCH, conditional heteroscedasticity, volatility, time-varying correlation

JEL Classification: C32, C53, F31

1.0 Introduction

The foreign exchange market is very crucial in international trade, as many world economies are directly or indirectly linked through export and import trades. Nigeria, a growing third world economy, is not left out in this loop of inter-linkages as most of its raw material and machinery needed for industrial production are usually imported. Thus, the Nigerian foreign exchange market plays a vital role in this regard. Sudden and unexpected changes in the dynamics of exchange rates if not adequately monitored could lead to economic crises such as the Mexican Peso crisis, Euro zone currency and sovereign debt crisis, and the South East Asian crisis. Regular monitoring of the dynamics (especially, exchange rate volatilities and co-volatilities) that characterize the foreign exchange market will ensure a stable economy and further boosting of investors' confidence.

¹Corresponding Author: Department of Statistics, University of Ibadan, Nigeria. E-mail: isenaiUI@gmail.com

In order to ensure economic stability in the country, the Central Bank of Nigeria has intervened actively in maintaining order by issuing exchange rate policies in the Nigerian foreign exchange market. The market had undergone four regimes of policy regulations between 1959 and 2010². Within this period, the floating exchange rate system was introduced. Unlike the fixed exchange rate system, the floating exchange rate system introduces a lot of randomness in the rates' dynamics thereby making it difficult for precise forecasting of future values.

Several studies on the Naira exchange rates have been conducted on the Nigerian foreign exchange market, especially the rates of the Naira vis-à-vis foreign currencies such as the US dollar, British Pound Sterling, Euro, etc. Some of these studies are concerned with the investigation of relationships between exchange rates and macroeconomic variables. Recent studies include: Adamu (2005), Mordi (2006), Yaya and Shittu(2010), Mbutor (2010), Kelilume and Salami (2012), Usman and Adejare (2013) and Fapetu and Oloyede (2014). While others examined modeling and forecasting of exchange rates volatilities in the time series context using univariate *autoregressive conditional heteroscedasticity* (ARCH) model of Engle (1982) and the *generalized ARCH* (GARCH) model of Bollerslev (1986), as well as various extensions of these models³. Though, these univariate models are well known for their ability in capturing adequately volatility and stylized facts of univariate economic and financial time series, they are however not adequate when interest is bothered on modeling volatilities and co-volatilities of a system of time series.

In finance, the knowledge of joint movements of a set of assets (in terms of conditional variances and conditional covariances) is an essential requirement for efficient management and monitoring of financial portfolios. Forecasting of *Value-at-Risk* (VaR) thresholds also require the knowledge, while hedging and asset specialization strategies can be determined with the knowledge of conditional cross-correlations amongst assets (Caporin and McAleer, 2009). The *multivariate GARCH* (MGARCH) models provide avenues where these financial tasks can be easily carried out. They are capable in modeling second-order moments and inter-linkages inherent in a multivariate set of time series. Since the aim of this study is to forecast the dynamics (i.e. conditional

²The four exchange rate regime include: the Fixed Parity (1959-1985), the Second-Tier Forex Market (SFEM, 1986 – 1994), the Autonomous Forex Market (AFEM, 1995 – 1999), and the Inter-Bank Forex Market (IFEM, 2000 – 2010).

³Reviews of the studies are presented in the literature review section.

volatilities and conditional correlations) of a system of five foreign exchange rates vis-à-vis the Nigerian Naira, we resort to a class of the MGARCH models called the *generalized orthogonal* GARCH (GO-GARCH) models. This class of models is based on the assumption that the co-movements of financial returns are driven by a small number of common underlying variables called *factors*.

The rest of the paper is structured as follows: Section 2 presents literature review; Section 3 presents structures of the general MGARCH and the GO-GARCH models, and forecast performance comparisons; Section 4 presents empirical data analysis, results and discussion; while Section 5 concludes the paper.

2.0 Literature review

Modeling and forecasting of exchange rate dynamics has many applications in economics, finance and other investment related fields. For investors and policy makers, the importance of exchange rate volatility in planning and decision making cannot be ruled out. The univariate ARCH/GARCH models have been quoted to record tremendous successes in modeling second-order moments of financial and economic time series. These models have found applications in modeling and forecasting of volatilities in financial markets such as stock exchanges, bond markets as well as the foreign exchange markets. Earlier studies which have applied the univariate ARCH/GARCH schemes in the modeling of second-order moments or volatilities of foreign exchange rates are those of Bollerslev (1987), Hsieh (1989) and Andersen and Bollerslev (1998). Some of the recent studies that have applied the schemes successfully in the modeling of exchange rate volatilities include: Balaban (2004), Cheong-Vee et al. (2011), Alam and Rahman (2012), and Xu et al. (2012).

Balaban (2004) compare performances of symmetric and asymmetric GARCH (1, 1), GJR-GARCH (1, 1) and the EGARCH (1, 1) models in forecasting volatility of the US Dollar/Deutsche Mark returns. The results of their study show that the EGARCH and the GARCH models relatively performed better than the GJR-GARCH model. Cheong-Vee et al. (2011) evaluated volatility forecasts of the US Dollar against the Mauritian Rupee exchange rate using GARCH (1, 1) models with GED and Student's *t* error distributions. Daily data spanning the period 30/06/2003 and 31/03/2008 was used in the study. Results of the study show that the GARCH (1, 1) model with GED errors slightly

outperformed the other models. Alam and Rahman (2012) examined the BDT/US Dollar exchange rate volatility using GARCH-type models with daily data for the period 03/07/2006 to 30/04/2012. Their findings show the current volatility is significantly affected by past volatilities. Xu et al. (2012) in their study compare the performance of Realized GARCH model with GARCH (1, 1) and IGARCH (1, 1) models using 10-minute intra-day closing prices of spot rates of eight exchange rates (AUD/USD, EUR/GBP, EUR/JPY, EUR/USD, GBP/USD, CAD/USD, CHF/USD & JPY/USD) that span the period 04/08/2003 and 03/08/2010. The results of their study show that the Log-Linear Realized GARCH model outperformed the other models both in the in-sample and out-sample data sets. Considering weekly returns data, the GARCH (1, 1) model outperformed the other models in the out-sample data. A noteworthy shortcoming associated with the modeling method adopted by these authors is that the joint movements and inter-linkages amongst the exchange rates were not accounted for. Knowledge of these co-movements will be vital for investment planning. An alternative method is to model the rates simultaneously using a multivariate volatility model.

In Nigerian, the univariate ARCH/GARCH models have equally been used by some researchers in analyzing the Naira rates vis-à-vis other foreign currencies. Such studies include those of Olowe (2009), Awogbemi and Alagbe (2011), Adeoye and Atanda (2012), and Bala and Asemota (2013) to mention a few. Olowe (2009) examined the log-returns volatility of the average Naira/Dollar exchange rates using GARCH (1, 1), GJR-GARCH (1, 1), EGARCH (1, 1), APARCH (1, 1), IGARCH (1, 1) and TS-GARCH (1, 1) models using monthly data spanning the period January, 1970 to December, 2007. The study assessed the effects of asymmetry and volatility persistence, as well as the impact of deregulation of the Nigerian foreign exchange market. The results of study show strong evidence of volatility persistence during the sampled period as well as significant asymmetric effects on the volatility process. Awogbemi and Alagbe (2011) examined volatility of the Naira/US Dollar and the Naira/Pound Sterling exchange rates using separate GARCH (1, 1) models and monthly data that spanned the period 2006 and 2010. Their finding indicates existence of volatility persistence in the exchange rate returns. As an observation, the separate use of univariate GARCH models in modeling the two exchange rates however fails to capture their joint movements over time. Knowledge of these co-movements could facilitate proper planning and decision making by importers, exporters and investors who embark on foreign businesses. This drawback as seen in the study could easily be solved by simultaneously

modeling the two rates via a bivariate GARCH model. Adeoye and Atanda (2012) examined consistency, persistency and the degree of volatility in the Naira/US Dollar exchange rates using monthly data for the period 1986 through 2008. The ARCH/GARCH models were used in assessing the severity of volatility in the nominal and real exchange rates. Their results also confirm the existence of volatility persistence in both the nominal and real exchange rates. Bala and Asemota (2013) examined volatility of three exchange rates (US Dollar, Pound Sterling and Euro) vis-à-vis the Naira using GARCH models and monthly data that spanned the period January 1985 and July 2011. The study compared performance of variants of the GARCH models with and without the incorporation of exogenous breaks in model estimation. The findings of their study show that performance of the models improved by incorporating volatility breaks in the estimated models. Furthermore, all of the asymmetric models fitted in the study reject existence of leverage effects in the volatility processes. As an alternative, a trivariate MGARCH model could have been used to simultaneously capture the second-order moments as well as the inter-links inherent in the system of exchange rates. Musa et al. (2014) also examined volatility of the Naira/US Dollar rates using symmetric GARCH, GJR-GARCH, TGARCH and TS-GARCH models with daily data covering the period June 2000 to July 2011. Statistically significant asymmetric effects were reported from the fitted GJR-GARCH and TGARCH models. Also in terms of forecast performance, the TGARCH model was reported to provide better forecasts than the other models.

Each of the studies cited above used univariate GARCH-type models in the modeling of volatilities of exchange rates. But when interest is bothered on modeling of the joint evolution of a system of time series, these models become inadequate and needed to be extended to a multivariate framework. The MGARCH framework provides avenues for modeling second-order moments and interlinks existing in a system of time series. Bauwens et al. (2006) and Silvennoinen and Terasvirta (2008) provide reviews on the MGARCH models.

The MGARCH models have been applied successfully in the modeling and forecasting of volatilities and dynamic correlations in foreign exchange markets. Some of the recent exchange rate studies in the MGARCH context include: Bollerslev (1990), Hartman and Sedlak (2013), Patnaik (2013) and Pelinescu (2014). Bollerslev (1990) introduced the CCC-GARCH model. This model was the first model used in examining exchange rate volatilities of five exchange rates in the multivariate context with the assumption of constant

conditional correlations. Patnaik (2013) investigated exchange rate volatilities of the Indian Rupee vis-à-vis the US dollar, Pound Sterling, Euro and the Japanese Yen using daily data spanning the period 5/4/2010 and 18/7/2011. Evidence of volatility spillovers among the rates was reported, even though they are not statistically significant. The study further revealed that volatility spillovers seem not to pose serious problems in the Indian foreign exchange market. In Pelinescu (2014), the diagonal BEKK-GARCH models with scalar restriction was used in analyzing the Romanian RON/Euro, the US Dollar/Euro, the Polish Zloty/Euro and the Czech Republic Koruna/Euro exchange rates. Strong asymmetry was discovered in the rates, it was also discovered that the returns were highly correlated with volatilities. In similar studies, Zahnd (2002), Andersen et al. (2003), Pesaran et al. (2008), Hartman and Sedlak (2013) have also applied MGARCH models in the analyses of exchange rate volatilities.

In Nigeria, and to the best of our knowledge, no study on the Naira exchange rate volatility co-movements using the MGARCH framework had been conducted or was found as at the time of this review. As such, the study aims at modeling the joint evolution of the Naira exchange rates vis-à-vis five foreign currencies using a variant of the MGARCH models (the GO-GARCH model), with the intention of forecasting the exchange rates volatilities and dynamic conditional correlations.

3.0 Statistical preliminaries

3.1 The general MGARCH model

Let $\{\mathbf{y}_t\}$ denote a covariance stationary $N \times 1$ dimensional vector stochastic process with properties $E(\mathbf{y}_t|\mathcal{F}_{t-1}) \equiv \boldsymbol{\mu}_t(\boldsymbol{\theta})$ and $var(\mathbf{y}_t|\mathcal{F}_{t-1}) \equiv \mathbf{H}_t$, where the sigma field generated by the vector process denoted by \mathcal{F}_{t-1} is the information set of the process up to time $t - 1$, and N is the number of time series in \mathbf{y}_t . Bauwens et al. (2006) defines $\{\mathbf{y}_t\}$ as:

$$\mathbf{y}_t = \boldsymbol{\mu}_t(\boldsymbol{\theta}) + \boldsymbol{\varepsilon}_t \quad (1)$$

where $\boldsymbol{\mu}_t(\boldsymbol{\theta})$ is a conditional mean vector dependent on a finite parameter vector $\boldsymbol{\theta}$.⁴ The innovations vector process $\{\boldsymbol{\varepsilon}_t\}$ is heteroscedastic and is defined as:

$$\boldsymbol{\varepsilon}_t = \mathbf{H}_t^{1/2}(\boldsymbol{\theta})\boldsymbol{\eta}_t \quad (2)$$

⁴Note that both $\boldsymbol{\mu}_t$ and \mathbf{H}_t depend on the parameter vector $\boldsymbol{\theta}$.

where $\boldsymbol{\eta}_t$ is a martingale-difference sequence with properties: $E(\boldsymbol{\eta}_t|\mathcal{F}_{t-1}) \equiv \mathbf{0}$ and $var(\boldsymbol{\eta}_t|\mathcal{F}_{t-1}) \equiv E(\boldsymbol{\eta}_t\boldsymbol{\eta}_t'|\mathcal{F}_{t-1}) = \mathbf{I}_N$. The conditional covariance matrix of $\{\mathbf{y}_t\}$ denoted by $\mathbf{H}_t \equiv [h_{ij,t}]$ for $i, j = 1, 2, \dots, N$ (leaving out $\boldsymbol{\theta}$ notation for convinience) is given by:

$$\begin{aligned} var(\mathbf{y}_t|\mathcal{F}_{t-1}) &= var(\boldsymbol{\varepsilon}_t|\mathcal{F}_{t-1}) = \mathbf{H}_t^{1/2} var(\boldsymbol{\eta}_t|\mathcal{F}_{t-1}) (\mathbf{H}_t^{1/2})' \\ &= \mathbf{H}_t \end{aligned} \quad (3)$$

In general, Eq. (1) and Eq. (2) specify the structure of the MGARCH models. The interest in MGARCH is on the formulation and specification of the time-varying conditional covariance matrix, \mathbf{H}_t .

3.2 The generalized orthogonal-GARCH (GO-GARCH) model

Suppose that $\{\boldsymbol{\varepsilon}_t \equiv \mathbf{y}_t - \boldsymbol{\mu}_t, t = 1, 2, \dots, T\}$ denotes an N -dimensional innovation vector process, then the GO-GARCH scheme imposes a structure on the vector process $\{\boldsymbol{\varepsilon}_t\}$ through a linear invertible mapping matrix \mathbf{W} and is defined as:

$$\boldsymbol{\varepsilon}_t = \mathbf{W}\mathbf{f}_t \quad (4)$$

The linear map is an $N \times N$ parameter matrix that is constant over time, and $\mathbf{f}_t \equiv (f_{1,t}, f_{2,t}, \dots, f_{N,t})'$ denotes a vector of unobserved independent components or factors. The factors are defined by:

$$\mathbf{f}_t = (\mathbf{H}_t^f)^{1/2} \boldsymbol{\eta}_t \quad (5)$$

where $\mathbf{H}_t^f \equiv E(\mathbf{f}_t\mathbf{f}_t'|\mathcal{F}_{t-1}) = diag(h_{1,t}^f, h_{2,t}^f, \dots, h_{N,t}^f)$ is an $N \times N$ diagonal matrix of conditional variances, and $\boldsymbol{\eta}_t \equiv (\eta_{1,t}, \eta_{2,t}, \dots, \eta_{N,t})'$. The random vector process $\{\boldsymbol{\eta}_t\}$ has the properties: $E(\boldsymbol{\eta}_t|\mathcal{F}_{t-1}) \equiv \mathbf{0}$ and $E(\boldsymbol{\eta}_t\boldsymbol{\eta}_t'|\mathcal{F}_{t-1}) \equiv \mathbf{I}_N$, since $\eta_{i,t}$ and $\eta_{j,t}$ are independent for every $i \neq j; i, j = 1, 2, \dots, N$. It implies that the conditional expectations: $E(\mathbf{f}_t|\mathcal{F}_{t-1}) \equiv \mathbf{0}$ and $E(\boldsymbol{\varepsilon}_t|\mathcal{F}_{t-1}) \equiv \mathbf{0}$. The unconditional distribution of the factors is characterized by: $E(\mathbf{f}_t) \equiv \mathbf{0}$ and $E(\mathbf{f}_t\mathbf{f}_t') \equiv \mathbf{I}_N$, which in turn implies that the unconditional distribution of the innovation vector process is also characterized by $E(\boldsymbol{\varepsilon}_t) = \mathbf{0}$ and $E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t') = \mathbf{W}\mathbf{W}' = \mathbf{H}$. The conditional covariance matrix of the innovation vector $\boldsymbol{\varepsilon}_t$ is then defined as:

$$\mathbf{H}_t = E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'|\mathcal{F}_{t-1}) = \mathbf{W}\mathbf{H}_t^f\mathbf{W}' = \sum_{k=1}^N \boldsymbol{\omega}_{(k)}\boldsymbol{\omega}_{(k)}' h_{k,t}^f \quad (6)$$

where $\omega_{(k)}$, for $k = 1, 2, \dots, N$ are the columns of \mathbf{W} and $h_{k,t}^f$ are the diagonal elements of \mathbf{H}_t^f . The k^{th} factor or component GARCH (p, q) is defined as:

$$h_{k,t}^f = \omega_k + \sum_{i=1}^q \alpha_k f_{k,t-i}^2 + \sum_{i=1}^p \beta_k h_{k,t-i}^f, \quad k = 1, 2, \dots, N \quad (7)$$

And the conditional correlation matrix is obtained from Eq. (6) and is defined as:

$$\mathbf{R}_t = \mathbf{D}_t^{-1} \mathbf{H}_t \mathbf{D}_t^{-1} \quad (8)$$

where $\mathbf{D}_t^{-1} \equiv (\mathbf{H}_t \odot \mathbf{I}_N)^{1/2}$ and \odot denotes the Hadamard product operator.

3.3 Estimators of the GO-GARCH model

Maximum likelihood (ML) estimator

The two-step ML estimator of van der Weide (2002) is obtained by maximizing the following multivariate Gaussian log-likelihood function:

$$L(\boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{\beta}) = -\frac{1}{2} \sum_{t=1}^T N \log_e 2\pi + \log_e |\mathbf{W}_\theta \mathbf{W}_\theta'| + \log_e |\mathbf{H}_t| + \mathbf{f}_t' \mathbf{H}_t^{-1} \mathbf{f}_t \quad (9)$$

The first step identifies part of the linear mapping matrix, while the second step estimates the remaining part of the mapping matrix and the parameters of the component GARCH models.

Nonlinear least squares (NLS) estimator

The three-step NLS estimator of Boswijk and van der Weide (2006) is obtained by minimizing the nonlinear least squares criterion given by:

$$\begin{aligned} S(\mathbf{A}) &= \frac{1}{T} \sum_{t=1}^T \text{tr}([\mathbf{V} \mathbf{s}_t \mathbf{s}_t' \mathbf{V}' - \mathbf{I}_N - \mathbf{A} \mathbf{V}(\mathbf{s}_{t-1} \mathbf{s}_{t-1}' - \mathbf{I}_N) \mathbf{V}' \mathbf{A}]^2) \\ &= \frac{1}{T} \sum_{t=1}^N \text{tr}([\mathbf{s}_t \mathbf{s}_t' - \mathbf{I}_N - \mathbf{B}(\mathbf{s}_{t-1} \mathbf{s}_{t-1}' - \mathbf{I}_N) \mathbf{B}]^2) \\ &= S^*(\mathbf{B}) \end{aligned} \quad (10)$$

where $\mathbf{f}_t = \mathbf{V} \mathbf{s}_t$ and $\mathbf{s}_t = \boldsymbol{\Lambda}^{-1/2} \mathbf{U}' \boldsymbol{\varepsilon}_t$. The estimates $\hat{\mathbf{A}}$ and $\hat{\mathbf{B}}$ minimize respectively $S(\mathbf{A})$ and $S^*(\mathbf{B})$ from the first-order conditions, and $\hat{\mathbf{B}} = \mathbf{V}' \hat{\mathbf{A}} \mathbf{V}$. This implies that \mathbf{V} is simply a matrix of eigenvectors of matrix \mathbf{B} from which

the linear mapping matrix \mathbf{W} and its inverse matrix \mathbf{W}^{-1} can be computed. The authors show in their study that the eigen-vector matrix $\hat{\mathbf{V}}$ of $\hat{\mathbf{B}}$ is a consistent estimator of \mathbf{V} .

Fast Independent Component Analysis (Fast-ICA) estimator

The Fast-ICA method of Broda and Paoletta (2008) estimates the link matrix \mathbf{W} by factoring it as $\mathbf{W} = \mathbf{H}^{1/2}\mathbf{V}$ using a two-step estimation procedure based on the *shrinkage estimators* proposed by Ledoit and Wolf (2003). The following conditional log-likelihood function is maximized to give estimate of \mathbf{W} and coefficients of the component-GARCH:

$$L(\hat{\boldsymbol{\varepsilon}}_t | \boldsymbol{\theta}, \mathbf{W}) = T \log_e |\mathbf{W}^{-1}| + \sum_{t=1}^T \sum_{i=1}^N \log_e \left(GH_{\lambda_i}(f_{i,t} | \theta_i) \right) \quad (11)$$

where $GH_{\lambda_i}(f_{i,t} | \theta_i) \equiv GH \left(f_{i,t}; \lambda_i, \mu_i \sqrt{h_{i,t}}, \frac{\omega_i}{\sqrt{h_{i,t}}}, \frac{\alpha_i}{\sqrt{h_{i,t}}}, \frac{\beta_i}{\sqrt{h_{i,t}}} \right)$ and $\boldsymbol{\theta}$ is a vector of unknown parameters in the marginal densities (Ghalanos, 2013).

Method-of-moment (MM) estimator

Boswijk and van der Weide (2009) MM estimator is obtained via a three-step estimation procedure. The procedure involves the autocorrelation properties of the zero-mean matrix-valued processes $\mathbf{S}_t = \mathbf{s}_t \mathbf{s}_t' - \mathbf{I}_N$ and $\mathbf{F}_t = \mathbf{f}_t \mathbf{f}_t' - \mathbf{I}_N$. For the process $\mathbf{s}_t = \mathbf{V} \mathbf{f}_t$, the autocovariance and autocorrelation matrices satisfy:

$$\mathbf{V} \boldsymbol{\Gamma}_i(f) \mathbf{V}' = E(\mathbf{S}_t \mathbf{S}_{t-i}) = \boldsymbol{\Gamma}_i(s) \quad (12)$$

as such,

$$\mathbf{V} \boldsymbol{\Phi}_i(f) \mathbf{V}' = \boldsymbol{\Phi}_i(s) = [\boldsymbol{\Gamma}_0(s)]^{-1/2} \boldsymbol{\Gamma}_i(s) [\boldsymbol{\Gamma}_0(s)]^{-1/2} \quad (13)$$

The MM estimator $\hat{\mathbf{V}}_i$ is then obtained as a matrix of eigenvectors from the symmetric matrix $\frac{1}{2} \left(\hat{\boldsymbol{\Phi}}_i(s) + \left(\hat{\boldsymbol{\Phi}}_i(s) \right)' \right)$, where:

$$\hat{\boldsymbol{\Phi}}_i(s) = [\hat{\boldsymbol{\Gamma}}_0(s)]^{-1/2} \hat{\boldsymbol{\Gamma}}_i(s) [\hat{\boldsymbol{\Gamma}}_0(s)]^{-1/2} \quad (14)$$

with $\hat{\mathbf{F}}_i(s) \equiv \frac{1}{T} \sum_{t=i+1}^T \mathbf{S}_t \mathbf{S}_{t-i}'$, and the standardized matrix $(\hat{\mathbf{F}}_0(s))^{-1/2}$ is derived from the singular value decomposition of the covariance matrix at lag zero.

3.4 Forecast comparisons: Diebold-Mariano (DM) test and Model Confidence Set (MCS)

The Diebold-Mariano's test compares two competing models based on the assumption of *Equal Predictive Ability* (EPA), while the MCS approach constructs a *Set of Superior Models* (SSM) with the assumption of EPA not rejected. In this study, we will consider the multivariate *Mean Squared Error* (MSE) loss function which is defined as:

$$L_{i,t} = \frac{1}{N^2} \text{vec}(\hat{\mathbf{H}}_{i,t} - \tilde{\mathbf{H}}_t)' \text{vec}(\hat{\mathbf{H}}_{i,t} - \tilde{\mathbf{H}}_t) \quad (15)$$

where $L_{i,t}$ denotes the MSE of model i at time t ; $\hat{\mathbf{H}}_{i,t}$ is the model's h -step-ahead forecast covariance matrix, and $\tilde{\mathbf{H}}_t$ is the time t true covariance matrix. The true covariance matrix is unobservable, and as such, it is usually approximated by a proxy in the literature. Caporin and McAleer (2010) suggests the outer-product of the mean forecast errors defined by: $\tilde{\mathbf{H}}_t \equiv \hat{\mathbf{e}}_t \hat{\mathbf{e}}_t'$, where $\hat{\mathbf{e}}_t \equiv \mathbf{r}_t - \hat{\boldsymbol{\mu}}_t$ as a proxy for the true covariance matrix.

The Diebold-Mariano's test statistic for testing the null hypothesis $H_0: E(d_{ij,t}) = E(L_{i,t}) - E(L_{j,t}) = 0$ between two competing models i and j is given as:

$$t_{ij} = \frac{\bar{d}_{jl}}{[\text{var}(\bar{d}_{jl})]^{1/2}} \xrightarrow{a} N(0, 1) \quad (16)$$

where $d_{ij,t} \equiv L_{i,t} - L_{j,t}$ denotes the loss differentials between the models at time t ; $\bar{d}_{ij} \equiv \frac{1}{h} \sum_{l=1}^h \bar{d}_{ij,t+l}$, h denotes the forecast horizon and $\text{var}(\bar{d}_{ij})$ is the *Heteroscedasticity and Autocorrelation Consistent* (HAC) estimate of the asymptotic variance of \bar{d}_{jl} . For significant t -values (i.e. H_0 is rejected), the sign of the test statistic suggest model preference: positive (negative) values indicate a preference for the second (first) model as it is associated with smaller losses. This test only facilitates pair-wise comparison of models at a time. It does not indicate the order or rank the compared models based on their forecast performances.

The MCS procedure of Hansen et al. (2011) facilitates multiple comparison and ranking of models in the order of forecast performance. The procedure creates a set of models with statistically equivalent forecast performance, using as input all pairwise loss differentials $d_{ij,t}$; $\forall i, j = 1, 2, \dots, P$ for a given loss function, where P denotes the total number of fitted models. It then starts with a set M_0 containing the loss series of the models to be compared, performs sequential elimination of the models by testing the null hypothesis $H_0: E(d_{ij,t}) = 0$ for $i > j$ and for all $i, j \in M_0$. If the null hypothesis is rejected at certain confidence level α , the worst performing model is excluded from the set. The procedure is repeated iteratively until the null hypothesis is not rejected. Hansen et al. (2005) proposed two test statistics for testing the null hypothesis based on Eq. (16). These statistics are:

$$T_R = \max_{i,j \in M_0} |t_{ij}| \quad (17)$$

$$T_{SQ} = \sum_{i,j \in M_0, i>j} (t_{ij})^2 \quad (18)$$

If the null hypothesis is rejected, the worst model can be identified with:

$$i = \operatorname{argmax}_{i \in M_0} \sum_{j \in M_0} \frac{\bar{d}_{ij}}{\operatorname{var}(\sum_{j \in M_0} \bar{d}_{ij})} \quad (19)$$

4.0 Data Description, Analysis and Discussion of Results

4.1 Data description

The data set consists of daily *central* exchange rates of five foreign currencies vis-à-vis the Nigerian Naira. The exchange rates are the *Danish Kroner* ($y_{1,t}$), *Euro* ($y_{2,t}$), *Japanese Yen* ($y_{3,t}$), *British Pound Sterling* ($y_{4,t}$), and *Swiss Franc* ($y_{5,t}$), which span the period 02/01/2009 through 19/03/2015. Each exchange rate time series consists of $T = 1531$ data points, and their respective percentage arithmetic return processes are denoted by $\{r_{N,t}; N = 1, 2, \dots, 5\}_{t=1}^T$. The data set was split into two subsets: (i) the *In-Sample* data consists of the first 1510 data points covering the sample period 02/01/2009 to 05/03/2015 used for model estimation and in-sample forecast evaluations; and (ii) *Out-of-Sample* data consists of the remaining 11 data points covering the period 06/03/2015 to 19/03/2015 which are used for model out-sample forecast evaluations. The data

set is available and can be downloaded from the Central Bank of Nigeria website: www.cenbank.org/rates/ExchRateByCurrency. The choice of the selected exchange rates is based on the availability of data in the sampled time period, and also on the fact that the respective currencies represent some of the major countries or economic zones Nigeria has trade relationships with. The value of the N^{th} exchange rate at time t is denoted by $y_{N,t}$, while its corresponding percentage arithmetic-returns is defined as:

$$r_{N,t} = 100 \times \left(\frac{y_{N,t} - y_{N,t-1}}{y_{N,t-1}} \right) \quad (20)$$

for $N = 1, 2, \dots, 5$ and $t = 1, 2, \dots, T$. The descriptive sample statistics, normality tests and the concurrent correlation matrix of the returns are presented respectively in Tables 1 and 2.⁵ As shown in Table 1, the minimum percentage arithmetic returns ranges from -32.05% for the Japanese Yen to -4.94% for the Pound Sterling. Similarly, the maximum of the returns ranges from 17.61% for the Swiss Franc to 46.67% for the Yen. The sample means and medians of the returns strictly lie in the half-open interval $[0, 0.04)$, while the standard deviations which can be viewed as a measure of unconditional volatility of the data ranges from 0.88% for the Pound Sterling to 1.98% for the Yen. The coefficients of skewness for all of the series are different from zero (they are positively skewed), while the coefficient of excess kurtosis (*Fisher's coefficient*) are all greater than 3. The normality tests (*Shapiro-Wilks* and *Jarque-Bera*) out rightly rejects the assumptions of empirical normal distribution of the return series. Table 2 reports the unconditional correlations among the return series. The table also shows that the Euro zone currency returns are more highly correlated with one another. Even though, the concurrent correlation between the Japanese Yen and the Euro is about 56%, its concurrent correlations with the other currencies (i.e. the Kroner, Pound Sterling and the Swiss Franc) are less than 50%. The estimated concurrent correlation coefficients imply that the returns co-move in a positive direction over time.

⁵Note that aberrant and missing values occur in the data set. Where any of these occurred, they are estimated with: $\hat{y}_{N,t} = \frac{1}{2}(y_{N,t-1} + y_{N,t+1})$ for the N^{th} exchange rate time series prior to data analysis.

Table 1: Descriptive statistics of the percentage arithmetic returns

Statistics	Danish Kroner	Euro	Japanese Yen	Pound Sterling	Swiss Franc
Minimum	-14.5652	-14.2577	-32.0466	-4.9352	-11.778
Median	0.0136	0.0074	0.0063	0	0.028
Mean	0.017	0.0148	0.0269	0.0325	0.037
Std. deviation	1.2513	1.06	1.9802	0.8752	1.0804
Maximum	18.7085	18.7054	46.6655	18.738	17.607
Skewness	3.1841	4.7649	7.8433	7.3159	4.6825
Kurtosis	86.1208	126.2672	308.5123	149.3389	103.1044
Normality Tests					
Shapiro - Wilks	0.5414	0.5653	0.2577	0.6559	0.5923
(p - value)	-2.20E-16	-2.20E-16	-2.20E-16	-2.20E-16	-2.20E-16
Jarque - Bera	476692.5	1057456.7	6099475.9	1439232.9	685124.1
(p - value)	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2: Concurrent correlation matrix of the exchange rate arithmetic returns

	Danish Kroner	Euro	Japanese Yen	Pound Sterling	Swiss Franc
Danish Kroner	1				
Euro	0.7618	1			
Japanese Yen	0.4802	0.5598	1		
Pound Sterling	0.6042	0.7223	0.3395	1	
Swiss Franc	0.4856	0.5744	0.3048	0.544	1

In order to eliminate dynamic linear dependences inherent in the data, optimal orders of $\text{VAR}(p)$ were determined using the `VARorder` function of R package `MTS`. The AIC and HQIC information criteria select optimal order of $p = 10$, while the BIC selects the order $p = 4$. Table A1 shows the results of the order determination. The $\text{VAR}(10)$ mean model was estimated and its residuals diagnosed for adequacy. The multivariate Ljung-Box test shows that the fitted model captures all of the linear dependences inherent in the data adequately. Figure A1 of Appendix A shows results of these diagnostic checks. Similarly, the multivariate ARCH-LM tests on the squared residuals indicate the presence of significant ARCH effects, which implies that the conditional variances of the exchange rate returns are time-varying. Results of the ARCH test are presented in Table A2.

4.2 Estimation and Analysis of GO-GARCH model

The innovation vector: $\{\hat{\epsilon}_t = \mathbf{r}_t - \hat{\boldsymbol{\mu}}_t; t = 1, 2, \dots, T\}$, where $\hat{\boldsymbol{\mu}}_t \equiv \boldsymbol{\phi} + \sum_{i=1}^{10} \hat{\boldsymbol{\Phi}}_i \mathbf{r}_t$ denotes the fitted VAR (10) model was employed in the estimation of the GO-GARCH models. The four estimators discussed earlier were used for fitting the GO-GARCH models. A GARCH (1, 1) structure was assumed for the latent factors.⁶

4.3 Diagnostics of estimated GO-GARCH models

The fitted models were assessed for goodness-of-fit using the Hosking (1980) and Li and McLeod (1981) multivariate portmanteau tests for assessing the fit of our estimated GOGARCH models. The results of the tests for each of the estimated GO-GARCH (1, 1) models are presented in Table B1. All of the fitted models are adequate at the $\alpha = 5\%$ level of significance, but the GO-GARCH model estimated by the maximum likelihood estimator appears to have a better fit to the data compared with the other estimators.

4.4 Forecast performance evaluations

We evaluate forecast performance of the fitted models by testing the null hypothesis of EPA using the DM test for both the in-sample and out-of-sample data sets. The results for the DM tests and their corresponding p-values are presented in Tables B2 and B3 respectively. From Table B2, it is noted that all of the estimated models are statistically equivalent at $\alpha = 10\%$ level of significance. However, the null hypothesis of EPA is rejected (at the $\alpha = 5\%$ level of significance) for the tests between the ML and NLS estimators, and NLS and MM estimators for forecast horizon $h = 1$ and $h = 5$; and also between NLS and MM estimators for $h = 30$. The results indicate preference for the GO-GARCH model estimated with the NLS estimator. The DM tests in the out-of-sample show that the models estimated with the ML, NLS and MM estimators are preferred to the model estimated with the Fast-ICA estimator.

To rank the models in the order of forecast performance in the in-sample and out-of-sample data sets, the MCS test procedure was used. The results of the in-sample and out-of-sample MCS test results are presented in Tables B4 and B5 respectively. From Table B4, it is obvious that the estimated models are

⁶Details of the results of the fitted models are not presented here due to space and size of the outputs, but are available upon request.

statistically equivalent at $\alpha = 10\%$, $\alpha = 5\%$ and $\alpha = 1\%$ confidence levels respectively; as such none of the models was eliminated. But then, the rankings of the models in terms of their forecast performance indicate that the GO-GARCH model estimated with the NLS estimator is ranked 1st, the MM estimator ranked 2nd, the ML estimator ranked 3rd and the Fast-ICA estimator ranked 4th. In the out-of-sample test results, the set superior models created include only the GO-GARCH models estimated with the NLS and MM estimators respectively. These models are ranked 1st and 2nd respectively. Having determined the set of superior models for forecasting the system of exchange rates, the study proceed to fit two forecast models (i.e. the GOGARCH-NLS and GOGARCH-MM) using the entire data set. A brief summary of the fitted coefficients of are presented in Tables 3 and 4 respectively (Appendix B presents detailed summary of the fitted models).⁷ The Hosking and Li and McLeod tests on the residuals of these models does not show any lack of fit.

The results presented in Table 3 and Table 4 show that some of the estimated component GARCH processes are highly persistent, especially component GARCH 2 and 4 for the GOGARCH-NLS model, and component GARCH 1, 3 and 4 for GOGARCH-MM model respectively. Another observation from the tables is that the estimated shock coefficients from the NLS estimator (defined by $\hat{\alpha}_2$, $\hat{\alpha}_4$ and $\hat{\alpha}_5$) decay at a faster rate compared to those of the MM estimator. Likewise, the shocks from the MM estimator (defined by $\hat{\alpha}_1$ and $\hat{\alpha}_3$) decay faster compared to those of the NLS estimator. These models provide different magnitudes of estimates of the time-varying conditional variances. Figures B1 and B2 present the time plots of the estimated conditional variances, while Fig. B3 and Fig. B4 present the time plots of the estimated pair-wise conditional correlations for the GOGARCH-NLS and GOGARCH-MM models respectively. The conditional variance time plots that the estimates of the conditional variances are higher in the NLS estimator. Both estimators however capture three regimes of high volatilities in the exchange rate return processes. The period of highest volatility occurs towards the end of the sample data; the cause of this volatility may be attributed to devaluation of the Naira. Table B6 presents the sample ranges of the estimated time-varying conditional variances for each exchange rate returns series.

⁷All of the GOGARCH models considered in this study were estimated using the R package 'gogarch' of Pfaff (2014).

The time plots of the conditional correlations also show periods of high volatilities in the co-movements of the exchange rates. For the NLS estimator, the time-varying pair-wise correlations follow decreasing trends towards the end of the sample period. The pair-wise conditional correlations between the Euro & Kroner, Pound & Euro, Swiss Franc & Euro, Pound & Yen, Swiss & Yen, and Swiss & Pound follow slightly increasing trends but also decrease towards the end of the sample period. The other pair-wise correlations fluctuate about their respective average conditional correlations. The estimated pair-wise conditional correlations for the MM estimator are similar to those of the NLS estimator, but they appear to be more volatile and more random. These pair-wise correlation coefficients also decrease towards the end of the sample except for those between the Euro & Kroner, Swiss & Yen, and Pound & Yen which appear to decrease slowly. It is worth to note that the magnitudes of the estimated pair-wise correlation coefficients are essentially the same for both the NLS and the MM estimators. These pairwise conditional correlations are reported in Table B7.

Table 3: Estimated coefficients of GOGARCH model via NLS estimator

Linear Mapping Matrix					
	[,1]	[,2]	[,3]	[,4]	[,5]
[,1]	0.46605	-0.21169	-0.8136	-0.39821	-0.06275
[,2]	0.22917	0.02223	-0.7911	-0.10471	-0.4137
[,3]	-0.58665	-0.68155	-1.05678	-0.0131	-0.06938
[,4]	-0.03791	0.37736	-0.60218	-0.37617	-0.06419
[,5]	0.25829	0.29226	-0.81302	0.35659	0.32485
GARCH Coefficients					
Component	omega	alpha	beta		
1	1.0855e-01	0.11032	0.79975		
2	1.0820e-03	0.08559	0.92813		
3	3.8624e-01	1	0.14495		
4	1.0007e-06	0.04919	0.96647		
5	2.0211e-01	0.20548	0.63909		

Table 4: Estimated coefficients of GOGARCH model via MM estimator

Linear Mapping Matrix					
	[,1]	[,2]	[,3]	[,4]	[,5]
[,1]	0.85718	0.4019	0.14043	0.37538	0.17193
[,2]	0.57261	0.69076	0.12615	0.13858	-0.14422
[,3]	0.58351	0.27526	1.20138	0.01707	-0.26568
[,4]	0.08942	0.63013	0.18898	0.42098	0.18462
[,5]	0.35201	0.63884	0.21769	-0.35188	0.5853
GARCH Coefficients					
Component	omega	alpha	beta		
1	0.00753	0.03476	0.96507		
2	0.05507	1	0.45554		
3	0.00186	0.09491	0.91804		
4	0.00187	0.05311	0.96258		
5	0.26801	0.31404	0.4767		

5.0 Conclusion

The study aimed at estimating GO-GARCH models for forecasting the dynamics of a system of five exchange rates vis-à-vis the Nigerian Naira. Four estimators were considered for fitting the models, and tests for forecast performance in both in-sample and out-of-sample were conducted using the Diebold-Mariano (DM) tests and the Model Confidence Set (MCS) procedure. The results of the tests show that the fitted models are statistically equivalent in terms of in-sample forecast performance, but in the out-of-sample tests, the GO-GARCH models estimated with the NLS and MM estimators constitute the Set of Superior Models (SSM). These models were considered best for forecasting the dynamics of the system of Naira exchange rate returns within the GO-GARCH framework. The estimators were based on the assumption of multivariate normal distribution. As to whether the choice of returns distributions will improve forecast performance of the models was not considered in the study, but is left for further research.

References

- Adamu, P. A. (2005). The impact of exchange rate volatility on private investment in Nigeria: an error correction representation. *The Nigerian Journal of Economic and Social Studies*, 47(2), 301–317.

- Adeoye, B. W. and Atanda, A. A. (2012). Exchange rate volatility in Nigeria: consistency, persistency and severity analysis. *CBN Journal of Applied Statistics*, 2(2), 29–49. Retrieved from www.cenbank.org/out/2012/ccd/cbn%...
- Alam, Z. and Rahman, A. (2012). Modeling volatility of the BDT/USD exchange rate with GARCH model. *International Journal of Economics and Finance*, 4(11), 193–204. Retrieved from <http://dx.doi.org/10.5539/ijef.v4n11p193>
- Andersen, T. and Bollerslev, T. (1998). Answering the skeptics: yes, standard volatility models do provide accurate forecasts. *International Economic Review*, 39, 885–906.
- Andersen, T. G., Bollerslev, T., Diebold, F. X. & Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica*, 71, 529–626.
- Awogbemi, C. and Alagbe, S. (2011). Empirical modeling of Nigerian exchange rate volatility. *Mathematical Theory and Modeling*, 1(3), 1–15. Retrieved from <http://www.iiste.org>
- Bala, D. A. and Asemota, J. O. (2013). Exchange rates volatility in Nigeria: application of GARCH models with exogenous break. *CBN Journal of Applied Statistics*, 4(1), 89–116. Retrieved from www.cenbank.org/Out/2013/SD/Exchange...
- Balaban, E. (2004). Forecasting exchange rate volatility. *SSRN Working Paper*. Retrieved from <http://ssrn.com/abstract=494482>
- Bauwens, L., Laurent, S. & Rombouts, J. V. K. (2006). Multivariate GARCH models: a survey. *Journal of Applied Econometrics*, 21, 79–109. <http://doi.org/10.1002/jae.842>
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics*, 31, 307–327.
- Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of returns. *The Review of Economics and Statistics*, 69, 542–547.
- Bollerslev, T. (1990). Modeling coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *Review of Economics and Statistics*, 72, 498–505.
- Boswijk, H. P. and van der Weide, R. (2006). Wake me up before you GO-GARCH. *Discussion Paper: 2006/03, Amsterdam School of Economics, University of Amsterdam - September 2006*.

- Boswijk, H. P. and van der Weide, R. (2009). Method of moments estimation of GO-GARCH models. *Discussion Paper: 2009/05, Amsterdam School of Economics, University of Amsterdam - January 2009*. Retrieved from <http://dare.nl/document/166819>
- Broda, S. A. and Paoletta, M. S. (2008). CHICAGO: a fast and accurate method for portfolio risk calculation. *Swiss Finance Institute, Research Paper Series No. 08-08, Zurich*. Retrieved from www.unibas.ch/fileadmin/wwz/redakti...
- Caporin, M. and McAleer, M. (2009). Do we really need both BEKK and DCC? A tale of two covariance models. *Documentos de Trabajo Del Instituto Complutense de Analisis Economico (ICAE); No. 0904*. Retrieved from <http://eprints.ucm.es/8590/>
- Cheong-Vee, D. N., Gonpot, P. N. & Sookia, N. (2011). Forecasting volatility of USD/MUR exchange rate using a GARCH(1, 1) model with GED and Student's t errors. *University of Mauritius Research Journal*, 17, 1–14. Retrieved from www.ajo.info/.../59342
- Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50, 987–1007.
- Fapetu, O. and Oloyede, J. A. (2014). Foreign exchange management and the Nigerian economic growth (1960-2012). *European Journal of Business and Innovation Research*, 2(2), 19–31. Retrieved from www.ea-journals.org
- Ghalanos, A. (2013). The rmgarch models : background and properties, 1–23. Retrieved from http://cran.r-project.org/web/packages/rmgarch/vignettes/The_rmgarch_models
- Hartman, J. and Sedlak, J. (2013). Forecasting conditional correlation for exchange rates using multivariate GARCH models with historical Value-at-Risk application. *B.Sc. Thesis, Uppsala Univeristy; Spring 2013*. Retrieved from www.diva-portal.org/smash/get/diva2:632910/FULLTEXT02.pdf
- Hosking, J. R. M. (1980). The multivariate portmanteau statistic. *Journal of American Statistical Association*, 75, 602–608.
- Hsieh, D. (1989). Modeling heteroscedasticity in daily foreign exchange rates. *Journal of Business & Economic Statistics*, 7, 307–317.
- Kelilume, K. and Salami, D. (2012). Exchange rate volatility and corporate performance in Nigeria: a panel regression approach. *Global Conference*

on Business & Finance Proceedings, 7(1), 582–.

- Ledoit, O. and Wolf, M. (2003). Improved estimation of the covariance matrix of stock returns with application to portfolio selection. *Journal of Empirical Finance*, 10, 603–621.
- Li, W. K. and McLeod, A. I. (1981). Distribution of the residual autocorrelations in multivariate ARMA time series models. *Journal of the Royal Statistical Society Series B*, 43, 231–239. Retrieved from www.jstor.org/stable/2984853
- Mbutor, M. O. (2010). Exchange rate volatility, stock price fluctuations and the lending behaviour of banks in Nigeria. *Journal of Economics and International Finance*, 2(11), 251–260. Retrieved from <http://www.academicjournals.org/JEIF>
- Mordi, C. N. O. (2006). Challenges of exchange rate volatility in economic management in Nigeria. *CBN Bullion*, 30(3), 17–25.
- Musa, Y., Tasi'u, M. & Bello, A. (2014). Forecasting of exchange rate volatility between Naira and US Dollar using GARCH models. *International Journal of Academic Research in Business and Social Sciences*, 4(7), 369–381. Retrieved from www.hrmar.com/hrmars-papers/
- Olowe, R. A. (2009). Modeling Naira/Dollar exchange rate volatility: application of GARCH and asymmetric models. *International Review of Business Research Papers*, 5(3), 377–398.
- Patnaik, A. (2013). A study of volatility spillover across select foreign exchange rates in India using dynamic conditional correlations. *Journal of Quantitative Economics*, 11(1 & 2), 28–47.
- Pelinescu, E. (2014). Volatility analysis of the Romanian exchange rate. *Procedia Economics and Finance*, 8, 543–549. Retrieved from www.sciencedirect.com/science/article/pii/
- Pesaran, M. H., Schleicher, C. & Zaffaroni, P. (2008). Model averaging in risk management with an application to futures markets. *CESIFO Working Paper No. 2231*. Retrieved from <http://www.cesifo-group.de/>
- Pfaff, B. (2014). Package “gogarch.” Retrieved from <http://r-forge.r-project.org/projects/>
- Silvennoinen, A. and Terasvirta, T. (2008). Multivariate GARCH models. *SSE/EFI Working Paper Series in Economics and Finance No. 669*. Retrieved from <http://swopec.hhs.se/hastef/papers/hastef0669.pdf>

- Usman, O. A. and Adejare, A. T. (2013). Effect of exchange rate volatility on Nigeria economy (1991-2010). *International Journal of Academic Research in Economics and Management Sciences*, 2(6), 172–184. <http://doi.org/10.6007/IJAREMS/v2-i6/801>
- van der Weide, R. (2002). A multivariate generalized orthogonal GARCH model. *Journal of Applied Econometrics*, 17(5), 549–564.
- Xu, J., Gupta, S., Lu, H. & Yu, H. (2012). Modeling exchange rate volatility using realized GARCH. *SSRN Paper No. 2504338*. Retrieved from <http://ssrn.com/abstracts=2504338>
- Yaya, O. S. and Shittu, O. I. (2010). On the impact of inflation and exchange rate on conditional stock market volatility: a re-assessment. *American Journal of Scientific and Industrial Research.*, 1(2), 115–117. <http://doi.org/10.5251/ajsir.2010.1.2.115.117>
- Zahnd, E. (2002). *The application of multivariate GARCH models to turbulent financial markets*. Department of Economics & Business; University of Basel, Switzerland. Retrieved from <http://www.dissertation.de/FDP/3898254429.pdf>

Appendix A

Table A1: Selected optimal orders of VAR (p) models based on the multivariate information criteria⁸

Selected order: AIC = 10 Selected order: BIC = 4 Selected order: HQIC = 10 Summary table:					
<i>p</i>	AIC	BIC	HQIC	M(<i>p</i>)	<i>p</i> - value
0	-0.8303	-0.8303	-0.8303	0	0
1	-1.3694	-1.2823	-1.337	863.7682	0
2	-1.51	-1.3357	-1.4452	260.8567	0
3	-1.726	-1.4646	-1.6287	373.0804	0
4	-1.8505	-1.5019	-1.7208	235.0789	0
5	-1.8724	-1.4367	-1.7103	81.3806	0
6	-1.895	-1.3722	-1.7005	82.1574	0
7	-1.8911	-1.2811	-1.6641	42.5949	0.0155
8	-1.9161	-1.2189	-1.6566	85.0168	0
9	-2.0268	-1.2426	-1.735	210.9399	0
10	-2.3067	-1.4352	-1.9823	457.9651	0
11	-2.2963	-1.3378	-1.9396	32.6606	0.1398
12	-2.2825	-1.2368	-1.8933	27.3626	0.338
13	-2.2735	-1.1407	-1.8519	34.4824	0.098

⁸The functions `refVAR`, `mqand` and `MarchTest` of the R package `MTS` of Tsay(2014) was used in the estimation and diagnostics of the VAR models.

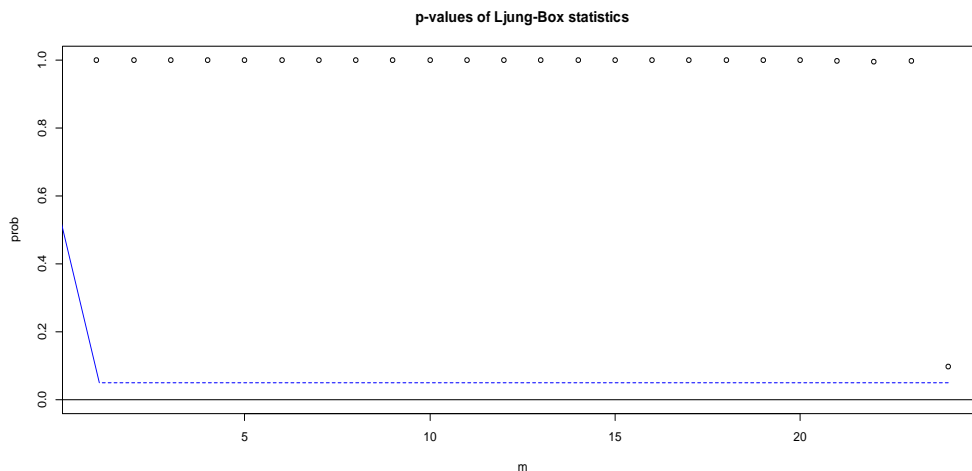


Figure A1: Diagnostic plot of multivariate portmanteau Ljung-Box test on the residuals from the fitted VAR (10) models.

Table A2: Multivariate ARCH tests on squared residuals from fitted VAR (10) model

Lag	ARCH - LM Test	Statistic	p - value
10	$Q(m)$	170.3796	0.0000
10	$Q^*(m)$	2358.738	0.0000
20	$Q(m)$	171.7346	0.0000
20	$Q^*(m)$	2399.078	0.0000
30	$Q(m)$	363.1023	0.0000
30	$Q^*(m)$	6091.971	0.0000
40	$Q(m)$	364.9385	0.0000
40	$Q^*(m)$	6153.335	0.0000

Appendix B

Table B1: Goodness-of-fit tests on the estimated GOGARCH models⁹

Estimator	Lag	Statistic	Hosking Test		Li & McLeod Test	
			Degree of freedom	p - value	Statistic	p - value
Maximum likelihood	5	139.2904	125	0.2288	139.2579	0.2288
	10	250.1662	250	0.3996	250.155	0.3986
	15	363.6848	375	0.4745	363.7675	0.4745
	20	444.6371	500	0.7922	445.25	0.7912
Nonlinear least squares	5	193.1833	125	0.031	193.0506	0.031
	10	319.028	250	0.0579	318.8363	0.0569
	15	422.1668	375	0.1518	422.1666	0.1508
	20	521.0518	500	0.2637	521.355	0.2587
Method of moment	5	186.0793	125	0.042	185.9549	0.042
	10	316.192	250	0.08	315.9793	0.08
	15	433.2828	375	0.1269	433.1307	0.1269
	20	528.3005	500	0.2478	528.5132	0.2468
Fast ICA	5	264.2012	125	0.013	263.9584	0.013
	10	389.7878	250	0.017	389.4889	0.017
	15	470.1582	375	0.0629	470.2288	0.0619
	20	568.4552	500	0.1169	568.844	0.1159

Table B2: In-sample forecast performance evaluations – p values in parenthesis

Test for h=1				
	ML	NLS	MM	Fast - ICA
ML	-	2.4854 (-0.01296)	0.9715 (0.3298)	0.4435 (0.6574)
NLS		-	-2.1165 (0.0343)	-1.0182 (0.3086)
MM			-	-0.2236 (0.823)
Test for h = 5				
	ML	NLS	MM	Fast - ICA
ML	-	2.204 (0.02756)	0.8897 (0.3736)	0.4226 (0.6726)
NLS		-	-2.1881 (0.02869)	-1.0129 (0.3111)
MM			-	-0.2223 (0.8241)
Test for h = 30				
	ML	NLS	MM	Fast - ICA
ML	-	1.6712 (0.09473)	0.7514 (0.4525)	0.3581 (0.7203)
NLS		-	-2.3269 (0.02)	-0.9779 (0.3282)
MM			-	-0.2186 (0.827)

Note: p-values in parentheses

⁹The multivariate portmanteau tests were carried out with the use of the R package ‘portes’ developed by Mahdi et al.(2014)

Table B3: Out-of-sample forecast evaluations (EPA)

Test for h=1				
	ML	NLS	MM	Fast - ICA
ML	-	1.1254 (0.26659)	1.5054 (0.1387)	-3.2108 (0.00234)
NLS		-	1.5664 (0.1237)	-3.3666 (0.0015)
MM			-	-4.3974 (5.9e-05)

Table B4: In-sample MCS test results: the created Superior Set of Models (SSM)

Estimator	Rank R	TSQ		Rank R	TR	
		v_R	p - value		v_R	p - value
		alpha = 10%			alpha = 10%	
ML	3	0.2947	0.7408	3	0.2933	0.74
NLS	1	-0.0336	1	1	-0.0336	1
MM	2	0.0336	0.9964	2	0.0336	0.995
Fast ICA	4	0.5642	0.3914	4	0.564	0.4046
alpha = 5%					alpha = 5%	
ML	3	0.2932	0.7372	3	0.2928	0.744
NLS	1	-0.0336	1	1	-0.0336	1
MM	2	0.0336	0.9958	2	0.0336	0.996
Fast ICA	4	0.5712	0.3968	4	0.5629	0.4058
alpha = 1%					alpha = 1%	
ML	3	0.2911	0.747	3	0.2939	0.7442
NLS	1	-0.0336	1	1	-0.0336	1
MM	2	0.0335	0.9968	2	0.0336	0.9962
Fast ICA	4	0.5683	0.3882	4	0.5627	0.3988

Table B5: Out-of-sample MCS test results: the created Superior Set of Models (SSM)

		TSQ			TR	
Estimator	Rank R	v_R	p - value	Rank R	v_R	p - value
		alpha = 10%			TR: alpha = 10%	
NLS	1	-0.9994	1	1	-0.9995	1
MM	2	0.9995	0.1778	2	0.9994	0.187
		alpha = 5%			TR: alpha = 5%	
NLS	1	-0.9989	1	1	-0.9997	1
MM	2	0.9999	0.1764	2	0.9992	0.1856
		alpha = 1%			TR: alpha = 1%	
NLS	1	-0.9995	1	1	-0.9996	1
MM	2	0.9994	0.1792	2	0.9993	0.169

Table B6: Ranges of the estimated conditional variances by the NLS and MM estimators

Estimator	Danish Kroner	Euro	Japanese Yen	Pound Sterling	Swiss Franc
NLS	0.45 – 196.83	0.41 – 183.63	0.74 – 331.68	0.20 – 105.79	0.42 – 194.11
MM	0.26 – 35.82	0.16 – 98.73	0.26 – 76.29	0.09 – 82.84	0.28 – 99.53

Table B7: Averages of estimated pair-wise conditional correlations

Exchange rate pair	NLS estimator	MM estimator
Danish Kroner & Euro	0.8154	0.8411
Danish Kroner & Japanese Yen	0.4586	0.5375
Danish Kroner & Pound Sterling	0.6832	0.6612
Danish Kroner & Swiss Franc	0.4571	0.5256
Euro & Japanese Yen	0.5207	0.6189
Euro & Pound Sterling	0.7082	0.6678
Euro & Swiss Franc	0.4628	0.4919
Pound & Japanese Yen	0.4141	0.341
Swiss Franc & Japanese Yen	0.3199	0.2974
Swiss Franc & Pound Sterling	0.4248	0.4796

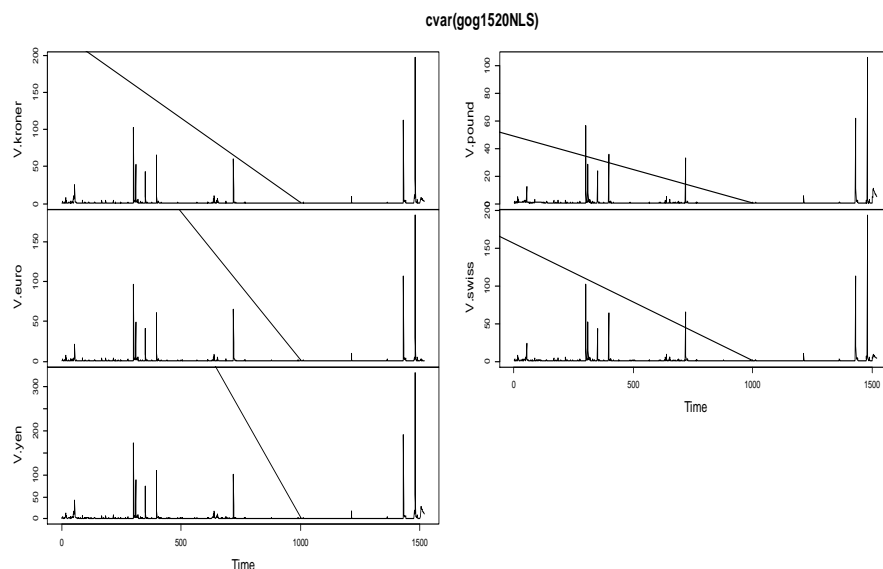


Figure B1: Time plots of conditional variances estimated with the NLS estimator.

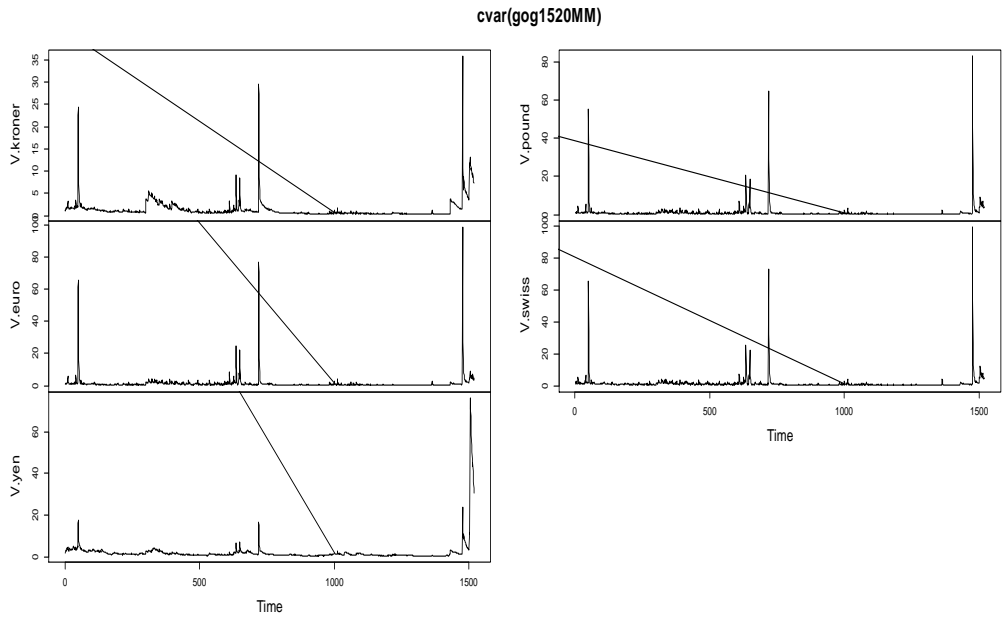


Figure B2: Time plots of conditional variances estimated with the ML estimator.

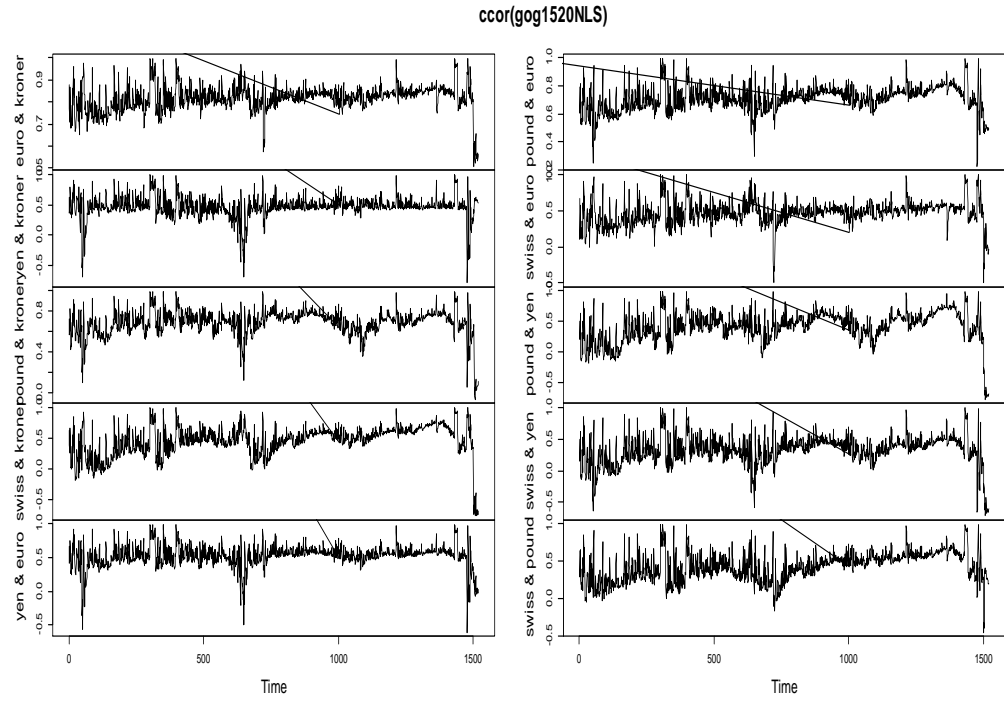


Figure B3: Time plots of conditional correlations estimated with the NLS estimator.

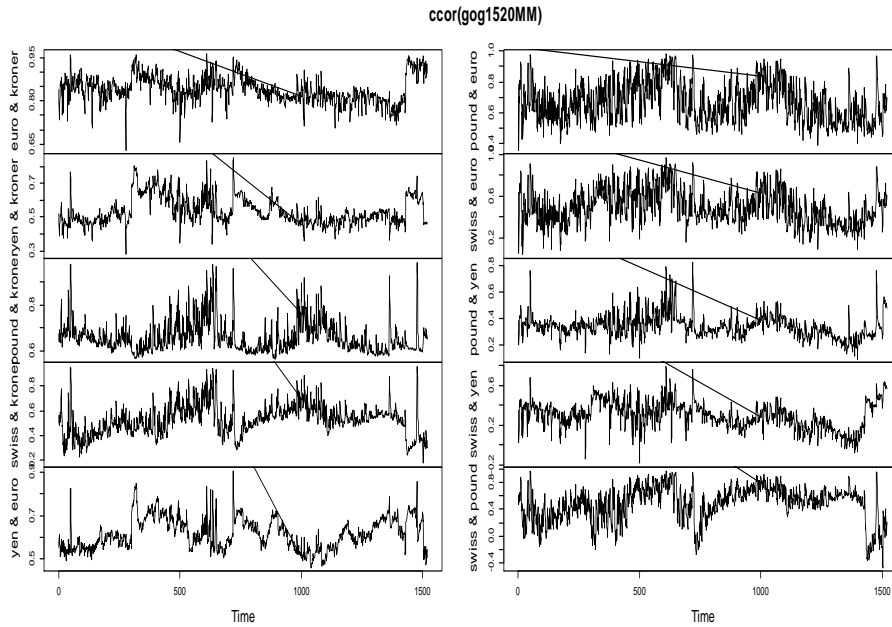


Figure B4: Time plots of conditional correlations estimated with the ML estimator.

Appendix C

R output of GOGARCH (1, 1) model estimated with Nonlinear Least Squares(NLS) estimator

*** Summary of GO-GARCH Model ***

Used object: resVAR10

Components estimated by: non-linear Least-Squares

Formula for component GARCH models: ~ garch(1, 1)

The Inverse of the Linear Map Z:

	[,1]	[,2]	[,3]	[,4]	[,5]
[1,]	0.96966862	0.2862890	-0.66067452	-0.8536580	0.2421152
[2,]	-0.80825129	0.2819243	-0.46145859	1.0977372	0.3212513
[3,]	-0.06114769	-0.2166278	-0.29281943	-0.2421137	-0.3980627

[4,] -0.95611777 0.9540715 0.04550961 -1.1412227 0.8145626

[5,] 0.85264668 -2.0707199 0.15765528 0.3379239 0.7064122

*** **Estimated Component GARCH models** ***

Component GARCH model of y1

	Estimate	Std. Error	t value	Pr(> t)
omega	0.1085455	0.01937282	5.602981	2.106969e-08
alpha1	0.1103192	0.02226585	4.954636	7.246569e-07
beta1	0.7997489	0.03245385	24.642648	0.000000e+00

Component GARCH model of y2

	Estimate	Std. Error	t value	Pr(> t)
omega	0.001082012	0.001149684	0.9411381	0.3466341
alpha1	0.085592868	0.010067268	8.5020946	0.0000000
beta1	0.928128959	0.007903403	117.4340863	0.0000000

Component GARCH model of y3

	Estimate	Std. Error	t value	Pr(> t)
omega	0.3862408	0.04155187	9.295389	0.000000000
alpha1	1.0000000	0.12058007	8.293244	0.000000000
beta1	0.1449505	0.04501710	3.219899	0.001282356

Component GARCH model of y4

	Estimate	Std. Error	t value	Pr(> t)
omega	1.000658e-06	0.001033519	9.682049e-04	0.9992275
alpha1	4.918693e-02	0.004523904	1.087267e+01	0.0000000
beta1	9.664675e-01	0.002550307	3.789613e+02	0.0000000

Component GARCH model of y5

	Estimate	Std. Error	t value	Pr(> t)
omega	0.2021125	0.04200716	4.811383	1.498895e-06
alpha1	0.2054795	0.04599183	4.467740	7.905023e-06
beta1	0.6390892	0.04651573	13.739207	0.000000e+00

R output of GOGARCH (1, 1) model estimated with Method-of-Moment (MM) estimator

*** Summary of GO-GARCH Model ***

Used object: resVAR10

Components estimated by: Methods of Moments

Formula for component GARCH models: ~ garch(1, 1)

The Inverse of the Linear Map Z:

	[,1]	[,2]	[,3]	[,4]	[,5]
[1,]	1.0949315	0.2359173	-0.003628352	-1.0093441	0.0532223
[2,]	-0.8637336	1.2016431	-0.172174134	0.6139712	0.2779993
[3,]	-0.1651165	-0.7439843	0.840390967	0.4464983	0.1058159
[4,]	0.7777578	-0.7903328	-0.051498300	1.2431143	-0.8386995
[5,]	0.8132359	-1.6518964	-0.153421744	0.5181983	0.8295037

*** Estimated Component GARCH models ***

Component GARCH model of y1

	Estimate	Std. Error	t value	Pr(> t)
omega	0.007532605	0.001097025	6.866395	6.584511e-12
alpha1	0.034763166	0.005033877	6.905843	4.990675e-12
beta1	0.965068372	0.003430494	281.320503	0.000000e+00

Component GARCH model of y2

	Estimate	Std. Error	t value	Pr(> t)
omega	0.05507291	0.009268705	5.941813	2.818872e-09
alpha1	0.99999999	0.081375353	12.288733	0.000000e+00
beta1	0.45553837	0.031340200	14.535273	0.000000e+00

Component GARCH model of y3

	Estimate	Std. Error	t value	Pr(> t)
omega	0.001856764	0.001426215	1.301882	1.929569e-01

alpha1 0.094905797 0.012505648 7.589035 3.219647e-14

beta1 0.918035078 0.010606470 86.554255 0.000000e+00

Component GARCH model of y4

	Estimate	Std. Error	t value	Pr(> t)
omega	0.001869039	0.0008741639	2.138087	3.250967e-02
alpha1	0.053106309	0.0065918963	8.056302	8.881784e-16
beta1	0.962580715	0.0028507718	337.656183	0.000000e+00

Component GARCH model of y5

	Estimate	Std. Error	t value	Pr(> t)
omega	0.2680146	0.03355344	7.987692	1.332268e-15
alpha1	0.3140414	0.05223245	6.012381	1.828181e-09
beta1	0.4766946	0.04769808	9.993999	0.000000e+00