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Abstract

The need to capture foreign exchange (FX) and stock markets nexus in Nigeria is underscored by the rapidly expanding financial markets integration due trade and financial liberalization policies which seem to have enhanced the inflow of capital as well as accelerated investment/business interactions. Theoretically, the relationship between the two markets can be either positive or negative and can also run either way. This study therefore captures returns, shocks and volatility spillovers between the FX and stock markets in Nigeria. It also accounts for possible asymmetric effects in the spillovers. This study employs variants of recently developed VARMA-AMGARCH models by McAleer et al. (2009). The variants include options for CCC, DCC and BEKK in order to evaluate robustness of the estimation results. The study finds significant and persistent volatility spillovers from stock market to FX market. Also, there is evidence of negative returns spillover from stock market to FX market while shock spillovers are relatively insignificant. The results of the asymmetric effects reveal that volatility persistence in the stock market is accentuated by bad news in the market and moderated by good news in the FX market. Finally, the study finds that ignoring the asymmetric effects may exaggerate the spillover results.

Keywords: Foreign exchange (FX) market, Stock market, Spillovers, VARMA-AMGARCH, Nigeria

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1.0 Introduction

Empirical studies involving foreign exchange (FX thereafter) and stock markets are extensive. This growing trend in research may not be unconnected with the increased sophistication in understanding the dynamics of these two markets. More importantly, the extended financial markets globalization due to increasing rate of economic integration, trade agreements, and custom unions among other trade liberalization policies have accelerated investment/business interactions among countries in recent years. Also, these studies are prompted by an attempt to fulfill essential needs of (i) policy makers such as Central Banks in determining appropriate monetary and exchange rate policy measures; (ii) the international investors in determining the optimal investment portfolio and (iii) investment analysts in forecasting foreign exchange and stock exchange markets behaviour.

Meanwhile, empirical findings over the years reveal some disparities across countries/regions. The inconsistencies have been attributed to specificities of the timing of the relationship and the structural peculiarities of countries such as the level of dependence on foreign capital and depth of the local stock market (see Ulku and Demirci, 2011). Quite a number of these studies have also anchored the cross country differences in the empirical results on level of development. Thus, some studies have focused on Developed economies (see for example, Aggarwal, 1981; Ajayi and Mougoue, 1996; Hau and Rey, 2002; and Stavarek, 2005); some have concentrated on Emerging or Transition economies (see Phylaktis and Ravazzolo, 2005; Ulku and Demirci, 2011; Rey, 2012; and Rjoub, 2012) while some others have studied Developing economies (see Rahman and Uddin, 2009; Zia and Rahman, 2011; and Kenani et al, 2012). The underlying intuition for using level of development to account for cross country differences is to examine the influence of the depth of financial development on stock market-FX market nexus. Nonetheless, studies have also found mixed results even among countries with relatively similar level of development.

The present study therefore attempts to complement previous studies in the following distinctive ways: (i) it captures returns, shocks and volatility spillovers between stock market and FX

market; (ii) it employs variants of recently developed Vector Autoregressive Moving Average - Asymmetric Multivariate Generalized Autoregressive Conditional Heteroscedasticity (VARMA-AMGARCH) models by McAleer et al. (2009); and (iii) it accounts for possible asymmetric effect in the volatility spillovers. In addition to the less computational complications in obtaining estimates of the unknown parameters compared to other multivariate specifications, the VARMA-AMGARCH models allow for the joint estimation of shocks, returns and volatility spillovers. Also, any possible asymmetric effects can be determined using this approach. Moreover, ignoring the spillovers and asymmetric effects when they are evident may bias the results. To the best of our knowledge, there is no study in the literature that has adopted this methodology to capture the spillovers between exchange rate and stock market.

The focus of this study is on Nigeria. What can we learn from Nigeria? First, the inconclusive findings in the literature suggest that evidence from other countries or regions cannot be generalized. Second, the increasing foreign direct investment trends in Nigeria with probable attendant impact on the flow of FX and cash flows further justify the need for a separate analysis. For instance, the country retained her status as the favourite African destination for FDI according to UNCTAD (2013) report which revealed that FDI inflows to Nigeria stood at \$7.03 billion compared with \$4.57 billion going to South Africa, \$3.29 billion going to Ghana, \$2.79 billion going to Egypt and \$1.98 billion going to Angola. This is also coupled with the increasing supply of FX occasioned by the increasing exports particularly from crude oil. Thirdly, the activities at the Nigerian stock market are becoming increasingly vibrant, attractive and therefore, the volatility of the market is expected to influence some macroeconomic fundamentals including the FX market.

The rest of the paper is arranged as follows: Section 2 presents literature review; Section 3 describes the data used and some preliminary analyses; Section 4 deals with methodological framework of the study and analyses of empirical results while Section 5 concludes the paper.

2.0 Review of relevant literature

2.1 Theoretical Framework

There are two theoretical classifications of models on foreign exchange – stock exchange markets nexus. They are the flow model and the stock model. Flow model is dominated by the good approach to exchange rate determination as propounded Dornbush and Fisher (1980). This model proposes a positive relationship between foreign exchange and stock exchange markets while it assumes that the causality runs from exchange rates to stock prices. For example, if exchange rate of home country depreciates, it will enhance its trade competitiveness which leads to an increase in its production, profits and by extension stock returns, where stock return is defined as the net present value of the future cash flow of a company.

In the case of the stock model, there are two versions, namely; the Portfolio Balance model and the Monetary model. These versions of the stock model are inconsistent in terms of the direction of relationship between the two markets, although they seem to agree that the causality runs from stock prices to exchange rates. The Portfolio Balance model by Branson (1983) and Frankel (1983) supports negative relationship between the two markets, with the proposition that investors are risk averse and they move their investments to country with higher stock returns, which by implication leads to currency appreciation in countries with higher stock returns and depreciation in countries with lower stock returns (see also Ulku and Demirci, 2011). Monetary model however supports positive relationship and also argues that the relationship is a monetary phenomenon. The mechanism works in such a way that a rise in stock prices raises the rate of return thus making money less attractive since it earns a zero return. The fall in demand for money increases the price level which via PPP, increases the exchange rate. This predicts positive relationship between the two markets (Groenewold and Paterson, 2011). In addition, a recently developed model on foreign exchange and stock exchange markets nexus is the Portfolio Rebalancing Approach by Hau and Rey (2004). This model also suggests positive relationship between the two markets just like the monetary model. The proponents of this approach imagine an internationally-diversified investor who, following an increase in domestic stock prices, finds the portfolio is over-weighted in domestic stocks and so sells domestic and buys foreign equities, which puts pressure on the domestic currency to depreciate, i.e. for the exchange rate to rise (Groenewold and Paterson, 2011).

From the foregoing, it is evident that the relationship between the two markets can be either positive or negative and can also run either way. Thus, the nature of financial market development and response of the two markets to macroeconomic shocks including external shocks may influence the direction and magnitude of their interactions.

Meanwhile, the proposed underlying theory for this study is the Portfolio Balance model by Branson (1983) and Frankel (1983). This theory proposes negative relationship between exchange rate and stock market as against the flow model and the monetary model which lend support to a positive relationship. This model is considered most appropriate for Nigeria being one of the most attractive investment centres in Africa for resource seeking multinational oil corporations, and market seeking multinational companies. Thus, increase in stock price in Nigeria is expected to attract more investment inflows which consequently lead to currency appreciation through expected increase in the demand for the Nigerian local currency unit (*Naira*).

2.2 *Empirical findings*

In the empirical literature, the relationship between foreign exchange and stock exchange markets has remained inconclusive. A number of studies have attributed the mixed and inconsistent results to inappropriate methodology (see Phylaktis and Ravazzolo, 2005) and misspecification problem (see Ulku and Demirci, 2011), while some others have attributed it to differences in level of dependence on foreign capital and depth of stock market and foreign exchange market (see for example, Hau and Rey, 2002; and Ulku and Demirci, 2011).

For developed economies which are considered to have well developed stock market and foreign exchange market, the results have been inconsistent. For example, Hau and Rey (2002) find a positive relationship from exchange rate to stock prices while Dimitrova (2005) find negative relationship. On the other hand, Richards et al. (2009) find a negative relationship from stock prices to exchange rate. While others, find mixed result or no relationship between the two markets (Stavarek, 2005 and Groenewold and Paterson, 2011).

Whereas, for emerging or transition economies, which are considered to depend heavily on foreign capital inflow (see Ulku and Demirci, 2011), the results were as follows; positive relationship from exchange rate to stock prices (see Phylaktis and Ravazollo, 2005), positive

relationship from stock prices to exchange rate (see Welfen and Borbely, 2004) and negative relationship from stock prices to exchange rate. Some studies find that the causality runs from exchange rate to stock price but unable to define the sign of the relationship (see Morales, 2007; Li and Hung, 2009; and Imarhiagbe, 2010), while others find no relationship between the two markets (see for example, Lean, Halim and Wong, 2005).

Meanwhile, for developing economies with less developed stock market and foreign exchange market, some of the related studies find mixed results in terms of the directions and extent of interactions between the two markets (see for example, Tabak, 2006; Rahman and Uddin, 2009; Zia and Rahman, 2011; and Kenani et al. 2012). Mutiu et al. (2012) provide a review of related studies in Nigeria and also reveal the inconclusive evidence in the literature.

Also, a review of methodology implemented by relevant studies shows that most of them adopted OLS, 2SLS and 3SLS (see Welfen and Borbely, 2004 and Dimitrova, 2005), VAR and VECM (see Kim, 2003; Stavarek, 2005; Phylaktis and Ravazzolo, 2005; Ramasamy and Yeung, 2005; Morales, 2007; Aydemir and Demirhan, 2009; Rahman and Uddin, 2009; Richards et al., 2009; Groenewold and Paterson, 2011; Rjoub, 2011, Zia and Rahman, 2011; Kenani et al. 2012; Mutiu et al., 2012; and Rey, 2012), SVAR (see for example, Ulku and Demirci, 2011), non-linear approach (see Chang et al., 2009; Ismail and Isa, 2009; Zhao, 2010; Narayan, 2009; Wong and Li, 2010). However, in the presence of spillovers (returns, shocks and volatility) and asymmetric effects, statistical inferences from these approaches will be invalid. Thus, this study adopts the newly developed VARMA -AMGARCH model which allows for both spillovers as well as asymmetry effect in financial markets.

3.0 Data and preliminary analyses

Essentially, this study utilizes data on Wholesale Dutch Auction System (WDAS) exchange rate for FX market and All Share Index (ASI) for stock market. Both were obtained from the database of the Central Bank of Nigeria and they cover the period from May 1999 to December 2013. Exchange rate (EXR) is measured in *Naira* per unit of U.S. dollar; thus, an increasing exchange rate or a positive exchange rate returns will mean exchange rate depreciation while negative returns will mean exchange rate appreciation. Stock index (ASI) is calculated from weighted stock prices; an increase in stock index or a positive stock index return will mean stock

market appreciation while negative returns will mean stock market depreciation. The returns for FX (REXR) and All Share Index (RASI) are computed respectively as follows:

$$REXR_t = 100 * [\Delta \log(EXR_t)] \quad (1)$$

$$RASI_t = 100 * [\Delta \log(ASI_t)] \quad (2)$$

where Δ is a first difference operator.

The preliminary analyses involve discussion of the statistical properties of the series. This consists of the descriptive statistics, unit root tests, Ljung Box Q – statistics test and ARCH – LM test. Table 1 below summarizes the descriptive statistics and the results for the Ljung Box Q – statistics and ARCH – LM tests while table 2 shows the results for the unit root test.

From table 1, we can infer from the high standard deviation values for both ASI and EXR that both series have high variations and are such prone to high volatility. This is further confirmed by the ARCH LM test indicating the presence of statistically significant ARCH effects in both series. This point is also reinforced by the graphical presentations of the conditional variances of both series as presented in figures 2a and 2b. The skewness statistic shows that ASI is positively skewed while EXR is negatively skewed. This implies that both series are not symmetric; while ASI has extreme tail to the right while EXR has extreme tail to the left. Also, the kurtosis statistic shows that ASI is platykurtic or thin tailed while EXR is leptokurtic or fat tailed. The Jarque – Bera statistic which combines both skewness and kurtosis statistics show that we can reject normality assumption for both ASI and EXR.

Insert Figure 1

In addition, figure 1 above shows the graphical presentation of the relationship between ASI and EXR. The trend in this relationship shows four patterns which are divided into four quadrants accordingly. In quadrant 1, a positive relationship is apparent with both series following an upward trend. In quadrant 2, there is a persistent rise in ASI while EXR falls steadily; thus, indicating a negative relationship between the two series. This period coincides with the period the Central Bank of Nigeria embarked on recapitalization of the banking sector which led to large investment inflow and exchange rate appreciation. Unfortunately, this trend was truncated

by the shock of the global economic and financial crises as evident in the third quadrant. As shown in quadrant 3, a negative relationship is also observed during this period as falling share prices depressed the stock market; leading to large investment outflow and eventually exchange rate depreciation. Meanwhile, quadrant 4 coincides with the period of gradual recovery from the global financial crisis as ASI rises gradually while EXR is relatively unchanged. Summarily, the relationship between ASI and EXR is inconclusive from the viewpoint of the graphical presentation.

Insert Table 1 here

Insert Table 2 here

Insert Figure 2a here

Insert Figure 2b here

From the foregoing, investigating the relationship between the return series will require consideration of the possibility of volatility spillover effects between them. This therefore justifies the estimation of multivariate volatility models since a single equation ARCH or GARCH model would ignore the possibility of causality between the conditional variances of the two series. The pioneering multivariate GARCH model is the Vector Conditional Heteroscedasticity (VECH) GARCH model; however, due to problem of curse of dimensionality (too many parameters) associated with this model, other multivariate GARCH models were developed with some restrictions and with the possibility of allowing for volatility transmission between the return series. These extensions include the Constant Conditional Correlations (CCC)-GARCH (see Bollerslev, 1990) model, BEKK-GARCH model (attributable to Baba, Engle, Kraft and Kroner's representation) (see Engle and Kroner, 1995), and Dynamic Conditional Correlations (DCC)-GARCH model (see Engle, 2002). Recently, Ling and McAleer (2003) developed the VAR-GARCH model with less computational procedure over the previous multivariate models. The VAR-GARCH model was further extended to account for Moving average terms as well as asymmetric effects. In the present study, we consider the VARMA-AGARCH model where in we infuse the DCC and BEKK representations in addition to the

underlying CCC option embedded in the model. Thus, we are able to come up with different variants of the VARMA-AGARCH model and we are also able to evaluate the robustness of these variants. Also, the CCC option is time invariant and this assumption may seem unrealistic in real world; therefore, allowing for time dependence in the conditional correlations may enhance robustness of empirical results. The section that follows describes this model with relevant variants.

4.0 Model and Empirical Analyses

4.1 The Model

As earlier mentioned, in this study, our specification follows the VARMA-AMGARCH Model developed by McAleer et al. (2009). Consequently, we estimate different variants of this model namely: (i) VAR-MGARCH; (ii) VARMA-MGARCH; (iii) VAR-AMGARCH; and (iv) VARMA-AMGARCH. The VAR-MGARCH model allows us to capture both returns and volatility spillovers while in addition to these features, VAR-AMGARCH model accounts for asymmetric effects in the variance equation. The VARMA-MGARCH model, in addition to the underlying features of VAR-MGARCH, also accounts for shocks spillovers in the mean equation. Finally, the VARMA-AMGARCH, while incorporating the principal features of VARMA-MGARCH, also captures possible asymmetric effects in the model. All these variants are evaluated with options of CCC, DCC and BEKK in order to ensure that all the possible features inherent in the series are properly accommodated in the estimation process. The bi-variate VARMA(p, q)-AMGARCH(1,1) model is specified below¹:

The Conditional Mean Equation:

$$R_t = \phi + \Psi_1 R_{t-1} + \Psi_2 R_{t-2} + \dots + \Psi_p R_{t-p} + \Upsilon_1 \varepsilon_{t-1} + \Upsilon_2 \varepsilon_{t-2} + \dots + \Upsilon_q \varepsilon_{t-q} + \varepsilon_t, \quad \varepsilon_t \sim N(0, H_t) \quad (3)$$

Putting equation (3) in a more compact form using Lag operator, we have:

$$\Psi(L)R_t = \phi + \Upsilon(L)\varepsilon_t; \quad \Psi(L) = I - \Psi_1 L - \dots - \Psi_p L^p \quad \text{and} \quad \Upsilon(L) = I + \Upsilon_1 L + \dots + \Upsilon_q L^q \quad (4)$$

$$\varepsilon_t = H_t^{1/2} v_t, \quad v_t \sim N(0,1), \quad \varepsilon_t \sim N(0, H_t) \quad (5)$$

$$H_t = \begin{bmatrix} h_{ijt} \end{bmatrix}; \quad i, j = 1, 2; \quad 1 \Rightarrow REXR \quad \text{and} \quad 2 \Rightarrow RASI \quad (6)$$

where $R_t = (REXR_t, RASI_t)'$ denotes the returns series; $\phi = (\phi^{REXR}, \phi^{RASI})'$ is a vector of constants for $REXR_t$ and $RASI_t$ mean equations respectively; $\Psi = \begin{pmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{pmatrix}$ is a (2×2) matrix of coefficients on the lagged terms of the returns series; $\Upsilon = \begin{pmatrix} \Upsilon_{11} & \Upsilon_{12} \\ \Upsilon_{21} & \Upsilon_{22} \end{pmatrix}$ is a (2×2) matrix of coefficients on the lagged terms of the residuals and $\varepsilon_t = (\varepsilon_t^{REXR}, \varepsilon_t^{RASI})'$ is a vector of disturbance terms for $REXR_t$ and $RASI_t$ mean equations respectively; $v_t = (v_t^{REXR}, v_t^{RASI})'$ is a vector of white noise errors; and $H_t = [h_{ijt}]$ is a (2×2) matrix of conditional variances.

The Conditional Variance Equation:

What remains now is how to specify the $H_t = [h_{ijt}]$ matrix. As previously mentioned, three options (CCC, DCC and BEKK) are infused into the VARMA-AGARCH model. Interestingly, the traditional VARMA-AGARCH model is implemented with the underlying assumption of CCC. Therefore, the conditional variance for the CCC-VARMA(p, q)-AMGARCH(1,1) follows the procedure below:

Let $H_t^{1/2} = D_t$; then, $\text{var}(\varepsilon_t | \Sigma_{t-1}) = H_t = D_t \Gamma D_t$;

where Σ_{t-1} is the past information available at time $t-1$, $\Gamma = E(v_t v_t' | \Sigma_{t-1}) = E(v_t v_t') = \{\rho_{ij}\}$ and it denotes the constant conditional correlation matrix of the unconditional shocks which is also equivalent to the constant conditional covariance matrix of the conditional shocks (ε_t). And since the H_t is the conditional covariance matrix, it can be used to accommodate the interdependencies of between the two assets. Following, the Ling and McAleer (2003), then H_t can be specified as:

$$H_t = \Omega + A\varepsilon_{t-1}^2 + C I_{t-1} \varepsilon_{t-1}^2 + B H_{t-1} \quad (7)$$

where $H_t = (h_t^{REXR}, h_t^{RASI})'$ and consequently, $D_t = \text{diag}(h_1^{1/2}, h_2^{1/2})$; $\varepsilon_t^2 = (\varepsilon_{REXR,t}^2, \varepsilon_{RASI,t}^2)'$, and Ω , A , and B are (2×2) matrices of constants, ARCH effects and GARCH effects respectively.

$I_t = \text{diag}(I_t^{REXR}, I_t^{RASI})$ is the asymmetric effects such that $I_t = 0$ if $\varepsilon_{it} > 0$ and $I_t = 1$ otherwise.²

For the conditional variance in the case of DCC-VARMA-AMGARCH model,

$$\Gamma_t = \left\{ \left(\text{diag}(H_t)^{-1/2} \right) \right\} H_t \left\{ \left(\text{diag}(H_t)^{-1/2} \right) \right\} \quad (8)$$

And H_t is a positive definite matrix given as:

$$H_t = (1 - \delta_1 - \delta_2) \bar{H} + \delta_1 I_{t-1} v_{t-1} v'_{t-1} + \delta_2 H_{t-1} \quad (9)$$

where δ_1 and δ_2 are scalar parameters to deal with the effects of previous shocks and previous dynamic conditional correlations on the current dynamic conditional correlation, and δ_1 and δ_2 are non-negative scalar parameters. By imposing the restriction $\delta_1 = \delta_2 = 0$, \bar{H} reduces to the CCC (Caproin and McAleer, 2009 provide the estimation procedure for the DCC).

The conditional variance for the BEKK-VARMA (p, q) -AMGARCH (1,1) can be represented as:

$$H_t = \Omega \Omega' + A' \varepsilon_{t-1} \varepsilon'_{t-1} A + C' I_{t-1} \varepsilon_{t-1} \varepsilon'_{t-1} C + B' H_{t-1} B \quad (10)$$

Also here, A , B and C are square matrices while Ω is a low triangular matrix defined as:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, \quad B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}, \quad C = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}, \quad \Omega = \begin{bmatrix} \Omega_{11} & 0 \\ \Omega_{21} & \Omega_{22} \end{bmatrix}$$

The components of the asymmetric effects capture the impacts of positive and negative shocks on volatility. In addition to the distinctions in the statistical procedure of these variants, another major difference particularly among the asymmetric multivariate GARCH models lies in the way the asymmetric effect is accommodated. In the case of CCC and DCC, only own market asymmetric effect is accounted for while the BEKK version allows for both own market as well as cross markets asymmetric effects.

The structural and statistical properties of VARMA-GARCH were first established in Ling and McAleer (2003) and further extended by McAleer et al. (2009). These include the necessary and sufficient conditions for stationary and ergodicity, sufficient conditions for the existence of moments of ε_t , and sufficient conditions for consistency and asymptotic normality of the Quasi-Maximum Likelihood Estimator in the absence of normality of v_t .

In addition, the model with the best fit under each model category having considered the three options mentioned, was determined using standard model selection criteria namely, Schwartz Bayesian Criterion (SBC) and Akaike Information Criterion (AIC).

4.2 Empirical analyses

4.2.1 Presentation of Results

The results obtained from the analyses of the different variants are presented in tables a(a) through 3(d) below. Under each model category, the estimated models are ranked and the model with the best fit is determined using the SBC and AIC. Consequently, discussion of results focuses on the selected best fit models. From these tables, it is observed that BEKK option dominates the other two options. This may be due to the need to compute conditional correlation coefficient by both CC and DCC MGARCH options which is not required by the BEKK option. More specifically, under VAR–MGARCH, BEKK-VAR(1)-MGARCH(1,1) is preferred (see table 3(a)); BEKK-VAR(3)-AMGARCH(1,1) is the best fit for VAR-AMGARCH (see table 3(b)); BEKK-VARMA(1,1) - MGARCH(1,1) is chosen under VARMA-MGARCH (see table 3(c)) and BEKK-VARMA(3,3)-AMGARCH(1,1) for VARMA-AMGARCH model (see table 3(d)). Table 4 presents the selected best fit models.

Insert Table 3a here

Insert Table 3b here

Insert Table 3c here

Insert Table 3d here

Insert Table 4 here

4.2.2 Discussion of Parameter estimates for selected variants of VARMA-AGARCH Model³

The estimation results of the best fit models are presented in table 5. First, we discuss the result of the selected VAR-GARCH model which is considered as the benchmark model. From the

mean equation, the result shows that there is significant negative return spillover (ψ_{21}^1) from stock market to foreign exchange market. On the other hand, there is no significant return spillover from foreign exchange market to stock market ψ_{12}^1 but significant short term volatility spillover exists. This implies that if we have positive stock return (stock market appreciation) in the current period, we may have negative exchange rate return (exchange rate appreciation) in the next period. This suggests that the inclusion of stock market performance when modelling foreign exchange may improve its forecast performance. This result validates the proposition of portfolio balance model on the relationship between stock prices and exchange rates. In addition, it is similar to the result of Dimitrova (2005) both in terms of direction and sign of relationship between the two markets. It is also consistent with the result obtained by Abdelaziz et al. (2008) for Saudi Arabia which is also a net oil exporting country like Nigeria, but different in terms of direction of causality from the result of Adebisi et al. (2009) which find causality running from stock returns to real exchange rate in Nigeria.

Meanwhile, the result from the variance equation shows that there is volatility persistence in stock market with positive significance ARCH term (α_{11}) and GARCH term (β_{11}). This implies that shocks and past period volatility are major drivers of stock market volatility. In other words, an unanticipated rise/fall in stock prices and fluctuation in number of deals experienced by stock investors in the immediate past period may fuel volatility in the stock market. In essence, greater uncertainties in the stock market in the current period may lead to panic stock trading and consequently generate higher volatility in the future period. Furthermore, the result reveals that there is no volatility persistence in foreign exchange market with the presence of insignificant GARCH term (β_{22}). Nonetheless, the volatility in the market is shown to be due to shocks and innovations in the immediate past period. This implies that if we have an unanticipated rise/fall in exchange rate in the current period, we may experience greater fluctuations in exchange rate in the next period. Meanwhile, considering the result of the volatility spillover effect between the two markets, the result shows that there is significant short term volatility spillover from foreign exchange market to stock exchange market (α_{12}) and persistent volatility spillover from stock market to foreign exchange market (β_{21}) and are positive and statistically significant. This implies that persistent volatility in stock market have significant effect in increasing the current period volatility in the foreign exchange market. In other words, persistent panic stock trading in the stock market will increase the rate of exchange rate instability. This is however not

impossible since exchange rate returns is significantly dependent on past value of stock market returns which is inadvertently affected by persistent volatility in the market.

Second, we discuss the result of VAR-GARCH model with asymmetry. This validates the VAR-GARCH result discussed above, but in addition, it shows that there is negative significant asymmetric effect from foreign exchange market to stock exchange market (π_{12}) which leads to significant reduction in the magnitude of short term volatility spillover from foreign exchange market to stock market (α_{12}) from 0.165 to 0.133. This implies that good news in foreign exchange market is capable of reducing stock market volatility.

Third, we consider the result of VARMA-GARCH model. The results do not differ significantly from that of the VAR-GARCH model; thus, indicating that the effect of own shocks and shocks spillovers between the two markets are rather small to effect any significant change on the established relationship.

Fourth, we examine the result of VARMA-GARCH model with Asymmetric effect. It reveals an improvement over the VAR-GARCH and VARMA-GARCH models by showing that the two markets are not only dependent on their own shocks and innovations but also on shocks and innovations from the other market. In essence, it shows bidirectional returns spillovers between the two markets. Meanwhile, although the nature of volatility relationship established by the VAR-GARCH model still persists, positive significance asymmetric effect in the stock market π_{11} shows that bad news increases the volatility persistence in the stock market by increasing effect of past shocks on volatility from 0.370 to 0.519. In addition, the result further confirms the VARMA-GARCH result that good news in foreign exchange market reduces stock market volatility, as short term volatility spillover from foreign exchange market to stock market (α_{12}) reduced from 0.165 to 0.102.

In the meantime, we can observe that VAR-GARCH model exaggerates volatility persistence in the stock market by assuming symmetric effects between good news (positive shock) and bad news (negative shock). Thus, the consideration of asymmetric effects in modeling conditional spillovers between stock market and exchange rate will offer more useful information. In addition, residual diagnostics of the model using Ljung-Box and McLeod-Li tests show that the null hypothesis of no serial correlation and no ARCH effects could not be rejected for all the

models, thus confirming the efficiency of VARMA-AMGARCH models in dealing with the problem of time varying conditional variances in a multivariate framework.

Insert Table 5 here

5.0 Concluding remark

This paper empirically examines the joint dynamics of foreign exchange and stock markets in Nigeria. Essentially, we offer the following distinctive contributions to the literature: (i) we capture returns, shocks and volatility spillovers between foreign exchange and stock markets; (ii) we employ variants of recently developed VARMA-AMGARCH models by McAleer et al. (2009); and (iii) we account for possible asymmetric effect in the volatility spillovers. Our findings reveal that there is significant negative return spillover and significant persistent volatility spillover from stock market to foreign exchange market; whereas, there is no return spillover but short term volatility spillover exists from foreign exchange market to stock market. In addition, we find that shocks spillover is relatively insignificant but asymmetric effect reveals that stock market volatility persistence is accentuated by bad news in the market but is reduced by good news in the foreign exchange market. This implies that better performance of stock market is a predictor of good foreign exchange performance. Lack of confidence and panic stock trading in Nigerian stock market may cause panic exchange rate trading at least over short periods. Expectation of future loss in stock returns (bad news) accentuates panic trading in the market but expectation of future gain in foreign exchange returns (good news) reduces panic trading in stock market.

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¹Note that we allow for more than one lag for the mean equation (VAR) while the variance equation only contains one lag (i.e. MGARCH (1,1)). This is because if the mean model is wrong; this implies that there is more dynamics in the model than included and this can be fixed by reasonably by increasing the number of lags in the mean equation. However, in the case of the variance equation (MGARCH), the rejection of MGARCH means that the GARCH part of the model is somehow inadequate. It is not common to add lags to a GARCH in an attempt to fix

this problem; instead, a different version of the MGARCH such as CC/DCC/BECK-MGARCH model or the inclusion of asymmetric effects may be considered to fix the problem.

² Note that the different variants of the VARMA(p, q)-AMGARCH(1,1) were estimated by imposing restrictions on relevant terms in either the mean equation or variance equation or both. For example, the CCC-VAR-GARCH Model can be obtained by setting $\Upsilon(L) = 1$ and $C = 0$ for the two assets being studied while the CCC-VARMA-GARCH can be obtained by setting just $C = 0$. Also, Silvennoinen and Terasvirta (2008) and Tansuchat, Chang and McAleer (2010) provide a review of the theoretical structure for the three options when dealing with multivariate GARCH models.

³ Comprehensive results of all models are available on request. Also, the RATS code for the estimation of the different variants of VARMA-AMGARCH Model is available on request.