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**ABSTRACT**

In this paper, two innovations are evident: (i) we capture returns, shocks and volatility spillovers between stock market and money market while drawing evidence from Nigeria; and (ii) we employ variants of recently developed VARMA-AMGARCH[1] models by McAleer et al. (2009) which account for both spillovers as well as asymmetric effects. We find significant returns spillovers from stock market to money market while shocks and volatility spillovers are bidirectional. We also find that ignoring the asymmetric effects in the model will exaggerate the returns and shocks spillovers and underestimate the volatility spillover. In all, the spillover effects between the two markets seem transitory rather than permanent.

**Keywords:** Shocks, Returns, Volatility, Asymmetric effect, VARMA-AMGARCH models

**JEL classification:** C58, G10

[1] VARMA-AMGARCH is the Vector Autoregressive Moving Average -Asymmetric Multivariate Generalized Autoregressive Conditional Heteroscedasticity.

## 1. Introduction

Portfolio diversification has become a veritable investment strategy for mitigating the unpredictability of markets for investors. It helps to reduce portfolio loss and volatility particularly during periods of increased uncertainty. The Modern Portfolio Theory appears to be the bedrock for diversifying portfolios. It assumes that by combining assets that are not perfectly correlated, the risks embedded in a portfolio are lowered and higher risk-adjusted returns can be achieved. In essence, while one asset class is confronted with high uncertainty over a particular period, the other may not and therefore, a combination of these asset classes, for example, may reduce overall investment risk and prevent damaging a portfolio's performance by the underperforming asset. Thus, an effective combination of these asset classes will necessarily require rigorous analysis of any possible spillovers between the assets.

In this paper, we focus on two financial markets in Nigeria namely the money market and stock market. Consequently, we provide two innovations: (i) we capture returns, shocks and volatility spillovers between these markets; and (ii) we employ variants of recently developed VARMA-AMGARCH models of McAleer et al. (2009) which account for both spillovers as well asymmetric effects. 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 and ignoring these 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 spillovers between money market and stock market.

Nonetheless, recent studies in the literature dealing with financial markets interdependencies (whether international, regional or local) include, but not limited to, Hammoudeh et al. (2009), Jaiswal-Dale and Jithendranathan (2009), Koulakiotis et al. (2009), Beirne et al. (2010), Dean et al. (2010), Karmakar (2010), Corradia et al. (2012), Diebold and Yilmaz (2012), Raimony and El-Nader (2012), Abbas et al. (2013), Dua and Tuteja (2013), Gatfaoui (2013), Kanga et al. (2013), Louzis (2013), Wahyudi and Sani (2013), Weber (2013), and Nguyen and Nguyen (2014). Our contributions however are non-existent in the existing literature.

Following this introduction section, the remaining sections of the paper are divided into four. Section 2 describes the data and also provides some preliminary analyses. Section 3 presents the econometric methodology implemented in the study. Section 4 discusses the empirical results while Section 5 concludes the study.

## 2. Data and Preliminary Analyses

Essentially, this study covers two variables namely the stock market and the money market with the former proxied by All Share Index (ASI) of the Nigerian Stock Exchange while the latter is denoted by the Nigerian money market Interest Rate (IR). The variables are sourced from the Central Bank of Nigeria's Statistical bulletin over the period of January 2000 to December 2013.

This section provides some preliminary analyses involving the description of relevant statistical properties of the variables under consideration. These analyses are carried out in two phases: the first provides descriptive statistics for the two variables including their returns while the second involves performing ARCH LM tests and serial correlation to justify the consideration of time varying volatility models. The returns are computed as follows:

$$RASI_t = 100 * \Delta \log\left(ASI_t\right) \quad (1)$$

$$RIR_t = 100 * \Delta \log\left(IR_t\right) \quad (2)$$

where $\Delta$ is a first difference operator. Table 1 below shows the descriptive statistics for ASI and IR including their returns denoted by RASI and RIR respectively. There seems to be evidence of significant variation in the trend of both the stock market and money market as shown by the large differences between their respective minimum and maximum values.

**Table 1: Descriptive Statistics**

| | **Stock Market** | | **Money Market** | |
|---|---|---|---|---|
| **Statistics** | ASI | RASI (%) | IR (%) | RIR (%) |
| Mean | 26116.23 | 0.927 | 17.755 | -0.139 |
| Maximum | 65652.4 | 32.352 | 61.46 | 131.503 |
| Minimum | 9159.8 | -36.588 | 8.93 | -137.646 |
| Std. dev. | 12106.58 | 7.466 | 4.107 | 16.745 |
| Skewness | 1.1975 | -0.5267 | 7.3526 | -0.3427 |
| Kurtosis | 4.2098 | 8.404 | 78.373 | 52.984 |
| Jarque-Bera | 50.0948 (0.000) | 210.921 (0.000) | 41035.55 (0.000) | 17387 (0.000) |
| Unconditional Correlation (ASI and IR) | -0.180 | | -0.180 | |

| | | | | |
|---|---|---|---|---|
| Unconditional Correlation (ASIR and IRR) | | 0.198 | | 0.198 |
| Observations | 168 | 167 | 168 | 167 |

Source: Computed by the Authors.
Note: The probability values are in parenthesis

The notable difference in IR between its minimum value of 8.93% and maximum value of 61.46% as well as when these values are compared with the mean value of 17.75% suggest some sort of volatility in the series. Similar evidence can also be deduced from ASI statistics based on the minimum, maximum and mean values of the series. However, the magnitude of fluctuations in ASI indicates higher volatility than IR as shown by the standard deviation of the series. With respect to the statistical properties of the returns (i.e. RASI and RIR), the findings are in tandem with the findings from the descriptive statistics for ASI and IR. Unlike ASI and IR, RIR appears to exhibit a higher volatility than RASI judging by their standard deviations as well.

Regarding the statistical distributions, the series (i.e. ASI and IR) are negatively skewed while their returns namely RASI and RIR are positively skewed thereby implying that the right tail are particularly extreme for the returns while the left tail is to the extreme for the series. Thus, as expected of a volatile series, all the series as well as their returns are leptokurtic in nature which is an indication of fat tails than the normal distribution. Overall, this implies non-zero skewness and excess kurtosis while the Jarque-Bera (JB) statistic that takes into consideration information from skewness and kurtosis to test for normality suggests non-normality of all the variables.

**Table 2: ARCH LM and Ljung – Box Tests**

| | Stock Market | | | | Money Market | | | |
|---|---|---|---|---|---|---|---|---|
| | *P=5* | | *P=10* | | *P=5* | | *P=10* | |
| 2(A): ARCH tests | *ASI* | *RASI* | *ASI* | *RASI* | *IR* | *RIR* | *IR* | *RIR* |
| **F-test** | 331.993* | 6.2173* | 177.86* | 3.4307* | 0.004 | 13.643* | 0.006 | 6.483* |
| ***nR²*** | 148.916* | 26.918* | 145.93* | 29.873* | 0.0212 | 49.288* | 0.064 | 48.278* |

| 2(B): LB tests | | | | |
|---|---|---|---|---|
| | *ASI* | *RASI* | *IR* | *RIR* |
| ***LB(5)*** | 697.09* | 13.305** | 21.126* | 25.103* |
| ***LB(10)*** | 1087.3* | 17.927*** | 24.336* | 25.964* |
| ***LB²(5)*** | 586.60* | 31.874* | 0.023 | 37.203* |
| ***LB²(10)*** | 759.15* | 35.793* | 0.067 | 37.498* |

Source: Computed by the Authors
Note: The ARCH LM tests refer to the Engle (1982) test for Conditional Heteroscedasticity while the LB and $LB^2$ imply the Ljung-Box tests for autocorrelations applied to standardized residuals in levels and squared standardized

residual respectively. *,**,*** imply rejection of the null hypothesis at 1%, 5% and 10% respectively with *p* denoting the lag length for the test statistics. The null hypothesis for the ARCH LM test is that the series has no ARCH effects (that is, it is not volatile) while LB test for null hypothesis is that the series is not serially correlated.

As earlier mentioned and shown in table 2 above, some pre-tests such as ARCH LM tests and serial correlation tests are also conducted to further justify the need for the consideration of time-varying volatility models. The results of the ARCH LM tests indicate the presence of ARCH effect in all the series and their returns. These variables therefore exhibit conditional heteroscedaticity that has to be captured when modeling. Similarly, the results of the serial correlation conducted using the Ljung – Box tests for both residuals in levels and squared standardized residuals also reveal the existence of serial correlation in all the series.

Furthermore, a graphical illustration of the relationship between ASI and IR as well as their respective returns is depicted in Figs. 1 and 2 below. As shown in these figures, there seems to be a fairly traceable relationship between stock market and money market and is partitioned into three quadrants namely the period before, during and after financial crisis. The time series plot in fig.1 seems to be in conformity with the descriptive properties of the variables with ASI exhibiting a higher volatility trend than IR while fig. 2 on the other hand reveals higher volatility for RIR.

**Fig.1: A combined graph for ASI and IR (2000-2013)**

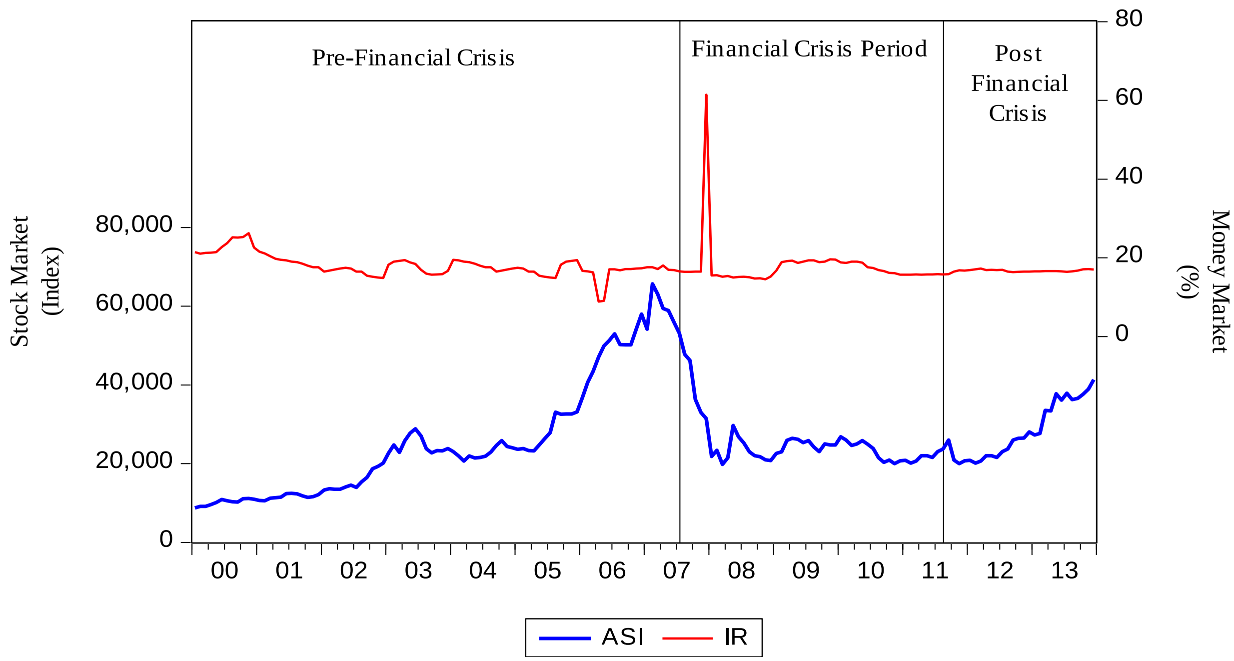
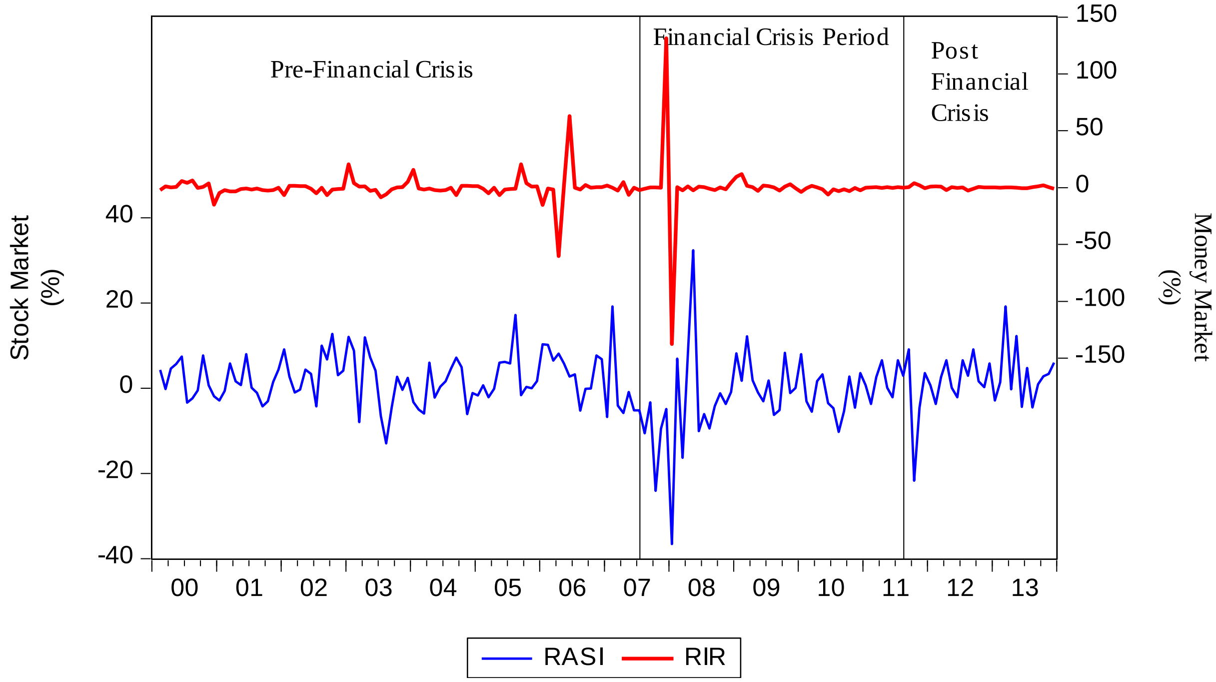


**Fig. 2: A combined graph for RASI and RIR (2000-2013)**




In addition to the negative correlation between ASI and IR (see table 1), the period before financial crisis (i.e. pre-financial crisis) in fig.1 shows that ASI and IR are moving in opposite directions with ASI rising steadily while IR on the other hand declines slowly. In relation to the second quadrant (the financial crisis period), ASI is seen to be declining from its peak while IR still maintains a steady decline although with evidence of a notable spike in the mid year of 2007 that coincided with the period marking the beginning of the financial crisis. The post-financial crisis period however, revealed that the IR moves within a fixed bound while the upward trend of ASI is an indication that the stock market is gradually recovering from the financial crisis shock.

Furthermore, the graphical representation of the markets returns (see fig. 2) shows how volatility has changed in the two markets over time. The two markets reveal evidence of volatility clustering in the two markets in which periods of volatility are followed by periods of tranquility.

## 3. Econometric Model

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 captures 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 deals with shocks spillovers in the mean equation. Finally, the VARMA-AMGARCH, in addition to the underlying features of VARMA-MGARCH, also captures possible asymmetric effects in the model. All the variants are evaluated with options of CC, DCC and BEKK[2] in order to evaluate the robustness of estimation results as well as ensure that all the possible features inherent in the series are properly reflected in the estimation process. Table 3 summarizes the statistical features of the models estimated.

**Table 3: Summary of Model Features**

| Model | Returns spillovers captured? | Volatility spillovers captured? | Shocks spillovers captured? | Asymmetric effects captured? |
|---|---|---|---|---|
| VAR-MGARCH | Yes | Yes | No | No |
| VAR-AMGARCH | Yes | Yes | No | Yes |
| VARMA-MGARCH | Yes | Yes | Yes | No |
| VARMA-AMGARCH | Yes | Yes | Yes | Yes |

Source: Compiled by the authors

The bi-variate VARMA$(p,q)$-AMGARCH$(1,1)$ model is specified below[3]:

**The Conditional Mean Equation**:

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

[2]CC denotes the Constant Correlations, DCC is the Dynamic Conditional Correlation and BEKK is the Baba, Engle, Kraft and Kroner's representation of the conditional variance equation.

[3]Note that we allow for more than one lag for the mean equation (VARMA) 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 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.

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

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

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

Where $R_t = \left(RASI_t, \quad RIR_t\right)'$ denotes the returns series expressed; $\phi = \left(\phi^{RASI}, \quad \phi^{RIR}\right)'$ is a vector of constants for $RASI_t$ and $RIR_t$ mean equations respectively; $\Psi_i = \begin{pmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{pmatrix}$ $\forall\ i = 1,\ldots,p$ is a $(2\times 2)$ matrix of coefficients on the lagged terms of the returns series; $\Upsilon_j = \begin{pmatrix} \Upsilon_{11} & \Upsilon_{12} \\ \Upsilon_{21} & \Upsilon_{22} \end{pmatrix}$ $\forall\ j = 1,\ldots,q$ is a $(2\times 2)$ matrix of coefficients on the lagged terms of the residuals and $\varepsilon_t = \left(\varepsilon_t^{RASI} \quad \varepsilon_t^{RIR}\right)'$ is a vector of disturbance terms for $RASI_t$ and $RIR_t$ mean equations respectively; $v_t = \left(v_t^{RASI}, \quad v_t^{RIR}\right)'$ is a vector of white noise errors; and $H_t$ is a symmetric matrix of conditional variances in which the diagonal elements of $H_t$ are the variance terms, and the off-diagonal elements of $H_t$ are the covariance terms. In essence, $H_t^{1/2} = diag\left(\sqrt{h_t^{RASI}}, \quad \sqrt{h_t^{RIR}}\right)$ where $h_t^{RASI}$ and $h_t^{RIR}$ are the conditional variances for $RASI_t$ and $RIR_t$ respectively.

**<u>The Conditional Variance Equation:</u>**

The conditional variance for the $\text{VARMA}(p,q)\text{-AMGARCH}(1,1)$ is given as:

$$H_t = \Omega + A\varepsilon_{t-1}^2 + CI_{t-1}\varepsilon_{t-1}^2 + BH_{t-1} \tag{6}$$

where $H_t = \left(h_t^{RASI}, h_t^{RIR}\right)'$, $\varepsilon_t^2 = \left(\varepsilon_{RASI,t}^2, \quad \varepsilon_{RIR,t}^2\right)'$, and $\Omega$, $A$, and $B$ are $(2\times 2)$ matrices. $I_t = diag\left(I_t^{RASI}, \quad I_t^{RIR}\right)$ such that $I_{t-1} = 0$ if $\varepsilon_t > 0$ and $I_{t-1} = 1$ otherwise.[4] The components of the

[4] Note that the different variants of the $\text{VARMA}(p,q)\text{-AMGARCH}(1,1)$ were estimated by imposing restrictions on relevant terms in either the mean equation or variance equation or both. For example, the VAR-GARCH Model can be obtained by setting $\Upsilon(L) = 1$ and $C = 0$ while the VARMA-GARCH can be obtained by setting just $C = 0$. Also, as earlier mentioned, three options were considered in the estimation of the different variants of the $\text{VARMA}(p,q)\text{-AMGARCH}(1,1)$ namely CC, DCC and BEKK (see McAleer et al., 2009 for the computational procedure of these options). Also, Silvennoinen and Terasvirta (2008) provide a review of the theoretical structure for the three options when dealing with MGARCH models.

asymmetric effects capture the impacts of positive and negative shocks on volatility. The structural and statistical properties of VARMA-MGARCH 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 $\varepsilon_t$, 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. Empirical Analyses

The results obtained from the analyses of the different variants of VARMA-AMGARCH are presented in tables 3(a) through 3(d) below. From these tables, it is observed that only BEKK MGARCH is able to achieve convergence after certain number of iterations while CCC and DCC MGARCH have problem of achieving convergence. This may be due to the need to compute conditional correlation coefficient by both MGARCH options which is not required by the BEKK MGARCH. The best fit MGARCH is however, selected from each model category and thus presented in table 4 below.

**Table 3:**

3(a): VAR-MGARCH MODEL

| **Model** | **Convergence Status** | **Model Selection Criteria** | | | **Rank** |
|---|---|---|---|---|---|
| | | AIC | SBC | HQ | |
| BEKK: VAR(1)-MGARCH(1,1) | Achieved | 13.492 | 13.811 | 13.621 | **1** |
| BEKK: VAR(2)-MGARCH(1,1) | Achieved | 13.529 | 13.924 | 13.689 | **2** |
| BEKK: VAR(3)-MGARCH(1,1) | Not achieved | 12.982 | 13.456 | 13.175 | - |
| CC: VAR(1)-MGARCH(1,1) | Not achieved | 13.931 | 14.212 | 14.045 | - |
| CC: VAR(2)-MGARCH(1,1) | Not achieved | 13.740 | 14.097 | 13.885 | - |
| CC: VAR(3)-MGARCH(1,1) | Not achieved | 13.684 | 14.119 | 13.861 | - |
| DCC: VAR(1)-MGARCH(1,1) | Not achieved | - | - | - | - |
| DCC: VAR(2)-MGARCH(1,1) | Not achieved | 14.463 | 14.840 | 14.616 | - |
| DCC: VAR(3)-MGARCH(1,1) | Not achieved | 14.627 | 15.081 | 14.811 | - |

Source: Compiled by the Authors

3(b): VARMA-MGARCH MODEL

| Model | Convergence Status | Model Selection Criteria | | | Rank |
|---|---|---|---|---|---|
| | | AIC | SBC | HQ | |
| BEKK: VARMA(1,1)-MGARCH(1,1) | Achieved | 13.540 | 13.934 | 13.700 | **1** |
| BEKK: VARMA(2,2)-MGARCH(1,1) | Achieved | 13.626 | 14.171 | 13.847 | **2** |
| BEKK: VARMA(3,3)-MGARCH(1,1) | Not achieved | 13.259 | 13.959 | 13.543 | - |
| CC: VARMA(1,1)-MGARCH(1,1) | Achieved | 13.970 | 14.326 | 14.114 | **3** |
| CC: VARMA(2,2)-MGARCH(1,1) | Not achieved | 13.959 | 14.465 | 14.163 | - |
| CC: VARMA(3,3)-MGARCH(1,1) | Not achieved | 13.664 | 14.326 | 13.933 | - |
| DCC: VARMA(1,1)-MGARCH(1,1) | Not achieved | - | - | - | - |
| DCC: VARMA(2,2)-MGARCH(1,1) | Not achieved | 14.569 | 15.096 | 14.783 | - |
| DCC: VARMA(3,3)-MGARCH(1,1) | Not achieved | - | - | - | - |

Source: Compiled by the Authors

3(c): VAR-MGARCH MODEL with Asymmetry

| Model | Convergence Status | Model Selection Criteria | | | Rank |
|---|---|---|---|---|---|
| | | AIC | SBC | HQ | |
| BEKK: VAR(1)-AMGARCH(1,1) | Not achieved | 13.422 | 13.816 | 13.582 | |
| BEKK: VAR(2)-AMGARCH(1,1) | Not achieved | 13.234 | 13.705 | 13.425 | - |
| BEKK: VAR(3)-AMGARCH(1,1) | Not achieved | 13.057 | 13.605 | 13.279 | - |
| CC: VAR(1)-AMGARCH(1,1) | Not achieved | 14.178 | 14.497 | 14.307 | - |
| CC: VAR(2)-AMGARCH(1,1) | Not achieved | - | - | - | - |
| CC: VAR(3)-AMGARCH(1,1) | Not achieved | 13.454 | 13.926 | 13.646 | - |
| DCC: VAR(1)-AMGARCH(1,1) | Not achieved | 14.453 | 14.790 | 14.590 | - |
| DCC: VAR(2)-AMGARCH(1,1) | Not achieved | 14.568 | 14.982 | 14.736 | - |
| DCC: VAR(3)-AMGARCH(1,1) | Not achieved | - | - | - | - |

Source: Compiled by the Authors

3(d): VARMA-MGARCH MODEL with Asymmetry

| Model | Convergence Status | Model Selection Criteria | | | Rank |
|---|---|---|---|---|---|
| | | AIC | SBC | HQ | |
| BEKK: VARMA(1,1)-AMGARCH(1,1) | Achieved | 13.674 | 14.143 | 13.865 | **2** |
| BEKK: VARMA(2,2)-AMGARCH(1,1) | Achieved | 13.591 | 14.213 | 13.844 | **1** |
| BEKK: VARMA(3,3)-AMGARCH(1,1) | Not achieved | 13.214 | 13.989 | 13.528 | - |
| CC: VARMA(1,1)-AMGARCH(1,1) | Not achieved | 14.349 | 14.743 | 14.509 | - |
| CC: VARMA(2,2)-GARCH(1,1) | Not achieved | 14.508 | 15.054 | 14.730 | - |
| CC: VARMA(3,3)-AMGARCH(1,1) | Not achieved | 14.370 | 15.069 | 14.653 | - |
| DCC: VARMA(1,1)-AMGARCH(1,1) | Not achieved | - | - | - | - |
| DCC: VARMA(2,2)-AMGARCH(1,1) | Not achieved | 14.214 | 13.989 | 13.528 | - |
| DCC: VARMA(3,3)-AMGARCH(1,1) | Not achieved | 14.831 | 15.549 | 15.123 | - |

Source: Compiled by the Authors

**Table 4: Selected Best Fit MGARCH Model in each Model Category**

| Model | Convergence Status | Model Selection Criteria | | | Rank |
|---|---|---|---|---|---|
| | | AIC | SBC | HQ | |
| BEKK: VAR(1)-MGARCH(11) | Achieved | 13.492 | 13.811 | 13.621 | **1** |
| BEKK: VARMA(11)-MGARCH(11) | Achieved | 13.540 | 13.934 | 13.700 | **2** |
| BEKK: VARMA(22)-AMGARCH(11) | Achieved | 13.591 | 14.213 | 13.844 | **3** |

Source: Compiled by the Authors

Note: Only models that achieved convergence are considered for selection and same were consequently ranked based on their AIC, SBC and HQ values.

### 4.1. Discusion of Results[5]

This section discusses results obtained from the parameter estimates of selected variants of VARMA-AMGARCH. The VAR-MGARCH model in table[6] 5 below, accounts for the returns and volatility spillovers between the two variables via their mean and variance equations, while VARMA-MGARCH and VARMA-AMGARCH, in addition, account for shocks transmission and asymmetric effects respectively.

#### 4.1.1. Model 1: VAR-MGARCH

Estimation results of the return spillovers from the VAR(1)-MGARCH(1,1) model are reported in table 5(a) below. The returns spillovers are captured in the mean equation. The results reveal evidence of statistically significant returns spillover effects from stock market to money market $\Psi_{21}$ while the stock market does not actively respond to returns in the money market. Thus, higher returns in stock market are capable of driving higher returns in the money market. The implication of this to policy makers is the fact that stability of the stock market is crucial for money market stability.

Also, the volatility spillover effects of the estimation are captured in the variance equation of the estimated VAR(1)-MGARCH(1,1) model reported in table 5(b). The results reveal evidence of statistically significant short-term and long-term cross-market volatility spillovers from money

[5]Comprehensive results of all models are available on request. Also, the RATS code for the estimation of the different variants of VARMA-AMGARCH Model can as well be provided on request.

[6]The subscript 1 is for stock market and 2 for money market. In the variance equation, $\Omega$ denotes the constant term, $A$ denotes the ARCH term and $B$ denotes the GARCH term while $\Pi$ accounts for the asymmetric effects. In the mean equation, $\phi_{10}$ represents the effect of ASIR own intercept parameter on current period while $\phi_{20}$ explains same for RIR. The coefficient $\Psi_{12}$ and $\Psi_{21}$ for example denote returns spillover effects from RIR to ASIR and ASIR to RIR while $\Upsilon_{12}$ and $\Upsilon_{21}$ represent shock transmission from RIR to ASIR and ASIR to RIR respectively.

market to stock market (i.e. $A_{12}$ and $B_{12}$) as well as from stock market to money market (i.e. $A_{21}$ and $B_{21}$). In essence, there is bidirectional volatility transmission between stock and money markets. Thus, volatility in one market may fuel volatility in the other market.

#### 4.1.2. Model 2: VARMA-MGARCH

Taking a closer look at the mean and variance equations of VARMA(1,1)-MGARCH(1,1) model, with the exception of the introduced MA components, we find evidence that is similar to the VAR(1)-MGARCH(1,1) estimates. Essentially, the MA components account for shocks to returns of the two markets in their respective mean equations and the results indicate that both stock and money markets respond significantly to own shocks and cross market shocks and the sign is positive. This indicates that exogenous own and cross market shocks affect returns.

#### 4.1.3. Model 3: VARMA-AMGARCH

This is the most sophisticated model applied as it allows for both the time-varying volatility and the asymmetric effects to be tested. By comparing the results with the previous models, we find that when the asymmetric effects are not captured in the model, the returns and shocks spillovers are exaggerated while the volatility spillover effect is underestimated. We also find statistically significant own-market asymmetric effects although with insignificant cross asymmetric effects. Thus, bad (good) news in each market may fuel higher (lower) volatility in the affected market but may not substantially drive higher volatility in the other market. Nonetheless, our findings further strengthen the fact that the stock market is more vulnerable to shocks than money market. Therefore, investors should take cognizance of this when diversifying their portfolio investments in Nigeria. Interestingly however, the spillover effects between the two markets seem transitory rather than permanent.

#### 4.1.4. Post Estimation

The two main diagnostic tests considered to validate the estimated VARMA-AMGARCH models are the LB tests and the McLeod-Li test. Both tests are applied to standardized residuals, and a significant LB test implies that the mean equation is wrong while a significant McLeod-Li test is an indication that the variance equation of the model is somehow inadequate. However, the result of the LB test indicates absence of serial correlation and the McLeod-Li test also validates the adequacy of the GARCH effects in the variance equation. Therefore, the theoretical structure of the estimated models in terms of their mean and variance equations is appropriate when dealing with returns, shocks and volatility spillovers between markets.

**Table 5: Parameter estimates for selected variants of VARMA-AGARCH Model**

| **5(a): Returns Spillover Effects** | | | |
|---|---|---|---|
| Mean Equation | VAR(1)-GARCH(1,1) | VARMA(1,1)-GARCH(1,1) | VARMA(2,2)-AGARCH(1,1) |
| $\phi_{10}$ | 1.5446 (0.3151)$^{*}$ | 1.5446 (0.3108)$^{*}$ | 0.6788 (0.3998)$^{***}$ |
| $\Psi_{11}$ | -0.0907 (0.0619) | -0.0907 (0.0606) | 0.0699 (0.3370) |
| $\Psi_{12}$ | -0.0215 (0.0437) | -0.0215 (0.0443) | -0.0338 (0.0594) |
| $\phi_{20}$ | 0.9907 (0.1814)$^{*}$ | -0.9907 (0.1743)$^{*}$ | -1.1339 (0.3053)$^{*}$ |
| $\Psi_{21}$ | 0.2283 (0.0361)$^{*}$ | 0.2283 (0.0362)$^{*}$ | -0.3020 (0.0412)$^{*}$ |
| $\Psi_{22}$ | 0.1624 (0.0419)$^{*}$ | -0.1624 (0.0433)$^{*}$ | 0.2848 (0.0509)$^{*}$ |
| $\Upsilon_{11}$ | | 0.0144 (0.0000)$^{*}$ | 0.0265 (0.0000)$^{*}$ |
| $\Upsilon_{12}$ | | 0.0443 (0.0000)$^{*}$ | -0.0149 (0.0000)$^{*}$ |
| $\Upsilon_{21}$ | | 0.0383 (0.0000)$^{*}$ | -0.0242 (0.0000)$^{*}$ |
| $\Upsilon_{22}$ | | 0.1479 (0.0000)$^{*}$ | -0.0154 (0.0000)$^{*}$ |
| **5(b): Volatiltiy Spillover Effects** | | | |
| Variance Equation | | | |
| $\Omega_{11}$ | 3.9667 (0.7475)$^{*}$ | 3.9666 (0.7845)$^{*}$ | 4.0974 (0.8959)$^{*}$ |
| $\Omega_{21}$ | -0.0734 (0.5038) | -0.0734 (0.5272) | 0.6511 (0.6904) |
| $\Omega_{22}$ | 0.0000 (1.2670) | -0.0000 (1.2784) | 1.0004 (0.6054)$^{***}$ |
| $A_{11}$ | 0.2145 (0.0923)$^{**}$ | 0.2145 (0.0958)$^{**}$ | -0.0481 (0.1011) |
| $A_{12}$ | -1.1983 (0.0833)$^{*}$ | -1.1983 (0.0886)$^{*}$ | 0.7773 (0.0883)$^{*}$ |
| $A_{21}$ | 0.3931 (0.1186)$^{*}$ | 0.3931 (0.1213)$^{*}$ | 0.2167 (0.1039)$^{**}$ |
| $A_{22}$ | 1.7767 (0.1363)$^{*}$ | 1.7767 (0.1406)$^{*}$ | 1.6713 (0.2398)$^{*}$ |
| $B_{11}$ | 0.7115 (0.0951)$^{*}$ | 0.7115 (0.0986)$^{*}$ | 0.7414 (0.1228)$^{*}$ |
| $B_{12}$ | -0.1373 (0.0432)$^{*}$ | -0.1373 (0.0426)$^{*}$ | -0.0381 (0.0647) |
| $B_{21}$ | -0.1280 (0.0462)$^{*}$ | -0.1280 (0.0480)$^{*}$ | -0.0423 (0.0508) |
| $B_{22}$ | 0.0571 (0.0237)$^{**}$ | 0.0571 (0.0241)$^{**}$ | 0.0066 (0.0275) |
| $C_{11}$ | | | 0.3350 (0.1671)$^{**}$ |
| $C_{12}$ | | | 0.0080 (0.1267) |
| $C_{21}$ | | | -0.2232 (0.1267) |
| $C_{22}$ | | | -1.1984 (0.3989)$^{*}$ |
| *Log L* | -1102.8242 | -1102.8242 | -1088.2979 |
| *AIC* | 13.492 | 13.540 | 13.591 |
| *SBC* | 13.811 | 13.934 | 14.213 |
| **Diagnostics** | | | |

| | | | |
|---|---|---|---|
| *LB(10)RASI* | 0.9999 | 0.9990 | 0.9571 |
| *LB(10)RIR* | 0.9989 | 0.9989 | 1.0000 |
| *LB(5)RASI* | 0.9345 | 0.9345 | 0.8884 |
| *LB(5)RIR* | 0.9226 | 0.9226 | 0.9942 |
| *McLeod-Li(10) RASI* | 1.0000 | 1.0000 | 0.9999 |
| *McLeod-Li(10) RIR* | 1.0000 | 1.0000 | 1.0000 |
| *McLeod-Li(5) RASI* | 0.9976 | 0.9976 | 0.9929 |
| *McLeod-Li(5) RIR* | 0.9939 | 0.9939 | 0.9995 |

Notes: Standard errors are reported in parentheses. *, ** and *** represent significance at 1%, 5% and 10% respectively.

## 5. Conclusion

In this paper, we examine the spillover effects between money market and stock market in Nigeria. Essentially, we estimate returns, shocks, and volatility transmission across the two markets using the VARMA-AMGARCH model and its variants. The results of the mean equations suggest a higher spillover effect of returns from stock market to the money market. Nonetheless, the transmission of shocks to returns across the two markets is bidirectional and investors are likely to be more risk averse towards the stock market assets than money market assets.

The variance-equations of the models prominently indicate that the two markets are sensitive to own innovations and previous period volatilities. Also, comparing the results of the estimated models, we find that the returns and shocks spillovers are exaggerated while the volatility transmission is under estimated when the asymmetric effects are not captured in the model. The evidence revealed suggests statistically significant own-market asymmetric effects although with insignificant cross asymmetric effects. Thus, bad (good) news in each market may fuel higher(lower) volatility in the affected market but may not transmit into higher volatility in the other market. In all, the spillover effects between the two markets seem transitory rather than permanent.

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