RETURN AND VOLATILITY SPILLOVERS BETWEEN GHANAIAN AND NIGERIAN EQUITY MARKETS

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Abstract

The study employs a VARMA-AMGARCH estimation to evaluate the cross transmission of return and volatility spillovers between the Nigeria stock exchange (NSE) and the Ghanaian stock exchange (GSE) to infer the extent of interdependence of the two stock markets. The study uses daily data on All Share Price Index of the Nigeria Stock Exchange market (NGSE) and the Ghanaian Stock market (BNKIALL) between January 5, 2009 and October 12, 2018. The results of the empirical analysis suggest that the Nigeria's stock market and Ghana's stock markets are functionally dependent and the spillover effect from Ghana stock market to Nigeria stock market is stronger than from Nigeria to Ghana in absolute value. Moreover, the results suggest that Ghana's stock returns appear to experience higher long run shock persistence than the Nigeria's Stock market returns. The magnitude of the short run persistence of shocks for Nigeria stock market returns is estimated as 0.04766 which is quite small compared to Ghana's stock market returns which are 0.1909. The paper concluded by showing a significant cross-transmission between the two countries market returns and shock spillovers.

Keywords: Return Spillover, Shock Spillover, Shock Persistence, Asymmetric VARMA-GARCH model

JEL classification: C58, G10

Introduction

Financial liberalization of economies and relaxation of capital flows barriers facilitated by the growth and advancement of electronic trading technologies coupled with improved news and events transmission has resulted in increased integration of economies and international financial markets. This development has trickled down to regional markets and has resulted in regional markets of developing countries becoming interconnected. Regional markets of emerging economies are becoming integrated due to regional cooperation and trade barriers relaxation. This had undoubtedly increased the interconnectedness of the regional economies, especially in Sub-Saharan Africa (SSA). In the West African sub region, Nigeria and Ghana are the two most dominant economies, commodity driven and both are anglophone economies. Furthermore, the ECOWAS regional body aims to achieve regional integration of the ECOWAS member countries before the middle of the millennium. Given the interlinkages between the two (2) countries in terms of colonial and developmental history, and the recent expansion of Nigerian and other multinational organisations in both Nigeria and Ghana, their economies are invariably intertwined. The interconnectedness of the two (2) big economies in the ECOWAS sub region, is evidenced by the level and degree of their equities market over the past two decades.

The Magnitude of risk in a portfolio is not totally dependent on the risks of one country's assets, but also on the co-movements between individual country's assets in the portfolio. If the price of one portfolio asset in Nigeria and the other in Ghana tend to move in opposite directions, investing in both portfolios would be less risky than investing in each country's asset alone, the reason is, a decline in one asset's price would be partially offset by a rise in the other asset's price, and vice versa. The prime aim of an investor is to maximize profit on his/her investment and any information about the extent of spillovers provides useful insights to portfolio investors on how to diversify his/her investments. Likewise, decisions taken on policy require that this information is identified, and a proactive measure is taken to safe guide any financial market that is susceptible to higher risks and uncertainties. The study employs a VARMA-AMGARCH estimation to evaluate the cross transmission of return and volatility spillovers between the Nigeria stock exchange (NSE) and the Ghanaian stock exchange (GSE), as this would offer useful insights to investors willing to diversify their asset base.

Thus, the paper seeks to address the following research questions. Is there any volatility spillovers effect between the Ghanaian stock market and the Nigerian stock market? what is the magnitude of long run and short run persistence of shocks? Which of the stock market volatility is more sensitive to shock? Therefore, this paper is structured as follows: After the introduction, Section 2 presents the literature review, conceptual review, Ghanaian and Nigerian stock market overview and the empirical review; Section 3 offers data description and preliminary analysis; Section 4 presents the Specification of Asymmetric VARMA-GARCH Model and its underlying assumptions; Section 5 presents results on VARMA-AGARCH Model, post-estimation diagnostics, Return, Shock and Persistence of Shocks; lastly, Section 6 provides the conclusion.

Literature review

Modern theory finance is built upon the principle of risk and arbitrage. The presence of risk in financial transaction entailed the presence of opportunity. Where Opportunity exist, there is the probability to make gains. But the key underlying idea is the ability to measure and quantify this risk level which is synonymous with the level of gains to be made. Thus, the challenge is the ability to measure the level of riskiness and thus quantify the gains to be accrued. Investors and financial advisors resorted to the world of mathematics and quantitative analytics to answer these challenges, gauge the availability of the opportunities and quantify the level of risk. The index of such riskiness is the presence of volatility in the returns of the various financial instruments and equities invested in the market.

Conceptual Review

Volatility as a statistical concept of measures the deviation of the price of a financial instrument in series as exhibited in the financial market. In finance, it is synonymous with presence of risk. Quantifying the level of the volatility allows for the measurement of the level of risk in the instrument as measured over time. Market forces affect the returns on the instrument invested, thus contributing to the uncertainty of the returns. This uncertainty leads to certain measure of risk when the investor holds or owns assets over a given period of time. Therefore, a sound

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knowledge of volatility and its estimation is desirable for estimating the true price of an asset or the expected returns from a risky asset. Therefore, volatility of an asset can be defined as the measure of the variability of its value over time. Thus, in terms of financial assets, volatility describes the deviation, measured in standard deviation, of the value of the assets from its expected value. The value can be in its prices or its returns. While volatility -spillover refers to the concept of volatility transmission between two or more different markets that are connected or integrated. This means that, the different markets can be affected by the same news events or shocks from the different markets, because of the integration.

There are two measures of volatility:

i. unconditional volatility
ii. Conditional or stochastic volatility.

Impliedly, unconditional volatility involves deviations or dispersion that are time invariant. While, the conditional or stochastic volatility means that the measure of variability itself or volatility changes over time. Consequently, the variance of the stochastic process, i.e. conditional volatility of the prices or returns distribution of the asset is itself randomly distributed. This implies that volatility fluctuates over time, thus, it is expected that, it will exhibit certain characteristics of a stochastic processes.
The properties of the stochastic are important for the modelling of the processes to evaluate the magnitude of the risk levels in the returns of the assets being modelled. Nelson (1996), tested the properties of the conditional volatility, and asserts that, it tends to be serially correlated and thereby exhibits mean reversion. In other words, it means that observations (returns or prices) have a tendency to show trends. Secondly, because of the serial correlation, conditional or stochastic volatility exhibits volatility clustering. According to Cont (2007) this was first observed by Mandelbrot (1963) and later validated by Fama (1965). Where volatility clustering refers to the phenomenon where “huge variations tend to be followed by huge fluctuations of either sign (positive or negative) and slight deviations tend to be followed by minor deviations”. Furthermore, stochastic volatility shows asymmetry. This means that, concurrent returns and conditional returns volatility are found to be negatively correlated. The, negative or positive returns are generally associated with upward or downward movement of conditional volatility, as the case may be.
There are several approaches to measuring equity market connectedness. One of the methods is the forecast error variance decomposition which was developed by Diebold and Yilmaz (2009). Tis approach entailed running VAR analysis, then decomposing the error variances of the joint asset return forecasts of the VAR system. The whole system of VAR is developed into a network of markets as nodes and weights determined by variance shares. A second approach is the methodology of spillover indices. This method analyses the return-to-volatility spillovers using the rate of returns on a time basis, either daily, weekly, or monthly return series of the stock markets.

Empirical Review

The movement of stock market prices, otherwise known as volatility is the crucial basis of the various researches related to market efficiency. The financial theory of Market efficiency, underpinned the theoretical basis of all studies of volatility as a phenomenon and a concept which is central to modern financial markets and academic research.

The nexus between volatility and returns were academically studied by Fama (1965) in the study of stock market prices. The research laid the foundation of the behaviour of stock market prices. Essentially, the argument was that; the past behaviour of the prices determines the future prices of the stock, while the random walk theory states that, the future price of a security or future path is dependent upon the cumulative paths of series of random numbers. Statistically, it implies that, the cumulate price changes are independent and identically distributed events, i.e. the prices changes have no memory, implying that past events do not influence future positions. As such the it cannot be used to predict the future. The presence risk has been to some measure, the key determinant of value for most stocks. Therefore, stock market price volatility is not an anathema. Nevertheless, the presence of time dependent financial phenomena, such as the end period effect and volatility clustering enables the estimation of stock prices and their magnitude of movement. In practice, Goetzman and Phillipe (1999) asserted that, stock volatility can be used to determine the basis for efficient price discovery; conversely, volatility dependence implies predictability.

The generality of the literature centred around the stock markets of developed economies of western Europe and America. Majority of the emerging countries (developing and transition) have not studied the connectedness of their stock markets and the global markets, or within the regional context. In this research efforts will be concentrated on the literature on the emerging economies and regional blocs.

In the literature, there are several key researches that had dwelled on the important topic of volatility transmission from one market to another market. Key papers like Bekaert and Harvey (1997), examined the transmission channels of the volatility in emerging market, by volatility spillover model by assuming two sources of volatility, domestic and global sources which is important in determining the cost of capital investment and resource allocation decisions. Furthermore, their model allows for the allocation of importance to be attached to news or information on relative basis to change through time in both the expected returns and conditional variance processes. Ng (200) extended their model to incorporate 3 different sources of information in terms of its magnitude and dynamic nature. The model incorporates volatility spillovers form Japan and US to 6 pacific equity markets. Some of the findings include; apart from the effect of the global source of transmission, the regional spillovers are significant too. Furthermore, financial reforms, exchange rate regimes and other country specific factors did show to have significant effect on the volatility relative to the global factors.

Christiansen (2003) analysed the volatility spillover from the US markets and the European bond markets. The study modelled the individual European bond markets using a GARCH volatility-spillover model. The study found that there is a strong statistical evidence of volatility-spillover effects from both the US, Europe and the individual European bond markets. The volatility-spillover effects between the US and the other European Monetary Union (EMU) countries are weak, but, the European volatility-spillover effects and the EMU are strong. Conversely, the volatility spillover between non-EMU countries and the responding countries is strong. The introduction of the euro in the Union has an effect on the magnitude of the spillover, by strengthening the European volatility-spillover effects for the EMU countries.

(Kuttu, 2015) used a multivariate VAR-EGARCH to investigate the returns and volatility dynamics between thin-traded adjusted equity returns from four different Africa countries (Nigerian, South Africa, Kenya and Ghana) and found a reciprocal return spillover between Kenya and Ghana, and between South Africa and Nigeria. Highly persistent volatility was observed for all the four markets with Ghana, Kenya and South Africa displaying volatility asymmetry. The result also suggests that, compared to cross-market volatility spillover, own market volatility innovations appear to be more visible in the Ghanaian, Nigerian and South African equity markets.

Jebran and Iqbal (2016) examined the levels of the returns and volatility spill over between the stock markets of the major Asian markets of Pakistan, India, Sri Lanka, China, Japan, and Hong Kong. The study employed the generalized autoregressive conditional heteroskedasticity (GARCH) model on daily data for the periods 4 January 1999 to 1 January 2014, consisting five trading days from Monday to Friday of the stock market working days. The research found out that, there is significant bidirectional spillover of returns and volatility between China and Japan, which happens to be the major financial centres in Asia. Furthermore, evidence of bidirectional volatility transmission between the equity markets of the following countries; Hong Kong and Srilanka, china and Srilanka too. However, the research showed only unidirectional transmission of volatility of the stock markets of India to China, Srilanka to Japan, Pakistan to Srilanka, Others are Hongkong to India and Joan respectively. From the foregoing the study concluded that, the established of the direction of these volatilities between the Asian stock markets, is invaluable to both financial policy decisions as well as investors, given the level of the markets interdependencies.

In Sub Saharan Africa, Auwal and Sanusi (2016) examined the interdependence between the continent's largest economies; Nigeria and South Africa. The paper the examined the spillover effects between the two economies in the context of effects of political instability on the level of investments and thus spillover effects. Testing the hypothesis that, volatilities introduced by political events, such as Boko Haram attacks in Nigeria, and civil uprisings in South Africa, being determinants of investment decision; these events could have significant spillover effects between the Nigerian and South African Stock Markets. Therefore, in the study, they examined the impacts of political uncertainty, generated by these terror attacks, on the stock markets by employing a GARCH model of Conditional Correlation. Furthermore, they then examined the nature and dynamics of the volatility spillover between two African stock markets. The result showed that, the two markets react differently to political events, but there is heavy volatility in both markets. While the conditional correlation showed significance between the two markets, with a negative sign, despite these political events, but there is little evidence to suggest

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integration of the two markets. In conclusion, the papers assert that, the hypothesis of political events affecting investment levels in financial markets has been tested and the model is robust to theoretical assumptions and conditions.

In the same vein, Phume and Bonga-Bonga (2018) examined the returns and spillover between Nigeria and South Africa stock markets. Th paper argued that given the sizes of the two dominant economies of Africa, in terms of their GDP, portfolio investors might be interested in uncovering the connection between the two markets, and whether or the two markets are complimentary to each other, and the cross - transmission between the two markets. Thus, the magnitude of the interdependence between the markets will be determined. This will provide asset diversification opportunities for investors and thus allow for substitutability between the two markets. To achieve that, a GARCH (Generalised autoregressive conditional heteroscedasticity) model was applied to weekly share index data at closing prices, ranging from 28 September 2000 to 8 September 2016. The results showed that, there is evidence that suggest there is a unidirectional transmission from the South African stock market to the Nigerian Stock market and not the other way around. Furthermore, the study determined the optimal hedge ratio for investors between the two markets. In conclusion, the authors gave insight into the optimal hedge ratio by a combination of assets in both market and suggested that investors should adopt a dynamic balancing of the hedging weights in the portfolio decisions. Managi et al (2013) studied the correlations between the commodity markets and stock markets. The study tried to establish the linkages between commodities like and energy markets with food indices. The research employed a VAR-GARCH on stock market and commodity market data from S&P 500 (standard and Poor's) 500 fortune companies in that sector. The study used data ranging over the turbulent period of global finance between 2000 to 2011. Objectively, the research tried to understand the behaviour of prices, in terms of the return and spillover during the period, especially volatility and spillover transmission effects from the commodity markets and its consequent spillover tot eh energy and food indices. It was established that, there is significant spillover or transmission amongst the S&P 500 stocks and commodity markets. This is evidenced by the effect of the past shocks and volatility emanating from oil and gold markets, as shown by the conditional correlation between the S&P 500 and gold index, which was the highest. Furthermore, the research also analysed the optimal weights and hedge ratios for the commodities and the S&P 500 portfolios. This was done through the usage of the estimates form the Indices of the different markets. Overall, the study, concluded that, the findings would be of great benefit to the decisions of portfolio managers, as the model encompassed risk management.

Data Description and Preliminary Analysis

This study uses daily data on All Share Price Index of the Nigeria Stock Exchange market (NGSE) and the Ghanaian Stock market (BNKIALL) between January 5, 2009 and October 12, 2018. The data on both variables were sourced from Thomson Reuters Data stream for two West African countries. The data excludes weekends, while holidays and previous period figures are represented by periods of inactivity in either of the two markets; it is assumed that no trading took place, so the figures remained unchanged.

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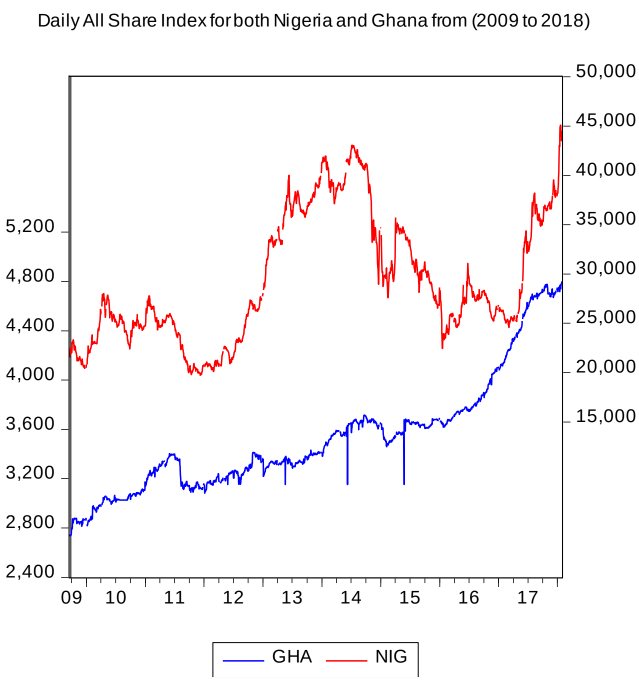
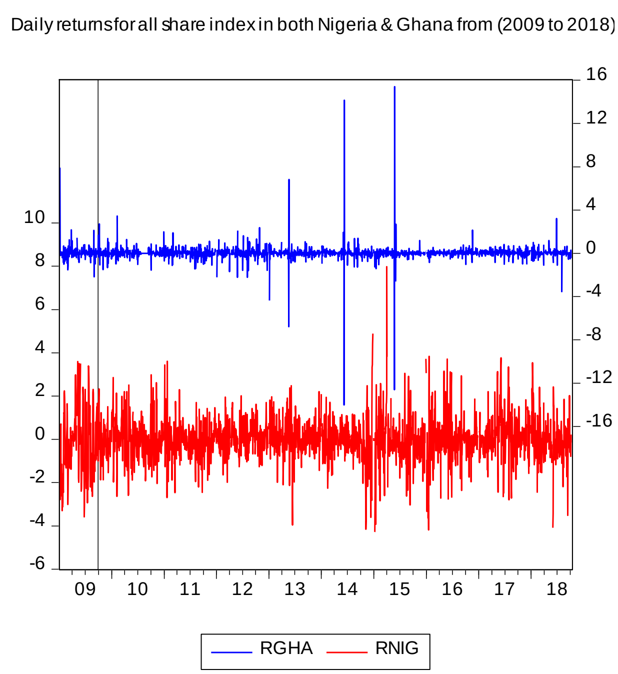
The graphical presentation of both series is shown in both figure 1 and 2. The series captures the developments in the Ghana's stock market and the Nigeria's stock exchange market between January 2009 and October 2018, the return series suggest that the two markets have different rate of volatility (Figure 2). The returns in both markets during the study period indicates that periods of significant volatility in Nigeria's stock market corresponds to periods of moderate volatility in Ghana's stock market (Figure 2), although a significant number of structural breaks were highly visible. This development suggests that an investment in a portfolio comprising the two assets may be sub-optimal and exposes investors to downside swings, as investors may seek an asset that moves in the opposite direction to moderate the downside risk in the event of a downfall in the fortunes in either market. In order to further examine the relationship between the two markets, a descriptive statistics and formal pretests of the data series were carried out on both the actual and the returns series to evaluate their statistical properties. Below shows the descriptive statistics of the data series as presented in Table 1.

Figure 1 and 2: Daily Ghana's and Nigeria's Stock Market Prices (2009-2018)





The observed trend in figure 1 and 2 shows the movement of both Ghana's and the Nigeria's all share indexes. Both countries show a different pattern in their behavior. The actual series for Ghana tend to consistently move in an upwards direction with three noticeable spikes in 2013, 2014 and 2015. While, the Nigeria's stocks price saw a period of high boom due to the flow of external capital by portfolio investors. By the end of 2014 the Nigeria's all share index saw a rapid decline in the value of its stocks. Figure 1 also reveals that at the end of 2016 to 2018 both countries experience an upward trend in the value of their stock, though it is evident that the

Nigerian stocks appears to be more volatile and prone to higher risk than that of Ghana. The daily return series from 2009 to 2018 for both Ghana and Nigeria is presented in Figure 2. Both the two series show evidence of volatility, although Ghana's stock returns over the observed period shows an increasing trend with stable volatility accompanied by periodic spikes, best described as structural breaks.

In addition, the properties of the distribution were measured by skewness, kurtosis, mean and standard deviation statistics (table 1). The mean returns in both markets are positive, suggesting a recovery in the market, while the standard deviation measure indicates that the returns in the Nigeria's stock exchange market are more volatile than those in the Ghana's stock market with 1.04 and 0.73, respectively. The table also indicates that the distribution of both variables is positively skewed (i.e. leptokurtic, implying both series have distributions with fat tails and that there are lesser chances of extreme outcomes compared to a normal distribution) and not normally distributed based on the skewness, kurtosis and Jacque-Bera statistics, fulfilling a condition for ARCH effects

Table 1: Descriptive Statistics

	Ghana	R Ghana	Nigeria	R Nigeria
Mean	3563.6830	0.0304	29597.68	0.0004
Median	3405.3200	0.0214	27513.69	0.0000
Maximum	5047.5600	15.4113	45092.83	7.9848
Minimum	2460.4500	-14.0184	19732.34	-4.2765
Std. Dev.	612.4674	0.7330	6690.7440	1.0359
Skewness	0.7850	2.2047	0.4550	0.2548
Kurtosis	2.9175	241.5081	1.9669	6.8020
Jarque-Bera	251.160	5783026.000	192.621	1495.372
Probability	(0.00)	(0.00)	(0.00)	(0.00)
Observations	2439	2439	2439	2439

Note: * represents Statistical significance at alpha level.

Furthermore, we conducted a formal test to evaluate the statistical features of the series in order to justify the consideration of volatility models for the spillover analyses. The results show the distributions for Ghana's and Nigeria's returns series are positively skewed and leptokurtic (implying both series have distributions with fat tails and that there are lesser chances of extreme outcomes compared to a normal distribution). Consequently, Jarque-Bera (1980) statistics indicate rejections of the null hypotheses and since both stocks Returns do not follow normal distribution, the estimation of GARCH models becomes more appropriate for the analysis of their spillover effects.

As part of the formal tests, we needed to investigate the presence of symmetry or asymmetry of shocks and volatility spillover of the returns from the Nigeria's stock market to Ghana's stock market and vice versa, as well as the presence of Auto Regressive Conditional Heteroscedasticity (ARCH) effect and serial correlation effect in the data series. The results of the formal pre-tests consisting of ARCH LM and Ljung-box tests for heteroscedasticity and serial correlation are presented in Table 2. The test results of the Ljung-box test suggest the presence of serial correlation at 5 and 10 lags for both the actual and return series of the Ghana's and Nigeria's stock market. Similarly, heteroscedasticity is observed at 5 and 10 lags for the actual and return series both for Ghana and Nigeria respectively. The finding implies that both the Ghanaian and Nigerian stock market, respectively, exhibit significant level of conditional heteroscedasticity.

Table 2: Conditional Heteroscedasticity and Autocorrelation Test

	.BNKIALL INDEX		.NGSE INDEX	
	Ghana	R Ghana	Nigeria	R Nigeria
Arch LM(5)	852.4892 (0.00)	864.404 (0.00)	381.9396 (0.00)	143.4823 (0.00)
Arch LM(10)	870.1972 (0.00)	684.7508 (0.00)	327.6998 (0.00)	120.909 (0.00)
Ljung-Box Q(5)	332.04 (0.00)	94.371 (0.00)	370.84 (0.00)	9.2897 (0.10)
Ljung-Box Q2 (5)	341.36 (0.00)	96.763 (0.00)	372.5 (0.00)	15.943 (0.10)
Ljung-Box Q(10)	537.69 (0.00)	535.29 (0.00)	534.44 (0.00)	196.15 (0.00)
Ljung-Box Q2 (10)	538.53 (0.00)	535.41 (0.00)	620.83 (0.00)	230.04 (0.00)

Note: *The Engle (1982) test for conditional heteroscedasticity is represented as the ARCH LM tests, whereas the LB and LB2 suggest that the Ljung-Box tests for autocorrelations includes the standardized residuals in levels and squared standardized residuals respectively. The null hypothesis for the ARCH LM and LB test means the return series has no ARCH effects and not serially correlated, respectively. While, the actual probability values are presented in parentheses.*

To model the behavior of this financial series, we employed Engle and Ng (1993) test for asymmetry in volatility to determine whether an asymmetric model is required for the return series or if a symmetric GARCH model would be more appropriate. It has been argued in the literature (Nelson, 1991) that positive and negative shocks of the same magnitude may not give identical impacts on the conditional variance. An Asymmetry test and CCC test was carried out to verify the presence of asymmetry effect. A negative sign implies that positive shocks will increase volatility more than negative shocks of the same magnitude and a positive sign implies a negative shock will increase volatility in the returns compared to positive shocks of equal magnitude.

In addition to the Engle-Sheppard (2001) CCC test, there is need to also pre-test the presence of asymmetric effect before modelling with CCC-AMGARCH model. In other words, rather than modelling the asymmetry directly; Engle and Ng (1993) propose three pre-tests: the sign bias test, the negative size bias test and the positive size bias test to verify the presence of asymmetric effect. The logic of the tests is to see whether having estimated a GARCH model, an asymmetry dummy variable is significant in predicting the squared residuals (Harris and Sollis, 2003). The tests are of the null hypothesis that the null model is correctly specified suggesting that there is no remaining asymmetry (Harris and Sollis, 2003). These sign and size bias tests are individually computed using the following regressions:

Sign bias test: $$\upsilon_t^2 = a + bS_{t-1}^{-} + e_t \qquad (1)$$

Negative size bias test: $$\upsilon_t^2 = a + bS_{t-1}^{-}u_{t-1} + e_t \qquad (2)$$

Positive size bias test: $$\upsilon_t^2 = a + bS_{t-1}^{+}u_{t-1} + e_t \qquad (3)$$

Where u_t is the error term under the null, S_{t-1}^{-} is a dummy variable that takes the value of one when $u_{t-1} < 0$ and zero otherwise (vice versa for S_{t-1}^{+}). $\upsilon_t^2 = u_t^2 / h_t^{1/2}$ where h_t is the conditional variance under the null. The sign bias test is the t-statistic for testing $H_0: b = 0$ in (8); the negative size bias test is the t-statistic for testing $H_0: b = 0$ in (9); and the positive size bias test is the t-statistic for testing $H_0: b = 0$ in (10). These tests can also be carried out jointly using the following regression:

$$\upsilon_t^2 = a + b_1 S_{t-1}^{-} + b_2 S_{t-1}^{-}u_{t-1} + b_3 S_{t-1}^{+}u_{t-1} + e_t \qquad (4)$$

The LM test of the joint null hypothesis $H_0: b_1 = b_2 = b_3 = 0$ has a χ_3^2 distribution.[i] Therefore, for the asymmetric version to be valid, you are expected to reject the null hypotheses of symmetric effects for both the individual and joint tests.

Where there are contradictions between the individual tests and the joint test (although very rare), Engle and Ng (1993) note that the joint test is more powerful than the individual tests and therefore should be used to determine the presence of asymmetric effect.

Further tests were also carried out for the presence of Constant Conditional Correlation in the data series, and the results obtained from applying these tests are also reported in Table 3. Overall, the asymmetric test indicates that only the positive size bias test seems to be significant, while the Engle-Sheppard CCC chi-square test is not significant. The result does not support the presence of Constant Conditional Correlations in the returns for Ghana and Nigeria's stock markets. However, these results further strengthen our choice of volatility modeling framework for this study. The pre-formal tests informed the decision to adopt two multivariate volatility models to estimate the relationship between the two returns. (see, Harris and Sollis, 2003).

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Table 3: Asymmetry test and CCC test

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	.BNKIALL INDEX	.NGSE INDEX
Sign bias test	1.4636(0.14342)	0.78(0.44)
Negative size bias test	0.1754(0.86079)	0.00(1.00)
Positive size bias test	2.2644(0.02363) **	0.29(0.77)
Joint bias test	5.3635(0.14704)	0.74(0.86)
Engle-Sheppard CCC χ_2^2 test	0.4730716(0.79)	
Observations	2439	2439

Note: * represents Statistical significance at alpha level.

Model Specification

In this section we adopt the use of VARMA-AGARCH model established by McAleer, Hoti and Chan (2009). The model is based on the GJR-type of asymmetry used to measure the asymmetric effects of unconditional shocks on conditional variances. The choice of this model was because, it enables a more appropriate examination of the conditional volatility dynamics, the conditional interdependence/cross effects and the volatility transmission between two stock market returns. When compared with numerous other multivariate specifications such as VECH and BEKK model, the VARMA-AGARCH does not suffer from the problem of dimensionality. This approach has increasingly been adopted by many authors in several literatures. For example, it has been applied by, among others, Chang and McAleer (2010) to analyze the volatility spillover and asymmetric effects across and within the four markets, and Chen Sang et al. (2013) to determine the relationship between the volatility of Thai rubber price return and the volatility of different exchange rates, Asai and McAleer (2011) to examine the dynamic conditional correlations for asymmetric processes, and Caporin and McAleer (2010) introduced a multiple thresholds and time-dependent structure in the asymmetry of the conditional variances.

when measuring a vector of stock returns, R, the VARMA-GARCH model of Ling and McAleer (2003), assumes symmetry in the effects of positive and negative shocks of the same magnitude on the conditional volatility, and is as follows:

Conditional Mean equation: $R_t = E\left(R_t \middle| F_{t-1}\right) + \varepsilon_t;$ (5)

$$\Phi(L)(R_t - \mu) = \Psi(L)\varepsilon_t \tag{6}$$

$$\varepsilon_t = D_t \eta_t$$

Conditional Variance equation: $Var\left(\varepsilon_t \middle| F_{t-1}\right) = H_t = D_t \eta_t \eta_t' D_t = D_t \Gamma D_t$ (7)

$$H_t = W + \sum_{l=1}^{r} A_l \varepsilon_{t-l}^2 + \sum_{l=1}^{s} B_l H_{t-l} \tag{8}$$

where $R_t = (r_{1t}, \ldots, r_{mt})'$ denotes $m \times 1$ vector which explains the decomposition of R into its predictable (conditional mean) and random components; $\mu = (\mu_1, \ldots, \mu_m)'$ is a vector of constants for the mean equations of the series; $\Phi(L) = I_m - \Phi_1 L - \cdots \Phi_1 L^p$ and $\Psi(L) = I_m - \Phi_1 L - \cdots \Phi_1 L^q$ are polynomials in the lag operator (L), and F_t is the past information available to time t; $D_t = diag\left(h_{i,t}^{1/2}\right)$ for $i = 1, \ldots, m$; $\eta_t = (\eta_{1t}, \ldots, \eta_{mt})'$ is a sequence of independently and identically distributed random vectors; $H_t = (h_{1t}, \ldots, h_{mt})'$, $\varepsilon^2 = (\varepsilon_{1t}^2, \ldots, \varepsilon_{mt}^2)'$.

$$h_{i,t} = \omega_i + \sum_{k=1}^{p} \alpha_{ik} \varepsilon_{i,t-k}^2 + \sum_{r=1}^{q} \beta_{ir} h_{i,t-r}^2; \qquad (9)$$

where $k = 1, \ldots, p$; $r = 1, \ldots, q$; $\sum_{k=1}^{p} \alpha_{ik}$ signifies the ARCH effect or short run persistence, of shocks to series i, and $\sum_{k=1}^{p} \alpha_{ik} + \sum_{r=1}^{q} \beta_{ir}$ denotes the long run persistence of shocks to series i.

The VARMA-GARCH model accounts for both return and shock spillovers and assume constant conditional correlations. However, it does not allow for asymmetric effect. An extension of the VARMA -GARCH model considered for this study is the VARMA -AGARCH model of McAleer, Hoti and Chan (2009), it allows for the measurement of asymmetric effect of both positive and negative shocks and examines the conditional volatility dynamics of stock market returns as well as the conditional interdependence/cross effects and volatility transmission between Ghana's and Nigerian stock market returns. An extension of (8) to accommodate the asymmetric impacts of the unconditional shocks on the conditional variances with respect to ε_{it} is as follows

$$H_t = W + \sum_{l=1}^{r} A_l \varepsilon_{t-l}^2 + \sum_{l=1}^{r} C_l I_{t-1} \varepsilon_{t-l}^2 + \sum_{l=1}^{s} B_l H_{t-l} \qquad (10)$$

In which C_l are $m \times m$ matrices for $l = 1, \ldots, r$, and $I_t = diag(I_{1t}, \ldots, I_{mt})$ is an indicator function that captures the discrepancies between the impact of negative and positive shocks of the same magnitude on conditional volatility, specified as:

$$I_{it} = \begin{cases} 1, & \varepsilon_{it} \le 0 \\ 0, & \varepsilon_{it} > 0 \end{cases} \qquad (11)$$

In case of $m = 1$, equation (8) reduces to the asymmetric univariate GARCH, or GJR, model of Glosten et al. (1992):

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$$h_t = \omega + \sum_{j=1}^{r} (\alpha_j + \gamma_j I(\varepsilon_{t-j}))\varepsilon_{t-j}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \qquad (12)$$

In a situation where $C_i = 0$ with A_i and B_i being diagonal matrices for all l, then VARMA-AGARCH becomes:

$$h_{it} = \omega_i + \sum_{l=1}^{r} \alpha_l \varepsilon_{i,t-l} + \sum_{l=1}^{s} \beta_l h_{i,t-j} \qquad (13)$$

The model in equation (13) represents the CCC model of Bollerslev (1990). Based on equation (11), the CCC model is said to be inherently univariate in nature as such, it does not capture the asymmetric effects of positive and negative shocks on conditional volatility and does not have volatility spillover effects across different stock market returns.

Since the two-return series of interest in this study are the Nigerian and Ghanaian stock market returns. Hence, a bivariate VARMA-AGARCH (1,1) model is adopted. The conditional mean and conditional variance equations for the VARMA-AGARCH model are properly stated in 4.1 and 4.2 respectively.

The Conditional Mean [VARMA (1, 1)]:

$$R_t = \mu + \Phi_1 R_{t-1} + \Psi_1 \varepsilon_{t-1} + \varepsilon_t \qquad (14)$$

Where $R_t = \left(r_{Gha,t}, r_{Nig,t}\right)'$ represents the return series for Ghana's and Nigeria's stock market, respectively; $\Phi = \left(\phi_{Gha,t}, \phi_{Nig,t}\right)'$ is a (2×1) vector of coefficients on the lagged terms of the return series and it captures return spillovers; $\theta = \left(\theta_{Gha,t}, \theta_{Nig,t}\right)'$ is a (2×1) vector of coefficients on the lagged terms of the residuals and $\varepsilon_t = \left(\varepsilon_{Gha,t}, \varepsilon_{Nig,t}\right)'$ is a vector of disturbance terms for mean equations of stock and money. The return spillovers are better appreciated using the individual mean equations below:

$$r_{Gha,t} = \mu_{Gha} + \phi_{Gha} r_{Gha,t-1} + \theta_{Gha} r_{Nig,t-1} + \varepsilon_{Gha,t}$$

$$(15) \quad r_{Nig,t} = \mu_{Nig} + \phi_{Nig} r_{Nig,t-1} + \theta_{Nig} r_{Gha,t-1} + \varepsilon_{Nig,t} \qquad (16)$$

Equations (11) and (12) are the respective mean equations for Ghanaian stock market $(r_{Gha,t})$ and $(r_{Nig,t})$ is the Nigerian stock market returns. The return spillover from Nigerian stock market to Ghanaian stock market is measured by (ϕ_{Gha}) while from Ghanaian stock market to Nigerian stock market.

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The Conditional Variance Equation [GARCH (1, 1)]:

$$H_t = W + A\varepsilon_{t-l}^2 + CI_{t-1}\varepsilon_{t-l}^2 + BH_{t-l}$$

where $H_t = \left(h_{Gha,t}, h_{Nig,t}\right)'$, $\varepsilon_t^2 = \left(\varepsilon_{Gha,t}^2, \varepsilon_{Nig,t}^2\right)'$, and W , A, and B are (2×2) matrices of constants, ARCH effects and GARCH effects respectively. Equation (13) can be further simplified into individual conditional variance equations for the two-return series as described below (see Arouri et al., 2011):

$$h_{1t} = c_1 + \alpha_{11}\varepsilon_{1t-1}^2 + \gamma_1\varepsilon_{1t-1}^2 I_{1,t-1} + \alpha_{12}\varepsilon_{2t-1}^2 + \beta_{11}h_{1t-1} + \beta_{12}h_{2t-1} \quad (17)$$

$$h_{2t} = c_2 + \alpha_{21}\varepsilon_{1t-1}^2 + \alpha_{22}\varepsilon_{2t-1}^2 + \gamma_2\varepsilon_{2t-1}^2 I_{2,t-1} + \beta_{21}h_{1t-1} + \beta_{22}h_{2t-1} \quad (18)$$

The parameters in equations (5), (8), (10) and (13) can be reached by maximum likelihood estimation (MLE) using a joint normal density, given as

$$\hat{\theta} = \arg\min \frac{1}{2}\sum_{t=1}^{n}(\log|Q_t| + \varepsilon_t^r Q_t^{-1}\varepsilon_t) \quad (19)$$

Where $|Q_t|$ represents the determinant of Q_t, the conditional covariance matrix. While θ is the vector of parameters to be estimated on the conditional log-likelihood function. The major reason for chosen the QMLE is not far from the fact that η_t is assumed to be non-normal. However, when the distribution of η_t does not follow a joint multivariate normal, then the appropriate estimator is the QMLE.

Results

The results of the Asymmetric VARMA (1,1) GARCH are presented in table 3. We also estimate Symmetric VARMA (1,1) GARCH to compare their performance using the standard model selection criteria (i.e. SIC, AIC and Hannan-Quin). The results are presented in table 4. As depicted in the table, the Asymmetric VARMA (1, 1)-GARCH appears to give the best fit among the two models based on the information criteria. Our interpretation of the Asymmetric VARMA (1,1)-GARCH results essentially focuses on three issues: return spillovers, shock spillovers and shock persistence (both short run and long run). Table 5 presents the post-estimation diagnostics which serve as an additional check in choosing the desirability model.

Table 3: Asymmetric VARMA- GARCH Results

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Variables	Ghana's stocks	Variables	Nigeria's stocks
Mean Equation			
μ_{Gha}	0.00825*(0.000)* *	μ_b	-0.01749*(0.000)* *
ϕ_{Gha}	-0.17366*(0.000)* *	ϕ_b	-0.0088*(0.000)* *
θ_{Gha}	0.00347*(0.000)* *	θ_b	0.29829*(0.000)* *
Variance Equation			
c_1	0.07355*(0.000)* *	c_2	0.08018*(0.000)* *
α_{11}	0.31775*(0.000)* *	α_{21}	-0.04766*(0.000)* *
α_{12}	0.1909*(0.000)* *	α_{22}	0.24065*(0.000)* *
β_{11}	0.70893*(0.000)* *	β_{21}	0.02711*(0.000)* *
β_{12}	1.17495*(0.000)* *	β_{22}	0.70582*(0.000)* *
γ_1	-0.02023*(0.000)* *	γ_2	-0.03611*(0.000)* *
Long run shock Persistence	1.027	Long run shock Persistence	-0.02055
CCC between Nigerian stock & Ghanaian stock	0.04888*(0.000)* *		

Note: * represents Statistical significance at alpha level.

Table 4: Model selection Criteria

Information Criteria	Asymmetric VARMA-GARCH (1,1)	VARMA-GARCH (1,1)
AIC	4.163	4.178
SBC	4.208	4.218
Hannan-Quinn	4.179	4.192
(log) FPE	4.163	4.178

Note: * represents Statistical significance at alpha level.

Diagnostics

The results from the post diagnostic tests in table 5 shows that there are no left over of ARCH effects in the return series for both Nigerian stocks and the Ghanaian stocks after the estimation of the Asymmetric VARMA CCC-GARCH. The McLeod-Li tests and the Ljung-Box tests for Nigerian stocks indicate no evidence of ARCH effect and presence of serial correlation at both 2

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and 5 lags. Similarly, stock returns for Ghana also shows no evidence of ARCH effect at both 2 and lags, but the null of serial independence is rejected (see Salisu and Isah, 2016).

Table 5: Diagnostics (Post-Estimation)

Independence Tests for Ghana's return series		Independence Tests for Nigeria's return series	
Test	Statistic	Test	Statistic
Ljung-BoxQ (2)	2.18259(0.3358)	Ljung-Box Q (2)	6.4592678(0.0396) *
Ljung-Box Q (5)	5.13972(0.3991)	Ljung-Box Q (5)	15.410595(0.0087) *
McLeod-Li (2)	0.03673(0.9818)	McLeod-Li (2)	2.3843557(0.3036)
McLeod-Li (5)	0.05984(1)	McLeod-Li (5)	5.902892(0.3158)

Note: * represents Statistical significance at alpha level.

Return Spillovers

As observed from the results of the Asymmetric VARMA-GARCH model presented in Table 3, the return spillover from Nigerian stock to Ghanaian stock (θ_e) is estimated as 0.00347and statistically significant with positive sign. Holding all things constant, a 1% increase in Nigerian stock market returns will increase Ghanaian stock market returns in the upcoming month by approximately 0.003% on average. Similarly, the return spillover from Ghanaian stock to Nigerian stock (θ_b) is estimated as 0.29829 and found to be statistically significant with positive sign. This suggest that a 1% increase in Ghanaian Stock market returns will increase Nigerian stock market returns in the upcoming month by approximately 0.3% on average. Overall, the return spillover estimates are statistically significant, suggesting that the returns in the Ghanaian stock market significantly influence returns in the Nigerian stock market. This finding further confirms that the Nigeria’s stock market and Ghana’s stock markets are functionally dependent and the spillover effect from Ghana stock market to Nigeria stock market is stronger than from Nigeria to Ghana in absolute value. Nonetheless, the own lagged returns for both Nigeria and the Ghanaian stock market in the conditional mean equations help to ensure that spillover effects are not confounded with serial dependence. The result suggests that a percentage decline in the return of the Ghanaian stock market in the previous month leads to 0.17 per cent increase in the current period return in its own market. Similarly, a percentage fall in the previous month returns of the Nigeria stock market leads to a 0.0088 per cent increase in current period returns in its

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own market. The one period lagged own return estimated coefficient are negative and statistically significant. In addition, the result suggests that investors should take advantage of the immediate past returns of own markets in their investment decisions.

Shock Spillovers and Persistence of Shocks

When looking at the shock spillovers and persistence of shocks, the most prioritizes parameters are the ARCH (α_{ij}) and GARCH (β_{ij}) terms [$i, j = 1, 2$] and the parameters are all statistically significant. Specifically, lagged own shocks (α_{ii}) and lagged own conditional variance (β_{jj}) for all values of [$i = 1, 2$] significantly and positively influence the volatilities of the two stock markets.

The volatilities of Ghanaian stock market return and Nigerian stock market returns are sensitive to both past own shocks as well as past own conditional variance. In clear terms, volatilities in these two stock markets may be heightened by their own shocks. The implications of these findings include: (1) unanticipated events in the Ghanaian market in the current period, for example, can increase the level of volatility in the market in the immediate succeeding period. (2) Volatility of the market in one period has the potentiality of driving a higher volatility in the immediate later period.

Similarly, we find evidence for significant shock spillovers between the two countries stock markets. Considering the shock spillovers and looking at the Nigerian stock market returns, the result shows that a 1% increase in the shocks to Nigerian stock market returns in the current month will increase the volatility of Ghanaian stock market returns by 0.2% in the upcoming month. However, the shock spillover from Ghanaian stock returns to Nigerian stock market returns seems higher (although marginally) as a 1% increase in the shock to Ghanaian stock returns in the current period is likely to increase the volatility of Nigerian stock market returns by 0.24% in the upcoming month. Nonetheless, the cross-country stock market shock spillovers are both positive and statistically significant. In other words, there is possibility of contagion effect between stock market returns of both Ghana and Nigeria.

In terms of persistence of shocks, we find that Ghana's stock returns appear to experience higher long run shock persistence than the Nigeria's Stock market returns. The magnitude of the long run persistence of shocks to Ghana's stock returns is greater than one (1.027) implying that shocks have persistent effects on Ghana's stock and are likely not to die out overtime and thus are permanent. However, the long run persistence of shocks to Nigerian stock market returns is small (0.02055); therefore, indicating strong mean reversion.

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The magnitude of the short run persistence of shocks for Nigeria stock market returns is estimated as 0.04766 which is quite small compared to Ghana's stock market returns which is 0.1909. This implies that, a more distinct shock which is expected in the short run would have persistent effects on the returns of the Ghanaian stock market in the short run. Finally, the constant conditional correlation coefficient between Nigerian and Ghana's stock is (0.04888) and statistically significant; thus, validating the assumption of constant correlations between both countries stock markets.

In summary, the following conclusions are apparent from the results: (1) Generally, the Ghanaian stock market is more sensitive to shocks than Nigerian stock market judging by both the long run and short run persistence of shocks. This is understandable given the size of the Nigeria economy and the magnitude of foreign portfolio investments into Nigerian. (2) Also, there is a significant contagion effect between the Ghanaian stock market and the Nigerian stock market. In other words, a shock to the Ghanaian market is more likely to spill over to Nigerian stock market; thus, resulting into a higher volatility in the Nigerian stock market. (3) We also find evidence of cross transmission of spillover effect between Nigeria and Ghana stock market. Nevertheless, we recommend more studies to examine the transmission mechanism in order to reveal the supposed complex interactions between Ghana and Nigeria stock markets.

Conclusion

The objective of this paper is to examine the extent of return and shock spillovers between Ghanaian stock market and Nigerian stock market using daily data for the period January 2009 to October 2018. To model the spillovers, we used the Asymmetric VARMA-GARCH model after conducting the Asymmetry CCC test and the model selection criteria. Our main findings are as follows.

First, Ghanaian stock market is more volatile than the Nigerian stock market. Second, shocks to Ghanaian stock market returns tend to persist when they occur while shocks to Nigerian stock market returns tend to die out over time. There are two implications of these findings: (i) these findings imply that the behaviour of Ghanaian stock market returns tends to change over time while that of the Nigerian stock market appears stable; and (ii) it then follows that investors need to consider this nature of Ghana's and Nigeria's stock market behaviour when making investment decisions.

Lastly, we find significant cross-transmission between two countries market returns and shock spillovers although the Ghanaian stock market volatility seems more sensitive to Nigerian stock market volatility than it is from the former to the latter. In addition, both Ghanaian and the Nigerian stock markets is more susceptible to internal shocks than a cross boarder shock.

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