Stock Market Volatility Clustering and Asymmetry in Africa: A Post Global Financial Crisis Evidence

Emenike, Kalu O.

Kampala International University

7 October 2018

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Kalu O. Emenike
Department of Accounting and Finance
Kampala International University
P.O. Box 20000, Kampala
Uganda
emenikekaluonwukwe@yahoo.com

Abstract

This paper evaluates the nature of stock market volatility in Africa after the global financial crisis. Specifically, the paper examines volatility clustering and volatility asymmetry in aftermath of the global financial crisis for Botswana, Régionale des Valeurs Mobilières (BRVM), Egypt, Ghana, Kenya, Malawi, Mauritius, Morocco, Namibia, Nigeria, Rwanda, South Africa, Tunisia, Uganda, and Zambia. The paper employs autoregressive asymmetric generalized autoregressive conditional heteroscedasticity (AR(i)-GJR-GARCH(1,1)) model. The major findings are as follows: (i) there is evidence of volatility clustering in Africa stock markets returns after the global financial crisis, although with varying degrees; (ii) there is existence of volatility persistence in the African stock market returns after the global financial crisis except for few countries, which are not very persistent; (iii) after the global financial crisis, Africa stock markets returns are asymmetric, with negative shocks producing higher volatility in the immediate future than positive shocks of the same magnitude in some countries, and positive shocks producing higher volatility in other countries. The findings provide comparative basis for assessing market patterns, predicting market risk, and gauging market sentiment in Africa stock markets, as well as provide foreign portfolio managers required evidence for harvesting volatility through portfolio rebalancing for optimal performance.

JEL Classification Numbers: G10, C22, N27
Keywords: stock market returns, volatility clustering, asymmetry, GARCH models, Africa

1 Introduction

Stock market plays important roles in stimulating economic development through providing channel for mobilising domestic savings and facilitating allocation of financial resources from dormant to more productive activities. Understanding the nature of Africa stock market volatility has become more pertinent because of devastating impact of Global financial Crisis (GFC) on investors' wealth and confidence. Bekaert, Ehrmann, Fratzscher and Mehl (2014) observe that the financial crisis of 2007 to 2009 is arguably the first truly major global crisis since the Great Depression of 1929 to 1932. While the crisis initially had its origin in the subprime mortgage market in United States, it rapidly spread across virtually all economies as well as across economic sectors. Emenike (2017) observes that Nigeria stock market, for example, collapsed by 70% and so many retail investors lost confidence in the stock market and exited, institutional investors adjusted their portfolios towards money market instruments and real estate. Uganda Stock Exchange (USE) also witnessed exit of both foreign and local investors resulting mainly from panic sales. Ssewanyana, Bategeka, Twimukye and Nabiddo (2009) note that USE all share index fell by 30% in February-June 2008 before losing 39% in July-October 2008, with the month of October 2008 recording the biggest loss of 28%. Although there is a significant disparity between the level of development, size and liquidity of exchanges across Africa, the GFC had devastating effect on equity markets in Africa, with many countries experiencing even sharper stock market crashes than Nigeria and Uganda exemplified above.

Volatility is one of the enduring characteristics of stock markets, though it changes with time. High volatility implies that stock prices can change dramatically over a short time period in either direction, and low volatility suggests that stock prices do not fluctuate dramatically, but changes in price at a steady pace over a period of time. Stock return volatility, according to Martin, Hansen, Link and Nicoski (2011), gives shrewd investors opportunity to take advantage of price swings to buy when prices fall well below intrinsic and sell otherwise. Similarly, Horan (2012) reports that volatility actually creates alpha-generating rebalancing opportunities for any core portfolio. Portfolio managers therefore can harvest more volatility through portfolio rebalancing as the volatility increases. Volatility therefore plays important roles in gauging market sentiment and forecasting of risk for relevant assets prices and market indices. Degiannakis and Xekalaki (2004) posit that predicting volatility is of great importance in pricing financial derivatives, selecting portfolios, measuring and managing investment risk more accurately. There is therefore need for continual evaluation of volatility.

Many scholars have actually conducted studies on volatility for various stock markets in Africa (see for example, Emenike, 2010; Namugaya, Weke & Charles, 2014; Kais, 2015; Owidi & Mugo-Waweru, 2016). Many other studies have also examined volatility behaviour in few Africa markets (see, Abdalla & Winker, 2012; Tah, 2013). But majority some of these studies were conducted before the GFC or used data that overlap the period of GFC. African stock markets have shown improvement after the GFC. According to Africa Stock Exchanges Association Yearly Statistics, the total number of transactions in Botswana stock exchange, for example, increased from 4978 in 2010 to 12907 in 2015, with turnover ratio (%) increasing from 3.5% to 6.2% in the same period. Similarly, total number of transactions in Bourse Régionale des Valeurs Mobilières (BRVM) exchange moved from 22315 in 2010 to 39352 by 2014, with turnover ratio (%) increasing from 1.8% to 2.5% in the same period. These improvements in Africa stock markets may also have changed the nature of volatility. Again, there is need for comparative studies on stock market volatility in Africa to provide basis for assessing market patterns, predicting market risk and gauging market sentiments, as well as provide foreign portfolio managers evidence for harvesting volatility through rebalancing of their investment portfolio for optimal performance.

The purpose of this paper is to evaluate the nature of stock market volatility in selected Africa countries after the global financial crisis. Specifically, the study aims at establishing the nature of volatility clustering, persistence and asymmetry in Botswana, BRVM, Egypt, Ghana, Kenya, Malawi, Mauritius, Morocco, Namibia, Nigeria, Rwanda, South Africa, Tunisia, Uganda, and Zambia. Understanding volatility behaviour in Africa stock markets would, for example, provide basis for investors (both national and international) to select combination of securities that will minimise their portfolio risk. It would also enhance stock market regulation as the regulators would gauge markets sentiments and adjust surveillance regime to keep excessive volatility under check, thereby stabilise the markets. It will further enrich existing knowledge on stock market volatility in Africa as well as provide literature for future researchers. The remainder of this paper is organised as follows: Section 2 embodies brief review of empirical literature. Section 3 contains methodology and data. Section 4 presents empirical results and discussions, and Section 5 provides conclusions and policy implication.

2 Brief Review of Empirical Literature

A considerable amount of literature exists on stock market volatility for various African countries. These studies were motivated by the important link between volatility and expected risk premium. Theoretically, an increase in volatility will increase the expected risk premium and thereby affect cost of capital. Evidence-based knowledge of volatility is therefore important for risk management and portfolio rebalancing. This importance has been established in literature. Mecagni and Sourial (1999) apply GARCH-in-mean model in their analysis of stock market efficiency and volatility in the Egyptian Stock Exchange using four indices for the September 1, 1994 to December 31, 1997 period. They report, amongst others, the existence of time-varying volatility that are serially correlated. In a related study, N'dri (2007) evaluates the relationship between stock market returns and volatility in the BRVM using weekly stock prices from 4 January 1999 to 29 July 2005. The results show, amongst others, the existence of stock market volatility persistence in BRVM. In a study of Mauritius Stock Exchange, Ushad (2009) also agrees that the market exhibit volatility clustering. In a study of volatility in Nigeria stock market, Emenike and Aleke (2012), using symmetric and asymmetric GARCH (1,1) models show evidence of volatility clustering and volatility persistence. A Similar study by Niyitegeka and Tewari (2013) for the Johannesburg Stock Exchange (JSE) indicate the presence of volatility clustering in the JSE, but could not establish asymmetric effect. In East Africa, Namugaya, Weke and Charles (2014), for example, modeled volatility of Uganda securities exchange (USE) returns using both symmetric and asymmetric univariate GARCH models for the period ranging from January 04 2005 to December 18 2013. The study concludes, among others, that the USE return series exhibit volatility clustering and leverage effects. In a Tunisian study, Kais (2015) analyse the volatility behavior for the January 1984 to June 2010 period. The results indicate that the Tunisian stock returns are highly volatile and moves in cluster. He concludes that volatility changes over time. In a later study, Owidi and Mugo-Waweru (2016) found evidence of volatility clustering and asymmetry in the Kenyan stock exchange market returns for the 3rd January 2003 to 31st December 2013 period.

Many other studies have also examined volatility behaviour in few Africa markets. Ogum, Beer and Nouyrigat (2005) study emerging market volatility using Nigeria and Kenya stock return series. Results of asymmetric GARCH model show evidence of negative asymmetric volatility in the Nigeria stock market and positive asymmetric volatility in Kenya, suggesting that positive shocks increase volatility more than negative shocks of an equal magnitude in Kenya. They also report evidence of volatility persistence in the two markets. In a similar study, Abdalla and Winker (2012) estimate stock market volatility in Khartoum Stock Exchange Sudan (KSE) and Cairo and Alexandria Stock Exchange Egypt (CASE) using daily closing prices of the general indices in the two markets over the period of 2nd January 2006 to 30th November 2010, and found, among others, evidence of volatility clustering and existence of leverage effects for the KSE index and CASE index returns series. Tah (2013) found similar evidence for Kenya and Zambia stock indices for February 1997 to October 2012 period. In recent study, Coffie (2018) reports amongst others, that the current shocks to the conditional variance have less impact on future volatility in Botswana and Namibia stock markets, and that news impact is asymmetric in both stock markets leading to the existence of leverage effect in stock returns. It is evident from the brief literature review that empirical literature covering many African countries is scant.

3 Methodology and Data

3.1 Methodology

To analyse volatility behaviour of Africa stock markets, preliminary analysis of returns data and asymmetric generalized autoregressive conditional heteroscedasticity (GJR-GARCH) models were conducted. The preliminary analysis of returns data involved estimating descriptive statistics, autocorrelation function (ACF), Ljung-Box Q (LBQ) statistics; unit roots tests, and heteroscedasticity test (For specification of descriptive statistics see, Jarque & Bera, 1987; Gujarati, 2003:148; Tsay, 2005:9-10). Augmented Dickey-Fuller (ADF) unit root test (from Dickey & Fuller, 1979) and KPSS stationarity test (from Kwaitkowski, Phillips, Schmidt & Shin, 1992) were used to evaluate the nature of stationarity of Africa stock markets series.

The ACF and LBQ statistic were adopted to examine Africa stock markets returns for serial correlation. The ACF measures linear dependence between returns at current period and its past periods. Evidence of serial correlation in market returns series is necessary to specify the apt conditional mean equation. If the return series (R_t) is uncorrelated sequence, the *p*-value is greater than the significance level (0.05). The lag-*i* sample autocorrelation of R_t was specified according to Tsay (2005:26). To test jointly that several autocorrelations of R_t are zero, we adopted Ljung-Box Q (LBQ) test proposed in Ljung and Box (1978). The null hypothesis is that the first *m* lags of ACF of ε_t^2 are zero (Tsay, 2005:27). The decision rule is to reject null hypothesis if the *p*-value is less than or equal to the significance level.

Existence of heteroscedasticity is a *sin qua non* for estimating GARCH models. As a result, it is necessary to confirm that residuals of a conditional mean equation is heteroscedastic (i.e., ARCH effect). Engle (1982) proposed the autoregressive conditional heteroscedasticity Lagrange Multiplier (ARCH-LM) test for examining whether a residual series is heteroscedastic. The ARCH-LM was estimated in accordance with Engle (1982), Tsay, (2005:102) and Rachev, Mittnik, Fabozzi, Focardi & Jasic (2007: 281). The decision rule is to reject the null hypothesis of no heteroscedasticity if the *p*-value is less than the level of significance. Evidence of no heteroscedasticity is an indication that GARCH models are not appropriate.

The GJR-GARCH (1,1), introduced by Glosten, Jagannamthan & Runkle (1993), was applied to investigate volatility asymmetry in Africa stock markets after the GFC. This was achieved by specifying the conditional mean model thus:

$$R_t = \phi + \delta R_{t-i} + \varepsilon_t \quad (1)$$

Where, R_t is a vector of Africa stock markets returns, δ is the coefficient of AR (*p*) term in the mean equation that accounts for serial dependence in returns, ε_t is the error term. The asymmetric conditional variance equation models are specified as follows:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \mu_{t-1}^2 \mathrm{I}_{\mu < 0}(\mu_{t-1}) \quad (2)$$

Where, ω is constant of the variance that correspond to long run average variance, α_1 is the first order ARCH term which transits news about volatility from the previous period, and β_1 the first order GARCH term, is the new information that was not available when the previous forecast was made (Engle, 2003), γ is the GJR-GARCH asymmetric coefficient that measures volatility asymmetry. The non-negativity constraints of the univariate GARCH models are $\omega > 0$, $\alpha_1 > 0$ and $\beta_1 \geq 0$. The parameters were estimated using the BHHH maximum likelihold algorithm (recommended in Berndt, Hall, Hall & Hausman, 1974) with correction for heteroscedasticity and misspecification.

Statistical significance of the volatility parameters were tested with marginal significance level and *t*-statistics. Under the null hypothesis of no volatility clustering in the African stock market returns, the marginal significance level is greater than the significance level (0.05), and the empirical *t*-statistics is lesser than theoretical *t* (±1.96). The $\alpha_1 + \beta_1$ show persistence in volatility clustering and ranges from *0* to *1*. The closer ($\alpha_1 + \beta_1$) to *1*, the more persistent is volatility clustering. Evidence volatility asymmetry were evaluated with GJR-GARCH (1,1) parameter specified in equation (2). With this formulation, a zero γ coefficient would imply that positive and negative shocks of the same magnitude have the same effect on volatility of Africa stock market returns. The effect of a volatility shock is asymmetric if $\gamma \neq 0$. A positive value of γ means that negative shock tend to increase the volatility in the immediate future more than positive shock of the same magnitude. The converse would hold if the value of γ were negative (Emenike, 2016).

3.2 Data

The stock price indices used in this study are broad-based and represent each of the selected Africa stock market as whole. The indices are: BSE Domestic Company index of Botswana, Bourse Régionale des Valeurs Mobilières (BRVM)[1] Composite Index, Egypt Stock market EGX30, GSE Composite index of Ghana, Nairobi Securities Exchange All Share index of Kenya, Malawi Stock Exchange All share index, Stock Exchange of Mauritius Index (SEMDEX), Casablanca Stock Exchange MASI of Morocco, Namibian All Share index, NSE All Share index for Nigeria, Rwandan All Share index, FTSE South Africa, Bourse de Tunis index (Tunindex) of Tunisia, Uganda Securities Exchange All Share index, and Lusaka Stock Exchange All Share index of Zambia. The indices are daily and range from 04 January, 2010 to

[1] The Bourse Régionale des Valeurs Mobilières (BRVM) is one of Africa two regional stock exchanges, located in Abidjan, Cote d'Ivoire. The BRVM serves the countries of Benin, Burkina Faso, Guinea Bissau, Côte d'Ivoire, Mali, Niger, Senegal and Togo.

31 December, 2015; except for Ghana series which starts from 04 January 2011, Uganda series from 12 August 2011, BRVM series from 04 March 2014, Malawi from 28 October 2013, Rwanda from 08 February 2013, and Zambia from 09 July 2012. The variations in the study periods across countries arose due to unavailability of data resulting from different stages of development of African stock markets. The data were collected from individual stock exchanges as well as from Investing Africa and Trending Economics databases, and converted into daily returns as follows:

$$R_t = Ln(P_t - P_{t-1}) \times 100 \qquad (3)$$

Where, R_t is a vector of daily returns of the country indexes specified in equation (1), P_t is a vector of closing price indexes at time t, P_{t-1} is the previous day closing price indexes, and *Ln* is natural logarithm.

4 Empirical Results and Discussions

4.1 Descriptive Statistics of Africa Stock Markets Returns

Table 1 reports descriptive statistics of Africa stock markets returns. Average percentage returns for all the stock markets are zero, except for Botswana, Ghana, Malawi and Zambia stock markets which are positive.

Under null hypothesis of normal distribution, skewness has asymptotic distribution of zero. The skewness of daily Africa stock markets returns differs significantly from the normal distribution in majority of the bourses. While majority of the Africa stock markets returns distribution is significantly negatively skewed at the 5% significance level, the Nigeria and Zambia stock markets returns are significantly positively skewed. However, for the stock markets of Mauritius, Morocco, South Africa, and Uganda, the distributions of returns are not skewed. Liu, Zhang and Wen (2014) opine that negatively skewed return distribution will increase the loss probability, while the positively skewed return distribution will increase the possibility of gaining.

Excess kurtosis of daily returns for all selected Africa stock markets are leptokurtic. This shows that they have higher peaks about the mean and thicker tails than the normal distribution. An implication of thick tails, according to Wilcox and Keselman (2003) and Hung, Lee and Liu (2008), is that investors can make very high returns and as well lose large amount of their investments.

Furthermore, estimates of Jarque-Bera joint test of symmetry and mesokurtosis indicate evidence of non-normality in daily Africa stock market returns.

Table 1: Descriptive Statistics for Africa Stock Markets Returns

Variable	Mean	Min. rtn.	Max. rtn.	Std. Dev.	Skewness	Kurtosis	J-B Stat.
Botswana	0.024	-4.774	4.239	0.331	-1.7651	59.589	231616.7
	(0.003)				(0.000)	(0.000)	(0.000)
BRVM	0.048	-3.602	3.399	0.757	-0.221	4.620	407.528
	(0.173)				(0.055)	(0.000)	(0.000)
Egypt	0.003	-11.11	7.314	1.445	-0.788	6.994	3502.454
	(0.929)				(0.000)	(0.000)	(0.000)
Ghana	0.053	-0.046	0.038	0.621	-0.244	43.822	104037.2
	(0.002)				(0.000)	(0.000)	(0.000)
Kenya	0.047	-33.72	32.007	1.522	-1.048	313.289	6101963
	(0.229)				(0.000)	(0.000)	(0.000)

Malawi	0.036 (0.007)	-3.054	2.934	0.306	-0.357 (0.000)	42.175 (0.000)	38922.59 (0.000)
Mauritius	0.006 (0.543)	-3.232	3.311	0.376	-0.042 (0.502)	10.541 (0.000)	6913.65 (0.000)
Morocco	-0.024 (0.139)	-3.034	2.957	0.602	0.008 (0.896)	2.446 (0.000)	349.335 (0.000)
Namibia	0.006 (0.831)	-8.298	5.892	1.259	-0.454 (0.000)	3.219 (0.000)	696.601 (0.000)
Nigeria	0.020 (0.422)	-8.741	11.758	1.003	0.941 (0.000)	19.837 (0.000)	25874.89 (0.000)
Rwanda	0.010 (0.789)	-11.26	17.712	0.995	0.061 (0.510)	171.64 (0.000)	862286.8 (0.000)
South Africa	0.038 (0.127)	-4.150	5.536	0.992	-0.105 (0.090)	1.855 (0.000)	227.157 (0.000)
Tunisia	0.001 (0.927)	-4.143	4.108	0.578	-0.665 (0.000)	13.394 (0.000)	10802.6 (0.000)
Uganda	0.053 (0.179)	-9.396	8.036	1.344	-0.381 (0.888)	6.680 (0.000)	1936.24 (0.000)
Zambia	0.046 (0.042)	-6.086	2.924	0.650	-1.008 (0.000)	14.298 (0.000)	7332.66 (0.000)

Note: Marginal significance levels are reported in brackets. Std. Dev. and J-B Stat are the standard deviation and Jarque-Bera statistics for the Africa stock markets returns.

4.2 Unit Root Tests for the Africa Stock Markets Price Indices

Table 2 presents results of ADF unit root test and KPSS stationarity test estimated to evaluate stationarity of African stock markets indices. As shown in *Table* 2, computed tau values of the ADF test statistics show that African stock markets level series contain unit root at the 5% significance level. This suggests that African stock markets level series are not stationary. However, African stock markets returns series do not contain unit root, implying that they are stationary. This is because the computed absolute values of the return series are less than the ADF 5% critical tau values. The KPSS stationarity test shows that African stock markets returns series are stationary with 99% confidence, thus confirm the results of ADF test. These results indicate that the African stock markets returns series are integrated of order *1*.

Table 2: Unit Root Tests Results for Africa Stock Markets Series

Variables	ADF 5%	Computed	KPSS 5%	Computed
		Log-level Series		
Botswana	-3.4152	-2.0579	0.1460	4.2235**
BRVM	-3.4215	-2.7101	0.1460	0.8865**
Egypt	-3.4150	-1.8542	0.1460	4.2642**
Ghana	-3.4157	-0.0369	0.1460	2.6246**
Kenya	-3.4153	-1.0759	0.1460	3.2886**
Malawi	-3.4203	-1.7659	0.1460	1.2760**
Mauritius	-3.4153	-1.0071	0.1460	1.3471**
Morocco	-3.4154	-1.7265	0.1460	4.2062**
Namibia	-3.4153	-2.6263	0.1460	0.8153**
Nigeria	-3.4151	-1.1073	0.1460	2.6972**

Rwanda	-3.4184	-1.7108	0.1460	1.8714**
South Africa	-3.4156	-1.4646	0.1460	3.4625**
Tunisia	-3.4154	-2.0391	0.1460	2.0446**
Uganda	-3.4165	-1.5123	0.1460	2.3365**
Zambia	-3.4174	-0.3011	0.1460	3.0326**
Return Series				
Botswana	-3.4152	-13.0056**	0.1460	0.0963
Cote d'Ivoire	-3.4216	-24.1487**	0.1460	0.0554
Egypt	-3.4151	-35.7040**	0.1460	0.1103
Ghana	-3.4157	-10.4005**	0.1460	0.0948
Kenya	-3.4153	-26.1223**	0.1460	0.1325
Malawi	-3.4204	-22.8124**	0.1460	0.0886
Mauritius	-3.4153	-29.7487**	0.1460	0.1317
Morocco	-3.4155	-33.0752**	0.1460	0.0769
Namibia	-3.4153	-40.2051**	0.1460	0.0634
Nigeria	-3.4152	-25.0341**	0.1460	0.1389
Rwanda	-3.4184	-37.2538**	0.1460	0.0586
South Africa	-3.4156	-30.7779**	0.1460	0.0411
Tunisia	-3.4154	-28.2463**	0.1460	0.0638
Uganda	-3.4165	-34.7546**	0.1460	0.1181
Zambia	-3.4174	-24.1657**	0.1460	0.1206

Note: ** refers to 1% statistical significance level. ADF and KPSS are the 5% critical tau value of the augmented Dickey-Fuller unit root test and Kwiatkowski, Phillips, Schmidt and Shin stationarity test.

4.3 Autocorrelation and Lag Analyses for African Stock Markets Returns

Table 3 displays ACF for the Africa stock markets returns series, and Ljung-Box Q-statistic used for joint testing of significance of the ACF coefficients. The lag lengths selected by Schwarz/Bayesian Information Criterion (BIC) is approximately 70 lags, except for except for Uganda which is 64 lags, BRVM Cote d'Ivoire 42 lags, Rwanda 52 lags, and Zambia 58 lags. The results of independence tests conducted using Ljung-Box Q-statistic indicate that African stock markets return series are serially correlation at the 5% significance level, except for BRVM, Namibia and Uganda. The existence of serial correlation in Africa stock markets returns series is suggests autoregressive (AR) specification in the mean model..

Table 3: Autocorrelation and Ljung-Box Q-Statistics for African Stock Market Returns

Lags	1	10	20	30	40	50	60	70
Botswana	0.09	0.03	0.00	-0.02	0.03	-0.02	0.01	-0.00
	[14.3]	[121.4]	[134.0]	[139.8]	[149.3]	[155.2]	[160.9]	[167.2]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BRVM	-0.12	0.01	-0.03	-0.02	-0.01	-0.08	-0.00	-0.01
	[7.3]	[15.3]	[19.1]	[29.1]	[35.5]	[43.7]	[58.3]	[72.9]
	(0.00)	(0.12)	(0.51)	(0.50)	(0.66)	(0.72)	(0.53)	(0.38)
Egypt	0.12	0.03	0.00	-0.03	-0.00	0.02	0.03	-0.02
	[24.6]	[40.9]	[48.4]	[65.6]	[80.6]	[84.9]	[92.2]	[98.7]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Ghana	0.14	0.13	0.04	0.07	0.05	0.04	0.01	0.02
	[27.9]	[210.1]	[292.0]	[358.8]	[404.0]	[418.2]	[427.5]	[450.8]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Kenya	0.37	-0.00	0.01	0.01	0.03	0.04	-0.01	0.06
	[205.5]	[248.6]	[257.2]	[267.5]	[379.7]	[399.8]	[413.8]	[434.5]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Malawi	0.03	0.03	-0.00	0.04	-0.02	-0.01	0.02	0.02
	[0.6]	[18.4]	[44.0]	[50.6]	[63.2]	[85.5]	[96.2]	[100.1]
	(0.40)	(0.04)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
Mauritius	0.25	0.03	-0.01	-0.02	-0.02	0.03	0.04	-0.01
	[99.7]	[122.7]	[135.7]	[145.2]	[172.3]	[186.7]	[234.0]	[238.1]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Morocco	0.12	0.06	0.04	0.01	-0.01	-0.04	-0.04	-0.03
	[20.6]	[42.5]	[59.2]	[66.9]	[75.3]	[83.1]	[91.9]	[106.2]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Namibia	-0.04	0.02	-0.00	-0.05	0.03	-0.04	-0.03	-0.05
	[2.4]	[15.5]	[22.4]	[41.8]	[48.7]	[61.5]	[79.3]	[89.9]
	(0.12)	(0.11)	(0.31)	(0.07)	(0.16)	(0.12)	(0.04)	(0.05)
Nigeria	0.02	0.01	0.02	0.03	0.05	-0.01	-0.02	-0.08
	[144.6]	[148.7]	[182.2]	[208.3]	[253.1]	[276.3]	[293.0]	[328.0]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Rwanda	-0.32	0.01	-0.04	-0.07	0.01	0.04	-0.15	0.01
	[74.6]	[100.6]	[109.2]	[117.3]	[127.7]	[123.2]	[185.0]	[219.3]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
South Africa	-0.04	0.01	0.00	-0.05	0.04	-0.00	0.04	0.02
	[2.8]	[19.8]	[25.4]	[39.1]	[50.5]	[54.9]	[71.8]	[77.3]
	(0.08)	(0.03)	(0.18)	(0.12)	(0.12)	(0.29)	(0.14)	(0.25)
Tunisia	0.28	0.01	0.07	-0.00	-0.02	0.01	0.00	0.05
	[113.6]	[144.1]	[203.8]	[211.1]	[216.1]	[272.6]	[284.5]	[317.1]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Uganda	0.00	0.04	-0.00	0.02	0.05	-0.00	-0.02	-0.02
	[0.00]	[4.8]	[15.8]	[28.2]	[47.4]	[52.9]	[66.1]	[72.6]
	(0.99)	(0.90)	(0.72)	(0.55)	(0.19)	(0.36)	(0.27)	(0.39)
Zambia	-0.08	-0.01	-0.01	0.04	-0.04	-0.01	-0.01	0.03
	[6.7]	[31.9]	[55.1]	[78.9]	[85.1]	[93.5]	[105.2]	[114.7]
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: Autocorrelation coefficients were estimated for each lag. Ljung-Box Q-statistics are presented in the square brackets [.] and their significance levels are shown in the brackets (.). The autocorrelation lag lengths are selected using BIC.

Table 4 reports Schwarz/Bayesian Information Criterion (BIC) lag analysis for Africa stock markets returns series. Rachev *et al* (2007:293) state that if the conditional mean is not specified adequately, then the construction of consistent estimates of the true conditional variance would not be possible and statistical inference and empirical analysis might be wrong. To provide a correct specification of the mean model, lags 1 to 6 of BIC were estimated. Notice from *Table 4* that returns series of Malawi, Namibia, South Africa and Uganda do not require any lag. For the stock markets returns of BRVM, Egypt, Morocco, Rwanda, and Tunisia, BIC selected lag 1. The Kenya, Nigeria and Zambia stock markets require lag 2 to contain serial dependence. The BIC selected 5e and 6 autoregressive lags for Botswana and Ghana respectively.

Table 4: Bayesian Information Criterion Lag Selection for African Stock Market Returns

	0	1	2	3	4	5	6
Botswana	-2.205	-2.209	-2.213	-2.212	-2.224	-2.228*	-2.224

BRVM	-0.543	-0.546*	-0.533	-0.524	-0.511	-0.498	-0.484
Egypt	0.741	0.730*	0.735	0.734	0.738	0.742	0.746
Ghana	-1.238	-1.254	-1.262	-1.266	-1.267	-1.266	-1.270*
Kenya	-0.740	-0.883*	-0.879	-0.875	-0.870	-0.865	-0.861
Malawi	-2.358*	-2.347	-2.337	-2.327	-2.318	-2.325	-2.314
Mauritius	-1.951	-2.015*	-2.011	-2.006	-2.001	-1.996	-1.991
Morocco	-1.010	-1.019*	-1.016	-1.016	-1.013	-1.008	-1.002
Namibia	0.465*	0.468	0.472	0.476	0.480	0.485	0.486
Nigeria	0.009	-0.082	-0.083*	-0.080	-0.076	-0.071	-0.069
Rwanda	-0.921	-1.024*	-1.014	-1.007	-0.999	-0.990	-0.984
South Africa	-0.013*	-0.010	-0.009	-0.004	-0.002	-0.001	-0.004
Tunisia	-1.091	-1.168*	-1.163	-1.158	-1.153	-1.150	-1.145
Uganda	0.498*	0.505	0.511	0.518	0.525	0.531	0.538
Zambia	-0.855	-0.855	-0.861*	-0.853	-0.847	-0.840	-0.833

Note: * indicate the lag length selected by BIC.

4.4 Estimates of the AR(i) Mean Models for African Stock Market Returns

Table 5 presents results of autoregressive mean models estimated to obtain residuals required to estimate volatility models for Africa stock markets returns. Notice from *Table 5* that the lag lengths selected by BIC in Table 4 are not misleading. Autoregressive lags of Botswana stock market returns, for instance, are significant up to lag 5, and f-test confirms that the coefficients are not zero. Similarly, the lag lengths selected for other Africa stock markets are all significant, except for South Africa where lag 0 is selected but the coefficients of lags 1 and 2 are significant. Significant lags coefficients suggest explanatory power of previous periods returns on current return. That is, Africa stock market returns do not fully reflect all the information contained in past return changes. Thus, historical return information may provide profitable trading opportunities; an indication of weak-form inefficiency.

Volatility estimates from serially correlated residual are not consistent and could result in misleading statistical inference. To check adequacy of the autoregressive mean models fitted to the African stock markets returns, Durbin-Watson and Ljung-Box Q statistics were applied. The essence of combining the two diagnostic tests is to ensure that the residuals are not serially correlated. While, Durbin-Watson only considers lag-1 serial correlation, Ljung-Box Q considers serial correlations at various lags. The Durbin-Watson coefficients reported in Table 5 show absence of any sign of first order serial correlation; the coefficients are approximately 2 for the residuals of the African stock market returns. Ljung-Box Q tests, conducted up to lags 5, indicate that the mean models for Africa stock markets returns are adequate at the 5% significance level, except for the stock market of Malawi. The *p*-levels of Ljung-Box Q statistics for the mean models show absence of serial correlation in residuals of the mean model, at the 5% significance level. Consequently, the estimated models are adequate.

Table 5: Mean Model Results for African Stock Market Returns

	ϕ	δ_{t-1}	δ_{t-2}	δ_{t-5}	*DW*-stat	*F*-stat	*LBQ* 5
Botswana	0.015	0.060	0.071	0.092	2.004	14.907	0.276
	(0.067)	(0.016)	(0.004)	(0.000)		(0.000)	(0.998)
BRVM	0.055	-0.126	-	-	1.989	7.373	2.662
	(0.116)	(0.006)				(0.006)	(0.751)

Egypt	0.002	0.122	-	-	1.999	24.968	10.160
	(0.941)	(0.000)				(0.000)	(0.070)
Ghana	0.037	-0.047	0.096	0.057	2.009	9.127	1.846
	(0.032)	(0.085)	(0.000)	(0.038)		(0.000)	(0.870)
Kenya	0.066	-0.344	-0.082	-	2.004	89.610	1.562
	(0.074)	(0.000)	(0.002)			(0.000)	(0.905)
Malawi	0.036	-	-	-	1.900	-	16.051
	(0.007)						(0.006)
Mauritius	0.003	0.257	-	-	2.016	106.435	1.477
	(0.678)	(0.000)				(0.000)	(0.915)
Morocco	-0.020	0.121	-	-	2.007	20.893	2.682
	(0.194)	(0.000)				(0.000)	(0.261)
Namibia	0.006	-	-	-	2.080	-	6.587
	(0.831)						(0.253)
Nigeria	0.015	0.327	-0.077	-	1.991	84.005	3.716
	(0.528)	(0.000)	(0.002)			(0.000)	(0.591)
Rwanda	0.012	-0.325	-	-	1.998	82.866	8.696
	(0.600)	(0.000)				(0.000)	(0.122)
South Africa	0.039	-0.042	-	-	2.005	2.889	5.279
	(0.116)	(0.089)				(0.089)	(0.382)
Tunisia	0.001	0.281	-	-	1.996	122.882	2.533
	(0.932)	(0.000)				(0.000)	(0.771)
Uganda	0.059	-0.081	-	-	1.997	6.872	1.603
	(0.171)	(0.008)				(0.008)	(0.900)
Zambia	0.055	-0.099	-0.118	-	1.995	9.340	2.055
	(0.012)	(0.003)	(0.001)			(0.000)	(0.841)

Note: (.) indicate the marginal significance level of regression coefficients. D-W stat. is the Durbin-Watson statistics, LBQ 5 is Ljung-Box Q statistics up to lags 5.

5.5 Estimates from Volatility Models for African Stock Market Returns

Table 6 reports results of ARCH-LM test conducted to examine African stock markets returns heteroscedasticity. Notice from Table 6 that there is existence of heteroscedasticity in the returns series. The null hypothesis of no heteroscedasticity is rejected for the Africa stock markets, except for Malawi and Zambia. Given the absence of heteroscedastic variance in Malawi and Zambia stock market returns, they were omitted in subsequent analysis. The presence of heteroscedasticity is a justification for GARCH modeling.

Table 6: Heteroscedasticity for African Stock Market Returns

	1	2	3	4	5	6
Botswana	114.10	62.62	41.79	32.61	26.31	21.92
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BRVM	68.60	35.60	23.72	18.25	14.71	12.87
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Egypt	35.80	26.16	18.90	14.16	12.06	10.14
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ghana	343.72	225.64	162.97	123.42	100.01	83.33
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Kenya	182.97	95.52	63.63	47.66	38.08	31.69
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Malawi	0.14	0.16	0.13	0.12	0.34	0.31
	(0.70)	(0.84)	(0.93)	(0.97)	(0.88)	(0.93)
Mauritius	267.36	235.97	160.50	130.86	104.84	89.14
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Morocco	57.39	41.39	28.40	23.38	18.70	15.56
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Namibia	83.40	42.08	30.63	24.37	19.60	16.31
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nigeria	40.07	118.61	80.16	64.18	52.77	45.17
	(0.00)	(0.00)	(0.00)	(0.000)	(0.00)	(0.00)
Rwanda	104.76	53.93	36.94	27.63	22.22	18.48
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
South Africa	25.07	31.38	25.40	21.51	22.45	19.17
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Tunisia	338.30	171.47	118.89	89.12	72.20	60.08
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Uganda	185.56	108.94	74.41	55.86	44.61	37.16
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Zambia	0.36	3.78	2.85	2.36	3.20	2.71
	(0.54)	(0.02)	(0.03)	(0.05)	(0.00)	(0.01)

Results of GJR-GARCH (1,1) model specified in equation 2 are presented in Table 7. Notice that coefficients for long-run average volatility are all significant at 1% significance level. This suggests that long-run average volatility has explanatory power on current volatility of Africa stock markets. Coefficients of ARCH parameter (α_1) are also significant, at 5% level, for Africa stock markets, except for Namibia and BRVM. Statistical significance of α_1 suggests that volatility from previous periods influence current volatility in Africa stock markets. GARCH coefficients (β_1) are also significant at 5% significance level for all Africa stock markets. This indicates evidence of volatility clustering in Africa stock markets, although with varying degrees. Observe also the existence of volatility persistence in Uganda, Ghana, Namibia, Mauritius, Nigeria and Morocco. Other stock markets with relatively high volatility persistence are Egypt, Kenya, South Africa, Tunisia, and Rwanda. Stock market volatility in Botswana and BRVM, however, are not very persistent. These results suggest that Africa stock markets still exhibit volatility clustering and persistence after the global financial crisis. These results are consistent with the findings of the volatility studies conducted before and during the global financial crisis. Niyitegeka and Tewari (2013) for example, find evidence of volatility clustering in Johannesburg Stock Exchange. N'dri (2007), Namugaya, Weke and Charles (2014), Kais (2015), and Owidi and Mugo-Waweru (2016) also document similar evidences for BRVM, Uganda, Tunisia, and Kenya respectively. A critical implication of stock market volatility is its impact on expected risk premium and cost of capital. As Smith (1989) observes, an expected increase in volatility will increase the expected risk premium and thereby affect a firm's cost of capital.

In addition, estimates of volatility asymmetry parameter are also reported in *Table 7*. Notice that there is evidence of volatility asymmetry in Botswana, Egypt, Mauritius, Morocco, Namibia, Rwanda and Tunisia. The asymmetry coefficients further suggest that positive and negative shocks of the same magnitude have same effect on volatility of BRVM, Ghana, Kenya, Nigeria, South Africa, Uganda stock markets returns. These results also concur with existing literature. N'dri (2007), for example, did not report existence of volatility asymmetry in the BRVM Cote d'Ivoire. Niyitegeka and Tewari (2013) did not also establish asymmetric effect in the Johannesburg Stock Exchange. The result however did not agree with Emenike and Aleke (2012), who find evidence of volatility asymmetry in Nigeria. This disagreement may have occurred as a result the time-varying nature of volatility (see, Schwert, 1989; Kais, 2015). The asymmetric coefficients are positive, suggesting that negative shocks tend to produce higher volatility in the immediate future than positive shocks of the same magnitude in Botswana, Egypt, Mauritius, Morocco, Namibia, Rwanda and Tunisia. These results agree with Coffie (2018), who reports amongst others, that current shocks to conditional variance have less impact on future volatility in Botswana and Namibia stock markets, and that news impact is asymmetric in both Botswana and Namibia stock markets.

Notice further from Table 7 that volatility clustering appear more pronounced in Namibia stock market returns, and least in Botswana stock market. Similarly, volatility appears more persistent in Uganda stock market, and least in Botswana stock market.

A possible explanation for asymmetric behaviour of Africa stock markets could be that positive changes in the stock market returns are viewed as favourable by investors and therefore do not stimulate returns volatility equal to a negative changes. Evidence of volatility being more responsive to negative news than positive news of the same magnitude provides support for risk aversion in some Africa stock markets. Investors generally are risk averse and negative news is more likely to result in hasty divestment decision than positive news. More so negative shocks make investors more averse to holding stocks due to uncertainty. As a result, investors are more likely to demand a higher risk premium in order to hedge against the increased uncertainty resulting volatility persistent. The higher risk premium will in turn results in a higher cost of capital, which contracts investments.

Diagnostic tests results, also presented in Table 7, show evidence of no serial correlation in residuals of the mean model at the 1% significance level but at the 5% significance level, Ghana, Kenya and Uganda failed. The variance models, however, are adequate for all Africa stock markets. Similarly, ARCH LM results show evidence of no remaining heteroscedasticity in squared standardized residuals. More so, estimates of the GJR-GARCH (1,1) parameters overcome the non-negativity constraints. Consequently, the models are adequate to explain volatility behaviour of Africa stock markets.

Table 7: Results of AR(i)-GJR-GARCH(1,1) for African Stock Market Returns

Coefficients	ω	α_1	β_1	$\alpha_1+\beta_1$	γ	ARCH-LM (8)	Ljung-BoxQ (36)	McLoed-Li(10)
Botswana	0.046	0.059	0.318	0.377	0.281	64.105	41.348	2.633
	(0.00)	(0.00)	(0.00)		(0.00)	[0.73]	[0.24]	[0.98]
BRVM	0.264	0.107	0.336	0.443	0.131	23.432	23.832	0.028
	(0.00)	(0.09)	(0.05)		(0.13)	[0.99]	[0.94]	[1.00]
Egypt	0.280	0.036	0.722	0.758	0.210	70.068	17.147	3.764
	(0.00)	(0.023)	(0.00)		(0.00)	[0.54]	[0.14]	[0.95]
Ghana	0.030	0.145	0.772	0.917	0.035	99.154	52.931	2.178

	(0.00)	(0.05)	(0.00)		(0.65)	[0.02]	[0.03]	[0.99]
Kenya	0.136	0.278	0.450	0.728	-0.011	85.275	51.977	3.488
	(0.00)	(0.00)	(0.00)		(0.91)	[0.24]	[0.04]	[0.96]
Mauritius	0.011	0.130	0.740	0.870	0.076	86.377	44.212	8.467
	(0.00)	(0.00)	(0.00)		(0.03)	[0.21]	[0.16]	[0.58]
Morocco	0.055	0.133	0.671	0.804	0.084	84.095	40.821	3.609
	(0.01)	(0.00)	(0.00)		(0.04)	[0.19]	[0.26]	[0.96]
Namibia	0.074	0.002	0.900	0.902	0.097	84.082	38.684	7.834
	(0.00)	(0.86)	(0.00)		(0.00)	[0.27]	[0.34]	[0.64]
Nigeria	0.151	0.246	0.564	0.810	0.087	80.019	44.087	4.614
	(0.01)	(0.00)	(0.00)		(0.31)	[0.24]	[0.16]	[0.91]
Rwanda	0.084	0.086	0.489	0.575	0.752	34.544	32.312	0.705
	(0.00)	(0.00)	(0.00)		(0.00)	[0.97]	[0.64]	[0.99]
South Africa	0.622	0.081	0.651	0.732	0.091	64.790	39.230	7.585
	(0.00)	(0.00)	(0.00)		(0.09)	[0.71]	[0.32]	[0.66]
Tunisia	0.059	0.191	0.421	0.612	0.375	73.382	36.726	3.413
	(0.00)	(0.00)	(0.00)		(0.00)	[0.43]	[0.43]	[0.96]
Uganda	0.305	0.309	0.617	0.926	-0.119	82.20	52.604	4.314
	(0.00)	(0.00)	(0.00)		(0.06)	[0.19]	[0.04]	[0.93]
Zambia	0.0003	0.080	0.936	1.016	-0.021	65.840	43.273	8.635
	(0.11)	(0.00)	(0.00)		(0.29)	[0.22]	[0.18]	[0.56]

Note: lag of diagnostic tests are displayed as (.).

5 Conclusions and Policy Implications

African stock markets play important roles of stimulating economic development through providing channel for mobilising domestic savings and facilitating the allocation of financial resources from dormant to more productive activities. Therefore, this paper evaluates the nature of stock market volatility in Africa after the global financial crisis. The stock market volatility of Botswana, BRVM, Egypt, Ghana, Kenya, Malawi, Mauritius, Morocco, Namibia, Nigeria, Rwanda, South Africa, Tunisia, Uganda, and Zambia were evaluated for clustering and asymmetry. Africa stock markets daily data were analysed using univariate asymmetric GARCH (1,1) model because of its capability to capture volatility clustering and asymmetry.

The Preliminary results show zero average daily return, leptokurtosis, skewness, significant departure from normal distribution, and absence of unit roots in Africa stock markets returns as well as presence of heteroscedasticity in the Africa stock markets returns residuals series. Results of the univariate asymmetric GARCH (1, 1) model indicate evidence of volatility clustering in Africa stock markets returns, although with varying degrees. The results also indicate existence of volatility persistence in the African stock market returns except Botswana and Cote d'Ivoire, which are not very persistent. The results further reveal that Africa stock markets returns are asymmetric, with negative shocks producing higher volatility in the immediate future than positive shocks of the same magnitude in some countries, and positive shocks producing higher volatility in other countries. It is therefore concluded that Africa stock markets returns exhibit volatility clustering, persistence and asymmetry.

One major policy implication of the findings is adjustment of expected risk premium and/or cost of capital in anticipation of increase in volatility. As the findings have shown, Africa stock market volatility exhibit clustering - periods in which stock returns show large changes, of either sign, for an extended period followed by periods of small price changes. This volatility pattern provides insight for designing investment strategies, portfolio risk management and portfolio rebalancing through volatility harvesting.

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