REGIME SWITCHING MODEL AMONG SELECTED AFRICAN STOCK MARKET

Yahaya Haruna Umar (Corresponding author)
Department of Statistics, University of Abuja, Abuja - Nigeria
Tel: +2348033468336 E-mails: yahaya.umar@uniabuja.edu.ng, yahagumau@gmail.com

Sani Fatima
Department of Statistics, University of Abuja, Abuja - Nigeria
Tel: +2348035951920 E-mail: fancymi002@yahoo.com

Mustapha Azeez Daramola
National Bureau of Statistics, Abuja - Nigeria
Tel: +2348066667697 E- mail: mdazeez@nigerianstat.gov.ng

Abstract

Over the past few decades, the world stock markets have surged, and emerging markets have accounted for a large amount of this boom. This has resulted into emergence of new market stock in Africa; hence the study examines the stock market's volatility in Nigeria, South Africa and Egypt using the Markov regime switching Model. The study utilizes monthly observations over the period from January 1997 to September 2019. The study utilizes two state Markov Switching Autoregressive (MS-AR) models in order to capture regime shifts behaviour in both the mean and the variance of the three countries All Share Index (ASI). The MS-AR results of the three countries ASI suggested evidence of a regime-switching behaviour. It shows that only extreme events can switch the series from regime 1 (appreciation) to regime 2 (depreciation), or vice versa. The results also identify that during all major global economic crises in the US sub-prime (2008) there was negative impact in all the three countries under study and European debt crisis (2010) did not really have any impact on the three countries under studies. The results further revealed that Nigeria ASI recorded the lowest appreciation regime of 10 months and the highest depreciation regime of 82 months against South-Africa ASI and Egypt ASI. Egypt recorded the highest appreciation regime of 69 months and the lowest depreciation regime of 18 months. Hence, the results shows that the Nigeria stock market is more sensitive to external shocks implying that there is ample scope of policy intervention.

Keywords: Africa Stock Markets, Markov Switching Autoregressive, All Share Index, Appreciating regime, Depreciation regime

1. Introduction

Over the past few decades, the world stock markets have surged, and emerging markets have accounted for a large amount of this boom. In Africa, new stock markets have been established in Ghana, Malawi, Swaziland, Uganda, and Zambia. Prior to 1989 there were just five stock markets in sub-Saharan Africa and three in North Africa. Today there are about 19 stock exchanges. Stock market development has been central to the domestic financial liberalization programs of most African countries. It seems any program of financial liberalization in Africa is incomplete without the establishment and development of stock market.

Financial investors are situated in a challenging environment, which is characterized by the uncertainty of financial markets. The risk/return-structures of the financial markets are in constant motion and present risks but also opportunities to investors. It is important for the investor to be informed about these dynamic processes in order to adequately model and forecast the markets and to be able to compose efficient portfolios. Many financial time series show certain patterns in their behavior, which are characterized by periodic, temporary and dramatic breaks. To minimize the risk of investments, we need to examine how the stock market is moving from one regime to another by the means of Markov regime switching Model.

This study will be relevant to most policy makers, macroeconomic experts, government, investors, shareholders and the general public since it is meant to provide an insight of the Africa Stock Market. Therefore there is a need to have an in-depth assessment of the performance of the sharply rising African stock exchanges.

Academically, the study aims at looking at the issue in a broader perspective; collecting and analyzing significant information and data on the focused topic so as to make room for further or future references and generalization of the findings. This paper attempts to offer an overview of the development and performance of African stock markets over time. Both practical and theoretical research may benefit from the study as it is set to measure and analyze current data obtained. This study also supplements the limited pool of current literature available on African stock markets. It further aims at obtaining results with objectivity and a sense of scholarly exactitude and is available to add-ons by other researchers should the need arise.

In addition, this study may serve as a guide for both local and foreign investors who have intentions of investing in the African stock markets.

The aim of this work is to examine the stock market's volatility in Nigeria, South Africa and Egypt using the Regime switching Model. That is looking at the possibility of moving from one regime to another and objectives are to examine the stylized fact of the series, to determine the trend and estimate the switch to use in the three market and finally to find appropriate switching model to use in the three Africa stock market.

2 Brief History on the Development and Trend of African Stock Markets

Following information on the history and development of African Stock Markets, it is difficult to overlook the fact that African Stock Markets have shown a collective sign of rapid maturity and development over time. Started with just 8 stock exchanges in the whole of Africa prior to 1987, the number of stock exchanges burgeoned to 29 by the year 2012 representing 38 nations' capital markets (Moin, 2007; ASEA, 2012). With Seychelles Stock Exchange and Egyptian Exchange as the latest and oldest African Stock Markets established in 2012 and 1883 respectively, it would be an erroneous expression to conclude that African Stock Exchanges has not seen substantial development overtime. Below is the list of various African Stock Markets and their dates of establishment.

Table 1: List of African Stock Exchanges

Economy	Exchange	Location	Founded
West African Regional Stock Exchange	Bourse Régionale des Valeurs Mobilières*	Abidjan(Côte d'Ivoire)	1998
Algeria	Algiers Stock Exchange	Algiers	1997
Botswana	Botswana Stock Exchange*	Gaborone	1989
Cameroon	Douala Stock Exchange*	Douala	2001
Egypt	Egyptian Exchange*	Cairo, Alexandria	1883
Cape Verde	Bolsa de Valores de Cabo Verde*	Mindelo	2005
Ghana	Ghana Stock Exchange*	Accra	1990
Kenya	Nairobi Stock Exchange*	Nairobi	1954
Libya	Libyan Stock Market*	Tripoli	2007
Malawi	Malawi Stock Exchange*	Blantyre	1995
Mauritius	Stock Exchange of Mauritius*	Port Louis	1988
Morocco	Casablanca Stock Exchange*	Casablanca	1929
Mozambique	Bolsa de Valores de Moçambique*	Maputo	1999
Namibia	Namibia Stock Exchange*	Windhoek	1992
Nigeria	Abuja Securities and Commodities Exchange	Abuja	1998
	Nigerian Stock Exchange*	Lagos	1960
Rwanda	Rwanda Stock Exchange	Kigali	2008
Seychelles	Seychelles Stock Exchange*	Victoria	2012
South Africa	Johannesburg Stock Ex-change*	Johannesburg	1887
Sudan	Khartoum Stock Exchange*	Khartoum	1994
Swaziland	Swaziland Stock Exchange*	Mbabane	1990
Tanzania	Dar es Salaam Stock Ex-change*	Dar es Salaam	1998

(*) members of African Securities Exchanges Association, ASEA
Source:Wikipedia,http://en.wikipedia.org/wiki/List_of_African_stock_exchanges

It is important to note that there has been a decline in the number of stock markets openings although it reached its peak in the 1990s. Smith et al. (2002) simply categorizes African stock markets into four groups based on their stage of development:

i. South Africa which is larger, more developed in terms of regulatory framework and more advanced in terms of technical infrastructure that its counterparts;
ii. Medium-sized markets which have been established for a long time (e.g. Egypt, Nigeria and Morocco);
iii. Small-sized new market which have grown rapidly (e.g. Ghana Mauritius and Botswana); and
iv. Small-sized markets that are still at an early stage of development (e.g. Swaziland, Zambia and Malawi).

The above categorization by Smith et al. (2002) provides an insight to the extent of growth of the various African stock markets but on the other hand, some of the stock markets have currently transcended their categories into another given the time and stock activities that have taken place with time. It is often documented that the apparent substantial increase in stock markets in Africa can be attributed to the extensive financial sector reforms undertaken by a number of African countries (Kenny and Moss, 1998). These financial reforms provide a platform for revamping dormant financial sectors in some of the African countries. They included the liberalization of their financial sectors, privatization of state-owned enterprises, the improvement of the investment climate, introduction of a more robust regulatory framework and improvements in the basic infrastructure for capital market operations. (De la Torre and Schmukler, 2005). However, as Yartey and Adjasi (2007) put it, 'the rapid development of stock markets in Africa does not mean that even the most advanced African stock markets are mature'. Maturity here denotes market capitalization in close comparison to market capitalization of other developed stock markets. It is relevant to note that albeit African stock markets have increased in numbers over the past years, it is still considered to be small 'by world standards and of limited local interest' (Tolikas, 2007). The South African Stock Exchange is seen to control a lion's share of the total market capitalization of African stock markets. The Johannesburg Securities Exchange (JSE) in South Africa has about 90 percent of the combined market capitalization of the entire continent (Yartey and Adjasi, 2007). This is followed by other giant African stock exchanges such as Nigeria, Egypt and Zimbabwe. This is not to disregard the fact that other African stock markets have been performing superbly on the world table. For instance, in 2004 the Ghana Stock Exchange was honored as the best stock market with the performance of 144 per-cent end-of-year return in USD terms compared with 30 percent return by Morgan Stan-ley Capital International Global Index (Mensah at al., 2012).

3. Literatures on Markov Regime Switching Model

Numerous studies have applied Markov regime switching model in identifying the regime switching behaviour of stock market. The first among these studies is that of Hamilton (1989) who enhanced the model of Goldfeld and Quandt (1973) by allowing the regime shifts in dependent data and developed the Markov switching autoregressive model (MS-AR). Since then, the model has been used extensively to capture the regime switching behaviourin economic and financial time series studies. However, the application of Markov regimeswitching model in financial econometrics, particularly in identifying the regime shifts, started with the pioneer work of Turner et al. (1989) to capture the regime shifts behaviour in stock market using MS-AR () model.Their study highlighted the usefulness of Markovswitching model allowing regime shifts to happen in mean and variance and fitting the data adequately compared to other specifications of Markov regime switching models. Cheu et al. (1994) examined the relationship between stock market returns and stock market volatility using the MS-AR model and concluded that there is nonlinear and asymmetric relationship between returns and volatility.

Walid and Nguyen (2014) use a regime-switching model approach to investigate the dynamic linkages between the exchange rates and stock market returns for the BRICS countries (Brazil, Russia, India, China and South Africa). Results of their analysis of a univariate model indicate that stock returns of the BRICS countries evolve according to a *low volatility* and a *high volatility* regimes and evidence from the Markov switching VAR models suggests that stock markets in the BRICS have more influence on exchange rates during both calm and turbulent periods.

A study by Aikaterini (2016) assesses the predictive power of regime switching models for stock market returns across the Canadian, UK and the US markets on the basis daily stock market data from 3rd January, 2010 to 16th November, 2015. Findings reveal that the transition probabilities from regime 1 to regime 2 and vice versa are really small and as a consequence, the probabilities of staying at the same regime are large and hence, his model is a one state model because the probability of changing state is very low. However, the expected duration of stay in the regimes is higher in the bu ll market than in the bear market. Further, the markets were characterized by negative returns in the latter market, and positive returns in the former.

Recently, Kayalidere, Gulec, Erer (2017) analyze the impact of economic instability on stock market performance on bear and bull markets using weekly credit default swaps, exchange rate volatility and stock market returns in Turkey.

The Markov Switching GARCH(1,1) model was employed and results of the analysis indicate that, both credit default swaps and exchange rate volatility adversely affect the stock market performance in bear and bull markets. The effects, however, are significantly stronger in bear market than in bull markets, thus, economic instability diminish stock market returns by increasing investors' risk perception in the Turkish economy.

Maheu and McCurdy (2000) used the Markov regime switching model to classify the USstock market in two different regimes characterized as high returns–stable-state and low return-volatile-state. Guidolin and Timmerman (2006) applied MS-VAR approach to study the relationship between US returns and bond yields. They concluded that four regimes MSVAR model is required to capture the time variation in the mean, variance and correlation between stock returns and bond yields. Wang and Theobald (2007) carried out a study using MS with switching–in-mean and variance model to investigate the regime switching volatility in six East Asian emerging markets i.e., Indonesia, Korea, Malaysia, Philippines, Taiwan and Thailand, from 1970 to 2004. They concluded that the markets for Malaysia, Philippines and Taiwan were characterized by two regimes while the markets for Indonesia, Korea and Thailand were characterized by three regimes over the sample period. Ismail and Zaidi (2008) examined the regime shifts behaviour in Malaysian stock market returns using MSAR model. They implemented the MS-AR framework to capture regime shifts behaviour in both mean and variance in four indices of Bursa Malaysia namely the Composite, Industrial, Property and Financial indices. They successfully captured the regime shifts in each index and concluded in favour of applying nonlinear MS-AR model against linear AR model.

4. Methodology

The statistical tools used for this research include Heteroscedasticity test (the ARCH effect), Markov Switching Autoregressive (MS-AR) and forecast evaluation criteria. The nature of this study necessitated the use of secondary data. Data were sourced from Nigeria, South-Africa and Egypt Stock Exchange websites; the study utilizes monthly time series data and covers a period of January 1997 to September 2019. The returns in each market are calculated and are represented as the differences in prices as $R_t = \log\left(\frac{P_t}{P_{t-1}}\right)$.The estimation of the model was carried out using the EViews 9.0 Statistical package.

4.1 HeteroscedasticityTest

The conditional variance of a time series is a function of past shocks; the autoregressive conditional heteroscedastic(ARCH) model. In this approach, the conditional variance $\sigma_t^2$is alinear function of lagged squared residuals e_t. To test for this heteroscedasticity, the Lagrange Multiplier (LM) testproposed by Engle (1982) is applied. In using this procedure, we obtain the residuals $e_t$from the ordinary least squares regression of the conditional mean equation. For an ARMA(1,1) model, the conditional mean equation will be:

$$r_t = \emptyset_1 r_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} \quad (1)$$

In addition, the squared residuals, $\varepsilon_t^2$is regress on a constant and q lags as in the equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 \quad (2)$$

The null hypothesis

$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_q = 0$; states that there is no ARCH effect up to order q against the alternative:

$H_1: \alpha_i > 0$;for at least one i = 1, 2, …, q.

Finally, the test statistic for the joint significance of the q-lagged squared residuals is the number of observations times the R-squared (TR^2) from the regression, where $TR^2$is evaluated against χ^2 (q) distribution.

4.2 Test of Nonlinearity

According to Brooks (2008), to determine whether a nonlinear model is suitable for a data, the decision should come from the financial theory; nonlinear model should be used where financial theory suggests that the relationship between the variable requires a nonlinear model (Mendy and Widodo, 2018). We focus on the most widely used tests known as BDS test developed by Brock, Dechert and Scheinkman (1987). The BDS test is based on an integral correlation of the series and is defined as follows;

$$BDS_{m.M}(r) = \sqrt{M} \frac{C_m(r) - {C_1}^r(r)}{\sigma_{m.M}(r)} \quad (3)$$

Where M is the surrounded points of the space with m dimension, *r* denotes the radius of the sphere centered on the X_i, *C* is the constant and$\sigma_{m.M}$is the standard deviation of$\sqrt{M} C_m(r) - {C_1}^r(r)$. Thus, the null hypothesis of the BDS test for detecting nonlinearity follows; series are linearly dependent

4.3 The Markov-Switching Model

The Markov switching (MS) model, a model that switch states or regime stochastically, it was initiated by Hamilton (1989). A Markov switching Autoregressive (AR) model (MS-AR) of states or regimes with an AR process of order *p* is stated as follows;

$$X_t = \begin{cases} c_1 + \beta_{11} X_{t-1} + \cdots + \beta_{p1} X_{t-p} + \varepsilon_t S_t = 1 \\ c_2 + \beta_{12} X_{t-1} + \cdots + \beta_{p2} X_{t-p} + \varepsilon_t S_t = 2 \\ c_3 + \beta_{13} X_{t-1} + \cdots + \beta_{p3} X_{t-p} + \varepsilon_t S_t = 3 \end{cases} \quad (4)$$

Where the regimes or states in equation (3.3) are indexed by $\boldsymbol{S_t}$.In this model, the intercept and the parameters of theAR part are dependent on the regime or state at time *t*. These regimes are assumed to be distinct unobservable variable(s). Hence, in this study, state or regime one describes the periods of upward trending of the All Share Returns, R_t, state or regime two symbolizes period of downward trending of All Share Returns, R_t and state or regime three symbolizes period of stationary of All Share Returns, R_tThe transitions that are between the regimes or states are presumed to follow an ergodic and intricate, a first order Markov process. This implies impacts of all past observations for the variables and the regime is fully captured in the recent observation of the regime variable as represented below;

$$\rho_{ij} = Prob\left(S_t = {}^{j}/_{S_{t-1}} = i\right) \quad \forall i,j = 1,2,3 \sum_{i=1}^{2} \rho_{ij} = 1 \quad (5)$$

Matrix P captures the probability of switching which is known as a transition matrix;

$$P = \begin{bmatrix} P_{11}P_{12} \quad P_{13} \\ P_{21}P_{22}P_{23} \\ P_{31}P_{32}P_{33} \end{bmatrix} \tag{6}$$

Where $\boldsymbol{P_{11} + P_{12} + \quad P_{13} = 1, P_{21} + P_{22} + P_{23}} = 1$ and $\boldsymbol{P_{31} + P_{32} + P_{33}} = 1$

The maximum likelihood estimator MLE was utilized to estimate the parameters of the MS-AR.Hence, the log likelihood function is presented as follows;

$$lnL = \sum_{t-1}^{T} ln\left\{\sum_{S_{t-1}}^{2} f(y_t/S_t, \Psi_{t-1})P(S_t/\Psi_{t-1})\right\} \tag{7}$$

Where Ψ_{t-1} and $P(S_t/\Psi_{t-1})$are filtered probabilities. Given that the MS-AR allows in making an inference about the observe regime value, through the behaviour of exogenous y_t. Hence, using y_t as observe at the end of the i^{th}iteration, thecalculated filtered probabilities by the iterative algorithm is written as;

$$P\left(S_t = \frac{j}{\Psi_t}\right) = \sum_{S_{t-1}=1}^{2} P\left(S_t = j, S_{t-1} = \frac{i}{\Psi_t}\right) \qquad for \quad t = 1, \dots, T \tag{8}$$

Correspondingly, the smoothed probabilities are gotten if the data set is used as a whole. Therefore, using all the information in the sample i.e. $\Psi_T = \{y_1, \dots, y_T\}$the calculatedsmoothed probabilities is;

$$P(S_t = j/\Psi_T) = \sum_{k=1}^{2} P(S_t = j, S_{t+1} = k/\Psi_T) \quad for\, t = T-1, T-2, \dots \tag{9}$$

Lastly, from the transition matrix in equation (3.5) above, the expected duration of the i^{th} regime is can be computed. This implies that the closer the probability$P_{ij}$is to one the longerit takes to shift to the next regime. In short, the expected duration is calculated as;

$$Expected\ duration = \frac{1}{1-P_{ij}} \tag{10}$$

Nevertheless, for model selection, this study employs both the Akaike information n criterion (AIC). Debatably the Akaike information criterion is one of the most extensively used criterion by researchers (Pan, 2001). The AIC was original established by Akaike(1973) a way to compare different model on a given outcome. Hence, given numerous models for a set of data the most preferred model is the model with minimum AIC value.

4.4 Forecasting Evaluation Criteria

Numerous error measures are available for forecasts evaluation; we evaluate the forecasting ability of MS-AR models by means of three different loss functions. These are root mean squared error (RMSE), mean absolute error (MAE) and Theil's U statistic which are defined as follows;

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \tag{11}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|(A_t - F_t)| \tag{12}$$

$$U_t = \frac{\sqrt{\sum_{t=1}^{n}(A_t - F_t)^2}}{\sqrt{\sum_{t=1}^{n}(A_t - A_{t-1})^2}} \tag{13}$$

Where A_t is the actual value in time *t*, and$F_t$is the forecast value in time *t.* Theil's U statistic compares the forecast accuracy of different models. It has the advantage of providing an immediate comparison of the forecasts with those of the simple methods.

5. Presentation and Analysis of Data

The data are monthly and generally covers the period from January 1997 to September 2019. E-Views 9.0 analysis package was utilized to carry out all the analysis in this study. Table 2 and 3 present the variables descriptions and summary statistics of the time series data considered in this study.

Table 2: Variables Description

Variables	**Code**	**Returns Code**
1. Nigeria All Share Index	NGR	NGRR
2. South-Africa All Share Index	SAF	SAFR
3. Egypt All Share Index	EGY	EGYR

Table 3: Descriptive Statistics of Returns

	NGRR	**SAFR**	**EGYR**
Mean	0.00491	0.007741	0.005712
Median	0.000119	0.008808	0.006586
Maximum	0.324064	0.133763	0.285414
Minimum	-0.36588	-0.35483	-0.28444
Std. Dev.	0.075758	0.053188	0.067009
Skewness	-0.39194	-1.25096	-0.19889
Kurtosis	7.683258	10.3209	5.612703
Jarque-Bera	255.5368	678.3583	79.15709
Probability	0.0000	0.0000	0.0000
Sum	1.3354	2.105618	1.55358
Observations	272	272	272

Source: Computed by the Researchers

Table 3; display the descriptive statistics of the three countries showing their respective returns. As observed, NGR has mean, median, maximum and minimum of 0.00491, 0.000119, 0.324064 and -0.36588 respectively for the time period examined. NGR has standard deviation and Jarque-Bera statistic value of 0.075758 and 255.5368 respectively with p-value of 0.01 less than 0.05 (level of significant). SAF has mean, median, maximum and minimum of 0.007741, 0.008808, 0.133763 and -0.35483 respectively for the time period examined. SAF also, has standard deviation and Jarque-Bera statistic value of 0.053188 and 678.3583 respectively with p-value of 0.00 less than 0.01 (level of significant). EGY has mean, median, maximum and minimum of 0.005712, 0.006586, 0.285414and -0.28444 respectively for the time period examined. And has standard deviation and Jarque-Bera statistic value of 0.067009 and79.15709 respectively with p-value of 0.00 less than 0.01 (level of significant).

Figure 1 to Figure 3 present the time series plots of the All Share Index of Nigeria, South-Africa and Egypt.

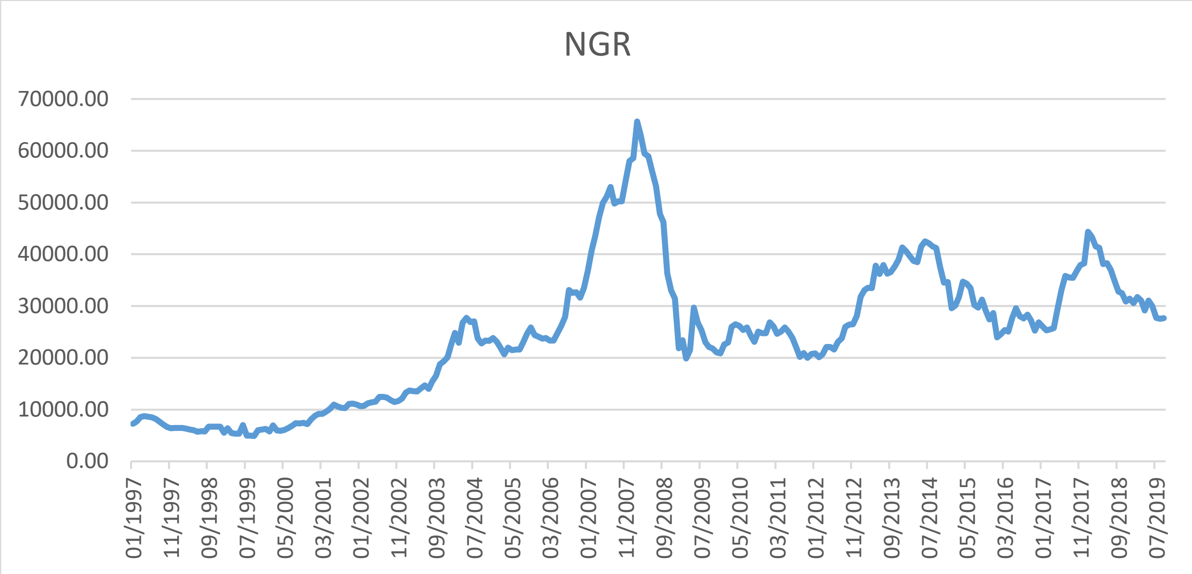


Figure 1: NGR Time Series Plot

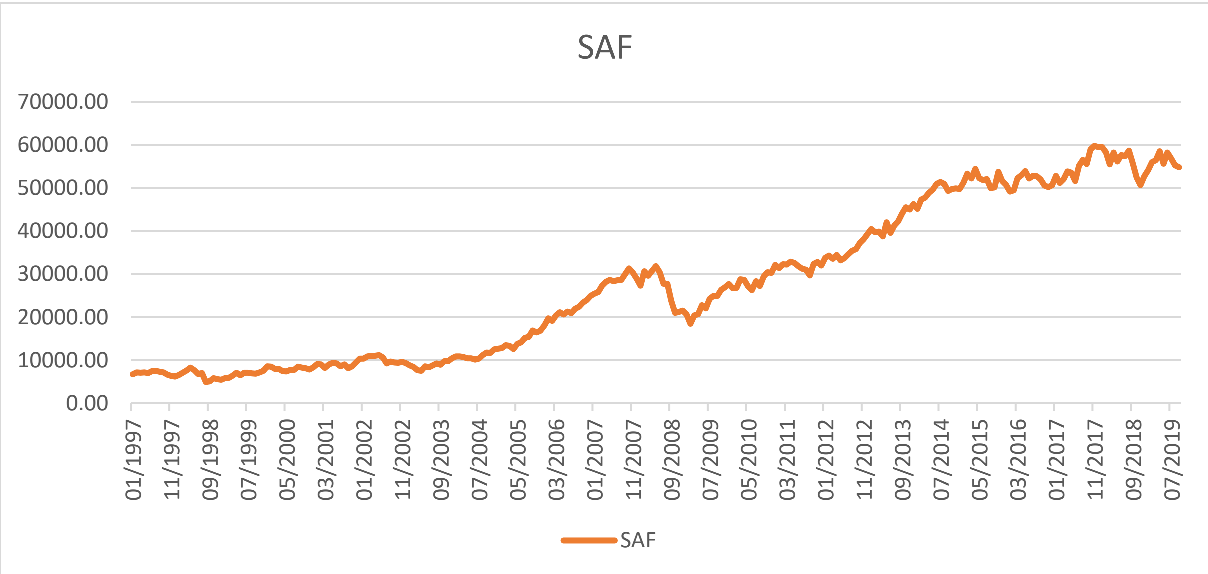
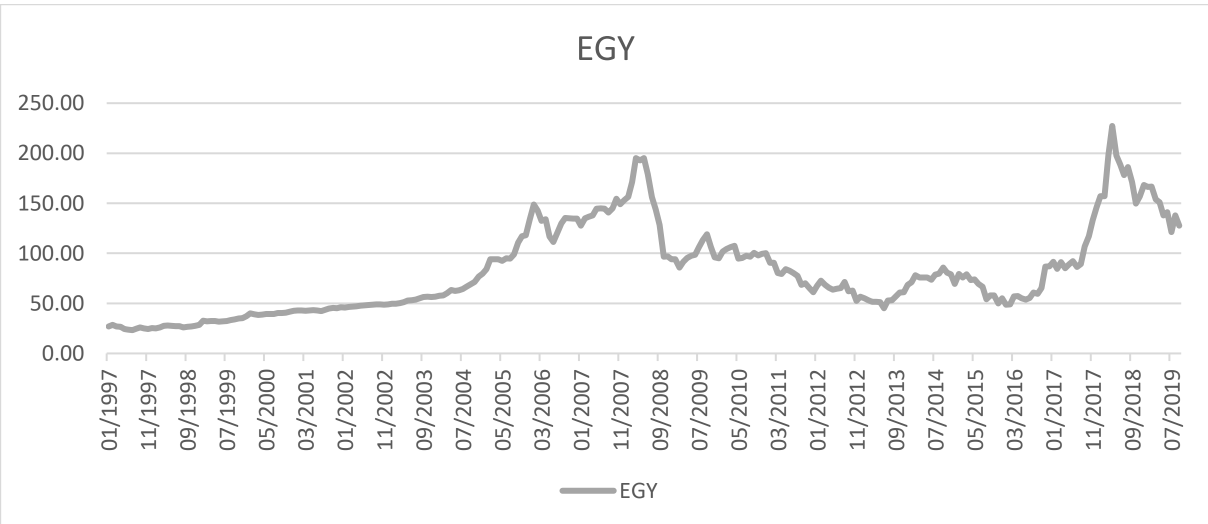


Figure 2: SAF Time Series Plot



ISSN 2224-5804 (Paper) ISSN 2225-0522 (Online)
Vol.10, No.6, 2020

Figure 3: EGY Time Series Plot

Figure 1 to Figure 3 provide evidence that time-varying volatility in monthly Nigeria, South-Africa and Egypt all share index respectively and the returns plots (see Figure 4.4)are empirically shown as clustering volatility. As observed the NGR, recorded the highest ASI between 40730.71&65652.38 in the period between February 2007 and February 2008;SAF recorded the highest ASI between 59504.67&54824.97 in the period between December 2017 and September 2019; also, EGY recorded the highest ASI between197.75&227.22 in the period between May 2018and April 2018. Hence, these features are referred to as the presence of volatility clustering (Humala& Rodríguez, 2010).The plots also show that the series exhibit non-stationary behaviour.

5.1 The Model

Before estimating the Markov Switching (MS) models for the NGR, SAF and EGY returns, we investigate the returns series in order to identify its statistical properties and to see if it meets the pre-conditions for the MS models that is, clustering volatility and ARCH effect in the returns. Figure 4 reports the results of the test of clustering volatility in the returns. The Figure shows that large and small returns occur in clusters, which imply that large returns are followed by more large returns and small returns are further followed by small returns.

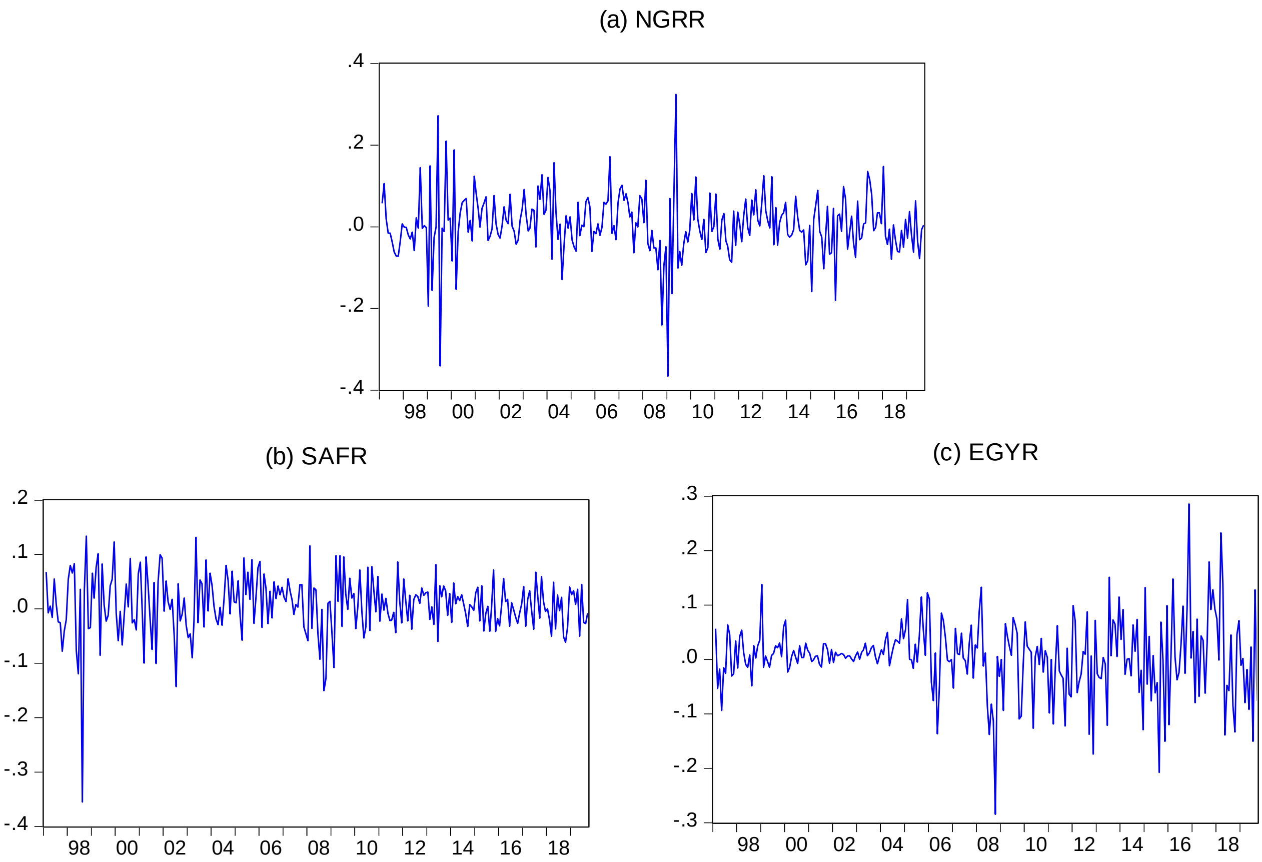


Figure 4: Returns Time Series Plots of NGR, SAF &EGY

Therefore, the Figure 4 suggests that periods of high ASI are usually followed by further periods of high ASI, while low ASI is likely to be followed by much low ASI. This clustering volatility suggests that returns are conditionally heteroscedasticity and it can be estimated by volatility models such as Markov Switching Autoregressive (MS-AR) model.

5.2 Heteroscedasticity Test

The volatility is concerned with a relationship within the heteroscedasticity, often termed serial correlation of the heteroscedasticity. It often becomes apparent when there is bunching in the variance or volatility of a particular variable, producing a pattern which is determined by some factor (see Figure 4). The NGR, SAF and EGY all share index returns are further subject to Heteroscedasticity test; Table 4 presents the test results.

Table 4: Heteroscedasticity Test

Variables	x^2	D.F	Prob
NGRR	254.5711	1	0.0000
SAFR	262.9980	1	0.0000
EGYR	229.9392	1	0.0000

H_0: no ARCH effects vs. H_1: ARCH (p) disturbance. Source: Authors computations using data from ASI, 2019

The results from Table 4.3 find that we can reject the H_0 in favour of the three variables considered. NGRR, SAFR and EGYR are individually statistically significant at the 1% significance level. Hence, the three variables' returns exhibit an ARCH effect, it is appropriate to apply volatility(MS-AR) model that is sufficient to cope with the changing variance in NGRR, SAFR and EGYR.

5.3 BDS Test for Nonlinearity

Before the estimation of the Markov switching models, a nonlinearity test might still benecessary to describe the important features of the data at hand. Table 5 below, reports the resultsof the nonlinearity test (BDS) developed by Brock, Dechert, and Scheinkman (1987).

Table 5: BDS Test

Dimension	**NGRR**		**SAFR**		**EGYR**	
	BDS Statistic	Prob.	BDS Statistic	Prob.	BDS Statistic	Prob.
2	0.014634	0.0075	0.013886	0.0016	0.018322	0.0022
3	0.022807	0.0088	0.038329	0.0000	0.038078	0.0001
4	0.02776	0.0075	0.051692	0.0000	0.049219	0.0000
5	0.033425	0.0020	0.059945	0.0000	0.06397	0.0000
6	0.032687	0.0017	0.062505	0.0000	0.068347	0.0000

Source: Researchers compilation using EViews

The BDS test results in Table 5 indicates that there is nonlinearity effect in NGRR, SAFR and EGYR. Shows that the probabilities are less than5%, consequently implying a rejection of the null hypothesis that the series is linearly dependent. This result is an indication of the messy behaviour of financial time series data therefore the data can be estimated using a nonlinear model.

5.4 Estimation of Markov Switching Autoregressive Model [MS-AR]

The MS-AR specification consists of three State Markov switching models in modeling with a single regressor means switching log(sigma) since the error variance is assumed to vary across the regimes. Table 6 to Table 7 present the estimations of MS-AR models, each table provides the estimations summary of five candidates MS-AR models for each of the returns (NGRR, SAFR and EGYR).

Table 6: MS-AR Model Estimation and Selection (NGRR)

Model [MS-AR]	No of states	No of Lags	Log likelihood	AIC value
MS(2)-AR(1)	2	1	-872.5220	6.6986
MS(2)-AR(2)	**2**	**2**	**-866.8087**	**6.6882**
MS(2)-AR(3)	2	3	-863.9303	6.6995
MS(2)-AR(4)	2	4	-861.0431	6.7108
MS(2)-AR(5)	2	5	-858.1956	6.7224

Note:NGRRshow no convergence at 3 regimes MS for the study period

Source: Computed by the Researchers

Table 7: MS-AR Model Estimation and Selection (SAFR)

Model [MS-AR]	No of states	No of Lags	Log likelihood	AIC value
MS(2)-AR(1)	**2**	**1**	**-793.0370**	**6.0919**
MS(2)-AR(2)	2	2	-790.0717	6.1002
MS(2)-AR(3)	2	3	-785.2050	6.0939
MS(2)-AR(4)	2	4	-782.4235	6.1037
MS(2)-AR(5)	2	5	-778.8237	6.1072

Note:SAFRshow no convergence at 3 regimes MS for the study period

Source: Computed by the Researchers

Table 8: MS-AR Model Estimation and Selection (EGYR)

Model [MS-AR]	No of states	No of Lags	Log likelihood	AIC value
MS(2)-AR(1)	2	1	-819.5384	6.2942
MS(2)-AR(2)	**2**	**2**	**-814.9151**	**6.2905**
MS(2)-AR(3)	2	3	-811.6662	6.2994
MS(2)-AR(4)	2	4	-807.1288	6.2944
MS(2)-AR(5)	2	5	-804.3019	6.3047

Note: EGYR show no convergence at 3 regimes MS for the study period

Source: Computed by the Researchers

From Table 6 to Table 8, using the specification measures such as the log likelihood and the Akaike information criteria (AIC), among the five estimated Markov switching models for each returns the selected models are MS(2)- AR(2), MS(2)-AR(1) and MS-AR(2) for NGRR, SAFR and EGYR respectively with the lowest AIC. After model estimations and selection, the models; MS(2)-AR(2), MS(2)-AR(1) and MS-AR(2) for NGRR, SAFR and EGYR respectively, the models' goodness of fit were diagnosed. The Q-statistics (independency) and Durbin Watson (DW; autocorrelation) test of residuals in each particular case were considered, the results of which are presented in Table 4.8.

Table 9: Model Diagnosis

	Q(p-value)	DW Statistics
MS(2)-AR(2) [NGRR]	16.181 (0.183)	2.3447
MS(2)-AR(1) [SAFR]	12.974 (0.371)	1.9360
MS(2)-AR(2) [EGYR]	9.0065 (0.702)	0.1423(0.7063)

Source: Computed by the Researchers

From the diagnosis of the goodness of fit of the models for the returns series data presented in Table 9 and the plot of the correlogram-Q in the Appendix, the models that have been fitted seem appropriate for the data at the 1% confidence level because the Q–statistics and DW statistics show that there is no statistically significant trace of dependency and autocorrelation left in the squared standardized residual indicating that the volatility models are adequately specified. Table 8 displays the estimations of the best selected models in 6 to Table 7 and the coefficients for their regimes specifically; the invariant error distribution coefficients. We see that all the regimes estimated coefficients of the MS-AR models are found to be significant at conventional level (5%). It also shows the parameters of the transition probability matrix, Log likelihood and AIC of the models.

Table 10: Markov Switching Model Estimation of NGRR, SAR and EGYR

Model		**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**	**Loglikelihood ( ), AIC [ ]**
MS(2)-AR(2) [NGRR]	**Log($\sigma^2_{Regime1}$)**	2.8199	0.1507	18.7241	0.0000	(-866.8087) [6.6882]
	Log($\sigma^2_{Regime2}$)	1.7271	0.0525	32.9201	0.0000	
	$\boldsymbol{\sigma^2_{Regime1} = 16.78\sigma^2_{Regime2} = 5.62}$					
	AR(1)	0.1818	0.0645	2.8182	0.0048	
	AR(2)	0.1029	0.0609	1.6891	0.0912	
	Transition Probability			**Expected Duration**		
		Regime 1	Regime 2	Regime 1	Regime 2	
	Regime 1	0.8991	0.1009	9.9105	82.4676	
	Regime 2	0.0121	0.9879			
MS(2)-AR(1) [SAFR]	**Log($\sigma^2_{Regime1}$)**	1.2212	0.0788	15.5060	0.0000	(-793.0370) [6.0919]
	Log($\sigma^2_{Regime2}$)	1.8872	0.07556	24.9766	0.0000	
	$\boldsymbol{\sigma^2_{Regime1} = 3.39\sigma^2_{Regime2} = 6.60}$					
	AR(1)	-0.0304	0.0644	-0.4719	0.6370	
	Transition Probability			**Expected Durations**		
		Regime 1	Regime 2	Regime 1	Regime 2	
	Regime 1	0.9843	0.0157	63.7260	57.5814	
	Regime 2	0.0174	0.9826			
MS(2)-AR(2) [EGYR]	**Log($\sigma^2_{Regime1}$)**	2.0209	0.0541	37.3875	0.0000	(-814.9151) [6.2905]
	Log($\sigma^2_{Regime2}$)	0.3596	0.1791	2.008	0.0447	
	$\boldsymbol{\sigma^2_{Regime1} = 7.55\sigma^2_{Regime2} = 1.43}$					
	AR(1)	0.1991	0.0710	2.8048	0.0050	
	AR(2)	0.0850	0.0549	1.5487	0.1214	
	Transition Probability			**Expected Durations**		
		Regime 1	Regime 2	Regime 1	Regime 2	
	Regime 1	0.9856	0.0144	69.4477	18.6542	
	Regime 2	0.0536	0.9464			

Source: Researchers' Compilations **Note:** $\sigma^2_{Regime} = exp\ (regime\ coefficients)$

Instead of focusing on the transition matrix parameters of the MS-AR models, we examine the transition matrix probabilities of the three models presented in Table 9; we see the transition probability matrix and the expected durations. The estimated transition probabilities for each MS-AR model show that there is a higher probability that the system stays in the same regime hence implying few switches in the regime. The results indicate that: MS(2)-AR(2)[NGRR] has a 90% probability of staying in an appreciation and a lower probability of 10% switching to the depreciation regime correspondently, when the system is in a depreciation regime, there is a 99%probability of staying in a depreciation regime and again a lower probability of 1% switching to the appreciation regime; MS(2)-AR(1) [SAFR] has a 98% probability of staying in an appreciation and a lower probability of 2% switching to the depreciation regime correspondently, when the system is in a depreciation regime, there is also a 98%probability of staying in a depreciation regime and again a lower probability of 2% switching to the appreciation regime; and lastly, MS(2)-AR(2) [EGYR] has 99% probability of staying in an appreciation and a lower probability of 1% switching to the depreciation regime correspondently, when the system is in a depreciation regime, it has a 95%probability of staying in a depreciation regime and again a lower probability of 5% switching to the appreciation regime. The transition probability results highlighted show that only extreme events can switch the series from regime 1 (appreciation) to regime 2 (depreciation), or vice versa. It further indicates that none of the regime is perpetual/lasting since all the estimated transition probabilities are less than one.

Based on expected duration results in Table 4.9, the appreciation regimes have average duration of 10 months, 64 months and 69 months for NGRR, SAFR and EGYR respectively while depreciation regimes have82 months, 57 months and 18 months durations for NGRR, SAFR and EGYR respectively. This implies that Nigeria All Share Index (Returns), South-Africa All Share Index (Returns) and Egypt All Share Index (Returns)will be in an appreciation regime for an average 10 months, 64 months and 69 months respectively and depreciation regime for an average of 82 months (NGRR), 57 months (SAFR) and 18 months (EGYR).This implies Nigeria All Share Index has the lowest appreciation regime of 10 months and the highest depreciation regime of 82 months while Egypt All Share Index has the highest appreciation regime of 69 months and the lowest depreciation regime of 18 months. Hence, Egypt All Share Index (market) and South-Africa All Share Index (market) are more favorable markets for people to invest than Nigeria All Share Index (market).Figure 4.5to Figure display the predicted regime probabilities for MS-AR-models.

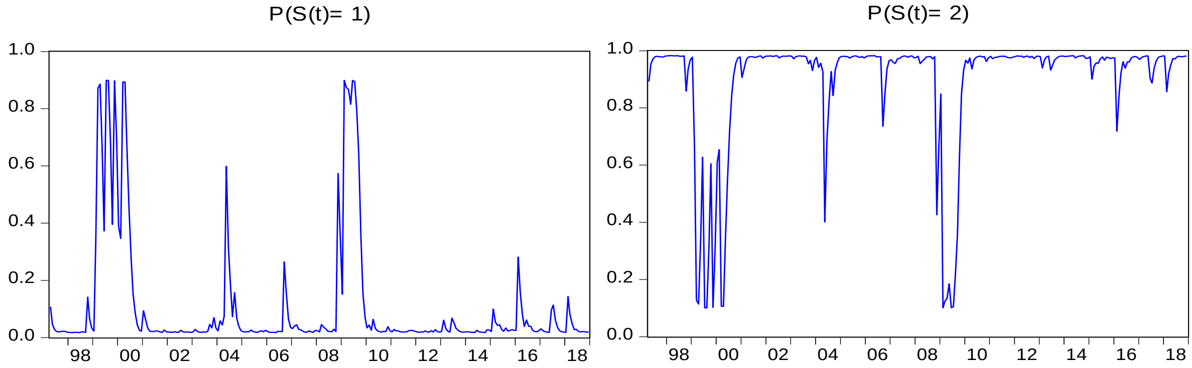


Figure 4.5: One-step Ahead Predicted Regime Probabilities (NGRR)

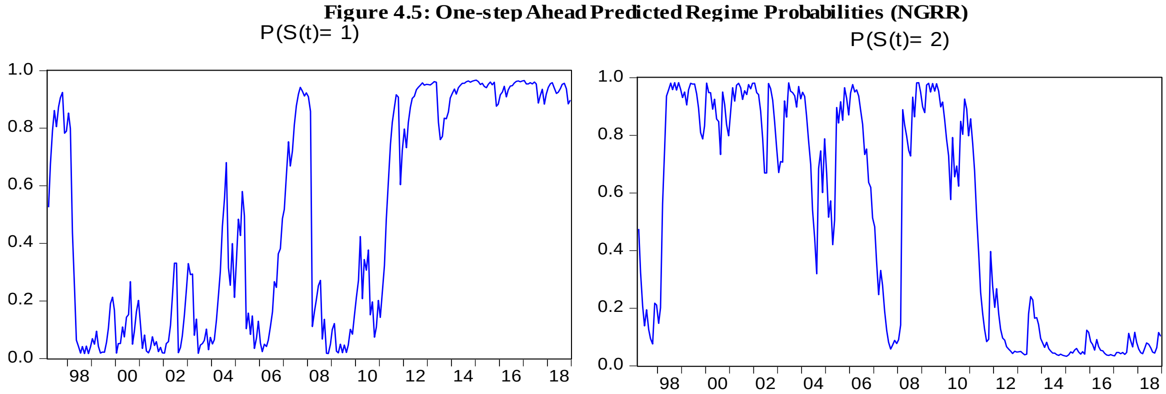


Figure 4.6: One-step Ahead Predicted Regime Probabilities (SAFR)

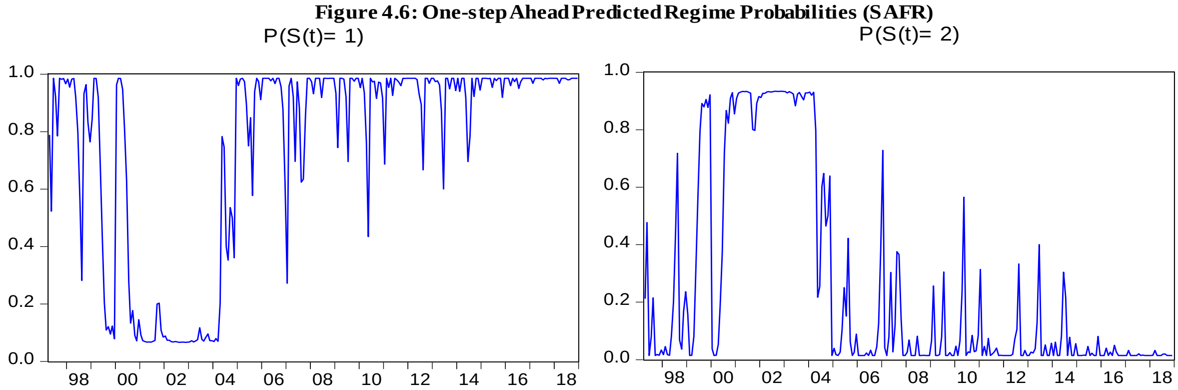
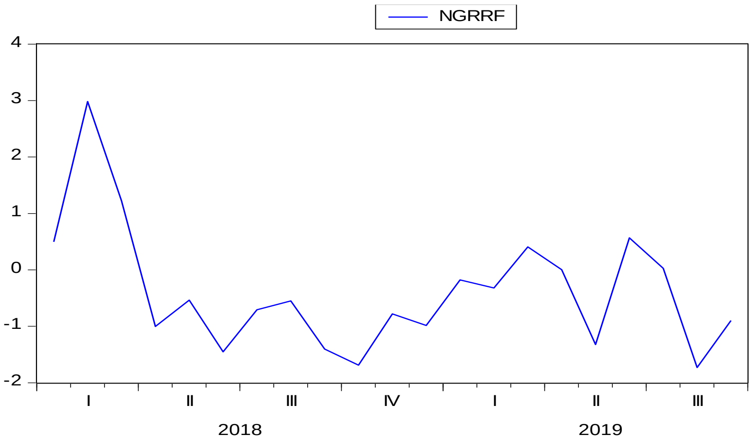


Figure 4.7: One-step Ahead Predicted Regime Probabilities (EGYR)

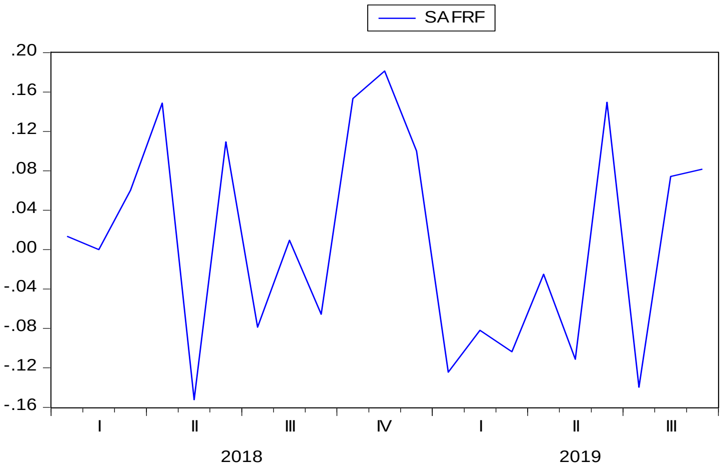
5.5 Forecast Evaluation

Since forecasting is an important application of time series analysis, MS-AR models' forecasts (i.e. from Jan. 2018 to Sept. 2019) of the series based on the model chosen by the prescribed information criteria are presented in Figure 4.8 to Figure 4.10. To determine the performance of the fitted models in forecasting future of NGRR, SAFR and EGYR patterns root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error(MAPE) and Theil's U criteria of the forecast samples (In and Out samples) of NGRR, SAFR and EGYR were computed (see Figure 8 to 10).



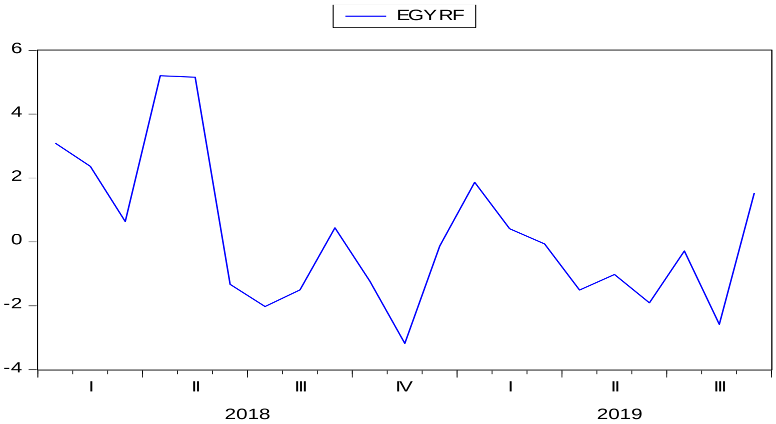
Forecast: NGRRF	
Actual: NGRR	
Forecast sample: 2018M01 2019M09	
Included observations: 21	
Root Mean Squared Error	5.508602
Mean Absolute Error	4.425684
Mean Abs. Percent Error	135.9428
Theil Inequality Coefficient	0.836753
Bias Proportion	0.034921
Variance Proportion	0.574976
Covariance Proportion	0.390103

Figure 4.8: MS(2)-AR(2) [NGRR] Forecast Evaluation



Forecast: SAFRF	
Actual: SAFR	
Forecast sample: 2018M01 2019M09	
Included observations: 21	
Root Mean Squared Error	3.490201
Mean Absolute Error	3.082928
Mean Abs. Percent Error	116.6741
Theil Inequality Coefficient	0.966906
Bias Proportion	0.009361
Variance Proportion	0.938815
Covariance Proportion	0.051824

Figure 4.9: MS(2)-AR(1) [SAFR] Forecast Evaluation



Forecast: EGYRF	
Actual: EGYR	
Forecast sample: 2018M01 2019M09	
Included observations: 21	
Root Mean Squared Error	10.12209
Mean Absolute Error	8.113437
Mean Abs. Percent Error	228.4180
Theil Inequality Coefficient	0.827298
Bias Proportion	0.001139
Variance Proportion	0.576986
Covariance Proportion	0.421875

Figure 4.10: MS(2)-AR(2) [EGYR] Forecast Evaluation

6. Summary, Conclusions and Recommendations

This research work aimed at modeling All Share Index using Markov Switching Autoregressive (MS-AR) models examined the monthly returns of All Share Index series of three different countries namely Nigeria, South-Africa and Egypt. The data span from January 1997 to September 2019.

In the preliminary analysis, the descriptive statistics and distribution of all the series revealed conventional facts. In subsequent analysis, the study further employed univariate specifications of two state Markov Switching Autoregressive (MS-AR) models.

The aim and objectives of the study have been basically achieved. The two state Markov Switching Autoregressive (MS-AR) models developed by Hamilton (1989) Engel and Hamilton (1990) was utilized to capture regime shifts behaviour in both the mean and the variance of the three countries All Share Index. All the series used exhibit heteroscedasticity and volatility clustering. The MS-AR results of the three countries All Share Index suggested evidence of a regime-switching behaviour. It shows that only extreme events can switch the series from regime 1 (appreciation) to regime 2 (depreciation), or vice versa. It further indicates that none of the regime is perpetual/lasting since all the estimated transition probabilities are less than one. The results further revealed that Nigeria All Share Index has the lowest appreciation regime of 10 months and the highest depreciation regime of 82 months while Egypt All Share Index has the highest appreciation regime of 69 months and the lowest depreciation regime of 18 months. Hence, Egypt All Share Index (market) and South-Africa All Share Index (market) are more favorable markets for people to invest than Nigeria All Share Index (market).

From the preceding the following recommendations were made:

i. Nigeria government, should direct more efforts towards improving the performance of her stock exchange market in order to make the market more favorable for investors;

ii. New strategies should be developed towards tackling significant events which not handle can affect the behaviour of the All Share Index when in appreciation state.

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ISSN 2224-5804 (Paper) ISSN 2225-0522 (Online)
Vol.10, No.6, 2020

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