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THE REGIME EXAMINATION OF NIGERIA EXCHANGE RATE VOLATILITY: EVIDENCE FROM MARKOV REGIME SWITCHING AUTOREGRESSIVE APPROACH

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ABSTRACT: *Inarguably, the escalation in dollar rates and the price instability in the Nigerian economy underwent significant structural and institutional changes. In assessing the importance of understanding exchange rates, it becomes imperative to build reliable models for predicting the volatility of exchange rates of home currency. Hence, this study aims to model the Nigerian exchange rate volatility using the Markov regime-switching model. The study analyses the Nigerian exchange rate returns in two and three distinct regimes by employing the Markov regime-switching autoregressive (MS-AR) model with data from 2nd January 2018 to 7th September 2020. Four MS-AR candidate models were estimated for the exchange rate series. Based on the least AIC value, MS(3)-AR(2) was returned as the most parsimonious model among the four candidate models. The MS(3)-AR(2) analysis established a high probability that the returns system remains in the liquidation and awareness states. It implied that only unconventional or severe events could switch the series from regime 2 (liquidation phase) and regime 3 (awareness). While there is a low probability that the system will stay in an imbalanced regime implies high switching of regime 1. Furthermore, an average duration period of 2 days, six days and five days were estimated for the imbalance, liquidation and awareness regimes, respectively. Thus, the findings, i.e. imbalance and liquidation regimes' identification and their average durations, show that the Naira in the foreign exchange market is not favourable for investors to trade. The study recommends that the Nigerian government should direct more efforts towards improving the performance of the Naira in the foreign exchange market to make the market more favourable for investors. Specifically, the CBN should develop new strategies towards tackling the behaviour of the Nigerian exchange rate when in a liquidation state.*

KEYWORDS: Markov process, regime switching, exchange rate, volatility.

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INTRODUCTION

Since the collapse of the Breton Woods international monetary system of fixed exchange rates among emerging market currencies to be précised, elevated volatility is a conspicuous attribute of exchange rates (May and Farrell, 2017). The exchange rate and its volatility are vibrant causes of many countries' economic instability, especially Nigeria. No wonder the exchange rate fluctuations in Forex (FX) market have attracted significant attention in recent studies. Exchange rate volatility can be referred to as the measure of fluctuations in an exchange rate, usually measured hourly, daily, weekly, monthly or annually. It is a vital factor in options trading and risk management as it provides a simple approach to calculating the value at risk of a financial asset. Numerous studies such as Suliman (2012), Adesina (2018), Onyeka-Ubaka (2018), May-Farrell (2017), Manamba-Epaphra (2017), and so on have pointed out that exchange rate volatility is a vital subject of macroeconomic analysis and has received a great deal of interest from academics, financial economists and policymakers, particularly after the collapse of the Breton Woods agreement of fixed exchange rates among major industrial countries. Thus, exchange rate volatility exposes economic agents to a greater exchange rate risk.

Besides, enormous variations have been observed in the foreign exchange market in the last few months, and its effect on the economy of any country cannot be overemphasised. Most financial analysts, risk managers and policymakers are specifically interested in obtaining worthy estimates of the conditional variance (a distinctive feature of volatility) to enhance portfolio shares or risk management. Over the years, a series of models have been established to evaluate exchange rate conditional volatility. The Robert F. Engle generalised autoregressive conditional heteroscedastic (GARCH) models developed in 1982 have been the commonly used models for volatility forecast. The volatility forecast has attracted much attention in recent years, mostly driven by the importance of volatility forecasts in the exchange rate.

It must be pointed out that before the introduction of conditional volatility models, there were the Box-Jenkins (1976) models, specifically, the Autoregressive Integrated Moving Average (ARIMA) models. However, ARIMA models are based on the inaccurate assumptions of constant variance for the time series of exchange rate returns (Goldfeld and Quandt (1976), Hamilton (1989), Shamsuddeen *et al.* (2015)). This shortcoming of ARIMA models has led to the emergence of various types of Engle-like models (examples are Tule *et al.* (2018), Adesina (2018), Onyeka-Ubaka (2018), Maqsood *et al.* (2017), May-Farrell (2017), Manamba-Epaphra (2017), Yaya *et al.* (2016), Bala and Asemota (2013), Wang (2006), Longmore-Robinson (2004), etc.). These new methods adopted various extensions of the GARCH models like the GARCH-M, IGARCH, EGARCH, TGARCH and PARCH, which consider the possibility of variation in the exchange rates.

Another example of an exchange rate volatility model is the regime-switching model, developed by Hamilton (1989). This model has become very prevalent, particularly in applied research. The regime-switching model has gained the attention of many scholars like Calvet and Fisher (2004), Masoud *et al.* (2012), Beckmann and Czudaj (2013), Lux *et al.* (2014), Nguyen and Walid (2014), Aliyu and Wambai (2018), Korkpoe and Howard (2019), Yahaya and Adeoye (2020) to mention but few. They have documented the distinctiveness and forecasting capabilities of Markov regime-switching against the commonly used GARCH models. The Markov regime-switching method of volatility analysis has recorded some

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advantages over time. More explicitly, the succeeding paragraphs distinctly discuss the studies mentioned above. Consequent to Webb (2020), who recognised that the market's exchange rate volatility is primarily and distinctly characterised by three regimes or phases which serve as indicators for investors to know when to invest and sell. Also, after the escalation in dollar rates and price instability, the Nigerian economy underwent significant structural and institutional changes. In the assessment of the importance of understanding of exchange rates, it becomes very imperative to build reliable models for the prediction of the volatility of exchange rates of home currency vis-before currencies of the developed nations, especially the nations with whom the home country have a bilateral economic relationship; such as the USA, China, Japan, to mention but few. Hence, on this background, this study seeks to analyze the Nigerian exchange rate volatility in three distinct phases: the imbalance, liquidation and awareness regimes.

DATA

The nature of this study necessitated the use of secondary data. Data was sourced from Central Bank of Nigeria websites; the study utilizes daily time series data and covers a period of 2nd January 2018 to 7th September 2020. The exchange rate returns are calculated and are represented as the differences in Naira/USD 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.

RESEARCH METHODOLOGY

Autoregressive Conditional Heteroscedastic (ARCH) Test

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 the ARCH effect, the Lagrange Multiplier (LM) test proposed by Engle (1982) is applied. We obtain the residuals $e_t$from the ordinary least square regression of the conditional mean equation using this procedure. For an ARMA(1,1) model, the conditional mean equation will be:

$$r_t = \emptyset_1 r_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} \qquad 3.1$$

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

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2$$

$$= \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 \qquad 3.2$$

The null hypothesis

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

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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 ^{2} (q) distribution.

Test of Nonlinearity

To determine whether a nonlinear model is suitable for the data. The decision should come from the financial theory; the nonlinear model should be used where financial theory suggests that the relationship between the variable requires a nonlinear model (Mendy & Widodo, 2018). We focus on the most widely used test, known as the 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;

$$BDS_{m.M}(r) = \sqrt{M}\frac{C_m(r) - {C_1}^r(r)}{\sigma_{m.M}(r)} \quad 3.3$$

Where M is the surrounded points of the space with m dimension, r denotes the radius of the sphere centred 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

The Markov Switching Autoregressive (MS-AR) Model

Generally, an autoregressive model of order n with first-order, N-state Markov-switching mean and variance may be written as:

$$\phi(L)(r_t - \mu_{S_t}) = e_{t,} \quad e_{t,} \sim N(0, \sigma^2_{S_t}), \quad 3.4$$

$$Pr[S_t = j \mid S_{t-1} = i] = p_{ij}, \quad i, j = 1, 2, \ . \ . \ ., N,$$

$$\sum_{j=1}^{M} \ p_{ij} = 1, \quad 3.5$$

$$\mu_{S_t} = \mu_1 S_{1t} + \mu_{2t} S_{2t} + \ . \ . \ . + \mu_N S_{Nt}, \quad 3.6$$

$$\sigma^2_{S_t} = \sigma^2_1 S_{1t} + \sigma^2_2 S_{2t} + \ . \ . \ . + \sigma^2_2 \sigma^2_2, \quad 3.7$$

where $S_{nt} = 1,$ if $S_t = n,$ and $S_{nt} = 0$ otherwise.

Let S_t be a variable that can assume only an integer value {1, 2, . . ., N}. Suppose that the probability that S_t, equals some particular value j depends on the past only through the most recent value S_{t-1}

$$Pr[S_t = j \mid S_{t-1} = i, \quad S_{t-2} = k, \ldots]$$

$$= Pr[S_t = j \mid S_{t-1} = i] = p_{ij} \quad 3.8$$

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Such a process is described as an N-state Markov Chain with transition probabilities $\{p_{ij}\}_{i,j=1,2,3,\ldots,N}$ the transition probability p_{ij} gives the probability that the state i will be followed by state j. Note that

$$p_{i1} + p_{i2} + p_{i3} + \ldots + p_{iN} = 1 \qquad 3.9$$

It is often convenient to collect the transition probabilities in an $(N \times N)$ matrix P known as the transition matrix

$$P = (P_{11} \quad P_{12} \ \ldots \ P_{1N} \ P_{21} \quad P_{22} \ \ldots \ P_{2N} \ \vdots \quad \vdots \ \ldots \ \vdots \quad P_{N1} \ P_{N2} \ \ldots \ P_{NN}) \qquad 3.10$$

The row j, column I element of P is the transition probability P_{ij} (Hamilton 1994). Denote $r_t = log\left(\frac{y_t}{y_{t-1}}\right)$, as stock returns, where y_t is the value of stock at time *t*.

Consider the model:

$$r_t = r_t = \mu_{S_t} + \varepsilon_t \qquad 3.11$$

Where $\varepsilon_t \sim i.i.d\ N(0, \sigma_{St}^2), S_t = 1, 2, 3, \ldots, k, \ t = 1, 2, 3, \ldots, T$.

Equation (3.11) denotes the simplest model with switching dynamics. The intercept μ takes k different values representing the expectations in the k different states, and also the volatilities σ_{St}^2 of ε_t. S_t is the unobservable Markov switching variable, which evolves according to the following transition in (3.10).

From (3.4) we consider a first order autoregression in which both the constant term and the autoregressive coefficient might be different for different sub samples:

$$r_t = c_{S_t} + \phi_{S_t}(r_{t-1}) + e_t \quad e_{t,} \sim i.i.d\ N(0, \sigma^2) \quad 3.12$$

The proposal will be to model the regime S_t as the outcome of an unobserved N-state Markov chain with S_t independent of e_t for all t.

The MS-AR model of three regimes, is a model that switch regimes stochastically, it was initiated by Hamilton (1989). According to Mendy and Widodo (2018), a MS-AR model of regimes with an AR process of order p is stated as follows;

$$Y_t = \{a_1 + \beta_{11}Y_{t-1} + \cdots + \beta_{p1}Y_{t-p} + \varepsilon_t \quad S_t = 1 \ a_2 + \beta_{12}Y_{t-1} + \cdots + \beta_{p2}Y_{t-p} + \varepsilon_t \quad S_t = 2 \ a_3 + \beta_{13}Y_{t-1} + \cdots + \beta_{p3}Y_{t-p} + \varepsilon_t \quad S_t = 3 \quad 3.13$$

Where the regimes in (3.8) are indexed by S_t. In the MS-AR model, the intercept and the parameters of the AR part depend on the regime at time *t*. These regimes are assumed to be distinct unobservable variables. Hence, in this study, regime one describes the periods of imbalance of the exchange rate returns, r_t, regime two symbolises the period of liquidation of the returns r_t and regime three symbolises an awareness phase of the returns r_t. The transitions that are between the regimes are assumed to follow an ergodic and intricate 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;

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

$\sum_{i=1}^{2} \quad \rho_{ij} = 1$

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

$P = [P_{11} \;\; P_{12}\, P_{13}\, P_{21} \;\; P_{22}\, P_{23}\, P_{31} \;\; P_{32}\, P_{33}\,]$ 3.14

where $P_{11} + P_{12} + P_{13} = 1$, $P_{21} + P_{22} + P_{23} = 1$ and $P_{31} + P_{32} + P_{33} = 1$. The closer the probability ρ_{ij} is to one the longer it takes to shift to the next regime.

The Expected Duration of a Regime in a Markov-Switching Model

The diagonal element of the matrix of the transition probabilities in (3.14) contains important information on the expected duration of the regime's state. Let *D* be defined as the duration of state *j*; we have:

$D = 1$, if $S_t = j$ and $S_{t+1} \neq j; Pr[D = 1] = (1 - p_{jj})$

$D = 2$, if $S_t = S_{t+1} = j$ and $S_{t+2} \neq j;\; Pr[D = 2] = p_{jj}(1 - p_{jj})$

$D = 3$ if $S_t = S_{t+1} = S_{t+2} = j; Pr\, Pr\, [D = 3] = p_{jj}^2(1 - p_{jj})$ ....

Then, the expected duration of regime *j* can be derived as

$$E(D) = \sum_{j=1}^{\infty} \quad j\, Pr\, Pr\, [D = j]$$

$= 1 \times Pr\, Pr\, [S_{t+1} \neq j\, | S_t = j] \quad + 2 \times Pr[S_{t+1} = j, S_{t+2} \neq j \mid S_t = j\,] + 3 \times Pr\, Pr\, [S_{t+1} = j, S_{t+2} = j, S_{t+3} \neq j \mid S_t = j\,] + . . .$

$=1 \times (1 - p_{ij}) + 2 \times p_{jj}(1 - p_{ij}) + 3 \times p_{jj}^2(1 - p_{ij}) + . . . = \frac{1}{1 - p_{ij}}$

Hence the expected duration for the system to stay in each regime is calculated as; $Expected\ duration = \frac{1}{1-P_{ij}}$.

Model Selection

In modelling volatility, the choice of an appropriate model from variants class of models portray the underlying data is often a difficult task. The importance of choosing the best model in time series analysis cannot be overemphasised. Model selection criteria provide useful tools and assess whether a fitted model offers an optimal balance between goodness-of-fit and parsimony, Miah and Raham (2016). This study utilised the common model selection criterion, the Akaike Information Criterion (AIC)

$AIC = T\, ln(residual\ sum\ of\ squares) + 2n,$

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where T is the number of operational observations, and n is the number of parameters to be estimated. The model best model is one with the smallest *AIC* values.

EMPIRICAL RESULTS

Descriptive Analysis

Table 4.2 display the descriptive statistics of the exchange rate and its returns. As observed, EXR recorded mean, median, maximum and minimum of 316.02, 306.40, 379.50 and 305.05, respectively, for the period examined. EXR has a standard deviation and Jarque-Bera statistic value of 22.20 and 440.63, respectively, with a p-value of 0.00 less than 0.01 (level of significance). Similarly, EXRR recorded mean, median, maximum and minimum of 0.002, 0.001, 0.007 and 0.00, respectively, for the period examined, and has a standard deviation and Jarque-Bera statistic value of 0.003 and 8438389.00, respectively, with a p-value of 0.00 less than 0.01 (level of significance).

Table 4.1. Descriptive Statistics of Exchange Rate and Its Returns

	EXR	**EXRR**
Mean	316.023	0.002
Median	306.400	0.001
Maximum	379.500	0.070
Minimum	305.050	0.000
Std. Dev.	22.201	0.003
Skewness	1.834	22.987
Kurtosis	4.557	552.936
Jarque-Bera	440.625	8438389.000
Probability	0.000	0.000
Observations	666	665

Note: EXR denote Exchange Rate (Naira/USD), EXRR denote Exchange Rate Returns

Source: *EViews Output*

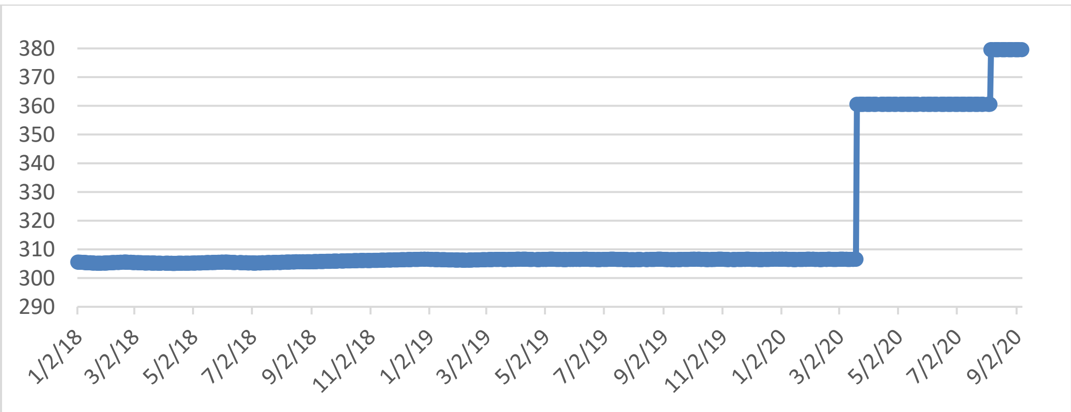

Fig 4.1. EXR Time Series Plot

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Fig 4.1 presents the time series plots of the Nigerian exchange rate. As observed from Fig 1, the exchange rate (Naira/USD) was relatively constant (i.e. between 305.45 and 306.5) from 2nd January 2018 to 19th March 2020. This was due to the consequence of the injection of $8.29 billion by the Central Bank of Nigeria (CBN) to stabilize the foreign market (Oladeinde, 2020). The exchange rate rose abruptly to 360.5Naira/USD on 26th March 2020 and was relatively constant, only on 11th August 2020 when it skyrocketed to 379.5Naira/USD. This can be attributed to the effect of the Covid-19 pandemic in Nigeria at that time.

Additionally, the returns plot (Fig. 4.2) empirically shows clustering volatility in the series, which depicts a relatively clustered returns across the periods of study. The evidence of clustering volatility in Fig 4.2 suggests that EXR are conditionally heteroscedasticity and can only be estimated by volatility models such as MS-AR model. This was further ascertained using ARCH test (see Section 4.2).

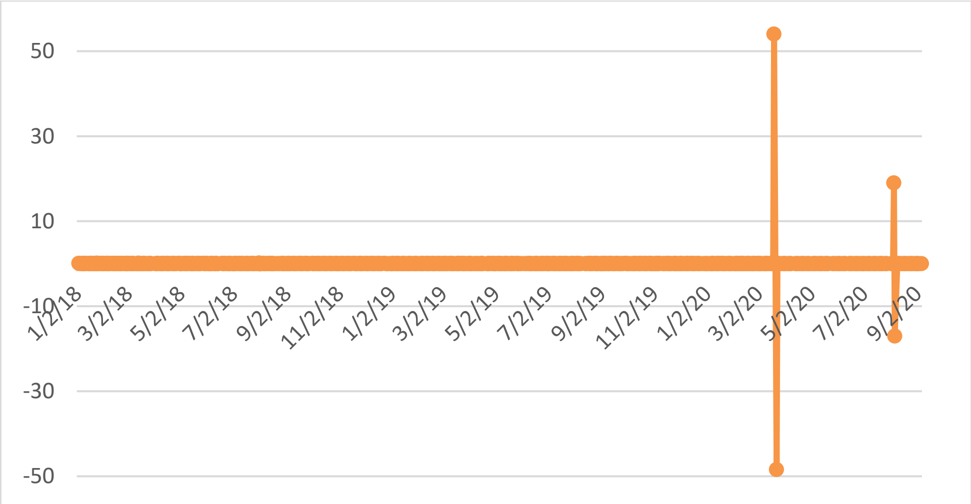

Fig 4.2. EXRR Time Series Plot

Result of ARCH test

Before MS-AR estimation, ASIR was tested for Heteroscedasticity. The results are presented in Table 4.2. The results provide evidence (i.e. p-value < 0.01) to reject H_0 (null hypothesis) in favor of H_1 (alternative hypothesis) of the heteroscedasticity test. Hence, EXRR exhibits ARCH effect. Therefore, it is suitable to apply MS-AR models that will sufficiently handle the changing variance in EXRR since the return series meets the pre-conditions for the MS-AR models.

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Table 4.2. ARCH Test

Variable	x^2	D.F	P-value
EXRR	655.0419	661	0.000*

Note: H_0*: there are no ARCH effects vs.* H_1*: there is ARCH (p) disturbance.* * denotes significant at 1% level of significance

Source: *Researchers' compilation EViews Output*

The Brock Dechert and Scheinkman (BDS) Test for Nonlinearity

Before the estimation of the Markov switching models, a nonlinearity test might still be necessary to describe the important features of the data at hand. Table 4.4 below reports the results of the nonlinearity test (BDS) developed by Brock, Dechert, and Scheinkman (1987).

Table 4.3. BDS Test

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.204728	0.005538	36.97025	0.0000*
3	0.346066	0.008798	39.33401	0.0000*
4	0.444008	0.010484	42.34958	0.0000*
5	0.512071	0.010941	46.80359	0.0000*
6	0.559424	0.010568	52.93751	0.0000*

Note: H_0*: there is no EXRR nonlinearity effects vs.* H_1*: there is EXRR nonlinearity effect.* * denotes significance at a 1% level of significance

Source: *EViews Output*

The BDS test results in Table 4.3 indicate a nonlinearity effect in the exchange rate returns (EXRR). It shows that the probabilities are less than 1%, consequently implying a rejection of the null hypothesis that EXRR is nonlinearly dependent. This result indicates the messy behaviour of financial time series data; therefore, the data can be estimated using a nonlinear model such as the MS-AR model.

Estimation of Markov Switching Autoregressive Model [MS-AR]

The MS-AR specification consists of three or two states of Markov switching models in modeling with a single regressor means switching $log\ (\sigma^2)$ since the error variance is assumed to vary across the regimes. Table 4.4 presents the summary estimations of four MS-AR candidate models for EXRR series. Using the specification measures, i.e. highest log-likelihood and minimum Akaike information criteria (AIC), among the five estimated MS-AR

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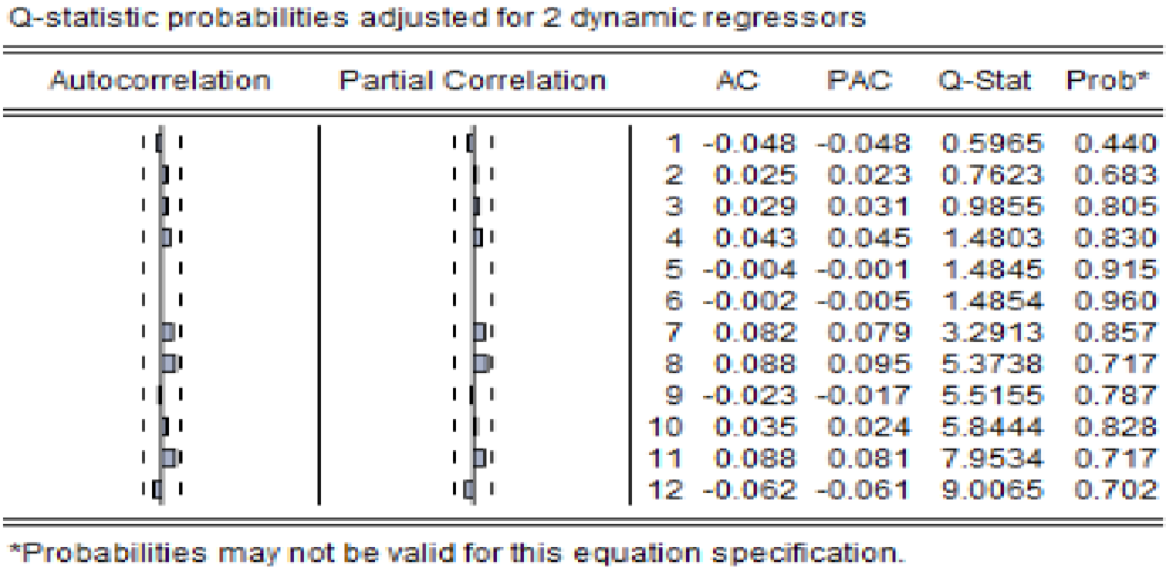
models for EXRR, the best model is MS(3)-AR(2) since it is the only model with the lowest AIC and highest log-likelihood.

Table 4.4. MS-AR Model Estimation and Selection (EXRR)

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(3)	2	3	-867.8303	6.6995
MS(2)-AR(4)	2	4	-861.0431	6.7108
MS(3)-AR(2)	**3**	**2**	**-866.9087**	**6.6882**

Source: *Researchers' compilations*

After model estimations and the selection of the most parsimonious model [MS(3)-AR(2)], the model was diagnosed for the goodness of fit. The Q-statistics (independency) and Durbin Watson (DW; autocorrelation) test of residuals were considered (see Fig 4.3 and Table 4.5 for more details).


Q-statistic probabilities adjusted for 2 dynamic regressors

	AC	PAC	Q-Stat	Prob*
1	-0.048	-0.048	0.5965	0.440
2	0.025	0.023	0.7623	0.683
3	0.029	0.031	0.9855	0.805
4	0.043	0.045	1.4803	0.830
5	-0.004	-0.001	1.4845	0.915
6	-0.002	-0.005	1.4854	0.960
7	0.082	0.079	3.2913	0.857
8	0.088	0.095	5.3738	0.717
9	-0.023	-0.017	5.5155	0.787
10	0.035	0.024	5.8444	0.828
11	0.088	0.081	7.9534	0.717
12	-0.062	-0.061	9.0065	0.702

*Probabilities may not be valid for this equation specification.

Fig 4.3. MS(3)-AR(2) Q-statistics

From the diagnosis of the goodness of fit of the models for the returns series data presented in Table 4.5 (DW Stat=2.0447) and the plot of the correlogram-Q in Fig 4.3, the model, MS(3)-AR(2), have been appropriately fitted for the EXRR data at high confidence level since the Q–statistics and DW statistics show no significant trace of dependency and autocorrelation left in the squared standardized residual indicating that the volatility models are adequately specified.

Table 4.5 displays the estimation of MS(3)-AR(2) and the coefficients for the regimes, specifically, the invariant error distribution coefficients. We see that all the regimes estimated coefficients of the MS(3)-AR(2) model were found to be significant at the conventional level

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(5%). It also displays the parameters of the models' transition probability matrix, log-likelihood and AIC.

Table 4.5. MS(3)-AR(2) Estimation

Model		Coefficient	Std. Error	z-Statistic	Prob.	Loglikelihood ( ), AIC [ ]	
MS(3)-AR(2) [EXRR]	**Log($\sigma^2_{Regime1}$)**	-0.9855	0.0778	-49.8221	0.0000	(2297.930) [-6.4240]	
	Log($\sigma^2_{Regime2}$)	-0.8902	0.1538	-37.010	0.0000		
	Log($\sigma^2_{Regime3}$)	-1.7688	0.07929	-60.1592	0.0000		
		$\sigma^2_{Regime1}$ = **0.3733** $\sigma^2_{Regime3} = 5.8638$			$\sigma^2_{Regime2} = 0.4106$		
	AR(1)	0.4206	0.1294	7.0445	0.0000		
	AR(2)	-0.2142	0.1364	-1.3903	0.7823		
	Transition Probability			**Expected Duration**			
		Regime 1	Regime 2	Regime 3	Regime 1	Regime 2	Regime 3
	Regime 1	0.3637	0.3200	0.3163	1.5715	5.7396	5.3604
	Regime 2	0.0020	0.8258	0.1722			
	Regime 3	0.0021	0.1845	0.8134	DW Stat = 2.0447		

Source: *Researchers' compilations using EViews*

As a substitute to the transition matrix parameters of the MS(3)-AR(2) model, we examine the transition matrix probabilities of the MS(3)-AR (2) presented in Table 4.5. We see the transition probability matrix and the expected durations. The results indicate that MS(3)-AR(2) has a 36% probability of staying in an imbalanced regime and a probability of 32% of switching to the liquidation regime and awareness regime. When the system is in a liquidation regime, it has an 83% probability of staying in a liquidation regime and a low probability of 17% and 0.20% of switching to the awareness and imbalance regimes, respectively. Also, when the system is in an awareness regime, it has an 81% probability of staying in the awareness regime and a low probability of 0.21% and 18% of switching to the imbalance and liquidation regimes, respectively. The transition probability results showed that only extreme events could switch the system when in liquidation and awareness regimes. The estimated transition probabilities show that there is a high probability that the system remains in the same regime when in liquidation and awareness regimes, implying few switches in the regimes. However, there is a

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low probability that the system will stay in an imbalanced regime. It further indicates that none of the regimes lasts since all the estimated transition probabilities are less than one.

Based on the expected duration results in Table 4.5, the imbalance regimes have an average duration of 2 days, while liquidation and awareness regimes have six days and five days durations, respectively, for Naira/USD returns.

Fig 4.4 display the predicted regime probabilities for MS(3)-AR(2)-model.

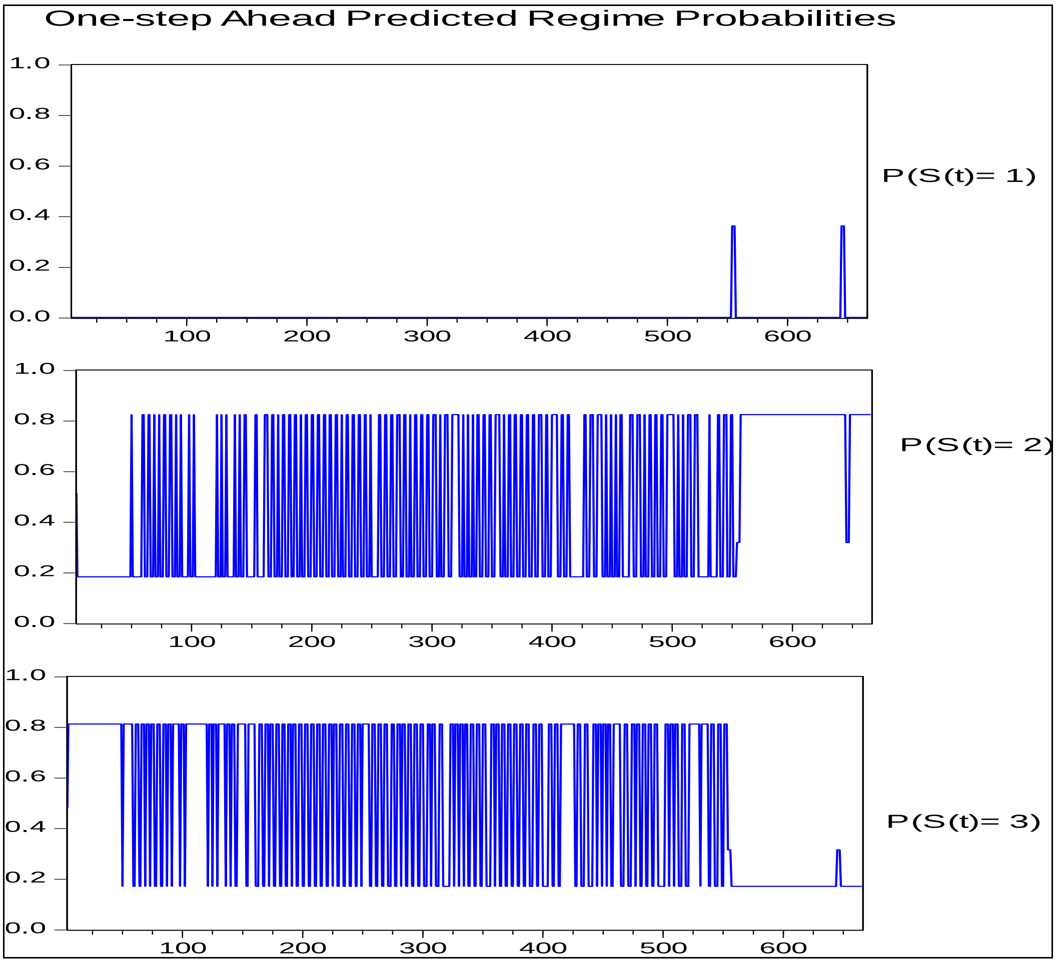

Fig 4.4. Predicted Regime Probabilities

CONCLUSIONS

This paper examined two and three states of Markov Switching Autoregressive (MS-AR) models developed by Hamilton (1989) to estimate the regime shifts behaviour in both the mean and the variance of the Nigeria exchange rate. Prior to the MS-AR estimation, the descriptive statistics and the time series plots of the data, i.e. Exchange rate (EXR) and its returns series (EXRR), were presented. ARCH test was also carried out to check that the return series meets

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the pre-condition (ARCH effect) for the volatility model. Lastly, the BDS test was conducted to identify the nonlinear feature of the EXRR series.

Four MS-AR candidate models were estimated for the exchange rate series.

Following the most negligible AIC value, MS(3)-AR(2) returned as the most parsimonious model among the four candidate models. The MS(3)-AR(2) goodness of fit test results [i.e. Q–statistics (p-value 0.702) and DW statistics (2.0447)] show that MS(3)-AR(2) was adequately estimated. The MS(3)-AR(2) estimation provides the empirical results of the Nigerian exchange rate returns in three distinct phases; imbalance, liquidation and awareness regimes. This finding is unique however, similar to Adejumo *et al.* (2020), whose study provided evidence of financial assets in three regimes (accumulation or distribution – regime 1; big-move – regime 2; and excess or panic phases – regime 3). Also, evidence from the three-regimes [MS(3)-AR(2)] estimation established a high probability that the returns' system remains in the liquidation and awareness states, it implied that only unusual events could switch the series from regime 2 (liquidation phase) and regime 3 (awareness). While there is a low probability that the system will stay in an imbalanced regime implies high switching of regime 1.

Further, an average duration period of 2 days, six days and five days for the imbalance, liquidation and awareness regimes, respectively, were indicated. However, the transition probability and expected duration of the liquidation phase were higher than the awareness and imbalance phases. This finding is similar to Adejumo *et al.* (2020), where higher transition probabilities were established in accumulation/distribution compared to big-move and excess/panic eras.

The findings mentioned above show that the imbalance and liquidation regimes' identification and their average durations are evident that the Naira in foreign exchange market is not favourable for investors to trade. Also, the regime's identification and its average duration would guide the stakeholders and risk managers who are interested in the state of the Nigerian exchange rate in making an investment policy that will enable them to trade in the market. Hence, it is evident that the MS-AR model is indubitably robust and a valuable addition to the toolbox for modelling the foreign exchange market volatility in the imbalance, liquidation and awareness phases. Nevertheless, the recommendations from those described above provide that the Nigerian government should direct more efforts towards improving the performance of the Naira in the foreign exchange market to make the market more favourable for investors. Also, new strategies should be developed to tackle the behaviour of the Nigerian exchange rate when in a liquidated state by reducing the quantity of the currency in circulation.

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