Economic regimes and stock market performance in Nigeria: Evidence from regime switching model

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Abstract

The paper analyzes volatility spillover between exchange rate and stock market in "turbulent" and "calm", otherwise, "bull" and "bear" periods in the Nigerian stock market from 1st January, 2010 to 31st December, 2017 using a regime heteroskedastic Markov switching model in line with Kim (1993). The approach allows regime shift in both mean and variance of a series where failure to allow for regime shift leads to an overstatement of persistence of the variance, Lamoureuex and Lastrapes (1990). Results from preliminary investigations reveal that both stock returns and exchange rate series are characterized with non-normal distribution, presence of unit root and ARCH effects. Further, evidence of two regimes, that is, bear and bull markets, was established with higher persistence, that is, high transition probabilities, in the bear as against the bull market at 0.9455 and 0.8686, respectively. However, duration of stay in the regime is higher in the bull market (regime 2) than in the bear market (regime 1) at 5958.12 days and 18.406 days, respectively. Further, analysis of volatility spillover between exchange rate and stock returns reveals that returns increases due to appreciation in the exchange rate in the bear market and diminishes in response to exchange rate depreciation in the bull market. Thus, adverse economic conditions leading to exchange rate volatility diminishes stock market returns by increasing investors' risk perception, especially in the bull market. No doubt, the findings are important to investors, regulators and monetary authorities.

Keywords: *Markov switching model, bull and bear markets, stock returns, exchange rate, volatility*

JEL Classification: C53, F36, G12, G15

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I. Introduction

Investigation into the behavior of stock market returns and volatility are of great importance to a number of people; researchers, investors, businesses, and policymakers. Accordingly, these have attracted mounting body of empirical literature. Following the seminal work of Hamilton (1989), modeling financial of variables inter alia, stock returns, exploits not only nonlinear models but incorporates the influence of economic regimes as well. Many researches use macroeconomic and financial variables to predict stock market returns (Aikaterini, 2016). Often, financial time series especially stock prices go through episodes in which the behaviour of the series seems to change quite dramatically in response to fundamental internal and external shocks. Further, it is well documented that stock returns are characterized by at least two distinct regimes (*bull* and *bear* markets). However, minor events such as at firm level are highly unlikely to influence the trends of the stock market as a whole, and the volatility effect, (Poon and Granger, 2003; Bloom, 2009; Jones & Olson, 2013).

A few studies assess the impact of movements in exchange rate in terms of regime classifications in the literature. For instance, Panopoulou and Unalmis (2008) report volatility spillover between exchange rate and stock market in "turbulent" and "calm" periods using Markov Switching method while Walid, Aloui, Masood and Fry (2011) opine that the volatility relationship between exchange rate-stock markets differentiates "high mean-low variance" regime and "low mean-high variance" regime employing Markov Switching EGARCH. Zhu and Zhu (2013) use fifteen macroeconomic economic variables to predict excess stock returns in the US and findings show that excess returns are more predictable during period of recession that during upswing while Humpe and MacMillan (2014) show that stock returns vary between markets and between regimes in the US and Japan.

Though no evidence of application of Markov Switching method is available on Nigeria, Aliyu (2012) using the rational expectation hypothesis (REH) found significant influence of monetary variables; MPR and M2, on stock returns using EGARCH model between January, 2007 and August, 2011. While Oseni and Nwosa (2011), Okoli (2010) corroborate strong influence of monetary policy innovations on stock returns in Nigeria, Abaenewe and Ndugbu (2012), Igbinosa and Obayagbona (2012) and show between weak and insignificant impact of monetary policy variables on stock returns and volatility in Nigeria. Further, Nwokoma (2007) applies the ARCH and EGARCH methodologies in analyzing stock returns in Nigeria while Salisu and Oloko (2015) use variants of the VARMA-AMGARCH. Their findings show that volatility persistence in the stock market is accentuated by bad news in the market and moderated by good news in the FX market.

Evidences show that the combined effects of sharp decline in crude oil prices, mounting government deficits, dwindling foreign reserves, rising inflation and unemployment rates plunged the Nigerian economy into recession with real growth rates of -0.36 and -2.06 percent in the first and second quarters in 2016, respectively. The economy further went into recession deep recession with a negative real growth rate of -2.24 percent in the third quarter of 2016 (Ekpo, 2017; and Tule, 2017). The period of recession was followed by massive depreciation of the naira from N197=$1 in the interbank segment of the market to a whopping N305=$1, a slide by 54.8 percent. The margin in the parallel segment was outrageously very wide with the dollar trading at N520=$1 as of January, 2017, a staggering depreciation of over 160 percent between the interbank and the parallel rates. Auspiciously, the economy emerged out the recession in the second quarter of 2017 following a marginal real GDP growth of 0.55 percent (NBS, 2017). According to the CBN (2017) the success was due to fiscal injections from the implementation of Economic Recovery and Growth Plan (ERGP) and the enhanced supply of forex into the economy arising from improved crude oil prices.

Notwithstanding, policy constraints such as; weak and underperforming monetary aggregates – M1 and M2 aggregates, for instance, contracted by 12.25 and 11.06 percent, respectively in August, 2017; oscillating money market interest rates; double digit inflation rate at 16.01 percent and the like are major drawbacks to steady credit flow to the real sector, foreign direct investment and effective private sector growth in Nigeria. Although evidence shows that external reserves position grew to US$34.9 billion on 16th November, 2017, total foreign exchange inflow through the Central Bank declined by 6.61 percent in October, 2017. Precariously, total outflows increased significantly by up to 18.77 percent. In the stock market however, the All Share Index (ASI) rose slightly by 3.38 percent from N35,504.62 on 31st August, 2017 to N36,703.58 on 17th November, 2017. Given the interconnectedness between stock market and the macroeconomy, an investigation into the impact of economic regimes with particular emphasis on exchange rate on stock returns in Nigeria would be a significant contribution.

Predicting stock returns during calm and turbulent periods are of special interest to investors and regulators as well. Learning about the probability of having a crisis in the home market today, following a negative shock to another market yesterday is instrumental to portfolio adjustment and higher returns. International investors, for instance, can adjust their portfolio strategies to a changing structure of spillovers in different regimes. Shen (2003) shows that by forecasting bear markets, investors can exploit profitable opportunities by optimally timing their portfolios. Equally, predicting the swings in the stock market provides useful information to both regulators and investors about business cycles (Estrella and Mishkin, 1998). Bernanke and Lown (1991) posit that widespread liquidity problems may account for credit crunches in the financial markets during bear market periods. Hence, monetary authorities can make use of information about future stock market booms (bull) and busts (bear) when implementing monetary policy *ex ante* (Rigobon and Sack, 2003).

Against this background, this paper on economic regimes and stock market performance in Nigeria: evidence from regimes switching model seeks to analyze volatility spillover between exchange rate and stock market in "turbulent" and "calm", otherwise, "bull" and "bear" periods. The paper applies the regime heteroskedastic Markov switching model using daily (5-days a week) data, for precision as higher frequencies lead to more precise estimates of the switches between bull and bear markets, on All Share Index (ASI) and exchange rate from 1st January, 2010 to 31st December, 2017. The rest of the paper is organized as follows: following the introduction, section two dwells on literature review and theoretical issues. Sections three outlines the data requirements and the econometric model employed by the paper. Section four conducts the empirical analysis and interpretation of results while section five presents the summary and conclusion.

II. Literature Review and Theoretical Issues

Modelling time series variables for identifying regime shifts started when Quandt (1958) introduces the switching regression model. Afterwards, Goldfeld and Quandt (1973, 1976) extend the switching regression model to allow the regime shifts to follow Markov chain. Building on Golfed and Quandt, Hamilton (1989 & 1990) studies regime shifts in dependent data and develops the Markov switching (MS) models. The MS is designed to capture sudden shifts in time series and assumes that a particular regime is an unobservable stochastic process hence movement between regimes or regime shifts are unrelated to past observations (Ismail and Isa, 2008). Further, the MS models also accommodate more than two regimes (see Guidolin and Timmermann, 2006; Maheu, McCurdy and Song (2012), and the transition probabilities of the Markov chain can be made time-varying as a function of predictor variables (see Diebold, Lee and Weinbach, 1994). And while the regimes identified by regime switching models are identified by an econometric procedure, they often intuitively match different periods in regulation, policy, and other secular changes (Ange and Timmermann, 2011).

It is well documented that stock returns are characterized by at least two distinct regimes; bull and bear markets (Schaller and van Norden, 1997; Guidolin and Timmermann, 2006). Further, including predictor macro-financial variables improves out-of-sample performance of the Markov switching models because it captures regime shifts in the mean, in the variance and also the parameter of interest (Ismail and Isa, 2008; Kole and Van Dijk, 2016). An emerging body of scholarly literature provides mounting empirical evidence regarding the relationship between macro-financial variables as predictor variables and stock market under two regimes; turbulent and calm periods (see Welch and Goya, 2008; Chen, 2009; Chen, Chen and Chou, 2013; Angelidis, Degiannakis and Filis, 2015).

In particular, the study by Chen, Chen and Chou (2013) unveils the empirical evidence from the US stock market that among the macro-financial variables investigated, the default yield spread, inflation, and the term spread are useful in predicting bear markets. It further found that the default yield spread provides superior out-of-sample predictability for bear markets one to three months ahead, which suggests that the external finance premium has an informative content on the financial market.

Zhu and Zhu (2013) assess the excess returns of the US stock market with fifteen economic variables as predictors of excess stock returns. Further, they introduced a new regime-witching combination process which captures uncertainty in three dimensions. Findings reveal two regimes that are correlated with the business cycle. The low variance regime, that is, bear market, is related to economic growth, while the high variance regime, that is, bull market, is connected with economic decline. That excess returns are more predictable when there is recession in the economy and less predictable during economic increase.

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.

In the United States, Angelidis, Degiannakis and Filis (2015) investigate the predictability of oil price returns, oil price shocks and oil price volatility on the state (high/low risk environment) of the US stock market returns and volatility. Findings suggest that oil price returns and volatility possess the power to forecast the state of the US stock market returns and volatility. Authors posit that the oil price shocks have an incremental power in forecasting the state of the stock market in the US.

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 bull 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.

III. Methodology of the Paper

A. Introduction

This section discusses the methodology adopted in the paper. We begin by carrying out the unit root tests on the series to ascertain their order of integration. Moreover, the test for the ARCH effects will be carried out to avoid running into econometric misspecification of the model. However, after the estimation, statistical diagnostic tests, namely serial correlation and multicollinearity tests will be carried out to ascertain the statistical adequacy of the model. Although, linear models are one of the popular and widely used statistical and econometric techniques, there exists convincing evidence in the literature that non-linear techniques such as the regime switching model are appropriate quantitative tools for modeling macroeconomic and financial relationships particularly those that are characterized by changes in regimes. In this paper, we use the regime heteroskedasticity Markov regime switching model with 2 regimes (assuming a period/regime of high volatility and a period/regime of low volatility) in order to examine the performance of the Nigerian stock market in the two different regimes. The Markov switching models have over the decades gained popularity in financial and economic modeling owing to business cycles identified in macroeconomics, monetary economics and finance (Wang, 2009). Stock market behavior is one of the areas to which Markov switching has been widely applied.

A. Data and Sources

The data used for the purpose of this paper covers the period from 4th January, 2010 to 30th June, 2017 and this yields a total of 1855 daily observations on the all share index (ASI) and, the Naira / Dollar exchange rate. The data was sourced from Bloomberg website. It is noteworthy that the series, namely; the stock prices using the All Share Index (ASI) as a proxy, and, the exchange rate (Naira vis-à-vis dollar) were transformed into their respective returns / percentage changes by taking first differences of their logarithms and multiplying by 100.

B. The Econometric Model

The econometric model derives from Kim (1993) empirical applications. We assume that the returns on the Nigerian stock market index $\partial \log(ASI)_t$ are amenable to a probability distribution that depends on a latent process denoted as: S_t. This process is dichotomized into two regimes, namely: S_1 and S_2. The stocks returns denoted as $\partial \log(ASI)_t$ are the first difference of logarithm of the prices. Hence, denoting $\partial \log(ASI)_t$ as y_t it implies that $y_t \sim \left\{ \begin{matrix} N(\mu_1, \sigma_1^2 \ if \ S_t = 1 \\ N(\mu_2, \sigma_2^2 \ if \ S_t = 2 \end{matrix} \right\}$.

It is assumed that in both regimes (first and second) the returns follow a normal distribution with different means and variances. Hence, the normal probability density function for the regimes is:

$$f(y,\mu,\sigma^2)=\frac{1}{\sqrt{2\pi\sigma}}\exp\{-\frac{(y-\mu)^2}{2\sigma^2}\} \tag{1}$$

Brooks (2008) establishes that under the Markov switching approach, the universe of possible occurrences is split into *m* states of the world, denoted as S_i where *i= 1,…, m,* corresponding to *m* regimes. In other words, it is assumed that y_t switches regime according to some unobserved / latent variable (S_t) which takes on integer values. As mentioned earlier, this paper considers two regimes in the process. Hence, m = 1 or 2. In colloquial terms, if $S_t = 1$ the process is in regime 1 at time *t*, and if $S_t = 2$, the process is in regime 2 at time *t*. He shows that the Markov process can be expressed as:

$$\Pr[a<y_t \le b \mid y_1,\ldots y_{t-1}]=\Pr[a<y_t \le b \mid y_{t-1}] \tag{2}$$

According to him, equation (2) above implies that the probability distribution of the state at any time *t* depends only on the state at time *t-1* and not on the states that were passed through at times *t-2*, *t-3*. Hence, Markov processes are not path-dependent. This implies that the probability for regime 1 to occur at time *t* depends solely on the regime at time *t-1*. It is noteworthy that a Markov chain is a stochastic process $\{S_t, t=0,1,\Lambda\}$ that takes finite number of integer values denoted by *i, j* and that the transition probability of any future value of S_{t+1} equals *i , j*, that is, the conditional distribution of any future state S_{t+1} given the past state S_{t-1} and the present state S_t is dependent only on the present state and independent of the past state. This can algebraically be stated as:

$$\Pr\{S_{t+1}=j \mid S_t=i_{t,}\ S_{t-1}=i_{t-1}, S_2=i_2, S_1=i_1\}=\Pr\{S_{t+1}=j \mid S_t=i_t\}=p_{ij} \tag{3}$$

Where p_{ij} is the probability that the state / regime will next be *j* when the immediate preceding state is *i*, and is termed as the transition probability from *i* into *j*. Since the paper considers 2 regimes, the transition matrix for the probabilities associated with the 2 states / regimes is:

$$p=\begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$$

Where: $p_{11} + p_{12} = 1$, and also, $p_{21} + p_{22} = 1$, and in each case, the probability is non-negative.

The transition probabilities can be written as a multinomial logit function:

$$p_{ij}\,(G_{t-1,}\,\delta_i) = \frac{\exp(G_{t-1}^{'}\delta_{ij})}{\sum_{s=1}^{M}\exp(G_{t-1}^{'}\delta_{ij})} \tag{4}$$

For *j = 1,…, M*, and *i = 1,…,M,*

Although, the Markov switching models are generally specified with constant probabilities, in this paper, we adopt the approach by Kim, Charles and Nelson (1999) by assuming regime heteroskedasticity and hence, time-varying transition probabilities. Thus, following Bhar and Hamori (2004) the econometric specification of the regime heteroskedasticity Markov switching model with two regimes used in this paper is:

$$\begin{aligned}\partial\log(ASI)_t &= \tau_t + \mu_1 S_{1,t} + \mu_2 S_{2,t} + (\alpha_0 + \alpha_1 \log\sigma_1 S_{1,t})\varepsilon_t + \partial\log(ASI)_{t-1} + \partial\log(ASI)_{t-2} + \partial\log(ASI)_{t-3} + \\ &\partial\log(ASI)_{t-4} + \partial\log(ASI)_{t-5} + \partial\log(ASI)_{t-6} + \mu_1\rho_{11} + \rho_{11}\partial\log(EXR)_{t-1} + \mu_2\rho_{21} + \rho_{21}\partial\log(EXR)_{t-1}\end{aligned} \tag{5}$$

Where: $\tau_t = \tau_{t-1} + (\beta_0 + \beta_1 \log\sigma_2 S_{2,t})\nu_t$, the terms $\mu_1 S_{1,t}$ and $\mu_2 S_{2,t}$ are the two economic regimes with their corresponding means, the terms $\log\sigma_1 S_{1,t}$ and $\log\sigma_2 S_{2,t}$ which is subsumed under the variable (τ_t) are the log standard deviations which provide information about the degree of volatility in the two regimes. The regressors from $\partial\log(ASI)_{t-1}$ to $\partial\log(ASI)_{t-6}$ are common regressors of the two regimes. However, we use the regressor $\partial\log(EXR)_{t-1}$ which is one period lag of the exchange rate as the predictor / probability regressor in the model. Finally, the terms $\mu_1\rho_{11}$ and $\mu_2\rho_{21}$ are the time-varying transition probabilities, and, ε_t and ν_t are disturbance terms that are assumed to be independently and identically distributed, that is, $\varepsilon_{s,t} \sim N(0,1)$ and $\nu_t \sim N(0,1)$.

C. Estimation

Conventionally, regime switching models are estimated via two approaches, namely by the Gibbs sampling technique and by maximum likelihood technique (Kuan, 2002). In this paper, the maximum likelihood technique has been employed to estimate the model. Hence, following (Kuan, 2002), the quasi log likelihood function upon which the estimation is based is given as:

$$\lambda_T(\theta) = \frac{1}{T}\sum_{t=1}^{T}\log f(Z_t\,|\,Z^{t-1};\theta) \tag{6}$$

and the full log likelihood function to be maximized is :

$$\lambda(\beta,\gamma,\sigma,\delta)=\sum_{i=1}^{T}\log\{\sum_{m=1}^{M}\frac{1}{\sigma_m}\psi(\frac{y_t-\mu_t(m)}{\sigma(m)})\cdot P(s_t=m\,|\,\xi_{t-1,}\,\delta)\} \qquad (7)$$

VI. Empirical Results

This section presents and discusses the results. It begins by presenting the descriptive statistics of the returns of Nigeria's stock prices and the returns of the Naira/Dollar exchange rate. Moreover, the results of the unit root test, the autoregressive conditional heteroskedasticity (ARCH) test and the Markov switching regime heteroskedasticity model are also presented and discussed.

A. Descriptive Statistics of the Returns

The Table 1 below provides the descriptive statistics of the returns of stocks prices and the exchange rate. It can be observed from the Table that the distribution of the two series is non-normal as indicated by their respective Jacque-Bera statistic. The null hypothesis of normality is rejected for both the stock prices and exchange rate returns at the 5% level. The skewness and kurtosis of the returns corroborate the fact that they are characterized by a non-normal distribution and hence fat-tailed distribution which is typical of most financial time series. More so, the standard deviations show that the volatility of the two series is almost the same, though with exchange rate returns series being a little more volatile than the stock market returns, that is, the values of 0.45 and 0.43, respectively.

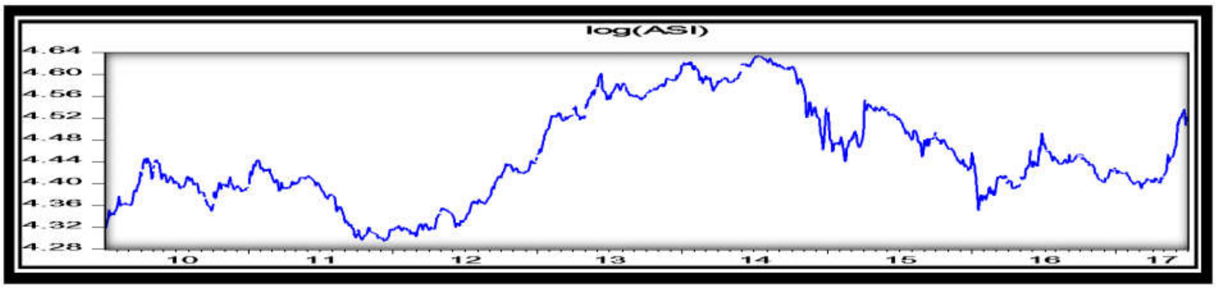
Table 1: ***Descriptive Statistics of the Returns***

Variable/ Statistic	**∂(log ASI)**	**∂(log EXR)**
Mean	0.010851	0.018000
Median	-0.001414	0.000689
Maximum	3.463477	15.21654
Minimum	-1.902986	-1.933381
Standard Deviation	0.43021	0.452968
Skewness	0.289405	20.50919
Kurtosis	8.097874	687.3202
Jacque-Bera	2033.478	36305695
(Probability)	(0.000)	(0.000)
Observations	1855	1855

Source: Authors' computation

Notes: The figures in parentheses are the *p*-values

The graphs of the two series are presented in Figure 1. It is very clear that the distribution of the series is non normal which corroborates the above statistics.



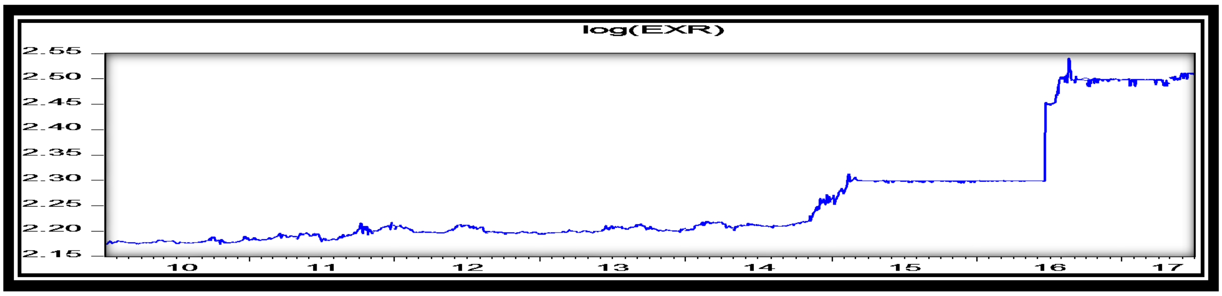


Figure 1: Time Plots of Daily Nigerian Stock Price (ASI) and Exchange Rate (EXR)

B. Unit Root Tests

Table 2 reports the results of the unit root tests. It can be observed from the results that unit roots cannot be rejected in the levels of the two series. Hence, the two series, namely logarithm of the daily stock prices using all share index (ASI) as a proxy and logarithm of the exchange rate.[3] These two series have been found to be non-stationary at level but stationary at their first differences.

Table 2: Unit Root Tests

	Test at level		*Test at First Difference*	
Variable/Statistic	***Log (ASI)***		***Log (ASI)***	
	Tests with constant	*Tests with constant & Trend*	*Tests with constant*	*Tests with constant & Trend*
ADF	-1.745015	-1.704265	-30.10713***	-30.10355***
PP	-1.670749	-1.604306	-29.72748***	-29.72177***
KPSS	1.589883	0.809639	0.148602***	0.111057***
Variable/Statistic	***Log (EXR)***		***Log (EXR)***	

[3] The returns were computed by taking the percentage changes in the series, namely by taking the first difference of logarithms of the series and multiplying by 100.

	Tests with constant	Tests with constant & Trend	Tests with constant	Tests with constant & Trend
ADF	0.649733	-1.173158	-47.18495***	-47.23272***
PP	0.737457	-1.122663	-47.37232***	-47.48353***
KPSS	3.911909	1.0077	0.354345*	0.049206***

Source: Computed by the Authors
Notes: The asterisks *** and * indicate statistical significance at 1% and 10%.

C. The ARCH-LM Test

The test for the ARCH-effects has been carried out on the returns. Ignoring ARCH effects, is has been observed, could lead to misspecification of the model. Presence of ARCH effects in time series is an important guide and a justification for analysis of volatility effects on the series. The autoregressive conditional heteroskedasticity Lagrange multiplier (ARCH-LM) test was carried out on the two returns series. Results presented on Table 3 indicate that the null hypothesis of homoskedasticity can be rejected for stock returns and hence reveals evidence of ARCH effects. However, the same is not true for the exchange rate returns as the *p-values* of the LM test statistics are both greater than 5% level indicating absence of ARCH effects.

Table 3: The ARCH-LM Test

	$\partial \log(ASI)$		
F-stat.	*70.67472*	*Prob. F(1,1850)*	*0.0000*
*Obs*R-squared*	*68.14771*	*Prob. Chi-Square(1)*	*0.0000*
	$\partial \log(EXR)$		
F-stat.	*0.269994*	*Prob. F(1,1850)*	*0.6034*
*Obs*R-squared*	*0.270247*	*Prob. Chi-Square(1)*	*0.6032*

Source: Computed by the Authors

Table 4 below reports the results for the Markov-regime switching model with regime heteroskedasticity. The upper panel of the table shows the regime specific coefficients while the lower panel reports the common coefficients for the two regimes. From the Table, it can be observed that the means of the returns, although not statistically significant, for the stock returns are -0.0047 and 0.0313 for regimes 1 and 2, respectively. In line with findings of Ismail and Isa (2008) in the Malaysian stock market, this implies that on the average, the stock returns falls by -0.0047 percent daily in the bear market while it gains by 0.0313 daily in the bull market, that is, regime 2. The log standard deviations are both statistically significant at -1.436935 for regime 1 and -0.430628 for regime 2 and, the corresponding implied standard deviations are 0.2377 and 0.6501 for the two regimes respectively[4]. The values further reinforce the existence of low volatility regime (regime 1) and the high volatility regime (regime 2). However, as mentioned earlier, the regime specific coefficients are reported in the upper panel of the Table while the common coefficients associated with the non-switching regressors are reported in the lower panel and in each case, common error variance is assumed. It can be observed from the results that up to AR(6) autoregressive terms were used as non-switching regressors to check for serial correlation in the residuals. All the coefficients of the regressors are not statistically significant with the exception of only those of $\partial \log(ASI)_{t-1}$, and $\partial \log(ASI)_{t-5}$ at the 5 percent level.

Table 4: *Regime Heteroskedasticity Markov Switching Results*

Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
		Regime 1		
μ_1	*-0.004667*	*0.007550*	*-0.618139*	*0.5365*
$\log(\sigma_1)$	*-1.436935*	*0.031629*	*-45.43034*	*0.0000*
		Regime 2		
μ_2	*0.031336*	*0.029556*	*1.060222*	*0.2890*
$\log(\sigma_2)$	*-0.430628*	*0.042665*	*-10.09317*	*0.0000*
		Common		
$\partial \log(ASI)_{t-1}$	*0.265611*	*0.025230*	*10.52757*	*0.0000*
$\partial \log(ASI)_{t-2}$	*-0.003928*	*0.024200*	*-0.162309*	*0.8711*
$\partial \log(ASI)_{t-3}$	*-0.006800*	*0.022889*	*-0.297077*	*0.7664*
$\partial \log(ASI)_{t-4}$	*0.041987*	*0.021761*	*1.929469*	*0.0537*
$\partial \log(ASI)_{t-5}$	*0.046311*	*0.020947*	*2.210843*	*0.0270*
$\partial \log(ASI)_{t-6}$	*-0.015186*	*0.019890*	*-0.763502*	*0.4452*
		Transition Matrix Parameters		
$\rho_{11}\_\mu_1$	*2.851519*	*0.216795*	*13.15308*	*0.0000*
$\rho_{11}\_\partial \log(exr)_{t-1}$	*0.129813*	*0.968746*	*0.134001*	*0.8934*
$\rho_{21}\_\mu_2$	*-1.894650*	*0.251442*	*-7.535131*	*0.0000*
$\rho_{21}\_\partial \log(exr)_{t-1}$	*-0.693904*	*0.767593*	*-0.904000*	*0.3660*

[4] It is worth noting that the implied standard deviations were computed by taking the exponential of the log standard deviations.

Mean dep. var	*0.009065*	*Std. dev. dep. Var.*	*0.429560*
s.e. of regression	*0.405517*	*SSR*	*302.2483*
D-W Stat.	*1.814455*	*Log likelihood*	*-696.7813*
AIC	*0.769244*	*SIC*	*0.811076*
HQ	*0.784665*		

Source: Computed by the Authors using Eviews version 9.0.

Moreover, we used one-period lag of the exchange rate returns as probability regressor / predictor of the movements in the stock price returns in the two regimes. The results reported under the transition matrix parameters suggest that exchange rate returns positively (also statistically significant as well) affect the stock price returns in the regime 1 and negatively in the second 2. The transition matrix parameters further reveal that increases in the stock returns are associated with higher probabilities of being in the low volatility regime (regime 1) lowering the transition probability out of regime 2 and increasing the transition probability from regime 2 (high volatility regime) into regime 1. In other words, the chances that higher exchange rate (appreciation) would increase the volatility of stock returns are greater than the chances that lower exchange rate (depreciation) would increase the volatility of stock returns.

This derives from the fact that the coefficient of the probability regressor has positive value in regime 1, that is, bear market, and this is associated with higher probability value which implies positive relationship between stock returns and the exchange rate returns while in regime 2 the coefficient is negative indicating a negative link between the two variables with a lower probability value. Thus, the finding goes that exchange rate appreciation leads to decline in stock returns in regime 1, than depreciation causes in regime 2. The model selection was guided by the robustness of the results apropos to the information criteria, residuals sum of squares (*RSS*) as well as the value of the log-likelihood ratio.

Further, the use of the additional regressors did not violate the model's orthogonality property as can be seen from Table 5 where all the values of the variance inflation factor (VIF), both centered and uncentered, reveal that the regressors are non-multicollinear.

Table 5: ***Multicollinearity Test***

Variable	*Coefficient* σ^2	*Uncentered VIF*	*Centered VIF*

Regime 1			
μ_1	*5.70E-05*	*1.033018*	*NA*
$\log(\sigma_1)$	*0.001000*	*1.370495*	*1.367228*
Regime 2			
μ_2	*0.000874*	*1.029343*	*1.009621*
$\log(\sigma_2)$	*0.001820*	*1.372475*	*1.370574*
Common			
$\partial\log(ASI)_{t-1}$	*0.000637*	*1.131148*	*1.129691*
$\partial\log(ASI)_{t-2}$	*0.000586*	*1.170833*	*1.169813*
$\partial\log(ASI)_{t-3}$	*0.000524*	*1.163721*	*1.162098*
$\partial\log(ASI)_{t-4}$	*0.000474*	*1.116570*	*1.115816*
$\partial\log(ASI)_{t-5}$	*0.000439*	*1.121856*	*1.121469*
$\partial\log(ASI)_{t-6}$	*0.000396*	*1.101596*	*1.101539*
Transition Matrix Parameters			
$\rho_{11}\_\mu_1$	*0.047000*	*1.867638*	*1.867222*
$\rho_{11}\_\partial\log(exr)_{t-1}$	*0.938469*	*1.036849*	*1.036161*
$\rho_{21}\_\mu_2$	*0.063223*	*1.838777*	*1.838223*
$\rho_{21}\_\partial\log(exr)_{t-1}$	*0.589199*	*1.026156*	*1.025991*

Source: Computed by the Authors

Table 6 below reports the diagnostic test on the residuals of the model. The Ljung Box Lagrange Multiplier (LM) test on the residuals reveals that the null hypothesis cannot be rejected as indicated by the *p*-values of the Q-statistics which are not significant at almost all the lags used for the test. Hence, the model can be deemed statistically adequate.

Table 6: The Residuals Serial Correlation Test

Autocorrelation	***Partial Correlation***		***AC***	***PAC***	***Q-Stat***	***P-value***
| |	| |	*1*	*0.056*	*0.056*	*5.7035*	*0.017*
| |	| |	*2*	*0.035*	*0.032*	*8.0217*	*0.018*
| |	| |	*3*	*-0.021*	*-0.025*	*8.8268*	*0.032*
| |	| |	*4*	*-0.021*	*-0.02*	*9.6276*	*0.047*
| |	| |	*5*	*-0.012*	*-0.008*	*9.8824*	*0.079*
| |	| |	*6*	*-0.004*	*-0.002*	*9.9164*	*0.128*
| |	| |	*7*	*0.004*	*0.004*	*9.9405*	*0.192*
| |	| |	*8*	*-0.019*	*-0.02*	*10.578*	*0.227*

		9	0.041	0.042	13.632	0.136
		10	0.026	0.023	14.852	0.138
		11	-0.003	-0.009	14.866	0.189
		12	0.007	0.007	14.953	0.244
		13	-0.001	0.001	14.957	0.310
		14	0.029	0.030	16.502	0.284
		15	0.003	0.001	16.520	0.348
		16	0.053	0.051	21.780	0.150
		17	0.040	0.038	24.787	0.100
		18	0.020	0.013	25.535	0.111
		19	0.004	0.000	25.567	0.143
		20	-0.028	-0.025	27.014	0.135
		21	0.003	0.009	27.033	0.170
		22	0.057	0.062	33.208	0.059
		23	-0.033	-0.043	35.256	0.049
		24	-0.001	-0.001	35.258	0.065
		25	-0.016	-0.013	35.719	0.076
		26	0.012	0.010	36.011	0.091

Source: Authors' computation

D. Time-varying Markov Transition Probabilities and Expected Durations

Table 6 reports the time varying probabilities of being in a regime. It shows that the probability of being in regime 1 is 0.95 and that of being in regime 2 is 0.87. The magnitude of these probabilities (P_{11} and P_{22}) suggests that the low volatility regime, otherwise bear market, is more persistent than the high volatility regime, that is, bull market. However, the expected durations for being in each regime, looking at the mean (μ) is shorter in regime 1 with only 18.41 days, while the time-varying expected duration for being in regime 2 is up to 5958.1 days. Therefore, the duration for being in the second regime (high volatility regime) is much longer than that of being in the first regime (low volatility regime). This shows that only an extreme event can switch the series from regime 2 to regime 1 or from a bull market to a bear market.

Table 6: *Time-varying Probabilities and Expected Durations*

Regime		1	2
μ	1	0.945457	0.054543
	2	0.131442	0.868558
		1	2
σ	1	0.002181	0.002181
	2	0.023241	0.023241
Time-varying expected durations:			

Regime	1	2
μ	18.40603	146.4379
σ	2.583101	5958.124

Source: Authors' computation

Our findings partly concur to that of Walid and Nguyen (2014) that show that regardless of the market in the BRICS, the probability of being in regime 1 is higher than the probability of staying in regime 2. This however implies that low volatility regime is more persistent than the regime of high volatility. Accordingly, the low volatility regime lasts longer than the high volatility regime. Similarly, Aikaterini (2016) reports 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. Therefore, his model is a one state model because the probability of changing state is very low. However, the author found that the expected duration of stay in the regimes across the markets studied is higher in the bull markets (35,774, 41,882 and 50,965 weeks in the FTSE S&P/TSX and S&P500, respectively) than in the bear markets (8,377, 14,807 and 17,410 weeks in the FTSE S&P/TSX and S&P500, respectively). Further, Kayalidere, et al. (2017) estimate two regimes; bear (low) and bull (high) volatility regimes in Turkey and findings show higher persistence in the bear market than in the bull market. Again, the duration of stay of 680 in the bear market is higher than that of only months in the bull market for stock returns.

E. Smoothing and Filtering

Smoothing entails making an inference about the regimes using future information, while filtering entails the process by which the probability estimates are updated. The inference is usually drawn from the probabilities associated with the regimes. The smoothed estimates for the probabilities of the regimes in each period avail the information set in the final period, while the filtered estimates use only the contemporaneous information about the estimates. In colloquial terms, using information about future realizations of the dependent variable which is $\partial \log(ASI)$, improves the estimates of being in a regime in a particular period as the Markov transition probabilities connect together the likelihood of the observed data in different periods. The figures below are plots of the smoothed and filtered probabilities. Looking at both the smoothed and filtered probabilities, there seems to be a clear pattern of inverse correlations in the two regimes. Evidently when the probability of regime 1 is close to one the probability of regime 2 is close to zero and vice versa. The finding indicates that our model performs quite well in getting the direction of change in the series either in regime 1 or regime 2.

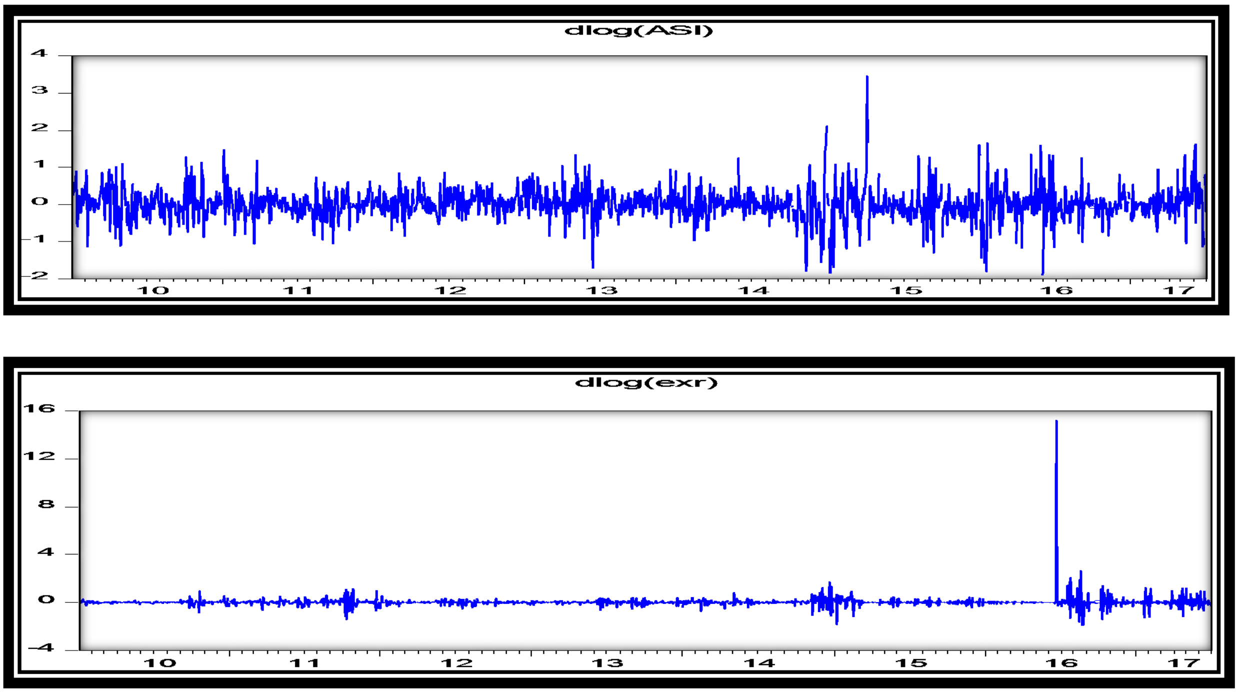


Figure 2: Plots of Daily Returns of ASI and EXR (% changes)

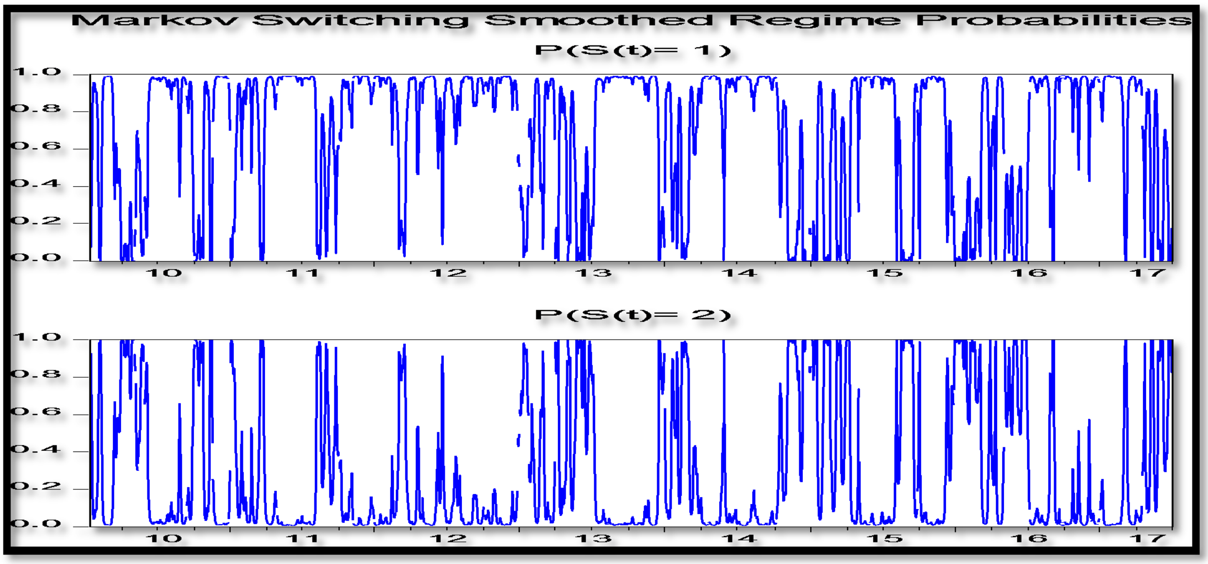


Figure 3: Markov Switching Regime Smoothed Probabilities

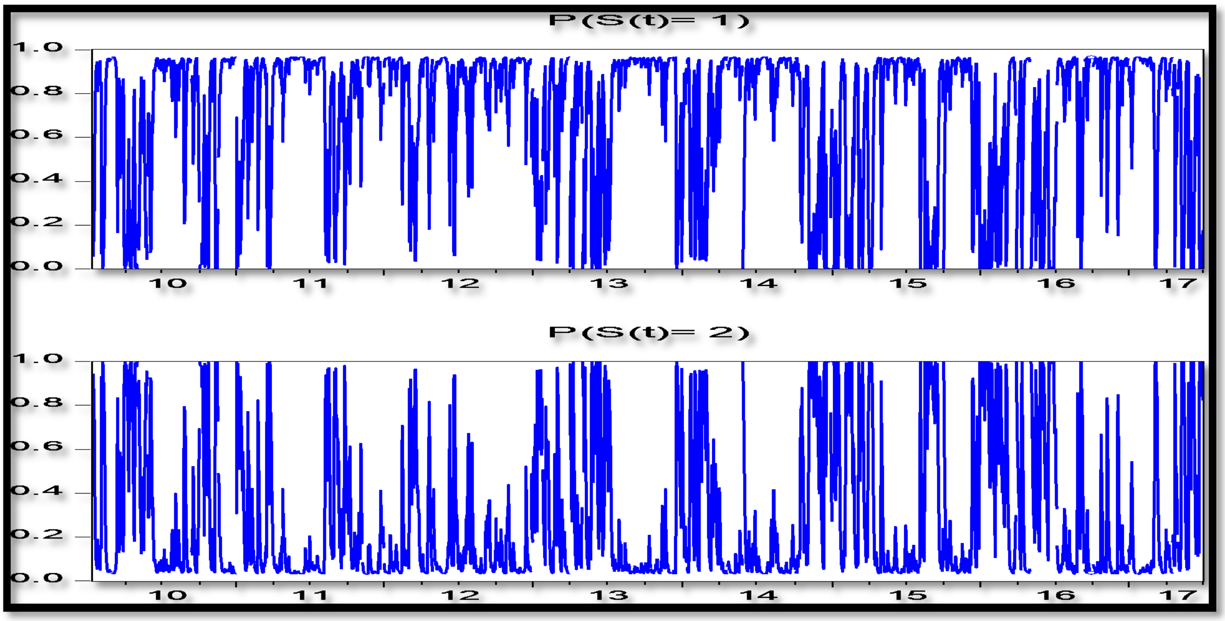


Figure 4: Markov Switching Regime Filtered Probabilities

5.0 Conclusion and Recommendations

This paper on economic regimes and stock market performance in Nigeria seeks to capture regime shifts behaviour in both the mean and the variance in the Nigeria's stock market otherwise volatility spillover in "turbulent" and "calm" periods. The paper applies the regime heteroskedastic Markov switching model in line with Kim (1993) on the basis of daily (5-days a week) data, on All Share Index (ASI) and exchange rate from 1st January, 2010 to 31st December, 2017. That while the literature recognizes that failure to allow for regime shifts leads to an overstatement of the persistence of the variance of a series, the Markov switching model allows regime shift in the mean and hence adequately addresses this problem.

Results from preliminary investigations reveal that the series are characterized by a non-normal distribution, presence of unit root and ARCH effects in stock returns. Further, the regime heteroskedastic Markov switching model reveal evidence of two regimes, that is, regime 1 and 2 (bear and bull markets) with more persistence in the bear as against the bull markets at 0.9455 and 0.8686, respectively. However, the duration of stay in any regime is higher in regime 2 than regime 1 at 5958.12 days and 18.406 days, respectively. Further, the incorporation of exchange rate as a predictor variable in line with experiments in the empirical literature reveals a positive effect of exchange rate returns on the latent variable, the stock market returns, in regime 1 whereas a negative influence in regime. This implies that exchange rate appreciation during bear period yields positive stock returns while exchange rate depreciation during bull market lowers stock returns. Although both effects are significant, it is more pronounced in the bear market than in the bull market. The identification of the regimes is particularly important to investors who want to predict the state of the market and adjust the portfolio of assets they hold across each regime, that is, switching between bear and bull markets. Further, the need for policymakers to pursue stable exchange rate policy and transparent rules to mitigate investors' risk perception are highly desirable for stability of the Nigerian stock market.

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