Do presidential elections affect stock market returns in Nigeria?

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ABSTRACT

Evidences thrive globally on the effects of political regimes, presidential elections, on stock market returns. In the same vein, this paper analyses the effects of general elections on stock returns and volatility around the election periods at the Nigerian Stock Exchange (NSE) market. The paper applies an event study approach to delineate event windows, a 5-month event window for each election was adopted comprising of an election month, and 2 months before and after each election. Returns were calculated using daily closing prices of NSE's All Share Index (ASI) for a total of 6 elections held between 1999 and 2019. Asymmetric GARCH – EGARCH and TARCH and the Markov Switching autoregressive methodologies were applied. ASI exhibits nonlinearity and structural breaks across all the presidential elections which makes single regime model ill appropriate for modelling stock runs volatility. Evidence of an unstable and explosive conditional variance is noticeable in the 2015 presidential election market returns while leverage effect was found in the 1999 and 2007 elections, that is, bad news produces more volatility on stock returns than good news. The MS-AR (3) model neatly characterizes the NSE's daily stock returns into bearish and bullish regime, i.e., high (low) volatility low (high) returns as regime 1 and 2, respectively. The time varying transition volatility and regime durations corroborate, in different magnitude, the regime characterization across the 6 time horizons. The paper pioneer's an analysis of effects of elections on stock returns in Nigeria and a useful information to investors.

Keywords: Political event, stock market returns, volatility, Markov regime switching model

JEL Codes: C22, G10, G15, P16.

I. INTRODUCTION

Stock market returns, in the literature, is swayed by several factors within and outside a macroeconomy. Literature documents myriad of factors that influence stock market performance; change in government policy, macroeconomic fundamentals, stock market returns, composition of investors, markets sentiments; corporate governance, global events such as booms and recessions, energy crises and inter alia, political event otherwise, election (Gartner, 1995; Lee, 1998; Mishkin and Eugene, 2002; Aliyu, 2009; Aliyu, 2012; Blanchard, et al., 2018; Balaji, Kusuma, and Kumar, 2018). As politics and economy remain keenly intertwined (Huang, 2011), presidential elections have the tendency to affect stock returns in a number of ways; electioneering often results in huge spending (Bloomberg and Hess, 2001), influence sustainability or otherwise of government

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policies and or regulatory environment (Fiorina, 1991; Blanchard, et al., 2018), breeds uncertainty (Black, 1988; Campello, 2007 and Mehdian, Nas and Perry, 2008; Bialkowski, et al., 2008), affects corporate governance (Bloomberg and Hess, 2001; and Menge, 2013), expectations or market sentiment (Siegel, 1998 and Leblang and Mukherjee, 2005); increase in price volatility (Park, 2016) and the like.

According to the political business cycle (PBC) model, competitive elections within democracies lead to unfavourable economic outcomes, such as a post-election recession or inflation. Evidences show that regardless of political orientation, a government in power will pursue policies that maximizes its chances of re-election (Nordhaus, 1975 and Vuchelen, 2003). Invariably, it will try to selfishly adjust business cycle to the timing of elections, that is, stimulating the economy via unsustainable expansionary policies before the elections and resorting to tough measures geared at curbing the resultant inflation at the beginning of new term of office. However, such policy induced cycles will be transient if economic agents and voters follow rational expectations (Rogoff, 1990; Kaplan, 2007; Park, 2016). However, the Uncertain Information Hypothesis (UIH) by Brown et al. (1988, 1993) assumes that investors set prices before an event takes place.

No doubt a number studies that assessed the impact of elections on stock market returns blossomed among researchers and market analysts in the recent past. Germane issue of concern is whether political events influence investor's sentiments in a manner which affect market returns? Substantial body of evidence using 'event study methodology' mostly in the US, suggests that political events affects stock market returns though with variations on the event cycle (Niederhoffer, Gibbs and Bullock, 1970; Black, 1988; Booth and Booth, 2003; Wong and McAleer, 2007). A study by Molenkamp (2017), for instance, shows that the Republican presidents exert more negative influence on stock market returns compared to the Democratic presidents whereas Blanchard, et al (2018) found that a bit more than half of the increase in the aggregate U.S. stock prices from the presidential election to the end of 2017 is attributable to higher actual and expected dividends.

Elsewhere, evidence show that the Nairobi Stock Exchange (NSE) significantly responds to political event (Irungu, 2012; Menge, 2013; Menge, Mwangi and Kimani, 2014; Kabiru, Ochieng and Kinyua, 2015). Further, Balaji, Kusuma and Kumar (2018) show that the India's National Stock Exchange (NSE) responds more to elections in short term, less in medium term and subsequently diminishes in the long term.

Since the return of democracy in the year 1999, Nigeria has had a number of presidential elections intermittently after every four years. Notwithstanding, as small open economy, the Nigeria's stock market (NSE) in particular was affected by global events notably; the 2007/2008 US financial cum the 2008 oil price crisis, the 2014/2015 oil price shock and the Nigeria's 2016/2017 recession – a huge body of empirical literature covering these major events has been documented. However, it is particularly pertinent to assess whether pattern of stock market returns during elections provide useful insights to investors. A cursory look at the trends on the floor of the NSE shows that the market responded differently to successive elections between 1999 and 2019. Stock returns measured as a percentage change in the level of all share index (ASI), for instance, fell consistently a month preceding the national elections and during the election month for the 2003 and 2007 elections while the returns were consistently negative for two months after the April, 2011 elections, that is, in May and June, 2011. Further, the returns shaded a negative of -0.28% only during the election month in 2015 while in the build up to the 2019 elections, the market recorded the highest slide (gain) of -1.61% (0.67%) a week before the election and was consistently negative a week following the election except for the marginal gain recorded of 0.57% on the 25th February, 2019. Other market indices like market capitalisation and number of market deals also followed suit.

As this background, it is pertinent to investigate the pattern of movements of stock market returns in Nigeria since the return to democracy in the year 1999. That is, whether market returns correlate with elections and in what sense? Unless we accurately predict what pattern stock returns had been during elections, it would be difficult to advise investors and regulators on what action they should take in a manner that would best maximize their returns and or guide market operations during elections periods, respectively. Thus, this underscores the need for an investigation. The paper is organized in five sections. Following the introductory section, section II presents a review of empirical studies and theoretical issues, research methodology is presented in section III while sections IV and V cover presentation of empirical results and concluding remarks, respectively.

II. REVIEW OF EMPIRICAL EVIDENCES AND THEORETICAL ISSUES

Evidences a bound on how political process affects economic activity to the extent that political violence impedes economic progress and throw nations into serious crises. In particular, studies on the behaviour of stock market around election periods have been carried out over the last several decades.

Among the earliest studies in the US, Niederhoffer, Gibbs and Bullock (1970) found that stock market returns show abnormal behaviour 17 weeks surrounding the election-day. Testing different event periods, the study shows that abnormal returns are different from zero, 10 days surrounding the event until 8 weeks surrounding a presidential election. A period larger than (-28, 28 weeks) results in insignificant *p*-values. We could conclude that since 1970 information speed is higher through which stock market returns reflect election effects sooner. The election's effect on stock market returns shifts from 17 weeks surrounding election - day to 8 weeks surrounding the event using elections after 1980. Investors are afraid of investing at the time when there is a likelihood of political and economic instability (Black, 1988).

Santa-Clara and Valkanov (2003) reveal that smaller cap stocks outperform their larger counterparts under democratic presidents. Similarly, Chan et al., (2005) found that the real returns, particularly for small stock business, performed better under democratic leadership. On the other hand, Booth and Booth (2003) report no significant difference between the returns of large cap stocks during the terms of both democratic and republican presidents in the US. However, they show that market performs better during the second half of the presidential term in office. An extension by Oumar & Ashraf (2011) show that the market performs better when Democrats are in control of the presidency than when the Republicans are in the office.

In Germany, Roland & Michael (2007) analyse the effect of expected government partisanship on stock market performance in the 2002 federal election. Their results show that small-firm stock returns were positively (negatively) linked to the probability of a right- (left) leaning coalition winning the election. Moreover, they found that volatility increased as the electoral prospects of right-leaning parties improved, while greater electoral uncertainty had a volatility-reducing effect. Similarly, Fuss and Bachtel (2008) analyse how partisan politics affects stock market returns in Germany. Authors opine that ideal policies suggest that firms should perform better under right- than under left-leaning governments.

In the United States, Wong and McAleer (2007) conduct a study on mapping the presidential election cycle on stock markets. Their study reveals that in the almost four decades from January 1965 through to December 2003, US stock prices closely followed the four-year Presidential Election Cycle where in general, stock prices fell during the first half of a Presidency, reached a trough in the second year, rose during the second half of a Presidency, and reached a peak in the third or fourth year. This cyclical trend was found to hold for the greater part of the last ten administrations, starting from President Lyndon Johnson to the present administration under President George W. Bush, particularly when the incumbent was a Republican.

Furthermore, Oehler, Walker and Wandt (2009) investigate the effects of election results on stock price performance using evidence from 1976 to 2008 in the United States and found that stock market participants incorporate expectations about political change into stock prices prior to an election and adjust their opinion according to the actual decision making following the election. Durnev (2012) examines real effects of political uncertainty by looking at elections and investment sensitivity to stock prices. In a large panel of elections around the world, investment is 40% less sensitive to stock prices during election years compared to non-election years. The decrease in investment-to-price sensitivity appears to be due to stock prices becoming less informative during election years making them noisier signals for managers to follow. Further, the drop in investment-to-price sensitivity is larger when election results are less certain, in countries with higher corruption, large state ownership, and weak standards of disclosure by politicians.

In Kenya, Lusinde (2012) assesses stock returns volatility of listed companies around general elections in Kenya for the 1997 to 2007. Findings show that volatility in stock returns increases around general elections. Further, Menge (2013) using ANOVA methodology found that expected returns as well as market returns in the Nairobi Stock Exchange (NSE) were significantly higher before elections than after the elections. That stock markets generate positive abnormal returns fifteen-day period before and after the presidential elections. Also, the magnitude of abnormal return is greatest in the presidential elections held in less-free countries when an incumbent loses (Mange, 2013).

Similarly, Kituku (2014) applies the event study methodology to assess the impact of political regime changes (elations) on the performance of the Nairobi Stock Exchange (NSE). Using an estimation window of 80 days categorized into 40 trading days before the event and 40 trading days after the event date, the study finds that while the 2002 election affected the NSE positively, it negatively affected it during the 2007 election. However, the market was stable before and after the regime in 2013. ANOVA results corroborate the mixed effects of elections on the NSE indices prior, during and after elections. In a related development, Kabiru, Ochieng and Kinyua (2015) found that the NSE's reaction to elections is highly negative or positive depending on the volatility of election environment. Analysis of the cumulative abnormal returns (CAR) shows that the 2002 and 2013 general elections were insignificant, while the CAR around the 1997 and 2007 general election events were found to be significant at 5% level of significance.

Jeribi, Fakhfekh, and Jarboui (2015) assess the impact of political uncertainty from the Tunisian Revolution on volatility of major sectorial stock indices in the Tunisian Stock Exchange (TSE). The paper applies the fractionally integrated exponential generalized autoregressive conditional heteroscedasticity model (FIEGARCH), which helps maintain a direct shock-persistence as well as a shock asymmetric volatility measurement. Results suggest that the shock impact throughout the Revolution period on construction, industries, consumer services, financial services, financial company indices and the TUNINDEX return volatilities proved to be permanent, while its persistence on the other indices has been discovered to be transitory. Further, results reveal a low leverage effect on all indices. This is particularly very important since the Tunisian Revolution turns out to have a very important effect on the TSE

In the United Kingdom, Smales (2016) examines how political uncertainty outside election cycle influence financial market uncertainty using the Brexit referendum on EU membership as a political event. Empirical findings reveal that implied volatility in both the UK and German financial markets rises as uncertainty around the polling result increases. That political uncertainty is most important for investors as the polling date draws and when opinion polls indicate the outcome is particularly close. The paper concludes that the findings have implications for firms making financing and investment decisions, and while making portfolio choices around important political events.

Using the socio-psychological and rational choice models in voting behaviour, Park (2016) applies EGARCH model to analyse stock returns at firm and macro levels. Simulation results show that participants' initial beliefs about a candidate's winning probability, confirmation biases in accepting information, and monetary incentives strongly increase changes in participants' beliefs about the electoral outcome captured by price volatility in the prediction market. Further, expected government partisanship matters for specific industrial sector or firm profitability during an election period. The empirical findings from EGARCH models confirm that the probability of an ideologically different party winning influences the returns of the defence and health care sectors while at the firm level, result shows that the public announcement of Sarah Palin as John McCains's running mate decreases both actual and abnormal returns of firms associated with Obama's key policies.

In the Egyptian market, Ahmed (2017) analyses the impact of political events on equity market behaviour in terms of returns and volatility using an event study approach and a univariate VAR-EGARCH model. Empirical results suggest that political uncertainty has a profound impact on the risk return profiles of almost all market sectors though with different degrees of intensity. That both price and volatility effects are most pronounced in banks, financial services excluding banks and chemicals sectors, whilst food and beverages as well as construction and materials sectors are found to be the least responsive to these events. The 2013 military coup turns out to be the most pervasive event impinging on the market and sector-specific indices according to the findings. Further, Ahmed (2018) explores the differential impact of political risk on Sharia compliant and conventional stocks in developed and developing economies using a dynamic panel GMM techniques. His findings suggest that conventional equity markets of developed countries prove much more sensitive to political uncertainty than their Islamic counterparts.

Molenkamp (2017) assesses the impact of US presidential elections on volatility, stock market returns and political cycles over the period 1978-2016. The researcher employs an event study methodology and a GARCH (1,1) model. Empirical analyses show that the days surrounding elections contain abnormal economic behaviour; average abnormal returns as well as average abnormal volatility that are different from zero within the event period of (-5;5), though a period smaller than (-5;5) yields different result. The paper concludes that the US presidential elections do affect stock market returns and volatility where the Republican presidents were found to have a more negative influence on stock market returns than the Democrats. This corroborates the earlier finding by Oumar & Ashraf (2011) on higher returns associated with the presidency of the Democrats as against that of the Republicans.

Haupenthal and Neuenkirch (2017) use an event study approach to assess the effects of Grexit-related (exit of Greece from the EU) statements made by six important euro area politicians (Merkel, Schaeuble, Tsipras, Varoufakis, Juncker, and Schulz) on intraday stock returns in Germany, Greece, and the euro area covering the period of 1st January, 2015 to 19th August, 2015. Results show that positive statements indicating that a Grexit is less likely lead to higher returns, and conversely negative statements lower stock returns. However, the overall impact of negative statements is more prominent while the cumulative absolute effects on stock returns are sizeable of up to 58% points in the ATHEX.

Hartwell (2018) investigates the effects of formal and informal political volatility in the new EU countries of central and Eastern Europe using an asymmetric GARCH modelling. Findings show that informal political volatility has a significant negative effect on stock returns, while formal political institutions generate much higher financial volatility than changes in monetary policy.

Balaji, Kusuma and Kumar (2018) analyse the impact of general elections on stock markets in India covering the period from 1998 to 2014 in which a total of 5 *Lok Sabha* elections were held. Results from empirical analyses show that an individual election has maximum impact (positive or negative) in the short-term, diminishes in the medium-term and further reduces in the long-term in comparison to the pre-election period. In particular, results show no any negative return in the India's NIFTY 50 index around the pre-election and post-election periods but the SENSEX index records positive and negative returns in the post and pre-election periods. However, the returns were negative in the 2004 election both before and after the election for the SENSEX index.

Blanchard, et al (2018) posit that a bit more than half of the increase in the aggregate U.S. stock prices from the presidential election to the end of 2017 can be attributed to higher actual and expected dividends, a general improvement in economic activity and a decrease in economic policy uncertainty around the world—contrary to what was forecast before the U.S election—were the main factors behind the stock market increase.

In North Korea, Huh and Pun (2018) explore whether dangerous nuclear tests influence financial market outcomes. The study applies a time-varying structural vector autoregression model with block exogeneity restrictions. Findings show that investors' attention paid to nuclear threats exert heterogeneous effects on South Korea's stock prices across industries and over time, especially in the banking industry, during the entire sample period.

Li, Li, and Xu (2018) investigate stock tail risk around national elections worldwide over the period 1982-2012. Empirical findings show that firm stock is less likely to crash during the election years but are more likely to crash during the post-election period. According to the authors, this inter-temporal pattern is consistent with suppression of negative information when there is heightened political uncertainty around elections and with subsequent release of adverse news when the level of uncertainty is reduced. Further, Chen, Chen, Wang and Zheng (2018) investigate how political uncertainty affects the supply of value relevant information about a firm using an emerging market setting where political leaders are expected to exert significant influence on economic activities. The study finds that political uncertainty reduces the amount of idiosyncratic information about a firm in the market.

The foregoing review shows that though different methodologies were applied in the literature, yet findings support the adverse effect of political events on stock market returns at the firm, industry and the market levels at large. Thus, in addition to symmetric and asymmetric GARCH models, this paper applies the Markov switching autoregressive model to identify possible occurrence of multiple regime behaviour in the Nigerian stock exchange market.

III. RESEARCH METHODOLOGY

A number of methodological approaches have been applied in investigating the effect of political events on stock returns in the literature. The common approach being event study approach, others applied the ANOVA methodology, Molenkamp (2017) applied the GARCH, Wing-Keung Wong and Michael McAleer (2007), Walid (2017) and Hartwell (2018) applied asymmetric GARCH methodology. For instance, Kituku (2014) uses an event study methodology with an estimation window of 80 days; categorized into 40 trading days before the event and 40 trading days after the event date.

3.1 ARCH and GARCH Models

To model a time series using ARCH process, let ϵ_t denote error terms (returns residuals, with respect to a mean process), that is, the series terms. The ϵ_t can be divided into a stochastic process z_t and a time-dependent standard error sigma such that:

$$\in_t = \sigma_t z_t \qquad (1)$$

The random variable z_t is *iid*, that is, white noise process, while the σ_t^2 is modelled as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_q \epsilon_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \epsilon_{t-i}^2, \tag{2}$$

where $\alpha_0 > 0, \alpha_i \geq 0$ and $i > 0$.

3.1.1 GARCH (p, q) Model

Given mean of the series *Y* as a function of exogenous variables with an error term and equation (3) which gives a one-period ahead forecast variance based on past information is called the *conditional variance*. If we assume an autoregressive moving average model (ARMA) for the error variance, the model becomes a generalized autoregressive conditional heteroskedasticity (GARCH). In the case of GARCH (p, q), p is the order of the of the GARCH terms σ^2 while q is that of the ARCH terms $\in^2$. The following notation holds.

We begin with the simplest GARCH (p, q) specification:

$$Y = X'\theta + \epsilon_t \tag{3}$$

where $\in_t \ |\psi_{t-1} \sim N(0, \sigma_t^2)\ |$

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_q \epsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2 = \omega + \sum_{i=1}^{q} \alpha_i \in_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, \sigma_{t-i}^2 \tag{4}$$

In equation (4), the conditional variance equation expressed as a function of three terms; a constant term: ω, news about volatility from the previous period measured as the lag of the squared residual from the mean equation: $\in_{t-i}^2$ (the ARCH terms) and last period's forecast variance: σ_{t-i}^2 (the GARCH terms). That the sum of $\sum_{i=1}^{q} \alpha_i \in_{t-i}^2 + \sum_{i=1}^{p} \beta_i < 1$, in order to ensure that the conditional variance is positive and stationary.

As well, equation (4) can be extended to allow for the inclusion of exogenous or predetermined regressors, *z*, in the variance equation:

$$\sigma_t^2 = \omega + \sum_{i-1}^{q} \alpha_i \in_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + Z_t'\pi \tag{5}$$

Often, the forecasted variances from this model are not guaranteed to be positive hence one may wish to introduce regressors in a form where they are always positive. This will minimize the possibility that a single, large negative value generates a negative forecasted value.

3.2 Asymmetric GARCH Models

3.2.1 Exponential GARCH Model

The EGARCH model is an extension of the of the GARCH model by Nelson (1991) in order to capture asymmetric effects of positive and negative innovation or shock on the variable of interest.

$$\log \sigma_t^2 = \omega + \sum_{k=1}^{q} \beta_k g\,(Z_{t-k}) + \sum_{k=1}^{p} \log \sigma_{t-k}^2 \tag{6}$$

Alternatively, stated as:

$$\ln(h_t) = \omega + \sum_{i=1}^{q} \alpha_i \left\{ \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right\} + \sum_{k=1}^{r} \gamma_k \left[\frac{\varepsilon_{t-1}}{\sigma_{t-k}} \right] + \sum_{j=1}^{p} \beta_j \ln\left(h_{t-j}\right) \tag{7}$$

where $g(Z_t) = \theta Z_t + \lambda(|Z_t| - E(|Z_t|))$ equivalent to $\left[\frac{\varepsilon_{t-1}}{\sigma_{t-k}}\right]$ in equation (7). The asymmetric and leverage effects are represented by λ *and* γ, respectively. Z_t may be a standard normal variable or come from a generalized error distribution. The $\omega, \beta, \alpha, \theta$ *and* $\lambda(\gamma)$ are coefficients to be estimated and $\gamma \neq 0$ *and* $\gamma < 0$, signify asymmetry and leverage effects, respectively.

3.2.2 The Threshold GARCH (TARCH) Model

The TARCH model was independently developed by Glosten, Jaganathan and Runkle (1993) and Zakoian (1994). In a generalized form, the conditional variance is specified as:

$$h_t = \omega + \sum_{i-1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \sum_{k=1}^{v} \gamma_k \, \varepsilon_{t-k}^2 \, d_{t-k}^- \qquad (8)$$

Where: $d_t^- = 1$ if $\varepsilon_t = 0$ and 0 otherwise. Unlike in the in the GARCH model, good news in the TARCH model is given by $\varepsilon_t > 0$, and bad news is given by $\varepsilon_t < 0$. Suffice to say that good news has an impact of α_i, while bad news has an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$, it implies that bad news generates more volatility, which suggests presence of leverage effect. However, if $\gamma_i \neq 0$, the impact of news is asymmetric. The conditional variance equation for the TARCH (1,1) model is specified as:

$$h_t = \omega + \alpha_{i1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma \varepsilon_{t-1}^2 \, d_{t-1}^- \qquad (9)$$

Invariably, there are five distributional assumptions in the estimation of GARCH models; the normal distribution (ND), Student's-t distribution (STD), Skewed Student's-t Distribution (SSTD), Generalized Error Distribution (GED) and Skewed Generalized Error Distribution (SGED). Their specifications are, however, not provided here.

3.3 Markov Switching Model

The basic regime switching model assumes that there is a different regression model associated with each regime. Given regressors X_t and Z_t, the conditional mean of y_t in regime m is assumed to be the linear specification as:

$$\mu_t(m) = X_t'\beta_m + Z_t'\gamma \qquad (3)$$

Where β_m and γ are k_X and k_Z vectors of coefficients. The β_m coefficients for X_t are indexed by regime and that the γ coefficients associated with Z_t are regime invariant. Also, the regression errors are *iid* with a variance that may depend on a regime such as:

$$y_t = \mu_t(m) + \sigma(m)\epsilon_t \qquad (4)$$

Where $s_t = m$, and ϵ_t is *iid* standard normally distributed. Note that the standard deviation may be regime dependent, $\sigma(m) = \sigma_m$.

The likelihood contribution for a given observation may be formed by weighting the density function in each of the regimes by the one-step ahead probability of being in that regime:

$$L_t(\beta, \gamma, \sigma, \delta) = \sum_{m=1}^{M} \frac{1}{\sigma_m} \phi \left(\frac{y_{t-} \mu_t(m)}{\sigma_m} \right) . P(s_t = m | \Im_{t-1}, \delta) \quad (5)$$

$\beta = (\beta_1, ..., \beta_M)$, $\sigma = (\sigma_1, ..., \sigma_M)$, δ are parameters that determine the regime probabilities, $\phi(.)$ is the standard normal density function, while $\Im_{t-1}$is the information set in period $t - 1$. In the simplest case, the δ represents the regime probabilities themselves. The full log-likelihood is a normal mixture as follows:

$$l(\beta, \gamma, \sigma, \delta) = \sum_{t=1}^{T} log \left\{ \sum_{m=1}^{M} \frac{1}{\sigma_m} \phi \left(\frac{y_t - \mu_t (m)}{\sigma_m} \right) . P(s_t = m | \Im_{t-1}, \delta) \right\} \quad (6)$$

The above can be maximized with respect to $(\beta, \gamma, \sigma, \delta)$.

3.3.1 The Markov Switching Autoregressive Model (MS-AR)

We consider a univariate autoregressive process where the AR is subject to regime shifts. Hamilton (1989) assumes a single regime shift in the mean while trends in the literature now allows both the mean and the variance to shift simultaneously across the regimes. It is, in other words, a dynamic specification of the Markov Switching approach to assume that the errors are serially correlated. It is called the "Markov switching autoregressive" (MSAR) (Hamilton, 1989 and Fruhwirth-Schnatter, 2006) or the "Markov switching mean" (MSM) model (Krolzig, 1997). Thus, the MSAR model is often referred to as the "Hamilton model" of switching with dynamics. This paper uses daily stocks returns on the flow of the NSE during the event window of 5-months, that is, 2-months prior to and post national elections in Nigeria. Fitting a Markov switching autoregressive model of two regimes with an AR process of order ρ, we have:

$$y_t = \mu(s_t) + \left[\sum_{i=1}^{p} \alpha_i \left(y_{t-i} - \mu \left(s_{t-i} \right) \right] + u_i \right. \quad (7)$$

$$u_t \sim i.i.d(0, \sigma^2(s_t) \quad and, \qquad s_t = j, \; s_{t=i} = i; \quad i, j \, \epsilon \, 1, 2$$

Where s_t and s_{t-i} are the unobserved regime variables that take the values of either 1 or 2. The first-order Markov process requires that the probability or transition between regimes depends on the previous state, so that:

$$P(s_t = j \,| s_{t-1} = i) = p_{ij}(t) \quad (8)$$

Where $i, j \, \epsilon \, 1, 2$, we have:

$$P(s_t = 1 \,| s_{t-1} = 1) = p_{11}$$

$$P(s_t = 1 \,| s_{t-1} = 2) = p_{12} = 1 - p_{11}$$

$$P(s_t = 2 \,| s_{t-1} = 1) = p_{21} = 1 - p_{22}$$

$$P(s_t = 2 \,| s_{t-1} = 2) = p_{22}$$

Where:[2] $p_{11} + p_{12} = p_{21} + p_{22} = 1$.

The Markov process is assumed to be ergodic, that is, the likelihood of reverting to its previous state, and irreducible so that an absorbed regime never exists.

And, the steady state probabilities that are probabilities at the first period $P(s_o = m \mid Y_0)$ with $m = 1,2$. Given equation (8) these are:

$$P(s_o = 1 \mid Y_0) = \frac{1 - p_{22}}{2-(p_{11}+p_{22})} \tag{9}$$

$$P(s_o = 2 \mid Y_0) = \frac{1 - p_{11}}{2-(p_{11}+p_{22})} \tag{10}$$

Next, the transition probabilities in equation (8) also yields expected regime duration, that is, expected length a system stays in a given regime, 1 or 2. When we assume *D* to be the duration of regime j, it can be expressed as:

$$E(D) = \frac{1}{1-p_{jj}}, j = 1,2 \tag{11}$$

Estimation of the MSAR model requires finding the joint probability density function for y_t, $s_t = i \; and \; s_{t-1} = j;\ i = 1,2$ given information on past values of Y_{t-1}, with $Y_{t-1} = (y_{t-1}, y_{t-2}, \dots y_{t-n})$. This is expressed as:

$$g(y_t, s_t, s_{t-1} \mid Y_{t-1}) = g(y_t \mid s_t, s_{t-1}, Y_{t-1})\, g(y_t, s_t, s_{t-1} \mid Y_{t-1}) \tag{12}$$

Given that:

$$g(y_t \mid Y_{t-1}, s_t, s_{t-1}) = \frac{1}{\sqrt{2\pi\sigma^2(s_t)}} eks\left(-\frac{u_t^2}{2\sigma^2(s_t)}\right), \tag{13}$$

Where: $u_t = (y_t - \mu(s_t)) - \sum_{i=1}^{p} \alpha \left(y_{t-i} - \mu(s_{t-i})\right)$.

Afterwards, to obtain the parameters of the MSAR model, the log-likelihood function of Equation (12) is maximized with respect to $\theta = (\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, p_{11}, p_{22})$ as expressed earlier in equations (5) and (6), that is,

$$\begin{aligned} \ln L\,(\theta \mid Y_T) &= ln \textstyle\sum_{t=1}^{T} g(y_t, s_t, s_{t-1} \mid Y_{t-1}; \theta) \qquad (13) \\ &= \textstyle\sum_{t=1}^{T} \ln\left\{\sum_{j=1}^{2}\sum_{i=1}^{2} g(y_t \mid s_t = j, s_{t-1} = i, Y_{t-1})\, P(s_t = j, s_{t-1} = i \mid Y_{t-1})\right\} \end{aligned}$$

Where: $P(s_t = j, s_{t-1} = i \mid Y_{t-1}) = P(s_i = i \mid s_{t-1} = j)$ (14)

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[2] The transition probabilities equation (8) can be re-written in a transition matrix as:

$$p(t) = \begin{bmatrix} p_{11}(t) & \dots & p_{1M}(t) \\ . & \dots & . \\ p_{M1}(t) & \dots & p_{MM}(t) \end{bmatrix}$$

The ij-th element represents the probability of transitioning from regime i in period $t-1$ to regime j in period t.

Once we are able to estimate our model using the filtering algorithm, we also can make inference on the regime, s_t using all the information from the sample as suggested by Kim (1994) and Ismail and Isa (2008). Further, estimation of smoothing probabilities follows a two-step algorithm using Equation (14).

3.4 Data Metric

The data used for the investigation are daily stock market index, the All Share Index (ASI), from the Nigerian Stock Exchange (NSE) market. The paper uses an event study approach to demarcate event windows. An 8 weeks before and after an election month window was adopted, thus, giving a total of 16 weeks. The paper covers a total of 6 presidential elections held in 1999, 2003, 2007, 2011, 2015 and 2019. Series corresponding to each event window were analysed in returns, which is the first difference of natural logarithm multiplied by 100. The use of daily returns series, high frequency data, allows us to more clearly observe regime shifts within each event window. Plots of the returns series for all the 6 elections in Figure 1, for instance, suggest that regime shifts happen during these periods.

A look at plots of the series across the events windows shows excessive gains and losses that suggest evidences of regime shifts during the periods. In particular, the market returns dipped in the early and towards the end of December, 1998, persisted January, 1999 and through the election week, that is, 27th February, 1999. However, some dots of post-election gains were recorded in later in March and April, 1999. Similar pattern is noticeable in the 2003 election. The 2007 election window showed huge negative returns is the month of February, 2007 but the margins narrowed afterwards. Furthermore, while the 2015 election window recorded positive returns around the election week, there were more indications regime shifts in the plots for the 2011 and 2019 election windows.

IV. RESULTS AND INTERPRETATION

4.1 Testing for Nonlinearity, Structural Break and Stationarity

The paper tests for normality in the returns series using the Jacque-Bera test and uses two portmanteau tests and two structural breaks tests to capture nonlinearity and structural break in the return series across the 6 events windows, that is, presidential elections in Nigeria. The two portmanteau tests are the Regression Error Specification Test (RESET) test and the BDS test. The RESET test was proposed by Ramsey (1969) which is a specification test for linear least squares regression analysis. The BDS test as described in Brock, Dechert, Scheinkman and LeBaron (1996) tests the null hypothesis of independently and identically distributed (*iid*) in the data.

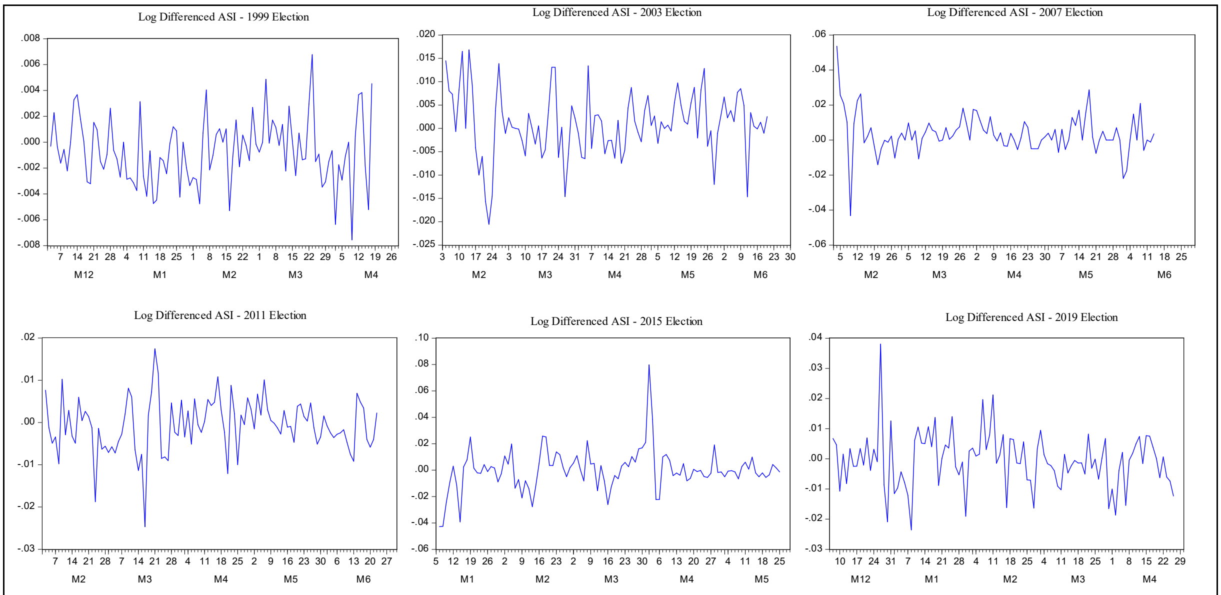

Figure 1: Monthly Returns Series

The three structural breaks tests are the CUSUM of squares test, the Quandt-Andrew single break and the Bai-Perron multiple breaks tests. The CUSUM of squares test was developed by Brown, Durbin and Evan (1975) based on a plot of cumulative sum of the squared one-step-ahead forecast error resulting from recursive estimation between two critical lines. The movement outside the critical line is suggestive of parameter or variance instability. The Quandt-Andrews test tests for one or more unknown structural breakpoints in the sample for a specified equation. It is based on two test statistics; the Likelihood Ratio F-statistic and the Wald F-statistic. Andrews (1993) and Hansen (1997) provided approximate asymptotic p-values. The Bai-Perron test was introduced by Bai and Perron (1998, 2003a & 2003b). The test estimates the timing of the structural break or the break date(s) using least squares method. While the CUSUM tests allows visualization of break, the Bai and Perron test reports (multiple) break date(s).

Evidence of non-normal distribution was found using Jacque-Bera statistic (see: Table 1A) test except for the returns series for the 2019 election window. Further, from the results on Table 1, the BDS test and the RESET test suggest that linear model may be inadequate in capturing the stochastic properties of the return series. The two tests show significant results with small and high p-values for the BDS and RESET tests, respectively. In Figure 2, it is clear that the cumulative sum of the squared values moves out from the 5% significant line which reveal instability in all the returns series. Further, the Quandt-Andrew test found a single break date in all the returns series while a couple of break dates are obtained using the Bai-Perron test. Also, except for the 2015 election, the ADF structural break test rejects the null hypothesis of stationarity at level which necessitates first differencing of the series.

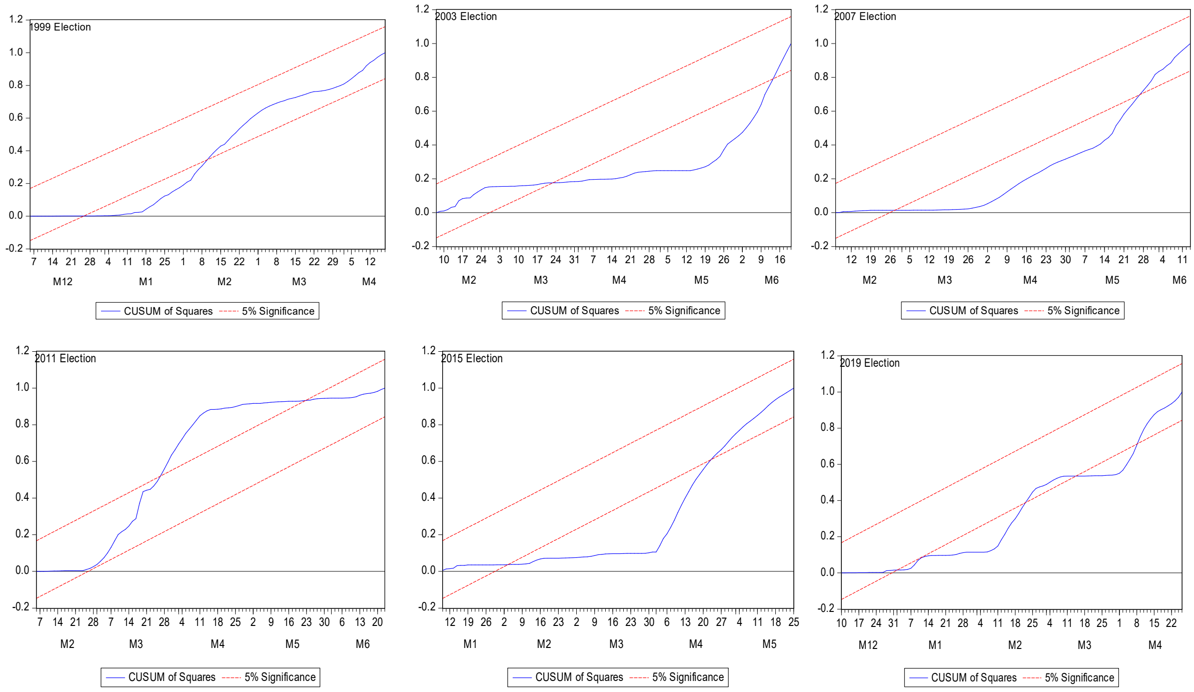

Figure 2: CUSUM of Squares Tests, 1999 – 2019 Elections

Thus, we conclude from all the results that there is statistical evidence of departures from linear behaviour and structural changes in the returns series across the 6 event horizons. Next, we are going to model the four return series using Markov switching autoregressive model.

Table 1: Nonlinearity, Structural Break and Stationarity Tests

EVENT WINDOW	**LINEARITY**		**STRUCTURAL BREAK**		**STATIONARITY**
	BDS Test	Ramsey REST Test	Quandt-Andrews Test	Bai-Perron Test	ADF Test with Structural Break
1999 Election	33.971 (0.000)	1.501 (0.224)	1/15/1999	12/28/1998 1/15/1999 2/04/1999 3/05/1999 3/30/1999	-3.079 (Level) -8.877 (1^{st} Diff.)
2003 Election	24.718 (0.000)	0.772 (0.382)	5/20/2003	2/21/2003 5/20/2003	-3.399 (Level) -7.141 (1^{st} Diff.)
2007 Election	42.334 (0.000)	2.271 (0.135)	04/02/2007	3/13/2007 4/02/2007 5/14/2007	-2.608 (Level) -8.749 (1^{st} Diff.)
2011 Election	28.838 (0.000)	0.036 (0.850)	2/28/2011	2/28/2011 3/22/2011 4/12/2011 6/02/2011	-3.552 (Level) -8.751 (1^{st} Diff.)

2015 Election	38.529 (0.000)	0.593 (0.443)	04/02/2015	1/29/2015 2/24/2015 4/02/2015	-6.308 (Level) -9.418 (1^{st} Diff.)
2019 Election	23.072 (0.000)	0.181 (0.672)	04/01/2019	2/07/2019 3/11/2019 4/01/2019	-2.379 (Level) -9.788 (1^{st} Diff.)

The critical value for the ADF test with Break is -4.949

4.2 Results of Symmetric and Asymmetric GARCH (1,1) Variant Models

From the short reconnaissance into the nature of the data across the 6 time horizons (event windows) using standard statistics and returns plots as well as checks on linearity, structural break and stationarity, it is expedient to explore evidence of volatility clustering and leverage effects in the NSE's daily stock returns. This will help us gauge the level of risks and uncertainty and possible reactions from both investors and market regulators.

Table A3 presents the parameter estimates of the symmetric GARCH (1,1) and the asymmetric EGARCH (1,1) and TARCH (1,1) for the daily return series across the 6 events windows. In particular, the results of the symmetric GARCH (1,1) in the variance equations show that majority of the estimated coefficients, (α and β), across the 6 horizons, are statistically insignificant. This implies that news about volatility in the previous period does not explain current volatility of stock market returns. However, the sum of shock persistence for all the time horizons except the 2015 election are less than unity ($\alpha + \beta > 1$) suggesting that the conditional variance is stable and non-explosive. Meaning, there is absence of excessive gains and losses in the market, a condition often tenable only in developed markets.

Furthermore, the results of estimated asymmetric EGARCH (1,1) for all the 6 event windows in the variance equations reveal mixed outcomes with majority of the β coefficient being correctly signed and statistically significant. In addition, the shock persistence measure is greater than unity ($\alpha + \beta < 1$) in the 2003, 2007 and 2015 elections but not in others. This suggests that the conditional variance processes in the EGARCH (1,1) are unstable and explosive leading to long memory, that is, possibility of excessive margins, positive and negative, in the NSE. The asymmetric (leverage) effect coefficient ($\gamma < 0$) reveals presence of leverage effect during the 2011 election where the coefficient (-0.186) is both statistically significant and correctly signed. The presence of leverage effect in the daily stock returns signifies that negative shock (bad news) generates more volatility that positive shock (good news) of the same magnitude.

In a similar fashion, the asymmetric TARCH (1,1) empirical results in the variance equation show that almost all the β coefficients, except for the 2011 election window, are statistically significant and correctly signed. The sums of ($\alpha + \beta$) are greater than unity only in the 2015 and 2019 election periods' daily market returns. Like the GARCH (1,1) model, this implies that the conditional variance is stable and non-explosive. However, unlike the EGARCH (1,1) where we established leverage effect in the 2011 election, the TARCH model reveals no leverage effect throughout the 6 horizons. Table A4 presents news impact on conditional volatility for the EGARCH (1,1) and

TARCH (1,1) models. The former model reveals presence of three asymmetric effects during the 1999, 2011 and 2019 while the latter reveals asymmetric effects during the 2011, 2015 and 2019.

Using asymmetric GARCH models – EGARCH (1,1) and TARCH (1,1), Kuhe (2018) reports presence of leverage effects using monthly series in the NSE over the period of January, 1985 and March, 2017 and its absence using both models over the period of 3rd July, 1999 and 12th June, 2017. Using particular case of the Guinness Nigeria Plc's market returns as proxy for the Nigeria's stock market returns between 01/02/1995 and 24/11/2014, Kuhe and Ikughur (2017) found that GARCH (1,1) model reveals evidence of volatility clustering and mean reversion while the conditional volatility was quite persistent. Their asymmetric PGARCH (1,1) and TARCH (1,1) models show evidence of asymmetry and leverage effects. Further, Sikiru, Fasanya and Falola (2018) using a sample of eight agro-allied companies on the NSE's platform covering the period of 9th January, 2015 and 31st August, 2016 found evidence of leverage effect in all except two out of a total of eight companies. However, their symmetric models appeared superior to the asymmetric models (PGARCH and TARCH). Others include: (Dikko, Asiribo and Samson, 2015; Kuhe and Chiawa, 2017; and Chiawa and Kuhe, 2018).

4.3 Results of MS-AR (1) Results

Using the maximum likelihood estimation, the paper estimates the stock market returns for each of the 6 presidential elections (event windows) using a two regimes univariate Markov switching autoregressive (MS-AR) model to identify the presence of regime switching behaviour. We use an MS-AR (1), for parsimony in the estimation process. Meanwhile, we use the likelihood ratio test suggested by Garcia and Perron (1996), to test the null hypothesis of no switching in the NSE during the periods under consideration represented by EGARCH (1,1) and TARCH (1,1) models against an alternative specification, an MS-AR (1), for regime switching in the Nigeria's NSE. The LR test statistic is computed as $LR = 2 \left| LR_{MS-AR(1)} - LR_{EGARCH\ (1,1)} \right|$. The critical value is based on Davies (1987) p-value as suggested by Garcia and Perron (1996). The results in Table A2 suggest strong rejection of the null hypothesis of no switching at 1% or 5% critical values. Meaning, there is a strong evidence of regime shifts in the NSE during the presidential elections, 1999 – 2019, and justifies the application of nonlinear MS-AR (1) model.

Table 3: Estimated MS-AR (3) Model for Daily Returns Series

Event / Parameter	1999 Election	2003 Election	2007 Election	2011 Election	2015 Election	2019 Election
$\mu(St = 1)$	-6.891* (1.801)	10.953 (9.705)	307.29* (117.89)	-22.391 (13.762)	71.943 (99.963)	97.487 (599.34)
$\mu(St = 2)$	21.374* (4.539)	9.661 (13.448)	38.651 (30.799)	-63.546* (4.713)	-10.675 (42.304)	-34.687 (34.762)
$\sigma(St = 1)$	2.418* (0.105)	3.249* (0.486)	6.447* (0.142)	5.075* (0.077)	6.476* (0.267)	6.501* (0.596)

$\sigma(St = 2)$	2.051* (0.412)	4.692* (0.111)	5.398* (0.113)	2.404* (0.348)	5.052* (0.247)	5.499* (0.123)
P_{11}	0.919	0.659	0.861	0.988	0.859	2.69E-07
P_{12}	0.306	0.886	0.919	0.793	0.877	0.955
$E(Ds_{t=1})$	12.472	2.937	7.192	82.668	7.108	1.000
$E(Ds_{t=2})$	1.441	8.767	12.277	4.837	8.140	22.425
AR (3)	0.216 (0.085)	-0.015 (0.855)	-0.133 (0.090)	-0.279* (0.080)	-0.071 (0.686)	0.204* (0.099)

Note: Results are obtained from estimation of Equation (7) using maximum likelihood method.
Figures in the parenthesis are standard errors of estimated parameters. *significance at the 5% level or better.

The estimated parameters for the MS-AR (1) model using maximum likelihood estimation using BFGS optimisation method are presented in Table 3. The empirical results clearly identify, for each event window, two regimes; bear and bull market. Invariably, regime 1 for each of the stock market returns captures the behavior of the stock markets in a downturn phase, otherwise bear market, characterized by high volatility as measured by the standard deviation for each regime (σ) and low expected return (μ). Regime 2 follows with lower volatility and higher expected (mean) return. It is also clear from the results that except for the 2003 election, the $\sigma(St = 1)$ is consistently greater than the $\sigma(St = 2)$ and all are statistically significant and conforms to the a priori expectation. This reflects higher volatility in the bear market than in the bull market. Further, the expected returns across the two regimes show mixed results with some in the bear market shedding and gaining over the event horizons. Similarly, the bull market which supposedly is for recovery or expansion records minuses as well. Overall, the 1999 election window records most consistent and statistically significant results; higher volatility (lower) and lower expected return (higher) in the bear (bull) market of 2.42 and -6.89 (2.05 and 21.37), respectively.

Furthermore, the probabilities of staying in regime 1 (P_{11}) are smaller than the probabilities of staying in regime 2 (P_{22}) except during the 1999 and 2011 elections. In particular, the 2007 election shows the most persistent regimes with probabilities of 0.861 and 0.919 for bear and bull regimes, respectively. Thus, going by equation (8) above, there is $1 - P_{11}$, that is, $1 - 0.861 = 0.139$ probability of regime 1 drifting to regime 2, while there is only $1 - P_{22}$, that is, $1 - 0.919 = 0.081$ probability of regime 2 switching to regime 1. In consonance to these, the expected duration of stay in regime 2 ($E(Ds_{t=2})$) is higher than in regime 1 $\left(E(Ds_{t=1})\right)$ in 4 out of the 6 event windows; 2003, 2007, 2015 and 2019 elections with 8.77 days, 12.28 days, 8.14 days and 22.43 days, respectively. This finding suggests that only a major event such as election could trigger movement from the bull to the bear market. However, the highest duration of stay recorded in regime 1 occurred during the 2011 election with a total of 82.67 days. Thus, regime 2 leads across the 6 horizons with low volatility, higher duration of stay, though with mixture of both positive and negative returns. The AR (3) shows presence of no ARCH effect except in the 2011 and 2019 elections when the coefficient was found to be statistically significant.

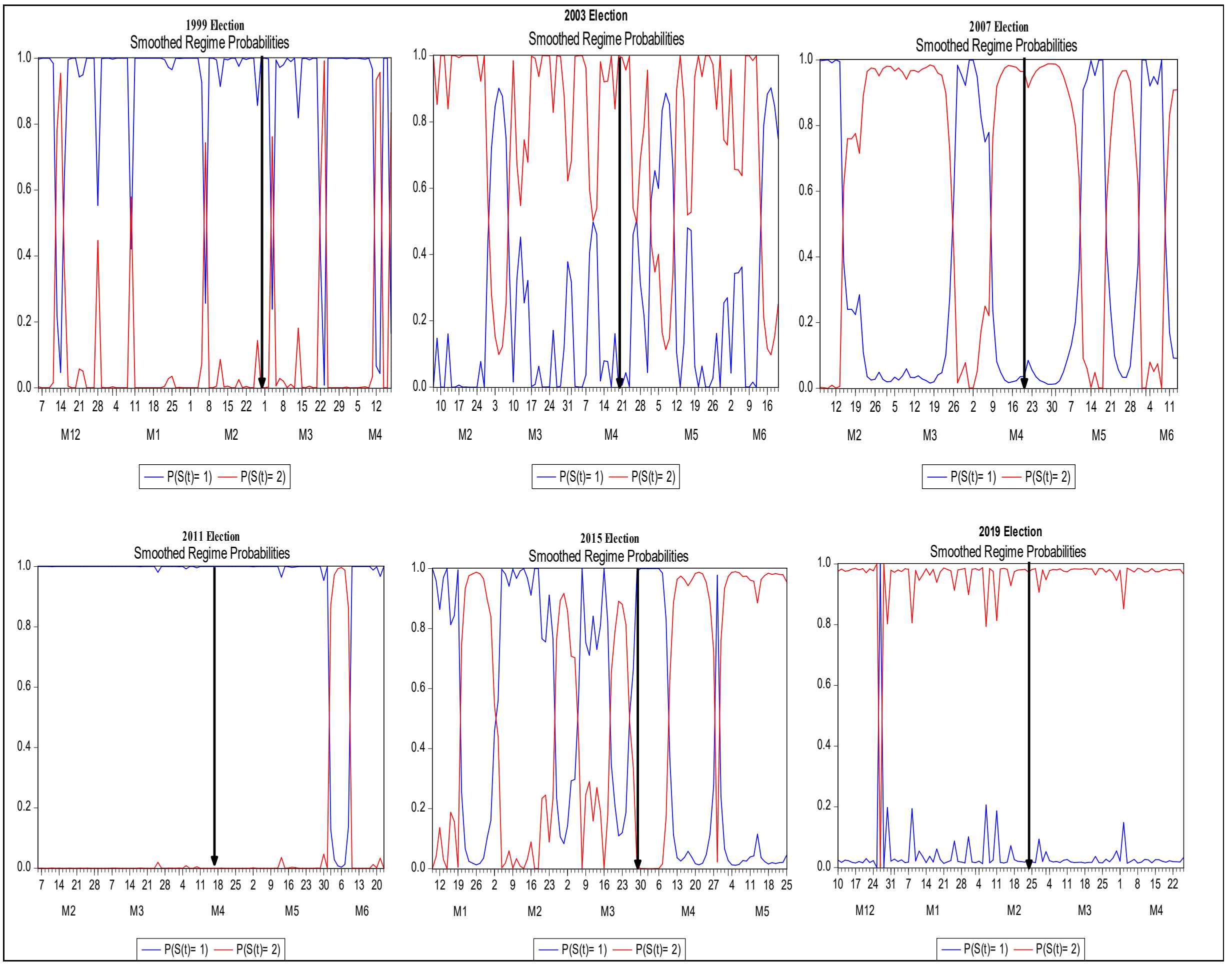

Figure 3: Smoothed Probabilities of Regime 1 and 2 (combined graphs)

The above findings are reinforced by the smoothed probability plots for the two regimes fitted by the MS-AR (3) model across the 6 event windows as presented in Figure 3. The plots show clear pattern of correlation relationship between the smoothed probabilities of regime 1 and 2, that is, as the probability of regime 1 is close to unity, the probability of regime 2 is close to zero and vice versa. In particular, trading on the flow of the NSE on the eve of the elections across the 6 time horizons; Friday 26th February, 1999; Friday, 18th April, 2003; Friday, 20th April, 2007; Friday, 15th April, 2011; Friday, 27th March, 2015 and Friday, 22nd February, 2019 were marked using a vertical line. Also, the lines clearly re-echo the strong correlation relationship between regime 1 and 2. Generally speaking, the findings indicate that the MS-AR (3) performs well in capturing the direction of movements of the return series at the NSE across the regimes 1 and 2 over the event windows.

Furthermore, the forecast ability of the three models; MA-AR (3), EGACH and TARCH was evaluated using dynamic forecast with the aid of standard statistics; the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Theil

Inequality coefficient and Bias proportion. Results presented in Table A5 reveal mixed forecast performance of the three models with EGARCH model leading with lower RMSE and MAE in the 1999 election window. The MS-AR (3) model proved superior in 2003 – 2015 in at least three out of the five forecast evaluation statistics. Lastly, the TARCH model offers better forecast performance over the others except in the Theil inequality coefficient. Empirical findings by Shuaibu (2018) show that among other macroeconomic variables forecasted, the stock market demonstrates bearish sentiments in the build up to the 2016 recession in Nigeria. His results show that the static model outperforms the dynamic version in terms of robustness of forecast statistics. Other studies include: Okafor and Shuaibu (2013), CBN (2015), Akpan and Atan (2015) and Ekong and Effiong (2015).

V. Concluding Remarks

A lot of studies have assessed the impact of political events on stock market returns in the literature using assorted research methodologies. This paper employs multifaceted approaches; event study, GARCH and MS-AR methodologies. The study assesses the impact of presidential elections held in Nigeria between 1999 and 2019 on NSE's stock returns which the paper decomposes into 6 event windows.

A preliminary reconnaissance into the nature of the data across the 6 time horizons (event windows) using standard statistics and returns plots reveals incidences of nonlinearity, structural break and non-stationarity. We expediently explore evidence of volatility clustering and leverage effects in the NSE's daily stock returns using both symmetric and asymmetric GARCH models in order to gauge the level of risks and uncertainty in the NSE. The EGARCH (1,1) and TARCH (1,1) unveil evidence of asymmetric effects during the 1999, 2011 and 2019 elections in the former and during the 2011, 2015 and 2019 in the latter. Further, we establish presence of leverage effect in the EGARCH (1,1) during the 2011 election.

Results from the MS-AR (3) model proved to more robust over both the symmetric and asymmetric models. In line with evidence in the literature, the model neatly characterized the NSE's daily stock returns in terms high (low) volatility low (high) returns as regime 1 and 2, respectively. Overall, regime 2 leads across the 6 horizons with low volatility, higher duration of stay, though with mixture of both positive and negative returns. The AR (3) shows presence of no ARCH effect except in the 2011 and 2019 elections when the coefficient was found to be statistically significant. In forecasting stock returns across the event windows, the MS-AR- (3) model proves superior than it counterparts, the EGARCH and TARCH models.

It is therefore imperative for investors to take cognizance and invest wisely around the election periods in the market. The regime characterization is also useful to regulators as well in forestalling crisis in the market through continuous monitoring of volatility around major events like national election in this case.

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Table A1: Normality Test

Event Window/ Statistic	1999 Election	2003 Election	2007 Election	2011 Election	2015 Election	2019 Election
Mean	5487.762	13837.21	45359.88	25515.46	31739.72	30904.88
Median	5427.42	13699.7	46925.33	25424.42	30617.96	30831.48
Maximum	5715.97	14684.7	51702.83	26928.67	35728.12	32715.2
Minimum	5290.89	13291.55	36452.84	24336.85	27585.26	29149.46
Std. Deviation	131.0651	368.2082	4194.644	651.833	2390.521	921.7087
Skewness	0.499764	0.737511	-0.022375	0.496087	0.199331	0.065429
Kurtosis	1.766754	2.267763	1.666664	2.431013	1.402878	2.406006
Jarque-Bera Probability	10.39481 (0.005531)	11.18642 (0.003723)	7.04499 (0.029526)	5.559665 (0.062049)	11.40345 (0.00334)	1.572299 (0.455596)

Table A2: Log Likelihood Ratio Test

Model/ Event	LR EGARCH (1,1)	LR TARCH (1,1)	LR MS-AR (3)	LR Statistic (EGARCH)	LR Statistic (TARCH)
1999 Election	-398.90	-399.00	-386.23	160.52 (0.000)	163.07 (0.000)
2003 Election	-586.30	-585.88	-568.09	331.60 (0.000)	316.48 (0.000)
2007 Election	-708.47	-708.82	-675.95	1057.55 (0.000)	1080.44 (0.000)
2011 Election	-657.22	-648.02	-634.83	501.31 (0.000)	173.98 (0.000)
2015 Election	-745.11	-740.31	-717.28	774.51 (0.000)	530.38 (0.000)
2019 Election	-714.87	-719.69	-693.67	449.44 (0.000)	677.04 (0.000)

Note: Probability values in parenthesis are from Davies (1987) P [LR > 6.9] = .250, P [LR > 17.53] = .003 and, P [LR > 38.5] ≈ .000.

Table A3: Symmetric and Asymmetric GARCH Regression Results

EVENT/ PARAMETER	1999 Election			2003 Election			2007 Election			2011 Election			2015 Election			2019 Election		
	GARCH	EGARCH	TARCH	GARCH	EGARCH	TARCH	GARCH	EGARCH	TARCH	GARCH	EGARCH	TARCH	GARCH	EGARCH	TARCH	GARCH	EGARCH	TARCH
C(1) μ	3.662* (0.009)	-3.70* (0.006)	-4.018* (0.003)	10.73 (0.196)	16.484 (0.058)	13.80 (0.118)	110.23* (0.020)	127.29* (0.006)	110.66* (0.016)	-15.777 (0.339)	-19.00 (0.054)	-18.537 (0.251)	15.120 (0.547)	5.256 (0.856)	17.479 (0.551)	-15.594 (0.628)	-23.20 (0.477)	-9.398 (0.644)
C(2) ω	151.51 (0.253)	1.160 (0.237)	46.22 (0.332)	1586.9 (0.230)	0.970 (0.364)	1149.4 (0.241)	23382 (0.053)	1.061 (0.095)	22114.3 (0.098)	5022.1 (0.502)	0.855* (0.000)	6693.5 (0.231)	22741.1 (0.078)	11.127* (0.000)	22861.1 (0.084)	15137.6 (0.602)	16.364* (0.038)	8110.0* (0.039
C(3) α	-0.115 (0.287)	-1.654 (0.328)	-0.099 (0.230)	0.339 (0.810)	0.469 (0.052)	0.382 (0.132)	0.111 (0.053)	0.248 (0.123)	0.215* (0.035)	0.157 (0.198)	-0.26* (0.000)	-0.001 (0.997)	0.952* (0.000)	1.589* (0.000)	0.098* (0.000)	0.015 (0.749)	-0.180 (0.462)	0.096* (0.008)
C(4) γ		-0.114 (0.307)	0.136 (0.271)		0.078 (0.424)	-0.212 (0.323)		0.107 (0.118)	-0,150 (0.181)		-0.186* (0.000)	0.307 (0.170)		0.059 (0.766)	-0.082 (0.826)		-0.075 (0.673)	-0.25* (0.000)
C(5) β	0;333 (0.585)	0.805* (0.000)	0.801* (0.000)	0.5110 (0.134)	0.851* (0.000)	0.611* (0.002)	0.730* (0.000)	0.895* (0.000)	0.706* (0.000)	0.645 (0.107)	0.936* (0.000)	0.584 (0.068)	0.267* (0.027)	-0.039 (0.720)	0.270* (0.049)	0.047 (0.799)	-0.440 (0.533)	0.928* (0.000)
$\alpha + \beta$	0.219	0.639	0.703	0.850	1.319	0.992	0.841	1.143	0.921	0.802	0.672	0.583	1.218	1.550	1.251	0.815	-0.620	1.024
AIC	8.163	8.162	8.159	11.94	11.94	11.95	15.02	15.03	15.02	12.99	12.80	12.98	14.83	14.76	14.85	14.19	14.21	14.12
SIC	8.268	8.293	8.290	12.04	12.07	12.07	15.13	15,16	15.15	13.09	12.93	13,11	14.94	14.89	14.91	14.29	14.34	14.24
LR	-400.1	-399.0	-398.9	-587.0	-585.9	-586.3	-709.3	-708.8	-708.5	-659.4	-648.0	-657.2	-745.1	-740.3	-745.1	-719.6	-719.7	-714.9

Note: values in (.) are p-values and * indicates significance at the 5% level or better. γ stands for the leverage effect in the asymmetric GARCH where [$\gamma < 0$] and [$\gamma > 0$] signify presence of leverage effect in the EGARCH (1,1) and TARCH (1,1), respectively.

Table A4: News Impact on Conditional Volatility

Model/ Event Window	**EGARCH**			**TARCH**		
	Good News	Bad News	Impact of Bad on Good News	Good News	Bad News	Impact of Bad on Good News
Election 1999	0.886	1.114	1.257	0.099	0.037	0.374
Election 2003	1.078	0.922	0.855	0.382	0.170	0.445
Election 2007	1.107	0.893	0.807	0.215	0.065	0.302
Election 2011	0.814	1.186	1.457	0.001	0.306	306.0
Election 2015	1.059	0.941	0.889	0.098	0.899	9.173
Election 2019	0.925	1.075	1.162	0.096	0.150	1.562

Note: Asymmetry is as $\frac{|-1-\hat{\gamma}|}{1+\hat{\gamma}}$ for the EGARCH (1,1) and $\frac{\hat{\alpha}-\hat{\gamma}}{\hat{\alpha}}$ for the TARCH (1,1) where the numerator represents the bad news while the denominator represents the good news impact on volatility.

Table A5: MS-AR (3), EGARCH & TARCH Forecast Evaluation

VARIABLE/EVENT/MODEL		**RMSE**	**MAE**	**MAPE**	**THEIL**	**BIAS**
1999 Election	MS-AR(3)	13.968	10.957	1763.49	**0.7570**	0.0000
	EGARCH	**13.870**	**10.827**	1612.35	0.7679	0.0000
	TARCH	13.871	10.829	**1596.36**	0.7696	0.0000
2003 Election	MS-AR(3)	**95.545**	**70.370**	**1235.61**	0.9010	**0.0000**
	EGARCH	96.424	71.249	1928.17	**0.8482**	0.0015
	TARCH	96.359	71.168	1627.75	0.8681	0.0001
2007 Election	MS-AR(3)	**437.98**	**309.63**	12677.6	**0.7310**	**0.0002**
	EGARCH	486.96	332.30	**1134.31**	0.7643	0.0028
	TARCH	488.12	331.07	9870.40	0.7867	0.0076
2011 Election	MS-AR(3)	**158.122**	**120.82**	**101.940**	0.9010	0.0012
	EGARCH	158.48	121.97	104.57	**0.8878**	0.0000
	TARCH	158.48	121.99	104.32	0.8901	0.0000
2015 Election	MS-AR(3)	**459.133**	**295.59**	107.125	**0.9320**	**0.0000**
	EGARCH	497.460	319.87	**100.76**	0.9897	0.0003
	TARCH	497.82	320.31	103.05	0.9667	0.0018
2019 Election	MS-AR(3)	285.133	208.90	136.63	**0.9070**	0.0008
	EGARCH	282.210	207.15	127.67	0.9227	0.0005
	TARCH	**282.140**	**207.04**	**116.86**	0.9460	**0.0000**