

## Markov Switching Vector Autoregressive Modelling of the Nigerian Stock Price and Oil Price Series

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### History Article

Received: August 24, 2018  
Accepted: October 12, 2018  
Published: December 1, 2018

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**Keywords:** MS-VAR, VAR, Crude oil prices, Stock prices, Markov Switching, Structural break

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**JEL Codes:** C10; H54

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### Abstract

This article studied the relationship between stock prices and crude oil prices of Nigeria using a Markov switching model. Certain properties of the stock price series and crude oil price series such as breaks and stationarity, which are necessary before choosing a multivariate time series model for this relationship were investigated. Unit root and cointegration structural break tests were used where evidence of breaks exists. In particular, each of the series was found to be a nonlinear and nonstationary series with evidence of a structural break. The results of the unit root and cointegration tests in the presence of structural breaks indicated evidence of  $I(1)$  and no cointegration between the series. Consequently, a Markov switching VAR (MSM(2)-VAR(1)) model with two regimes was fitted to the data having established the suitability of the series to regime switching models. The results showed that high volatility regime occurs when the economy was under recession. Furthermore, there exists a positive relationship between stock prices and crude oil prices during the high volatility regime and a negative relationship during the low volatility regime.

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### How to Cite:

Okereke, E. W., & Uwaeme. O. R. (2018). Markov Switching Vector Autoregressive Modelling of the Nigerian Stock Price and Oil Price Series. *Quantitative Economic Research*, 1(2), 95–107.

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### INTRODUCTION

The study of the impact of crude oil prices on the economic growth of Nigeria has been carried out by several authors. This is because Nigeria is known to be an oil-dependent country that depends heavily on oil revenue as evident in the fact that the budget is anchored on the production and revenue accrued from oil. This makes the study on the impact of oil on key microeconomic variables of Nigeria very interesting. The performance of the oil revenue impacts the economy either positively or negatively if it is good or bad respectively. If the performance is good or exceeds its expectation, it will boost other sectors of the economy which depends heavily on it. Hence any shock on oil prices affects major sectors of the economy and GDP. Considering the role of crude oil prices on the Nigerian economy, many studies dealing with the relationship between crude oil prices and one or more microeconomic variables has been carried out Yusuf (2015); Ogboru et al. (2017); Osuji (2015); Iheanacho (2016); Oriavwote & Eriemo (2012). Of these relationships between oil prices and key economic variables in Nigeria, the relationship between oil prices and stock prices has garnered few interest to the best of our knowledge. This is despite the fact that the stock market plays a key role in the financial market as it funds public and private borrowings while encouraging savings through its

shares. Hence, improved oil revenue is expected to have an effect on the stock market as many firms and corporations which depends on oil both directly and indirectly (oil firms, Power companies, etc.) will experience a boost in their earnings and stock prices which will in turn lead to an increase in the demand for shares as well as prompt payment of dividends to investors.

Akomolafe & Danladi (2014) examined the impact of oil prices on the stock prices of Nigeria, using the cointegration and vector error correction framework. They showed that oil prices has a negative impact on the stock market. Okere & Ndubuisi (2017); Ekong & Ebong (2016) also showed that crude oil prices affect the stock market performance. Effiong (2014); Adaramola (2012) also found crude oil price shocks affects the volatility of the stock market in Nigeria. However, Fowowe (2013) found an insignificant relationship between stock prices and crude oil prices of Nigeria. This, he attributed to a number of reasons such as the fact that the stock market is dominated by the banking sector with few oil firms participating among others. These findings correspond with other studies outside Nigeria such as Hong et al. (2002), O'Neill et al. (2008); Park & Ratti (2008) which reported a negative relationship between crude oil prices and stock prices. While Sadorsky (2001); Gogineni (2008) reported a positive relationship between crude oil prices and stock market returns.

It is important to note that studying this relationship between crude oil prices and the stock market in Nigeria has been based on linear time series models. The vector autoregressive model under the cointegration and vector error correction framework are very common in examining this relationship. However, several studies have shown that crude oil prices and stock market returns are prone to nonlinear behaviors such as fluctuations, structural breaks, etc. and therefore should require a nonlinear time series model to study them (see Mustapha & Masih, 2017; Balcilar et al., 2017; Cuestas & Tang, 2015; Ismail & Isa, 2009).

Outside Nigeria, these two variables have been studied using nonlinear models such as the Markov switching models. Balcilar et al. (2015) examined the US crude oil and stock market prices from 1859 to 2013 using a regime switching model, they showed the effects of ignoring nonlinearity and their findings showed evidence of no relationship between oil price shock and stock price in the low volatility regime and a negative relationship for the high volatility regime. These findings correspond with that of Wei (2003); Huang et al. (1996) and Jones & Kaul (1996) respectively.

Furthermore, the problem of a structural break when modeling this relationship has not been addressed in the literature to the best of our knowledge. Many Economic time series data are known to be characterized by structural breaks caused by exogenous events during the period of observation. The consequences of ignoring structural breaks during analysis include the problem of spurious regression and type I error during testing and estimation procedures (see Hackl and Westlund (1989) for more). Many studies have been carried out in the presence of structural breaks, identifying and estimating relationships between economic variables.

In this paper, we use the regime-switching Markov switching vector autoregressive (MS-VAR) approach to study the relationship between crude oil prices and the stock market in Nigeria. We seek to establish evidence of nonlinear relationship between crude oil prices and stock market due to common regime-switching behavior occasioned by structural breaks. The remainder of the paper is organized as follows: Section 2 introduces the Markov switching vector autoregressive specifications and other methodologies. Section 3 presents the data analysis and results while section 4 concludes the paper.

## METHOD

### Markov Switching Vector Autoregressive Models

Following the introduction of Markov switching regressions by Goldfeld & Quandt (1973); Hamilton (1989) introduced the Markov switching autoregressive model (MS-AR) to explain the periodic shift in the US real GNP from a positive growth rate to negative growth rate regimes. He assumed that in an MS-AR model of order  $k$  with regime shifts in the mean and variance, a time series variable  $y_t$  is represented as follows:

$$y_t = \mu(s_t) + \left[ \sum_{i=1}^k \gamma_i (y_{t-i} - \mu(s_{t-i})) \right] + \sigma(s_t) u_t \quad (1)$$

$$u_t | s_t \sim NID(0, \sigma^2) \text{ and } s_t = 1, 2.$$

where  $\gamma_i$  represents the autoregressive coefficients.  $\mu$  represents the mean, while  $\sigma$  is the standard deviations which depends on  $s_t$ , the regime at time  $t$ .

This model in (1) can be easily extended to the MS-VAR model of order  $k$  and  $M$  regimes with regime shifts in the mean and variance as given below:

$$Y_t - \mu(s_t) = \sum_{i=1}^k \gamma_i (y_{t-i} - \mu(s_{t-i})) + u_t \quad (2)$$

where  $Y_t$  is an  $k$  dimensional time series vector,  $\mu$  is the vector of means,  $\gamma_i, i = 1, 2, \dots, p$  are matrices of the autoregressive parameters and  $u_t$  is a white noise vector process dependent on  $s_t$  such that  $u_t | s_t \sim NID(0, \Sigma)$ . The model (2) is also referred to as the MSM(M)-VAR(k).

The model in (2) contains a change in the regime after an immediate one-time jump in the process mean. Often times, after the transition from one state to another, the mean is plausibly assumed to smoothly approach a new level. Situations such as this require a model with a regime-dependent intercept term  $w(s_t)$  as shown below:

$$Y_t = w(s_t) + \left[ \sum_{i=1}^k \gamma_i ((s_t) y_{t-i}) \right] + u_t \quad (3)$$

The MSM(M)-VAR(k) and the MSI(M)-VAR(k) of the MS(M)-VAR(k) model are not equivalent as they both imply different dynamic adjustments of the observed variables after a change in regime (Krolzig, 1997b). There are other specifications of the MS(M)-VAR(k) models involving the autoregressive and the heteroscedasticity parameters respectively.

From the equations above, the state variables,  $s_t$ , triggers the behavior of  $Y_t$  to change from one regime to another and is generally assumed to follow an irreducible ergodic two-state markov process which implies that a current regime  $s_t$  depends on the regime one period ago,  $s_{t-1}$ . It is denoted by the transition probability between states as follows:

$$Pr(s_t = j | s_{t-1} = i, s_{t-2} = k, \dots) = Pr(s_t = j | s_{t-1} = i) = p_{ij}, \quad (4)$$

where  $p_{ij}$  is the transition probability from state  $i$  to state  $j$ . For two regimes, these transition probabilities is given by:

$$\begin{cases} P_{11} = Pr [s_t = 1 | s_{t-1} = 1] \\ P_{12} = Pr [s_t = 1 | s_{t-2} = 2] = 1 - P_{11} \\ P_{21} = Pr [s_t = 2 | s_{t-1} = 1] = 1 - P_{22} \\ P_{22} = Pr [s_t = 2 | s_{t-1} = 2] \end{cases} \quad (5)$$

Generally, the transition probability is characterized by an  $(n \times n)$  matrix denoted as:

$$\Pi = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{bmatrix} \tag{6}$$

with  $\sum_{j=1}^n P_{ij} = 1, i = 1, 2, \dots, n,$  and  $0 \leq P_{ij} \leq 1.$

The transition probabilities also provide the expected duration that is, the expected duration/ length of stay of a system in a certain regime. Let  $D$  be the duration of regime  $i.$  then, the expected length/ duration of regime  $i$  is given as:

$$E(D) = \frac{1}{1 - P_{ii}}, i = 1, 2, \dots \tag{7}$$

Inference about the state variable  $s_t$  in the MS-VAR is based on what is happening with the observed variable  $Y_t.$  It is represented by two probabilities;

$$\xi_{jt} = P(s_t = j | \Omega_t), j = 1, 2 \tag{8}$$

where  $\Omega_t = \{Y_t, \Omega_{t-1}\}$  and  $\Omega_{t-1} = \{Y_{t-1}, Y_{t-2}, \dots, Y_0\}.$  This two probabilities will sum to unity by construction. The inference is performed iteratively and the output provides us with probabilistic inferences about the unobserved regime,  $s_t;$  where smoothed probabilities  $\Pr(s_t = j | \Omega_T)$  are inferences about  $s_t$  by using all the information available in the sample with  $t = T - 1, T - 2, \dots, 1$  and filtered probabilities  $\Pr(s_t = j | \Omega_t)$  are inferences about  $s_t$  conditional on information up to time  $t, t = 1, 2, \dots, T.$  Also it can be shown that the smoothed probability is equal to the filtered probability when  $t = T.$  See Krolzig (1998); Hamilton (1989) for more on the Markov switching vector autoregression.

The MS-VAR model offers greater flexibility in capturing potential regime shifts in a data generating process. Hence the need for the test of structural break in a data set in necessary to explain the time-varying behaviors and interactions of the variables.

**Nonlinearity and Structural Break Tests**

From the literature, much of the studies of stock prices and oil prices has centered on the notion that the two variables are linear in nature. However, financial time series has been known to exhibit nonlinear features due to shocks and other economic disturbances. Hence testing for nonlinearity and the structural break is an important criterion before modeling a nonlinear time series data Okereke & Uwaeme (2017). Here, we adopt two nonlinearity tests: the BDS test and the Tsay test. The BDS test developed by Brock et al. (1996) tests the null hypothesis of independent and identically distributed (iid) in the data set while the Tsay test of Tsay (1989) tests for evidence of threshold nonlinearity under the null hypothesis of linearity in the dataset. Once there is evidence of nonlinearity, we proceed to check for the presence of structural break. Bai & Perron (1998, 2003) developed a test which tests for structural break in a series, creates a confidence interval which tests for the number of breaks in a series as well as the dates the breaks occurred. Hence for this study, in order to check for the presence of structural break and the number of breaks that occurred in the series, we adopt the Bai-Perron test.

### **Co-Integration and Stationarity Tests**

Testing for stationarity in a time series analysis is necessary since most macroeconomic time series data are characterized by unit roots which gives rise to spurious results if unchecked Khalid & Rajaguru (2010). In testing for unit root, it is necessary to consider the effects of structural breaks during unit root testing. Structural breaks play significant roles in that it can lead to misspecification of the deterministic function of the auxiliary regression that is used for either testing the null hypothesis of unit root or variance stationarity can lead to conclude in favor of variance non-stationarity Kim & Perron (2006).

Hence, unit root tests that allow for structural breaks have been developed over the years and is useful when the series to be examined is characterized by breaks. Structural break unit root tests are often used based on their ability to accommodate breaks. Some of the tests can only accommodate series with only one structural break Zivot & Andrews (1992), while others can accommodate two or more structural breaks Lee (1996); Lumsdaine & Papell (1997); Clemente et al. (1998); Lee & Strazicich (2003); Carrion-i-Silvester et al (2004); Bai & Carrion-i-Silvester (2004); Gadea et al. (2004).

In this study, we consider the structural break unit root test of Carrion-i-Silvester et al. (2009) which is a GLS-based unit root test with multiple structural breaks in both the null and alternative hypotheses. This test extends the earlier unit root test of Kim & Perron (2006) which allows for break in the trend function under the null and alternative hypotheses for a known and unknown break dates. This was done by allowing some changes in the slope and level of the trend function, adopting the quasi-GLS detrending method for local asymptotic power functions Elliott et al. (1992) and finally by improving on the class of M-tests developed by Stock (1990) and analyzed by Ng & Perron (2001).

For non-stationary and integrated series in the presence of structural breaks, we test for the co-integration relationship amongst the series using the Residuals-based tests for cointegration with generalized least-squares detrended data developed by Perron & Rodriguez (2016). This test follows from the work done by Elliott et al. (1992) and Elliot & Pesavento (2009) which highlighted the importance of residual-based test or GLS-detrending tests in the cointegration framework. This test improves on the seven M-class tests as proposed by Stock (1990) and Ng & Perron (2001) to form cointegration tests. It tests the null of no cointegration against the alternative of cointegration.

### **RESULTS AND DISCUSSION**

In this section, we present the results and discussions on the monthly returns of the crude oil prices and stock prices of Nigeria from 2006 – 2016.

#### **Time Plot of the Series**

A look at the time series plot of the oil prices and crude oil prices in figure 1 shows that stock prices rose and fell significantly with crude oil prices between 2006 and January 2009. From January 2009 to June 2014, the stock prices maintained a slow rise and fall with crude oil prices before dropping significantly in July 2015. Figure 1 also shows evidence of non-linearity hence we take the returns of the two series as shown in Figure 2.

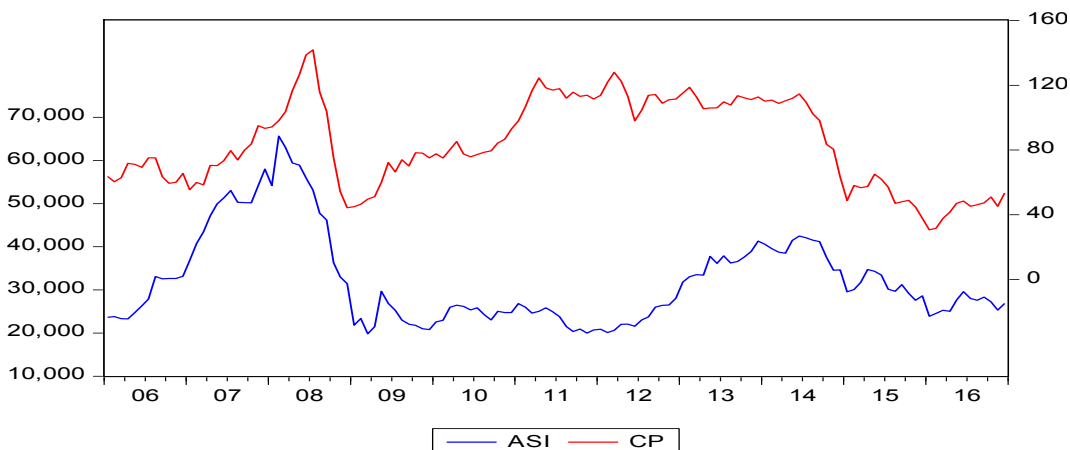


Figure 1. The time series plot of the original series.

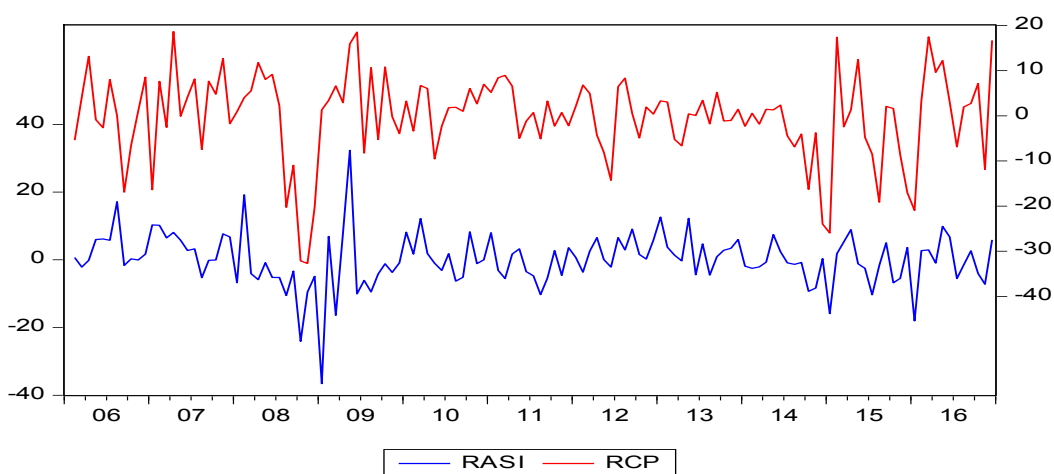


Figure 2. The time series plot of the returns

Figure 2 shows evidence of non-stationarity, volatility clustering and change in structure hence we proceed to test for nonlinearity, structural break, non-stationarity and cointegration in the next sub section.

### Nonlinearity and Structural Break Tests For the Returns

In this subsection, we present the results of the two nonlinearity tests and the Bai and Perron test for the number of breaks. The results from Table 1 shows that there is evidence of nonlinearity in both the Tsay and BDS test hence the series are nonlinear. Furthermore, the bai-Perron tests showed evidence of five structural breaks which occurred between 2001 and 2008 (see Appendix).

Table 1. the nonlinearity test results

Test series	BDS	Tsay
ASP	0.4328(0.0000)	1.993(0.0403)
CP	0.3939(0.0000)	2.606(0.0547)

Source: Authors (2018)

### Stationarity and Co-Integration Tests for the Returns

Here, we present the Carrion-i-Sylvester et al. (2009) GLS-based structural break unit root test for stationarity as well as the Residual-based test for cointegration of Perron & Rodriguez (2016) which tests for long-run relationships.

Table 2. The GLS-based unit root tests for Crude oil Prices.

Tests	Test Statistics	Critical Values (5%)
PT test	14.517275	5.9594833
MPT test	14.330206	5.9594833
ADF test	-2.1311683	-3.2690894
ZA test	-9.1777519	-21.585087
MZA test	-8.8513556	-21.585087
MSB test	0.23221028	0.15237865
MZT test	-2.0553757	-3.2690894

Source: Author (2018)

Table 3. The GLS-based unit root tests for All Shares Index Prices.

Tests	Test Statistics	Critical Values (5%)
PT test	31.942919	6.5931963
MPT test	29.009345	6.5931963
ADF test	-1.6547822	-3.4065606
ZA test	-5.3614863	-23.528337
MZA test	-5.2449147	-23.528337
MSB test	0.30864243	0.14453242
MZT test	-1.6188032	-3.4065606

Source: Author (2018)

The results in Table 2 and Table 3 shows that in the presence of structural breaks under the null and alternative hypotheses, the seven-unit root tests for both the all shares index and crude oil prices indicates the presence of unit root. Hence both series are integrated of order one,  $I(1)$  at 5% levels of significance.

Table 4. showing the residual-based test for cointegration.

Tests	Test Statistics	Critical Values (5%)
MZ_rho	-7.142303	-22.064
MSB	0.259679	0.172
MZ_t	-1.854703	-2.764
ADF	-1.864480	-2.764
Z_rho	-7.200088	-15.984
Z_t_rho	-1.869709	-2.764
MPT	13.254311	6.230

Source: Author (2018)

Table 4 shows that there is no co-integration among the series. This implies that there exists no long-run relationship between crude oil prices and stock prices. This can be attributed to the breaks in the series due to the crisis period in the Nigerian economy. Hence we proceed to fit a Markov Switching autoregressive model to the differenced series since the series are not co-integrated.

### Model Estimation

This section estimates the returns series of crude oil prices and stock prices using the MS-VAR models. Before proceeding with the analysis, we, first of all, determine the number of lags using the principle of parsimony. This suggests one (1) lag. Furthermore, we examine the justification of the nonlinear features of the Markov switching model over the linear VAR model. This is done using the likelihood ratio test under the null hypothesis of no switching using the linear VAR(1) specification against the alternative of MSM(2)-VAR(1) model

Table 6. Model comparison

	<b>MSM(2)-VAR(1)</b>	<b>VAR(1)</b>
LL	148.1772	285.081
AIC	-288.3544	-554.1621
BIC	-257.3544	-531.2218
LR test	-273.8076 [0.0000]***	

Source: Author (2018)

Furthermore, we compared the fitted MSM(2)-VAR(1) model with a VAR(1) model using the log-likelihood, AIC and BIC values. The result as presented in Table 6 shows that the fitted MS-VAR model is the best model. The result indicates that we fit a two-regime Markov switching vector autoregression of order one to the return series. The results of the fitted MSM(2)-VAR(1) model is shown in Table 5.

Table 5 showing the MSM(2)-VAR(1) results

	<b>CP<sub>t</sub></b>		<b>ASI<sub>t</sub></b>
$\mu(s_t = 1)$	0.0231(3.1216)**		0.0036(0.1286)
$\mu(s_t = 2)$	-0.0410(-1.8636)		0.0019(0.3393)
$CP_{t-1}$	0.0955(1.0977)		0.6519(2.6255)**
$ASI_{t-1}$	1.0424(4.6515)***		0.1747(0.02682)*
$\sigma^2(s_t = 1)$	0.0074		0.0280
$\sigma^2(s_t = 2)$	0.0220		0.0056
$p_{ij}$	$s_t = 1$	$s_t = 2$	$E(D_{st})$
$s_t = 1$	0.9751	0.0388	40.1978
$s_t = 2$	0.0024	0.0961	25.7655

Source: Author (2018)

From Table 5, the estimated parameters of regime 1 show that the expected returns,  $\mu(s_t = 1)$  of crude oil prices rises monthly by 0.02% and the expected returns of the stock price increases by 0.03% monthly. In regime 2, the monthly growth of the expected return of crude oil prices decreases by 0.04 % monthly with the expected returns of the stock prices increasing by 0.0019% on a monthly basis. These shows the persistence of the high volatility regime over the low volatility regime. Also, the variance in regime 1  $\sigma^2(s_t = 1)$  is higher than that of regime 2  $\sigma^2(s_t = 2)$  which implies that the interaction between crude oil prices and stock prices is more volatile in regime 1 than in regime 2.

This result implies that in regime 1, as crude oil prices increase, stock prices also increase. This can be attributed to the period of economic recession of 2008 when both the prices of crude oil and stock prices crashed significantly. While in regime 2, a decline in the crude oil prices was followed by a slight increase in the stock prices. This result in regime 2 can be attributed to the period of slow recovery of both the crude oil prices and stock prices during which they experience decline once in a while. Finally, the persistence in regime 1 was higher than in regime 2 where about 40 months were spent during this period while the period of growth in regime 2 lasted for about 25 months which suggests that the period of high volatility persisted more than the period of low volatility. This implies a positive relationship between crude oil prices and stock prices.

The filtered and smoothed probability plots specifies the different points in time a regime occur. These MS-VAR probability plots further gives more insights than the linear VAR framework as it shows the nature and timing of the significant



changes in the data series (Ismail and Isa, 2009). The probability plots of the fitted MS-VAR model is given in figure 5

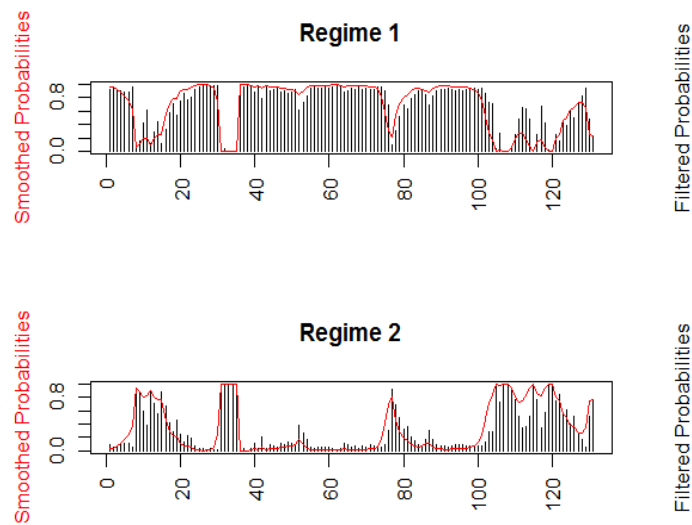


Figure 3. The filtered and smoothed probabilities

From the plots, it can be seen that there are five periods where the crude oil price returns and stock market returns are in regime 1 while in regime 2, there are four periods. Also, the periods in regime 1 all lasted for up till 12 months except the third period which lasted up to forty months between November 2008 and May 2012. It is interesting to know that this period coincides with the period of economic crises in Nigeria which led to a massive fall in the price of crude oil thereby affecting the stock market and other sectors of the economy. This result agrees with the conclusion of our findings based on the parameter estimations.

Furthermore, the smoothed and filtered probability plots of regime 2 show that the four periods last between three to six months except the last period which lasted for about twenty-five months between September 2014 and March 2016. This period coincides with the period of sustained recovery when the prices of crude oil gradually increased. This duration of stay in regime 2 also agrees with our conclusion based on the findings of the parameter estimation. These findings are in contrast with the findings of Balcilar et al. (2015) on the US stock prices and crude oil prices where a negative relationship was found between the two variables both in the low and high volatility regimes.

## CONCLUSION

This paper examined the dynamic relationship between crude oil prices and stock prices of Nigeria using monthly data from 2006 to 2016. This dynamic relationship was examined based on the nonlinear interactions of the two variables which is a deviation from other studies that examined this relationship in Nigeria. It was observed that crude oil prices and stock prices of Nigeria are characterized by nonlinearity, structural breaks, integrated of order one  $I(1)$  with no long-run relationship between them. The LR-test performed rejected the linearity in the series in favour of regime switching in the series. Hence a two-regime Markov switching vector autoregressive model MSM (2)-VAR(1) of order one with regime shifts in both the mean and variance was fitted to the return series of crude oil prices and stock prices in order to extract the common regime shifts behavior. The

results obtained showed a positive relationship between crude oil prices and stock prices during the high volatility regime and during the low volatility regime, stock prices were not affected by a decrease in crude oil prices. This result does not, however, agree with the findings by Balcilar et al. (2015) on the two series.

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**APPENDIX**

**Bai- Perron output for break points**

Optimal (m+1)-segment partition:

Call:

breakpoints.formula(formula = CP ~ 1)

Breakpoints at observation number:

m = 1            107  
m = 2     60  107  
m = 3  20  60  107  
m = 4  19 38 59  107  
m = 5  19 38 60 87 107

Corresponding to breakdates:

m = 1                            2008(11)  
m = 2            2004(12)    2008(11)  
m = 3  2001(8)    2004(12)    2008(11)  
m = 4  2001(7) 2003(2) 2004(11)    2008(11)  
m = 5  2001(7) 2003(2) 2004(12) 2007(3) 2008(11)

Fit:

m 0   1   2   3   4   5  
RSS 97507 59762 30644 27401 24683 24071  
BIC 1256 1201 1123 1118 1114 1120