# OIL PRICE SHOCKS AND NIGERIAN GROSS DOMESTIC PRODUCT GROWTH; A BAYESIAN MARKOV SWITCHING VAR ANALYSIS

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**Abstract**

Asymmetric behaviour is one of the major characteristics of many macroeconomic and financial time series during different phases of a business cycle. On this basis, this study examined the role of oil price shocks in predicting phases of the Nigerian business cycle associated with higher and lower growth regimes. The study adopted a regime dependent approach to investigate the impact of oil price shocks under two phases of the business cycle, namely high and low growth regimes. Nigeria as a net exporter and importer of oil is expected to be vulnerable to the vagaries of oil price irrespective of the phase of the business cycle. A Bayesian Markov Switching Vector autoregressive (MS–VAR) model was employed on quarterly data spanning from 1970Q1 to 2019Q4. The results show that the probability to sustain high growth state is smaller compared to the low growth state hence the Nigerian economy growth over the years has been stunted. The regime dependent impulse response functions (IRFs) were able to differentiate between the responses of the real output to oil price shocks under each regime with low growth regime being statistically significant. The policy import of this analysis is that Nigeria's vulnerability to future oil price shocks depends on the extent to which the non – oil domestic economy is reactivated to mitigate the full impact of the oil price shocks and the Concomitant Dutch Disease.

**Keywords:** Markov–Switching, Impulse Response Function, Output Growth Regime, Oil Price.

## 1.0. INTRODUCTION

After independence in 1960, Nigeria had an essentially mono cultural economy dependent on primary commodity exports for foreign exchange to export the capital goods needed by local import substitution industries. The urge to industrialize resulted in over protection, weak and largely inefficient local industries under the import substitution industrialization (1S1) strategy.

In spite of the fluctuating world prices of agricultural commodities, agriculture remained the mainstay of Nigerian economy. This sector contributed over 50 percent to GDP and represented about 70 percent. of total exports in the 1960s, the various marketing boards generated much revenue which was used by the government. To develop the basic infrastructure needed for the long term development of the country. The first development plan initiated during this period relied heavily on the resources from primary exports to implement most of the proposed projects. The main thrust of the policy was to maximize the benefit of the export–led development strategy, complemented by import substitution industrialization (Ndebbio & Ekpo, 1994, Olowookere & Ogebe, 2019).

From the early 1970s, the share of agriculture in GDP had begun to dwindle while the newly discovered crude oil assumed dominance and became the engine of growth of the economy. Oil revenue which was only 26.7 percent of total collected revenue in 1970 rose to over 67 percent by1978. At the same time, about 85 percent of total export earnings came from the oil sector.

During the oil boom, growth rate of GDP was quite high, ranging from 5.7 percent in 1970 to 6.2 and 6.0 percent in 1971 and 1975 respectively. However, which the oil boom afforded the government the much needed revenue. It also created serious structural problems resulting from crude oil price distributions.

In the recent past decade, the global energy market has witnessed several distributions in oil prices. These distortions usually came as a two-edged sword. Oil price shows have a strong potential to affect a major macroeconomic variable in an oil exporting country in the current account. Oil price shocks primarily affect the importing countries. It reduces the amount of savings available to ensure high investment levels and sustainable growth whereas the converse is the case for oil exporting countries (Chukwu, 2010).

A number of studies have been conducted to investigate the linear relationship between oil price shock and economic activities. Using Sim (1980) linear VAR model with the aid of impulse response analysis, in some instances, research findings reveal the existence of a negative relationship between oil price chocks and economic activities; while others posit positive relationship, however, the strength of the relationship in different countries are likely to depend on the energy intensity, structure of the economy and the sample period. (Abeysinghe, 2001; and Nkomo, 2006)

Despite the evidence of an overall positive relationship between oil price and economic activities occurring in a number of studies, when the oil price increased significantly, by as much 50 percent in real terms, recently for a number of countries it was found that the increase in oil price did not promote economic growth, giving rise to a renewed debate on oil price effects on economic activity.

More interestingly, Nigeria though net oil exporter still imports over 89 percent of refined oil used in the economy (NNPC, 2007) thereby, placing the country both in the categories of oil importing and exporting developing economies culminating in the well known Dutch decrease effect in the use of the oil-induced capital flows to fund imports of non-oil tradable and total neglect of non-oil tradable. The recent outbreak of corona virus pandemic (COVID -19) in December 2019 in China and spread to other countries in the world including Nigeria led to the fall of crude oil price in the world market to as low as $22. Perbarrel. Consequent upon this, Nigerian government reduced her capital budget by #1.5tn, and many macroeconomic indexes plummeted, while others appreciate in the first and second quarters of 2020 To this extent, a number of studies consequently focused on the possibility of symmetric and asymmetric relationships between oil price and economic activity.(Ogunjimi, 2020)

Given the importance of oil in the Nigerian economy, this study investigates the impact of oil prices shocks on Nigerian business cycle fluctuation using a two-state Bayesian Markov

Switching VAR, the asymmetric response of oil shocks during high and low growth phases of the business cycle will be analyzed through state–dependent impulse response.

The Markov switching model used in this study has been widely used in empirical literature to capture non-linearity and asymmetry among economic variables as shown in the literature. First, the model allows us to classify regimes as depending on the parameter switches in the full sample and therefore, it is possible to detect changes in dynamic interactions between the variables. Second, the model allows for many possible changes in the dynamic interactions between the variable of unknown periods. Third, it is possible to make probabilistic inference about the dates at which a change in regime occurred.

The rest of the study is organized as follows. Section 2 discusses the literature and theoretical underpinning of the links between oil price shocks and the dynamic of business cycles. In section 3, we present the Markov Switching-VAR model used in the analysis. Section 4 discusses the results and presents some highlights for policy, while section 5 concludes.

## 2.0. Review of Related Literature.

Oil price shocks have been identified in a number of studies as one of the contributing sectors influencing the state of the business cycle. For the US economy, Hamilton (1983, 1996 and 2005) finds that an increase in the oil price precede almost all the recessions in the US, which has attracted a number of researchers to investigate the role of an oil price shock in predicting business cycle fluctuations including Habibi, 2019, who showed the non linear impact of oil price shocks on USA industrial production and economic growth.

Raymond and Rich (1997) used a generalized Markov Switching (MS) model on post-war us economy where they find out that oil price do not predict the transition from the low growth to high growth phases of the business cycle and concluded that Hamilton (1983) study overstates the role of oil price shocks in predicting a recession.

De Miguel et. al. (2003) employed a standard dynamic stochastic general equilibrium (DSGE) for the small open Spanish economy, their results showed a negative impact of an increase in relation price of oil on welfare was identified. Schmidt and Zimmermann (2005) find the effect of an oil shock on Germany business cycle fluctuation to be limited and declining over time. Krolzig and Clement (2002) used a three stage Markov Switching VAR (MS VAR) to test whether oil prices can explain business cycle asymmetries. The authors find that oil price movements cannot adequately explain business cycle asymmetries. Maners and Coloni (2006) using Markov Switching analysis for the G-7 Countries find that regime dependent models to better Capture the output growth process

Engeman et.al (2011) in their study found that oil price affects the likelihood of moving into recession. Kilian (2009) argued that the impact of oil shocks on macroeconomic variables depends on the source of the oil shock. In this study, he considers oil supply shocks, global demand shocks and oil demand shocks. He found that oil supply shocks, are exogenous in explaining the impact of oil price in Nigeria, Chukwu (2010) investigated the relationship between oil price shocks and current account dynamic in Nigeria, a country that double as an oil exporter and importer using structural vector auto regression (SVAR), he found that there is no one-to-one effect of oil prices on the current account balances in the long run, but it exists in the short run.

Oil price shocks primarily affect the current account by distorting the saving-investment identity for oil importing countries, it reduces the amount of savings growth whereas the converse is the case for oil exporting countries olomola and Adejumo (2006) using quarterly data from 1970 to 2003 found that oil price shocks significantly affect the money in the long run using vector Autoregression technique (VAR). They conclude that their results suggest the tendency for the Dutch disease. Ayadi (2005) suggests that oil price changes affect industrial production indirectly through it effect on exchange rate, though the relationship is insignificant.(Olowookere & Ogebe. 2019)

Akpan (2009) shows a strong positive relationship between positive oil price changes and real government expenditure. Also, the impact of oil price shocks on industrial output growth was found to be marginal with observed significant appreciation of real exchange rate. (Ogunjimi, 2020) A study which reinforces that of olomola and Adejumo (2006) and Ayadi (2005) that oil price shocks tends to create the tendency for the Dutch disease syndrome in Nigeria.

Aliyu (2009) finds evidence of linear and non-linear impacts of oil price shocks on real GDP. The results of the asymmetric oil price increases in the non-linear models are found to have positive impacts on real GDP growth of a larger magnitude than for other specifications. Olomola (2006) investigated the impact of oil price shocks on aggregate economic activity (output, inflation, and the real exchange rate and money supply) in Nigeria using quarterly data from 1970 to 2003. The study found that contrary to previous empirical findings, oil price shocks do not affect output and inflation in Nigeria significantly. The author concluded that the oil price shocks may give rise to wealth stimulate the real exchange rate that may squeeze the export and increase import, giving rise to the 'Dutch Disease'

Taiwo and Akindele (2016) using quarterly data for Nigeria found that import and exchange rate respond spontaneously to oil price shocks hence recession most often results when oil price falls in Nigeria.

Given these findings in a number of studies of a weakened relationship between oil shocks and economic activities as observed in recent periods and the fact that the effect of oil price increases seem to matter in a non-linear setting. Studies that use linear models may be incapable of capturing the dynamic relation between oil price shocks and economic activities accurately. This study do not only examine the asymmetric and asymmetric impacts of price shocks, we also focus on the asymmetric and non-linear relationship over a period of time using the Bayesian Markov switching VAR and with higher frequency data (quarterly).

## 3.0. Methodology

The methodology we adopted is based on Vector Autoregressive (VAR) model with time varying parameters where, given our objectives, the parameter time-variation directly reflects regime switching.

In this approach, changes in the regime are treated as random events governed by an exogenous markov process, leading to the MS –VAR model. The state of the economy is determined by a latent markov process, with probability of the latent state process taking a certain value based on the sample information. In this model, inference about regime can be made on the basis of the estimated probability, which is the probability of each observation in the sample coming from a particular regime.

The MS–VAR model we use to analysis the time–varying dynamic relationship between the quarterly real spot crude oil price and real GDP is an extension of the class of autoregressive models studied in Hamilton (1990) and Krishnamurthy and Ryden (1998). It also allows for asymmetric (regime dependent) inference for impulse response analysis. The structure of the MS –VAR model we use is based on the model studied in Krolzig (1997) and Krolzig and clement (2002). Our estimation approach is based on the Bayesian Markov-chain Monte Carlo (MCMC) integration method of Gibbs sampling, which allows us to obtain confidence intervals for the impulse response function of the MS-VAR model.

To be concrete, let $P_i$ and $Q_i$ denote the real crude oil price and real output, respectively. Define the time-series vector $X_i$ up to and including period t as $X_i$= [$P_i$ and $Q_i$] and let $S_t$= {$X_t$|t = t, t - 1,…1 – p), where p is a non-negative integers. For the vector valued time series $X_i$ of random variables, assume that a density (probability) function $f$ ($X_t|\mathfrak{z}_{t-1}$, ɵ) exists for each $_t$ ϵ {1, 2,…T).The parameter and parameter space are donated by ɵ and Θ. Let the stochastic variable $S_t$ ϵ {1,2,…q} follow a Markov process (chain) with q states. In the MS – VAR model, the latent state variable $S_t$ determines the probability of a given state in the economy at any point in time. Taking into account that the oil price and output series are not cointegrated and their dynamic interactions are likely to have time–varying parameters, our analysis is based on the following MS –VAR model:

$$\Delta X_t=\mu s_t+\sum_{k=1}^{p-1} T_{s_t}^{(k)}\,\Delta X_{t-k} + \varepsilon_t, t = 1,2,\dots,T \qquad (1)$$

Where p is the order of the MS –VAR model, [$\mathcal{E}_t$ |$S_t$ ~ N (0, $\Omega_{st}$)], and $\Omega_{st}$ is a (2x2) positive definite covariance matrix. The random state or regime variable $S_t$, conditional on $S_{t-1}$, is unobserved, independent of past Xs, and assumed to follow a q-state Markov process. In other words, Pr[$S_t = j|S_{t-1} = i, S_{t-2} = k_2, \dots, .s_{t-1}$]= Pr[$S_t = j|S_{t-1} = i, S_{t-1}$]=$p_{ij}$, for all t and ki, regimes i, j = 1,2,…., q, and 1 ≥ 2. More precisely $S_t$ follows a q state Markov process with transition probability matrix given by

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{1q} \\ \vdots & \vdots & \vdots \\ p_{q1} & p_{q2} & p_{qq} \end{bmatrix}, \qquad (2)$$

$$\sum_{j=1}^{q} p_{ij} = 1$$

Thus, Pij is the probability of being in regime j at time t, given that the economy was in regime i at time (t-1), where i and j take possible values in $\{1,2,\ldots,q\}$. The MS – VAR specified as above allows all parameters to depend on the latent regime or state variable, $S_t$, that is all parameters of the model including the variance matrix $\Omega_{s_t}$

In our particular application, the maintained hypothesis is that q = 2, that is, two states or regimes for each variable are sufficient to describe the dynamic interactions between the oil price and output. This is consistence with crises-recovery (recession-expansion) cycles observed in many macroeconomics time series. The MS-VAR model in Equation (1) – (2) has some appealing properties for analyzing the dynamic interactions of the variables. First, it allows us to classify regimes as depending in the parameter switches in the full sample and therefore, it is possible to detect changes in dynamic interactions between the variables. Second, this model allows for many possible changes in the dynamic interactions between the variables at unknown periods. Third, it is possible to make probabilistic inference about the dates at which a change in regime occurred. We will be able to evaluate the extent of whether a change in the regime has actually occurred, and also identify the dates of the regime changes. Finally, this model also allows us to derive regime dependent impulse response functions to summarize whether the impact of the oil price on the GDP varies with regimes.

### 3.1; Estimate Procedure

The empirical procedure for building a suitable MS-VAR model starts with identifying a possible set of model to consider. We determine the order p of the MS-VAR model using the Bayesian information Criterion (BIC) in a linear VAR (p) model. The MS-VAR model specifications may differ in terms of regime numbers (q) and the variance matrix specification. We only consider both regime-dependent (heteroscedastic) variance model because both the oil price and output series span a number of periods where volatilities vary significantly. Once a specific MS-VAR model is identified, we next test for the presence of nonlinearities in the data. When testing the MS-VAR model against the linear VAR alternative, we follow Ang and Bekaert (2002) and use the likelihood-ratio statistic (LR), which is approximately $X^2$ (q) distributed, where q equals to number of restrictions plus the nuisance parameters (i.e., free transition probabilities) that are not identified under the null. We use p-values based on the conventional $X^2$ distribution with q degrees of freedom and also for the approximate upper bound for the significance level of the LR statistic as derived by Davies (1987). Once we establish non-linearity, we can choose the number of regimes and the type of the MS model based on both likelihood-ratio statistic and the Akaike Information Criterion (AIC).

Since its first introduction in the influential work of Sims (1980), a natural tool to analyse the dynamic interaction between oil price variable and output is the impulse response function (IRF).

IRF analysis studies how a given magnitude of a shock in one of the variable propagates to all variables in the system over time, say for h = 1, 2... H steps after the shock in the system. Computing multi-step IRFs from MS-VAR models as well as from all nonlinear time series model proves complicated because no ordinary method of computing the future path of the regime process exists. An ideal IRF analysis requires that we know the future path of the regime process, since the impulses depend on the regime of the system in every time period.

Ideally, the IRFs of the MS-VAR model should integrate the regime history into the propagation period, which is not easily resolved. Two approaches arose in the literature as a work around to history dependence of the IRS in the MS models. Ehrmann et al. (2003) suggested that regimes do not switch beyond the shock horizon Leading to Regime-Dependent IRFs (RDIRFs). On the other hand, krolzig (2006) acknowledges the history dependence and allows the regime process to influence the propagation of the shocks for the period of interest, h = 1, 2,. H. In Krolzig's approach conditional probabilities of future regimes $S_{t+h}$, are obtained given the regime $S_t$ and transition probabilities, P

One major attraction of the RDIRF analysis is the possibility of determining the time variation in the responses of variables to particular shock. The RDIRF traces the expected path of the endogenous variable at time t + h after a shock of a given size to the initial disturbance at time t, conditioned on regime i. the k-dimensional response vectors ϴki, 1, …, ϴki, h represents a prediction of the response of the endogenous variables (Ehrmam.et.al, 2003). The RDIRFs be defined as follows

$$\Psi_{ki,h} = \frac{\partial E_t X_{t+h}}{\partial u_{k,t}} | s_t = s_{i+1} = i \text{ for } h \geq 0 \qquad (3)$$

Where *uk, i,* are the structural shocks to the *kth* variables. In general, the reduced form shocks, $\varepsilon_t$ will be correlated across the equations and εki will not correspond to *uk, i*. This leads to the famous identification problems of several solutions exist. We assume that the structural shocks are identified as εi = Fst ut. To make structural inferences from the data, the structural disturbances and hence F must be identified. In other words, sufficient restrictions are imposed on the parameter estimates in order to derive a separate structural form for each regime, from which Regime Dependent Impulse Response Functions (RDIRFs) are computed. As in a standard VAR measuring the impact of the oil prices on output, we order the output last and use the recursive identification scheme, made popular by Sims (1980). The recursive identification scheme is based on the cholesky decomposition of the covariance matrix as Qsi = Ls and identifying structural shocks from $U_t = Fs^{-1}\varepsilon$, with $Fs_t = Ls_t$

Although the RDIRF analysis significantly simplifies derivation and allowed construction of confidence interval via bootsrap, it is not appropriate if the regime switching is likely during propagation of shocks. The solution of Krolzig (2006) is appealing, but it leaves out the construction of the confidence intervals. In this study, we combined RDIRF analysis with MCMC integration. Given our interest being whether the dynamic response of the oil price shocks depends on the state of the economy, such as the recession or recovery periods assuming a given regime-regime switching does not take place during the shocks propagation periods - and

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studying the propagation of the oil price shocks in the future is appropriate for our purpose based on Bayesian impulse responses for the linear VAR models using the posterior density of the RDIRFs

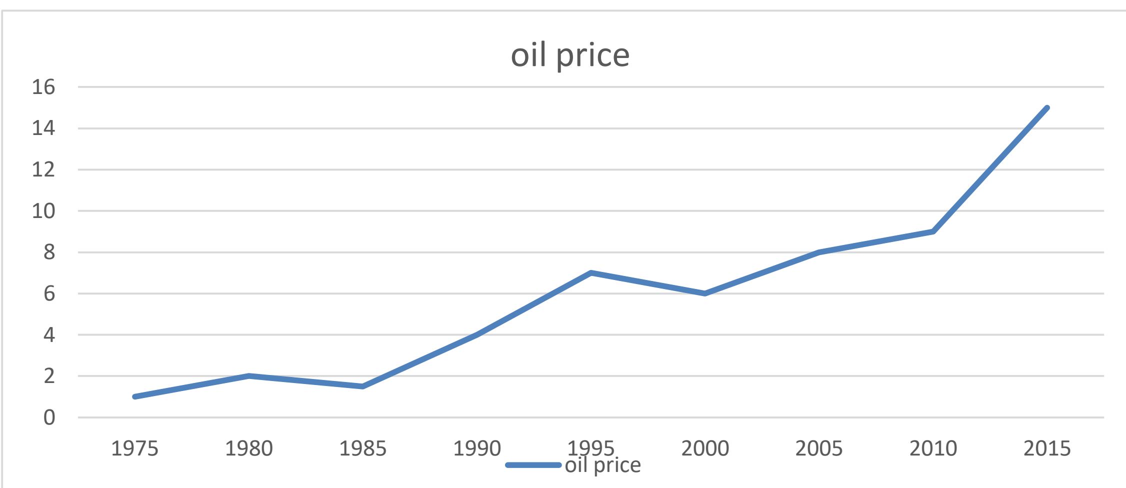
**4.0; Data and Source**

In this study, we employ quarterly data for the period 1970Q1 – 2019Q4 for real GDP and real oil price. Real Gross Domestic Product (LRGDP) at market prices were obtained from the central bank of Nigeria statistical bulletin in various editions and quarterly real oil price in Nigerian currency. P1 is a period of high economic growth with low inflation, unemployment and population growth rates due to oil boom and stable exchange rate (1970-1985, 1996-2010), while P2 is a period of low real gross domestic product with high inflation, unemployment and population growth rates, political and exchange instability and frequent macroeconomic policies change (1986-1995, 2011-2019). Brent crude oil spot price list were obtained from the U.S department of energy and Nigeria National Petroleum Co-operation (NNPC) monthly reports. Nominal oil price data are similarly adjusted using X-12 procedure and converted into the Nigeria Naira value using the Naira/US$ and official exchange rate from 1970Q1-2019Q4. Lastly, nominal values are properly deflated using CPI from the International Financial Statistics (IFS) of the International Monetary Fund (IMF) to obtain the real oil price.

**5.0: Empirical Findings.**

The empirical analysis opens with the description of the variables involved in the model. Some preliminary descriptive statistics are on quarterly real Gross Domestic Product (LGDP) of Nigeria and the quarterly oil spot price in US Dollar (LROP).

The graphical representation and summary statistics on both variables are presented in figure 1 and Table 1, respectively.



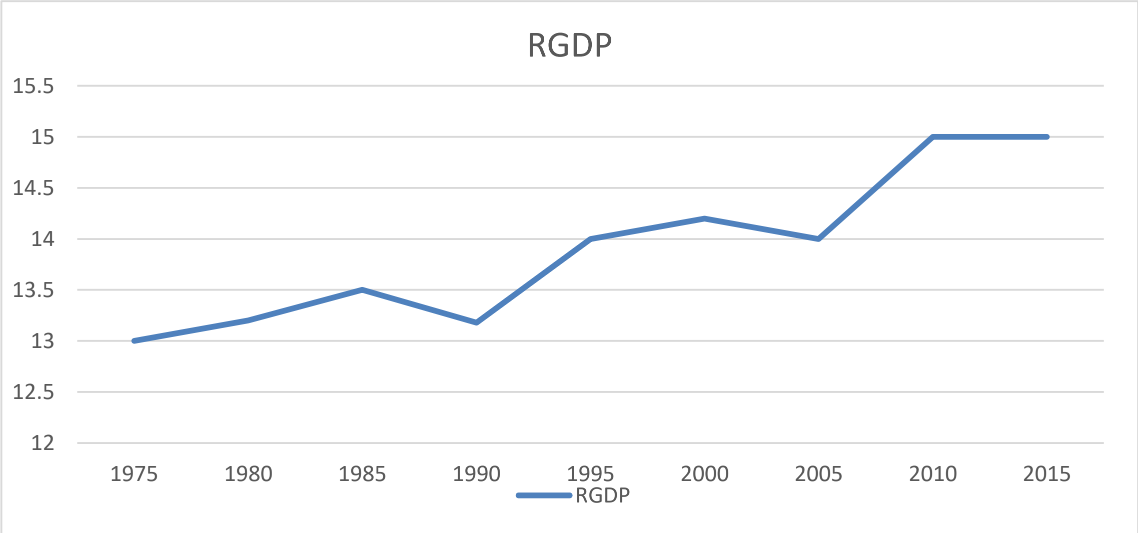



Fig.1; Time series plots of the real Brent crude oil price and real GDP.

From the Figure, 1; the Nigerian economy has gone through different cycles of boom and bust as regards crude oil price since it became an oil dependent economy in the mid-1970s. The first oil boom which started during the time lasted till 1980 before the price of oil crashed and Nigeria experienced a sustained oil price shocks that lasted up to two decades between 1981 and 1999. However, oil price rose again in 2000 and this lasted till 2014 except for a brief break during the great recession of 2008/2009. During the immediate past oil boom period, oil price per barrel rose from US$25 in 2002 to US$55 in 2005. It increased to an outrageous US$147 in mid 2008 and declined sharply during the recent recession of 2015with substantial increase in 2016 through 2019.

Persistent oil price shocks such as that of 1978, 1981, 1985-1986, 2008-2009 2015 and recently, 2020 have extensive effects on the macroeconomic variables, including real Gross Domestic Product (RGDP). This in turns induces challenges for policy makers in stabilizing the economy

**(A) Descriptive Statistics**.

Both variables presented in panel A of Table 1 below are expressed in natural logarithm at levels. Panel B gives the descriptive statistics for log difference or growth rate. The sample period covers 1970-2019Q4 with n =200 observations, In addition to the mean, standard deviation (SD), minimum (min), maximum (max), skewness and Kurtosis statistics, the table reports the Jargue- Bera (JB) normality test which shows that both level data and growth data on all the variables are normally distributed.

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Table 1: Descriptive Statistics

| | LROP | LRGDP |
|---|---|---|
| **PanelA: log levels** | | |
| Mean | 4.154 | 12.79 |
| S.D | 0.321 | 0.245 |
| Min | 3.341 | 12.456 |
| Max | 6.514 | 11.389 |
| Skewdness | 0.06 | -0.112 |
| Kurtosis | -1.111 | -0.212 |
| JB | 8.053 | 6.321** |
| Q(1) | 100.518** | 212.321** |
| Q(4) | 602.200** | 797.626** |
| ARCH(1) | 117.021** | 2B2.419** |
| ARCH(4) | 145.044** | 212.361** |
| **Panel B: Growth Rates** | | |
| Mean | 0.0121 | 0.008 |
| S.D | 0.132 | 0.231 |
| Min | -0.692 | -0.004 |
| Max | 1.124 | 0.046 |
| Skewdness | 1.449 | 0.149 |
| Kurtosis | 14.22 | 1.154 |
| JB | 2147.211** | 17.761** |
| Q(1) | 3.261 | 2.512** |
| Q(4) | 10.245 | 28.161** |
| ARCH(1) | 0.436 | 12.921** |
| ARCH(4) | 0.506 | 18.462** |
| N | 200 | 200 |

The Ljung –Box first (Q1) and the fourth (Q4) autocorrelation tests show no sign of serial correlation with their respective lags for level and growth variables. The First (ARCH (1) and the fourth ARCH (4) order lagranger multiplier (LM) tests for autoregressive conditional heteroscedasticity (ARCH) shows that the variance of the growth rate of real GDP to be time varying, while, variance of growth rate of real oil price as well as the various data on real GDP and real oil price are constant over time.

### (B) Unit Root Tests

Different unit root tests were performed to investigate the univariate characteristics of both level variables. The set of formal unit root tests presented in Table 2 reveals that both variables are *l*(1), hence non stationary in levels but stationary after first differencing.

Table. 2: Unit Root Test

| Panel A:unit root tests at levels | LROP | LRGDP |
|---|---|---|
| ADF | -0.421(5) | -2.776(7) |
| Zα | -4.322(0) | -1.484(2) |
| Mzα | -6.317(0) | -1.238(2) |
| $Mz_t$ | -3.121(0) | -0.994(2) |
| DF-Gls | -3.1571(0) | -0.7992(2) |
| Kpss | -1.030(0) | 1.103(2) |
| Zivot and Andrews | -4.379(5) | -3.166(6) |
| **Panel B: unit root test in first difference** | | |
| ADF | -7.163(4) | -3.469(6) |
| Zα | -163.391(0) | -51.721(2) |
| $M_{Z\alpha}$ | -114.521(0) | 21.449(2)* |
| $Mz_t$ | -8.319(0) | -4.416(2) |
| DF-Gls | -13.815(0) | -2.112(2) |
| KPSS | -0.0821(8) | -1.362(6) |

*Note: panel A, reports unit root test results for the log levels of the series with a constant a linear trend in the equation. Panel B reports unit root test results for the first differences of the log series with a constant in the equation. ADF is the augmented Dickey- fuller (Dickey and fuller, 1979) test, Z α is the Phillips-Perron Z α unit root (Philips and Perron 1988), MZ α and MZ t are the modified Phillips- perron tests of Perron and Ng (1996) DF- GLS is the augmented Dickey Fuller text of Elliot et. al (1996) with generalized least squares (GLS) detrended. KPSS is the Kwiakowsi et. al (1992) stationary text, and Zivot – Andrews is the endogenous structural break unit root test of Zivot and Andrews (1992) with breaks in both the intercept and linear trend Zα, MZα and $MZ_t$ tests are based on GLS defending. For the ADF unit root statistic; the lag order is selected by sequentially testing the significance level. The band with or the lag order for the MZα, $MZ_t$, DF-GLS and KPSS tests are selected using the modified Bayesian information criterion ( BIC)- based data dependent method of Ng and Perron (2001).*

****, ** and * represent sig. at the 1`%, 5% and 10% levels respectively.*

Source; Author's Computation

Given the non stationarity of the log of the real GDP and log of real oil price, in order to estimate the MS-VAR model, we make use of the growth of real GDP and growth of real oil price which are both stationary or *1*(0). The sample period used to estimate the MS-VAR is $1970Q_1$ to $2019Q_4$.

**(C) Multivariate Cointegration Tests**

Having confirmed the level of stationarity, we proceed to investigate if there exists any long run relationship between the two variables under investigation. The results of the multivariate cointegration tests for the VAR (p) model of variables LROP and LRGDP are presented in Table 3.

Table 3: Multivariate cointegration tests

Panel A: VAR Order Selection Criteria

| Lag (P) | 1 | 2 | 4 | 6 | 8 |
|---|---|---|---|---|---|
| AIC | -11.001 | -11.403 | -11.496 | -132.563 | 13.771 |
| HQ | -11.320 | -14942 | -12.956 | 13 945 | 12.02 |
| BIC | -14.45 | -14.850 | -13.823 | 12.772 | 12.74 |

Panel B: Johanson Cointegration Tests.

| Eigenvalue | Critical value; | 0.062<br>0.034 | | | Cointegr. | Vector |
|---|---|---|---|---|---|---|
| Ho | ʎmax | 10% | 5% | 1% | LROp | LRGDP |
| r = 1 | 6.892 | 5.211 | 7.151 | 8.321 | 1.0000 | 1.000 |
| r = 0 | 8.140 | 9.399 | 13.385 | 11.385 | -5.245 | -1.024 |
| Ho | ʎtrace | 10% | 5% | 1% | LROP | LRGDP |
| r <1 | 6.256 | 4.901 | 7.974 | 8.381 | -0.004 | -0.0611 |
| r = 0 | 12.112 | 15.102 | 13.921 | 14.321 | 0.001 | 0.015 |

Panel C; Stock Watson Coint. tests

| Ho:q(k.k-r) | Statistic | Critical value for q (4,.3) |
|---|---|---|
| q(2,0) | -0.218 | 1% - 23.362 |
| q(2,1) | -12.204 | 5% -21.434 |
| | | 10% -18.321 |

Source; Author's Computation.

The VAR order is selected based on minimum BIC and is 1. Two tests of cointegration by Johansen (1988, 1991) report maximal Eigen value (ʎmax) and trace (ʎtrace) cointegrating test results. Non – rejection of r = 0 for the Johanson tests implies no cointegration. Using both trace and maximum Eigen value, both tests fail to detect any long run relationship between the variables. Stock and watson (1998) common trends testing confirms that the real oil prices and real GDP series are not cointegrated. Balcilar et. al. (2017) found that there is no long run relationship between South African real GDP and real oil price.

Since Johansen cointegration tests failed to show any existence of a long–run relation between real oil price and real GDP, we then proceed in our estimation using a Bayesian MS-VAR with 4 lags from 1970$Q_1$ to 2019$Q_4$ given that growth rate of the series and stationary. Note that we opt for a two-state Ms- VAR and a linear VAR model as a benchmark for our analysis.

**(D) Estimation results.**

Table 4a and 4b report model selection criteria and estimation results for the Ms –VAR model given by Equations (1) and (2). The order selected by the Bayesian information Criterion (BIC) is 1 for both linear VAR and MS- VAR models.

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The MS- VAR model is estimated using the Bayesian Monte Carlo Markov Chain (MCMC) method.

From Table 4a, the likelihood ratio (LR) statistics test the linear VAR model under the null against the alternative MS-VAR model.

The test statistic is computed as the likelihood ratio (LR) test. The LR test is nonstandard since they are unidentified parameters under the null. The $X^2$ p-values (in square brackets) with degrees of freedom equal to the numbers of restrictions plus the numbers of parameters unidentified under the null given.

Table. 4a; MS–VAR Esimation Results

| Model selection criteria | Ms(2) VAR | Linear VAR (1) |
|---|---|---|
| Log likehood | 720.331 | 605.624 |
| AIC criterion | -7.351 | -6.395 |
| HQ criterion | -7269 | -6.203 |
| BIC criterion | -6.069 | -6.129 |
| LR linearity Test | Statistic | P – value |
| | 169.059 | $x^2$ (8) = [0.000]***<br>$x^2$ (10) = [0.000]***<br>Davies = [0.000]*** |

*** Significant @ 1%
Source; Author's Computer

From the table, the LR test shows that the Ms Model is superior to the linear VAR model. The p-value of the Davis (1987) text is also given in square brackets and shows strong rejection of linearity. Regime properties include ergodic probability of a regime (long run in average probabilities of the Markov process), where observations fail in a regime based on a regime probabilities and average duration of a regime. Specifically, in our multivariate model regime probability is a function of past values of real GDP growth, past values of oil price changes as well as shifts in conditional variances and co variances.

From the literature, the results suggest two distinct regimes: Regime 1 that appears to be associated with higher real economic growth rate in the Nigeria economy as well as less volatility in the oil market: and "Regime 2, Marked by low and negative economic growth rates during periods of political and civil disturbances, Boko haram, pipe line vandalization and financial crisis as well as oil price shocks and higher oil price volatility.

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**Table 4b; Transition Probability Matrix**

Transition Probability Matrix

$$P = \begin{bmatrix} 0.832 & 0.168 \\ 0.264 & 0.736 \end{bmatrix}$$

| Regime properties | Probability | Observations(Quarters) | Duration (Years) |
|---|---|---|---|
| Regime (1) | 0.520 | 124 | 31 |
| Regime (2) | 0.480 | 76 | 19 |

Source; Author's Computer

From Table 4b the probability of being in regime 1 at time t, given that the economy was in regime 1 at time (t-1) is 0.832, while the probability of being in regime 2 at time t, given that the economy was in regime 2 at time (t-1) is 0.736. These indicate that both regimes are persistent. Furthermore, the long run average probabilities of regime 1 and 2 equal 0.520 and 0.408 respectively. That is, for the observations in our sample, we expect regime 1 (high growth-low oil prices volatility) to occur on 124 occasions, while we except regime 2 (low and negative growth higher oil price volatility) to occur on 76 occasions.

From the point of business cycle upswings and downswings, the high growth (low oil price volatility) and oil price shocks could be linked. It may be expected that lower growth-higher volatility regimes will also be associated with downswings and recessions. From the literature (DU plessis, 2006) stressed that the probability of a state of lower growth or a contractionary phase should be smaller than the probability of a high growth state, or expansionary phase, since recessions tend to be short-lived than expansions. Similarly, we could also except to find fewer periods of lower growth. Our results support this fact, namely suggesting an average duration of the high growth regimes of 31years compared to the low growth regime that lasts on average for 19 years.

The estimate of the smoothed probabilities of a low growth regime (also associated with higher oil price volatility and oil price shocks, labeled regime 2) of the Ms-VAR model stated in equations 1 and 2 is plotted in figure 2.

The lag order of the estimated MS-VAR model is 1 as selected by the BIC. The Ms-VAR model is estimated using a Bayesian Monte Carlo Markov chain (MCMC) technique. The smoothed probabilities in figure 2 are drawn for each time period based on the Forward Filter Backward Sampling (FFBS) algorithm (Multi- move Sampling) posterior draws

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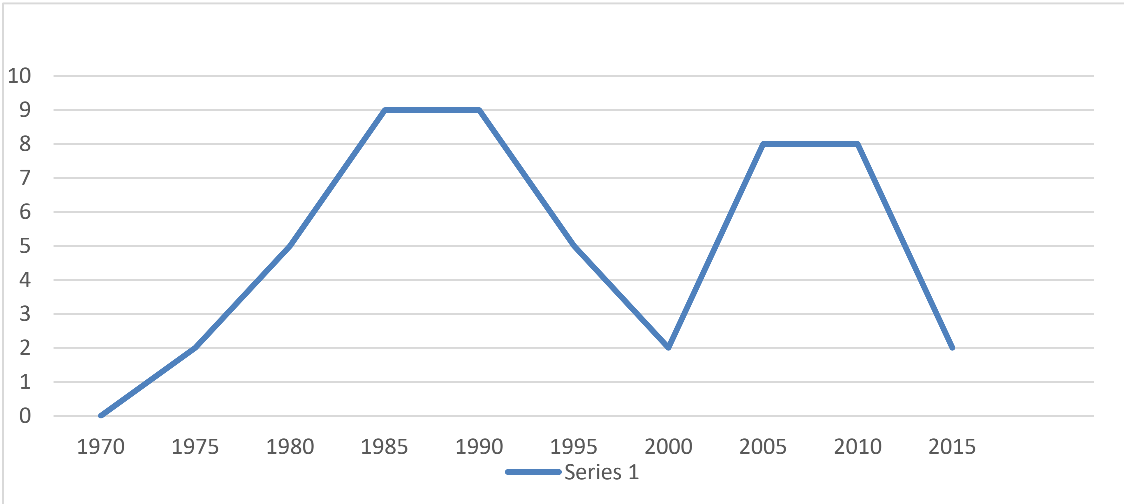


Fig. 2; Smoothed probability estimates of low growth regime (Regime 2)

*Note; a, b, c, & d corresponds to the probabilities of being in low growth regime with high oil price.*

The curve in figure 2 corresponds to the periods where smoothed probability of the low grow regime is at the maximum.

Economic crises generated by oil price slides and shocks are not new to Nigeria and its impact on Nigerian economy resulted in low or high growth regimes as shown in figure 2. The 1985 – 86 oil price decline episode is associated with the global oil glut of that period. In the face of an over supply in the world oil market, member of the organization of oil exporting countries (OPEC) decided to partly reverse their previous production cuts. As a result, average oil price fell by 48% between 1985 and1986, this induced a severe economic recession in Nigeria. The economy contracted at a rate of 8% for two consecutive years, while the naira depreciated by more than 70%.

As part of the Asian financial crisis of 1997, oil price fell progressively from about $20 per barrel in early 1997 to below $11 in February, 1999. The impact of this oil price decline on the Nigerian economy was worsened by the deteriorating political situation associated with the death of Gen. Sani Abacha in 1999. This combination generated an economic down turn in the context of which the naira experienced a depreciation of 75% with the economy grinding to a halt in early 2000s.

The next big down turn was associated with the Global financial crisis of 2008 – 2009. The build–up to this event started during 2003 when world oil price rose above $30 per barrel to reach $60 per barrel in August, 2005 and finally peaked at $149.30 per barrel in July, 2006. The resulting recession in the global economy caused demand for energy to shrink and oil price to collapse to $32 per barrel in December, 2008 and the low growth rate in Nigeria as shown in Figure 2. Asymmetrically, the Nigerian economy was able to peak up it growth at the pre 2008

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level only two years later because the government had accumulated $22 billion in the Excess Crude Account (ECA), which she was able to draw to smoothen the volatility in the oil sector.

The recent large and abrupt oil price decline in June, 2014 do not have immediate adverse impact on economic growth until early 2016 when the economy slipped into technical recession in late 2016 and early 2017. The asymmetric nature of oil price shocks came to limelight in 1980, 1998, and 2005 when oil price increased astronomically with large capital inflow generated by oil boom result in the appreciation of real exchange rate, in turn, retards the growth of non-oil tradable (Dutch Disease) coupled with high import bills and corruption in high places living the economy at low ebb.

Figures 3 and 4, represent real GDP growth rates and real oil price changes respectively. The multivariate MS – VAR model identifies regime 2 based on either occurrences of oil price shocks and oil price volatility, or periods of low and negative growth rates or both of these.

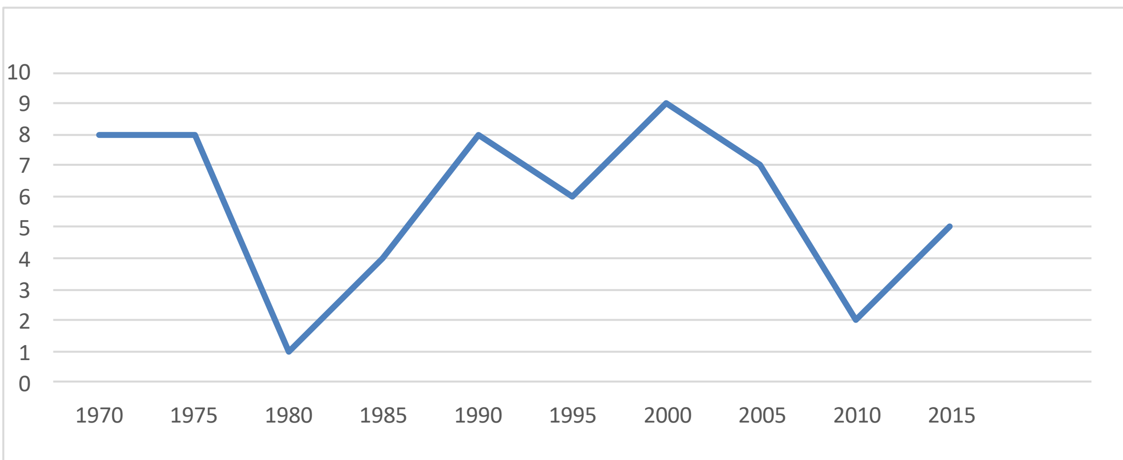


Fig. 3; Real GDP growth Rate

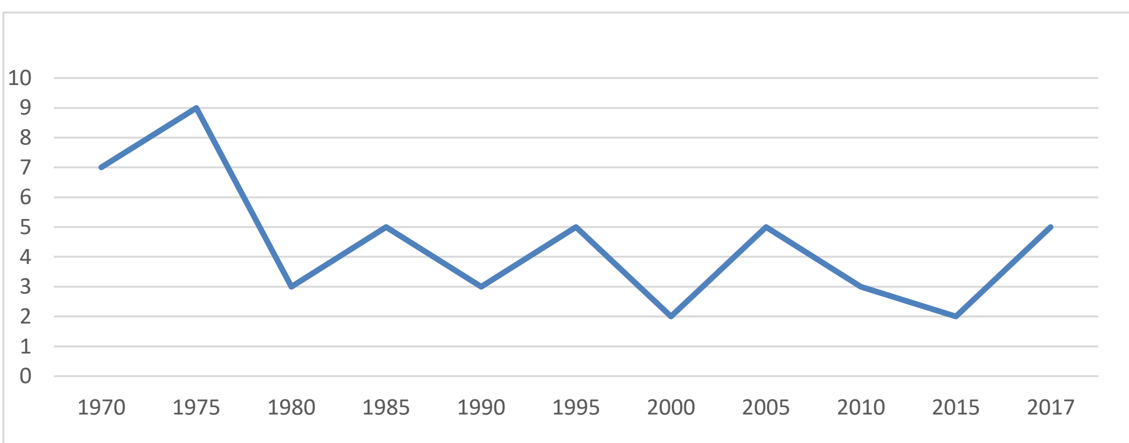


Fig.4; Real Oil Price change

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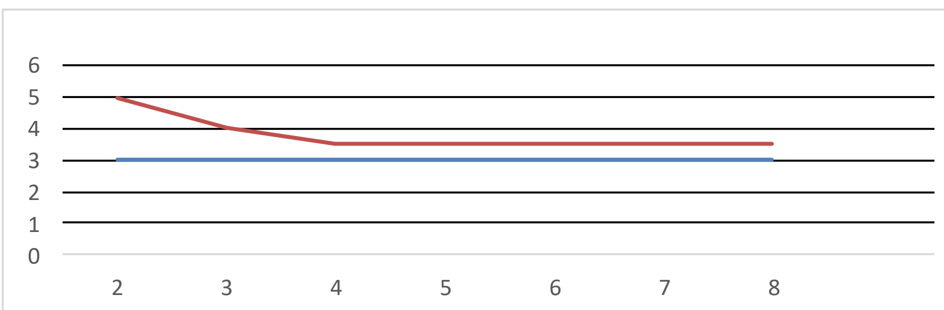
The volatility in oil price could be seen in figure 4. These volatilities are evidenced in 1970-1973, 1983-199, 2003, 2005, 2010-2015, (boom) and 1978, 1981, 1985-1986, 1997, 2008 – 2009 and 2014 (bust). This dynamic variation impinged on the real GDP growth rate as shown in figure 3. More specifically, the presence of a dominant and booming oil price sector has exposed the Nigerian economy to venerability to external shocks that are generated by oil price volatility over the years and recently by COVID-19, 2020.

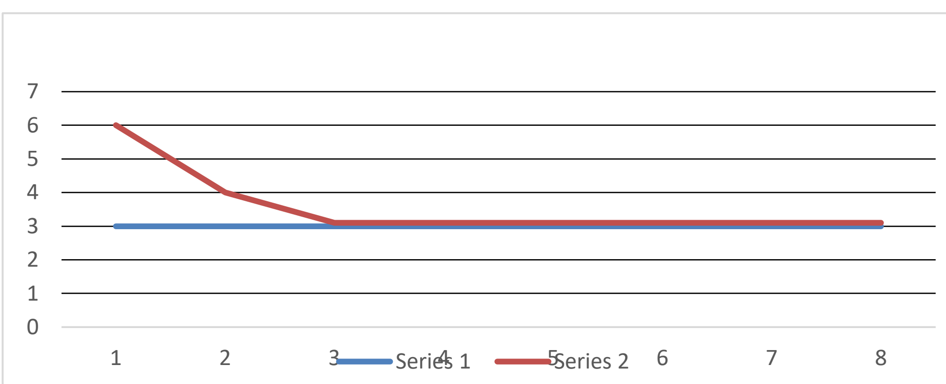
The vulnerability to external shocks imposed on the Nigerian economy by the dominant oil sector and its volatile price regime boom and bust have rendered macroeconomic stability unattainable indirectly made high economic growth rates unsustainable. Olowookere and Ogebe, 2019 had similar results in their comparative analysis.

### (E) Impulse Response Function (IRF)

Impulse response function (IRF) analysis studies how a given magnitude of a shock in one of the variables propagates to all variables in the system over time. Computing multi–step IRFs from MS- VAR models as well as from all nonlinear time series models proves complicated because no ordinary method of computing the future path of the regime process exists. An ideal IRF analysis requires that we know the future path of the regime process, since the impulse depends on the regime of the system in every time period.




Figure;5a; Response of RGDP to Real Oil Price (ROP) Shocks in Regime 1 of MS-VAR Model.




Figure; 5b; Response of RGDP to Real Oil Price Shocks in Regime 2 of MS- VAR Model.

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Figures 5(a) and (5b) show that the output growth response to an oil price shock in a high growth regime is short–lived and the output growth stabilizes to its equilibrium value and even beyond in some cases due to incidence of "Dutch – disease" effect in the context of which large capital inflow generated by the oil boom tend to appreciate the real exchange rate that in turn retards the growth of non oil tradable. The negative effects of corruption and cost of governance were not unexpected. This is why the impact of high oil price shocks on economic growth is statistically insignificant. This further confirmed Ubi and Udah findings in 2019 with respect to economic growth in Nigeria

The response of output growth to oil shock during low growth regimes tends to be positive and significant. The effect is also more instantaneous and persistent with output growth stabilizing to equilibrium after five quarters. The reason behind the persistence of an oil price shock during the low growth regime could be attributed to (1), the non oil domestic economy that had in built strong growth fundamentals that helped to mitigate the full impact of the sector decline. (2), due to weakness of the US dollar to which the naira was pegged, the naira did not have to fall more than 20% against the dollar before it downward pressure was relieved. (3), by 2008, the government had accumulated $22 billion in the Excess crude Account (ECA), which it was able to draw from to smooth the volatility in the oil sector. Hence, the Nigerian economy was able to resume its growth at the pre – 2008, and pre- 2014, 2014 and 2017 level after short-lived recession of 2016.

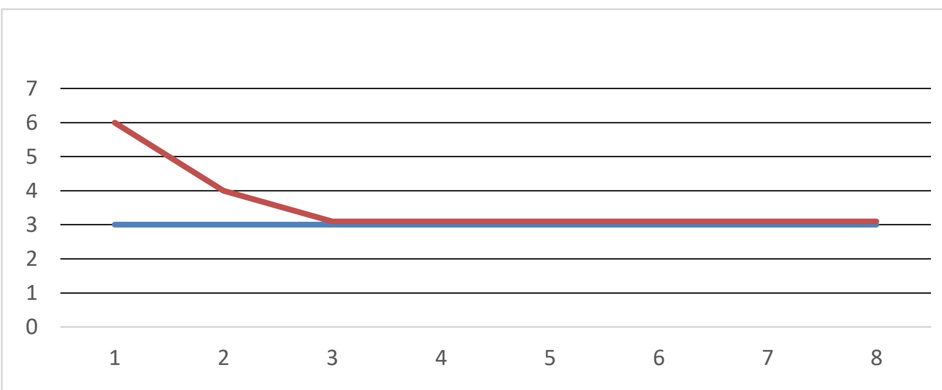


Fig. 5c; Response of RGDP to Real Oil Price Shocks in Linear VAR Model

The linear VAR model impulse response function in figure 5c showed no effect of oil price shocks on real output in Nigeria, these further demonstrate the relative advantages of nonlinear regime switching models over the linear alternative, which does not distinguish between the different characteristics under each regime. Also, under the linear VAR the positive and negative effects of oil price shocks fizzle out in the process of model linearization where the highest polynomial is one (unit). The regime dependent IRF allows the asymmetries in terms of the magnitude and persistence of impact in each regime as depicted in figures 5a and 5b.

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## 6. Concluding Remark

Using linear VAR as a benchmark, the study employed a Bayesian MS – VAR to investigate the role of oil price in different states or regimes, namely a high growth low oil price volatility regime and a low growth – high oil price volatility regime during the period 1970Q1, to 2019Q4. From the analysis, it could be observed that the nonlinear model is preferred to linear alternative as the former appeared more realistic than the latter method. It also implies that a regime switching model exists for Nigerian business cycle. The result showed that the duration of the high growth regime on average is longer compared to that of the low growth regime. Oil price shocks increase the probability to be in a low growth regime (though most often short lived).

The probability of being in both regimes is very high and persistence as long as the shock persists as indicated by transition probability. From the regime dependent impulse response function, comparatively, the oil price shocks tend to be more persistent during low growth states compared to high growth state and the impact on real output growth is also statistically significant. This might not be unconnected with the hitherto dormant economic situation before the price shock, the emerging growth potential of the non oil subsector and the asymmetric reaction of monetary authorities to mitigate the inflationary effect of oil price shocks during low growth regimes.

The results clearly show that where as VAR shows no impact of oil price shocks on real output growth, the regime dependent. IRFs are able to differentiate between responses to oil price shocks under each regime with low growth regime being statistically significant.

The policy implication of this analysis within its broad political economic context, Nigeria's vulnerability to future oil price shocks dependent on the extent to which the non oil domestic economy is reactivated to mitigate the full impact of the oil sector price shocks as exporter of crude oil and importer of refined oil. Since there is no one–to-one effect of oil prices on real output growth as shown from the analysis, it beholds on policy makers to propose and implement reserve augmenting strategies, stringent monetary policy and intensified international financial integration. The Dutch disease effects of crude oil price shocks could be stemmed by introducing and implementing an inward looking strategy of the BRICS model or the manufacturing subsector and domestic consumption and renewable energy sources like solar and wind require more attention and support to supplant crude oil.

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