International Journal of Applied Science and Mathematics
Volume 10, Issue 5, ISSN (Online): 2394-2894

Modelling Oil Price in Nigeria Using BMA and DMA Techniques

O.B. Akanbi* and K.A. Alobaloke
Department of Statistics, University of Ibadan. Ibadan Nigeria.
*Corresponding author email id: muhdbashola@yahoo.com

Date of publication (dd/mm/yyyy): 04/11/2023

Abstract **– As a result of the adverse macroeconomic effect of oil price fluctuations on welfare, fiscal budgeting, trade performance, international competitiveness and the whole economy, oil prices remain a subject of utmost concern and interest to policy makers. Therefore, the need to investigate predictors of oil price measures arises. The model averaging methods considered uncertainty as part of the model selections, and includes information from all candidate models. Thus, this study investigated the main predictors for Nigerian Oil prices using the Bayesian and Dynamic Model Averaging (BMA, DMA) Techniques. The study considered sixteen (16) predictors cutting across oil and financial sectors of the Nigerian economy. The results for both model techniques showed that refinery capacity and the exchange rate are the main potential determinants of oil prices in Nigeria. These predictors can be considered as the leaders of the modelling procession over the selected periods.**

Keywords **– Bayesian Model Averaging, Dynamic Model Averaging, Oil Price, Exchange Rate.**

I. INTRODUCTION

The prices of Oil remains a subject of interest and concern not only to econometricians, statisticians, and economists but majorly to the monetary authorities in Nigeria. The reasons are quite many, including: the macroeconomic effect on savings and investments; the uncertainty effect on fiscal budgeting; and the impact on international competitiveness and trade performance. Considerable and sudden fluctuations of oil prices often have significant impact on the economic performance of both oil importing and oil exporting countries. On one hand, a sharp increase in oil prices has a negative effect on economic growth and inflation in oil importing countries. On the other hand, as oil prices play a vital role in determining macroeconomic aggregates, including real GDP (Akanbi et'al 2018) and inflation (Tumala et'al 2018, 2019), a drop in oil prices creates a series of budgetary problems for oil exporting countries. Thus, an accurate model of oil prices provides useful information which helps government agencies or other policy makers to plan and manage their resources in more efficient manner.

In addition, there are many sectors in the economy that depend precisely on the model of crude oil prices in their business. For instance, the oil-related industries such as airline and automobile heavily depend on the models of oil prices to determine their service, production, and hedging strategies. Other utility companies use the model of oil prices in deciding whether to extend capacity or build new plants. Homeowners also benefit from the model of oil prices in deciding the timing of their heating oil purchases or whether to invest in energy-saving home improvements. Model of oil prices also play a crucial role in generating projections of energy use, modelling investment decisions in the energy sector, predicting carbon emissions and climate change, and designing regulatory policies. The central banks use the model to assess the values of other economic variables (Kilian and Vigfusson, 2013) and the responses to their macroeconomic policies. In financial markets, obtaining more reliable model of oil prices is also important as unexpected oil shocks can cause high degrees of co-movement of financial assets (Wang et al., 2015), and hence reduce diversification benefits. In this context, predictability of oil prices is a crucial input into the policymaking process. Unsurprisingly, many researchers have implemented various techniques to model crude oil prices and its determinants. Empirical results concerning the key determinants of oil prices are mixed. For example, Hamilton (2009) using a small set of indicators supports the conventional view that the major oil price shocks were due to significant disruptions of crude oil production caused by geopolitical events.

Model averaging techniques are unlike standard model estimators that are based on some pre-tests and post-tests for model estimation, thus, the techniques have a coherent way of making inference on the regression parameters of interests by taking into account the uncertainty due to both the estimation and the model selection steps. The two model averaging methods applied in this paper are the Bayesian Model Averaging (BMA) and Dynamic Model Averaging (DMA). The two techniques take into account all available information from various models; they are unlike the classical estimation methods via Ordinary Least Square (OLS) models where a final model that represents best the dataset is picked based on information criterion. It worth applying the techniques on Nigerian oil prices to determine its predictors. In this paper, both BMA and DMA estimation methods were considered. The burning research question is: what are the factors determining oil prices in Nigeria?

II. METHODOLOGY

A. *Bayesian Model Averaging*

The use of BMA for model combination was first introduced by Min and Zellner (1993). The usefulness was demonstrated by Akanbi and Oladoja (2019), Eicher et al (2011), Fernandez et al (2001a, b), and Lee and Huh (2017). Stock and Watson (1999, 2005, 2006) have provided detailed empirical evidence demonstrating the gains in model accuracy through model combination and have demonstrated the success of simple averaging (equal weights) along with BMA. The BMA implementation begins the formulation of all feasible models and specifying the prior beliefs about the probability that each model is the true one. After that the posterior probability that each model is the true one is computed. This looks like a shrinkage methodology, but with the shrinkage over the possible models and not just over the parameters. In situations where many potential explanatory variables exist, alternative models can be defined based on the set of explanatory variables they include. In general, if there are R potential explanatory variables in a study, then 2^R models are possible. It is obvious that as R gets larger, the number of possible models grow larger. Two major problems are usually confronted. First is how to handle this considerable number of models. The second relates to priors elicitation for the models and set of parameters in the models. These problems have largely been surmounted by Bayesian Model Averaging (BMA) as would be examined during this discussion.

Consider a linear regression model with a constant term, ψ_0 and R potential explanatory variables X_1, X_2.. $,_R$:

$$y = \psi_0 + \psi_1 X_1 + \psi_2 X_2 + ... + \psi_R X_R + \varepsilon \tag{1}$$

From model (1), there are 2^R different feasible models based on inclusion and exclusion of each predictor. If Y_t for t = 1, 2, 3, …, R denotes the different models under consideration, and having constructed the model space, the posterior distribution of any coefficient, say ψ_s, given the data H is:

$$P(\psi_t / H) = \sum_{t=1}^{2^R} P(\psi_t / Y_t) P(Y_t / H) \tag{2}$$

The logic of Bayesian inference requires one to obtain result for every model under consideration and average them. The weights in the averaging are the posterior model probabilities, $P(Y_t / H)$. These weights are the key features for estimation via the BMA. The Posterior Model Probability (PMP) is the ratio of its marginal likelihood to the sum of marginal likelihoods over the entire model space, and is given by

$$P(Y_t / H) = \frac{P(H / Y_t)\, P(Y_t)}{P(H)} = \frac{P(H / Y_t)\, P(Y_t)}{\sum_{i=1}^{2^R} P(H / Y_t)\, \mathrm{P}(Y_t)} \tag{3}$$

Where the marginal likelihood for the t^th model is:

$$P(H / Y_t) = \int P(H / \psi^t, Y_t) P(\psi^t / Y_t) d\psi^t \tag{4}$$

and ψ^t is the vector of parameters from model Y_t, $P(\psi^t / Y_t)$ is a prior probability distribution assigned to the parameters of model Y_t, $P(Y_t)$ is the probability that Y_t is the true model and $P(H / \psi^t, Y_t)$ is the likelihood. The posterior mean and standard deviation of $\psi = \psi^t$ (quantity of interest) are then constructed as

$$E(\psi^t / H, Y_t) = \sum_{t=1}^{2^R} P(Y_t / H) \tag{5}$$

$$V(\psi^t / Y_t) = \sum_{t=1}^{2^R} \left(\mathrm{var}\left[\psi \mid H, Y_t\right] + \psi_t^{\,2} \right) P(Y_t / H) - E\left[\psi / H\right]^2 \tag{6}$$

Where, $\psi_t = E\left[\psi^t \mid H, Y_t\right]$.

B. *Dynamic Model Averaging*

The dynamic model averaging (DMA) model, as the name implies, average across various models. To understand the econometric methodology regarding DMA, suppose that we have a set of *K* models which are characterized by having different subsets of z_t as predictors.

Denoting these subsets by $z^{(k)}$ for *k = 1,…,K,* our set of models can be written as:

$$y_t = z_t^{(k)} \theta_t^{(k)} + \varepsilon_t^{(k)} \tag{7}$$

$$\theta_{t-1}^{(k)} = \theta_t^{(k)} + \eta_t^{(k)} \tag{8}$$

where y_t is the dependent variable being model i.e., the oil price series and $z_t^{(k)}$ are regression parameters, given by a column vector, and the row vector $\theta_{t-1}^{(k)}$ is the set of predictors of model *k* including the intercept. It is assumed that $\varepsilon_t^{(k)} \sim N(0, V_t^{(k)})$ and $\delta_t^{(k)} \sim N(0, W_t^{(k)})$. Also, $E(\varepsilon_t^{(k)}, \eta_t^{(k)}) = 0$. Allowing different models to hold at each point in time and performing model averaging, gives rise to the terminology "Dynamic Model Averaging (DMA)". To be precise, when modelling time t variables using information through time *t-1*, DMA involves calculating the probabilities $Pr(Lt = k \mid y^{t-1})$ for the models *k =1,..,K,* and averaging models across those *K* models, using these probabilities. DMA involves selecting the single model with the highest value for $Pr(Lt = k \mid y^{t-1})$ and then, using this model as the model. However, there are problems with such a framework, since many of the models can have a large number of parameters, and the computational burden which arises when K is large implies that estimation can take a long time. Thus, a full Bayesian approach to DMA can be quite difficult. Following Koop and Korobilis (2012), approximations as suggested by Raftery *et al.*, (2010) were used. These approximations involved two parameters for the coefficients and the models: λ and α, which they referred to as the forgetting factors, and fix them to numbers slightly below one.

To explain the role of these forgetting factors, first consider the *standard state space model* below for $t = 1 \dots T$:

$$y_t = z_t \theta_t + \varepsilon_t \tag{9}$$

$$\theta_t = \theta_{t-1} + \eta_t \tag{10}$$

For this study, the output vector y_t is the oil price, the vector $z_t = [1, x_{t-1}, y_{t-1}, \dots, y_{t-p}]$ is a *1* x *m* vector of predictors for the oil prices, the vector $\theta_t = [f_{t-1}, \beta_{t-1}, y_{t-1}, \dots, y_{t-p}]$ is an *m* x *1* vector of coefficients (states), and $\varepsilon_t \sim N(0, H_t)$ and $\eta_t \sim N(0, Q_t)$ are the errors which are assumed to be mutually independent at all leads. For given values of the variance-covariance matrices H_t and Q_t, the standard filtering and smoothing results can be used to carry out recursive estimation. Kalman filtering begins with the result that

$$\theta_{t-1} \mid y^{t-1} \sim N\left(\hat{\theta}_{t-1}, \Sigma_{t|t-1}\right), \tag{11}$$

for $\hat{\theta}_{t-1}$ and $\sum_{t-t|t-1}$ which are defined below as standard. Note here that these parameters depend on variance-covariance matrices H_t and Q_t for the errors. Then Kalman filtering proceeds, using:

$$\theta_t \mid y^{t-1} \sim N\left(\hat{\theta}_{t-1}, \Sigma_{t|t-1}\right) \tag{12}$$

where

$$\sum_{t|t-1} = \sum_{t-1|t-1} + Q_t \tag{13}$$

Raftery *et al.* (2010) note that things simplify substantially if this latter equation is replaced by:

$$\sum_{t|t-1} = \frac{1}{\lambda} \sum_{t-1|t-1} \tag{14}$$

or, equivalently, $Q_t = (1 - \lambda^{-1}) \sum_{t-1|t-1}$ where 0 < λ < 1. The term "forgetting factor" is suggested as observations j periods in the past have weight λ^j. An alternative interpretation is that, it implies an effective window size of $1/(1-\lambda)$. In the literature, it is common to choose a value of λ near one, which suggests a gradual evolution of coefficients. Raftery *et al.* (2010) set λ = 0.99. For monthly macroeconomic data, this suggests observations five (one) years ago receive approximately 50% (90%) as much weight as last period's observation. This would be consistent with fairly stable models where the coefficient's change is gradual. However, setting λ = 0.95, suggests that observations five years ago receive only 5% as much weight as last period's observation. This would suggest substantial parameter instability with rapid change in coefficients.

III. Result and Discussion

All the data used in this study are yearly, spanning from 1981 to 2022 (42 observations) and were sourced fr-

-om the 2022 CBN Statistical Bulletin, Organization of the Petroleum Exporting Countries (OPEC) and World Development Indicators (WDI). The study variables are Crude Oil Price (CPR) while the 16 predictors considered are Crude Oil Production (CPROD), Crude Oil Export (CEX), World Oil Demand (WOD), Refinery Capacity (RC), World Output of Petroleum Product (WOP), All Share Index (ASI), Oil Rents (OR), Broad Money (BMNEY), Foreign Direct Investment (FDI), Gross National Expenditure (GNE), Total Reserves (TR), Lending Interest Rate (LIR), Exchange Rate (EXR), Inflation Rate (INFL), Net Domestic Credit (NDC) and Gross Domestic Savings (GDS). Also, all the tables and figs. in this paper are the outputs of the data analysis using BMS and DMS packages in R programming.

A. *Preliminary and Descriptive Analysis*

The external behaviour of the variables was examined by computing the appropriate measures of location and spread. The summary statistics of the variables are presented in Table 1. The highest historical volatility as defined by standard deviation is bestowed on all share indexes followed by Nigeria's crude oil export. Interestingly, the country's gross domestic savings has the lowest volatility. Nigeria's spot crude oil price has the highest correlation with the stock price (0.818) and the lowest with oil rents (-0.015). It is also interesting to note that the correlation with crude oil production is 0.225, while it is 0.651 with crude oil export. As expected, the correlation is negative with foreign direct investment (−0.03) and national expenditure (−0.062). Few of the variables have excess kurtosis, with the inclusion of inflation rate and foreign direct investment, the spot crude oil price and many others have lower kurtosis than the normal distribution. Very few of the variables are negatively skewed, while the others are positively skewed. Interestingly, above half of the variables do not have normal distribution as evidenced by the Jarque–Bera statistic.

Table 1. Descriptive Statistics of the study variables.

Variables	Mean	Max.	Min.	Std.	Kurt[a]	Skew[b]	CV[c]	J-B[d]	Correlations of CPR with the Predictors
CPR (Dependent Variable)	45.745	114.21	12.62	31.093	2.585	0.894	0.67	5.893*	
ASI	16395.280	50424.7	5.52	15872.190	1.939	0.502	0.96	3.732	0.818***
BMNEY	16.781	27.38	9.06	6.030	1.504	0.445	0.36	5.306*	0.754***
CEX	1800.619	2464.12	935.2	424.691	2.189	-0.396	0.23	2.25	0.651***
CPROD	1773.872	2365.95	1235.5	289.537	2.305	-0.101	0.16	0.917	0.225
EXR	108.752	358.81	0.62	104.692	2.510	0.724	0.95	4.089	0.587***
FDI	1.498	5.79	0.2	1.214	6.337	1.771	0.8	41.435***	-0.03
GDS	6.429	7.89	4.97	0.895	1.760	-0.295	1.29	3.298	0.710***
GNE	94.349	105.58	76.95	5.905	3.764	-0.723	0.06	4.681*	-0.062
INFL	18.733	72.84	5.39	16.515	5.460	1.892	0.87	35.654***	-0.398***
LIR	17.464	31.65	8.92	4.753	3.726	0.312	0.27	1.604	-0.209
NDC	6.040	7.94	4.2	1.145	1.706	0.000	1.45	2.932	0.715***

International Journal of Applied Science and Mathematics
Volume 10, Issue 5, ISSN (Online): 2394-2894

Variables	Mean	Max.	Min.	Std.	Kurt[a]	Skew[b]	CV[c]	J-B[d]	Correlations of CPR with the Predictors
OR	11.604	26.42	1.51	5.820	2.568	0.282	0.5	0.884	-0.015
RC	400.790	511.69	234	80.577	3.234	-1.324	0.2	12.361***	0.447***
TR	77.826	331.42	3.15	93.800	4.163	1.446	1.19	17.011***	0.798***
WOD	268.651	494.69	162.27	99.631	2.482	0.962	0.37	6.943**	0.606***
WOP	122.594	253.42	0.93	72.875	1.939	0.042	0.59	1.983	-0.665***

Notes: The sample period is from 1981 to 2022. a, b, c, d refer to kurtosis, skewness, coefficient of variation and Jarque–Bera statistics, respectively. *, ** and *** denote significance at the 10%, 5% and 1% significance levels, respectively.

Table 2. Posterior Model Probabilities of the five Top Models.

PMP (Exact)	PMP (MCMC)
0.958247	0.958247

Table 2 shows the importance of using the top models for inference instead of the full model (model space). With the best 2000 models, the MC3 sampler (PMP MCMC) estimate (0.958247) was accurate when compared with the posterior probability for the true (exact) model. This is because the sampler visited about 551% (360976) of the model space (65536) for its simulation. This is realized when all PMP values for the 360976 visited models and the exact models (65536) were summed separately and then compared.

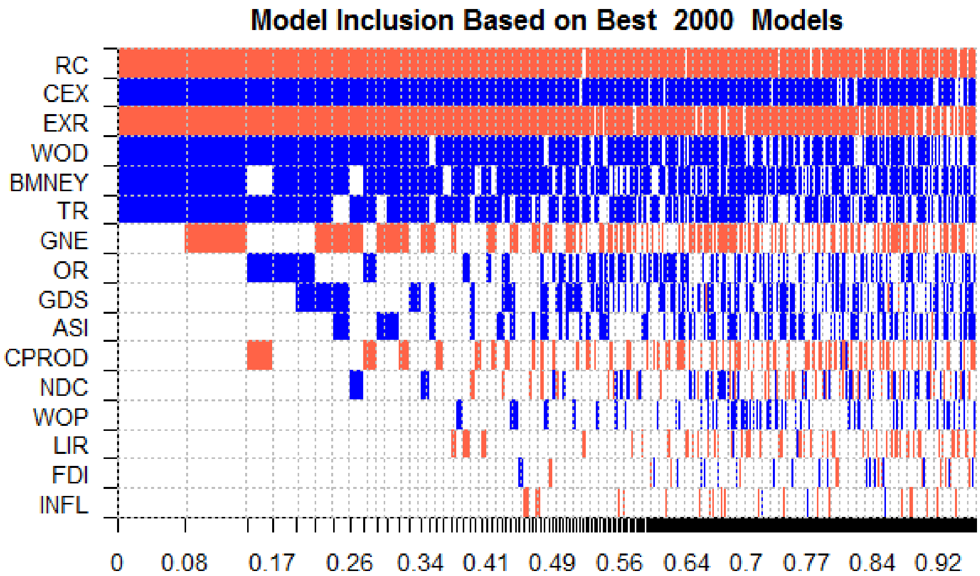

Fig. 1. Chart Showing Cumulative Probabilities on the best 2000 Model.

Fig. 1 depicts the inclusion probability for the models. It explains the best 2000 models scaled by their Posterior Model Probability (PMPs). This cumulates the probabilities for the 2000 best models out of the 36057 visited models. The fig. also indicates signs of the regressor coefficients in the models. The first six predictors, Refinery Capacity, Crude Oil Export, Exchange Rate, World Oil Demand, Broad Money and Total Reserves appear almost in all the 2000 best models and some have a negative sign with red while some with blue representing a positive coefficient for a regressor in a model.

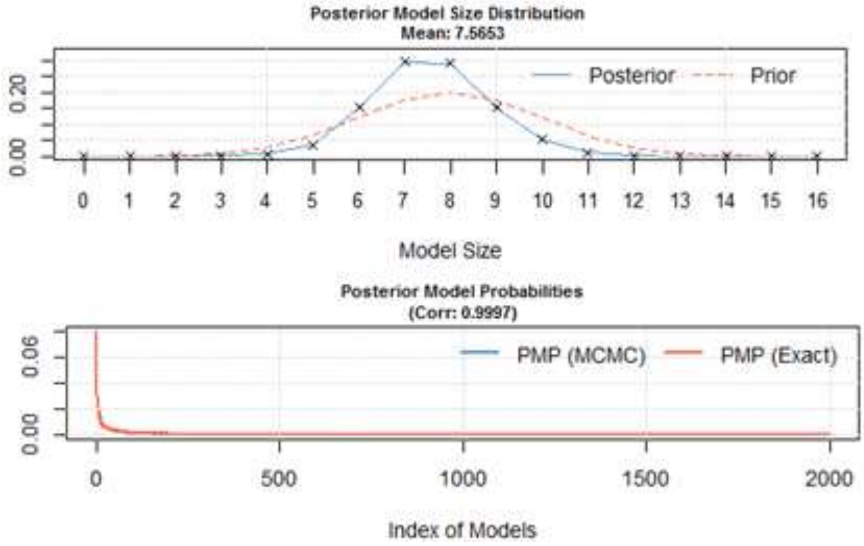

Fig. 2a (above). Model size plot & Fig. 2b (below). PMP convergence plot.

Fig. 2a shows the average number of the predictors (model size = 7.5653) for the 2000 best models. Figure 2b depicts the plot for the convergence of the model simulation. From the density plot, the correlation value (0.9997) for the model simulation convergence is also confirmed below.

B. *Model Estimation and Analysis*

Two different model averaging algorithms: Bayesian and Dynamic Model Averagings (BMA, DMA) were used to model the Nigeria oil prices for 1981-2022. The posterior model inference outputs for BMA and DMA were presented in Tables 3 and 4 respectively. The Posterior Probability assigned to the model that generated the data is one of the main indicators of the performance of the Bayesian Methodology. It is expected that the true model should be high for small or moderate values of the sample size (n) that are likely to occur in practice. Table 3 relates the importance of each predictor with its posterior mean, standard deviation, and conditional posterior sign across the plausible models. The relevance of the predictors is measured in BMA by the Posterior Inclusion Probability (PIP). The higher the probability, the more important is the predictor, especially when the PIP value is above 50%. Out of all the predictors, refinery capacity, crude oil export, exchange rate, world oil demand, broad money and total reserves have very good PIP of 97%, 96%, 93%, 85%, 81%, and 75% respectively and therefore are the most important variables when modelling Nigerian Oil Price. In addition, all other predictors have PIPs less than 50% and therefore are not strong determinants of oil price in Nigeria. All these redundant variables have their posterior standard deviations greater than their posterior means, thus suggesting parameter uncertainty (under model uncertainty). Table 4 shows the DMA inclusion probabilities of predictors for the last ten years. The DMA technique captured more variables in the modelling process when compared with the BMA selections. Full estimates of these PIP values are examined more carefully in fig. 1. It illustrates the posterior importance of the 16 variables at each point in time. These plots contain posterior inclusion probabilities for the predictors. It was noted that the general tendency for predictor like refinery capacity to increase over time. Oil Rent and Net Domestic Credit receives high posterior probability throughout the period, they seem very important. Refinery Capacity and Gross National Expenditure receive higher probabilities towards the end of the period. Overall, we observe a good amount of time-variation in these plots. Overall, the PIP values of 50% and above were considered more relevant.

International Journal of Applied Science and Mathematics
Volume 10, Issue 5, ISSN (Online): 2394-2894

Table 3. BMA Posterior Inclusion Probability for all the predictors.

Predictors	PIP	PostMean	PostSD
RC	0.9713	-0.2564	0.0971
CEX	0.9602	0.0468	0.0211
EXR	0.9350	-0.1758	0.0733
WOD	0.8521	0.1647	0.0900
BMNEY	0.8097	1.8767	1.2217
TR	0.7509	0.0988	0.0664
GNE	0.4595	-0.4250	0.5423
OR	0.3516	0.3652	0.5826
GDS	0.3501	12.0097	20.4448
ASI	0.2791	0.0002	0.0004
CPROD	0.2566	-0.0103	0.0223
NDC	0.1845	0.1492	9.8632
WOP	0.1310	0.0100	0.0343
LIR	0.1185	-0.1248	0.4944
FDI	0.0660	0.0187	0.5806
INFL	0.0637	-0.0037	0.0372

Table 4. DMA Posterior inclusion probabilities of the predictors in recent times.

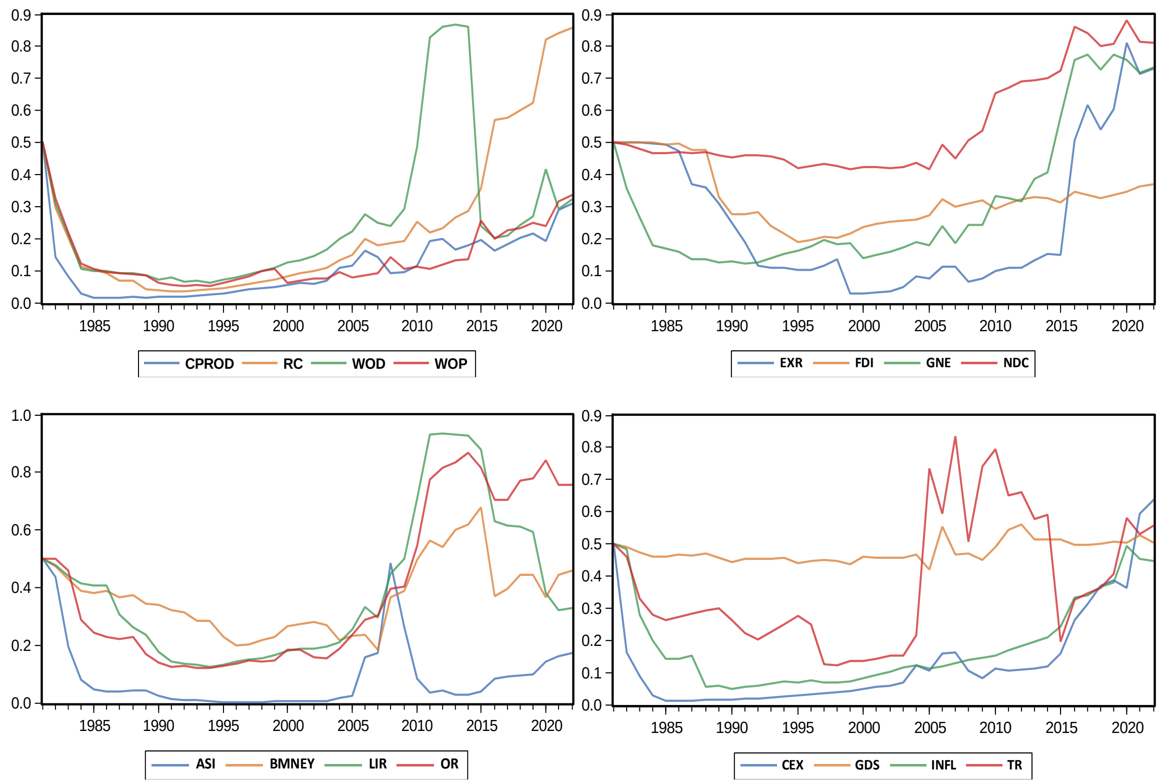

Fig. 3. Predictors importance for the DMA Model.

IV. CONCLUSION

This study uses the Bayesian and Dynamic Model Averaging (BMA and DMA) technigues to determine the predictors of oil prices for Nigeria. sixteen (16) macroeconomic variables were cconsidered for modelling the OPEC Nigerian oil prices. The modelling techniques identified refinery capacity, crude oil export, exchange rate, world oil demand, broad money, total reserves, net domestic credit, oil rents, gross national expenditure, lending interest rate, and gross domestic savings as drivers with refinery capacity and the exchange rate as the main potential determinants of oil prices in Nigeria. Also, it seems that the best predictors for modelling oil prices are changing considerably over time. The monetarists are of the view that oil price is a function of money; hence anything that affects the quantum of money in circulation affects the fluctuations of oil prices.

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AUTHOR'S PROFILE

First Author

Dr. O.B. Akanbi, He is a Senior Lecturer in Statistics Department, University of Ibadan, Nigeria. His area of research is Bayesian Statistics, focusing on prior elicitation in Bayesian Modelling, Model Averagings and Bayesian Analysis. He has Professional diploma, B.Sc., M.Sc., and Ph.D. in Statistics from the University of Ibadan, Nigeria. Dr. Akanbi has to his credit a number of refereed journal articles and conference papers within and outside Nigeria. He is a member of some statistical societies; International Statistical Institute (ISI); International Biometric Society (IBS) Group Nigeria (GNi); Statistics & Probability African society (SPAS); Nigerian Statistical Association (NSA); and Nigerian Young Sta--tisticians Group (NYSG).

Second Author

K.A. Alobaloke, She graduated from the Department of Statistics, Federal University of Agriculture, Abeokuta (FUNAA -B). She has completed her Master's degree programme specializing in Econometric Statistics from the department of Statistics, University of Ibadan. Her research interests are Econometrics and Statistical Modeling.