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Bayesian Model Averaging for Model Uncertainty in Inflation Rates Modeling in Nigeria

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ABSTRACT

Applied researchers are frequently faced with the issue of model uncertainty in situations where many possible models exist as a result of several regressors or predictors variables motivated by different theories. For instance, having over 40 regressors (k) to formulate model can cummulate into trillions of possible models (2^k). Thus, data analysts are unsure of which regressors are useful. An alternative approach to model selection is to compute a weighted average of the estimates of the all competing models. Bayesian model averaging (BMA) has a coherent mechanism for dealing with model uncertainty This is evident in the properties and uses of posterior model probabilities. Also of concern is the issues of which of the predictor variables included the models are relevant or significant in the data generating process. This study investigates the key drivers of inflation rates using thirteen likely predictors resulting in 8192 plausible models comprising of all possible combinations of the predictors. Each model was weighted accordingly with a model uniform prior and parameter prior. Using Markov Chain Monte Carlo (MCMC) algorithm, which generate draws from a Markov chain on the model space with the posterior model distribution as its stationary distribution. Model posterior probability and posterior inclusion probability were determined in order to obtain the most appropriate model for inflation rates. Hence the Bayesian model averaged for inflation rates consists of an average of four predictors showing the real interest rates with posterior inclusion probability equals to 1 and the mean number of regressors is 3.425 for the best 1527 models.

Keywords: Bayesian Model Averaging, Inflation Rates, Prior Distribution, Posterior Probability, Uncertainty.

INTRODUCTION

In regression analysis, picking a single model among competing models tends to ignore the uncertainty associated with the specification of a selected model as a result of overstatement of the strength of evidence via p-values that are too small (Clyde and George, 2004). Thus, Box (1976) states that “all models are wrong, but some are useful”. In reality, the true model for inflation rates is unknown. Hence, depending on a single model is unrealistic and misleading. An alternative approach to model selection is to compute a weighted average of the estimates of the all competing models. This approach called Bayesian model averaging (BMA) is able to incorporate model uncertainty into the analysis. Thus, BMA offers a more coherent mechanism for dealing with model uncertainty (Fernandez *et al*., 2001a). The application of BMA to modeling inflation rates in Nigeria is of great interest to determine the key drivers of inflation rates in Nigeria and at the risk of ignoring model uncertainty. Thus, a good understanding of the predictor variables driving inflation rates is required. The Bayesian model averaging (BMA) is an extension of the usual Bayesian inference methods in which one does not only model parameter uncertainty through the prior distribution, but also model uncertainty by obtaining model posterior probability. In BMA mechanism, the sum of Posterior Model

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Probabilities (PMP) for all models wherein a covariate was included is obtained as the Posterior Inclusion Probabilities (PIP). It indicates the importance of a regressor in explaining the data. However, the predictive ability and best model selection power of Bayesian Model Averaging (BMA) does not only depend on the prior used but to its ability to determine the best priors among the different priors of Bayesian model (Fernandez *et al*., 2001b).

It is common knowledge that inflation poses one of the most serious economic problems in any country. It causes instability and thus reduces efficiency and retards the growth of an economy in the long run. Inflation is defined as a persistent rise in the general level of prices of goods and services in an economy over a period of time. "The rate of inflation – the percentage change in the overall level of prices – varies greatly over time and across countries" (Mankiw, 2010). When the general price level in an economy such as in Nigeria rises, each unit of currency will buy fewer goods and services than the pre-inflation period, eroding the purchasing power of money in the economy. Inflation is measured by inflation rates; the annualized percentage change in the general price index (usually the Consumer Price Index) over time.

Nigeria has witnessed high and volatile inflation rates since 1970s. Masha (2000) indicated that the high inflation episodes in the country since the 1970s were largely driven by the growth of money supply and some factors reflecting the structural characteristics of the economy. These factors included climatic conditions, wage increases, the structure of production, currency devaluation and changes in terms of trade. Adenekan and Nwanna (2004) indicated that by 1988 and 1989, inflation had increased to more than 50 per cent in Nigeria. Furthermore, Bawa and Abdullahi (2012) stated that in spite of the fact that inflation rate declined to about 7.5 per cent in 1990, it rose to 44.8, 57.2 and 57.0 per cent, respectively, in 1992, 1993 and 1994. It reached an all-time high of 72.8 per cent in 1995. This according to Mordi *et al*., (2007) was due to excess money supply, scarce foreign exchange and severe shortages in commodity supply, as well as continual labour and political unrest following the annulment of the June 1993 elections. Olasunkanmi and Oladipo (2020); Augustine *et al*., (2020) and Idisi *et al*., (2023) discussed the inflation dynamics, causes and factors affecting inflation in Nigeria.

Extensive research to address inflationary problems in Nigeria by investigating its main determinants were conducted, with varying results largely pointing to the above factors, depending on the methodology applied and objectives set to achieve, among others. Thus, it is commonplace that the determinants of inflationary pressures in Nigeria are multi-dimensional. Mordi *et al*., (2007) grouped inflation rate factors into fiscal (financing of budget deficits), balance of payments or supply side factors (exchange rate movements) and institutional factors (the level of independence of the monetary authority). Others were structural factors, agro climatic conditions and inflation inertia.

The aim of this study is to employ Bayesian model averaging (BMA) in choosing the variables that best fit inflation economic data and account for the model uncertainties. The specific objectives are to: (i) determine models with high posterior model probabilities and regressors with high posterior inclusion probabilities; (ii) estimate the parameters of the BMA inflation rates model.

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MATERIALS AND METHODS

Bayesian Model Averaging (BMA)

Bayesian Model Averaging (BMA) is a technique designed to help account for the uncertainty inherent in the model selection process, BMA focuses on which regressors to include in the analysis. One way to account for model uncertainty is to allow all models to contribute to inference by averaging. By averaging across a large set of models one can determine those variables which are relevant to the data generating process for a given set of priors used in the analysis (Montgomery and Nyhan, 2010). Given a linear regression model with constant term β_0 and k regressors or potential explanatory variables x_1, x_2, …, x_k of the form:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + \varepsilon \ . \tag{1}$$

This gives rise to 2^K possible sampling models (indexed M_j, j = 1, 2, 3, …, 2^k), depending on whether we include or exclude each of the regressors (Hinne *et al.,* 2020). Once the model space has been determined, the posterior distribution of any coefficient of interest (say β_h), given the data D is (Feldkirch, 2012):

$$P(\beta_h \mid D) = \sum_{j=1}^{2^k} P(\beta_h \mid M_j) P(M_j \mid D). \tag{2}$$

BMA uses each model's posterior probability, $P(M_j \mid D)$ as weights. Each model (a set of regressors) receives a weight and the final estimates are constructed as a weighted average of the parameter estimates from each of the models. BMA includes all of the variables within the analysis, but shrinks the impact of certain variables towards zero through the model weights. These weights are the key feature for estimation via BMA and will depend upon a number of key features of the averaging exercise including the choice of prior specified (Fragoso *et al.,* 2018); (Raftery *et al.,* 1997, 2010).

The posterior model probability of M_j is given by:

$$P(M_j \mid D) = P(D \mid M_j) \frac{P(M_j)}{P(D)} = P(D \mid M_j) \frac{P(M_j)}{\sum_{i=1}^{2^k} P(D \mid M_i) P(M_i)} , \tag{3}$$

where $$P(D \mid M_j) = \int P(D \mid \beta^j, M_j) P(\beta^j \mid M_j) d\beta^j \tag{4}$$

and β^j is the vector of parameters from model M_j, $P(\beta^j \mid M_j)$ is a prior probability distribution assigned to the parameters of model M_j and $P(M_j)$ is the prior probability that M_j is the true model. The estimated means and variance of $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, ..., \hat{\beta}_k)$ are then constructed as:

$$E[\hat{\beta} \mid D] = \sum_{j=1}^{2^k} \hat{\beta} P(M_j \mid D) \tag{5}$$

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$$V\left[\hat{\beta} \mid D\right] = \sum_{j=1}^{2^k}\left(Var\left[\beta \mid D, M_j\right] + \hat{\beta}^2\right)P\left(M_j \mid D\right) - E\left[\beta \mid D^2\right] \quad (6)$$

2.1.1 Prior Specification for Model Selection in BMA

For a given set of models M, the effectiveness of the Bayesian approach rests firmly on the specification of the parameter priors $P(\theta_k \mid M_k)$ and the model space prior $P(M_1); \ldots ; P(M_K)$. The most common model prior in the literature is the uniform distribution that assigns equal prior probability to all models, so that $P(M_k) = 1/k$ for each k (Raftery, 1995) and (Yuan *et al.,* 2005).

$$P(M_j) = p_j, \qquad j = 1, 2, \ldots 2^k \qquad \text{with } p_j > 0 \text{ and } \sum_{j=1}^{2^k} p_j = 1 \quad (7)$$

Based on probability theory established above, $p_j = 2^{-k}$ so that we have a uniform distribution on the model space. This implies that the prior probability of including a regressor is $1/2^k$ independently of the other regressors included in the model.

RESULTS AND DISCUSSION

Annual data covering the period from 1970 to 2017 (48 observations) were obtained from the 2018 Central Bank of Nigeria (CBN) Statistical Bulletin (cbn.gov.ng) and the 2018 World Development Indicators (WDI) (worldbank.org). The study variable is Inflation Rates (IR) while the regressors or predictors' variables are Official Exchange Rate (OER), Oil Rent (OR), Access to Electricity (AE), Gross Domestic Product per capital (GDP), Real Interest Rate (RIR), Total Public Wage (TPW), Food Consumer Price Index (FCPI), Government Expenditure (GE), Terms of Trade (TOT), Money Supply (M2), Petroleum Local Price (PLP), Coal (CL), Net Barter Trade (NBT). Table 1 below is the summary statistics of the regressors/predictor variables.

Table 1: The Summary Statistics of the Predictors Variables

Predictors	N	Minimum	Maximum	1st Quartile	3rd Quartile	Mean	Median
OER	48	0.5470	305.790	0.7137	128.7945	63.8674	21.8850
OR	48	0	38.56	7.55	16.84	12.59	13.41
AE	48	37.43	59.30	26.29	47.71	37.43	37.40
GDP	48	161.5	3201.0	476.4	1852.7	1075.8	618.5
RIR	48	-65.860	18.180	-5.795	6.335	-1.673	1.030
TPW	48	8.620	18.850	9.848	14.010	11.992	10.510
FCPI	48	0.1000	214.230	0.520	7.965	39.392	7.965
GE	48	0.910	9.450	1.315	4.603	3.100	1.775
TOT	48	9.14	53.28	22.98	42.25	33.27	35.26
M2	48	9.06	28.63	11.55	21.61	16.03	16.03
PLP	48	0.200	145.60	0.200	65.075	28.645	7.225
CL	48	0.000	0.014	0.0003	0.000950	0.002977	0.0000950
NBT	48	0.00	224.35	55.98	155.45	99.69	89.55

Figure 1 below shows the time plots and density plots of official exchange rates (OER) and oil rents (OR) respectively. The time plot shows that there is upward movement in the

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trend of the data. The density plot show that the distribution of the data is positively skewed. The oil rent time plot shows a downward trend toward the year 2017 and the density plot shows that the distribution of the data is positively skewed. Figure 2 shows the time plots and density plots of Access to Electricity (AE) and gross domestic product per capital (GDP) respectively. The Access to electricity time plot shows that there is upward movement in the trend of the data. The density plot show that the distribution of the data is slightly positively skewed. The GDP plot shows a downward trend toward the year 2017 and the density plot shows that the distribution of the data is positively skewed.

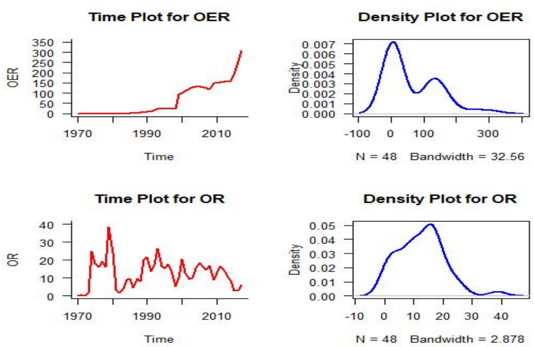

Figure 1: Time Plot and Density Plot for Official Exchange Rates (OER) and Oil Rent (OR)

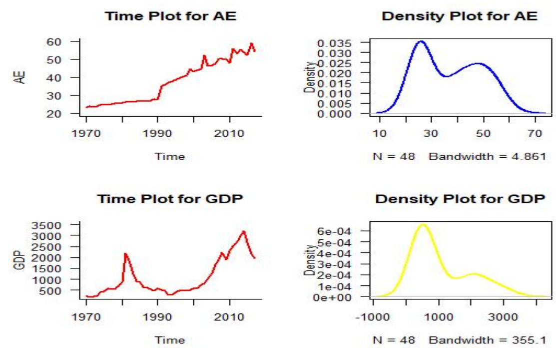

Figure 2: Time Plot and Density Plot for Access to Electricity (AE) and GDP.

Figure 3 below shows the time plots and density plots of Real Interest Rates (RIR) and Total Public Wage (TPW) respectively. The real interest rates time plot shows that there is upward and downward movement in the trend of the data. The density plot show that the distribution of the data is negatively skewed. The total public wage time plot shows an upward trend and a downward trend toward the year 2017 and the density plot shows that the distribution of the data is positively skewed. Figure 4 shows the time plots and density plots of Food Consumer Price Index (FCPI) and Government Expenditure (GE) respectively. The food consumer price index time plot shows that there is upward in the trend of the data. The density plot show that the distribution of the data is positively skewed. The Government Expenditure time plot shows an upward trend and a downward trend toward the year 2017 and the density plot shows that the distribution of the data is positively skewed.

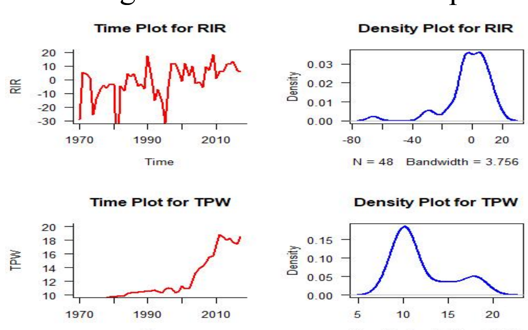

Figure 3: Time Plot and Density Plot for Real Interest

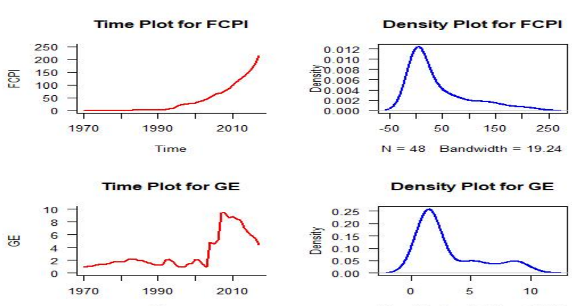

Figure 4: Time Plot and Density Plot for Food Con.

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Rates (RIR) and Total Public Wage (TPW)

Price Index (FCPI) and Govt. Expend. (GE)

Figure 5 below shows the time plots and density plots of Term of Trade (TOT) and Money Supply (M2) respectively. The Term of trade time plot shows that there is upward and downward in the trend of the data. The density plot show that the distribution of the data is negatively skewed. The Money supply time plot shows an upward trend and a downward trend toward the year 2017 and the density plot shows that the distribution of the data is not skewed. Figure 6 shows the time plots and density plots of Petroleum Local Price (PLP), Coal (CL) & Net Barter Trade (NBT) respectively. The Petroleum local price time plot shows that there is increments in price of petroleum yearly. The density plot show that the distribution of the data is positively skewed. The Coal time plot shows a parallel trend and the distribution of the data was positively skewed. The Net Barter Trade time plot shows an upward and downward in the trend of the distribution of the data. The density plot shows that the distribution of the data slightly symmetry.

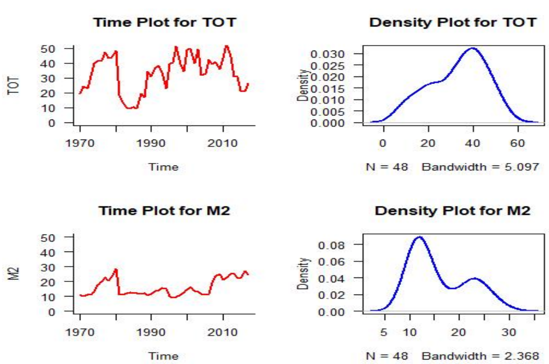

Figure 5: Time Plot and Density Plot for Term of Trade (TOT) and Money Supply (M2)

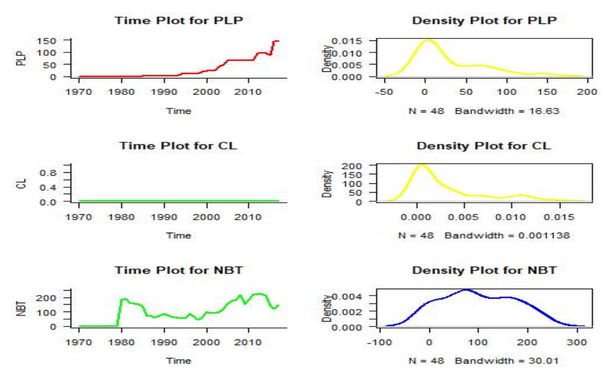

Figure 6: Time Plot and Density Plot for Petroleum Local Price (PLP), Coal (CL) & Net Barter Trade (NBT)

In summary from Figure 1 to Figure 6, all the regressors are positively skewed except TOT which is negatively skewed and Money supply which is not skewed.

Bayesian Model Analysis

To perform the BMA analysis, a uniform model prior and birth-death MCMC sampler is considered. The MC3 sampler utilizes a modified g-prior ($g = K^2$) with parameters of g=BRIC and 100000 draws following 20000 burn-ins with uniform distribution as the prior model. The data includes 13 predictors variables which means the combinations of our model is $2^{13} = 8192$ model combinations (See Table 2).

There is need to check for model sampling during Bayesian Model Averaging (BMA) analysis, and look for is simulation convergence. The number of observations for each predictors is 48, the model space is 8192 model combination. Table 2 shows the summary of our model of simulations in which the Posterior Model Probabilities (PMP) convergence. The correlation between iteration counts and analytical PMP's for 1527 best models is obtained as Corr PMP at 0.9977. This correlation is not perfect but already indicates a good degree of convergence. The top models show that the most performing predictor variable contributed 100% to the inflation rate and the mean number of the regressors is 3.4248 for 1527 models.

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Table 2: Checking for the PMP Convergence

Mean no. regressors "3.4248"	Draws "1e+05"	Burnins "20000"	Time "23.93086"	No. models visited "33264"
Model space 2^k "8192"	%visited "406"	%Top models "100"	Corr PMP "0.9977"	No. Obs. "48"
Model Prior "uniform / 6.5"	g-Prior "BRIC"	Shrinkage- Stats "Av = 0.9941"		

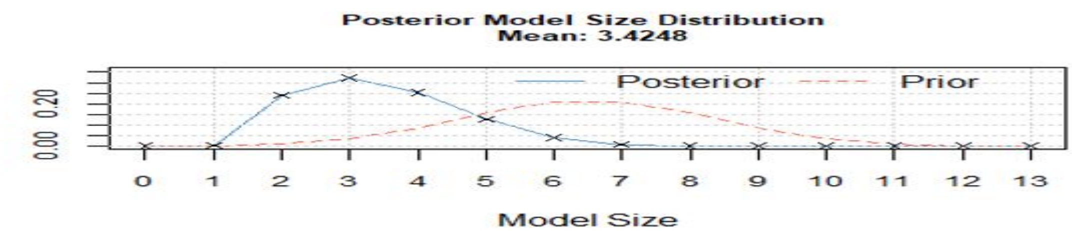

Figure 7: Posterior Model Size Distribution Plot

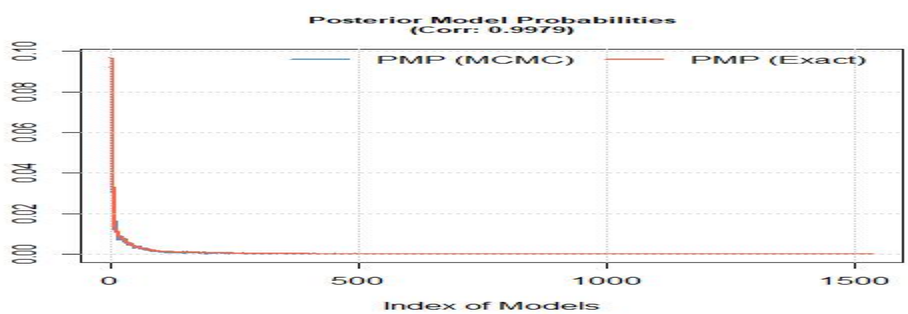

Figure 8: PMP Convergence Plot

From figure 8 shows the convergence plot for the posterior model probabilities and also present the best 1527 models encountered ordered by their analytical PMP (the red line), and their MCMC iteration counts (the blue line). Figure 7 shows the average number of the regressors (model size = 3.4248) for the 1527 best models.

Table 3 highlights the value of using the best models for inference rather than the complete model (model space). When compared to the posterior probability for the true (exact) model, the MC^3 sampler (PMP MCMC) estimate (1.0000) was precise with the best 1527 models. This is because the sampler visited about 100 % (33264) of the model space 8192 for its simulation.

Table 3: Cumulative Model Probabilities for the Exact and the MCMC

PMP (Exact)	PMP (MCMC)
1	1

Table 4 shows how each regressor's weight in relation to the feasible models is related by its posterior mean, standard deviation (SD) and conditional positive sign. The Posterior Inclusion Probability (PIP) of the BMA measures the relevance of the regressors. The

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regressor becomes increasingly significant as probability increases, especially when PIP is greater than 50%. From the whole regressors, it is only the real interest rate (RIR) that has the best PIP (100%) and this means that it is the most important variable when modeling Inflation rates. Additionally, the RIR regressor shows a standard deviation (0.1584844) and a negative average posterior mean (-2.136457). The conditional positive sign in the fifth column provides a straightforward explanation for this negative sign. The PIPs of all other regressors are also less than 50%, making them weak predictors of inflation rates. This is also evident in the posterior standard deviations of all these redundant variables being higher than the posterior means.

Table 4: Posterior Inclusion Probability for All the Regressors Using the MCMC Simulation

Regressors	PIP	Posterior Mean	Posterior SD	Cond.Pos.Sign	Idx
RIR	1.0000	-2.136457	0.1584844	0.000000	5
CL	0.43272	-670.6254	894.7259	0.000254	12
AE	0.37983	0.2842334	0.4494346	1.000000	3
NBT	0.35825	0.03071848	0.04875765	1.000000	13
GDP	0.25415	0.002139803	0.004743313	0.983789	4
PLP	0.14879	-0.02620073	0.1056975	0.205861	11
TPW	0.14555	-0.2674276	1.345951	0.316867	6
M2	0.13674	-0.0754979	0.2718317	0.066769	10
GE	0.12812	-0.1809152	0.7617844	0.149079	8
OR	0.12629	-0.034147	0.1343339	0.010531	2
OER	0.11497	0.006160681	0.03779821	0.786118	1
FCPI	0.10403	0.001514313	0.05086986	0.56849	7
TOT	0.09535	-0.000825455	0.0721367	0.588883	9

Table 5 consider the PIP's under exact = TRUE for first five predictors, it was observed that their PIP's are somewhat larger than with MCMC results. Also it was observed that the exact simulation's downgrade the PIP's of the worst variables. According to Fernandez et al. (2001b), most Bayesian prefer exact simulation for their inference.

Table 5: Posterior Inclusion Probability for the First Five Regressors Using the Exact Simulation

Regressors	PIP	Post Mean	Post SD	Cond.Pos.sign	Idx
RIR	1.0000	-2.1347	0.15817	0.0000000	5
CL	0.43136	-667.84	893.314	0.00005836	12
AE	0.36761	0.27474	0.44454	1.000000	3
NBT	0.36489	0.03125	0.04893	1.000000	13
GDP	0.26616	0.00221	0.00478	0.98295	4

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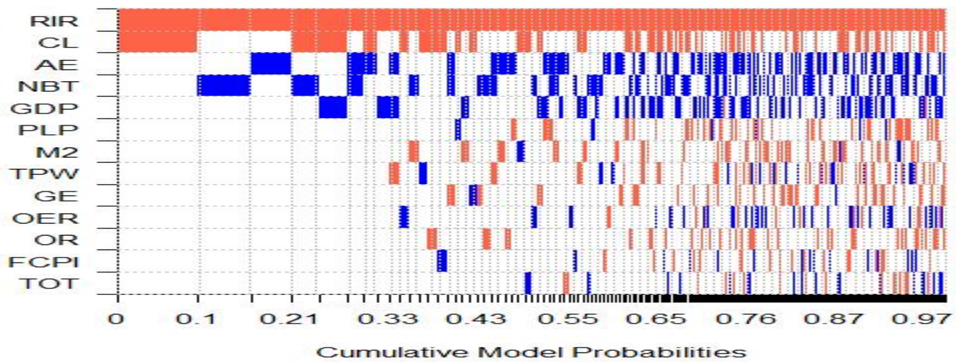

Figure 9: Cumulative Model Probability Based on Best 1527 Models

The Cumulative probabilities for the 1527 best models out of the 33264 visited models are totaled and scaled by posterior model probability (PMPs) for the models is shown in Figure 9. The model's regressor coefficients' signs are also indicated in Figure 9. That is, the RIR presents in all of the 1527 best model (PIP =100%) has a negative sign with red color, the blue color corresponds to a positive coefficient for a regressor in a model and the white color to non-inclusion (a zero coefficient).

The first 10 best models in the model space were selected based on their PMPs. The models are listed in Table 6 together with the coefficients (parameters estimates) of the regressors and their PMPs for both the analytical and MCMC counts. The best model (model1) for Nigerian inflation, according to the table, has PMP values of 0.097 (by Exact) and 0.091 (by MCMC), with coefficients of -2.101(RIR) and -1.921 (CL). It suggests that there is a 9.7% chance that model 1 is the real model. On the basis of Bayesian model selection principles, (model 1) is the best model and should be preferred above all other models.

Table 6: First 10 Best Models with Regressors Coefficients and PMPs (Analytical & MCMC) Counts

Regressors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
OER	-	-	-	-	-	-	-	-	-	3.100
OR	-	-	-	-	-	-	-	-	-	-
AE	-	-	0.649	-	-	0.383	0.334	-	1.221	-
GDP	-	-	-	-	4.394	-	-	0.007	0.015	-
RIR	-2.101	-2.098	-2.231	-2.125	-2.133	-2.200	-2.187	-2.086	-2.090	-2.156
TPW	-	-	-	-	-	-	-	-	-5.700	-
FCPI	-	-	-	-	-	-	-	-	-	-
GE	-	-	-	-	-	-	-	-	-	-
TOT	-	-	-	-	-	-	-	-	-	-
M2	-	-	-	-	-	-	-	-	-	-
CL	-1.921	-	-	-1.256	-1.517	-	-1.280	-	-	-1.615
NBT	-	0.099	-	5.932	-	0.064	-	-	-	-
PMP(Exact)	0.097	0.066	0.047	0.034	0.033	0.019	0.018	0.014	0.014	0.012

PMP(MCMC)	0.091	0.067	0.048	0.033	0.033	0.018	0.017	0.012	0.013	0.012

The marginal density of the real interest rate (RIR) and its PIP value (100%) are shown in Figure 10. The posterior predicted value (-2.23) for the model space is represented by the middle vertical line. This variable's posterior mean has a negative sign, which is consistent with the theoretical prediction. Theoretically, all market rates should decrease with an interest rate below zero, lowering the cost of borrowing for businesses and consumers alike.

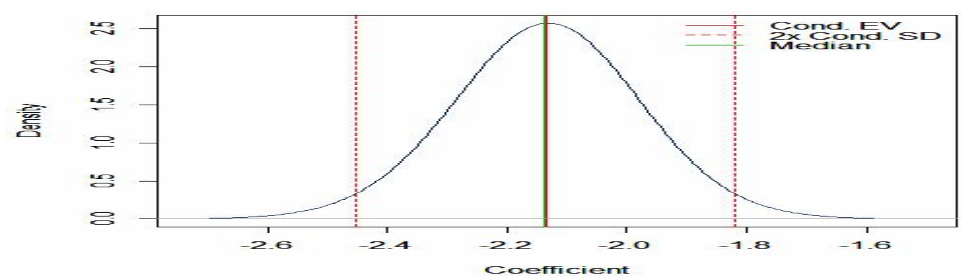

Figure10: Marginal Density of Real Interest Rate (RIR) with PIP 100%

For the year 2016 and 2017, the 47th and 48th observations respectively are given as in Table 7 along with the predicted values for the same years. Using the values of the regressors from years 1970 to 2015, the 2016 and 2017 forecasts are 1.132728 and -1.537809, respectively. The result of the forecast for 2016 shows a good fit (prediction) when compared with actual value (1.23367 for the year 2016). However, the prediction for 2017 raises the possibility of an anomaly or that the predictive model may not function as expected when compared with actual value (11.11892 for the year 2017). In order to enhance the true models other prior settings or data could then be examined.

Table 7: Predicted Response Variables for Years 2016 and 2017 Observations

Year (2016) 47th Observation	**Year (2017) 48th Observation**
1.132728	-1.537809

Table 8 displays the 2016 and 2017 95% credible interval (CI) for the predicted values. The years' predicted values fall within the bounds, intervals width indicating uncertainty about the estimated parameters.

Table 8: Credible Interval for Predicted Response Variables for Years 2016 and 2017 Observations

	95% Lower CI	95% Upper CI
Year (2016) 47th Observation	-39.47010	36.67348
Year (2017) 48th Observation	-49.46975	39.13942

Figure 11 simply shows the 2016 predictive density's expected value and distribution's standard error based on 500 models. The red solid line represents the expected predictive value, and the red breaking lines represent the distribution's standard error. This shows that the BMA prediction has good forecast.

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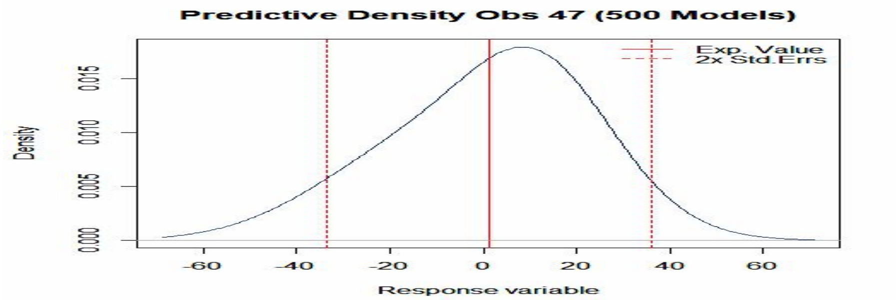

Figure 11: Predictive Density for Year 2016 Over 500 Models

Figure 12 displays the 2017 predictive density's expected value and distribution's standard error based on 500 models. The red breaking lines and solid line reflect the standard error of the distribution and the expected predictive value, respectively.

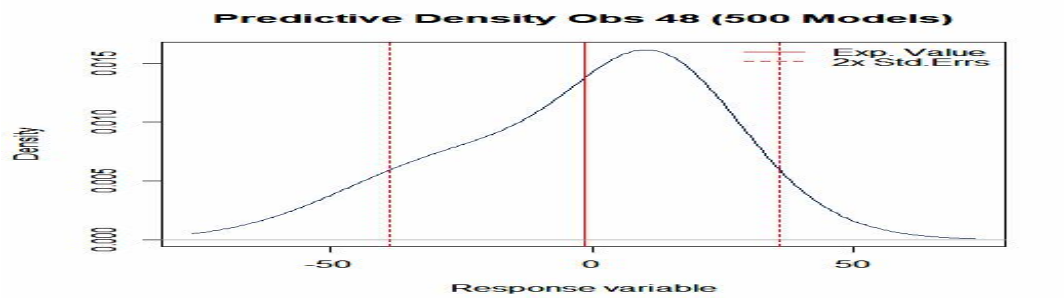

Figure 12: Predictive Density for Year 2017 Over 500 Models

CONCLUSION

In this study, Bayesian Model Averaging is used as an efficient tool for discovering promising regressors and models by obtaining estimates of their posterior probabilities via Markov chain Monte Carlo (MCMC). BMA provides a better average predictive performance that takes account of important source of uncertainty in the selected models. To ensure model uncertainty, the posterior model probabilities were used to select the best model combinations for model sampling during the Bayesian Model Averaging analysis. To ensure parameter uncertainty, the posterior inclusion probabilities was used to measure the relevance of the regressors. Among the 13 regressors, the real interest rate has the highest PIP as the most important variable when modeling inflation rate using economic data (see Table 4 and 5). Hence, policy makers should always review the real interest rate as it is a major factor in determining inflation rates in an economy.

This research is an improvement on the work of Olubusoye and Ogbonna, 2014; where lesser regressors (12 predictors) resulting into 4096 model combinations were considered compared with 8192 model combinations considered in this study. Also the scope of data collected for analysis was increased to 48 years (1970 – 2017) compared with 31 years (1980 – 2011) considered in the previous study.

Bayesian model averaging is an empirical tool in determining both model and parameter uncertainties towards ensuring almost perfect analysis to be applied by economists and policy makers.

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