Enhancing Nigerian Oil Price Forecasting: A Comprehensive Analysis of Model Averaging Techniques

Abstract

Numerous fields of endeavour have benefited greatly from statistical forecasting, which has aided decision-making by planners and policy makers. In this study, Bayesian Model Averaging (BMA) and Dynamic Model Averaging (DMA)areemployed to forecast oil prices in Nigeria. It aimedatpredicting the oil prices in Nigeria. Essentially, there are lot of model uncertainties in empirical growth researches. The predictive performance value considering the Mean Squared Forecast Error (MSFE) for BMA and DMA were 920.23 & 540.40 respectively. The DMA predicted the model better than the BMA. High levels of model uncertainties were indeed accounted for, in conformity with the theoretical knowledge.

Keywords: Log Predictive Score, Forgetting factor, Model Uncertainty, Oil Prices, MSFE.

1. INTRODUCTION

Oilimporting and exporting countriesneed consistent information on unsteadiness of oil prices. Sincerely, a lot of macroeconomic models are also predetermined by theprice of oil. Thus, the private investors, many government agencies and even central banks have keen interest in them. Forecasting oil price has different theoretical techniques in the literature.

Though, there several procedures for predicting the oil price but, econometric models are more popularwhen compared with others. For instance, Lanza et al. (2005) established the relationship among heavy crude oil prices and product prices. They made a comparison among ten heavy crude oil price series and fourteen petroleum product price series in Europe and America. The sample period was from 1994 to 2002, and they adoptedcointegration and Error Correction Model (ECM) tests to find out the relationships among the variables, and to model crude oil prices. The empirical results showed that product prices were related to heavy oil prices in both short and long terms. Furthermore, the comparison among ECM and naïve model did not show any dominant model in America; however, in the case of Europe, ECM marginally outperformed naïve model. Wang et al. (2005) carried out ARIMA approach to model the linear component of crude oil price time series. They use monthly WTI crude oil data spanned January 1970 - December 2003. The out-of-sample forecasting results indicated that the linear ARIMA model displayed the poorest forecasting power when compared with the nonlinear artificial neural network and the nonlinear integrated fuzzy expert system approaches. Xie et al. (2006) modelled WTI crude oil prices with the application of ARIMA procedure. They applied WTI spot prices spanned January 1970 - December 2003. Then they compared the results with those of support vector machine and artificial neural networks methods. The out-of-sample forecasting results showed that, the ARIMA model gave the poorest forecasting performance among the mentioned methods. Fernandez (2010) performs an out-of-sample forecasting for short- and long-term horizons with using ARIMA model. He employed daily natural gas and Dubai crude oil prices spanned 1994 - 2005. The result proved that for very short-term horizon, the ARIMA model outperformed the artificial neural networks and the support vector machine approaches; however, for long term horizon model, the ARIMA model provided the poorest accurate models.

In the case of structural models, different basicpredictors determine the oil price movement. The predictors that arefrequentlyconsidered for the oil price behaviour are OPEC behaviour, oil inventory level, oil consumption and production, and some non-oil variables such as economic activity, interest rate, exchange rate, and other commodity prices. Also, due to the difficulties and complexities of structural models, there are litle studies that performed structural analyses in order to model oil prices. Ye et al. (2005) predicted short term one month ahead nominal WTI crude oil spot price by assessing the impact of relative inventory level. In this model, the only explanatory variables are OECD industrial relative petroleum inventory level; moreover, 11 September 2001 terrorist attack and OPEC quota tightening in 1999 are dummy variables of the model. They did notinclude the lower-than-normal OECD inventory level variable from their new model as this variable increased the out-of-sample model error. They used monthly data spanned January 1992 - April 2003. Then, compared the results from the above relative stock model with the two benchmarks forecasting models: naïve autoregressive forecasting model and modified alternative model. The in and out-of-sample investigation criteria indicated that the relative stock model depicted the best forecastingperformance and the naïve model exhibited the poorest one.

Lee and Huh, (2017) used Bayesian procedure toforecasting oil prices with reflecting structural changes in the oil market. The main drivers for the forcast were world oil demand and supply, the financial situation, upstream costs, and geopolitical events. In order to test for the model's forecastingability, it was compared with a linear ordinary least squares model and a neural network model. The proposed model outperformed, on the forecasting performance ability even though the neural network model shows the best results on a goodness-of-fit test. Leng and Li, (2020) investigated the dynamic forecasting of crude oil prices via Bayesian and Econo-physics approaches by proposing information entropy to measure the predictability of crude oil prices and employed the rolling window approach to model the dynamic price of crude oil. Bayesian and Classical techniqueswere adopted simultaneously to estimate the parameters in the models. Comparison of forecasting results of the two methods indicated that both procedures can effectively estimate the parameters of Heston model.Wang et al. (2015) contributed to this strand through the use of a DMA method to improve forecasting accuracy of real oil prices. In DMA approach, forgetting factors are generally useful to approximate the evolution of model parameters and model switching probabilities, respectively. Drachal (2016) analysed the ability of predicting the crude oil price via fargetting factors in the DMA framework. The most important feature of this approach is that both coefficients and the set of predictors can change in time. It was found that certain versions of DMA prediction quality are higher than that of the naïve forecasting model.The methodology for the BMA (Akanbi and Oladoja, 2018, Tumala et'al, 2018, 2019) and DMA techniques investigate the important variables in a model selection process, and are presented in the next section of the paper.

2. FRAMEWORK AND METHODOLOGY

A. Bayesian Model Averaging

The problem of model uncertainty can be conquered by employing BMA Approach. This approach determines the order of important of the variables by averaging across the plausible models for certain priors elicitation. Estimations of the parameters in the models are achieved by averaging the weights attached to the models (Posterior Model Probability) over the entire model space (*M)*.

BMA Predictive Performance

Generally, BMA is employed because of its exhibition of the uncertainties imbeded in a model selection process and the ability toenhance the predictive performance for a data set splitted to training, T^D and prediction, P^D (Hoeting et al, 1999).

Log Predictive Score Rule

The logarithmic scoring rule (LPS) was established by Good in 1952. Firstly, for a single model, M a predictive performance will be constructed, as

$$-\sum_{\beta \in P^D} log\{P\, r(\beta | M,\, T^D)\} \tag{1}$$

And then, computethe predictive performancefor the plausible modelsin BMA by

$$-\sum_{\beta \in P^D} \left[log\{\sum_{j=1}^{l} P\, r(\beta | M_j,\, T^D)\, P\, r(M_j,\, T^D)\}\right] \tag{2}$$

The LPS is measured as the larger it is, for a given model or model average, the worst the predictive performance.

B. Dynamic Model Averaging

The DMA model prediction equation is given as

$$\pi_{t|t-1,k} = \frac{\pi^{a}_{t-1|t-1,k}}{\sum_{l=1}^{K} \pi^{a}_{t-1|t-1,l}} \tag{3}$$

where 0 < α ≤ 1 is another forgetting factor similar to λ. Thus, (3) becomes

$$\pi*_{t|t-1,k} = \frac{\pi_{t-1|t-1,kPk^{(y_t|y^{t-1})}}}{\sum_{l=1}^{K} \pi_{t|t-1,IPI}^{(y_t|y^{t-1})}} \tag{4}$$

where $P_l(y_t|y^{t-1})$ is the model predictive density measured at y_t. Recursive forecasting is achieved by averaging across the predictive results for every model with$\pi_{t|t-1,k}$. Thus,

TheDMA point predictionis given by:

$$E\left(y_t \mid y^{t-1}\right) = \sum_{k=1}^{K} \pi_{t|t-1,k^{z_t^{(k)}\hat{\theta}_{t-1}^{k}}} \tag{5}$$

In DMA forcasting procedure,model with thehighest value for$\pi_{t|t-1,k}$ at a particular time will be considered. Also,for α = 1, then $\pi_{t|t-1,k}$gives the marginal likelihood at time *(t-1)* and then approximates to BMA. Similarly, for λ = 1, then it arrives at BMA throughthe conventional linear forecasting models with no time variations in coefficients. Consequently, in this study, α = λ = 1 were set for the BMA procedure in order to compare it with the DMA forcasting performances.

3. RESULTS AND DISCUSSIONS

Table 1gives the predicted values for the year 2021 and the year 2022 representing the 41st and 42nd observations respectively. The predictions are 71.87 and 82.24 for 2021 and 2022 respectively. And when compared with their actual values (70.81, 81.94), the forecast for both years has a good fit (prediction), which suggest that our predictive model performs well.

Table 1: Predictions for years 2021 and 2022

Year 2021 (41st observation)	Year 2022 (42nd observation)
71.87177	82.23697

Figure 1 depicts only the expected value for the 2021 predictive density without comparing it with the actual value using 500 models. From the density, the expected predictive value of 71.87 in table 1 is confirmed (72) for this year. The expected predictive value is the red solid line while the red break lines arethe standard errors of the distribution in the figure below.

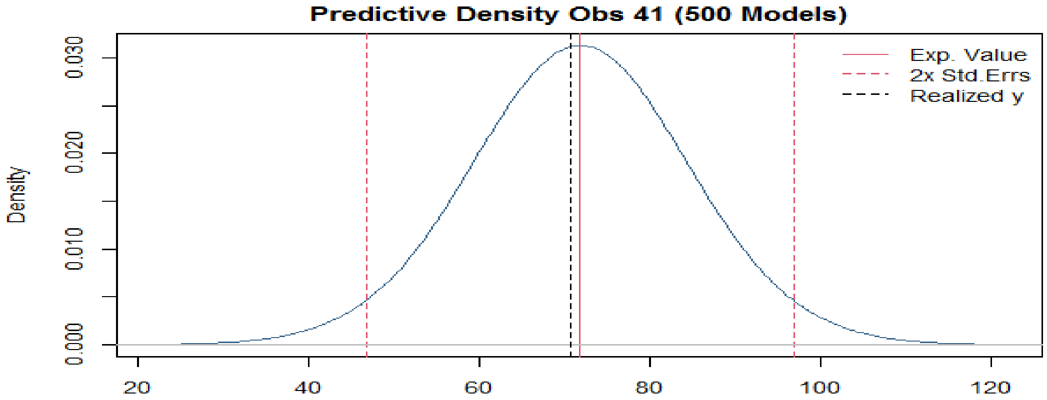

Figure 1: Predictive density for year 2021 over 500 models

4. Model Forecast Evaluation and Comparison

The forecast comparison of the DMAand the BMA models are considered in this section. The forcast was investigated with different forgetting factors from $\alpha = \lambda = 0.93$ to 0.99. The choice of forgetting factors and benchmark ($\alpha = \lambda = 0.99$) for a period (t) is based on the recommendations of Raftery et al. (2010). The forcast performance evaluations used for this study were theMSFE [for a point forecasts] and the sum of log predictive likelihoods [for the entire predictive performance]. A special case of DMA which approximately gives BMA (forgetting factors, $\alpha = \lambda = 1$) was also presented.

Table 2depicts the forecasting model performance comparison with different forgetting factors for the oil prices. In this table, it is shown that the DMA forecast with the two forgetting factors at equal value of 0.95 ($\alpha = \lambda = 0.95$) gave the best overall forcast, implying that the model and parameters are allowed to change. DMA shrinks the contribution of all models except one towards zero which is an advantage over the BMA. The outcome is consistent with forecasts gotten by Koop and Korobilis (2012) for inflation and Gupta et al. (2014) for foreign exchange reserves when similar models were considered. Both the sum of the log predictive likelihoods and the MSFE indicated that for a BMA model prediction,it has a poorer forecasting performance, when compared with the best, and the benchmark DMA as a result of the shrinkage factor in the DMA.

Table 2: Forecast Performance Comparison

Model	BMAand DMA	MSFE	Log (PL)

1	BMA&DMA(with $\alpha = \lambda = 1$)	920.376	-60.217
2	DMA ($\alpha = \lambda = 0.95$)	540.396	-52.704
3	DMA ($\alpha = \lambda = 0.99$)	884.748	-58.828
4	DMA ($\alpha = 1, \lambda = 0.95$)	767.308	-53.643
5	DMA ($\alpha = 1, \lambda = 0.99$)	926.957	-59.918

Figure 2 showed the actual and forecasted values of the crude oil price for the best-performing DMA model. It is noticeable from the plot that this model follows the actual oil price series rather well, producing broadly similar forecasts.

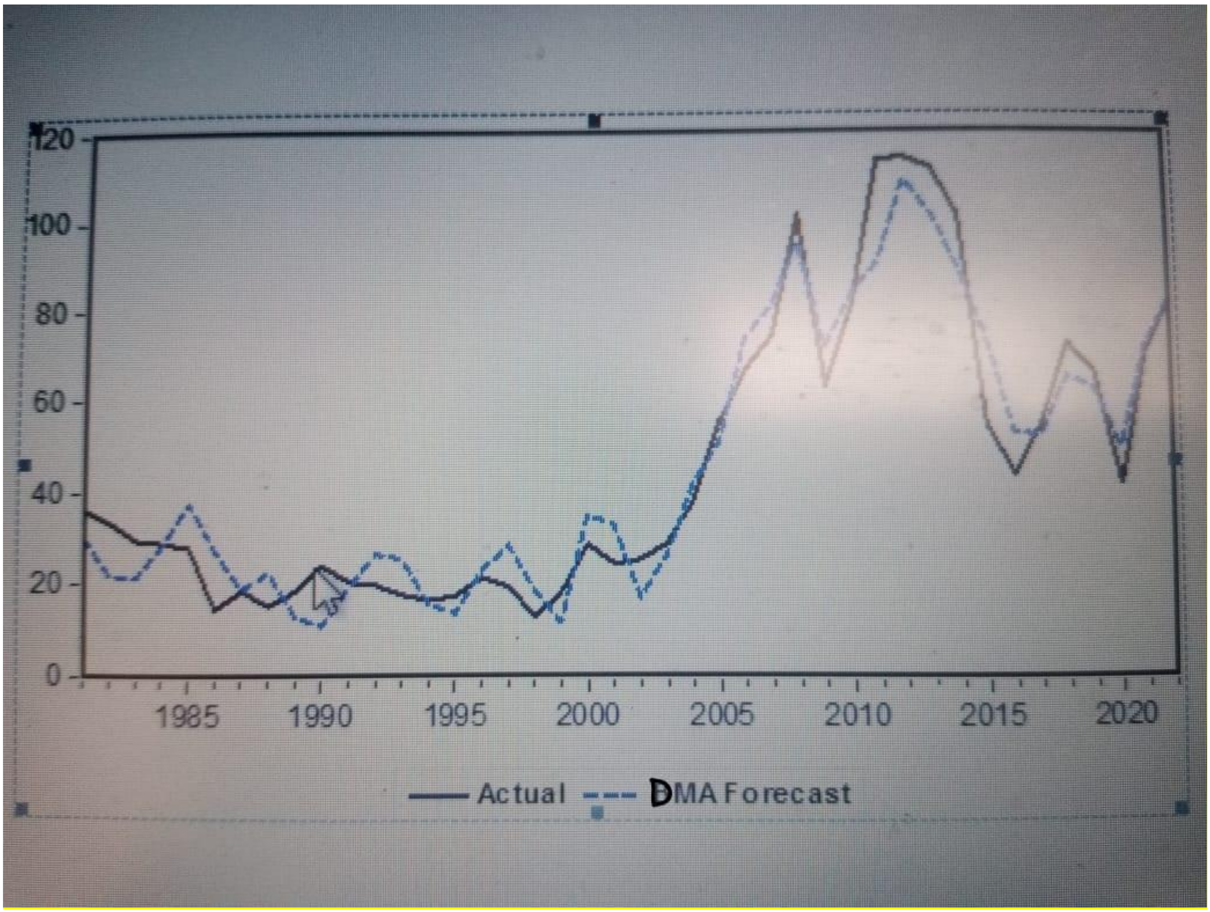

Figure 2: Plots the actual and the forecasted values of the price of crude oil for the best-performing DMA model.

5. CONCLUSION

Bayesian and Dynamic Model Averagings; BMA and DMA were adopted in this study. The predictive performance valuesusing the Mean Squared Forecast Error (MSFE) for BMA and DMA were 920.23 & 540.40 respectively. The DMA predicted the model better than the BMA. Moreover, high levels of model uncertainties were indeed accounted for, in conformity with the BMAtheoretical knowledge.

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