ForecastingNigerianOil Prices Using 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)are used to forecast oil prices in Nigeria. It aimed to understand the causes of oil prices as well as the most accurate model for predicting oil prices in Nigeria. Essentially, there are lot of model uncertainties in empirical growth researches. The predictive performance value using the Mean Squared Forecast Error (MSFE) for BMA and DMA were 920.23 & 540.40 respectively. Thus, a wider range of financial variables is needed in improving the predictive accuracy of the model. 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: Posterior Inclusion Probabilities, Posterior Model Probabilities, Model Uncertainty, Oil Prices.

1. INTRODUCTION

Oil price fluctuations are crucially important for both oil-importing and oil-exporting countries. Indeed, oil price is a key for many macroeconomic models. Therefore, they are of high interest not only for private investors, but also for several government agencies and central banks. There are various theoretical approaches to forecasting oil price.

Among existing oil price forecasting literature, econometrics models are the most frequently used methods. For instance, Lanza et al. (2005) estimate the relationship among heavy crude oil prices and product prices. The authors implement a comparison among ten heavy crude oil price series and fourteen petroleum product price series in Europe and America. The sample period is from 1994 to 2002, and they apply cointegration and error correction (ECT) tests to find out the relationships among the variables, and to model crude oil prices. The empirical results indicate, there is evidence that product prices are related to heavy oil prices in short and long term. Furthermore, the comparison among ECM and naïve model does not show any dominant model in America; however, in the case of Europe, ECM marginally outperforms naïve model. Wang et al. (2005) carry out ARIMA approach to model the linear component of crude oil price time series. They use monthly WTI crude oil data from January 1970 to December 2003. The out-of-sample forecasting results indicate that the linear ARIMA model displays the poorest forecasting power in compare with the nonlinear artificial neural network and the nonlinear integrated fuzzy expert system approaches which will be discussed broadly in the next section. Xie et al. (2006) model WTI crude oil prices with applying ARIMA method. They apply WTI spot prices from January 1970 to December 2003. Then they compare the results with those of support vector machine and artificial neural networks methods. The out-of-sample forecasting results indicate that, the ARIMA model provides 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. The author employs daily natural gas and Dubai crude oil prices from 1994 to 2005. The result proves that for very short-term horizon , the ARIMA model outperforms the artificial neural networks and the support vector machine approaches; however, for long term horizon model, the ARIMA model provides the poorest accurate models.

In the case of structural models, the oil price movement is function of a group of fundamental variables. The explanatory variables that commonly used to explain 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. In this context, there are many studies that investigate oil prices based on fundamental variables and some of them explain the price movement fairly well; however, it does not mean that they show good forecasting performance, as there is limitation on availability for future values of the explanatory variables; therefore, due to the difficulties and complexities of structural models there is a small number of 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 assessment 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. The authors exclude the lower-than-normal OECD inventory level variable from their new model as this variable increase the out-of-sample model error. They use monthly data from January 1992 to April 2003. They compare the results from the above relative stock model to the two benchmarks forecasting models: naïve autoregressive forecasting model and modified alternative model. The in and out-of-sample evaluation criteria indicates that the relative stock model shows the best forecasting performance, and the naïve model shows the poorest one.

Lee and Huh, (2017) suggests an alternative model for accurately forecasting oil prices while reflecting structural changes in the oil market by using a Bayesian approach. The model includes independent variables affecting oil prices, such as world oil demand and supply, the financial situation, upstream costs, and geopolitical events. To test the model's forecasting performance, it is compared with other models, including a linear ordinary least squares model and a neural network model. The proposed model outperforms on the forecasting performance test even though the neural network model shows the best results on a goodness-of-fit test. Leng and Li, (2020) investigate 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 employ the rolling window approach to model the dynamic price of crude oil. Bayesian approach is applied to estimate the parameters, at the same time, the classic estimate approach is also adopted. Comparison of forecasting results of the two methods indicates that (1) both estimate approaches can effectively estimate the parameters of Heston model.Wang et al. (2015) contributed to this strand of the literature by using a dynamic model averaging (DMA) method to improve forecasting accuracy of real oil prices. There are several distinct advantages of the DMA method. It not only allows the parameters and a set of predictors in a regression-based model (or broadly speaking, state space model) to change at each point in time, but also is computationally feasible to consider many predictors in the model by introducing two forgetting factors to approximate the evolution of model parameters and model switching probabilities, respectively. Drachal (2016) analysed the ability of predicting the crude oil price in 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 are presented in the next section of the paper.

2. MATERIALS AND METHODS

A. Bayesian Model Averaging

The problem of model uncertainty can be conquered by employing BMA Approach. 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. Each model (a set of variables) receives a weight, and the final estimates are constructed as a weighted average of the parameter estimates from each of the models.

Let us assume that in order to describe the data y we consider the possible models; M_j, *j = 1, . . ., J* grouped in the model space *M*. 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. Each model (a set of variables) 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 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 on several key features of the averaging exercise including the choice of prior specified.

BMA Predictive Performance

One of the main arguments for using the BMA is based on its ability to improve our predictions, as measured by the out-of-sample prediction error. In Hoeting et al. (1999) there are several examples of BMA applications, each equipped with a convincing out-of-sample validation in terms of its predictive performance. The cross-validation was performed by splitting each data set into two parts, training set, D^T and prediction set, DP.The training set is used for model selection and the second set for prediction. Two measures of predictive ability were used, the coverage for 90% predictive interval, measured by proportion of observation of the second set falling within the 90% of the corresponding posterior prediction interval (Hoeting et al., 1999).

Log Predictive Score Rule

The second measure is the logarithmic scoring rule of Good (1952). Specifically we measure the predictive ability of a single model M as

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

And compare it with predictive ability of BMA as measured by

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

The smaller the predictive log score for a given model or model average, the better 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 $0 < \alpha \leq 1$ is another forgetting factor similar to λ. Thus, (3) becomes

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

where $P_l(y_t|y^{t-1})$ is the predictive density for model l (which is simply a normal density) evaluated at y_t. Recursive forecasting can be done by averaging over predictive results for every model using $\pi_{t|t-1,k}$. Therefore,

TheDMA point predictionis given by:

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

DMA proceeds by selecting the single model with the highest value for $\pi_{t|t-1,k}$ at each point in time and simply using it for forecasting. Note also that, if α = 1, then $\pi_{t|t-1,k}$ is simply proportional to the marginal likelihood using data through time *t-1* and yields the standard approaches to BMA. If we also set λ = 1, then we obtain BMA using conventional linear forecasting models with no time variations in coefficients. In our forecast comparison exercise, we include BMA in our set of alternative forecasting procedures and implement this by setting α = λ = 1.

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.

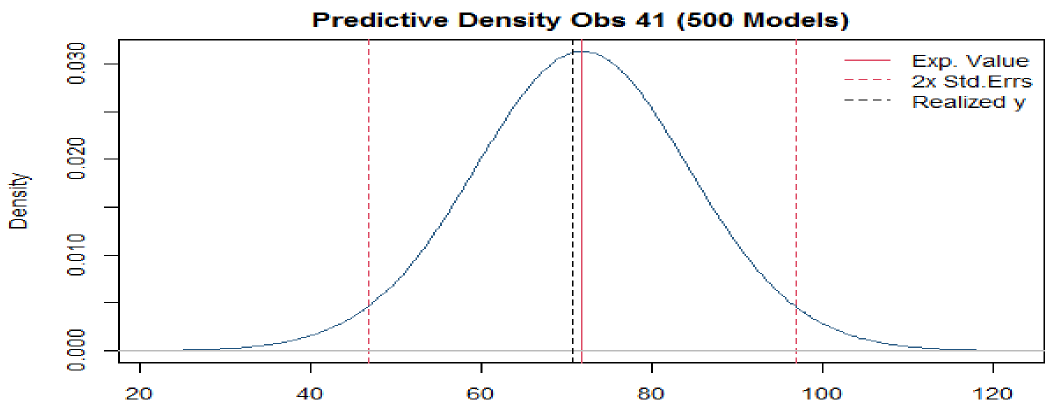

Figure 1: Predictive density for year 2021 over 500 models

4. Model Forecast Evaluation and Comparison

This section focuses on the forecast comparison of the DMA model to the BMA model described above. The reported results include the findings obtained from α = λ = 0.93 to 0.99. We use Mean SquaredForecastError (MSFE) and the sum of log predictive likelihoods in evaluating forecast performance. The MSFE is a standard measure of the performance of point forecasts, whereas the sum of log-predictive-likelihoods is a measure of the forecast performance of the entire predictive density. Formally, the predictive likelihood at time t is the predictive density (given information through t−1) evaluated at the actual outcome. We also present the results obtained from a special case of DMA known as Bayesian model selection (BMA) where both forgetting factors are equal to one (i.e., α = λ = 1).

In terms of forecasting models, results for the following models are reported:

- Forecasting using DMA with α = λ = 0.99;
- Forecasting using DMA with α = λ = 0.95; This is the best performing DMA model;
- Forecasting using DMA with α = 1 and λ = 0.95
- Forecasting using DMA with α = 1 and λ = 0.99; and
- Forecasting using BMA as a special case of DMA (i.e., α = λ = 1).

Model (1) involves using the benchmark values α = λ = 0.99. This allows not only for the parameters to change over time but also for the set of predictors. Models(3) and(4) areconstant models, but the parameter evolution is allowed, while in Model (5), through setting both forgetting factors to one, we obtain the Bayesian model averaging (BMA) which uses conventional linear forecasting models with no time variations in the coefficients. Our choice of forgetting factors and benchmark is based on the recommendations of Raftery et al. (2010). The benchmark of α = λ = 0.99 means that we allow for a substantial amount of change in the model and parameter over time.

Table 2. presents the results of our forecasting exercise for oil prices. From this result, it is clear that the DMA forecast generally well, with DMA (α = λ = 0.95) being the best overall, implying that the model and parameters are allowed to change. DMA can be interpreted as doing the shrinkage of predicting variables in different ways, DMA shrinks the contribution of all models except one towards zero. This additional shrinkage appears to have given DMA additional benefits over BMA. This finding is consistent with forecasts obtained by Koop and Korobilis (2012) for inflation and Gupta et al. (2014) for China's foreign exchange reserves using similar models. Both the sum of the log predictive likelihoods as well as the MSFE indicates that using a BMA model for forecasting results in poorer forecasting performance, relative to the best and the benchmark DMA. The poor forecast performance of the BMA model compared to DMA is an indication that the shrinkage provided by the latter models is of great value in forecasting.

Table 2: Forecast Performance Comparison

Model		**MSFE**	**Log (PL)**
1	BMA (DMA with α = λ = 1)	920.376	-60.217
2	DMA (α = λ = 0.95)	540.396	-52.704
3	DMA (α = λ = 0.99)	884.748	-58.828
4	DMA (α = 1, λ = 0.95)	767.308	-53.643
5	DMA (α = 1, λ = 0.99)	926.957	-59.918

Figure 2 shows the actual and forecasted values of the price of crude oil 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.

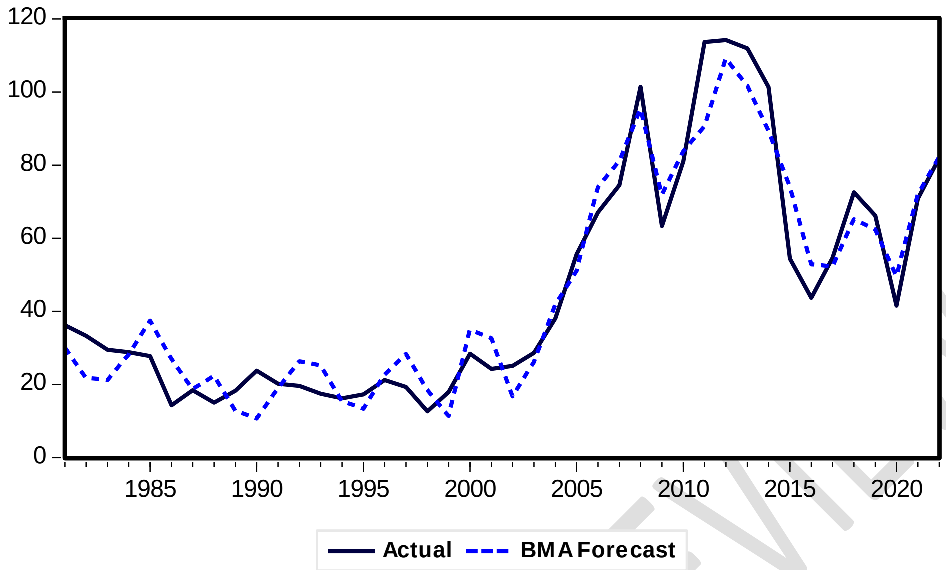

Figure 2: Plots the actual and the forecasted values of the price of crude oil for the best-performing DMA model.

5. CONCLUSION

Bayesian and Dynamic Model Averagings; BMA and DMA were adopted in this study. The predictive accuracy level for the model was also obtained using the BMA and DMA. The predictive performance value using the Mean Squared Forecast Error (MSFE) for BMA and DMA were 920.23 & 540.40 respectively. The refinery capacity, exchange rate, broad money and total reserve are the main drivers/predictors for forecasting the Nigerian oil prices. Thus, a wider range of financial variables is needed in improving the predictive accuracy of the model. The DMA predicted the model better than the BMA. High levels of model uncertainties were indeed accounted for, in conformity with the theoretical knowledge.

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