Modelling Inflation Process in Nigeria using Bayesian Model Averaging

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Second Bayesian Young Statisticians Meeting (BAYSM 2014)
Vienna, September 18–19, 2014

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Abstract

This paper is aimed at modelling inflation process in Nigeria using Bayesian Model Averaging approach. BMA offers a coherent mechanism for dealing with model uncertainty. The study investigated the key drivers of inflation movement. Twelve likely predictors were considered which resulted in 4,096 plausible models comprising the inclusion and non-inclusion of one or more predictors. Each model was weighted accordingly with a model prior and parameter prior. Model uncertainty and posterior inclusion probability of each predictor was determined. Crop production was the most probable. The top five models explained only 49.53% variation in inflation which reveals the risk of depending on single model prediction. Bayesian Model Selector (BMS) in R was used to analyse the data.

Keywords: Model Uncertainty; Prior Distribution; Posterior Distribution; Shrinkage; Forecasting.

1 Introduction

Inflation is one primary persistent threat that can destroy decades of economic growth if it is not curbed. Monetary policy over past decades has therefore been geared towards attaining price stability. In reality, the true model is unknown. Hence, depending on a single model is unrealistic and misleading. BMA offers a more coherent mechanism for dealing with model uncertainty. Its application to modelling inflation process in Nigeria is of interest to determine the key drivers of inflation in Nigeria and the risk of ignoring model uncertainty.

2 Literature Review

Several techniques are available in literature to describe economic relationships. For instance, a simple Phillip Curve uses a single economic slack to explain inflation outcomes[6], but several authors [3][21] have questioned its usefulness. This practice ignores the uncertainty of selecting the true model and results to Akaike information criterion, AIC[1], Bayesian information criterion, BIC[20] and cross validations or generalized cross validation[8] as model selection criteria.

Bayesian Model Averaging averages over all plausible models and estimates model uncertainty[15] and has been applied in various economic models[2][7][12][18] such as output growth forecasting[14][17], cross-country growth regressions[10][11], stock return prediction[4][9] and US inflation forecasting[13]. Avarmov and Cremers both report improved pseudo-out-of-sample predictive performance from BMA. Posterior probability is spread widely among many models. This suggests the superiority of BMA over choosing any single model[5]. In contrast to Levine *et al.*[16], the results of Carmen *et al.* broadly supports the more optimistic conclusion that some variables are important regressors for explaining cross-country growth patterns[19].

3 Methodology

An empirical inflation model assumed to be predicted by several indicators is specified. The true model is unknown but various candidate models exists. Consider a linear regression model

$$Y = X\beta + \epsilon \tag{1}$$

where there are k potential explanatory variables yields 2^k different combinations of predictor variables indexed by M_j for $j = 1, 2, ..., 2^k$. Specification of model prior indicates how probable one thinks the model is before looking into the data. Oftentimes, a uniform prior is employed. Renormalization then yields posterior model probabilities, PMPs which are used as weights for each coefficient, β_h in the model space given the data D. The posterior probability of each coefficient is

$$Pr(\beta_h|D) = \sum_{j:\beta_h \in M_j} Pr(\beta_h|M_j)Pr(M_j|D) \tag{2}$$

Posterior model probability $Pr(M_j|D)$ the ratio of its marginal likelihood to the sum of marginal likelihoods over the entire model space is given by

$$Pr(M_j|D) = \frac{Pr(D|M_j)Pr(M_j)}{Pr(D)} \tag{3}$$

$$Pr(M_j|D) = \frac{Pr(D|M_j)Pr(M_j)}{\sum_{i=1}^{2^k} Pr(D|M_i)Pr(M_i)} \tag{4}$$

$$Pr(M_j|D) = \frac{[\int Pr(D|\beta^j, M_j)Pr(\beta^j|M_j)d\beta_j]Pr(M_j)}{\sum_{i=1}^{2^k} Pr(D|M_i)Pr(M_i)} \tag{5}$$

where $\beta^j \rightarrow$ the vector parameters from model M_j
$Pr(\beta^j|M_j) \rightarrow$ prior probability distribution assigned to the parameters of model M_j
$Pr(M_j) \rightarrow$ prior probability that M_j is the true model. The estimated posterior means and standard deviations of $\hat{\beta}^j = (\hat{\beta}_0, \hat{\beta}_1, ..., \hat{\beta}_k)$ are then constructed as

$$E[\hat{\beta}|D] = \sum_{j=1}^{2^k} \hat{\beta} Pr(M_j|D) \tag{6}$$

$$V(\hat{\beta}|D) = \sum_{j=1}^{2^k} (var[\beta|D, M_j] + \hat{\beta^2}) Pr(M_j|D) - E[\hat{\beta}|D]^2 \tag{7}$$

4 Empirical Results

Annual data spanning $1980 - 2011$ on consumer price index (CPI), obtained from Economy Watch and World Development Indicators (WDI) was used to proxy inflation. Other series include GDP, money and quasi money (M2), exchange rate, real effective exchange rate, net income from abroad, net difference between import and export, interest paid on external debt, lending interest rate, imports, narrow money, GDP growth and crop production. The first 30 years was used for estimation and the remaining 2 for in-sampling forecasts.

Table 1: Bayesian Model Averaging Results

	PIP	Post Mean	Post SD	Cond.Pos.Sign	Idx
CRP	1.00000000	8.263934e-01	1.531850e-01	1.00000000	12
LIR	0.96281397	-1.112217e+00	3.800038e-01	0.00000000	8
EXR	0.90572719	1.661153e-01	7.650262e-02	1.00000000	3
M2	0.71307389	4.733007e-12	3.448659e-12	1.00000000	2
M1	0.33488109	3.839433e-06	7.207850e-06	0.86820826	10
NIFA	0.20430421	-1.791552e-12	4.437102e-12	0.00000000	5
GDP	0.15082129	9.003220e-12	2.812145e-11	0.98669857	1
REER	0.09424478	1.389250e-03	6.961321e-03	1.00000000	4
GDPGR	0.09375349	1.703688e-02	8.375622e-02	0.99243481	11
IPEDT	0.07613828	3.755754e-11	4.569311e-10	0.81381157	7
IMP	0.07104874	-6.658082e-12	1.042159e-10	0.45027050	9
BOT	0.06722674	-6.768846e-12	7.207111e-11	0.03183918	6

CRP, LIR, EXR, M2 and M1 have strong explanatory power in explaining inflation. The mean recommended number of covariates is five based on results obtained from 744 model samples considered from the 4,096 plausible models with shrinkage statistic 0.9931. The best model comprising M2, EXR, LIR and CRP has model uncertainty of 74% while the second best has 93% uncertainty. This shows the risk of explaining inflation process by a single model. The top five models comprising of CRP, LIR, EXR, M2, M1 and GDP can only explain 49.53% of the inflation process in Nigeria.

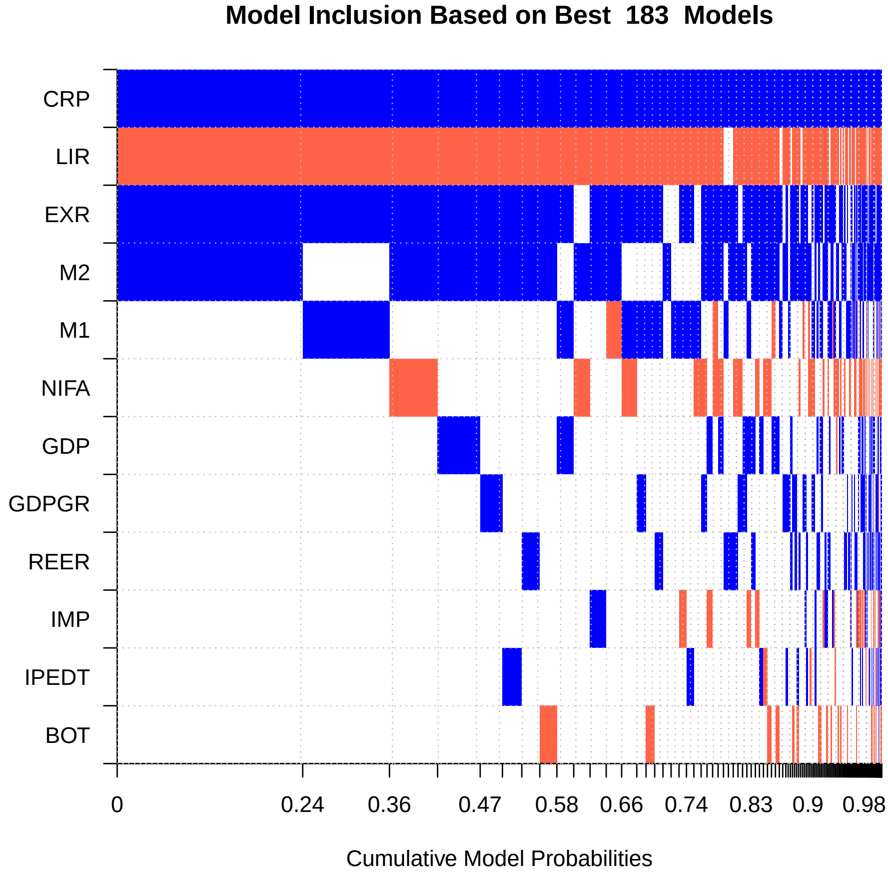

Figure 1: Chart showing cummulative model probabilities

The correlation between iteration counts and analytical PMPs for the 100 best models is 0.9737 which indicates a good degree of convergence. Figure 1 shows that CRP, the most probable covariate is positively signed (blue colour) while LIR is also highly probable but negatively signed. In-sample forecast for 2010 and 2011 yielded an error of 5.12 and 3.62 respectively. This shows the adequacy of BMA.

References

[1] Akaike,H. (1973). "Information theory and an extension of the maximum likelihood principle.", *Proc. 2nd Inter. Symposium on Information Theory*, 267-281, Budapest.

[2] Amini S.M., Parmeter C.F. (2011). "Bayesian Model Averaging in R." *Journal of Economic and Social Measurement*, **36**(4), 253–287.

[3] Atkeson, A. and Ohanian, L., (2001). "Are Phillips Curves Useful for Forecasting Inflation?" *Federal Reserve Bank of Minneapolis Quarterly Review*, **25**, 2–11.

[4] Avramov, D. (2002). "Stock Return Predictability and Model Uncertainty.", *Journal of Financial Economics*, **64**, 423–458.

[5] Carmen Fernandez, Eduardo Ley and Mark F. J. Steel, (2001). "Model uncertainty in cross-country growth" *Journal of Applied Econometrics J. Appl. Econ.*, **16**, 563–576.

[6] Cecchetti, S., R. Chu and C. Steindel (2000). "The Unreliability of Inflation Indicators.", *Federal Reserve Bank of New York Current Issues in Economics and Finance*, **6**, 1–6.

[7] Chipman, H., E.I. George and R.E. McCulloch (2001). "The Practical Implementation of Bayesian Model Selection, mimeo."

[8] Craven, P. and Wahba, G. (1979). "Estimating the Correct Degree of Smoothing by the Method of Generalized Cross-Validation.", *Numerische Mathematik*, **31**, 377–403.

[9] Cremers, K.J.M. (2002). "Stock Return Predictability: A Bayesian Model Selection Perspective.", *Review of Financial Studies*, textbf15, 1223–1249.

[10] Doppelhofer, G., R.I. Miller and X. Sala-i-Martin (2000). "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach.", *NBER Working Paper 7750.*

[11] Fernandez, C., Ley, E. and Steel, M. (2001). "Model uncertainty in cross-country growth regressions." *Journal of Applied Econometrics*, **16**(2), 563–576.

[12] Hoeting, J.A., D. Madigan, A.E. Raftery and C.T. Volinsky (1999). "Bayesian Model Averaging: A Tutorial.", *Statistical Science*, textbf14, 382–417.

[13] Jonathan H. Wright (2003). "Forecasting U.S. Inflation by Bayesian Model Averaging." *International Finance Discussion Papers*, No. 780.

[14] Koop, G. and S. Potter (2003): "Forecasting in Large Macroeconomic Panels Using Bayesian Model Averaging.", *Federal Reserve Bank of New York Staff Report, 163.*

[15] Leamer, E.E. (1978). *Specification Searches: Ad hoc inference with non experimental data.* Wiley, New York.

[16] Levine, Ross and David Renelt (1992). "A Sensitivity Analysis of Cross-Country Growth Regressions", *American Economics Review*, **82**(4), 942–63.

[17] Min, C. and A. Zellner (1993). "Bayesian and Non-Bayesian Methods for Combining Models and Forecasts with Applications to Forecasting International Growth Rates.", *Journal of Econometrics*, **56**, 89–118.

[18] Raftery, A.E., D. Madigan and J.A. Hoeting (1997). "Bayesian Model Averaging for Linear Regression Models.", *Journal of the American Statistical Association*, **92**, 179–191.

[19] Sala-i-Martin, Xavier, 1997. "I Just Ran Two Million Regressions.", *American Economic Review, American Economic Association*, **87**(2), 178–83.

[20] Schwarz, Gideon (1978). "Estimating the Dimension of a Model.", *The Annals of Statistics 6*, **2**, 461–464.

[21] Stock, J. H and Watson, M. W (2008). "Phillips Curve Inflation Forecasts." *NBER Working Papers 14322, National Bureau of Economic Research, Inc.*