On the Applicability of Advanced Forecasting Techniques to Developing Economies- A Case of Sri Lanka

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Abstract

This study attempts to find out whether advanced forecasting techniques that have been proved to be successfull in advanced countries can be employed to a developing country to forecast key macroeconomic variables. Five advanced forecasting models consisting of both univariate and multivariate models have been employed and the forecast accuracy of these models is evaluated againt that of benchmark ARMA model. Both point forecasts and density forecasts are produced from these models. Point forecast evaluation suggests that these models are superior to the benchmark model, though there is uncertainty in the significance of accuracy of mean inflation forecast. Density forecast performances of these models outperform the benchmark model without any doubt. This study has two main conclusions. First, these models can be included in the forecasting practice at the Central Bank of Sri Lanka to improve policy analysis. Second, the application of these models can be extended to any other developing country without large modifications.

Key Words: Bayesian Estimation, Forecasting, Stimulation, State-space models,Gibbs sampling

JEL Classification: E17,E37,C11,C15,C32,C53 & C55

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1 Introduction

Forecasting inflation and output has always been one of the key research interests in macroeconomics. Empirical studies for advanced economies have a long history and the forecasting methodology is being improved constantly in the recent years. Studies covering emerging and developing countries are just a handful and are only in the evolutionary stage. Moreover, many such studies are built on regression based or Vector Autoregression (VAR) based methodology. Recent advances in forecasting techniques have several superiority over these traditional approaches and were successful in forecasting key economic variables in advanced economies, at least before the recent financial crisis. It is worth applying these methods to a country like Sri Lanka to check their applicability to economies in transition. No study has been carried out to forecast output and inflation for Sri Lanka in the past, though there were some attempts to model inflation (see Cooray,2008; Ratnasiri,2009; Harischandra,2010 and Bandara,2011). This study fills the gap in the empirical literature. The findings of this study need not to be limited to Sri Lanka. If the advanced forecasting methods developed and applied in advanced economies are found to be working for Sri Lanka, then these techniques could be applied to any other developing and emerging economy that share similar characteristics of Sri Lankan economy.

This paper employs 5 main forecasting techniques that are widely used at central banks and academic research in the advanced economies in the recent times. Firstly, the baseline Bayesian Vector Autoregression (BVAR) consisting of 3 fundamental economic variables, such as GDP growth, inflation and short-term interest rate. These variables largely capture future movements of output and inflation in economies with less frictions. However, these fundamental variables may be inadequate to forecast Sri Lankan output and inflation. As a small open economy in transition Sri Lanka is vulnerable to shocks emanating from external environment. Also there is empirical evidence that domestic supply and external shocks play an important role in explaining the movements of key economic fundamentals in Sri Lanka (Cooray,2008; Ratnasiri, 2009). Adding variables to capture domestic supply side and external sector movements could improve forecast accuracy. Therefore, in addition to the baseline model a large BVAR (LBVAR) model is also being considered in this study. Exchange rate, international oil price, monetary aggregate, international trade and current account dynamics and output gap are examples of such variables included in the large BVAR model.

Fixed parameter models are often criticized because of the possibility of parameters changing over time and with policy interventions. In order to deal with this issue Time Varying Parameter BVAR (TVP-BVAR) model with 3 fundamental variables is included as the third technique. Due to computational difficulties all the variables included in the large BVAR could not be included in TVP-BVAR approach. The fourth model is a univariate Unobserved Component Trend-Cycle model with stochastic volatility (UC_SV) proposed by Stock and Watson (2007). In this model the forecast variable is represented as the sum of permanent stochastic trend component and a serially uncorrelated transitory component. It has been successful in forecasting inflation in the USA. All the technique discussed above are data driven univariate and multivariate models. Parameters of these models are based on the data. Fully micro-found Dynamic Stochastic General Equilibrium models (DSGE) are increasingly becoming popular both in policy analysis and forecasting. Thus the DSGE model estimated for Sri Lanka by the author in a separate research (Jegajeevan,2014) is employed as the fifth forecasting technique in this study. The forecast obtained from these models are compared with the forecast of univariate ARMA model to assess whether these methods are successful in beating the forecast performance of ARMA model. Univariate AR, ARMA and ARIMA models are generally applied in forecasting macroeconomic variables like output and inflation.

Sample covers a period between 1996 and 2014 on quarterly frequency. The beginning of the sample is limited by the availability of quarterly GDP data and some other data series[1]. Sample covering around 20 years of quarterly data is not surprising for a less-advanced country that suffers from data limitations. Data has been collected mainly from data sources of Central Bank of Sri Lanka(CBSL) and Department of Census and Statistics(DCS).

Forecasting exercise not only includes point forecasts but also density forecasts. Density forecasts have a merit over the point forecast since it provides details of uncertainties surrounding the point forecasts. Due to this reason density forecasts have become popular in forecasting exercises in the recent periods, especially after the financial crisis. Also, density forecasts contain useful information for the policy makers since prediction about future uncertainties are made available. Forecast accuracy of point forecasts is mainly evaluated by Root Mean Squared Error (RMSE) and that of density forecast is assessed by log predictive density, known as log score. However, in order to verify robustness of the point forecast evaluations other methods such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) based evaluations have also been included in this study. The main discussion about the forecasting exercise is based on recursive forecasts, though outcomes of rolling forecasts are also reported.

The rest of the paper has been organized as follows. *Section 2* briefly discusses historical movements of the key variables in question and reviews related literature on the advancement of forecasting tools in advanced economies and recent research on forecasting in less-advanced economies. Models have been described in detail in *Section 3*. A brief explanation about the data and forecasting exercise including the method of evaluating forecast accuracy is given in *Section 4*. Result of forecasting exercise and evaluation of forecast accuracy of these techniques are reported in *Section 5*. *Section 6* includes a brief conclusion and possible future extensions.

[1]Two other alternatives of including interpolated annual GDP or industrial production index to extend the sample are not considered in this study as these series are not the perfect proxies for quarterly GDP series for Sri Lanka.

2 Historical movements of output growth and inflation and review of literature

2.1 Dynamics of output growth and inflation in Sri Lanka

2.1.1 GDP growth

Sri Lankan economy has recorded reasonably stable output growth during the past several decades. As shown in *Figure 1* a recession has emerged in the recent periods around 2001 as measured by year-on-year growth in GDP. Sri Lankan policy authorities quoted several global factors and domestic supply side disturbances as the root causes for this recession. The recent financial crisis did not lead to a recession as opposed to many advanced economies, though reported output growth was well below the average level. Sri Lankan output is relatively less volatile and the year-on-year growth hovered marginally around the average growth rate of 6% to 6.5% in normal times.

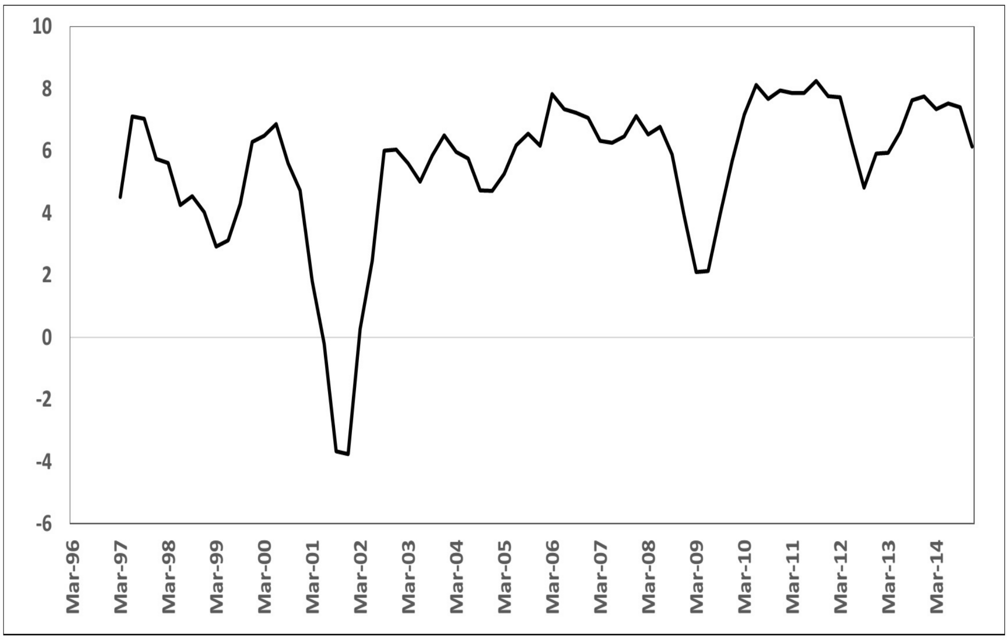

Figure 1: Movements of GDP growth

2.1.2 Inflation

Inflation in Sri Lanka is measured by year-on-year change in Colombo Consumer Price Index (CCPI). The index began with the base year of 1952 and this base year was in effect without any revision over 50 years. The need for a more reflective new index was felt to be important and a new index incorporating better representative consumer group and changes in expenditure patterns was introduced recently with 2002 as the base year. This was again revised and the current index is based on 2006-2007 as the base year. Consumer price index in developing economies differ from that of advanced economies due to differences in the expenditure patterns of the consumer groups in these economies. A comparison of weights allocated to individual categories of the items included in the baskets of Sri Lankan index and an advanced economy (the UK) is given in the *Appendix Table A.1* to highlight these differences. The most prominent feature of a less-advanced economy's index is relatively higher weight given to food categories. Sri Lankan index assigns a weight of 41% for food and non-alcoholic beverages that includes restaurants and hotel, while the total weight on these two items in the UK basket is only around 23%. Similarly, the weight on housing, water,electricity and gas in Sri Lankan index is much higher than the UK's index. Other notable difference is the highest weight on recreation and culture in the UK's index compared to just 1.5% weight to the same in the Sri Lankan index. This discussion highlights two important points. First, the variables that are helpful in capturing the dynamics of inflation in the advanced economies may not be successful in doing the same job for a less-advanced economy. Second, there might be a need to include additional variables especially supply side variables such as prices of food categories and oil to essentially improve the modelling and forecasting of inflation in Sri Lanka.

Sri Lanka had experienced historically high inflation in the past, though it has stabilized to lower single digit level in the recent years. The average year-on-year inflation during the sample period is around 9%, with the highest inflation of around 25% recorded in 2008. Sri Lanka has not opted for inflation targeting framework yet. However, official documents often suggest an implicit target of around mid single digits. Since it has been already shown that the food category dominates in the weighting it is worth analyzing the movements of food and non-food inflation in the past. The *Figure 2* portrays the year-on-year inflation of these two categories in addition to the overall inflation. Accordingly, the historically highest inflation recorded during 2007-2008 periods is largely driven by the food inflation. The deceleration in inflation in the recent times comes from the non-food inflation. An overview of the movement of inflation in Sri Lanka reveals a fact that Sri Lankan inflation was much more volatile than advanced economies. A possible explanation could be the explicit inflation targeting framework adopted by the advanced economies. Thus, inflation in these countries tend to fluctuate around a narrower margin, while inflation in developing countries fluctuates widely.

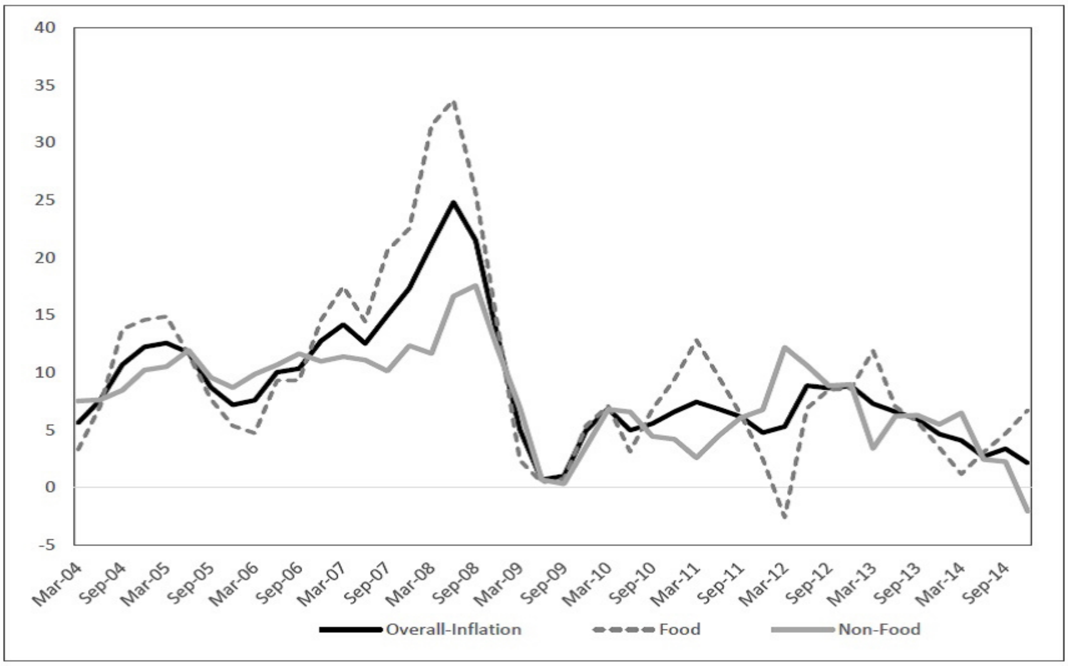

Figure 2: Movements of inflation and major components

2.2 Related studies

Academia and central banks in advanced economies are constantly involved in improving forecasting models with the advancement of computing power to improve forecast accuracy. Smets and Wouters (2004) used a DSGE model estimated for Euro area to perform both conditional and unconditional forecasts. They provided evidence that forecast accuracy of the DSGE model was better than other competing models and the accuracy improves in longer horizon. They extended their work to calculate probability distribution to assess forecast uncertainties. They concluded that DSGE model could be an additional useful tool for forecasting at the central banks. Stock and Watson(1999, 2003 and 2007) have continuously worked on the improvement of inflation forecasts. Stock and Watson (2007) developed unobserved component model with stochastic volatility to answer many univariate and multivariate forecasting puzzles. Using USA inflation data they showed that there was parameter instability in the univariate inflation process. Such instability could be dealt with an integrated moving average process with time-varying parameters. Banbura *et al.*(2010) employed BVAR of different sizes and showed that forecast accuracy of small monetary model can be improved by adding additional macroeconomic variables and sectoral information. The large-BVAR model with 130 variables produced better forecasting result than the traditionally considered small BVAR models. Another novelty in the recent forecasting literature is to construct a model with data observations of different frequencies. Schorfheide and Song (2013) constructed a VAR model using data with mixed-frequencies of quarterly and monthly frequencies and showed that information that were available within the quarter improved the forecast performance in real times.

As far as emerging and developing economies are concerned majority of existing the studies rely on univariate models and traditional theoretical models. A multi country study of Mohanty and Klau (2001) tried to generalize determinants of inflation in 14 emerging economies. Main conclusions were that a larger part of movements in inflation was driven by food and oil prices, exchange rate changes were closely linked to inflation, higher unemployment coincided with lower inflation in many countries and output gap was poorly related to inflation. Among country specific studies, Bokil and Schimmeldfennig (2005) attempted to forecast inflation for Pakistan employing three classes of models: univariate model, unrestricted VAR model and leading indicator model. They concluded that leading indicator model outperformed other two and monetary variables helps to improve forecast accuracy. Relatively a large number of studies attempted to model and forecast inflation in India. Kapur (2012) identified the volatility in international oil and commodity prices and domestic food supply dynamics as the challenges in forecasting inflation for India. In an augmented Phillips curve framework both demand and supply factors were found to be the drivers of headline inflation. Further, disaggregated analysis of inflation revealed that non-food manufactured product inflation was more persistent than headline inflation and that was strongly influenced by the demand factors. In a recent study, Mumtaz and Kumar (2012) have applied a set of contemporary univariate and multivariate forecasting techniques to forecast output,inflation and short-term interest rate for India. They found that rich information content of large Bayesian VAR improved forecast accuracy and that model outperformed any other model over the longer horizon.

In Sri Lankan context, there has been some attempts in the recent times to model inflation. Ratnasiri (2009) have employed Vector Error Correction Model (VECM) to identify the main determinants of headline inflation in Sri Lanka. His findings suggested that monetary aggregates and rice price were the main factors influencing movement of inflation. Another attempt to model inflation in Sri Lanka by Cooray (2008) based on regression based closed and open economy models confirmed that supply side factors have greater influence on price level in Sri Lanka and open economy model identified exchange rate and import price as the important variables. Bandara(2011) have reported money supply, exchange rate and GDP as the leading indicators that helped to explain the behavior of inflation during 1993-2008. There has been no research to forecast output and inflation for Sri Lanka, though Central Bank of Sri Lanka relies on some internally developed models for its monetary policy decision making. This study fills the gap in the empirical literature.

3 Models

3.1 Autoregressive moving average (ARMA)

This paper employs ARMA model as the benchmark model to evaluate forecasting ability of these competing advanced models, since ARMA is one of the best univariate models to forecast less volatile variables successfully. ARMA(p,q) model is given below.

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma^2),$$

where Y_t is GDP growth or inflation. With $(p, q) = (2, 1)$ ARMA(2,1) is selected as the benchmark model that satisfies standard order selection criteria as well. The estimation is carried out with Bayesian techniques with Gibbs sampling approach. The model is expressed in the state form and the MA terms $\theta_j \varepsilon_{t-j}$ are treated as unobserved state variables. Then, Carter & Kohn (1994) algorithm is used to generate draws of the state vector.

3.2 Bayesian vector autoregression (BVAR)

BVAR models are increasingly being used in modelling and forecasting macroeconomic variables in the recent years. When classical VAR model is extended with large number of endogenous variables to avoid omission bias the model estimation will suffer from curse of dimensionality and the result could be spurious. Estimation using Bayesian approach helps to overcome this problem by imposing shrinkage prior on the parameters to reduce parameter uncertainty. Further, Bayesian based simulation method such as *Gibbs sampling* easily estimates the uncertainties surrounding the point estimates of these models.

The BVAR of order p is summarized as follows

$$Y_t = c + \sum_{j=1}^{p} B_j Y_{t-j} + \varepsilon_t$$
$$\varepsilon_t \sim N(0, \Sigma), \qquad t = 1, 2, ..., T$$

where Y_t is the vector of $N \times 1$ vector of endogenous variables,c is the $N \times 1$ is the vector of constant, B_j is the $N \times N$ matrix of coefficients and ε_t is $N \times 1$ is the vector of random shocks.

This model can be compactly written as follows.

$Y_t = X_t B + \upsilon_t$

$\upsilon_t \sim N(0, \Sigma), \qquad t = 1, 2, ..., T$ where X_t is the $K \times 1$ vector of regressors with $X = \{c_i, Y_{i,t-1}, Y_{i,t-2,}....., Y_{i,t-p}\}$ and $K = (Np + 1)$.Coefficients matrix $B = \{c : B_1 : B_2 : ..... : B_p\}$ with $N \times K$ elements and ':' is the horizontal concatenation.

Since all the equations in (2) has identical regressors that equation can be rewritten as follows.

$y = (I_N \otimes X)b + V$

where $y = vec(Y_t), b = vec(B)$ and $V = vec(\upsilon_t)$ and $\otimes$ is the Kronecker product.

Priors and Posterior distributions

The prior for VAR coefficient b is normal and given by

$p(\underset{\sim}{b}) \sim N(vec(\widetilde{b_0}), H)$

where $\widetilde{b_0}$ is a vector of prior mean and H is a matrix consisting of diagonal elements as variance of the prior.

The prior for VAR covariance matrix is inverse Wishart distribution as follows.

$p(\Sigma) \sim IW(\bar{S}, \alpha)$

where $\bar{S}$ is the scale matrix and α is the degree of freedom

Initial prior values are natural conjugate priors based on the priors implemented by Banbura (2007). Incorporating prior information through covariance matrix H is computationally demanding when number of variables in the model are large. To simplify computing an alternative approach of incorporating priors through dummy observations or artificial data is proposed by Bandura (2007). This study follows that approach to incorporate priors by generating dummy observations Y_D and X_D and then add those dummy observations to the actual data observations.

$$Y_D = \begin{bmatrix} diag(\varkappa_1\sigma_1.......\varkappa_N\sigma_N)/\tau \\ 0_{N\times(p-1)\times N} \\ .... \\ diag(\sigma_1.......\sigma_N) \\ .... \\ 0_{1\times N} \end{bmatrix} \qquad X_D = \begin{bmatrix} \frac{J_p \otimes diag(\sigma_1.......\sigma_N)}{\tau} 0_{NP\times 1} \\ 0_{N\times NP} \quad 0_{N\times 1} \\ .... \\ 0_{1\times NP} \quad c \end{bmatrix}$$

where $\varkappa_i$ are the coefficients and σ_1^2 are variances of the error terms of the regression and $J_p = diag(1.......P)$. The value of hyperparameter τ that measures the overall tightness of the prior is chosen by maximizing the marginal data density $p(Y)$ of the model. The optimal lag level for the VAR also has been chosen by maximizing marginal likelihood of data.

Dummy observations are added to the actual observations to compute mean of the conditional posterior distribution of the VAR coefficients and variance.

Gibbs sampling algorithm is implemented as follows.

1. Choose priors for VAR coefficients b and covariance matrix Σ.

2. Draw b from a distribution that is conditional on variance of error term Σ is normal and given by $H(b\backslash\Sigma, Y_t) \sim N(M^*, V^*)$

where

$M^* = (H^{-1} + \Sigma^{-1} \otimes X_t' X_t)^{-1}(H^{-1}\widetilde{b_0} + \Sigma^{-1} \otimes X_t' X_t \hat{b})$

$V^* = (H^{-1} + \Sigma^{-1} \otimes X_t' X_t)^{-1}$

3. Draw covariance Σ from conditional distribution $H(\Sigma\backslash b, Y_t) \sim IW(\bar{\Sigma}, T + \alpha)$.

where $\bar{\Sigma} = \bar{S} + (Y_t - X_t B^1)'(Y_t - X_t B^1)$ in which B^1 is the draw of the VAR coefficient reshaped into a matrix to be consistent with X_t and T is the sample size.

4. Draw of b and Σ are repeated for M number of times and the draws after the burn-in period is used for forecasting.

3.2.1 Baseline BVAR(BVAR)

Baseline model consists of three fundamental economic variables such as GDP growth, inflation and treasury bill rate. These fundamentals are expected to have information about the behavior of output and inflation when economy is stable and less volatile. Such a model is fairly successful in forecasting output and inflation in advanced economies.

3.2.2 Large BVAR (LBVAR)

Two different LBVAR models are employed for output growth and inflation, respectively, since it is evident from the existing work on Sri Lanka and the analysis carried out in *Section 2* that supply side factors have important influence on Sri Lankan inflation. LBVAR model for inflation includes more supply side factors. LBVAR model for output includes 11variables: GDP growth, inflation, treasury bill rate, exchange rate depreciation, money supply growth, real consumption growth, real investment growth, import growth, export growth,output gap,current account to GDP. LBVAR for inflation includes 15 variables: GDP growth, inflation, treasury bill rate, exchange rate depreciation, money supply growth, domestic credit. international oil price inflation, domestic rice price inflation, food price inflation,inflation based on whole sale price index,import price index, output gap,unemployment, domestic oil price adjustment and domestic gas price adjustment[2]. Description of data is given in *Appendix Table A.2*.

3.3 Time-varying parameter BVAR (TVP-BVAR)

The TVP-BVAR model is given below.

$$Y_t = c_t + \sum_{j=1}^{p} B_{j,t} Y_{t-j} + v_t$$
$$VAR(v_t) = R$$
$$v_t \sim N(0, R_t), \qquad t = 1, 2, ..., T$$

where Y_t is the vector of $N \times 1$ vector of endogenous variables that includes GDP growth, inflation and short-term treasury bill rate,c is the $N \times 1$ is the vector of time-varying intercepts, $B_{j,t}$ is the $N \times N$ matrix of time-varying coefficients and v_t is $N \times 1$ is the vector of random shocks with R_t being $N \times N$ time-varying covariance matrix.

State space form of the model is as follows.

$$Y_t = Z_t B_t + v_t$$
$$v_t \sim N(0, R),$$

where $Z_t = (I_N \otimes X_t'), X_t = \left\{1, Y_{t-1}', Y_{t-2}', ..., Y_{t-p}'\right\}', B_t = vec(\Phi_t')$
and $\Phi_t = \{c_t, B_{1,t}, B_{2,t}, ..., B_{p,t}\}$.

X_t is the $K \times 1$ vector of regressors and $K = (Np + 1)$ and $\Phi_t$is the $N \times K$ matrix of time-varying coefficients and B_t is the $m \times 1$ vector of all coefficient with $m = N \times K$.

Based on Cogley and Sargent (2005) the covariance matrix has the following representation:

$$R_t = A_t^{-1} H_t A_t^{-1\prime}$$

The time-varying matrices H_t and A_t are given by

[2]Fiscal variables are important leading indicators to forecast inflation for country like Sri Lanka. However, quarterly data on fiscal variables are not readily available for researchers.

$$H_t = \begin{bmatrix} h_{1,t} & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 \\ 0 & 0 & .... & 0 \\ 0 & 0 & 0 & h_{N,t} \end{bmatrix} \qquad A_t = \begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{2,1,t} 1 & & 0 & 0 \\ ... \ .... & & 1 & 0 \\ a_{N,1,t} ... & a_{N,N-1,t} & & 1 \end{bmatrix}$$

The transition equations for B_t, H_t and A_t are given as follows.

$B_t = B_{t-1} + e_{t,} \qquad e_t \sim N(0, Q)$

$a_{i,j,t} = a_{i,j,t-1} + u_{t,} \qquad u_t \sim N(0, \Omega)$

$h_{i,t} = h_{i,t-1} + z_{t,} \qquad z_t \sim N(0, g)$

Further $A_t v_t = \varepsilon_t, \qquad VAR(\varepsilon_t) = H_t$

This implies that following equations.

$v_{1,t} = \varepsilon_{1,t}$

$v_{2,t} = -a_{12,t} v_{1,t} + \varepsilon_{2,t}, \qquad VAR(\varepsilon_{2,t}) = h_{2,t}$

$v_{3,t} = -a_{13,t} v_{1,t} + -a_{23,t} v_{2,t} \varepsilon_{3,t}, \qquad VAR(\varepsilon_{3,t}) = h_{3,t}$

and

$a_{12,t} = a_{12,t-1} + V_{1,t}, \qquad VAR(V_{1t}) = D_1$

$$\begin{pmatrix} a_{13,t} \\ a_{23,t} \end{pmatrix} = \begin{pmatrix} a_{13,t-1} \\ a_{23,t-1} \end{pmatrix} + \begin{pmatrix} V_{2,t} \\ V_{3,t} \end{pmatrix}, \qquad VAR(\begin{pmatrix} V_{2,t} \\ V_{3,t} \end{pmatrix}) = D_2$$

The model is estimated using MCMC algorithms with

1) Carter and Kohn (1994) algorithm within the *Gibbs sampling* to get posterior distributions of B_t and A_t

2) Independence *MH algorithm* for the stochastic volatility $h_{i,t}$.

Main steps of *Gibbs* and *MH* algorithm for this model are as follows:

1. Set prior for Q and starting value for Kalman filter.Prior for Q is $p(Q\ ) \sim IW(Q_0, T_0)$. Since the degree of time variation allowed in the model is measured by the prior for Q this prior is important and training sample is often used to set this prior. A pre-sample of T_0, that is 20 quarters of sample, is used to estimate VAR coefficients and set the prior for scale matrix Q_0.

   $Q_0 = \Sigma_0 \otimes (X_{0t}' X_{0t})' \times T_0 \times \tau$

   where Σ_0 and $(X_{0t}' X_{0t})'$ are estimated based on training sample and τ is the scaling factor chosen by the researchers. A lower number assigned to τ indicates that the estimates based on small training sample could be imperfect. Considering short overall sample and training sample in this study and following many other studies, a lower value of $\tau = 1^{-4}$ is assigned.

2. Set priors for $D_1$and D_2. ($p(D_1) \sim IG(D_{10}, T_{10})$ and $p(D_2) \sim IG(D_{20}, T_{20})$ and $D_{10} = 0.001$ and $D_{20} = \begin{pmatrix} 0.001 & 1 \\ 1 & 0.001 \end{pmatrix}$.

3. Set starting values for $h_{i,t}$.

4. Conditional on A_t, H_t and Q draw β_t using Carter and Kohn (1994) algorithm.

5. Based on the calculation of residuals of the transition equation$(\beta_t - \beta_{t-1})$ sample Q.

6. Conditional on β_t, D_1, D_2 and H_t draw $a_{i,t}$ the elements of A_t.

7. Conditional on $a_{i,t}$ calculate residuals $V_{i,t}$.Draw $D_1$and D_1.

8. Based on the draws of A_t calculate $\varepsilon_t = A_t v_t$.Draw $h_{i,t}$ from *MH algorithm*.

9. Repeat 4-8 a large number of times and after the burn-in period use the draws for inferences.

3.4 Unobserved Component Model with Stochastic Volatility (UC-SV Model)

This model follows the work of Stock and Watson (2007), who found that univariate inflation process is subject to stochastic volatility. In this model variances of the permanent (η_t)and transitory disturbances (ε_t) evolve randomly over time. That is log of the variances of $\eta_t$and $\varepsilon_t$evolve as independent random walks. The UC-SV model is as follows.

$$\pi_t = \tau_t + \eta_t \qquad \text{where } \eta_t = \sigma_{\eta,t}\zeta_{\eta,t}$$
$$\tau_t = \tau_{t-1} + \varepsilon_t \qquad \text{where } \varepsilon_t = \sigma_{\varepsilon,t}\zeta_{\varepsilon,t}$$
$$\ln \sigma^2_{\eta,t} = \ln \sigma^2_{\eta,t-1} + \upsilon_{\eta,t}$$
$$\ln \sigma^2_{\varepsilon,t} = \ln \sigma^2_{\varepsilon,t-1} + \upsilon_{\varepsilon,t}$$

where $\zeta_t = (\zeta_{\eta,t}, \zeta_{\varepsilon,t})$ is i.i.d $N(0, I_2)$ and $\upsilon_t = (\upsilon_{\eta,t}, \upsilon_{\varepsilon,t})$ is i.i.d $N(0, \gamma I_2)$, ζ_t and υ_t are independently distributed and γ is a scaler parameter. The parameter γ controls the smoothness of the stochastic volatility process.

Like TVP-BVAR model first 20 quarter are taken as training sample.

3.5 DSGE

The DSGE model forecast is based on the model estimated for Sri Lanka by the author (Jegajeevan,2014). The model economy consists of multi sectors characterized by price and nominal rigidities, incomplete pass through to import prices, adjustment cost in investment, habit persistence in consumption, oil in the consumption basket and as a factor of production, division of households into optimizing and non-optimizing household groups, presence of worker remittances and current account dynamics. Agents in the model economy consist of households,intermediate production firms, importers, both home and foreign final good assemblers, capital leasing firm, government and a monetary authority.

DSGE model solution has the following reduced form representation.

$$x_t = A(\theta)x_{t-1} + B(\theta)\varepsilon_t$$

$y_t = C(\theta)x_t$

where the matrices A, B and C are non linear function of θ, x_t is the vector of unobserved states and y_t is the vector of observed variables. It is not possible analytically to characterize the predictive density. However, with the help of simulation algorithms it is possible to approximate the predictive density well. The algorithm is given below.

1. Generate a draw $\theta^{(j)}$ from $p(\theta \mid y_{1:T})$

2. Use Kalman filter to compute mean and variance of $p(x_T \mid \theta^{(j)}, y_{1:T})$. Generate a draw from this distribution, $x_T^{(i)}$

3. Generate a sequence of draws from ε, i.e. $\varepsilon_{T+1:T+h}^{(k)}$ and iterate on the ABC representation as follows.

$x_\tau^{(i)} = A(\theta^{(j)})x_{\tau-1}^{(i)} + B(\theta^{(j)})\varepsilon_\tau^{(k)}$
$y_\tau^{(i,j,k)} = C(\theta^{(j)})x_\tau^{(i)}$

for $\tau = T + 1, ..., T + h$

A point forecast $\hat{y}_{T+h}$of y_{T+h}can be obtained by specifying a loss function determining the prediction that minimizes the posterior expected loss. Under the quadratic forecast error loss function the optimal predictor is the mean across all trajectories. Dynare version 4.4.3 has been used to estimate the DSGE and generate forecasts.

Convergence of sampling algorithm

When sampling technique like *Gibbs sampling* is employed in the model estimation convergence of sampling is verified to be confident that conditional posterior distribution has converged to the marginal posterior distribution. Even though many tests have been proposed in the literature to do this task simple techniques like the plots of the sequence of retained draws, autocorrelation functions and recursive means of the retained draws are still being used widely. In this study plots of recursive means have been used to check the convergence of the sampling algorithm. For DSGE model convergence was tested based on Brooks and Gelman (1998). The reported recursive means are expected to be stable to confirm the convergence. Both ARMA and baseline BVAR models have been estimated based on 20000 draws and the last 5000 draws have been used for checking the convergence and to produce forecasts. Other models use 50000 draws and the retained draws of 5000, since they did not converge at the 20000 draws. TVP-VAR model draws have converged only with more than 200,000 draws and it was very consuming (more than 15 hours per attempt). Given that the forecast has been carried out both based on recursive and rolling windows and the forecasts have been produced for 28 periods in order to minimise the computational burden only 50,000 draws have been used in the forecasting exercise. However, it has been confirmed that the forecasts based on 50,000 draws and 200,000 draws did not deviate too much. The plot for convergence of these models are reported in *Appendix Figures A.1-A.5*.

4 Empirical application

4.1 Data

Data sample covers a period from 1996:Q2 to 2014:Q4 at quarterly frequency. The sample is limited by the availability of quarterly GDP and some other data series. It is a known fact that less advanced economies suffer from the limitation in availability of high frequency data spanning over long period of time. Modelling with shorter sample of around 20 years is not uncommon for developing country based studies. However, the outcome of time-varying BVAR and unobserved component model forecasts have to be interpreted carefully, as first 20 quarterly data points are taken as training sample leaving only a shorter sample for estimation. Data has been mainly collected from the Central Bank of Sri Lanka (CBSL) and Department of Census and Statistics (DCS). All the time series have been tested for stationary and when necessary they have been transformed to log difference to ensure stationarity. Short-term interest rate is proxied by 91-day Treasury bill rate not only to comply with the usual practice, but also for the reason that policy interest rate is not stationary. Data series that suffer from seasonality have been de-seasonalized using Census X-12 methodology before transforming to log. Detailed description of all data series has been provided in *Appendix Table A.2*.

4.2 Forecasting exercise

Forecasting exercise carried out in this paper includes forecasts that are obtained both on recursive estimation and rolling estimation. Initial forecast for recursive forecast is obtained using a sample of 1996:Q2 to 2007:Q4 to get 4 quarters ahead forecasts starting from 2008:Q1. At each step next quarter data is added to the initial estimation window, so that the estimation window expands over time. Forecasts are obtained for 28 quarter starting from 2008:Q1. For the rolling forecast, at each step ahead a new quarter data is added while a quarter at the beginning of the sample is removed to keep the size of estimation window fixed. In recursive forecasting both past data and current data are assumed to be important in forecasting future path of the variable as opposed to rolling forecast that prioritize the role of current data in the forecast. Rolling forecast is expected to outperform recursive forecast if there are structural breaks during the sample period. Given the fact that total sample for this study is shorter the rolling forecast is not expected to report very different forecast. Therefore, to keep the analysis precise forecasting performance of recursive forecast is discussed in detail and the forecasts based on rolling forecast are shown in the *Appendix*. Reported forecasts are for quarterly GDP growth and quarterly inflation. Forecast accuracy is evaluated on 'relative terms'. In-line with a common approach of comparing the forecasting ability of competing models on the basis of a loss function, in this paper also forecast error of the competing models discussed above are evaluated against univariate ARMA(2,1) model. This paper includes both point forecasts and density forecasts.

4.3 Evaluation of forecast accuracy

4.3.1 Point forecast

Point forecasts are mainly evaluated using root mean squared error (RMSE).

$$RMSE_{i,h}^{M} = \sqrt{\frac{1}{n}\sum(\overset{\Lambda(i)}{y_{t+h}}(M) - y_{t+h}^{(i)})^2}$$

where $\overset{\Lambda(i)}{y_{t+h}}$ is the forecast of ith variable in horizon ahead h by the model and $y_{t+h}^{(i)}$ is the corresponding actual observed value.

The forecast error of all the models are reported in relative to the forecast error of the bench mark model(ARMA(2,1) model.

$$RRMSE_{i,h}^{M} = \frac{RMSE_{i,h}^{M}}{RMSE_{i,h}^{ARMA}}$$

The relative RMSE of a model should be below 1 to outperform the bench mark ARMA(2,1) model.

It is important to test whether the forecasting performance of these models are statistically significant. Test for statistical significance helps to check the difference in loss function, in this case squared forecast error, is significantly different from zero. The null hypothesis is that the forecast gain or loss of the competing models against the bench mark are zero and both models forecasting ability are not statistically different. If this null is rejected then the forecasting performance of the competing models is statistically different from the benchmark model. Diebold and Mariano (1995) test is carried out to serve this purpose as it is a widely used test that works for non-nested model under both recursive and rolling forecasting schemes. It simply tests whether the reported predictive accuracy gain or loss is due to good luck or an indication of statistical significance. The accuracy of each forecast is measured by squared loss function. It is possible that the forecasts are serially correlated when the forecast horizon is above 1. So that the p-value of Diebold and Mariano test is adjusted for serial correlation for forecast horizon above 1. The statistics is further adjusted for the small sample adjustment proposed by Harvey *et al.* (1997) since the sample period in this study is shorter.

It is important to verify whether forecasting performance evaluated based on RMSE is robust to different methods of evaluation. For this purpose evaluations based on two alternative evaluation techniques namely Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are also reported under robustness check.

The MAE is a method of evaluation that measures the average magnitude of forecast error without considering the direction of errors, i.e. whether forecast errors are positive or negative. The MAE can be shown by the following equation.

$$MAE_{i,h}^{M} = \frac{1}{n}\sum\left|\overset{\Lambda(i)}{y_{t+h}}(M) - y_{t+h}^{(i)}\right|$$

Another popular method of point forecast evaluation is MAPE. It measures the prediction accuracy of forecasting model as it calculates forecast errors as a percentage of actual realised values. It is shown by the following equation. The values obtained from the equation can be multiplied by 100 to show the values in percentage.

$$MAPE_{i,h}^{M} = \frac{1}{n}\sum\left|\frac{\overset{\Lambda(i)}{y}_{t+h}(M)-y_{t+h}^{(i)}}{y_{t+h}^{(i)}}\right|$$

4.3.2 Density forecast

When comparing forecast accuracy of density forecast of a number of models predictive likelihood that is the height of the predictive density at the realized actual value is important. Average of log predictive likelihood (Log-score) of a model is given as follows.

$$LS_{i,h}^{M} = 1/n\sum\log p(y_{t+h}^{(i)} \mid \overset{(t)}{y}, M)$$

where $p(.)$ is the predictive density function obtained by univariate kernel estimation of the gibbs sampling output. Like point forecast evaluation, density forecast evaluation is also reported in relative terms as shown below.

$$RLS_{i,h}^{M} = LS_{i,h}^{M} - LS_{i,h}^{ARMA}$$

where $RLS_{i,h}^{M}$is the average difference in log-score. Any value of RLS that is above zero indicates that the model's density forecast outperforms that of benchmark model. Similar to the statistical significant test carried out for the point forecast, density forecasts of the models are also evaluated based on Amisano and Giacomini (2007) test. This a likelihood ratio test based on the differences in log predictive density scores of the models being tested. Even though this test is recommended for the forecasts obtained from rolling forecast, this can also be used as an approximation for evaluating recursive forecasts as well. Similar approach has been followed by Carriero *et al.* (2015). The statistics is further adjusted for the small sample adjustment proposed by Harvey *et al.* (1997) since the sample period in this study is shorter.

5 Forecasting outcome

Forecasting performances of 5 competing models in forecasting GDP growth and inflation are reported in four tables. *Tables 1 & 2* report point forecast evaluations and *Tables 3 & 4* report density forecast evaluations under recursive forecasting approach. Point forecast and density forecast of rolling forecast are reported in *Appendix*.

5.1 Point forecast

5.1.1 GDP growth

The RMSE of all the models including the benchmark ARMA(2,1) model and relative RMSE of the competing models against ARMA in forecasting GDP growth are reported in *Table1*. The reported RMSE of each model at each forecast horizon is the average over the forecast evaluation period of 2008Q1: 2014:Q4 covering 28 quarters. Any model that reports an RMSE that is lower than the RMSE reported by the benchmark ARMA(2,1) for the corresponding forecast horizon outperforms the benchmark model. Such models are shown in bold. Statistical significance of relative forecast performance of the competing models are tested by Diebold-Mariano(1995) test as discussed earlier. This is serial correlation adjusted t-statistics. The test statistic is further adjusted to incorporate the small sample in this study by Harvey *et al.* (1997) test. The relative RMSE that is statistically significant at 90%,95% and 99% confidence level is marked with '*','**' and '***', respectively.

Point forecasts for GDP growth produced by baseline BVAR, TVP-BVAR and LBVAR models outperform the benchmark ARMA model at all forecast horizons. Unobserved component model and DSGE model produce better forecasts than the benchmark model at certain forecast horizons. Further, baseline BVAR forecast at shorter horizon up to 2 quarters are more accurate than any other model. The large BVAR model does a good job at longer horizons at quarter 3 &4. An important point to note is that the better performance of baseline BVAR and LBVAR models over the benchmark is statistically significant. Acknowledging the fact that relative RMSE of baseline BVAR model at forecast horizons 1& 2 are only marginally lower than that of large BVAR forecast, it can be conveniently concluded that LBVAR model is the best model in forecasting GDP growth.

GDP point forecasts at horizon 1 and 4 along with the actual realized values are portrayed in *Appendix Figure A.6* & *Figure A.7*. In order to improve clarity only the best forecasts at the forecast horizon,i.e. baseline BVAR for horizon 1 and LBVAR for horizon 4, and model average, excluding the benchmark model, are shown in the figures.

5.1.2 Inflation

Similar analysis for inflation point forecast is reported in *Table 2*. It is clear from the table that none of the competing models could outperform the forecast of the benchmark model at the immediate forecast horizon. This result is statistically significant against TVP-BVAR, LBVAR and UC-SV models. Competing models produce better forecasts than the benchmark at the remaining forecast horizons. DSGE model reports lower relative RMSE compared to the benchmark and other competing model and the forecast performance is much better at longer horizon. Also, this result is statistically significant at 95% confidence level. It should be kept in mind while analyzing the results of both TVP-BVAR model and the UC-SV model that the relative merit of these models over the benchmark is achieved amid the very short sample used for estimation after taking first 20 quarters of data as training samples to form priors for these models. Therefore, it is clear that these models could perform even better when a longer sample data series is used to estimate these models. The DSGE model outperforms all the models, followed by TVP-BVAR model.

The analysis for the inflation point forecast highlights two important points to note. First, forecast error(RMSE) reported by all the models including the benchmark is much higher than the forecast error reported for GDP growth forecasts. Secondly, superiority of the relative performance of a number of models are not statistically significant, except for the DSGE model and baseline BVAR model at horizon 3. This indicates that forecasting Sri Lankan inflation is harder than forecasting GDP growth.

Inflation forecasts at horizon 1 and 4 along with the actual realized values are portrayed in *Appendix Figure A.8* & *Figure A.9*. The best forecasts at the forecast horizon,i.e. DSGE for both horizon 1 and 4, and the forecast produced by the model average are shown in the figures. Forecasts from benchmark ARMA model has been included in the figure for forecast horizon 1, since none of the competing models could beat the benchmark at this forecast horizon.

As already discussed under forecasting exercise, results obtained from 2 other point forecast evaluation methods are reported in *Appendix Tables A.3 and A.4* as robustness check. The tables reassure the fact that forecast error of GDP forecasts are much lower than that of the inflation forecast and forecasting performance of these models in forecasting GDP growth is more promising. Also, Large-BVAR model is the best model in forecasting GDP growth while DSGE model is the best at forecasting inflation. In conclusion, the reported outcome of point forecasts of these competing models are robust to different methods of forecast evaluation.

Table 1: Point forecast evaluation-GDP growth (Recursive forecast)

	Forecast Horizon	RMSE	Relative RMSE
ARMA- Benchmark	1	0.6633	1.0000
	2	0.7763	1.0000
	3	0.7539	1.0000
	4	0.7576	1.0000
Baseline BVAR	1	0.6068	**0.9147**
	2	0.6722	**0.8660****
	3	0.6750	**0.8953*****
	4	0.6810	**0.8990***
TVP-BVAR	1	0.6534	**0.9851**
	2	0.7228	**0.9312**
	3	0.7395	**0.9810**
	4	0.6973	**0.9205**
Large BVAR	1	0.6070	**0.9151**
	2	0.6731	**0.8671***
	3	0.6654	**0.8826****
	4	0.6672	**0.8807***
UC-SV	1	0.6304	**0.9504**
	2	0.7410	**0.9546**
	3	0.8223	1.0908
	4	0.7750	1.0230
DSGE	1	0.7412	1.1175
	2	0.7452	**0.9600**
	3	0.7380	**0.9789**
	4	0.7634	1.0077

Diebold and Mariano (1995) t-statistics that are statistically significant at the confidence levels of 90%, 95% and 99% respectively are denoted by *,** and ***.

Table 2: Point forecast evaluation-Inflation (Recursive forecast)

	Forecast Horizon	RMSE	Relative RMSE
ARMA- Benchmark	1	1.5245	1.0000
	2	1.8245	1.0000
	3	1.8398	1.0000
	4	1.7880	1.0000
Baseline BVAR	1	1.7089	1.1210
	2	1.8131	**0.9938**
	3	1.7407	**0.9461****
	4	1.7371	**0.9715**
TVP-BVAR	1	1.8452	1.2100*
	2	1.7847	**0.9782**
	3	1.6651	**0.9050**
	4	1.5959	**0.8926**
Large BVAR	1	1.7524	1.1495*
	2	1.8246	1.0001
	3	1.7478	**0.9500**
	4	1.7522	**0.9800**
UC-SV	1	1.9432	1.2746*
	2	1.8209	**0.9980**
	3	1.7137	**0.9315**
	4	1.7407	**0.9735**
DSGE	1	1.6550	1.0856
	2	1.5566	**0.8532**
	3	1.4989	**0.8147****
	4	1.4107	**0.7890****

Diebold and Mariano (1995) t-statistics that are statistically significant at the confidence levels of 90%, 95% and 99% respectively, are denoted by *,** and ***.

5.2 Density forecast

5.2.1 GDP

Density forecast result of GDP growth forecast is reported in *Table 3*. The table includes average log-scores of the individual models along with the relative forecast accuracy gain or loss of the competing model forecasts against the benchmark model forecasts. As discussed in *Section 4* when relative log-score of a model is positive the model's density forecast outperforms that of benchmark. In the table the relative log-score is shown as accuracy gain in percentage by multiplying the change in log score by 100. All the competing models outperform the benchmark ARMA model at all forecast horizons in forecasting uncertainty surrounding central tendency of the forecasts. LBVAR reports greater density forecast accuracy gain at all the forecast horizons, while DSGE forecast accuracy is only slightly higher than the benchmark forecasts. LBVAR model's forecast accuracy gain over the benchmark is around 36%-42%. Accuracy gain reported by other models are slightly lower than LBVAR model. The analysis of density forecast of GDP growth highlights that the competing models are superior in forecasting the uncertainty surrounding the point forecasts better than the univariate benchmark model.

5.2.2 Inflation

As reported in *Table 4* density forecast performance of the competing models in forecasting inflation is much better than the point forecasts of the same models. Like density forecasts of GDP growth, density forecast accuracy of all the models in forecasting inflation outperform the benchmark forecast,except for unobserved component model at horizon 1. Similar to the result of point forecast, density forecast of the benchmark model at forecast horizon 1 is better than other horizons. This has been confirmed by a very small accuracy gain reported by the competing models at that horizon. In contrary to the outcome of the point forecast, density forecasts of TVP-BVAR outperform the DSGE forecasts at forecast horizons 2 to 4. LBVAR that did not forecast the mean path of inflation very well has reported promising results for density forecasts. The reported outcomes of density forecast for inflation suggests that the competing advanced models do a good job in predicting the uncertainty in forecasting future inflation, though the mean forecasts of inflation are not that accurate.

Table 3: Density forecast evaluation-GDP growth (Recursive forecast)

	Forecast Horizon	Log score	Accuracy Gain
ARMA- Benchmark	1	-1.3266	
	2	-1.4299	
	3	-1.4388	
	4	-1.4467	
Baseline BVAR	1	-1.0151	31.1%***
	2	-1.0888	34.1%***
	3	-1.1073	33.1%***
	4	-1.1111	33.6%***
TVP-BVAR	1	-1.0503	27.6%***
	2	-1.1178	31.2%***
	3	-1.1414	29.7%***
	4	-1.1481	29.9%***
Large BVAR	1	-0.9634	36.3%***
	2	-1.0208	40.9%***
	3	-1.0241	41.5%***
	4	-1.0615	38.5%***
UC-SV	1	-1.0829	24.4%**
	2	-1.2135	21.6%
	3	-1.2899	14.9%
	4	-1.1872	26.0%
DSGE	1	-1.2961	3.0%
	2	-1.3686	6.1%**
	3	-1.3770	6.2%*
	4	-1.3950	5.2%

Amisano and Giacomini (2007) t-statistics that are statistically significant at the confidence levels of 90%, 95% and 99% respectively are denoted by *,** and ***.

Table 4: Density forecast evaluation-Inflation (Recursive forecast)

	Forecast Horizon	Log score	Accuracy Gain
ARMA- Benchmark	1	-2.0559	
	2	-2.1982	
	3	-2.1990	
	4	-2.2024	
Baseline BVAR	1	-1.9646	9.1%
	2	-2.0187	17.9%***
	3	-2.0003	19.9%***
	4	-2.0111	19.1%
TVP-BVAR	1	-1.9825	7.3%
	2	-1.9674	23.1%*
	3	-1.8878	31.1%***
	4	-1.8807	32.2%***
Large BVAR	1	-1.9626	9.3%
	2	-1.9739	22.4%*
	3	-1.9063	29.3%***
	4	-1.9455	25.7%
UC-SV	1	-2.0620	-0.6%
	2	-2.0847	11.4%
	3	-2.0107	18.8%**
	4	-2.0015	20.1%
DSGE	1	-2.0170	3.9%
	2	-2.0061	19.2%***
	3	-1.9540	24.5%***
	4	-1.9541	24.8%***

Amisano and Giacomini (2007) t-statistics that are statistically significant at the confidence levels of 90%, 95% and 99% respectively are denoted by *,** and ***.

5.3 Sub-sample analysis

The role of advanced forecasting models has been questioned and criticized by researchers and the media after their failure in predicting recent financial crisis. Several studies on macroeconomic forecasting have acknowledged that the models that have been producing more accurate forecasts during normal times have failed during the crisis period. Historical movements of GDP growth and inflation shown in *Section 2* clearly show that these variables were highly volatile during 2008-2009. Inflation movements during this time can be linked to the highest fluctuations in international oil and commodity prices, in addition to the financial crisis.

The forecasting exercise will not be complete without a discussion about the forecasting performance of these models during this abnormal time. This will also be helpful in identifying the successful models at abnormal times and normal times. The following part will include a brief discussion about the forecasting performance disaggregated into two sub-sample periods: 2008-2009 and 2010-2014. This sub-sample analysis is only limited to point forecasts obtained from recursive forecasting approach to avoid over loading the thesis with too many tables.

Point forecast evaluations of both GDP growth and inflation are reported in *Table 5*. It is evident from the table that GDP growth forecasting performance of models other than baseline-BVAR and DSGE are not as good as that of benchmark forecasts at the times of abnormal economic conditions. Baseline BVAR forecasts are better than the benchmark forecasts at all forecast horizons, even though only normal times forecasts are statistically significant. Another interesting outcome is that DSGE model forecasts GDP growth more accurately during the crisis period than normal times. LBVAR outperforms all other models during the normal times and this result is statistically significant. DSGE model is not able to beat the benchmark ARMA forecasts normal times. Regarding inflation forecast, competing models forecast performances are poor compared to univariate benchmark forecasts at the highly volatile period of inflation. Similar to the finding from GDP forecasts DSGE model forecasts inflation better during the turmoil than other models. Also LBVAR model has reported lower forecast errors during this time. It could be because that model includes oil price, commodity prices, disaggregated monetary and credit aggregates that largely explain the movements of inflation during this period. Even though the t-statistics obtained from Diebold and Mariano test are statistically significant for LBVAR and DSGE models, they become insignificant when the t-statistics is adjusted for small sample proposed by Harvey *et al.* (1997). All the competing models except LBVAR model outperforms the benchmark forecast during normal times, with DSGE model on the lead. The overall evidence from the point forecasts of sub-samples suggests that the competing models forecast well during normal times than abnormally high volatile times. Further the structural model, the DSGE, reports lower forecast error during the volatile period both for GDP growth and inflation forecasts. Unobserved component model was not successful in beating the benchmark model in forecasting both GDP growth and inflation.

Table 5: Point forecast evaluation-Sub-sample analysis (Recursive)

		GDP growth		Inflation	
	Horizon	Rel.RMSE	Rel.RMSE	Rel.RMSE	Rel.RMSE
		2008-2009	2010-2014	2008-2009	2010-2014
ARMA	1	1.0000	1.0000	1.0000	1.0000
	2	1.0000	1.0000	1.0000	1.0000
	3	1.0000	1.0000	1.0000	1.0000
	4	1.0000	1.0000	1.0000	1.0000
BVAR	1	**0.9528**	**0.8889******	1.2380*	**0.9982**
	2	**0.9658**	**0.7971***********	1.0262	**0.9613**
	3	**0.8846**	**0.9039**	**0.9490**	**0.9438******
	4	**0.8489**	**0.9309**	**0.9460**	**0.9905**
TVP-BVAR	1	1.0981	**0.9033**	1.4157*	**0.9783**
	2	1.0955	**0.8116***	1.0088	**0.9476**
	3	1.0382	**0.9319**	**0.8282**	**0.9620**
	4	**0.9256**	**0.9170**	**0.7522**	**0.9863**
Large BVAR	1	1.0346	**0.8274******	1.2549	1.0405
	2	1.0690	**0.7122***********	**0.9952**	1.0048
	3	**0.9332**	**0.8394***	**0.8950**	**0.9917**
	4	**0.8518**	**0.8995**	**0.9050**	1.0335
UC-SV	1	1.0414	**0.8857**	1.4866**	1.0361
	2	1.1874	**0.7740******	1.0798	**0.9119**
	3	1.2953	**0.8908**	1.0171	**0.8569***
	4	1.1459	**0.9318**	1.0478	**0.9128**
DSGE	1	1.1107	1.1219	1.1751	**0.9939**
	2	**0.9026**	**0.9943**	**0.8186**	**0.8854**
	3	**0.7776***	**1.1159**	**0.7543**	**0.8599***
	4	**0.9172**	**1.0639**	**0.6518**	**0.8793***

5.4 Rolling forecasts

Rolling forecasts evaluations are included in this study to ensure completeness of this forecasting exercise. Given that the sample is really short , rolling forecasts are not expected to perform well. Both point forecast and density forecast evaluation of rolling forecast approach are reported in *Appendix Tables A*.5 - *A.8.* Baseline BVAR and LBVAR outperforms the benchmark ARMA model based rolling forecast at all the horizons for GDP growth forecast. Relative

forecast performance of the competing models, excluding the DSGE model, are poor in forecasting inflation. Density forecast outcomes also confirms that baseline BVAR, LBVAR and

TVP- BVAR models are forecasting the uncertainty better than the ARMA model in case of GDP growth forecast. All the competing models report marginal forecast accuracy gain at the longer forecast horizon. Benchmark model continued to perform well at the immediate forecast horizon.

6 Conclusion and way forward

6.1 Conclusion

This study aims to forecast GDP growth and inflation for Sri Lanka in order to find out whether advanced forecasting techniques employed for advanced economies are helpful tools for a less advanced economy. Five advanced techniques, such as baseline BVAR, large BVAR, time varying BVAR, unobserved component model and DSGE are employed to produce forecasts for two key macroeconomic variables. The forecast is not just limited to mean forecasts, but also extended to density forecasts. Both recursive and rolling forecasting approaches have been exercised, though much of the discussion is based on recursive forecasting. The forecast accuracy of these competing models is evaluated against benchmark univariate ARMA model.

Point forecast evaluations of GDP forecasts of these models report that these models beat the benchmark model at all forecast horizons. Also, reported forecast error measured by RMSE of all the models, including the benchmark, are relatively lower. The superiority of these models are mostly statistically significant. The same analysis for point forecasts of inflation did not show very promising results. Though a number of models outperform the benchmark model, the statistical significance of such superiority could not be proved widely. Also, the forecasting errors of all the models including the benchmark model, were much higher than that of GDP growth forecast. One has to keep in mind that inflation in Sri Lanka is much volatile than GDP and therefore this finding of mean forecast is not surprising. Density forecasts of both GDP growth and inflation are promising and confirm that the uncertainty around the mean forecast is well captured by these models than the benchmark model. All the models have shown accuracy gain over the benchmark model for both GDP growth and inflation at all forecast horizons. A sub-sample analysis is carried out for the recursive point forecasts to evaluate forecasting performance of these model at the most volatile crisis period and the periods under normal economic conditions. This analysis reveals that forecasting errors of the models, including the benchmark,are much higher during the crisis times. But, univariate benchmark model performs better than a number of competing models at the volatile times.

In overall, large BVAR model is found to be the best of all the models to forecast GDP growth, while DSGE model is the best model for forecasting inflation at forecast horizons above 2 quarters. No model could beat the benchmark ARMA model in forecast inflation at the immediate quarter. Baseline BVAR model is successful in both GDP growth and inflation forecast. DSGE model has been forecasting both of these variables better in highly volatile times at longer horizons. Superior performance of the competing models at normal times is commendable.

Based on these findings, following conclusions can be made. The forecasting models that work well in advanced economies are useful in forecasting key economic variables for a developing economy too. These models have reported good forecasting performance regardless of the shorter sample of data and high volatility of inflation in Sri Lanka. Forecast accuracy gains of density forecasts suggest that these models can be used at the Central Bank of Sri Lanka for policy discussions, since density forecasts provide complete description of forecast uncertainty. Another finding is that the model with fundamental variables, the baseline BVAR, performs reasonably well in forecasting both GDP growth and inflation. Adding more variables in the model did not play any big role in improving forecast accuracy of inflation forecasts in the normal times, though large BVAR model is helpful at volatile times. Expanding sample could improve forecast accuracy of time varying model and unobserved component model that are based on priors estimated from training sample. Improving sample will help these models to capture the break and changes in parameters well. Further, micro-found DSGE model is successful in producing better forecasts for inflation. Acknowledging the fact that none of the economic models predict future perfectly regardless of the complexity of the model, size of the sample and the nature of the economy, it should be accepted that these advanced models can be used to model and forecast key economic variables for a developing country to carry out informed policy analysis and to take better policy decisions. It is recommended that the Central bank of Sri Lanka can employ these models, including the benchmark ARMA model, as a starting point in its forecasting exercise for forecasting macro variables for policy analysis.

6.2 Future extensions

This study can be extended further with some improvements in the future. The first suggestion is to extend the sample period and forecast evaluation period. Since the unavailability of quarterly GDP data is the main reason for the short sample considered in this research alternatives to quarterly GDP series could be tried. This includes interpolated annual GDP growth series prior to 1996 or considering industrial production index as a proxy for the GDP series. Second possibility is to concentrate on the DSGE model. Though the DSGE model employed in this study in its current set-up was not successful in forecasting GDP growth improving the current DSGE model could improve forecast accuracy of both GDP growth and inflation. This extension could include but not limited to incorporating more frictions such as financial frictions, detailed modelling of fiscal sector. When the DSGE model is more reflective of the Sri Lankan economy the accuracy of the forecasts generated by such model could improve. Further, the observed success of the forecasting ability of data driven BVAR model and structural DSGE model gives a hint that a model incorporating the features of these models, the DSGE-VAR model, can be included in forecasting exercise in the future.

Appendix:

Table A.1: CPI baskets and weights- Sri Lanka vs the UK

Categories	*UK*	*Sri Lanka*
1. Food and non-alcoholic beverages	11.2	41.0
2. Alcoholic beverages and tobacco	4.5	_*
3. Clothing and Footwear	7.2	3.1
4. Housing, water,electricity and gas	12.9	23.7
5. Furnishing and household equipment	6.0	3.6
6. Health	2.4	3.2
7. Transport	15.2	12.3
8. Communication	3.2	4.8
9. Recreation and culture	14.4	1.5
10. Education	2.2	3.9
11. Restaurants and Hotels	12.0	_
12. Miscellaneous goods and services	8.8	2.9
	100.0	**100.0**

* Alcoholic beverages and tobacco has been excluded from the current cpi index of Sri Lanka

Table A.2: Description of Data

Variable	Description	Source
GDP	Quarterly GDP growth. (2002 prices)	CBSL & DCS
Inflation	Colombo Consumer Price Index (CCPI) based quarterly inflation (2006/2007=100)	CBSL & DCS
Short-term interest rate	91-day Treasury bill rate (End period)	CBSL
Exchange rate	Quarterly depreciation measured by US dollar - Rupee exchange rate (End period)	CBSL
Money Supply	Quarterly growth rate of M_{2b} money supply	CBSL
Oil price	Quarterly oil price inflation measured by actual purchase price of oil by Ceylon Petroleum Corporation	CBSL
Rice price	Quarterly rice price inflation measured by the average rice price	CBSL
WPI	Quarterly inflation measured by Whole Sale Price Index (WPI) (1974=100)	CBSL
Real Consumption	Quarterly growth of real private consumption expenditure	CBSL*
Real Investment	Quarterly growth of real private investment expenditure	CBSL*
Import	Quarterly growth of Import expenditure denominated in Sri Lankan rupee	CBSL
Export	Quarterly growth of Export earnings denominated in Sri Lankan rupee	CBSL
Output Gap	Output gap obtained by the difference between HP detrended real GDP and actual real GDP	CBSL*
Current A/C to GDP	Quarterly current A/C balance as a ratio of quarterly GDP	CBSL
Food price	Quarterly growth of Food and Agricultural Organization's (FAO) food price index (2002-2004=100)	FAO
Import price index	Detrended import price index(2010=100) in logs	CBSL
Unemployment	Detrended unemplyment rate	CBSL
Domestic credit	Quarterly growth rate of domestic credit	CBSL
Domestic oil price	Quarterly growth of average domestic oil price	CBSL
Domestic gas price	Quarterly growth of domestic gas price	CBSL

* Annual data of private consumption and private investment have been interpolated based on Chow Lin procedure.
For further details see Chapter 3.

Table A.3: Point forecast evaluation-MAE and MAPE (GDP growth)

	Forecast Horizon	MAE	MAPE
ARMA- Benchmark	1	0.5456	0.5531
	2	0.5960	0.6498
	3	0.5708	0.7233
	4	0.6318	0.7671
Baseline BVAR	1	0.4934	0.5110
	2	0.5531	0.6571
	3	0.5644	0.6781
	4	0.5832	0.6574
TVP-BVAR	1	0.5175	0.4924
	2	0.5937	0.6119
	3	0.6218	0.7645
	4	0.6084	0.6667
Large BVAR	1	0.5248	0.5074
	2	0.5382	0.5556
	3	0.4988	0.5959
	4	0.4941	0.5178
UC-SV	1	0.4831	0.5344
	2	0.5861	0.8422
	3	0.6165	0.9050
	4	0.6139	0.9124
DSGE	1	0.6091	0.5174
	2	0.5704	0.5713
	3	0.6037	0.6341
	4	0.6104	0.6848

Table A.4: Point forecast evaluation-MAE and MAPE (Inflation)

	Forecast Horizon	MAE	MAPE
ARMA- Benchmark	1	1.1803	1.0951
	2	1.2609	1.5442
	3	1.3278	1.7966
	4	1.3295	1.8255
Baseline BVAR	1	1.2471	1.2232
	2	1.3174	1.5825
	3	1.2848	1.7374
	4	1.3149	1.7880
TVP-BVAR	1	1.3726	1.2695
	2	1.3064	1.5185
	3	1.2364	1.7397
	4	1.1830	1.6810
Large BVAR	1	1.2941	1.2571
	2	1.3406	1.6455
	3	1.2986	1.7832
	4	1.3372	1.8406
UC-SV	1	1.4031	1.3411
	2	1.3532	1.6334
	3	1.2931	1.6265
	4	1.2826	1.6314
DSGE	1	1.3388	1.0812
	2	1.2121	1.2965
	3	1.2058	1.3996
	4	1.0905	1.3978

Table A.5: Point forecast evaluation-GDP growth (Rolling forecast)

	Forecast Horizon	RMSE	Relative RMSE
ARMA- Benchmark	1	0.6354	1.0000
	2	0.7542	1.0000
	3	0.7270	1.0000
	4	0.7371	1.0000
Baseline BVAR	1	0.6015	**0.9466**
	2	0.6596	**0.8746***
	3	0.6425	**0.8837***
	4	0.6587	**0.8936*****
TVP-BVAR	1	0.6207	**0.9770**
	2	0.7326	**0.9714**
	3	0.7392	1.0167
	4	0.7080	**0.9604**
Large BVAR	1	0.6181	**0.9727**
	2	0.7023	**0.9311**
	3	0.6829	**0.9394**
	4	0.6529	**0.8858**
UC-SV	1	0.6983	1.0990
	2	0.6907	**0.9159**
	3	0.7041	**0.9685**
	4	0.7383	1.0016
DSGE	1	0.6462	1.0171
	2	0.7515	**0.9964**
	3	0.7778	1.0699
	4	0.7940	1.0772

Diebold and Mariano (1995) t-statistics that are statistically significant
at the confidence levels of 90%, 95% and 99% respectively, are denoted by *,** and ***.

Table A.6: Point forecast evaluation-Inflation (Rolling forecast)

	Forecast Horizon	RMSE	Relative RMSE
ARMA- Benchmark	1	1.5200	1.0000
	2	1.8567	1.0000
	3	1.8491	1.0000
	4	1.8060	1.0000
Baseline BVAR	1	1.7369	1.1427*
	2	1.8633	1.0036
	3	1.8319	**0.9907**
	4	1.8382	1.0178
TVP-BVAR	1	1.8582	1.2225**
	2	2.0424	1.1000
	3	1.9637	1.0620
	4	1.9654	1.0882
Large BVAR	1	1.7388	1.1439
	2	1.8535	**0.9983**
	3	1.7852	**0.9655**
	4	1.8093	1.0018
UC-SV	1	2.0367	1.3399*
	2	2.2909	1.2339
	3	2.2647	1.2248
	4	2.0390	1.1290
DSGE	1	1.7467	1.1492
	2	1.6537	**0.8907**
	3	1.4321	**0.7745****
	4	1.3556	**0.7506****

Diebold and Mariano (1995) t-statistics that are statistically significant
at the confidence levels of 90%, 95% and 99% respectively are denoted by *,** and ***.

Table A.7: Density forecast evaluation-GDP growth (Rolling forecast)

	Forecast Horizon	Log score	Accuracy Gain
ARMA- Benchmark	1	-1.2689	
	2	-1.3563	
	3	-1.3661	
	4	-1.3822	
Baseline BVAR	1	-0.9373	33.2%***
	2	-0.8257	53.1%***
	3	-0.9919	37.4%***
	4	-1.0197	36.2%***
TVP-BVAR	1	-0.9819	28.7%***
	2	-1.0936	26.3%***
	3	-1.1232	24.3%***
	4	-1.1342	24.8%***
Large BVAR	1	-0.9364	33.3%***
	2	-1.0040	35.2%***
	3	-0.9890	37.7%***
	4	-0.9967	38.5%***
UC-SV	1	-1.1221	14.7%
	2	-1.1414	21.5%
	3	-1.1718	19.4%
	4	-1.1094	27.3%*
DSGE	1	-1.1928	7.6%*
	2	-1.3268	3.0%
	3	-1.3368	2.9%
	4	-1.3718	1.0%

Amisano and Giacomini (2007) t-statistics that are statistically significant
at the confidence levels of 90%, 95% and 99% respectively are denoted by *,** and ***.

Table A.8: Density forecast evaluation-Inflation (Rolling forecast)

	Forecast Horizon	Log score	Accuracy Gain
ARMA- Benchmark	1	-2.0040	
	2	-2.1649	
	3	-2.1890	
	4	-2.1891	
Baseline BVAR	1	-1.9626	4.1%
	2	-2.0763	8.9%
	3	-2.0512	13.8%**
	4	-2.0638	12.5%
TVP-BVAR	1	-2.0221	-1.8%
	2	-2.1180	4.7%
	3	-1.9976	19.1%
	4	-2.0023	18.7%
Large BVAR	1	-1.9887	1.5%
	2	-2.0420	12.3%
	3	-2.0185	17.1%**
	4	-2.0865	10.3%
UC-SV	1	-2.1434	-13.9%
	2	-2.2238	-5.9%
	3	-2.1807	0.8%
	4	-2.1516	3.8%
DSGE	1	-1.9990	0.5%
	2	-1.9989	16.6%**
	3	-1.9117	27.7%***
	4	-1.8896	30.0%***

Amisano and Giacomini (2007) t-statistics that are statistically significant
at the confidence levels of 90%, 95% and 99% respectively are denoted by *,** and ***.

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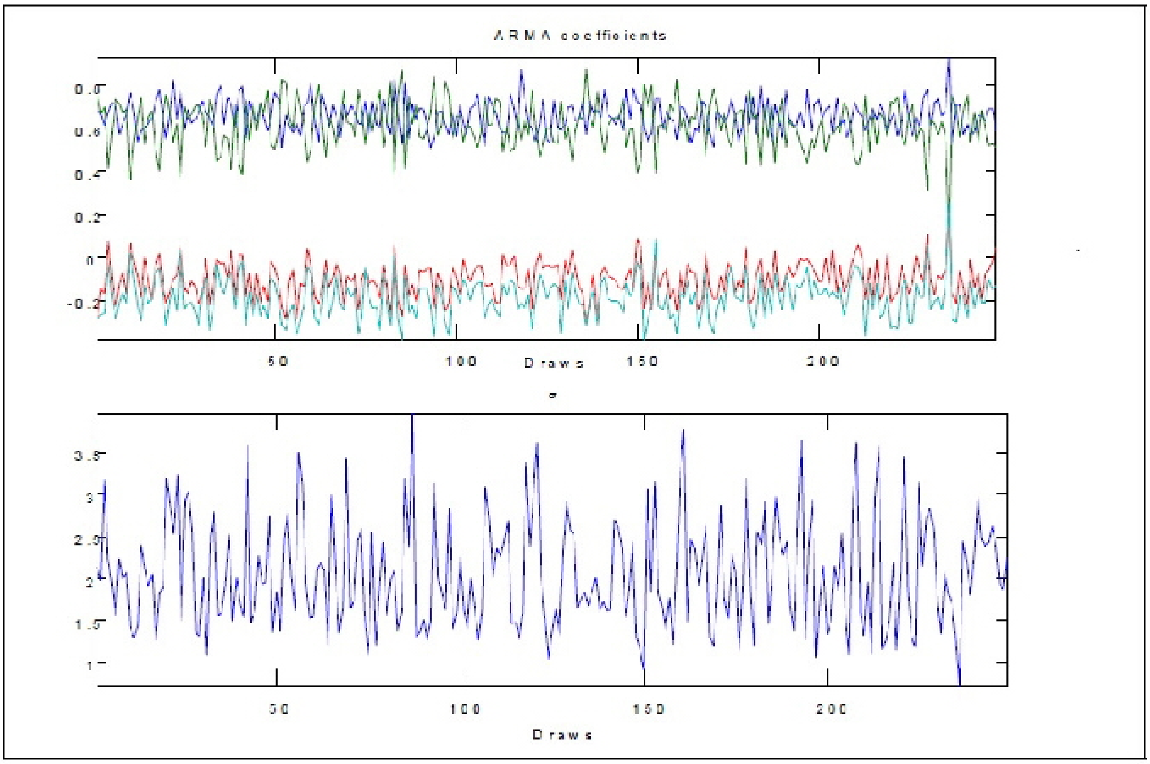

Figure A.1: Recursive means of retained Gibbs draws- ARMA model

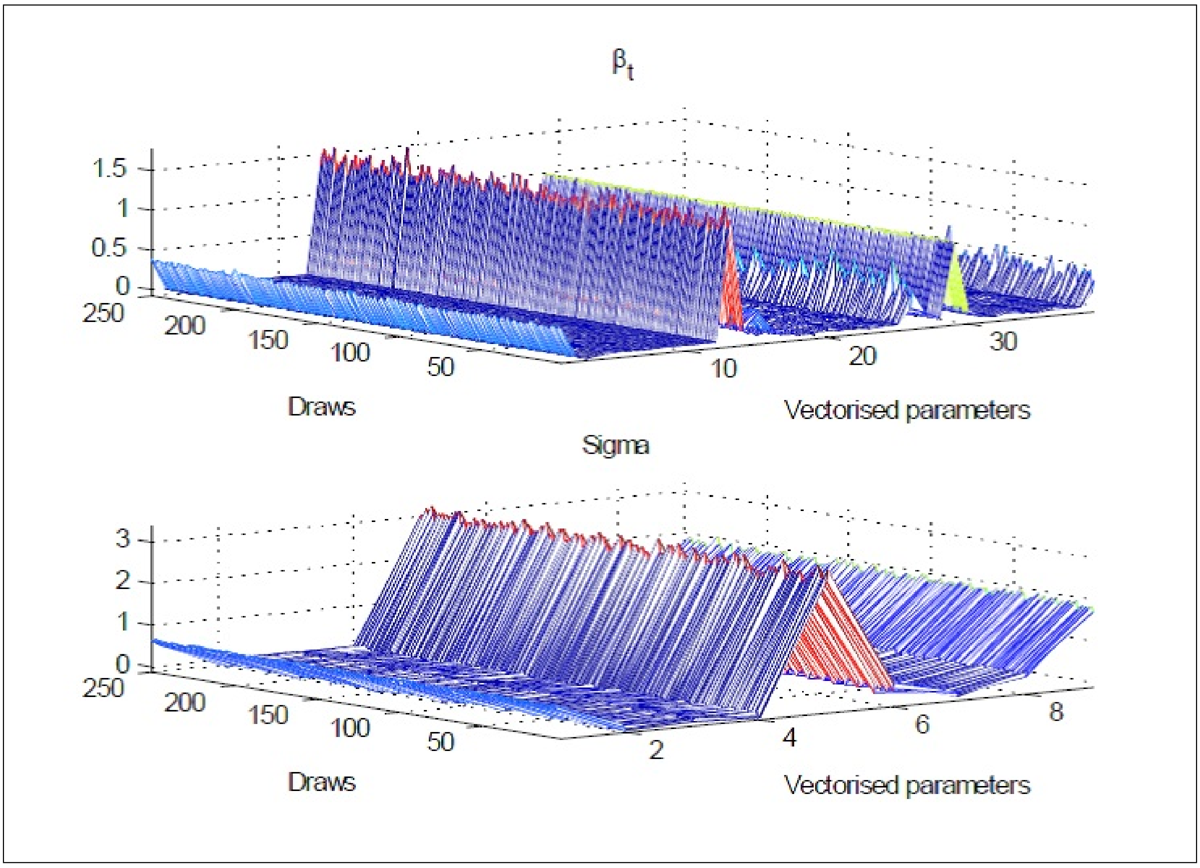

Figure A.2: Recursive means of retained Gibbs draws- BVAR model

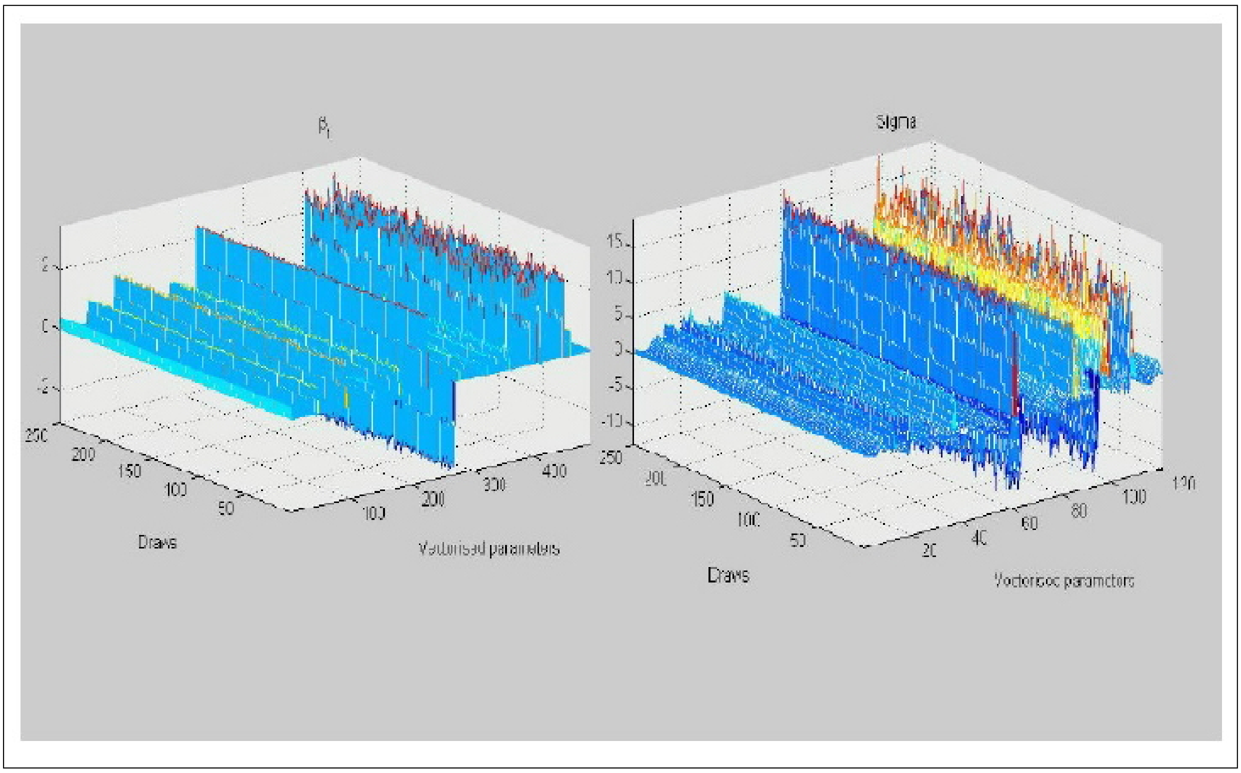

Figure A.3: Recursive means of retained Gibbs draws- LBVAR model

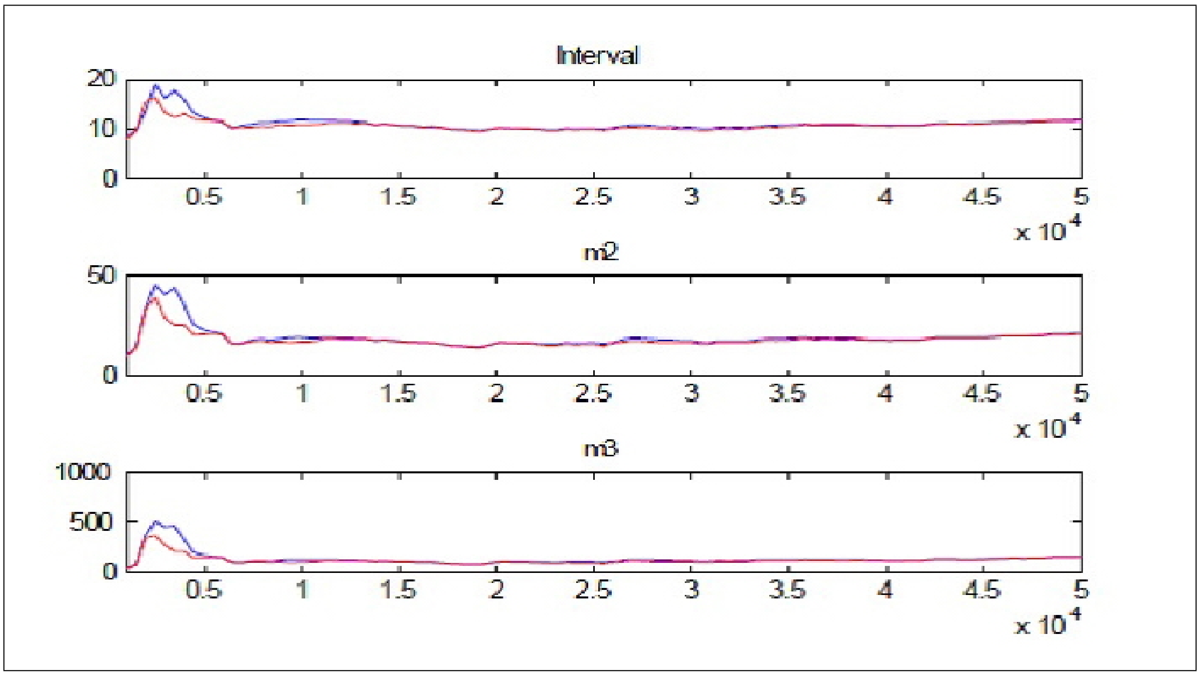

Figure A.4: Multivariate diagnostic (Brooks and Gelman, 1998)

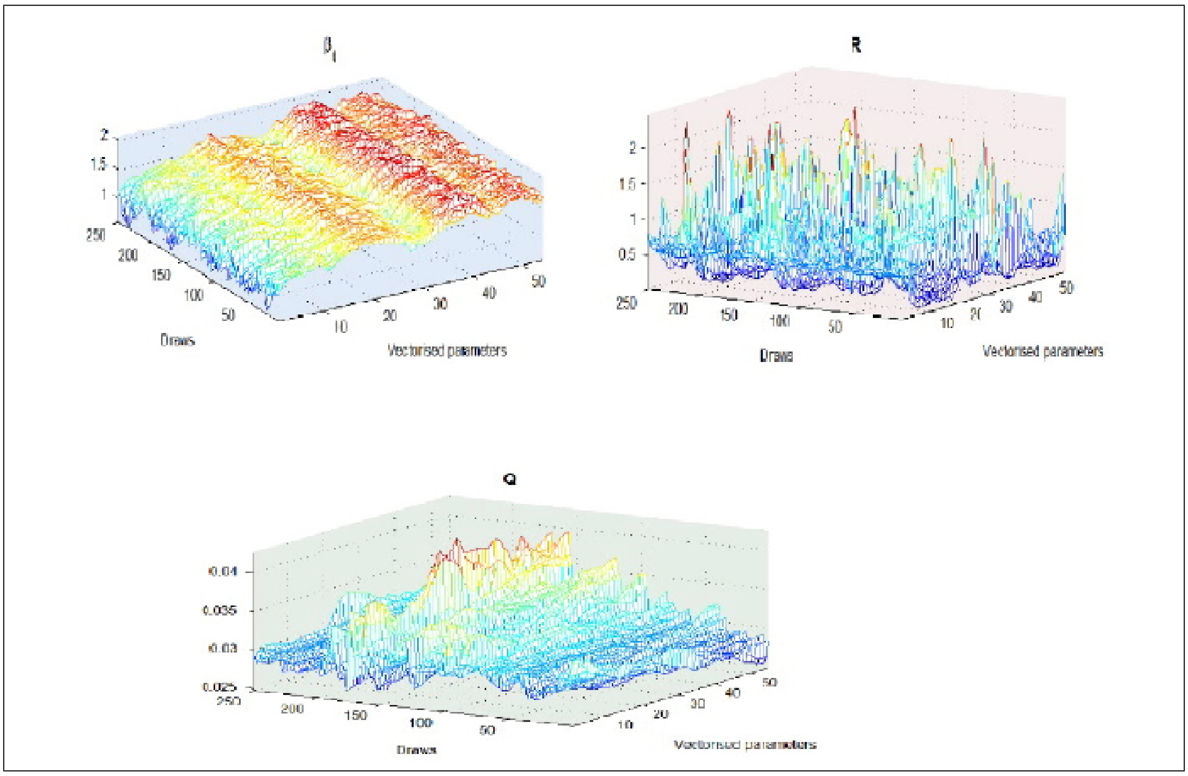

Figure A.5: Recursive means of retained Gibbs draws-UC-SV model

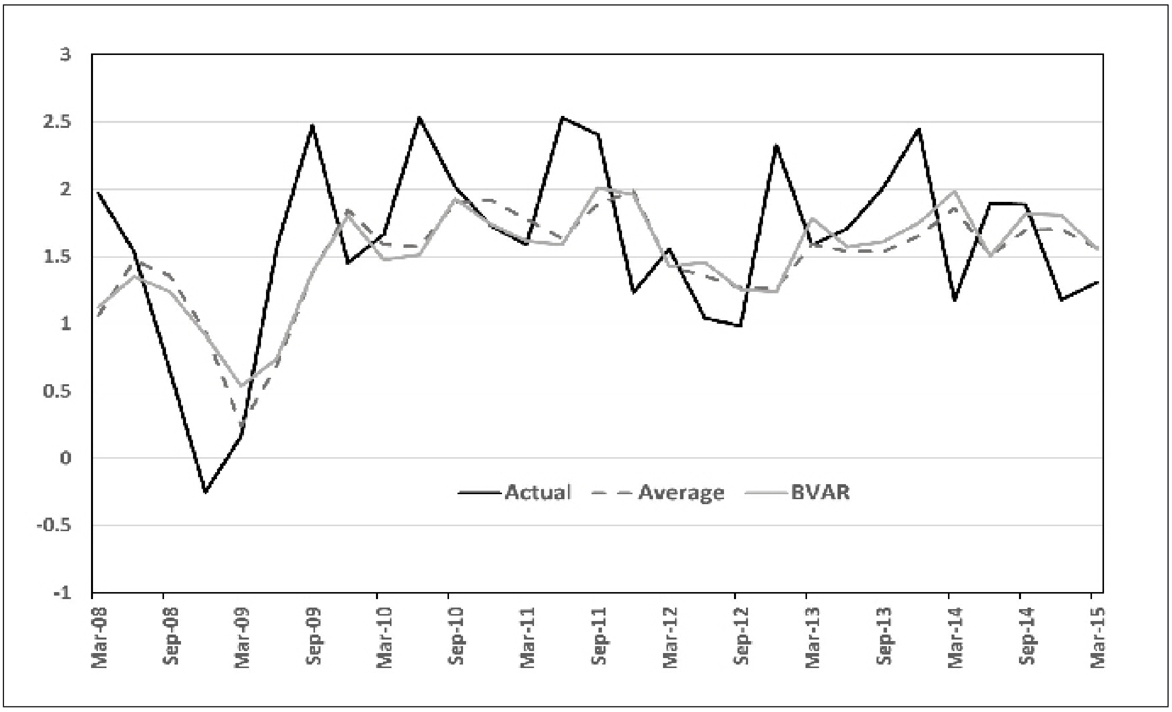

Figure A.6: Point forecast of GDP growth- Horizon 1

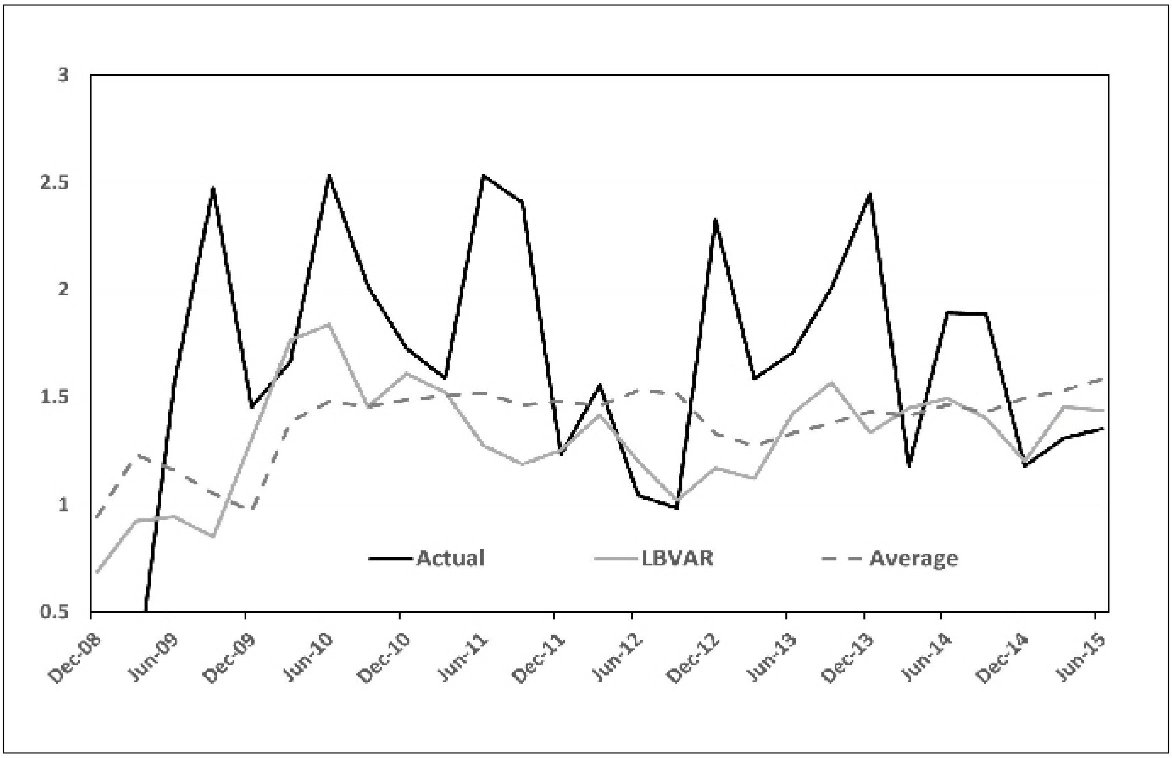

Figure A.7: Point forecast of GDP growth- Horizon 4

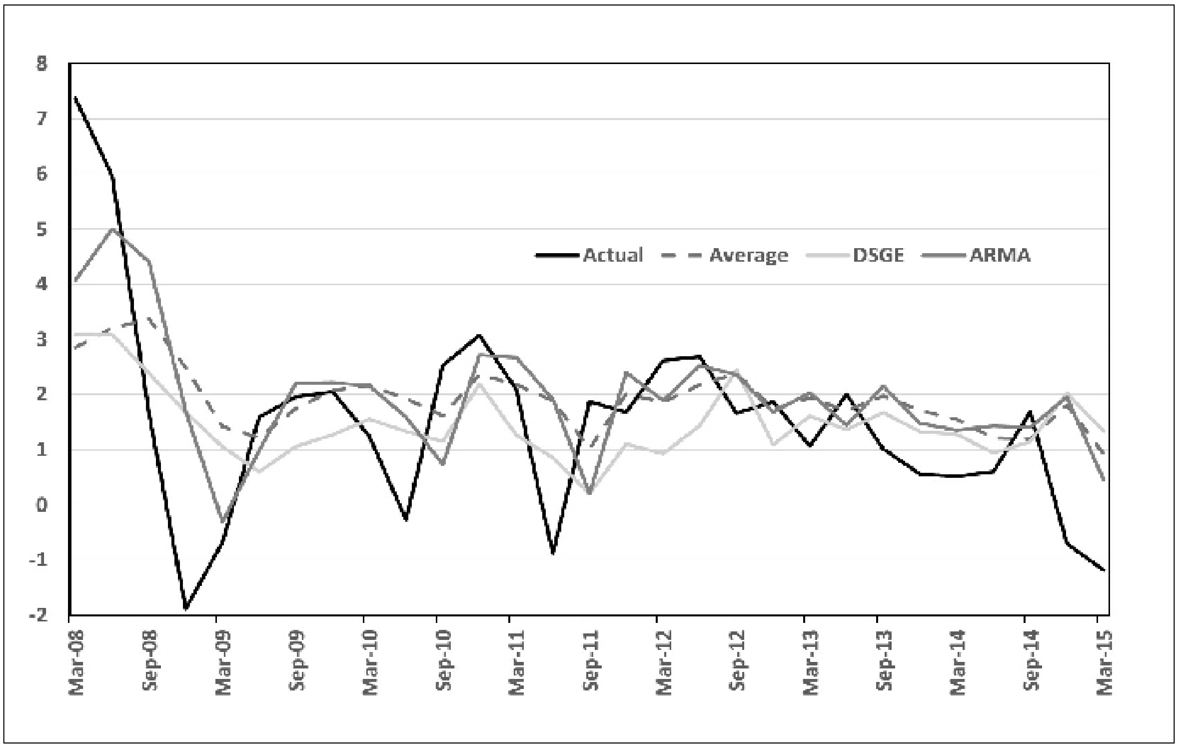

Figure A.8: Point forecast of inflation- Horizon 1

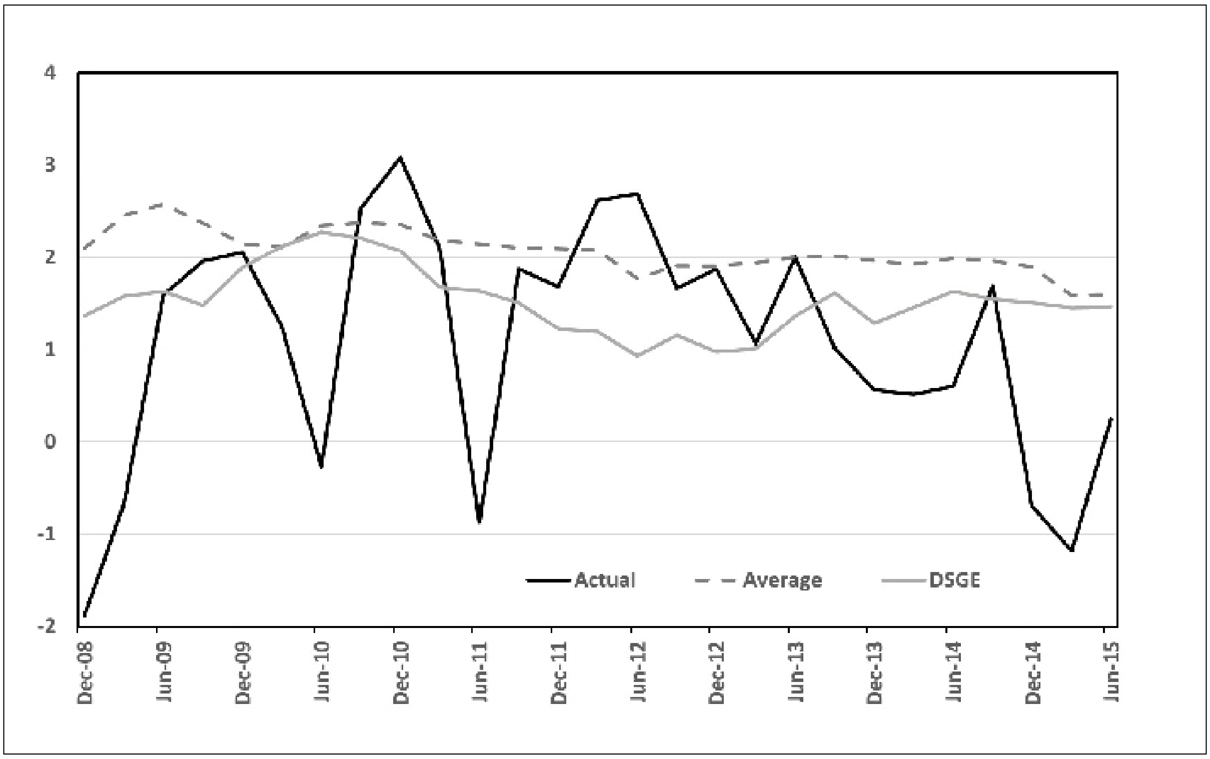

Figure A.9: Point forecast of inflation- Horizon 4

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