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A Bayesian Vector Autoregression Approach to Inflation Forecasting in India

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Abstract: Forecasting inflation is the key but challenging task for the monetary authority that aims to stabilise price levels conducive to sustained economic growth. The standard autoregressive models overly depend on inter-temporal macro variables and their lags rendering inaccurate estimation and poor forecast accuracy. The Bayesian vector autoregression (BVAR) estimation allows more endogenous variables and prior information and enables more accurate inflation forecasts. This paper forecasts inflation over short horizons (up to 6 quarters ahead) using the quarterly data from Q2-1996 to Q1-2019 data applying the BVAR method with rolling and expanding window forecast strategies. The best prior is selected by comparing the out-of-sample forecast accuracy. Two BVAR models that describe the important dynamics and interactions between the determinants of inflation are estimated. The BVAR model is compared with other benchmark models. The BVAR inflation forecasting outperforms the benchmark univariate and VAR models. The fan charts for modelling inflation through the Bayesian VAR model show that the model delivers a decent performance and can be used to forecast inflation for short horizons.

Keywords: Inflation, forecasting, Bayesian vector autoregression, forecast evaluation

JEL classification: B23, C11, C53, E31, E37

INTRODUCTION

Accurate and reliable forecasting of the inflation rate and other macroeconomic variables are crucial for policy designs that aim at sustainable economic growth. Inflation is the rise in the general level of prices where a unit of currency effectively buys less than it did in prior periods indicating a decrease in the purchasing power of a nation's currency. Demand-pull or cost-push factors cause inflation. The commonly used inflation forecasting methods are either univariate models like autoregressive and moving average models or a combination of both, or multivariate models such as vector autoregression (VAR). Attempts to analyse inflation in India have generally focused on the determinants of inflation, and little on the forecasting for inflation, frequently using the output gap methods and univariate models.

In India, Balakrishnan (1991) finds a significant negative relationship between inflation and the output gap or the 'activity' variable in a sample from 1950 to 1980. He observes that inflation is not purely a monetary phenomenon as the continuous slowing down of money (M3) growth has not been able to dampen the inflationary pressure in India. Pandit (1993) argues that excessive emphasis placed in India on the demand-pull factors overlooking the cost-push factors hurts the economy and results in stagnation at least in the short run. Callen and Chang (1999) find that developments in monetary aggregates are an important indicator of future inflation and foreign inflation and stock prices have predictive content for inflation in short time horizons. Srinivasan *et al.* (2006), arguing that the monetary policy in India is more focused on core inflation, estimate an augmented Phillips curve to examine the effect of supply shocks on inflation in India. The OLS estimates show that supply shocks have only a transitory effect on both headline inflation and core inflation. Ball *et al.* (2016) modelling inflation in India using the Phillips curve approach in which the inflation rate depends on a slow-moving average of past inflation and the deviation of output from the trend find that the headline inflation is more volatile than core as it fluctuates due to large changes in the relative prices of certain industries, mostly food and energy. Balakrishnan and Parameswaran (2019) show that inflation dynamics in India could not be accounted for by the output gap and monetarist models, instead, a structuralist approach that uses oil price, relative price of agriculture and sectoral balance is shown to be a decent model in India.

Multivariate forecasting models incorporate the past information of the target variable and the intertemporal dependence of other variables in the VAR estimation improving the accuracy and forecast performance. However, owing to the number of variables and their lags, these models require the estimation of many parameters leading to the problems of over-parameterisation and inaccurate estimation of the parameters. The Bayesian Vector Autoregression (BVAR) model overcomes this problem by providing more information in the form of prior distributions of parameters resulting in more accurate estimates of the VAR model. The BVAR approach has a distinct advantage in that it generates not only a forecast but a complete multivariate probability distribution for future outcomes of the economy that appears to be more realistic than those generated by other competing approaches. Empirical studies have shown the superior forecasting performance of BVAR models for different countries at different periods of time for different measures of inflation like WPI, deflator and harmonised indices (Doan *et al.* 1984; Litterman, 1986; Carriero *et al.* 2019).

This paper uses the BVAR method in an attempt to provide accurate forecasts of the inflation rate in India. The main objectives of this paper are to examine the determinants of inflation and to forecast inflation over short horizons (up to 6 quarters ahead). This paper considers real GDP, money supply (M3), call money rate, short-term interest rate, BSE 100 index, exchange rate, crude oil price, and import price (US producer price) as the covariates in explaining the inflation rate in India. The quarterly data from Q2-1996 to Q1-2019 data are derived from the RBI and OECD databases. After testing for stationarity of the time series data by the unit root test, the empirical analysis is performed applying the BVAR method.

REVIEW OF LITERATURE

Quinn *et al.* (1999) examine three alternative VAR models for forecasting Irish inflation. The first model includes a domestic harmonised index of consumer prices - the import weighted measure of foreign consumer prices and the nominal effective exchange rate. The second model uses wages, prices and domestic demand. The third model is the monetary model which accounts for domestic credit and short-term nominal interest rates. In each case, the Bayesian approach to parameter estimation results in a dramatic improvement in forecasting performance relative to unrestricted models. In the monetary model, the confidence interval on the one-step-ahead forecast of inflation in an unrestricted VAR was almost three times as large as that of its Bayesian counterpart.

Kasuya and Tanemura (2000) estimate several Bayesian VAR models for Japan for the period 1973Q2-1999Q3 with 8 variables: consumer price index (CPI), money supply, real gross domestic product (GDP), GDP deflator, 10-year government bond yields, nominal exchange rate, investment and unemployment rate. They find that the forecast performances of the BVARs are superior to that of an ordinary VAR by one-step forecasts and Monte Carlo experiments.

Lack (2006) analyse VAR models to forecast Swiss inflation. He finds that models specified with respect to levels of variables are superior to those specified with respect to differences in variables. Simulations also show that optimal forecasts are obtained from a pool of only seven monetary and price variables (CPI, the real exchange rate, mortgage loans, M2, M3, the bond yield and an index of rents for new apartments), of which mortgage loans and M3 are the most relevant.

Banbura *et al.* (2010) consider 131 monthly macro-indicators for the time span from January 1959 through December 2003. The results show that the BVAR produces better forecasting results than the typical small VARs. They argue that the large unrestricted VARs can be dealt with by using the Bayesian VAR method over one hundred variables.

Yiping *et al.* (2010) show that for China, liquidity, output gap, housing prices and stock prices positively affect inflation. The effects of real interest rates and exchange rate on inflation are relatively weak. The impulse response analysis shows that most effects occur during the initial 5 months and disappear after 10 months.

Poghosyan (2013) uses three forecasting methods - VAR, BVAR and FAVAR (Factor Augmented Vector Autoregression) - to forecast Armenian macroeconomic variables using quarterly data from 2000 to 2012. The three models are evaluated by the RMSE criteria for 1-4 quarters ahead of forecast horizons. The Diebold-Mariano test results reveal no statistically significant differences in the forecasting performance for any macroeconomic variables - real GDP growth, inflation and nominal interest rate.

Ogunc (2019) examine the forecasting performance of BVAR models for Turkish inflation under alternative model sizes and specifications like at levels, differences, tightness and the accuracy of conditional and unconditional forecasts. He finds that the BVAR model that uses a small number of variables in the log-difference form outperforms the one using variables in log-levels form and has relatively lower forecast errors.

In the context of India, Srinivasan *et al.* (2006) analyse the effects of supply shocks on inflation. The results suggest that supply shocks have only a robust transitory effect on both headline and core measures of inflation. The potential explanation is that monetary policy has not provided the basis for a sustained change in the inflation process by accommodating supply shocks i.e. expanding the money supply in response to negative supply shocks. They argue that monetary authorities implicitly focus only on a core measure of inflation by discounting price movements that are expected to be reversed in the short run. The study suggests that what is crucial in inflation determination is not supply shocks per se but how policymakers respond to these shocks.

Biswas *et al.* (2010) use a BVAR model to forecast inflation and IIP growth for the quarterly data on WPI, M1 and IIP during the period from the first quarter of 1994-95(Q1) to the last quarter of 2007-08(Q4). The BVAR model forecasts perform better than a VAR model for inflation as well as IIP growth.

Kishor and Koenig (2012) attempt to forecast the headline inflation in India using monthly inflation data from 2012:M1 through 2018:M5 applying the Hodrick-Prescott filter method, a smoothing method used to obtain trend and cycle components of non-stationary series to obtain inflation gap, on inflation. The results show that forecasts from a univariate model of inflation gap significantly outperform the forecasts of the random walk model. Further, exchange rate movements help improve forecasts from the univariate model of inflation gap for short horizons.

Ball *et al.* (2016) examine the behaviour of quarterly inflation, both headline inflation and core inflation, in India since 1994, as measured by the weighted median of price changes across industries. They explain core inflation with a Phillips curve in which the inflation rate depends on a slow-moving average of past inflation and the deviation of output from the trend. The headline inflation is more volatile than core as it fluctuates due to large changes in the relative prices of certain industries, which are largely but not exclusively industries that produce food and energy. They find that the effect of the output gap on core inflation is positive and statistically significant, but insignificant on headline inflation. There is some evidence that changes in headline inflation feed into expected inflation and future core inflation.

Balakrishnan and Parameswaran (2019) favour a structuralist model than the monetarist and output-gap model that underlines inflation targeting in India. The estimates show a limited influence of expected inflation and the insignificance of the output gap on the inflation dynamics. In support of the structuralist model, the GMM-IV estimates for 1996-97(Q1)-2017-18(Q3) show significant effects of oil price, relative price of agriculture and sectoral balance on inflation.

DATA AND METHODOLOGY

The study period for this paper is 90 quarters starting from the third quarter of 1996 (Q3) to the last quarter of 2018 (Q4), consisting of 81 observations. The data used in this paper are the quarterly data on CPI (combined), real GDP, broad money (M3), crude oil price, exchange rate, BSE 100 index, call money rate, short term interest rate and US producer price. The data for CPI (combined), real GDP, broad money and crude oil price are derived from the OECD database. The data on the exchange rate, call money rate, short term interest rate and closing value of the BSE100 index are obtained from the RBI database. The data for US producer prices are sourced from the International Financial Statistics (IFS) database. The inflation variable is computed based on the CPI-Combined, released by the Ministry of Statistics and Programme Implementation, Government of India.

Bayesian Vector Autoregression (BVAR) Method

In contrast to the classical approach of estimating a set of parameters, Bayesian estimation specifies a set of prior probabilities about the underlying parameters to be estimated. The Bayesian approach distinguishes the difference between the prior and posterior distributions and how a given prior is constructed. With the use of this prior information, the Bayesian model gets shrinkage and is able to provide more information compared to the same sample estimated with an unrestricted VAR. The objective of Bayesian estimation is to produce coefficient estimates which combine the evidence from the sample data with the information contained in the prior.

More formally, consider the AR (p) process:

$$y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + \ldots + \theta_p y_{t-p} + \varepsilon_t \tag{1}$$

where ε_t is a white noise disturbance term. Let $g(\theta)$ be a prior probability density function of the non-sample prior information about the set of parameters to be estimated, $\theta = \{\theta_1, \theta_2, \ldots, \theta p\}$. Prior probability statements about θ can be expressed as integrals of the prior probability density function:

$$\frac{\int_{-\infty}^{\infty} E[\theta_1] = \theta_1 g(\theta_1) d\theta_1}{\int_{-\infty}^{\infty} E[p] = \theta_p g(\theta_p) d\theta_p} \tag{2}$$

where E[.] denotes the expectations operator. One notable feature of the priors is that they can easily be modified. For example, one prior that is based on the 'random walk' model believes that the coefficients on higher order lags are more likely to be zero than lower order lags, therefore, imposes a condition that the $E[\theta_1]$ i.e. mean is equal to unity whereas the means of all other autoregressive parameters of higher order other than one are zero. This 'tightening' of the prior for higher lags could be achieved by letting the prior variance decrease with increasing lag length.

The information contained in the sample data can be summarised in the sample probability density function, $g(y_t \mid \theta)$, which is the density of the random variable y_t conditional on the value taken by the parameters **q**. Using the Bayes' theorem, the two types of information - prior and sample - are combined into a posterior density function $g(\theta \mid y_t)$ as:

$$g(y_t) = \frac{g(y_t \mid \theta)_g(\theta)}{g(y_t)} \tag{3}$$

where $g(y_t)$ is the unconditional density of y_t used as normalisation to ensure that $g(y_t \mid \theta)$ is a well-behaved probability density function. The posterior density function contains all the available information about **q** and from it, point estimators can be derived. The mean of the posterior distribution is often taken as a point estimate for **q**.

The n variable vector autoregression of order p, VAR(p), is simply a set of equations in which each variable depends on a constant and lags 1 through p of all variables in the system. Each equation in the VAR contains exactly the same number of explanatory variables and can be estimated by the ordinary least squares method. However, such estimation of the unrestricted VARs often yields imprecise coefficient estimates as the system has $[n + pn^2]$ parameters to be estimated. To counter the problem of this over-parameterisation, Litterman (1986) suggests that each series is best described as a random walk around an unknown deterministic component and Doan, Litterman and Sims (1984) suggest the application of Bayesian procedures in the estimation of the parameters. Hence, the prior distribution is centred around the random walk specification for variable j as:

$$y_{jt} = \mu_t + \theta_1 y_{jt-1} + \varepsilon_{jt} \tag{4}$$

where the mean of the prior distributions on the first lag of variable n equal to unity and the mean of the prior distribution on all other coefficients is equal to zero.

Further, the prior distributions on all the parameters are assumed to be independent normal and no prior information is assumed to be known about the prior mean on the deterministic components. Once the means are specified, the only other prior input is some estimate of the dispersion about the prior mean. Following Litterman (1986), the standard deviation of the prior distribution for the coefficient on lag l of variable j in equation i, sij can be specified as:

$$s_{ij} = \begin{cases} \dfrac{\gamma}{l} & if\ i = j \\ \theta\gamma \dfrac{\hat{\sigma}_i}{\hat{\sigma}_j} & if\ i \neq j \end{cases} \tag{5}$$

where γ is the standard deviation of the first lag of the dependent variable, j is own lag, s is the standard deviation of the prior distribution for the coefficient on lag l of variable j in equation i and θ represents a factor that reflects that own lags account for most of the variation in a given variable. The standard error on the coefficient estimate for lag l of variable j in equation i is given by a standard deviation function of the form $s[i, j, l]$:

$$s[i, j, l] = [\gamma g(l) f(i, j)] \frac{s_i}{s_j} \tag{6}$$

The hyperparameter γ and functions $g(l)$ and $f(i, j)$ determine the tightness or weight attaching to the prior. The function $g(l)$ determines the tightness of lag one relative to lag l. The tightness around the prior mean is normally assumed to increase with increasing lag length. This is achieved by allowing $g(l)$ to decay harmonically with a decay factor d i.e. $g(l) = l^{-d}$. The tightness of the prior on variable j relative to the variable i in the equation for variable i is determined by the function $f(i, j)$; this can be the same across all equations and the prior is said to be symmetric. The multiplicative ratio (s_i/s_j) reflects the fact that in general the prior cannot be completely specified without reference to the data. In particular, it corrects for differences in the scale used in the measurement of each variable included in the system. It should be noted that the flexibility inherent in the specification of a general prior simply transfers the problem of over-parameterisation to one of having to estimate or search over too many hyperparameters (Doan, 1990). However, in a situation where there are strong prior views that one of the variables is exogenous, the general prior may improve the forecasting performance.

Forecast Evaluation Statistics

Suppose the forecast sample is $t = t + 1, t + 2, \ldots, t+h$ and let the actual and forecasted value in period t as y_t and $\hat{y}_t$ respectively. Then, the forecast can be evaluated using any of the following evaluation measures:

Root mean squared error: $$\sqrt{\sum_{t=t+1}^{t+h} (\hat{y}_t - y_t)^2 / h} \quad (7)$$

Mean absolute error: $$\sum_{t=t+1}^{t+h} |\hat{y}_t - y_t| / h \quad (8)$$

Mean absolute percentage error: $$100 \sum_{t=t+1}^{t+h} \left| \frac{\hat{y}_t - y_t}{y_t} \right| / h \quad (9)$$

Theil inequality index: $$\frac{\sqrt{\Sigma_{t=t+1}^{t+h} (\hat{y}_t - y_t)^2 / h}}{\sqrt{\Sigma_{t=t+1}^{t+h} \hat{y}_t^2 / h} + \sqrt{\Sigma_{t=t+1}^{t+h} y_t^2 / h}} \quad (10)$$

Potential Benchmark Models

As potential benchmark models, this paper considers univariate models of random walk, autoregression and autoregressive integrated moving average (ARIMA), as they are hardly found to be beaten by large complicated models such as VARs and traditional structural macroeconomic models. Further, the univariate models are considered convenient for short data samples as they include fewer explanatory variables.

Random Walk (RW): In the random walk approach, the inflation forecast for any horizon h is equal to the previous actual value of inflation:

$$y_{t+h} = y_t + \varepsilon_{t+h} \tag{11}$$

Autoregressive Model (AR): The autoregressive model of order one AR(1):

$$y_{t+h} = \beta_0 + \beta_1 y_{t+h-1} + \varepsilon_{t+h} \tag{12}$$

Autoregressive Moving Average Model (ARIMA): The ARIMA model:

$$y_{t+h} = \mu + \phi_1 y_{t+h-1} + \ldots + \phi_p y_{t+h-p} - \theta_1 \varepsilon_{t+h-1} - \ldots - \theta_q \varepsilon_{t+h-q} \tag{13}$$

where ϕ_p and θ_q are the autoregressive (AR) and moving average (MA) polynomials respectively, p being the number of autoregressive lags and q being the number of MA lags.

Vector Autoregressive Model (VAR): The VAR approach averts the need for structural modelling by treating every endogenous variable in the system as a linear function of the lagged values of all of the endogenous variables in the system and possibly a set of exogenous variables:

$$y_t = \beta_0 + \Sigma_{i=1}^{p} \beta_1 y_{t-1} + \alpha_m x_m + \varepsilon_t \tag{14}$$

where $y_t = [y_{1t}, \ldots, y_{kt}]'$ is the vector of endogenous variables in the model, β_0 is the kx1 vector of constants, β_1 is the kxk matrix of coefficients of y_{t-i} and x_m are the m exogenous variables in the system.

Diagnostic Tests

LM Breusch Godfrey Test: The LM test states the serial correlation between the disturbance term and the dependent variable. The Breusch-Godfrey serial correlation LM test is a test for autocorrelation in the residuals in a regression model. The null hypothesis is that there is no serial correlation of any order up to p.

Jarque Bera Test for Normality: The normality test is to identify how likely a related random variable is to be normally distributed. This statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The null hypothesis is that the series is normally distributed.

White's Heteroschedasticity test: White's (1980) test is a test of the null hypothesis of no heteroskedasticity against heteroskedasticity of unknown general form. The test statistic is computed by an auxiliary regression where the squared residuals are regressed on all possible (nonredundant) cross products of the regressors. The F-statistic is a redundant variable test for the joint significance of all cross products excluding the constant.

Diebold-Mariano Test: The Diebold-Mariano test is a test of whether two competing forecasts have equal predictive accuracy. For one-step-ahead forecasts, the test statistic is computed as:

$$S = \bar{d} / s_d \tag{15}$$

where $d = L_1 - L_2$, L_i (i = 1, 2) being either a squared or absolute difference between the forecast and the actual: $L_i = (\hat{y}_i - y_i)^2$ or $L_i = |\hat{y}_i - y_i|$, and $\bar{d}$ and s_d are the mean and sample standard deviation of d. The test-statistic follows student's t-distribution.

Empirical Specification: In this paper, two empirical models, small scale and medium scale, are specified: The small scale model contains three variables, inflation rate, GDP growth rate and short-term interest rates and four quarter dummies. The estimation period is 1998:Q4-2017:Q2 and the forecast sample is 2017:Q3-2018:Q4.

$$\begin{aligned} Infr_t = & \sum_{j=1}^{k} \beta_{1j}\, Infr_{t-j} + \sum_{j=1}^{k} \beta_{2j} GDPgr_{t-j} + \sum_{j=1}^{k} \beta_{3j} Intr_{t-j} + \alpha_1 Q_1 + \\ & \alpha_2 Q_2 + \alpha_3 Q_3 + \alpha_4 Q_4 + \varepsilon_t \end{aligned} \tag{16}$$

The medium scale model contains eight variables, inflation rate, GDP growth rate, call money rate, broad money, exchange rate, BSE 100 index, crude oil price and US producer price and four quarter dummies. The estimation period is 1996:Q3-2017:Q2 and the forecast sample is 2017:Q3-2018:Q4.

$$\begin{aligned} Infr_t = & \sum_{j=1}^{k} \beta_{1j} Infr_{t-j} + \sum_{j=1}^{k} \beta_{2j} GDPgr_{t-j} + \sum_{j=1}^{k} \beta_{3j} InM3_{t-j} + \\ & \sum_{j=1}^{k} \beta_{4j} Excr_{t-j} + \sum_{j=1}^{k} \beta_{5j} BSE100_{t-j} + \sum_{j=1}^{k} \beta_{6j} COP_{t-j} + \\ & \sum_{j=1}^{k} \beta_{7j} USpp_{t-j} + \alpha_1 Q_1 + \alpha_2 Q_2 + \alpha_3 Q_3 + \alpha_4 Q_4 + \varepsilon_t \end{aligned} \tag{17}$$

To avoid the dummy variable trap, both models omit the intercept term in the estimation.

EMPIRICAL ANALYSIS

The whole sample period (1996:Q3-2018:Q4) is divided into two parts: the estimation sample and the forecasting sample periods. Two forecast strategies are used: expanding and rolling window. In both cases, the procedure starts with an estimation sample (1996:Q3-2017:Q2) and the forecasts are produced for 1 to 6-quarters ahead as the interest is in the short-term forecast performance of the models. In the first forecast round, in the case of the expanding window strategy, the estimation period expands recursively by one quarter, but its starting point will be the same. So, in this case, the number of observations will increase recursively by one in each forecast round. Thus, in the recursive window strategy, h =1 means 2017:Q2 to 2017:Q3 and h = 2 means 2017:Q2 to 2017:Q4. In the rolling window strategy, the whole estimation period, including its starting point, shifts by one quarter in each forecast round. For each round, 1 to 6 quarters ahead pseudo-out-of-sample forecasts are obtained using both of the forecast strategies. The estimation process is repeated until 2018:Q4. So, in the recursive window strategy, h = 1 means 2017:Q2 to 2017:Q3 and h = 2 means 2017:Q3 to 2017:Q4.

The descriptive statistics of the variables used in this paper are presented in Table 1. The average inflation rate for the period is 1.52 percent. The distributions for inflation rate and GDP growth rate are leptokurtic as their kurtosis values, the height of the peak and the flatness of the distribution are greater than 3. However, average exchange rate, BSE 100 index, call money rate, crude oil price, ln(M3), short term interest rate and US producer price are platykurtic suggesting that their distribution is flat relative to normal distribution. As the skewness values suggest, all variables are normally distributed, except US producer price which is skewed towards the left. The Jarque-Bera statistic rejects the null hypothesis of non-normal distribution for the variables since the probability values are lesser than 0.05.

As potential benchmark models, this paper considers univariate models of random walk, autoregression and autoregressive integrated moving average (ARIMA). These univariate models are hardly found to be beaten by large complicated models such as VARs and traditional structural macroeconomic models. Further, the univariate models are considered convenient for short data samples as they include fewer explanatory variables. Due to the problem of over-parameterisation and short time series, the VAR model is restricted to five endogenous variables viz. GDP growth rate, the logarithm of M3, average exchange rate, crude oil price as

Table 1: Descriptive Statistics of Variables

Variable	*Definition*	*Mean*	*Skewness*	*Kurtosis*	*Jarque-Bera*
Inflation rate (CPI)	Quarterly inflation rate as a percentage change of one quarter over the previous quarter, with the reference year 2015	1.519 (1.700)	0.015	4.767	10.546 [0.005]
Real GDP	GDP by the expenditure method, base year 2010 (US$ millions)	1.740 (1.725)	0.137	7.034	55.337 [0.000]
ln(M3)	Money supply, broad money, base year 2015	17.564 (17.660)	-0.159	1.647	6.519 [0.038]
Call money rate	Call money rate	6.724 (6.787)	-0.142	2.334	1.769 [0.413]
Interest rate	3-month MIBOR rate averaged to quarterly rate	8.045 (8.240)	-0.062	2.012	3.347 [0.188]
Exchange rate	Quarterly exchange rate (₹ per US$)	51.323 (9.021)	0.798	2.163	10.965 [0.004]
Crude oil price	US$ per barrel	55.915 (27.807)	0.353	2.031	4.854 [0.088]
BSE 100 index	Closing value for BSE 100 as a proxy for stock prices	4782.982 (3195.857)	0.463	2.153	5.315 [0.070]
US producer price	US producer price index (PPI) as a proxy for import prices, base year 2010	93.447 (96.730)	-0.353	1.609	8.214 [0.016]

Note: Standard deviations in parentheses and probability in brackets.

determinants of inflation. The BVAR overcomes this difficulty and allows the use of more variables.

Figure 1 plots the time series of the variables. The variables GDP growth rate and logM3 are showing an upward trend and constantly increasing over the period. The variables inflation rate, exchange rate, crude oil price and BSE100 index show seasonal elements suggesting that the variables are not stationary as the mean of these variables varies over time. The data series are further checked for stationarity by the Augmented Dicky-Fuller (ADF) unit root test before carrying out the time series analysis.

ADF Unit Root test: The ADF results presented in Table 2 show that all the variables are non-stationary at levels since their ADF values are less than the critical values. The null hypothesis of unit root at levels is accepted for all the variables but rejected at first difference. All the variables are integrated of order one i.e I(1), except ln(M3) which is integrated of order two i.e. I(2).

Table 2: Augmented Dicky-Fuller Unit Root Test for Stationarity

Variable	*At level*			*At first difference*		
	With constant	*Constant+ trend*	*Without constant+ trend*	*With constant*	*Constant+ trend*	*Without constant+ trend*
Inflation rate (CPI)	-2.251 (0.190)	-2.100 (0.538)	-0.734 (0.395)	-16.496** (0.0001)	-16.463** (0.0001)	-16.603** (0.000)
Real GDP	-8.345** (0.000)	-8.329** (0.000)	-1.353 (0.162)	-10.901** (0.0001)	-10.826** (0.000)	-10.972** (0.000)
ln(M3)	-2.816 (0.061)	1.780 (1.000)	-0.420 (0.529)	-0.096 (0.946)	-4.766** (0.001)	-0.927 (0.312)
Call money rate	-2.829 (0.059)	-2.800 (0.202)	-0.8859 (0.341)	-7.889** (0.00)	-7.848** (0.00)	-7.932** (0.00)
Interest rate	-2.479 (0.125)	-2.731 (0.227)	-1.020 (0.274)	-7.822** (0.00)	-7.804** (0.00)	-7.853** (0.00)
Exchange rate	0.667 (0.991)	-1.387 (0.857)	2.209 (0.993)	-6.727** (0.00)	-6.845** (0.00)	-6.467** (0.00)
Crude oil price	-1.977 (0.296)	-1.780 (0.705)	-0.414 (0.531)	-7.420** (0.000)	-7.456** (0.000)	-7.447** (0.000)
BSE 100 index	0.473 (0.985)	-2.801 (0.201)	2.423 (0.996)	-7.294** (0.000)	-7.351** (0.000)	-6.852** (0.000)
US producer price	-0.999 (0.750)	-2.039 (0.571)	2.414 (0.996)	-7.587** (0.000)	-7.566** (0.000)	-6.851** (0.000)

Note: Figures are t-statistics. Probability in parentheses. ** Significant at 5 percent level.

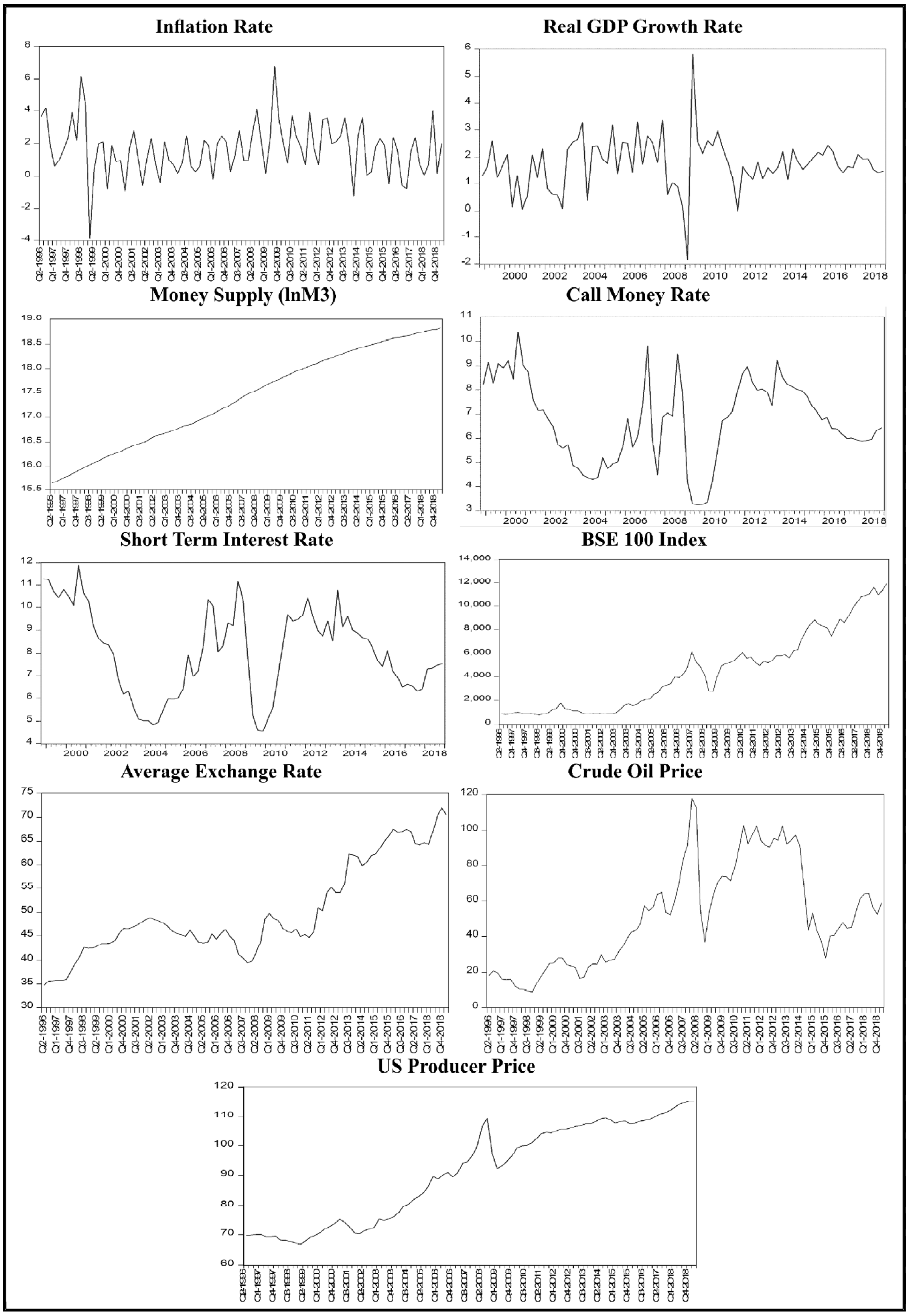
Optimal Lag Length: In order to determine the optimum lag length, sequentially modified likelihood ratio (LR), final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SIC) and Hannan-Quinn information criterion (HQ) tests are used. As Table 3 shows that three of the tests, FPE, AIC and SIC, show a lag length of 2, and hence the variables are lagged by 2 in this empirical analysis.

Table 3: Optimal Lag Length Selection Criteria

Lag	*lnL*	*LR*	*FPE*	*AIC*	*SIC*	*HQ*
0	-1603.272	NA	2814	37.018	37.216	37.098
1	-766.652	1519.378	0.387	18.912	20.499**	19.551
2	0686.901	132.001	0.195**	18.205	21.181	19.403**
3	-647.323	59.140	0.255	18.421	22.786	20.179
4	-597.212	66.815	0.277	18.396	24.149	20.713
5	-561.926	41.370	0.456	18.711	25.853	21.587

Note: ** Lag order selected by the criterion at 5 percent level.

Figure 1: Time Series Plots of Variables



Bayesian VAR Model Estimation

In principle, it is unclear whether transforming variables into differences can enhance the forecasting performance of the BVAR. The level specification can better take into consideration the existence of long-run (cointegrating) relationships across the variables, which get omitted in differencing specification. In a classical framework, differencing can improve forecasting performance in the presence of instability. Following the Litterman (1986) tradition, some BVAR forecasts use models with variables in levels or log levels, while some others use models in differences or growth rates (Del Negro and Schorfheide, 2011; Clark and McCracken, 2013; Giannone et al. 2015). This paper estimates the BVAR for seven priors, each with certain distributional properties of the variance-covariance matrix of the residuals in the VAR equation, both at levels and in differences and short and medium periods. The seven priors are Litterman/Minnesota, Normal-Flat, Norman-Wishart, Independent Normal-Wishart, Sims-Zha (Normal-Flat), Sims-Zha (Normal-Wishart), Giannone-Lenza-Primiceri (GLP) priors. Since the variable lnM3 is not stationary even at the first difference, the second difference of lnM3 is considered.

Since the model is not stationary at levels, but stationary at first difference, this paper considers the VAR model with differences. Tables 4 and 5 present the Bayesian VAR estimates of inflation rate for the seven different priors for short (1999:Q2-2017:Q2) and medium (1997:Q1-2017:Q2) periods. Each column in the tables corresponds to an equation in the BVAR and each row corresponds to a regressor in the equation. The exogenous variables are just the quarter dummy variables. The estimated coefficients corresponding to each independent variable in the row represent the posterior mean coefficients. Following Litterman (1980), the prior is selected by maximising the out-of-sample forecasting performance of the models over a pre-sample for seven different priors.

Since the interest is on the forecasting of the inflation rate, only the estimates of the equation for inflation rate are presented for small and medium models. For all the priors specified, the effect of GDP growth and broad money (M3) in the previous period on the current period inflation rate is positive. For the three priors - Normal-Flat, Normal-Wishart and Independent Normal Wishart - the effect of short-term interest rate on the current period inflation rate are positive. All the priors, except the Sims-Zha Normal-Wishart prior, show the effect of the exchange rate on the inflation rate is positive. For all the priors, the effects of stock price and call money rate on inflation rate are negative whereas the effect of crude oil prices on the current period inflation rate is positive. In all priors, apart from Normal-Flat, Normal-Wishart and Independent Normal Wishart priors, the effect of import price on the inflation rate is negative.

Table 4: BVAR Estimates of Inflation Rate for Short Scale Model

Variable/prior	*Litterman/ Minnesota*	*Normal-Flat*	*Norman-Wishart*	*Independent Normal-Wishart*	*Sims-Zha (Normal-Flat)*	*Sims-Zha (Normal-Wishart)*	*GLP*
Inflation rate(-1)	0.151	0.329	0.329	0.329	0.151	0.151	0.298
	(0.07)	(0.09)	(0.10)	(0.10)	(0.07)	(0.07)	(0.10)
Inflation rate(-2)	0.040	0.166	0.166	0.166	0.040	0.040	0.069
	(0.05)	(0.09)	(0.09)	(0.09)	(0.04)	(0.04)	(0.06)
GDPgr(-1)	0.092	0.268	0.268	0.268	0.093	0.093	0.233
	(0.08)	(0.11)	(0.11)	(0.11)	(0.07)	(0.07)	(0.11)
GDPgr(-2)	-0.019	-0.176	-0.176	-0.176	-0.019	-0.019	-0.051
	(0.005)	(0.11)	(0.11)	(0.11)	(0.04)	(0.04)	(0.06)
Interest rate(-1)	0.005	-0.006	-0.006	-0.006	0.005	0.005	0.019
	(0.07)	(0.13)	(0.13)	(0.13)	(0.07)	(0.07)	(0.09)
Interest rate(-2)	-0.002	0.035	0.035	0.036	-0.002	-0.002	0.013
	(0.05)	(0.14)	(0.14)	(0.14)	(0.05)	(0.05)	(0.07)
Quarter=1	-0,295	-1.152	-1.152	-1.160	-0.298	-0.298	-1.016
	(0.60)	(0.72)	(0.72)	(0.76)	(0.59)	(0.59)	(0.69)
Quarter=2	1.525	1.129	1.129	1.120	1.521	1.521	1.087
	(0.59)	(0.68)	(0.68)	(0.72)	(0.58)	(0.58)	(0.66)
Quarter=3	2.447	1.769	1.769	1.761	2.443	2.443	1.708
	(0.60)	(0.73)	(0.73)	(0.77)	(0.60)	(0.60)	(0.70)
Quarter=4	0.796	-0.123	-0.123	-0.133	0.793	0.793	-0.092
	(0.62)	(0.73)	(0.73)	(0.77)	(0.62)	(0.62)	(0.72)
R-square	0.541	0.597	0.597	0.600	0.541	0.541	0.581
Adj. R-square	0.476	0.539	0.539	0.539	0.476	0.476	0.521
F-statistic	8.252	10.367	10.367	10.367	8.260	8.260	9.70
Log-likelihood			-393.72	-171.933			-426.38

Note: Posterior standard errors in parentheses.

Table 5: BVAR Estimates of Inflation Rate for Medium Scale Model

Variable/prior	*Litterman/ Minnesota*	*Normal-Flat*	*Norman-Wishart*	*Independent Normal-Wishart*	*Sims-Zha (Normal-Flat)*	*Sims-Zha (Normal-Wishart)*	*GLP*
Inflation rate(-1)	0.061	0.205	0.205	0.209	0.061	0.061	0.156
	(0.08)	(0.11)	(0.11)	(0.12)	(0.07)	(0.07)	(0.10)
Inflation rate(-2)	0.005	-0.033	-0.033	-0.040	0.005	0.005	0.002
	(0.05)	(0.11)	(0.11)	(0.12)	(0.04)	(0.04)	(0.08)
GDPgr(-1)	0.089	0.344	0.345	0.341	0.090	0.090	0.256
	(0.10)	(0.15)	(0.15)	(0.16)	(0.09)	(0.09)	(0.14)
GDPgr(-2)	-0.031	-0.298	-0.298	-0.310	-0.032	-0.032	-0.150
	(0.06)	(0.14)	(0.15)	(0.16)	(0.05)	(0.05)	(0.10)

contd. table 5

Variable/prior	*Litterman/ Minnesota*	*Normal-Flat*	*Norman-Wishart*	*Independent Normal-Wishart*	*Sims-Zha (Normal-Flat)*	*Sims-Zha (Normal-Wishart)*	*GLP*
Exchange rate(-1)	-0.034	0.035	0.035	0.045	-0.035	-0.035	0.005
	(0.05)	(0.11)	(0.11)	(0.12)	(0.04)	(0.04)	(0.08)
Exchange rate(-2)	-0.019	-0.105	-0.105	-0.122	0.019	0.019	-0.048
	(0.04)	(0.11)	(0.11)	(0.12)	(0.03)	(0.03)	(0.07)
BSE100(-1)	-1.10E-05	-0.0003	-0.0003	-0.0003	-1.13E-05	-1.13E-05	-0.0001
	(0.00)	(0.0003)	(0.0003)	(0.0004)	(0.0001)	(0.0001)	(0.0002)
BSE100(-2)	1.10E-05	0.0004	0.0004	0.0004	1.02E-05	1.02E-05	0.0001
	(0.00)	(0.0004)	(0.0004)	(0.0004)	(0.0001)	(0.0001)	(0.0002)
Call money rate(-1)	-0.007	-0.147	-0.147	-0.149	-0.007	-0.007	-0.065
	(0.06)	(0.09)	(0.09)	(0.10)	(0.05)	(0.05)	(0.08)
Call money rate(-2)	0.011	0.161	0.161	0.161	0.011	0.011	-0.063
	(0.04)	(0.09)	(0.09)	(0.10)	(0.03)	(0.03)	(0.06)
Crude oil price(-1)	0.003	0.008	0.008	0.008	0.003	0.003	0.005
	(0.009)	(0.02)	(0.02)	(0.02)	(0.008)	(0.008)	(0.01)
Crude oil price(-2)	0.0003	-0.003	-0.003	-0.003	0.0003	0.0003	-0.002
	(0.006)	(0.02)	(0.02)	(0.02)	(0.005)	(0.005)	(0.01)
lnM3(-1)	2.652	0.637	0.637	0.533	2.693	2.693	11.644
	(6.50)	(2.44)	(2.44)	(2.22)	(5.560)	(5.560)	(12.08)
lnM3(-2)	-2.547	-0.387	-0.387	-0.225	-2.589	-2.589	-11.62
	(6.45)	(2.45)	(2.45)	(0.23)	(5.51)	(5.51)	(12.08)
US producer price(-1)	0.016	-0.020	-0.020	-0.019	0.016	0.016	0.013
	(0.05)	(0.11)	(0.11)	(0.12)	(0.04)	(0.04)	(0.07)
US producer price(-2)	0.006	0.014	0.014	0.003	0.006	0.006	0.006
	(0.03)	(0.08)	(0.08)	(0.09)	(0.03)	(0.03)	(0.06)
Quarter=1	-1.354	-1.375	-1.375	-1.383	-1.356	-1.356	-0.829
	(13.06)	(1.75)	(1.75)	(1.60)	(11.11)	(11.11)	(14.28)
Quarter=2	0.263	0.517	0.517	0.504	0.261	0.261	0.999
	(13.07)	(1.75)	(1.75)	(1.60)	(11.12)	(11.12)	(14.31)
Quarter=3	1.364	0.961	0.961	0.912	1.362	1.362	1.760
	(13.05)	(1.75)	(1.75)	(1.61)	(11.10)	(11.10)	(14.27)
Quarter=4	0.004	-0.152	-0.152	-0.170	0.003	0.003	0.438
	(13.05)	(1.75)	(1.75)	(1.60)	(11.10)	(11.10)	(14.27)
R-square	0.492	0.548	0.548	0.547	0.493	0.493	0.540
Adj. R-square	0.337	0.410	0.410	0.409	0.337	0.337	0.399
F-statistic	3.163	3.958	3.958	3.947	3.167	3.167	3.827
Log-likelihood			**-2190.22**	**-1620.96**			**-1747.00**

Note: Posterior standard errors in parentheses.

BVAR Inflation Rate Forecast Evaluation

Table 6 presents the forecast measures for the small and large BVAR models both at levels and in differences. The model in differences has higher forecast errors compared to the model in levels. It might be due to the small sample size, as the sample size is 81, and a reduction in the size of samples due to differencing results in loss of information and hence in lower forecast accuracy. By looking at the forecasting measures for all priors of Bayesian VAR models, the prior that gives the best forecasting accuracy among all priors are selected. For the short scale model, the forecast measures are low and close for three priors: Normal-Flat, Normal-Wishart and Independent Normal-Wishart. As two of the forecast measures (RMSE and MAE) are lowest for Normal-Flat prior, and hence Normal-Flat prior is selected. For the medium scale model, the forecast measures are low and close for three priors: Litterman, Sims-Zha (Normal-Flat) and Sims-Zha (Normal-Wishart). Two of the forecast measures (RMSE and MAE) are lowest for Sims-Zha (Normal-Wishart) prior, and therefore, Sims-Zha (Normal-Wishart) prior is selected. The selected priors correctly gauge the effects of different variables on the inflation rate as is expected by theory.

Table 6: Forecasting Evaluation Statistics in Levels vs Differences for Short and Medium Scale Models

Prior	*BVAR in levels*				*BVAR in differences*			
	RMSE	*MAE*	*MAPE*	*Theil*	*RMSE*	*MAE*	*MAPE*	*Theil*
Small BVAR model								
Litterman/Minnesota	0.874	0.769	19.738	0.222	1.388	1.079	80.106	0.390
Normal-Flat	0.832	0.680	64.135	0.219	1.424	1.173	99.388	0.408
Normal-Wishart	0.832	0.680	64.163	0.219	1.424	1.173	99.389	0.408
Ind. Normal-Wishart	0.834	0.687	54.283	0.219	1.412	1.158	96.027	0.404
Sims-Zha (Normal-Flat)	0.879	0.774	49.684	0.223	1.399	1.087	81.573	0.394
Sims-Zha (Normal-Wishart)	0.879	0.774	49.682	0.224	1.399	1.087	81.580	0.394
GLP	0.845	0.776	61.320	0.218	2.223	1.811	24864	0.992
Medium BVAR model								
Litterman/Minnesota	0.835	0.701	85.858	0.221	1.418	1.135	85.079	0.400
Normal-Flat	0.892	0.800	76.060	0.238	1.472	1.319	188.141	0.441
Normal-Wishart	0.891	0.799	76.159	0.238	1.470	1.317	206.287	0.457
Ind. Normal-Wishart	0.979	0.859	87.308	0.253	1,532	1.395	206.288	0.457
Sims-Zha (Normal-Flat)	0.828	0.697	72.394	0.220	1.411	1.131	83.743	0.397
Sims-Zha (Normal-Wishart)	0.828	0.697	72.348	0.220	1.411	1.131	83.743	0.397
GLP	0.832	0.721	65.940	0.226	1.5E+26	6.3E+25	99.998	1.000

Since the forecasting is a time-series analysis, the errors might be serially correlated. Table 7 reports the Edgeworth expansion corrected likelihood ratio statistics for the small and medium scale models. For the small scale model, for lag 1 the p-value is 0.046, which is less than 5 percent, and hence the model rejects the null hypothesis of no serial correlation at lag 1 but for lag 2, there is no serial correlation. The Jarque-Bera test does not reject the null hypothesis of normality. The White heteroscedasticity test shows no heteroscedasticity is present in the model since the p-value(0.068) is greater than 0.05. For the medium scale model, for lags 1 and 2 the p-values are 0.032 and 0.013 respectively and the null hypothesis of no serial correlation at lags 1 and 2 is rejected at 5 percent level. The Jarque-Bera test does not reject the null hypothesis of normality as the p-value is 0.067. The White heteroscedasticity test shows no heteroscedasticity is present in the model since the p-value (0.051) is greater than 0.05.

Table 7: BVAR Diagnostic Tests

Test	*Small scale model*		*Medium scale model*	
	LRE statistic	*Chi-square*	*LRE statistic*	*Chi-square*
VAR residual serial correlation test – lag 1	17.168 (0.046)	-	56.951 (0.033)	-
VAR residual serial correlation test - lag 2	16.54 (0.056)	-	73.308 (0.012)	-
Jarque-Bera normality test	-	0.564 (0.75)	-	10.401 (0.067)
White's heteroscedasticity test	-	*337.38 (0.07)*	-	*562.411 (0.051)*

Note: p-values in parentheses.

As a measure of forecast performance, root mean squared errors (RMSEs) are calculated separately for each forecast horizon for different forecast horizons and different models. In general, with the exception of the random walk (RW), the performances of other univariate models are not promising. Autoregressive (AR) models display very poor performance. Table 8 presents the RMSEs of each of the individual models relative to the random walk for different forecast horizons, starting from 1-quarter to 6-quarters ahead, for both expanding and rolling forecast strategies. If the relative RMSE is lower than one, the given model incurs a lower loss in comparison to the benchmark model and the respective model is superior to the random walk in terms of forecast performance. The differences in the forecast performance between the expanding and rolling window forecast strategies are not found to be significant.

Using the recursive window strategy, the VAR with 2 lags outperforms the random walk model in all the horizons, except the first and second horizons. The BVAR model displays good performance as it reports much lower forecast errors in comparison to other models. By the rolling window strategy also, the VAR(2) model produces better forecasts than all the univariate models and outperforms the random walk model in the starting horizons. Therefore, the random walk model and VAR model will be used

Table 8: RMSEs of Forecast Models Relative to Random Walk by Forecast Strategies

Model/quarter	*Q1*	*Q2*	*Q3*	*Q4*	*Q5*	*Q6*
			Recursive window strategy			
RW	1.000	1.000	1.000	1.000	1.000	1.000
AR(1)	2.642	2.068	1.642	1.719	1.142	1.123
ARIMA	1.257	1.270	1.330	1.360	1.380	1.400
VAR(2)	1.299	1.170	0.929	0.972	0.646	0.635
BVAR(small)	0.406	0.365	0.290	0.304	0.202	0.198
BVAR(medium)	0.391	0.352	0.279	0.292	0.194	0.191
			Rolling recursive window strategy			
AR(1)	2.642	2.749	1.721	1.051	1.729	1.980
ARIMA	0.656	0.883	1.119	1.060	1.880	2.093
VAR(2)	1.220	1.240	1.260	1.400	1.420	1.470
BVAR (small)	0.312	0.367	0.432	0.673	0.921	0.634
BVAR (medium)	0.342	0.476	0.543	0.762	0.981	0.812

as benchmarks for the evaluation of the forecast performance of the BVAR model. Since there are two BVAR models i.e. small scale and medium scale models and the forecasting errors are almost identical, the small scale BVAR model is chosen as it provides better forecasts in comparison to large-scale BVAR across all time horizons.

To assess whether the forecast performances of the two models i.e. BVAR vs RW and BVAR vs VAR(2) are on average statistically different over the out-of-sample period, the Diebold-Mariano (DM) test of equal predictive ability is applied. Table 9 reports the results of the DM test. The DM-statistic is significant in the case of the BVAR model but insignificant in the case of the VAR(2) model implying that the BVAR model provides an improvement in forecast accuracy relative to the random walk model, but not with respect to VAR with 2 lags.

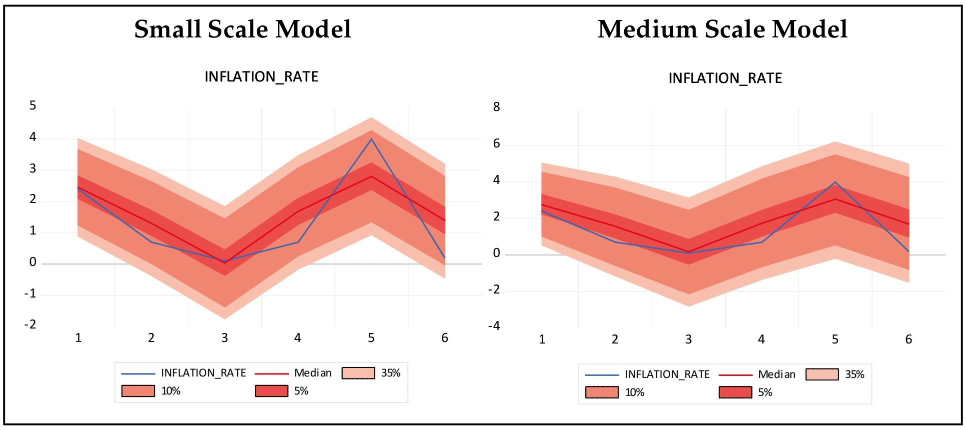
Table 9: Diebold-Mariano (DM) Test of Forecast Accuracy

Forecast sample	*BVAR vs RW*	*BVAR vs VAR(2)*
2017:Q3-2018:Q4	2.354 (0.019)	1.797 (0.072)

Note: p-values in parentheses.

Due to the uncertainty surrounding point forecasts, forecast densities (or fan charts) are used to describe the degree of uncertainty around the central forecasts that giving a better picture of forecasting evaluation. In the fan chart in Figure 2, the blue line represents the actual point forecasts, the red line represents the median forecast, the darkest area represents a 5 percent confidence interval and the lightest area represents the 35 percent

Figure 2: Fan Chart for BVAR Inflation Rate Predictions



confidence interval of forecasted values. The fan chart confirms that the BVAR model predictions are accurate. It is observed from the fan charts that the small scale model and medium scale model produce identical forecasts. However, the median forecast in the medium scale model is closer to the actual values, implying less variability in forecasts. This might be due to the fact that the medium scale model contains more information in comparison to the small scale model which only includes two variables as regressors.

CONCLUSION

Predicting inflation is the foremost but challenging task of the monetary policy that aims at stable inflation with sustainable economic growth. The standard autoregressive vector models consider past information and allow inter-temporal dependence with more macro variables. But they are plagued by over parameterisation due to the inclusion of several variables and their lags which ultimately leads to an inaccurate estimation of the parameters and poor forecast accuracy. This paper employs the Bayesian vector autoregression (BVAR) model to forecast the short term inflation in India, which allows the inclusion of more endogenous variables and enables in this way a more comprehensive explanation of inflation. This paper compares the forecast accuracy of the BVAR model in levels vs differences and finds the accuracy of the models specified in levels is higher. In the Bayesian VAR analysis, the best prior is selected by comparing the out-of-sample forecast accuracy. Two BVAR models, one with small scale (three) variables and the other with a medium scale (seven) variables, that describe the most important dynamics and interactions between the determinants of inflation in India are estimated. For the small scale model, Normal-Flat prior is chosen and for the medium scale model, the Sims-Zha (Normal-Wishart) prior is selected.

The given BVAR model is compared with other benchmark models like the Random Walk model, AR(1) model, ARIMA model and VAR model and it is found that the BVAR model provides the best forecast results out of all the models. However, when the DM test is conducted, it is found that the forecasting ability of BVAR is superior to the random walk model, there is no significant improvement in forecast ability when compared to the VAR model. In terms of forecast accuracy, not much difference is found with respect to the size of the model. Several econometric models are considered as possible benchmarks for the BVAR such as random walk, ARIMA unrestricted VAR. The best performing among them, random walk and VAR are used as benchmarks to evaluate the forecast performance of the BVAR model. The forecasting performance of the models is measured by RMSEs of the out-of-sample forecasts for each forecast horizon up to 6 quarters obtained using both rolling and expanding window forecast strategies and then they are compared to each other for different time horizons.

The estimated results show that the BVAR approach, which incorporates more economic information, outperforms the benchmark univariate and the VAR models in different time horizons of the forecast sample using both forecast strategies. The difference between models in their forecast performance is statistically significant for the random walk model and not statistically significant for VAR. The fan charts for modelling inflation through the Bayesian VAR model show that the model delivers a decent performance and can be used to forecast inflation for short horizons. This paper has attempted BVAR for short and medium time periods only. A forecast combination procedure of the BVAR with other short-term inflation forecasting models such as Bayesian model averaging could be a successful strategy to improve forecast performance over long time periods. By combining many misspecified models each incorporating information from different variables, such Bayesian model averaging could outperform forecasts from individual models.

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