An Evaluation of Alternative BVAR Models for Forecasting Iranian Inflation

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This paper investigates the use of different priors to improve the inflation forecasting performance of BVAR models with Litterman's prior. A Quasi-Bayesian method, with several different priors, is applied to a VAR model of the Iranian economy from 1981:Q2 to 2007:Q1. A novel feature with this paper is the use of g-prior in the BVAR models to alleviate poor estimation of drift parameters of Traditional BVAR models. Some results are as follows: (1) our results show that in the Quasi-Bayesian framework, BVAR models with Normal-Wishart prior provides the most accurate forecasts of Iranian inflation; (2) The results also show that generally in the parsimonious models, the BVAR with g-prior performs better than BVAR with Litterman's prior.[1]

1. Introduction

This paper focuses on the investigation of the use of different priors in Quasi-Bayesian vector autoregressive (BVAR) models to improve the inflation forecasting performance of Traditional BVAR models[2]. In this regard it follows Heidari (2011) and Heidari and Parvin (2008)

2. This model is known as BVAR with Litterman's prior or BVAR with Minnesota prior. In recent literature it is referred as Traditional BVAR.

among others[1]. Forecasting of prices, under inflation targeting strategy, has become more important from the standpoint of the monetary policy makers and private agents. Svensson (1997) points out that a problem of implementing an inflation targeting strategy is the central bank's imperfect control of inflation. Svensson (1997) documented that a conditional inflation forecast, as an intermediate target variable, can alleviate this problem. Using this makes the forecast the focal point in the monetary policy discussions. Apart from its role as an input into monetary policy, forecasts of inflation have a significant role in fiscal policy and the wage bargaining process. Additionally, they have a role in assessing likely trends in competitiveness in the international capital markets and projections of real economic activity.

There are a number of approaches to forecast inflation: Structural models based on macroeconomic theories of the small open economy (SOE); indicator analysis, including a composite leading indicator; and time series methods such as autoregressive integrated moving average (ARIMA), and vector autoregressive (VAR) models. Each of these approaches has particular advantages and certain limitations.

This paper, however, uses VAR models. One of the most successful applications of the VAR models in macroeconomics has been the forecasting of macroeconomic variables. These models, however, are not free of limitations (see, e.g., Canova, 1995; and Fry and Pagan, 2005, for some critiques and issues in using VAR models). A disadvantage of using Unrestricted VAR (UVAR) models based on unrestricted ordinary least square (OLS) estimates of the coefficients is the large number of parameters that need to be estimated. To restrict the parameters of the UVAR models and improve the forecasting performance of these models, Litterman (1984, 1986), and Doan, et al. (1984) suggested that these parameters could be estimated using Bayesian techniques. In pure Bayesian method, a Markov Chain Monte Carlo (MCMC) or other methods of sampling are employed to calculate posterior distribution. As Litterman (1984, 1986), and Doan, et al. (1984) fix many parameters (such as variance-covariance of

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1. Moshiri (2001) uses a structural (an augmented Phillips Curve), a time series (an AR(1) model), and an Artificial Neural Networks (ANN) models to forecast Iranian inflation. Structural and ANN models are out of the scope of this paper and VAR models are superior to the class of ARMA models in various respects.

innovations), the method that they used is referred to as the Quasi-Bayesian method in comparison with pure Bayesian method[1].

There is a lot of empirical evidence in the literature, which suggests that the BVAR models with Litterman's prior produce forecasts that exhibit a high degree of accuracy when compared with alternative methods such as univariate time series models, UVAR, and large scale macro-models (see,e.g., Artis and Zhang, 1990; Ballabriga and Valles, 1999; Ballabriga et al., 2000; Doan et al., 1984; Felix and Nunes, 2003; Heidari, 2011; Heidari and Parvin, 2008; Kadiyala and Karlsson, 1993 and 1997; Kenny et al., 1998; Litterman, 1984 and 1986; McNees, 1986; Robertson and Tallman, 1999; Sims, 1993; Sims and Zha, 1998; Todd, 1984). Although Traditional BVAR models can improve UVAR model forecasts through the use of extra information as priors, they cannot be used to get accurate forecasts in mixed drift models. Mixed drift models are referred to as the macroeconomic forecasting models which contain variables both with and without drift. In these models, Traditional BVAR models treat all variables in the model in the same way and use diffuse prior on the constant term and shrink the drift terms toward zero. This would create bias in the forecasts of those variables. This could be one of the possible reasons behind the weak results of recent studies on forecasting macroeconomic variables using a BVAR with Litterman's prior[2]. In the literature, the performance of the Traditional BVAR models has been somewhat unimpressive in inflation forecasting, as a driftless variable (see, e.g., Heidari, 2011; Kenny et al., 1998; Litterman, 1986; McNees, 1986; Robertson and Tallman, 1999; Webb, 1995; Zarnowitz and Braun, 1992).

This paper investigates the use of different priors to improve the inflation forecasting performance of Traditional BVAR models. A novel feature of this paper is the use of inexact prior restrictions of g-prior to the BVAR models. To study whether using g-prior in the Quasi-Bayesian VAR, improves the quality of the forecasts of

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1. In pure Bayesian method, all these parameters can be estimated and also forecasts are conditioned on expected values.
2. Heidari and Parvin (forthcoming) investigates the forecast accuracy of different BVAR models with different sources of time variation for forecasting Iranian inflation. They show that a modified time-varying BVAR model, where the autoregressive coefficients are held constant and only the deterministic components are allowed to vary over time, performs much better than other models regardless of the number of lags, hyperparameter that controls time variation, and forecast horizons.

inflation in the BVAR models, the present paper estimates and compares four models: a BVAR model with Litterman's prior, a BVAR model with Normal-Wishart prior, a BVAR model with g-prior, and a UVAR model.

The paper is organised as follows. Section 2 presents a discussion of VAR forecasting models. In this section there is also a brief introduction of the BVAR model with Litterman and Normal-Wishart prior's, and the g-prior. Section 3 describes the data. There are some alternative representations of BVAR models, which is fitted to quarterly data of the Iranian economy in section 4. Section 5 presents empirical results. Finally, section 6 offers some conclusions.

2. The VAR Models and Forecasting
A VAR model can be represented as follows:

$$y_t = a + A_1 y_{t-1} + ... + A_p y_{t-p} + u_t$$
$$t = 1,2,...,T \qquad u_t \sim N(0, \Sigma_u)$$

(1)

where y is an $n \times 1$ vector of the endogenous variables. The subscript t denotes time, a is an $n \times 1$ vector of deterministic variables, and u is an $n \times 1$ vector of error terms. The parameters which describe this model are a, A_l, for $l = 1,...,p$, the variance-covariance matrix, Σ_u, and the lag length, p. Since the model includes p lagged values of each of the variables, it is referred to as a VAR (p) model. In this model, each of the n equations has the same set of explanatory variables: p lagged values of the dependent variable and each of the others. In a VAR model, each variable in the system is supposed to be a linear function of previous values of the other endogenous variables. An important disadvantage of using a VAR model for forecasting based on unrestricted OLS estimates of the coefficients is the large number of parameters that need to be estimated (danger of over-parameterization)[1]. This problem is particularly acute in the small sample sizes which are generally available to macroeconomic forecasters. In any VAR model, the number of parameters to be

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1. VAR models become overparameterized when T (the size of the sample) is small and p (the number of lags) is large.

estimated, increases by $(2n+1)p+1$ with each additional variable for a given lag length and by n^2 with each additional lag. Forecasts made using UVAR models which suffer from over parameterization, will give good with-in-sample fit, but often have poor out-of-sample forecasts (see, e.g., Doan, 1992).

Restricting the parameters of the UVAR models may improve out-of-sample forecasts. Litterman (1984, 1986) and Doan, et al. (1984) suggest that the parameters of the UVAR models could be estimated using Bayesian techniques, which take into account prior information available to the forecaster. In the VAR context, introducing prior distributions over the parameters of the UVAR models can reduce the tendency of the UVAR models to be over-parameterized. Litterman (1986) suggested random walk prior mean for the coefficients with a parsimonious set of hyperparameters which govern their variance[1]. As many macroeconomic variables have stochastic trends, the best guesses of the Litterman prior are random walk with drift, with a vague prior on the drift.

Applying the random walk hypothesis to equation (1) requires the mean of the coefficient matrix on the first lag, A_1 to be equal to an identity matrix and the mean of the elements of A_l, for $l>1$, to be equal to zero. Of course, if the data suggests that there are strong effects from lags other than the first own lag or from the lags of all the other variables in the model, this will be reflected in the parameter estimates. No prior information is assumed to be known about the prior mean on the deterministic components in Traditional BVAR. Furthermore, the prior distributions on all of the parameters (coefficients) of the model are assumed to be independent normal.

The standard deviations of the prior distributions are forced to decrease as the lag length increases, tightening the distribution around the prior mean of zero at larger lags. Therefore, BVAR models estimated under Litterman's prior may show coefficients on first own lag close to one and most other coefficients close to zero, depending on the imposed tightness of the prior. This method isolates the

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1. Since this particular system of Bayesian priors has been developed by Litterman and others at the University of Minnesota and the Federal Reserve Bank of Minneapolis, it is known as the Minnesota system of prior beliefs or, more briefly, the Minnesota prior or Litterman's prior. It has also been referred as Traditional BVAR in recent years' studies.

systematic components of variation in the series, reduces the effect of over-parameterization, and often generates more accurate forecasts than UVAR models.

In more detail, Litterman (1986) pointed out that the standard deviation of prior distribution of the ij^{th} element of the lth lag coefficient matrix A_l can be nonzero, with the following specification

$$\lambda_1 \big/ l^{\lambda_3} \qquad\qquad\qquad\qquad if\ i = j$$
$$\sigma_i \lambda_1 \lambda_2 \big/ \sigma_j l^{\lambda_3} \qquad\qquad\qquad if\ i \neq j$$

where hyperparameters λ_1, λ_2, and λ_3 determine the tightness or weight attaching to the prior in random walk. The parameter λ_1 is the overall tightness (or weight) parameter and reflects how closely the random walk approximation is to be imposed. In general, this hyperparameter determines the relative weight of prior information. Decreasing λ_1 toward zero has the effect of shrinking the diagonal elements of A_l toward one and all other coefficients to zero. λ_2 is the hyperparameter that controls the cross variable relationship. Lowering λ_2 toward zero shrinks the off-diagonal elements of A_l toward zero. Setting $\lambda_2 = 1$ means that there is no difference between the lags of the dependent variable and the lags of other variables. The λ_3 is a parameter to indicate the extent to which the lags closer in time have greater informative content than those more distant in time. As λ_3 increases, the coefficients on high-order lags are being shrunk toward zero more tightly and when λ_3 is set to one, the rate of decay in the weight is harmonic. σ_i is the ith diagonal element of matrix Σ_u and in practice usually is set equal to the residual standard error from an OLS regression of each dependent variable on p lagged values. The ratio $\sigma_i \big/ \sigma_j$ is included in the prior standard deviations to account for the differences in the units of measurement of different variables. If the variability of $y_{i,l}$ is much lower than that of $y_{j,l}$, then the coefficient on $y_{j,l-1}$ in the ith equation is shrunk toward zero.

The usual OLS estimator of the coefficients of the ith equation of the VAR model in equation (1) is

$$\hat{b}_i^{OLS} = (X'X)^{-1} X'y_i \qquad i = 1,...,m,$$

where y_i is a $T \times 1$ vector and X is a $T \times (mp + 1)$ matrix (T is number of observations). By using Theil's (1963) mixed estimation technique, the coefficient estimator or the mean of the posterior distribution under the Litterman prior, is (see, e.g., Lutkepohl, 1993):

$$\hat{b}_i = (\overline{G}_i^{-1} + \sigma_i^{-2} X'X)^{-1} (\overline{G}_i^{-1} \overline{b}_i + \sigma_i^{-2} X'y_i)$$

where $\overline{G}_i$ is the prior covariance matrix of b_i, $\overline{b}_i$ is its prior mean, y_i is the ith row of y, and σ_i^2 is the ith diagonal element of the covariance matrix of residual.

Although there is a lot of empirical evidence to suggest that this kind of BVAR model produces forecasts (especially for real variables) that exhibit a high degree of accuracy when compared with UVAR model, they do have some limitations.

In using Litterman's prior, researchers assume a fixed and diagonal residual variance-covariance matrix and at the same time claim less than perfect information about the regression parameters in the VAR. This is strange; because generally it is easier to form beliefs about the regression parameters than about the residual variance-covariance matrix. The residual variance-covariance matrix, Σ_u, is taken to be fixed and diagonal and the likelihood function is the product of independent normal densities for A_l. The prior and posterior are independent between equations in the Litterman prior and they can be considered separately. This is a disadvantage of the Minnesota prior as it imposes severe restrictions on the likelihood in the form of the fixed and diagonal residual variance–covariance matrix. Kadiyala and Karlsson (1993) suggested families of prior distributions that allow for dependence between the equations. These prior are The Normal–Wishart prior, the Diffuse (Jeffreys') prior, the Normal–Diffuse prior and the Extended Natural Conjugate (ENC) prior.[1] They evaluate

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1. The Normal – Diffuse and ENC priors have a disadvantage, in that, they do not have closed form solutions for the posterior moments of the regression parameters and they must be

these priors based on the forecast performance and find that several of these methods give better forecasts than the Litterman prior.

When the assumption of a fixed and diagonal residual variance-covariance matrix is relaxed, the natural conjugate prior for normal data is the Normal-Wishart prior (see, e.g., Kadiyala and Karlsson, 1993 and 1997). Under a Normal-Wishart prior, the prior distribution of coefficients conditional to the residual variance-covariance matrix, Σ_u, is normal while the prior distribution of Σ_u is Inverse Wishart (IW). In this situation, the random-walk aspect of the Minnesota prior can be used without making independence across the equations of the VAR as an exact restriction (see, e.g., Dreze and Richard, 1983).

Although the Normal-Wishart prior is convenient to understand and implement, it has some shortcomings. With the Normal-Wishart, the structure of variance-covariance matrix of the regression parameters forces the researcher to treat all equations systematically in specifying the prior. For example, if we are going to be uninformative about a specific parameter in one equation by specifying a relatively big prior variance, we are forced to be uninformative about the corresponding parameter in the other equation as well (see, e.g., Kadiyala and Karlsson, 1997). Hence, the BVAR model with Normal-Wishart prior has the same limitation as the BVAR model with Litterman's prior, the precision in estimation of the drift parameters[1]. Bewley (2000) argues that the Traditional BVAR models perform better than the UVAR models mainly because they correct for the unit root, not because they reduces the over-parameterization, and that their long-run performance for driftless variables is poor. This is an important point. Traditional BVAR models, because of the vague prior on the constant, will not perform well in the long-run forecasting of I(1) variables either if they have no drift (See, e.g., Bewley, 2000 and 2001).

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evaluated numerically. Even when the posterior expectation and variance of A are known, numerical methods are often necessary in order to obtain forecasts, impulse response and other non- linear functions of the regression parameters. This procedure will be expensive, especially for large models, because it is quite time consuming. In order to overcome this problem, Kadiyala and Karlsson (1997) suggested methods of importance sampling and Gibbs sampling for evaluating the posterior distribution of functions of the regression parameters, which is beyond of the scope of this paper.

1. Clements and Hendry (1996), and Hendry and Clements, (2003), regardless of the kind of model, believe that precision in estimation of the drift parameters is one of the main sources of poor forecasting.

In practice, most of the macroeconomic forecasting models include variables that demonstrate both drift and no drift (mixed drift models). BVAR models with Litterman's prior use diffuse prior on the constant and shrink the drift term to zero. This would bias the forecasts of time series with drift in the model and hence, lead to poor estimations of the mean in mixed drift cases.

Heidari (2011) applies the Bewley (1979) transformation for reparameterization of the VAR model to restrict the mean of the change of inflation to zero in a four variable mixed drift model of the Iranian economy. His result show that using the Bewley (1979) transformation to force the drift parameter of change of inflation to zero in the VAR model improves forecast accuracy in comparison to the Traditional BVAR model.

In the Bayesian approach, shrinking some of the drift parameters toward zero, substantial improvements in forecast accuracy can be expected. The Traditional BVAR model uses diffuse priors on the constant and shrink the drift terms toward zero. This would bias the forecasts of those variables with drift in the mixed drift case. Without considering this nonlinear relationship, the forecaster has no constraint on the constant terms. In other words, the forecaster either supposes that none of the variables includes drift or imposes diffuse priors on the regression constants in Bayesian approach. Bewley (2000) argued that in this condition, the long-run forecast errors of time series without drift in mixed-drift models are dominated by insignificant drift parameter estimates.

As mentioned already, a novel feature of this paper is using g-prior for BVAR models. In fact, a way of thinking about alleviation of poor estimation of the mean in the Traditional BVAR models is using g-prior. Zellner (1986) reported that the g-prior is a special form of a Natural Conjugate prior distribution and can be considered as a reference for informative prior distributions. For the g-prior amounts, Zellner (1986) proposed specifying a normal prior for the parameters, conditional on Σ_u and a Jeffrey's prior for Σ_u:

(2)
$$A \mid \Sigma_u \sim N(A_0, \Sigma_u \otimes M_0^{-1})$$
$$p(\Sigma) \propto \Sigma_u^{-1}$$

where Zellner (1986) sets $M_0 = gX'X$. The researcher chooses A_0 and g, where g measures the amount of information in the prior relative to the sample. In the VAR case, let $E(A|\Sigma_u)$ be a random walk and the prior variance conditional on Σ_u be

$$(3) \qquad \text{var}(A|\Sigma_u) = \Sigma_u \otimes ((X'X/T) * np)^{-1}$$

where np is the number of prior observations and is the only hyperparameter to be specified. By using Theil and Goldberger (1961) mixed estimator, the mean of the posterior distribution under the g-prior is

$$(4) \qquad E(A|\Sigma_u, y) = \frac{1}{1+g}(gA_1 + \hat{A}_{OLS})$$

where $g = np/T$, $\hat{A}_{OLS}$ is OLS estimation of A, and A_1 is the prior mean.

In the case of random walk, the unconditional expected value of y, implied by the posterior mean of the parameters is $[(I - \hat{A}_{ols})^{-1}\hat{a}_{ols}]$, which is the same as OLS. Although the prior mean of A is the same as the Litterman's prior, this prior is a Conjugate prior, and cannot treat lags of the dependent variable and the lags of other variables differently (see, e.g., Karlsson, 2001). This is not the focus of this paper. As mentioned earlier, Kadiyala and Karlsson (1997) find that the Natural Conjugate prior, which treats all variables equally and allows for dependence between the equations, gives at least as accurate a forecast as the Traditional BVAR model. The important point here is that the combination of a random walk mean prior and variance prior in equation (3) indicates that it does not matter how big the hyperparameter, np, or how strong the prior is, the unconditional mean implied by the posterior coefficients of the BVAR ($[(I - A)^{-1}a]$) is exactly the same as the unconditional mean implied by the VAR. Hence, the BVAR model with g-prior shrinks the coefficients toward the random walk, without any effect on the long-run forecast. Because of this, the BVAR with g-prior may do well for variables without and with a small drift such as real GDP and inflation. In other words, estimation of the mean, in the VAR models

with g-prior are expected to be more accurate than the Traditional BVAR in the long-run.

3. Data Description

The data used for the analysis are quarterly from 1981:Q2 to 2007:Q1 and for the Iranian economy. All of the data is seasonally adjusted except for the exchange rate. Some of the variables show strong drift, including the log of GDP (Y), and the log of money supply (M2). The other variables do not contain drift; these include the change in the log of the implicit GDP deflator (INF), and the change in the log of black market exchange rate (Exc). Therefore, we have a mixed drift system of equations.

4. Empirical Application

This section presents various BVAR specifications to forecast the inflation rate for the first and the second quarters ahead and the first and second calendar years ahead, over the period from 2001:Q2 to 2007:Q1. The model estimated in this paper is the same as that presented in Heidari and Parvin (2008); in terms of the number of included variables in the model, lag length, and the process of choosing hyperparameters. The alternative specifications considered are:

- A BVAR specification with Litterman prior as described earlier. The hyperparameter that controls relative tightness on lags of other variables is fixed at 0.2. This is the same value that Sims and Zha (1998) used for quarterly data. We searched for the hyperparameter that controls the tightness of the prior distribution and automatically picked the values that maximize the log of the marginal likelihood function. For estimation, we used the original Litterman's equation by equation estimation. This specification is denoted as BVAR_Litt.

- A BVAR specification with Normal–Wishart prior. We fixed the hyperparameter that controls the tightness of the prior distribution at 0.2. Sims and Zha (1998) used this value for quarterly data. We searched for the hyperparameter that controls tightness of the constant. Our program automatically sets this hyperparameter to the value which maximizes the marginal likelihood function. For the parameters of the prior of

variance-covariance matrix, S_0 is automatically set to be the residuals from AR regressions and n_0 is set to be one which is corresponding to a diffuse prior on the variance-covariance matrix in practice. This specification is denoted as BVAR_NW.

- A BVAR specification with g-prior. The same as BVAR model with Normal-Wishart, for the parameters of the prior of variance-covariance matrix, S_0 is automatically set to be the residuals from AR regressions but n_0 is set to be one plus number of lags $(1 + nlags)$. We search for "the number of prior observations" (np). This specification is denoted as BVAR_gp.
- A UVAR specification where the variables are only logged. This specification is denoted as UVAR.
- In all of these representations, the sample period is divided into two sub-samples. First the model was estimated for the period from 1981:Q2 to 2001:Q1. Then we added the last 5 years of data (from 2001:Q2 to 2007:Q1) one quarter at a time. In doing so, we re-estimated the models (with new optimal hyperparameters), and forecast for different horizons carried out when new data arrived. This process continued until all the data has been used. The forecasts of inflation in each of these models, for the current and the subsequent quarter, as well as forecasts for the current and the subsequent calendar years, are compared with the actual values.

5. Results

Since the final goal of this paper is to find a model to accurately forecast inflation for the Iranian economy, the final criterion for making specification choices is forecast accuracy. In most forecast evaluations the accuracy measures are some form of average error, typically RMSE, Theil statistic or mean absolute error (MAE). The results reported below use the RMSE as the accuracy criterion, but it is acknowledged that using other forecast accuracy criteria may yield different model rankings.

Tables 1 present RMSE of the various BVAR and UVAR specifications for forecasting Iranian inflation. In the results presented

in this table, the period from 2001:Q2 to 2007:Q1 is used to examine the forecast performance of the models. The numbers in parentheses are the ratio of the RMSE of the BVAR model with Litterman's prior to the RMSE of the associated model at each horizon. A value greater than one means that the RMSE of the BVAR model with Litterman's prior is larger than the given model. This indicates that the given model's forecasts are more accurate than the Traditional BVAR model's forecasts.

In Table 1, the BVAR model with Normal-Wishart prior is the dominant model for forecasting Iranian inflation across forecast horizons. Our results show that the BVAR model with g-prior performs better than the BVAR with Litterman's prior for the inflation forecasts for all horizons when the number of lags is one. This model gives accurate forecasts of inflation in the first and second quarter horizons for lags numbering three.

Table 1. RMSE of Different VAR Specification Forecasts of Iranian Inflation 2001:Q2 - 2007:Q1

Models specification	First Quarter	Second Quarter	First Year	Second Year
Lag=1				
BVAR_Litt	0.00787	0.00900	0.0101	0.0109
BVAR_NW	0.00660 (1.1925)	0.00588 (1.5290)	0.00697 (1.4595)	0.00705 (1.5541)
BVAR_gP	0.00766 (1.0282)	0.00873 (1.0309)	0.01006 (1.0115)	0.01080 (1.0150)
UVAR	0.00789 (0.9981)	0.00901 (0.9981)	0.01018 (0.9993)	0.01097 (0.9994)
Lags=3				
BVAR_Litt	0.00669	0.00757	0.00941	0.01063
BVAR_NW	0.00584 (1.1467)	0.00602 (1.2584)	0.00768 (1.2247)	0.00729 (1.4572)
BVAR_gp	0.00600 (1.1150)	0.00711 (1.0646)	0.00920 (1.0228)	0.01047 (1.0152)
UVAR	0.00669 (1.0004)	0.00759 (0.9975)	0.00938 (1.0029)	0.01061 (1.0020)

Note: the numbers in parentheses are the ratio of the RMSE of the BVAR model with Litterman's prior to the RMSE of the associated model at each horizon. A value greater than one means that the RMSE of the BVAR model with Litterman's prior is larger than the given model. This indicates that the given model's forecasts are more accurate than the BVAR model with Litterman's prior forecasts.

In practice a VAR model with four variables and three lags is more common than a VAR model with four variables and one lag. On the other hand, in results presented in Table 1, RMSE of different BVAR and VAR specifications with three lags are generally smaller than VAR models with one lag. Hence, it makes sense to conclude that the BVAR model with Normal-Wishart prior performs better than others in forecasting Iranian inflation for a five year period of forecast comparison, from 2001:Q2 to 2007:Q1. Our results, however, show that using g-prior instead of Litterman's prior in BVAR model, can improve forecasts of Iranian inflation.

In summary, our results show that, generally the BVAR model with Normal-Wishart prior is the dominant model in forecasting Iranian inflation. In parsimonious models, using g-prior in the BVAR model, however, improves forecast of inflation in the Traditional BVAR models.

6. Conclusion

This paper shows a comparison of forecast accuracy between different specifications of VAR and BVARs with several different priors. The paper discusses the precision in estimation of the drift parameters as a main source of weak forecasts in the Traditional BVAR models. The novelty of the paper is applying g-prior in the BVAR model. We provide empirical evidence from the performance of various specifications of a four-variable BVAR in forecasting Iranian inflation. The results show that the performance of a model and its superiority depends on the number of lags and the forecast horizons. Moreover, our results show that in parsimonious models, the BVAR models with g-prior produce much more accurate forecasts of inflation than the BVAR models with the Litterman's prior using real data from Iranian economy.

References

Artis, M. and W. Zhang (1990), "BVAR Forecasting for the G-7", *International Journal of Forecasting*, No. 6**,** pp. 349-362.

Ballabriga, F. *et al* (2000), *A BVAR Macroeconometric Model for the Spanish Economy: Methodology and Results*, Spain, Banco de Espana.

Ballabriga, S. and J. Valles (1999), "European asymmetries", *Journal of International Economics*, No. 48, pp. 233-253.

Bewley, R. (1979), "The Direct Estimation of the Equilibrium Response in a Linear Dynamic Model", *Economics Letters*, No. 3, pp. 357-361.

Bewley, R. (2000), "Real-time Forecasting with Vector Autoregressions: Spurious Drift, Structural Change and Intercept-Correction", Working Paper, Sydney, Australia, University of New South Wales.

Bewley, R. (2001), "Controlling Spurious Drift in Macroeconomic Forecasting Models", Working Paper, Sydney, Australia, University of New South Wales.

Canova, F. (1995), "Vector Autoregressive Models: Specification, Estimation, Inference, and Forecasting", In M. Hashem Pesaran and M. Wickens (Eds.), *Handbook of Applied Econometrics: Macroeconomics*, (pp. 73-138), Blackwell, UK.

Clements, M. and D. Hendry (1996), "Intercept Correction and Structural Change, *Journal of Applied Econometrics*, Vol. 11, No. 5, pp. 475-494.

Doan, T. (1992), *RATS: User's Manual*, Version 4, Evanston, Illinois.

Doan, T., Litterman, R. and C. Sims (1984), "Forecasting and Conditional Projection Using Realistic Prior Distributions", *Econometric Reviews*, No. 3, pp. 1-100.

Dreze, J. and J. Richard (1983), "Bayesian Analysis of Simultaneous Equation System", In Z. Griliches and M. Intrilligator (Eds.), *Handbook of Econometrics*, Vol. 1 (pp. 517-598), Amsterdam, North – Holland.

Felix, R. and L. Nunes (2003), "Forecasting EURO Area Agrgation with Bayesian VAR and VECM Models", Working Paper #WP 4-03. Portugal, Banco de Portugal: Economic Research Department.

Fry, R. and A. Pagan (2005), "Some Issues in Using VARs for Macroeconometric Research", CAMA Working Papers Series, CAMA Working Paper # 19/2005.

Heidari, H. (2011), "An Alternative VAR Model for Forecasting Iranian Inflation: An Application of Bewley Transformation", *Quarterly Iranian Economic Research*, Vol. 46, pp. 77-96.

Heidari, H. and S. Parvin (2008), "Modelling and Forecasting Iranian Inflation with Time Varying BVAR Models, *Quarterly Iranian Economic Research*, No. 36, pp. 59-84

Hendry, D. and M. Clements (2003), "Economics Forecasting: Some Lessons from Recent Research, *Economic Modeling*, No. 20, pp. 301-329.

Kadiyala, K. and S. Karlsson (1993), "Forecasting with Generalized Bayesian Vector Autoregressions, *Journal of Forecasting*, No. 12, pp. 365-378.

Kadiyala, K. and S. Karlsson (1997), "Numerical Methods for Estimation and Inference in Bayesian VAR-models", *Journal of Applied Economics*, No. 12, pp. 99-132.

Karlsson, S. (2001), *Bayesian Methods in Econometrics*, Mimeo, Stockholm, Stockholm School of Economics.

Kenny, G., Meyler, A., and T. Quinn (1998), "Bayesian VAR Models for Forecasting Irish Inflation, Technical Paper, # 4/RT/98, Ireland, Central Bank of Ireland.

Litterman, R. (1984), "Forecasting and Policy Analysis with Bayesian Vectorauto Regression Models, *Federal Reserve Bank of Minneapolis, Quarterly Review*, No. 4, pp. 30-41.

Litterman, R. (1986). "Forecasting with Bayesian Vector Autoregressions–five Years of Experience", *Journal of Business and Economic Statistics*, No. 4, pp. 25- 38.

McNees, S. (1986), "Forecasting Accuracy of Alternative Techniques: A Comparison of US Macroeconomic Forecasts", *Journal of Business and Economic Statistic*, No. 4, pp. 5-15.

Moshiri, S. (2001), "Forecasting Inflation Using Structural, Time Series, and ANN Models", *Journal of Economic Research (F)*, No. 58, pp. 147-184.

Robertson, J. and E. Tallman (1999), "Vector Autoregressions: Forecasting and Reality". *Federal Reserve Bank of Atlanta*, *Economic Review*, No. 84, pp. 4-18.

Sims, C. (1993), "A Nine–Variable Probabilistic Macroeconomic Forecasting Model", In J. Stock and M. Watson (Eds.), *Business Cycle, Indicators and Forecasting* (pp. 179-212), Chicago, University of Chicago Press.

Sims, C. and T. Zha (1998), "Bayesian Methods for Dynamic Multivariate Models", *International Economic Review*, No. 39, pp. 949-968.

Svensson, L. (1997), "Inflation Forecast Targeting: Implementing and Monitoring Inflation Targets", *European Economic Review*, No. 41, pp. 1111-1146.

Theil, H. and S. Goldberger (1961), "On Pure and mixed Statistical Estimation in Economics", *International Economic Review*, No. 2, pp. 65-75.

Todd, R. (1984), "Improving Economic Forecasting with Bayesian Vector Auto Regression", *Federal Reserve Bank of Minneapolis, Quarterly Review*, No. 8, pp. 18-29.

Webb, R. (1995), "Forecast of Inflation from VAR Models", *Journal of Forecasting*, No. 14, pp. 268-285.

Zarnowitz, V. and P. Braun (1992), "Twenty-two Years of the NBER-ASA Quarterly Economic Outlook Surveysa Aspects and Comparisons Of Forecasting Performance", Working Paper, Working Paper # 3965, NBER.

Zellner, A. (1986), "On Assessing Prior Distributions and Bayesian Regression Analysis with G-piror Distributions", In P. Goel and A. Zellner (Eds.), *Bayesian Inference and Decision Techniques* (pp. 233-243), Amsterdam: Noth-Holland.