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An Alternative VAR Model for Forecasting Iranian Inflation: An Application of Bewley Transformation

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This paper focuses on the development of modern non-structural dynamic multivariate time series models and evaluating performance of various alternative specifications of these models for forecasting Iranian inflation. The Quasi-Bayesian method, with Literman prior, is applied to Vector autoregressive (VAR) model of the Iranian economy from 1981:Q2 to 2006:Q1 to assess the forecasting performance of different models over different forecasting horizons. The Bewley transformation is also employed for the re-parameterization of the VAR models to impose the mean of the change of inflation to zero. Applying 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.[1]

Keywords: VAR models, BVAR models, Forecasting, Bewley transformation, Inflation, Iran
JEL Classification: C11, C32, C53, E17, E31

1. Introduction

This paper investigates different Vector Autoregressive (VAR) specifications to improve the Iranian inflation forecasting by non-structural dynamic multivariate time series models. Following the Islamic revolution and during the 8-year war with Iraq, the government of the Islamic Republic of Iran (Iran) monetized budget

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deficit, and this along with the conversion of foreign currency from oil exports into domestic currency, meant that monetary policy was essentially a part of fiscal policy. With the implementation of the economic reform program in 1989 and a high rate of inflation in 1995, policy makers were persuaded to consider that the independence of monetary policy from fiscal policy was crucial for price stability.

It has been suggested that a significant problem for monetary policy makers, especially for independent Central Banks with an Inflation Targeting regime, is the central bank's imperfect control of inflation. Svensson (2000) documented that conditional inflation forecasts, as an intermediate target variable, can alleviate this problem. Using this makes the inflation forecasts the focal point in the monetary policy discussions.

Apart from their role as an input into monetary policy, inflation forecasts have a significant role in fiscal policy and the wage bargaining process. Inflation forecasts are also crucial for projections of real economic activity and in assessing likely trends in competitiveness in the international capital markets.[1] Therefore it can be claimed that inflation forecasts are important even in the countries with non-independent central banks.

In Iran, as other small open economies (SOE), the objective of price stability is pursued via an intermediate exchange rate target. The analysis and forecasting of inflation also plays an important role in these frameworks.

With respect to the importance of inflation forecasts for policy makers, agents and their advisors, we chose inflation in the Iranian economy to describe some practical problems in forecasting, using the modern non-structural dynamic multivariate time series models and evaluating performance of various alternative specifications of these models**.** The model studied is a VAR of four Iranian macroeconomic variables. Although this model is small and highly aggregated, it provides a convenient framework for illustrating several practical forecasting issues.

1. In order to highlight the importance of foreign investment, I do refer to the World Bank report (2003) on the economies of Middle Eastern and North African (MENA) countries. This report predicts unemployment crises in these countries in coming years and calls for trade and investment reforms to warrantee stable and sustainable growth and real employment opportunities.

VAR models have been used as a popular tool in empirical macroeconomics since their introduction by Sims (1980). Although Traditional Bayesian (BVAR) models can improve Unrestricted VAR (UVAR) model forecasts through the use of extra information as priors, they cannot be used to resolve a mixed drift case, which is common in the most of the macroeconomic forecasting models. It is documented that a BVAR with a Litterman prior has a poor estimation of the mean in mixed drift cases (see, e.g. Bewley, 2000 and 2001). The contribution of this paper is to improve the forecast of inflation in a mixed drift case by imposing a prior on the mean. We applied the Bewley (1979) transformation for re-parameterisation of the VARs to estimate drift parameters using instrumental variables and imposing restrictions on the mean.

Our results show that applying the Bewley (1979) transformation to impose a zero mean to the change of inflation, provides more accurate forecasts of inflation for the Iranian economy in comparison to the Traditional BVAR model.

The rest of the paper is organized as follows. In section 2, there is a discussion of VAR forecasting models and their forecasting accuracy particularly in forecasting inflation. In this section there is also a brief introduction to the Bewley (1979) transformation. Section 3 describes the data and their properties. There is a discussion on the specifications of BVAR models in section 3. Section 5 focuses on some alternative representations of the VAR model, which is fitted to quarterly data from Iranian economy. Finally, section 6 offers some conclusions.

2. The VAR models and Forecasting:

A VAR model can be represented in algebraic terms as follows:

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

where y is an $n \times 1$ vector of endogenous variables such as real GDP, money, inflation and so on. The subscript t denotes time, a is an $n \times 1$ vector of deterministic variables such as constants, time trends or seasonal dummies, and u is an $n \times 1$ vector of error terms. The parameters which prescribe this model are a, A_l, for $l = 1,\ldots,p$, 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 the others.

One of the most successful applications of the VAR models in macroeconometrics 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 in using VAR models). An important disadvantage of using a UVAR model for forecasting based on unrestricted OLS estimates of the coefficients is the large number of parameters that need to be estimated. In an attempt 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, which take into account any prior information available to the forecaster. The Litterman's prior is presented as embodying the idea that series should be random walks. As most of the macroeconomic variables have persistent trends, so the best guesses of the Litterman prior will be a random walk with drift, with a vague prior on the drift. In fact, Litterman (1986) suggested a class of priors for VAR models that induce a random walk mean for the coefficients and have a parsimonious set of hyperparameters, which govern their variance.[1]

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. As the best guess derived from the random walk hypothesis in the Minnesota prior is a Bayesian procedure, it is necessary the modeller submit the prior variance of the coefficient as a quantitative measure of confidence in each best guess. Litterman

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 prior in the jargon of econometrics. It also has been referred as Traditional BVAR in recent years' studies.

(1986) pointed that the standard deviation of the ij^{th} element of the l^{th} lag coefficient matrix A_l can be nonzero, with this specification

$$\begin{array}{ll} \lambda_1 / l^{\lambda_3} & \text{if } i = j \\ \sigma_i \lambda_1 \lambda_2 / \sigma_j l^{\lambda_3} & \text{if } i \neq j \end{array}$$

where the parameter λ_1 is the overall tightness 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 distinction 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 i^{th} diagonal element of matrix Σ_u and in practice usually is equal to the residual standard error from an OLS regression of each dependent variable on p lagged values. The ratio σ_i / σ_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 i^{th} equation is shrunk toward zero.

The usual OLS estimator of the coefficients of the i^{th} equation of the VAR model in equation (1) is

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

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 and Goldberger (1961) mixed estimation technique, the coefficient estimator or the mean of the posterior distribution under the Litterman's 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 i^{th} row of y, and $\sigma_i^{\ 2}$ is the i^{th} diagonal element of the covariance matrix of residual.

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[1] (see e.g., Artis and Zhang, 1990; Ballabriga *et al*., 1999 and 2000; Doan *et al*., 1984; Felix and Nunes, 2003; 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). The performance of the Traditional BVAR models, in forecasting inflation, however, has been somewhat less impressive (see e.g., Heidari and Parvin, 2008; Kenny *et al*., 1998; Litterman, 1986; McNees, 1986; Robertson and Tallman, 1999; Webb, 1995; Zarnowitz and Braun, 1992).

There are some possible explanations for the poor performance of the BVAR model with Litterman's prior in forecasting inflation[2]. One of the most important explanations is the precision in estimation of the drift parameters. In order to overcome poor forecasting, Hendry and Clements (2003) suggested intercept correction with vector error correction models (VECM). One of the ways of restricting the intercept correction is using Bewley (1979) transformation. Bewley (2000) argues that the Traditional BVAR models perform better than

1. Moshiri (2001) uses a structural (an augmented Phillips curve), a univariate 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.

2. Heidari and Parvin (2008) show that the structural break is one of the reasons for the poor performance of Traditional BVAR model in forecasting Iranian inflation. They conclude that applying a modified time varying BVAR model, where the autoregressive coefficients are held constant and only the deterministic components are allowed to vary over time can alleviate the poor performance of Traditional BVAR model in forecasting inflation.

the UVAR models mainly because they correct for the unit root, not because they reduce 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 long-run forecasting of I(1) variables either if they have no drift. 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 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.

For more technical discussion following Bewley's (2000, 2001) notation, an $n \times 1$ vector of $I(1)$ time series presented in equation (1) can be rewritten as the following VAR(p) model:

$$y_t = a + \sum_{i=1}^{p} A_i y_{t-i} + u_t \tag{2}$$

Add and subtract $A_p y_{t-p+1}$ to obtain:

$$y_t = a + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + (A_{p-1} + A_p) y_{t-p+1} - A_p \Delta y_{t-p+1} + u_t$$

Then add and subtract $(A_{p-1} + A_p) y_{t-p+2}$ to obtain:

$$y_t = a + A_1 y_{t-1} + A_2 y_{t-2} + \ldots - (A_{p-1} + A_p) y_{t-p+2} - A_p \Delta y_{t-p+1} + u_t$$

Continuing in this fashion, equation (2) can be written as a VEC model:

$$\Delta y_t = a + \alpha[\beta' y_{t-1}] + \sum_{i=1}^{p-1} B_i \Delta y_{t-i} + u_i \tag{3}$$

Where α and β are $n \times r$ matrixes and

$$B_i = -\sum_{i=j+1}^{p} A_i$$

$$\alpha\beta' = -(\mathrm{I} - \sum_{i=1}^{p} A_i)$$

Equation (3) is a VAR in differences with $p-1$ lags, DVAR (p-1). This equation can be rewritten as the following:

$$[\Delta y_t - \delta] = \alpha[\beta' y_{t-1} - \gamma] + \sum_{i=1}^{p-1} B_i [\Delta y_{t-i} - \delta] + u_t \qquad (4)$$

where γ is the mean of the EC terms, $\beta' y_{t-1}$ and δ are the means of Δy_t, and drift terms, respectively. Equation (4) can be estimated nonlinearly, but we cannot place a linear restriction on the constant, a, in equation (3) to get forecasts that have zero drift for some of the components of y_t and non-zero drift for the remainder. For more detail explanation, Bewley (2000) showed that the constant term in equation (3) could be expressed in terms of δ as following:

$$a = [(\mathrm{I} - \sum_{i=1}^{p-1} B_i)\delta - \alpha\gamma]$$

By using definition of B_i in equation (3) we will find:

$$a = [(\mathrm{I} - \sum_{i=1}^{p-1} \sum_{j=i+1}^{p} A_j)\delta - \alpha\gamma] \qquad (5)$$

As it is clear in equation (5), the constant term in the driftless equations, a, also shows the non- zero elements of δ, and is a nonlinear functions of δ (means) and the other parameters in the system. In forecasting application, however, those variables that do not have drift will have an estimated non-zero drift, which contributes to forecast error variance.

The Traditional BVAR model cannot be used to solve this problem. These models, as mentioned earlier, use 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 prior 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.

Applying the Bewley (1979) transformation for re-parameterisation of the VAR model to estimate drift parameters is an effort to impose this limitation. Applying this transformation to equation (3) gives:

$$\Delta y_t = \delta + \zeta[\beta' y_{t-1} - \gamma] + \sum_{i=0}^{p-2} C_i \Delta^2 y_{t-1} + v_t \tag{6}$$

where

$$C_j = [\mathrm{I} - \sum_{m=1}^{p-1} B_m]^{-1} \sum_{k=j+1}^{p-1} B_k \qquad j = 0,1,\ldots,p-2$$

$$\zeta = -[\mathrm{I} - \sum_{m=1}^{p-1} B_m]^{-1} \alpha$$

By using definition of B_i in equation (3) we find:

$$C_j = [\mathrm{I} - \sum_{m=1}^{p-1} \sum_{i=m+1}^{p} A_i]^{-1} \sum_{k=j+1}^{p-1} \sum_{i=k+1}^{p} A_i$$

$$\zeta = -[\mathrm{I} - \sum_{m=1}^{p-1} \sum_{i=m+1}^{p} A_i]^{-1} \alpha$$

In equation (6), zero can be imposed to a subset of the elements of δ to find out forecasts for time series which include drift and which do not. In fact, by restricting some of the drift parameters to be zero, substantial improvements in forecast accuracy can be expected.

3. Data Description and Their Properties

The data used for the analysis are quarterly from 1981:Q2 to 2006:Q1 and for the Iranian economy. All of the data is seasonally adjusted except for the exchange rate. Two of the variables show drift: M2, the log of the liquidity and y, the log of GDP. The other two variables may not contain drift: Exc, the change in the log of black market exchange rate, and Pr, the change in the log of implicit GDP deflator. Therefore we have a mixed drift system of equations.

3-1. Tests of Stationarity

The order of integration of the variables is investigated using the Augmented Dickey-Fuller (DF) and Phillips-Perron (PP) tests. Table 1 shows the results of the ADF and PP tests. We implemented the tests with and without the time trend. Panel A of the table reports the results for the log-levels of the data series, while panel B presents the results for their first differences. The results from panel A suggest that the null hypothesis of a unit root can be rejected for the Pr and Exc. For the other two variables, M2 and Y, the unit root hypothesis cannot be rejected, even at 10 % significance level.

From panel B, the null hypothesis for a second unit root is rejected for all series. Thus, the evidence seems consistently to suggest that the first-differenced are stationary.

Table 1. Integration Tests: 1981:Q2 – 2006:Q1

	ADF Tests		PP Tests	
Variables	No Trend	Trend	No Trend	Trend
A. Log Levels				
Pr	-9.0719	-9.5393	-9.1606	-9.5095
M2	2.4849	-1.2867	2.3221	-1.3333
Exc	-9.5009	-9.4419	-9.7819	-9.7276
Y	-0.9926	-2.6256	-0.9902	-2.3950
B. First Difference				
Pr	-11.299	-11.218	-54.018	-58.822
M2	-5.7433	-6.5446	-6.1394	-6.7939
Exc	-8.7885	-8.7651	-36.933	-37.426
Y	-11.458	-11.392	-11.458	-11.392

Note: entries under ADF and PP tests are t-Statistic for testing the null hypothesis that the variables have a unit root. The criteria for lag selection in ADF test is the Schwartz Bayesian Criterion (SBC). In PP test, we use Bartlet Kernel method for Spectral estimation. For lag truncation selection, we used Newey_West method. The critical values of the tests are taken from Mackinnon (1996).

4. Specifications of the Model

Traditional BVAR models are not fully data-determined models. These models require the pre-specification of several parameters, such as the lag length of the VAR, the setting of the hyperparameters that governs prior variances, etc. The first set of specification issues in these models are those associated with the UVAR model.

The first issue that arises in constructing a UVAR model is the choice of variables to be included in the model. Although we are interested in forecasting inflation, we should include any variable that may carry information about the behavior of inflation that can improve forecasting of this variable**.**

These variables can be selected by using in sample Bivariate Granger Causality tests and results from previous studies, or both. We search for the best specification using real GDP, nominal GDP, the black market exchange rate, the official exchange rate, money (M1), liquidity (M2), the CPI, and GDP deflator. To avoid large forecasting models and an excessive data use, we can restrict the model to four variables and choose the one that has the best in sample explanatory power for inflation in the Iranian economy.

Table 2 shows the results of bivariate Granger causality tests. I report the results for arbitrarily chosen lag lengths of 4 and 8 and for the lag lengths determined by the SBC. The results indicate that M2 does Granger cause inflation. For the other two variables, the null hypothesis that y and Exc do not Granger cause inflation is accepted, even at the 10 % level of significance. On the other hand, it is supported by theory and other studies that these two variables are significant determinants of inflation in Iran. For example, Celasun and Goswami (2002) show that the exchange rate is a significant determinant of inflation in Iran and Liu and Adedeji (2000) indicate that inflation in Iran has been mainly a monetary phenomenon**.**

Table 2. Bivariate Granger Causality Tests

	Lag Specification		
Null Hypothesis	4	8	SBC
(a) M2 dngc Pr	0.6893 (0.6893)	3.9741 (0.0009)	1.5164 (0.2220) [1]
Pr dngc M2	0.4470 (0.7741)	0.3203 (0.9547)	0.7692 (0.3832) [1]
(b) Y dngc Pr	1.2926 (0.2821)	1.5573 (0.1602)	1.6815 (0.1987) [1]
Pr dngc Y	0.4245 (0.7903)	0.5112 (0.8425)	0.2686 (0.6057) [1]
(c) Exc dngc Pr	2.2618 (0.0719)	0.8755 (0.5429)	1.1262 (0.2920) [1]
Pr dngc Exc	0.5369 (0.7091)	0.4177 (0.9052)	0.0296 (0.8637) [1]

Notes: entries under 'Lag Specifications' are F-statistics for testing the null hypothesis that the coefficients' sums of causal variables are zero. The numbers in parenthesis are probability values. The numbers in brackets are the optimal lag lengths determined by the SBC.
dngc = does not Granger cause.

We know that the Iranian economy is a SOE and we have to allow a role for the rest of the world variables. As the main aim of this paper is a forecasting comparison between different models and model building is beyond the scope of this paper, we ignore the rest of the world in our model and focus on a forecasting model, which contains four domestic macro variables from Iranian economy.[1]

The VAR model described in this article includes the logarithm of real GDP as a measure of real output, y, the first difference of the logarithm of the GDP deflator as a measure of inflation[2], Pr, the logarithm of liquidity as a monetary variable, M2, and the first difference of the logarithm of the black market exchange rate, Exc.

As the longer lags may raise the chance of over-fitting and thus lead to poor out-of-sample forecasting, the lag length specification in a UVAR model is another important step in constructing a UVAR model. There are many approaches to determining lag length in VAR models such as the Akiake Information Criterion (AIC), the Schwartz Bayesian Criterion (SBC), and the Hannan and Quinn Criterion (HQC). Table 3 shows the lag length selection by some of the most used criterions.

The result from this table suggests lag lengths of one for SBC and HQC, and three for LR, FPE and AIC criterions. Although SBC selects a more parsimonious model than AIC, we report comparison results for different model specifications for lag length one, and three in table 4. Another key issue in the estimation of BVAR model is the choice of hyperparameters. There are a couple of ways of selecting the tightness of hyperparameters. One is to use root mean square errors (RMSE) or Theil's U statistics (Theil statistic) of in sample forecast, as suggested by Litterman (1986). In this approach, in order to find the setting of hyperparameters that leads to the best forecast, the modeler tries to test many settings and pick the one that leads to a model whose replicated forecasting errors are smallest (trial - and – error approach). In this method, the final forecasting model uses available data to

1. Theoretically, some markets such as labor and capital markets can affect inflation. In Iranian economy, there is no active capital market, also there are no strong labor unions and wage rates are controlled by the authorities (e.g., Taiebnia 1995). Therefore, these two markets are ignored in this study.

2. The most important measures to examine inflation are Consumer Price Index (CPI) and GDP deflator. As there were extensive government subsidies on consumer goods such as fuel, foods… over the period of study, CPI cannot reflect the true inflation rate and, therefore, the GDP deflator is used in this paper

revise the prior probabilities associated with the best setting of the hyperparameters. Litterman (1986) calculated mean squared error (MSE) and Theil coefficients for each variable at each forecast horizon. For example, he tried values of 0.5, 0.3, 0.2 and 0.1 for the tightness parameter λ_1, and found the best result with $\lambda_1 = 0.2$.

Table 3. VAR Lag Order Selection Criteria

Lag	LR	FPE	AIC	SBC	HQC
0	NA	4.30E-13	-17.12407	-16.99351	-17.07234
1	82.29831	1.87E-13	-17.95980	-17.30700*	-17.70114*
2	27.29367	1.89E-13	-17.95182	-16.77678	-17.48623
3	48.84021*	1.26E-13*	-18.36923*	-16.67196	-17.69672
4	18.65541	1.43E-13	-18.26444	-16.04493	-17.38500
5	15.98139	1.70E-13	-18.13388	-15.39213	-17.04752
6	15.93590	2.00E-13	-18.03389	-14.76991	-16.74060
7	18.28673	2.19E-13	-18.03219	-14.24598	-16.53198
8	16.22838	2.49E-13	-18.02527	-13.71682	-16.31813
9	11.08163	3.31E-13	-17.91216	-13.08146	-15.99809

The asterisks * indicates lag order selected by the criterion.
LR is sequential modified Likelihood ratio (LR) test statistic, and FPE is final prediction error. Other criteria are defined in the text.

Another method is to use the Posterior Information Criterion (PIC), which is an information Criterion such as AIC and BIC.[1] Kasuya and Tanemura (2000) conducted Monte Carlo experiments for assessing these methods and found that the models optimized by PIC have a superior forecasting performance to the models selected by the in-sample forecast method.

As quarterly data for the Iranian economy is too short to use PIC, RMSE or Theil statistic of in sample forecast, this paper uses an empirical Bayesian method to pick hyperparameters. In this method hyperparameters are set to the values which maximize the marginal likelihood function. In doing so, we divided the sample into two sub-samples. First, we estimate the model by using data from 1981:Q2 through 2001:Q1. We then added the last 5 years of data (i.e. from 2001:Q2 to 2006:Q1) one observation at a time. We re-estimated the models and picked hyperparameters, which maximize the marginal

1. When the data are non-stationary, PIC imposes a greater penalty than SBC on the presence of additional non-stationary regressors. However, Phillips and Ploberger (1996) show that PIC generally outperforms SBC for both stationary and non-stationary data by Monte Carlo experiments.

likelihood in each re-estimation when new data arrive. This process continued until all the data had been used.[1]

5. Empirical Application

This section reports the results of using various VAR 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 2006:Q1. 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 VAR specification with Bewley (1979) Transformation. By using this transformation, we force the mean of the change of inflation into zero, while the mean of other variables are unchanged. This specification is denoted as BewVAR.
- A UVAR specification where the variables are logged and then differenced once. This specification is denoted as DVAR.
- 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 five years of data (from 2001:Q2 to 2006: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.

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1. Gauss codes for implementing this method along with priors which I have used in this paper are available from the author upon request.

5-1. Results

There are many specification tests that can be used for specification. As the purpose 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 forecast accuracy comparison, the researcher is looking for the forecast which is best with respect to a particular loss function. Hence the preferences or loss function of the forecast user is the key to the selection of the accuracy criteria. The loss function reflects the cost associated with various pairs of forecasts and realizations. In addition to the shape of the loss function, the forecast horizon is of crucial importance. Rankings of forecast accuracy may, of course, be very different across different loss functions and different horizons.

Table 4. RMSE of Different VAR Specification Forecasts of Iranian Inflation 2001:Q2 - 2006:Q1

Models specification	First Quarter	Second Quarter	First Year	Second Year
		Lag=1		
BVAR_Litt	0.00787	0.00900	0.0101	0.0109
BewVAR	0.00615 (1.2805)	0.00587 (1.5319)	0.00823 (1. 2350)	0.00887 (1. 2358)
DVAR	0.00619 (1.2725)	0.00591 (1.5207)	0.00839 (1.2127)	0.00920 (1.1922)
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
BewVAR	0.00642 (1.0417)	0.00686 (1.1032)	0.00859 (1.0948)	0.00865 (1.2292)
DVAR	0.00649 (1.0311)	0.00698 (1.0839)	0.00893 (1.0533)	0.00937 (1.1345)
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_Litt model 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 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. Table 4 presents RMSE of the various VAR specifications for forecasting Iranian inflation. In the results presented in this table, the period from 2001:Q2 to 2006:Q1 is used to examine the forecast performance of the various VAR specifications. 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 with Litterman's prior model is larger than the given model. This indicates that the given model's forecasts are more accurate than the Traditional BVAR model forecasts.

In Table 4, the VAR model where we use the Bewley (1979) transformation to impose the mean of the change of inflation into zero produces the smallest RMSE values for forecast of inflation in all forecast horizons. Our results, not surprisingly, show that the DVAR model almost as good as the BewVAR model. This result is in line with Robertson and Tallman (1999). But the point is that it is possible that the equations in differences may be mis-specified if there is a linear combination of those variables that is stationary. If any co-integration relations exist then an error correction model might improve forecast accuracy. Hendry and Clements (2001) believe that a VAR in first differences is mis-specified by omitting any co-integration relations and thereby gains robustness to equilibrium mean shifts.

In summary, our results show that, using Bewley (1979) transformation to force the mean of the change of inflation rate to zero in a mixed drift VAR model accretes forecasts of Iranian inflation in comparison to the BVAR model with Litterman's prior.

6. Conclusion

This paper shows the steps involved in producing real-time forecasts from modern non-structural dynamic multivariate time series models. These models are being increasingly used for forecasting and policy analysis in both the private and public sectors. It is hoped that the empirical techniques presented in this paper may be useful to those interested in understanding real-time forecasting with a VAR model. The paper discusses methods that attempt to improve VAR forecast accuracy by imposing inexact prior restrictions.

This paper shows a comparison of forecast accuracy between different specifications of VARs. 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 using Bewley (1979) transformation to impose a zero mean to the change of inflation in a mixed drift VAR model. We also provide empirical evidence from the performance of various specifications of a four-variable VAR model in forecasting Iranian inflation. The results show that using Bewley (1979) transformation to impose a zero mean to the change of inflation provides more accurate forecasts of inflation for the Iranian economy in comparison to the BVAR models with Litterman's priors. As imposing inexact prior restrictions in Quasi-Bayesian method or some numerical methods such as method of importance sampling, Gibbs sampling and Markov Chain Monte Carlo (MCMC) in pure Bayesian can improve forecast accuracy, considering these would be the next step of this research.

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