Forecasting Chinese inflation and output: A Bayesian vector autoregressive approach

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by

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Abstract

This study compares several Bayesian vector autoregressive (VAR) models for forecasting price inflation and output growth in China. The results indicate that models with shrinkage and model selection priors, that restrict some VAR coefficients to be close to zero, perform better than models with Normal prior.

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Keywords: BVAR, factor model, shrinkage priors

[†] This paper is based on my MSc thesis “Bayesian vector autoregressive models and macroeconomic forecasting”. I am extremely grateful to Dr. Dimitris Korobilis for providing me with his code for the paper Korobilis (2012).

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I. INTRODUCTION

Forecasts of price inflation and output growth are among the most important to macroeconomists. Forecasts of output have always been important for decades, because it is the ultimate measure (at least from an economic point of view) of wealth and wellbeing in an economy. Similarly, it is now well understood that expected (future) inflation is important for the design and implementation of monetary policy by central banks.

The subject of forecasting inflation and output is multidimensional and the numerous papers on this issue have addressed this issue using theoretical models, time series methods, and subjective judgements. This paper evaluates forecasts of inflation and output from the perspective of Bayesian vector autoregressive (VAR) models. VAR models have been very popular for forecasting since their introduction from Sims (1980) as a solution to the critiques of the large-scale macroeconometric models of the '70s. The Bayesian implementation of these models allows for rich, flexible modeling and improved forecast performance in high dimensions. As Koop and Korobilis (2010) explain, the Bayesian priors can be used to shrink heavily-parameterized models such as VARs.

Following existing studies, such as Kadiyala and Karlsson (1997), Koop and Korobilis (2010) and Koop (2011), we evaluate several Bayesian priors that have been proposed in the literature. Additionally, we consider both traditional VARS and VARS augmented with factors. This paper contributes to the previous studies by furthering our understanding of how priors affect

The data concern the economy of China and they are available for the period 1998-2012. Limited studies have examined forecasts of inflation and output in China, with most notable exceptions Mehrotra and Sánchez-Fung (2008) and Maier (2011); see also references therein.

Our results suggest that the Minnesota prior of Littermann (1986) is the best among all priors considered. This is an interesting result, since an empirical and subjective prior is performing better than carefully designed priors which are more data-driven. The Minnesota prior is fine-tuned to macroeconomic data in particular (see Littermann, 1986, for a complete discussion of these issues), something that shows why Bayesian VARS can provide more freedom to modellers by allowing subjective as well as objective fine tunning.

The next section describes the data and econometric methodology. The third section describes the implementation of the forecasting exercise and the results. The fourth section concludes.

II. ECONOMETRIC METHODOLOGY

III.1 Data

In this study we use 12 Chinese macroeconomic time series running through the period 1998q1-2012q2. Monthly variables are transformed to quarterly, and all variables are transformed to stationary. Inflation is defined as Consumer Price Index and output is the Gross Domestic Product. Details of each series can be seen in Table 1 below.

Table 1: Data used in VAR

No	Series name	Unit
1	Consumer Price Indices	Corresponding Period of Preceding Year=1
2	Retail Price Indices	Corresponding Period of Preceding Year=1
3	Purchasing Price Indices for Raw Materials, Fuels and Power	Corresponding Period of Preceding Year=1
4	Producer Price Indices for Manufactured Goods	Corresponding Period of Preceding Year=1
5	Sales Price Indices of Commercialized Houses	Corresponding Period of Preceding Year=1
6	Sales Price Indices of Second-hand House	Corresponding Period of Preceding Year=1
7	Growth Rate of Industrial Value-added	Rate
8	Total Assets	100 Million Yuan
9	Total Liabilities	100 Million Yuan
10	Value-added Tax Payable	100 Million Yuan
11	Total Production of Energy	10,000 Tons
12	Gross Domestic Product	Accumulative Value

II.2 Bayesian vector autoregressive (VAR) model

Let y_t be a $n \times 1$ vector of time series which the policy-maker want to forecast (including inflation and GDP growth). A VAR(p) model is defined as

$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \varphi_1 y_{t-2} + \cdots + \varphi_p y_{t-p} + \epsilon_t$$

where φ_0 is a $n \times 1$ vector and $\varphi_1, \dots, \varphi_p$ are $n \times n$ coefficient matrices, and ϵ_t is a Normal distributed error term with zero mean and $n \times n$ covariance matrix Σ.

In this study $n = 12$, that is, all the available variables in the dataset. VAR models assume that all variables are endogenous, therefore we obtain forecasts of all 12 variables. In the forecasts assessment in the next section we focus only on forecasts of CPI and GDP (and ignore the forecasts of the remaining 10 variables).

II.3 Bayesian factor augmented vector autoregressive (FAVAR) model

The Bayesian FAVAR model builds on the VAR model presented above. It assumes that one or more of the variables y_t are replaced by estimated factors. In our case we can write

$$x_t = \beta f_t + \varepsilon_t$$
$$y_t = \varphi_0 + \varphi_1 y_{t-1} + \varphi_1 y_{t-2} + \cdots + \varphi_p y_{t-p} + \epsilon_t$$

where now x_t contains the 10 variables on the dataset which we do not want to forecast, and f_t is the estimated factor.

There is a multitude of ways to estimate factors, and in this paper we use principal components. Additionally, we use everywhere one factor, which is a reasonable assumption given that we have only 10 macro series available for estimating factors.

II.4 Priors

Following Kadiyala and Karlsson (1997), Koop (2011) and Korobilis (2010)[1], we perform a forecast evaluation of several priors. The novel elements in this study is that we include the same priors also for the FAVAR model.

Normal prior

The normally distributed prior can be defined as a natural conjugate prior for the VAR model with normal error term. The coefficients φ have a prior which is of the form

$$\varphi \sim N(0, c \times I)$$

When no prior information is available we can use in the limit $c \to \infty$, which gives the least squares estimator.

[1] Estimation of all models is done in MATLAB. Code is from Koop and Korobilis (2010), available in http://personal.strath.ac.uk/gary.koop/bayes_matlab_code_by_koop_and_korobilis.html.

Hierarchical prior

A hierarchical prior is one that has two or more layers. Korobilis (2012) has used such a prior for shrinking the dimension of the VAR prior. This prior is

$$\varphi \sim N(0, c \times I)$$
$$c \sim \frac{1}{c}$$

Such prior allows for the data to estimate the value of the prior variance c. See also Korobilis (2011) for a richer comparison of hierarchical priors.

Minnesota prior

The Minnesota prior introduced in Litterman (1986) takes the form

$$vec(\varphi) \sim N(\Delta, M)$$

where

$$\Delta_{ij} = \begin{cases} 1, if\ i = j, for\ 1^{st}\ lag \\ 0, \qquad if\ i \neq \mathrm{j} \end{cases}, \quad M_{ij} = \begin{cases} \dfrac{\vartheta}{r^2}, & if\ i = j \\ \dfrac{\vartheta}{r^2} \times \left(\dfrac{\sigma_i}{\sigma_j}\right)^2, & if\ i \neq \mathrm{j} \end{cases}$$

and σ_i are the residuals of an AR(p) model for variable i, ϑ is a tuning parameter and r are the number of lags, for $r = 1,2, \ldots, p$.

SSVS prior

Korobilis (2008) and Koop and Korobilis (2010) use a stochastic search variable selection (SSVS) prior which restricts coefficients based on information in the likelihood. This prior is

$$\varphi \sim \pi N(0, c_1 \times I) + (1 - \pi) N(0, c_2 \times I)$$

where c_1 is set to a small value, and c_2 is set to a large value, so that with probability π the prior will be very "tight", and with probability $(1 - \pi)$ the prior will be similar to the normal, uninformative case. More details and forecasting results can also be found in Koop (2011).

III. EMPIRICS

III.1 Forecasting

Data from 1998q1 to 2005q4 are used for estimating the parameters, and the period 2006q1 to 2012q2 is used to evaluate the forecasts. Forecasts are implemented recursively, by adding each period one observation at the end of the initial sample. Inflation and GDP forecasts are calculated using the iterative methods (Marcellino, Stock and Watson, 2006) for horizons $h = 1,2,3$ and 4 quarters ahead.

The mean squared forecast error (MSFE) is used to evaluate the performance of each model. Denote by $y_{t+h|t}$ the forecast of y_{t+h} made at time t, then the MSFE is defined as

$$MSFE = \frac{1}{N}\sum_{t=t_0}^{t_1}\left(y_{t+h|t} - y_{t+h}\right)^2$$

where t_0 is the first forecasting period (2006q1) and t_1 is the last forecasting period (2012q2-h), and $N = t_1 - t_0$. All VAR models are estimated using 2 lags of each dependent variable.

III.2 Results

Tables 1 and 2 present the results of this forecasting exercise. We can see that the simple normal prior is not giving good results, given that the dataset is not particularly large. The best model for CPI and GDP differs with the forecast horizon. Though, the Minnesota prior is the one that performs best in most cases for both variables.

With regards to the model specification, it is clear that the factor VAR with the two variables we forecast and one factor, is doing worse than the VAR with all twelve variables. The expectation is that the factor VAR will further help reduce the number of coefficients, thus making forecasts less prone in overparametrization. The weird result we obtain is probably because the dimension of the data is not large enough to excuse the use of factor model.

The SSVS is not performing that well, but it is better than the normal in all forecasting cases. The hierarchical prior ranks next, but it is the Minnesota prior which clearly stands out as the best choice.

Table 1 - MSFE for inflation

Model	$h = 1$	$h = 2$	$h = 3$	$h = 4$
VAR-normal	0.554	0.583	0.602	0.616
VAR-hierarchical	0.502	0.541	0.589	0.594
VAR-minnesota	0.514	0.533	0.521	0.549
VAR-ssvs	0.550	0.581	0.594	0.622
FAVAR-normal	0.561	0.587	0.613	0.624
FAVAR-hierarchical	0.557	0.571	0.585	0.634
FAVAR-minnesota	0.540	0.533	0.588	0.609
FAVAR-ssvs	0.595	0.611	0.601	0.612

Table 2 - MSFE for output

Model	$h = 1$	$h = 2$	$h = 3$	$h = 4$
VAR-normal	1.550	1.932	1.613	1.712
VAR-hierarchical	1.539	1.738	1.739	1.707
VAR-minnesota	1.162	1.304	1.548	1.555
VAR-ssvs	1.571	1.872	1.746	1.649
FAVAR-normal	1.547	1.657	1.722	1.714
FAVAR-hierarchical	1.373	1.535	1.459	1.633
FAVAR-minnesota	1.415	1.511	1.659	1.733
FAVAR-ssvs	1.541	1.529	1.586	1.538

IV. CONCLUSIONS

This short paper evaluated the forecasting performance of Bayesian VAR models. The results are encouraging about the Minnesota prior of Litterman (1986). This prior reduces the mean squared forecast error of both Chinese inflation and output for the evaluation period 2006-2012. Future research will evaluate the effect of priors on VARS with time-varying parameters and and general nonlinearities (see Korobilis, 2012).

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