Accuracy of Bayesian VAR in forecasting the economy of Indiana

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ABSTRACT
This paper develops a forecasting model for important macroeconomic variables in the state of Indiana. In this study, we specify a Bayesian Vector Autoregression (BVAR) model with Litterman's prior. A comparison with the Vector Autoregression (VAR) model shows that BVAR improves forecast by reducing root mean square percent error.

INTRODUCTION

Accurate forecasts of regional economic variables undoubtedly have significant policy implications. It is therefore not surprising that economists are constantly in search of the "best" regional forecasting model. There is no universal standard as of what magnitude of forecast errors is acceptable. As West (2003) points out, "accuracy of regional forecasts is a function of regions, variables and forecast horizons". As a result, the arena of regional economic forecasting is largely occupied by studies that compare forecast accuracy among models to find a "better" model instead of the "best". Time series forecasting methods are generally more relevant than structural econometric model (SEM) in regional economic forecasting because regional data are generally too scarce and of too low frequency to allow a construction of complete SEMs based on economic theories (Anderson 1979). Many studies show that forecasting accuracy can be improved from univariate autoregression by adding national economic variables as driving factors (inputs), such as transfer functions (Weller 1990). Intuitively, a larger model such as the vector autoregression (VAR) that allows inter-temporal interdependence among all variables should perform better than transfer functions and univariate regressions. However, VAR suffers from overparameterization and a modified VAR (Bayesian VAR) imposing some prior restrictions on parameters sometimes perform better (Litterman 1980, Kinal and Ratner 1986). A particular type of Bayesian VAR (BVAR) imposing the Minnesota prior or Litterman's prior (Litterman 1980) have been used in many regional studies recently. Some of the important studies using Bayesian VAR of Litterman's type are for Minnesota (Litterman, 1980), New York state (Kinal and Ratner 1986), Texas (Gruben and Long 1988), Louisiana (Gruben and Hayes 1991), Iowa (Otrok and Whiteman 1998) and Philadelphia Metropolitan Area (Crone and McLaughlin 1999).

However, few researches have been conducted to develop a forecasting model of Indiana. In this paper, we develop a forecasting model for the state of Indiana allowing possibility of interactions among various national and state level variables. In this paper, we first develop a VAR model for the state of Indiana and then modify the model using Litterman's prior to develop a Bayesian VAR model. Next, we compare the out of sample forecasts from VAR with our modified VAR model.

The rest of the paper is organized as follows. Section 2 provides a short description of related literature and Litterman's prior, section 3 describes the data and variables used, section 4 describes the methodology and summarizes the results and section 5 concludes the paper.

RELATED LITERATURE AND DESCRIPTION OF THE LITTERMAN'S PRIOR

A simple VAR allows for interaction of different related variables in forecasting macroeconomic variables. VAR is sometimes criticized for overparameterization. The requirement to estimate a large numbers of coefficients in VAR often leads to large standard errors for inferences and forecasts. By imposing priors that assign probability distribution to each coefficient, Bayesian VAR (BVAR) approach provides more accurate forecasts (see Litterman (1980), Kinal and Ratner (1986)). BVAR is also superior to VAR since it is robust to the choice of national variables, even when misspecified national variables are included (Shoesmith, 1990).

Hence, a modified VAR restricting certain parameters are sometimes preferred. The modified VAR depends on the prior belief the forecaster has on different parameters before estimation. Litterman (1980) proposed a prior in forecasting VAR[1].

The Litterman's prior assumes that each variable in the system follows a random walk. In other words, the prior mean of the coefficient on the own first lag of each variable is one. Moreover, it assumes that the coefficients on the cross lags are close to zero.

As for example, writing the i^{th} equation in a VAR as

$$y_{it} = c_i + \Phi_{i1}^{(1)} y_{1,t-1} + \Phi_{i2}^{(1)} y_{2,t-1} + \ldots\ldots + \Phi_{in}^{(1)} y_{n,t-1} + \Phi_{i1}^{(2)} y_{1,t-2} + \Phi_{i2}^{(2)} y_{1,t-2} + \ldots\ldots + \Phi_{in}^{(2)} y_{n,t-2} + \ldots\ldots + \Phi_{i1}^{(p)} y_{1,t-p} + \Phi_{i2}^{(p)} y_{2,t-p} + \ldots\ldots + \Phi_{in}^{(p)} y_{n,t-p} + \varepsilon_{it} \tag{1}$$

$\Phi_{ij}^{(s)}$ gives the coefficient relating y_{it} to $y_{j,t-s}$. Litterman(1980) assumed that $\Phi_{ii}^{(1)} = 1$ and all other $\Phi_{ij}^{(s)} = 0$. These (0, 1) values characterize the mean of the prior distribution for the coefficients. Moreover, Litterman (1980) assumed that $\Phi_{ii}^{(1)} \sim N(1, \gamma^2)$, $\Phi_{ii}^{(s)} \sim N(0, \gamma^2/s^2)$ and $\Phi_{ij}^{(s)} \sim N(0, [(w.\ \gamma.\tau_i)/(s.\ \tau_j)]^2)$, where$(\tau_i / \tau_j)$ is a correction for the scale of series i compared with series j and $0<w<1$.

The above model requires choosing specific values for γ (the lag decay) and w (the tightness parameter) that will improve forecast. Litterman (1984a) found that tight priors around zero on coefficients of other variables provide better forecast. Doan (1990) recommended a value of $w = 0.5$ in concert with $\gamma = 0.20$. Kinal and Ratner (1986) used $w = 0.40$ and $\gamma = 0.90$.

In this paper, we used the Litterman prior as described in the previous paragraph to forecast the macroeconomic variables of the state of Indiana. This paper extends the existing literature by developing a Bayesian VAR forecasting model for the state of Indiana.

DATA AND VARIABLES

In this paper, we used quarterly data from 1978 Quarter 1 to 2001 Quarter 4. Table provides a description of the variables and their source. For Indiana, we employed variables such as total non-agricultural employment, personal income and wages and salaries. Retail sales would have been a better choice here, but personal income together with wages and salaries should provide a general idea about the level of economic activity in the state (Anderson 1979). We wanted to use consumer price index (CPI) of Indiana but due to unavailability of data, we used CPI for Midwest region. Variables at the national level are similar to Kinal and Ratner (1986). Table 2 provides a description of the transformation to achieve stationarity. We used the Akaike Information Criterion (AIC) to decide the number of lags[2]. The next section provides the methodology.

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[1] This prior is also known as the Minnesota prior.

[2] The number of lags for each variable is four.

METHODOLOGY AND RESULTS

First, we estimated a VAR model. Next, we estimated a BVAR model with Litterman's prior[3]. We used different combinations of the decay and tightness parameter and noted any improvement. By improvement, we imply a decrease in the Root Mean Square Percent Error (RMSPE)[4] of the out of sample forecasts. We had forecasts for four period ahead.

Out of different values for w and γ, the model (w = 0.7, γ= 0.9) produced the minimum RMSPE for Indiana's PI and employment. Although, we did not get minimum RMSPE for Indiana wages and salaries and Midwest CPI for this specification, nevertheless among all other combinations of w and γ, this model minimized Akaike's Information Criterion (AIC)[5] and Schwartz Bayesian Criterion (SBC). Hence, we selected w = 0.7, γ= 0.9 as the parameters for our BVAR model.

A comparison of RMSPE (in Table 3) for three state variables and the Midwest CPI for the BVAR model with that of VAR shows that the BVAR model improves forecast accuracy.

CONCLUSIONS

Improving economic forecasts for macroeconomic variables has always been a challenge for researchers. A VAR model which allows interactions of different regional and national macroeconomic variables has been popular in this regard. However, due to some of its drawbacks, researchers have resorted to a Bayesian VAR model which is a hybrid of VAR and univariate forecasting models. Specification of a modified VAR using Litterman's prior has been used by many studies to improve forecast accuracy. In this paper, we develop a BVAR model with Litterman's prior to improve forecast accuracy of important macroeconomic variables for the state of Indiana. The main conclusion of this paper is that, with suitable specification of the decay and tightness parameters in the Litterman prior, we get better forecasts than VAR.

At the beginning of the paper we mentioned that it is difficult to find the "best" forecasting model. However, it is more important to search for the "better" model. Although we have improved our forecast accuracy, still there is scope of improvement. For example, Kinal and Ratner (1986) did not assume a "random walk" for the coefficients. They used prior means that were different from (1, 0). In the future, we would like to incorporate such modifications to improve our results.

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[3] We used Varmax procedure in SAS to estimate the model.

[4] RMSPE = (100). (1/4). $\sqrt{\sum\left(\frac{(A_t - F_t)^2}{F^2{}_t}\right)}$

[5] AIC for this model turned out to be -52.37 and SBC is -43.12.

REFERENCES

Anderson, Paul A. 1979. "Help for the Regional Economic Forecaster: Vector Autoregression". Federal Reserve Bank of Minneapolis Quarterly Review.

Crone, Theodore M. and McLaughlin, Michael P. 1999. "A Bayesian VAR Forecasting Model for the Philadelphia Metropolitan Area". Federal Reserve Bank of Philadelphia Working Paper No.99-7.

Doan, Thomas, A. 1990. RATS User's Manual. VAR Econometrics, Suite 612, 1800 Sherman Ave., Evanston, IL 60201.

Eberts, Randall W. 1990. "Can State Employment Declines Foretell National Business Cycles?". Federal Reserve Bank of Cleveland Economic Commentary.

Gruben, William C. and Hayes, Donald W. 1991. "Forecasting the Louisiana Economy". Federal Reserve Bank of Dallas Economic Review.

Gruben, William C. and Long, William T. 1988. "Forecasting the Texas Economy: Applications and Evaluations of a Systematic Multivariate Time Series Model". Federal Reserve Bank of Dallas Economic Review.

Hamilton, James D. 1994. "Time Series Analysis". Princeton University Press, Princeton, New Jersey.

Kinal, Terrence and Ratner, Jonathan. 1986. "A VAR Forecasting Model of a Regional Economy: Its Construction and Comparative Accuracy". International Regional Science Review, vol. 10, no.2, p 113-126.

Litterman, Robert B. 1980. "A Bayesian Procedure for Forecasting with Vector Autoregressions". Federal Reserve Bank of Minneapolis.

Litterman, Robert B. 1984a. "Forecasting and Policy Analysis with Bayesian Vector Autoregression Models". Federal Reserve Bank of Minneapolis Quarterly Review.

Litterman, Robert B. 1984b. "Specifying Vector Autoregressions for Macroeconomic Forecasting". Federal Reserve Bank of Minneapolis Staff Report 92.

Otrok, Christopher and Whiteman, Charles. 1998. "Bayesian Leading Indicators: Measuring and Predicting Economic Conditions in Iowa". International Economic Review, vol.39, no.4, p997-1014.

Weller, Barry R. 1990. "Predicting Small Region Sectoral Responses to Changes in Aggregate Economic Activity: A Time Series Approach". Journal of Forecasting, vol.9, p273-281.

West, Carol T. 2003. "The Status of Evaluating Accuracy of Regional Forecasts". The Review of Regional Studies, vol.33, no.1, p 85-103.

Table 1: Data Source

Series Name	Source	Description
Indiana PI	BEA, Department of Commerce	Millions of $. Seasonally adjusted at annual rates.
Indiana Employment	BLS, Department of Labor	In thousands. Seasonally adjusted. Monthly data converted to quarterly.
Indiana Wages and Salaries	BEA, Department of Commerce	Wage and Salary disbursement by place of work. Millions of $. Seasonally adjusted at annual rates.
Midwest(all items) CPI	BLS, Department of Labor	1982-84 prices. Not Seasonally adjusted. Monthly data converted to quarterly.
US PPI (fuel and related products and power)	BLS, Department of Labor	1982 prices. Not seasonally adjusted. Monthly data converted to quarterly.
US PI	BEA, Department of Commerce	Millions of $. Seasonally adjusted at annual rates.
US CPI (all items)	BLS, Department of Labor	1982-84 prices. Seasonally adjusted. Monthly data converted to quarterly.
US IPI (all items)	Federal Reserve, Board of Governors	Base year = 1997. Seasonally adjusted. Monthly data converted to quarterly.
US T-Bill Rate (secondary)	Federal Reserve, Board of Governors	Three months. Not Seasonally Adjusted. Monthly data converted to quarterly.

Table 2: Stationarity Transformation (using augmented Dickey-Fuller Test)

Series Name	
Indiana PI	First Difference of Logs
Indiana Employment	First Difference
Indiana Wages and Salaries	First Difference of Logs
Midwest CPI	Second Difference of Logs
US PPI (fuel and related products and power)	First Difference of Logs
US PI	Second Difference of Logs
US CPI (all items)	Second Difference of Logs
US IPI (all items)	First Difference of Logs
US T-Bill Rate (secondary)	Second Difference of Logs

Table 3: Results from the Bayesian VAR (BVAR)
Data period: Quarterly, 1978.1 to 20001.4
Forecast: out of Sample (four periods ahead)
RMSPE for 2002

Variable	VAR	BVAR (Litterman: w = 0.7,γ= 0.9)
Indiana PI	1.78	0.26
Indiana Employment	0.30	0.29
Indiana Wages and Salaries	3.55	3.06
Midwest CPI	2.39	2.37