Real-time conditional forecasting with Bayesian VARs: An application to New Zealand

Chris Bloor and Troy Matheson

Economics Department - Reserve Bank of New Zealand

2009 CEF Conference
Overview

Methodology

- VAR
- BVAR
- Large BVAR
- Large structural BVAR
- Large structural BVAR (conditional forecasts)

Data

Real time forecasting

Tools for analysing the forecasts
Reserve Bank’s forecasting process

- First-pass forecasts
  - Monitoring quarter forecasts (incl. judgement)
  - Model-based forecasts (incl. judgement)
- Alternative forecasts and scenarios to highlight risks
- Published forecasts (incl. judgement)
$Y_t = (y_{1,t}, y_{2,t}, \ldots, y_{N,t})'$ is a set of time series with a reduced-form VAR($p$) representation:

$$Y_t = c + \sum_{k=1}^{p} B_k Y_{t-k} + u_t$$
The moments for the prior distribution of the coefficients are:

\[ \mathbb{E}[(B_k)_{ij}] = \begin{cases} 
\delta_i, & j = i, k = 1 \\
0, & \text{otherwise}
\end{cases} \]

and

\[ \mathbb{V}[(B_k)_{ij}] = \frac{\lambda^2 \sigma_i^2}{k^2 \sigma_j^2} \]
In addition to these priors, we also add a couple more priors that favour unit roots and co-integration. The sums of coefficients prior of Doan, Litterman and Sims (1984) and the co-persistence prior of Sims (1993).
In a Bayesian regression, De Mol, Gianonne and Reichlin (2008) show that a forecast based on point estimates converges to the optimal forecast as long as the tightness of the prior increases as the number of time series $N$ becomes larger.

Banbura, Gianonne and Reichlin (2008) apply this result to a large BVAR.
1. Select \( N^* \) (where \( N^* < N \)) benchmark variables for which in-sample fit will be evaluated;

2. Evaluate the in-sample fit of a VAR estimated with OLS on the \( N^* \) benchmark variables;

3. Set the sums of coefficients hyperparameter \( \tau \) and the co-persistence hyperparameter \( \theta \) to be proportionate to the overall tightness hyperparameter \( \lambda \) (\( \tau = \phi_1 \lambda \) and \( \theta = \phi_2 \lambda \), where \( \phi_1 \geq 0 \) and \( \phi_2 \geq 0 \));

4. Choose the overall tightness hyperparameter \( \lambda \) to have the same in-sample fit as the benchmark VAR.
New Zealand is a small open economy where the foreign sector can be assumed exogenous.

We estimate the model with strong recursive blocks (Zha 1999), and assume that the world is block exogenous to the domestic economy.
We use Waggoner and Zha’s (1999) conditional forecasting algorithm.

This allows us to forecast using an unbalanced panel, and to impose exogenous paths for some variables.
A (potentially) large structural BVAR, capable of producing conditional forecasts.

Estimation using Zha’s block-by-block approach and Wagonner and Zha’s conditional forecasting approach.

- Estimated parameters are conditional on structural assumptions (recursive ordering of blocks) and on assumed future paths for variables.
Real-time forecasting problem

- Data is released incrementally throughout the quarter.
- Data is subject to revision over time.
- At the same time the forecaster may have information available to them which is not captured by the model.

> We want to test the forecasting performance of our BVAR methodology, taking into account these features of the data.
Real time data

- Baseline variables: real GDP, non-tradable CPI, tradable CPI, 90-day rate, TWI
- 45 other macroeconomic indicators (both domestic and foreign)
- Quarterly data ranging from 1990Q1 to 2008Q3
- Real time panels run from 2000Q1 to 2008Q3
- All data in levels or log levels
Conditioning information for real-time forecasts

<table>
<thead>
<tr>
<th>Time</th>
<th>Activity</th>
<th>Prices</th>
<th>Financial</th>
<th>Foreign</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t - 2$</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>$t - 1$</td>
<td>FP</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>$t$</td>
<td>FP</td>
<td>FP</td>
<td>FP</td>
<td>FP</td>
</tr>
<tr>
<td>$t + h$</td>
<td>O</td>
<td>O</td>
<td>O</td>
<td>FP</td>
</tr>
</tbody>
</table>
## MSFE relative to FP MSFE

<table>
<thead>
<tr>
<th></th>
<th>Univariate</th>
<th>Multivariate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$AR^{SBC}$ Priors</td>
<td>$BL$ $BL^{SBC}$ $BL^{BVAR}$ $M$</td>
</tr>
<tr>
<td><strong>GDP</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1.000 1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>2</td>
<td>1.000 1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>3</td>
<td>0.954 0.986</td>
<td>1.235* 1.116 0.911 0.861 0.871*</td>
</tr>
<tr>
<td>4</td>
<td>0.934 0.932</td>
<td>1.762* 1.291 0.944 0.734 0.714*</td>
</tr>
<tr>
<td><strong>90 day</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1.000 1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>2</td>
<td>1.114 1.085</td>
<td>3.626* 1.808* 1.306* 1.294* 1.457*</td>
</tr>
<tr>
<td>3</td>
<td>1.144 1.150</td>
<td>4.265* 1.850* 1.487* 1.364* 1.468*</td>
</tr>
<tr>
<td>4</td>
<td>1.141 1.155</td>
<td>4.073* 1.770* 1.447* 1.266* 1.471*</td>
</tr>
<tr>
<td><strong>TR CPI</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1.015 1.000</td>
<td>1.080 1.022</td>
</tr>
<tr>
<td>2</td>
<td>1.015 0.988</td>
<td>1.178* 0.956 1.032 0.988 1.000</td>
</tr>
<tr>
<td>3</td>
<td>1.014 0.945</td>
<td>1.405* 0.966 1.032 0.975 0.965</td>
</tr>
<tr>
<td>4</td>
<td>1.010 0.918</td>
<td>1.644* 0.988 1.044 0.965 0.932</td>
</tr>
<tr>
<td><strong>NT CPI</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.968 0.977</td>
<td>1.092 0.977 0.981 0.999 0.977 0.967</td>
</tr>
<tr>
<td>2</td>
<td>0.972 0.977</td>
<td>1.336* 1.018 1.254 1.247* 1.063</td>
</tr>
<tr>
<td>3</td>
<td>1.097* 1.127</td>
<td>1.821* 1.040 1.562* 1.499* 1.180*</td>
</tr>
<tr>
<td>4</td>
<td>1.236* 1.321*</td>
<td>2.147* 0.980 1.733* 1.683* 1.303*</td>
</tr>
<tr>
<td><strong>TWI</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1.000 1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>2</td>
<td>1.037 1.098</td>
<td>1.449* 1.129* 1.120* 1.045 1.064</td>
</tr>
<tr>
<td>3</td>
<td>0.986 1.057</td>
<td>1.702* 1.112 1.135* 1.014 1.079</td>
</tr>
<tr>
<td>4</td>
<td>0.924 1.007</td>
<td>1.830* 1.069 1.121 0.983 1.134</td>
</tr>
</tbody>
</table>
Out of sample GDP forecasts

MPS date: 2000Q1

Forecast errors (year ahead)

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2000Q2

Forecast errors (year ahead)

First-Pass
BVAR
Actual

−5 −4 −3 −2 −1 0 1 2 3 4
Out of sample GDP forecasts

MPS date: 2000Q3

Forecast errors (year ahead)

First-Pass
BVAR
Actual

−5
−4
−3
−2
−1
0
1
2
3
4

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2000Q4

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson  
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2001Q1

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2001Q2

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

First-Pass
BVAR
Actual

MPS date: 2001Q3

Forecast errors (year ahead)

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2001Q4

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2002Q1

Forecast errors (year ahead)

First-Pass
BVAR
Actual

−5
0
5
10

Forecast errors (year ahead)

−4
−3
−2
−1
0
1
2
3
4

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2002Q2

Forecast errors (year ahead)

First-Pass
BVAR
Actual


-5 -4 -3 -2 -1 0 1 2 3 4

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2002Q3

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2002Q4

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

Chris Bloor and Troy Matheson
Out of sample GDP forecasts

MPS date: 2003Q2

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2003Q3

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2004Q1

Forecast errors (year ahead)

First-Pass
BVAR
Actual
Out of sample GDP forecasts

Chris Bloor and Troy Matheson

Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2004Q4

Forecast errors (year ahead)

First-Pass
BVAR
Actual


Forecast errors (year ahead)

Out of sample GDP forecasts

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2005Q2

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2005Q3

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2005Q4

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

![MPS date: 2006Q1](image)

**Forecast errors (year ahead)**

- **First-Pass**
- **BVAR**
- **Actual**

Chris Bloor and Troy Matheson

Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2006Q2

Forecast errors (year ahead)

First-Pass
BVAR
Actual

−5
0
5
10

−4
−3
−2
−1
0
1
2
3
4

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

Forecast errors (year ahead)

First-Pass

BVAR

Actual

MPS date: 2006Q3
Out of sample GDP forecasts

MPS date: 2006Q4

Forecast errors (year ahead)

First-Pass
BVAR
Actual
Out of sample GDP forecasts

Forecast errors (year ahead)

MPS date: 2007Q1

First-Pass
BVAR
Actual
Out of sample GDP forecasts

MPS date: 2007Q2

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson

Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

First-Pass  BVAR  Actual

Forecast errors (year ahead)

MPS date: 2007Q3

Chris Bloor and Troy Matheson  Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2007Q4

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2008Q1

Forecast errors (year ahead)
First-Pass
BVAR
Actual

−5
−4
−3
−2
−1
0
1
2
3
4

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2008Q2

Forecast errors (year ahead)

First-Pass
BVAR
Actual

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Out of sample GDP forecasts

MPS date: 2008Q3

Forecast errors (year ahead)

First-Pass
BVAR
Actual

−5
0
5
10

Forecast errors (year ahead)

−4
−3
−2
−1
0
1
2
3
4

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Useful tools

- Alternative scenarios
- Shock decompositions
Alternative Scenarios

Tradable CPI

Chris Bloor and Troy Matheson
Real-time conditional forecasting with Bayesian VARs
Recall, we have:

Foreign $\rightarrow$ Domestic

We can further decompose the domestic sector:

Foreign $\rightarrow$ Real activity $\rightarrow$ Prices $\rightarrow$ Financial
Useful tools: Shock decomposition

90-day rate

- Foreign
- Activity
- Prices
- Financial

1994:1 1999:1 2004:1
Useful tools: Shock decomposition
Large BVAR produces reliable forecasts for most variables considered.

The ability to present alternative scenarios and shock decompositions make BVARs more useful to policy makers than many competing methodologies.