Large time-varying parameter VARs [a]

By Gary Koop and Dimitris Korobilis

Comments by Sylvia Kaufmann

Bundesbank - ifo workshop
Uncertainty and Forecasting in Macroeconomics
Eltville, 1-2 June 2012

[a]The comments do not necessarily reflect the views of the SNB

Contribution of the paper

- introduce forgetting factors (λ_t, α)

$$P_{t|t-1} = \frac{1}{\lambda} P_{t-1|t-1} \qquad \pi_{t|t-1,j} = \frac{\pi^{\alpha}_{t|t-1,j}}{\sum_{l=1}^{J} \pi^{\alpha}_{t|t-1,l}}$$

$$\pi_{t|t,j} = \frac{\pi_{t|t-1,j} p_j \left(y_t|y^{t-1}\right)}{\sum_{l=1}^{J} \pi_{t|t-1,l} p_l \left(y_t|y^{t-1}\right)}$$

  to speed up real-time model estimation and selection

- choose (not update) the prior shrinkage parameter γ
  to adjust flexibly to changing model dimensions

$$\underline{V}_i = \begin{cases} \frac{\gamma}{r^2} \text{ for coefficients on lag } r \text{ for } r = 1, \ldots, p \\ \underline{a} \text{ for the interceps} \end{cases}$$

Comments

Above all...

this is a very useful approach

Comments

Above all...

this is a very useful approach

Some comments on:

- Parametrization
- Empirical application
- Performance

Parametrization

In a TVP-VAR for $t = 1, \dots, T$:

$$\begin{aligned} y_t &= b_{0t} + B_{1t} y_{t-1} + \cdots + B_{pt} y_{t-p} + \varepsilon_{it} \\ &\quad \varepsilon_t \sim \text{ i.i.d } N(0, \Sigma_t) \\ \beta_t &= vec\left([b_{0t}\ B_{1t} \dots\ B_{pt}]'\right) \end{aligned}$$

in B_{jt} on-diagonals might change less than off-diagonals
in Σ_t this is less clear

Parametrization

- the extension for λ might be coefficient specific and not time-specific

$$\lambda_t = \lambda_{\min} + (1 - \lambda_{\min}) L^{f_t}$$
$$\lambda_{it} = \lambda_{\min} + (1 - \lambda_{\min}) L^{f_{it}}$$
$$f_{it} = \begin{cases} -NINT\left(\tilde{\varepsilon}_{t-1}\tilde{\varepsilon}_{t-1}\right) \text{ if } \tilde{\varepsilon}_{i,t-1} = \max\left(\tilde{\varepsilon}_{t-1}\right) \\ 0 \text{ otherwise} \end{cases}$$

- Minnesota prior could differ between on- and off-diagonal coefficients
  see figure 1: the shrinkage prior implies that the standard deviation of autoregressive coefficients changes from 0.22 (small TVP-VAR) to 0.14 (large TVP-VAR)
  $\underline{V}_i = \gamma\tau_i/r^2$, $\tau_i = 1$ for on-diagonals, a weight related to data moments for off-diagonals.

Empirical application

- Mean adjustment and standardization are necessary because of the parametrization of a common λ and γ
- But: time-varying mean and standard deviations of variables
- And: Why include a constant if data are mean-adjusted?

It would be interesting to know whether λ_t is similar across the TVP-VARs of different dimension (Figure 2).

Are λ_t and $\pi_{t|t,j}$ correlated? It seems that small VARs correlate with periods of high λ_ts (Figure 2 and 3).

Performance

- Simulation exercises: time comparison (?)
- How does the approach perform in the presence of breaks, do the parameter estimates adjust quickly?
- With a 10 variable system (including inflation), you would have to evaluate 3570 models in each period

To finish:

If I had a (some) wish(es), I would like to

To finish:

If I had a (some) wish(es), I would like to

- work with the 10 variable system

- make λ coefficient specific, λ_i,

- make γ on- or off-diagonal specific,

To finish:

If I had a (some) wish(es), I would like to

- work with the 10 variable system
- make λ coefficient specific, λ_i,
- make γ on- or off-diagonal specific,
- and estimate a TVP-VAR which indicates the actually important variables for forecasting inflation, and restricting the insignificant coefficients to zero (chosen/evaluated by means of predictive likelihood).