Discussion of:

'Factor augmented VAR revisited - a sparse dynamic factor model approach' by Simon Beyeler and Sylvia Kaufmann

Marek Jarociński, *European Central Bank*

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What this paper does

- Estimates the **FAVAR** model of Bernanke, Boivin, Eliasz (2005), replacing a common **Gaussian** prior with a prior according to which some factor loadings are exactly **zero**

- This is useful, because with sparsity we might be able, with luck, to interpret factors

  $\rightarrow$ Addresses the common complaint that factor models are 'black boxes'

- Example application to the US: finds 7 interpretable factors in 224 series, studies impulse responses to several identified shocks

The econometric model: a FAVAR

$$X_t = \lambda^f f_t + \lambda^Y Y_t + \xi_t \tag{1}$$

$$\Phi(L) \begin{pmatrix} f_t \\ Y_t \end{pmatrix} = \eta_t \tag{2}$$

Sylvia's prior: many entries in λ^f are likely to be zero:

$$p(\lambda_{i,j}|\beta_{i,j}, \tau_j) = (1 - \beta_{i,j})\delta_0(\lambda_{i,j}) + \beta_{i,j} N(0, \tau_j)$$

Identification of factors

$$X_t = \lambda^f f_t + \lambda^Y Y_t + \xi_t$$

Well-known feature of factor models: λ^f and f_t are only identified up to **rotation** ($\lambda^f Q Q^{-1} f_t$) and **scale** ($\lambda^f \gamma \frac{1}{\gamma} f_t$).

Identification comes from the prior:

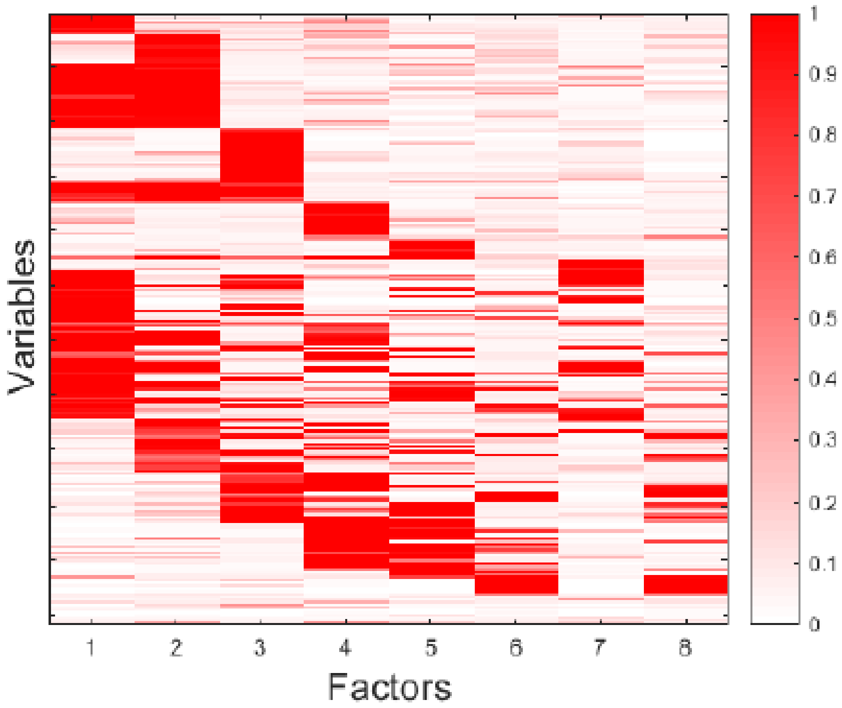
$$p(\lambda_{i,j}|\beta_{i,j}, \tau_j) = (1 - \beta_{i,j})\delta_0(\lambda_{i,j}) + \beta_{i,j} N(0, \tau_j)$$

- zeros in λ^f (induced by $\delta_0(\lambda_{i,j})$) pin down the **rotation** up to a permutation matrix

- τ_j pins down the **scale**

- factor **position** and **sign** are a matter of normalization. Handled when processing the Gibbs sampler output (Kaufmann, Schumacher 2013)

Empirical findings: The sparse λ^f for the US that they find



$$X_t = \lambda^f f_t + \lambda^Y Y_t + \xi_t$$

Empirical findings: seven factors summarize the McCracken-Ng (2015) dataset

... and these factors are amenable to an interpretation as: 1. production, 2. employment, 3. housing, 4. consumer prices, 5. producer prices, 6. term premium, 7. productivity

These common factors do not capture much variation of **capacity utilization, loans and stock market variables**.

$\rightarrow$ Jarocinski, Mackowiak, Granger causal priority and choice of variables in VARs (2017, ReStat) - impose zeros in a large VAR - **loans and stock market variables** least useful for modelling output, prices and interest rates

Empirical findings: IRFs to several identified shocks

- Reasonable IRFs for standard identifications used in the literature
  - Still some price puzzle after a recursively identified monetary policy shocks

A comment & 2 questions

An elegant approach to introducing sparsity in a FAVAR.

1. How do we know if we don't impose too much sparsity?
2. How different are the results from a-priori dedicated factors?

1. Too much sparsity $\Rightarrow$ problems w. capturing dynamic heterogeneity?

- This paper uses a **static** factor model: $X_t = \lambda f_t + ...$
- Without restrictions on λ, a static factor model is equivalent to a **dynamic** factor model
$$X_t = \tilde{\lambda}(L)\tilde{f}_t + ...$$
provided the number of lags is finite (Stock and Watson, 2002)
- With too much restriction on λ we might e.g. miss the dynamics.
- Some papers find important **dynamic heterogeneity** in macro data (e.g. Valle e Azevedo, Koopman, Rua 2006 JBES)

1. Capturing the dynamic heterogeneity

Example: Jarocinski, Lenza (2016), An inflation-predicting output gap in the euro area, ECB WP

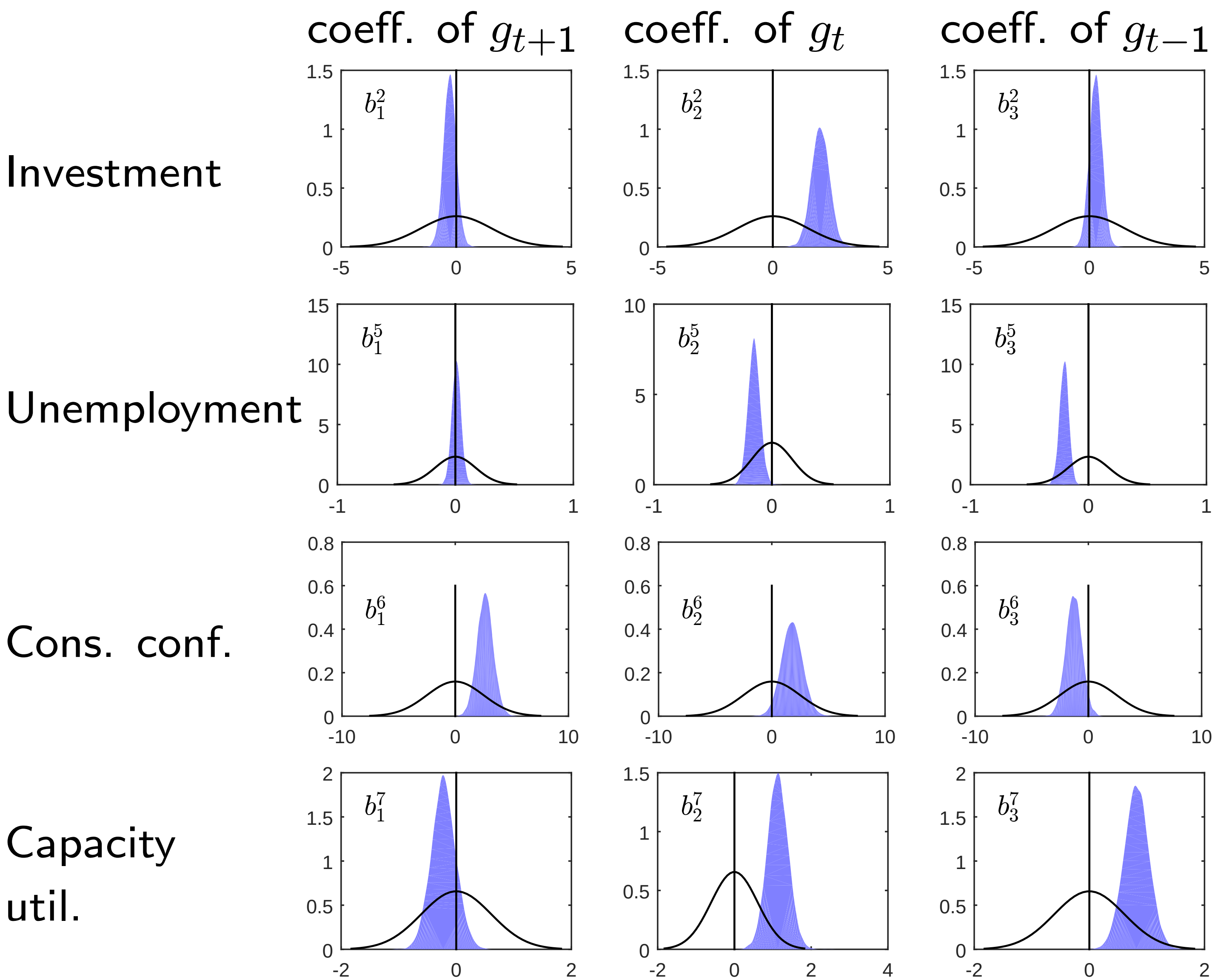
A small dynamic factor model at the core (g_t: unobserved common factor)

$$y_t^n = b_1^n\, g_{t+1} + b_2^n\, g_t + b_3^n\, g_{t-1} + ..., \text{ for } n = 1, ..., N$$

Current real activity variables load mainly on g_t. Unemployment rate loads mainly on g_{t-1}. Consumer confidence loads on g_{t+1}, but also on g_t and g_{t-1}. Capacity utilization loads on everything.

Back to Sylvia's paper: do **production** and **employment** factors capture all the dynamic heterogeneity in real activity? Empirical question. Compare fit with the non-sparse FAVAR.

Jarocinski, Lenza (2016): priors and posteriors of some factor loadings



2. How different is sparse factor model from a-priori dedicated factors?

‘A-priori dedicated factors’: group variables into natural categories, like production, employment, housing etc. and extract a separate factor from each group

- Compare the factors obtained with the two approaches

Conclusions

An elegant approach to introducing sparsity in a FAVAR.

1. How do we know if we don't impose too much sparsity?
   $\rightarrow$ Compare the fit with the usual FAVAR

2. How different is this approach from a-priori dedicated factors?
   $\rightarrow$ Compare with dedicated factors