Discussion of: Time-Varying Vector Autoregressive Models with Structural Dynamic Factors (Gorgi, Koopman and Shaumburg)

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Workshop on Advances in Nowcasting',

Idea of the paper

TVP-VARs have a lot of parameters, two solutions to the problem

- Data shrinkage
- Parameter shrinkage
  - A. Impose a factor structure in the parameters
  - B. Shrink the parameters in a desired direction

The paper goes for route A and casts the model in the state space representation:

$$\begin{aligned} y_t &= Z_t \alpha_t + v_t, \quad \eta_t \sim N(0, H_t) \\ \alpha_{t+1} &= T \alpha_t + \eta_t, \quad \eta_t \sim N(0, Q) \end{aligned}$$

where $Z_t = Z(Y_{t-1}, \gamma)$, and $f_t = vech(H_t)$ is score-driven

$$\begin{aligned} f_{t+1} &= \omega + B f_t + A s_t \\ s_t &= \mathcal{S}_t^{-1} \nabla_t \end{aligned}$$

This is a score-driven TVP State Space model, see Creal et al. (2013) and Harvey (2013)

Challenge in score driven models

How does this paper relate to the literature on score-driven TVP State Space models?

Score-driven TVP State Space models can be analyzed with the Kalman filter once you know how to update the vector of TVP

$$\begin{aligned} f_{t+1} &= \omega + Bf_t + As_t \\ s_t &= \mathcal{S}_t^{-1}\nabla_t \end{aligned}$$

where

$$\nabla_t = \frac{\partial \ell_t}{\partial f_t}, \quad \mathcal{S}_t = -E_t\left(\frac{\partial \ell_t^2}{\partial f_t \partial f_t'}\right) = \mathcal{I}_t$$

∇_t and $\mathcal{S}_t$ are typically a complicated function of the prediction errors and of the other System Matrices.

Score-driven TVP-State Space models

The general case

$$
\begin{aligned}
y_t &= Z_t \alpha_t + v_t, \quad \eta_t \sim N(0, H_t) \\
\alpha_{t+1} &= T_t \alpha_t + \eta_t, \quad \eta_t \sim N(0, Q_t) \\
f_{t+1} &= \omega + B f_t + A s_t
\end{aligned}
$$

is analyzed in Delle Monache, Petrella, Venditti (2016, CEPR DP 11590)

Scaled score in Score-driven TVP-State Space models

we provide formulae for the general case that look much simpler in restricted versions

$$\nabla_t^{DPV} = \frac{1}{2}\left[\dot{F}_t'(F_t^{-1}\otimes F_t^{-1})[v_t\otimes v_t - vec(F_t)] - 2\dot{V}_t' F_t^{-1} v_t\right]$$

$$\mathcal{I}_t^{DPV} = \frac{1}{2}\left[\dot{F}_t'(F_t^{-1}\otimes F_t^{-1})\dot{F}_t + 2\dot{V}_t' F_t^{-1}\dot{V}_t\right]$$

with these in hand you can compute the likelihood and estimate all the static parameters

How does this paper relate to the literature on TVP-VAR?

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$$\nabla_t^{GKS} = \frac{1}{2}\left[D_N'(F_t^{-1}\otimes F_t^{-1})[v_t\otimes v_t - vec(F_t)]\right]$$

$$\mathcal{I}_t^{DPV} = \frac{1}{2}\left[\dot{F}_t'(F_t^{-1}\otimes F_t^{-1})\dot{F}_t + 2\dot{V}_t' F_t^{-1}\dot{V}_t\right]$$

$$\mathcal{I}_t^{GKS} = \frac{1}{2}\left[D_N'(F_t^{-1}\otimes F_t^{-1})D_N\right]$$

with these in hand you can compute the likelihood and estimate all the static parameters

How does this paper relate to the literature on TVP-VAR?

A. TVP-VAR that impose a factor structure in the parameters

Footnote 10 in the Restud TVP-VAR paper by Primiceri (2005): an interest line of future research would be to assume the existence of common factors driving the dynamics of the coefficients

- Gambetti and De Wind (CPB discussion paper)
- Carriero, Clark and Marcellino (JBES, 2016), common volatilty factors
- Canova, Ciccarelli, Ortega (JME, 2007)

Does it work?

A. TVP-VAR that impose a factor structure in the parameters

- Clear trade off: fewer factors imply more 'static' parameters to estimate
- This requires some choices, Table 3 shows that indeed there are a lot of zeros in the loadings
- Canova, Ciccarelli, Ortega (2007) for example have a very strict structure, but it is very parsimonious
- How do you determine the number of factors? How do you decide restrictions?
- Could you not just restrict the number of loadings on the score?

$$f_{t+1} = \omega + Bf_t + As_t$$

- Maybe work out an information criteria that determines the optimal 'reduction'?

B. TVP-VAR that shrink the Parameters in the desired direction

- Koop and Korobilis (JoE, 2013) in a parametric context
- Imposes shrinkage on the initial condition
- Models Stoch Volatilities as an EWMA
- It is a score driven model!! See Appendix in Delle Monache, Petrella, Venditti (2016).

- Kapetanios, Marcellino, Venditti (CEPR DP, 2016) in a non-parametric context
- Add stochastic constraints to TVP-VAR
- Estimate with discounted least squares

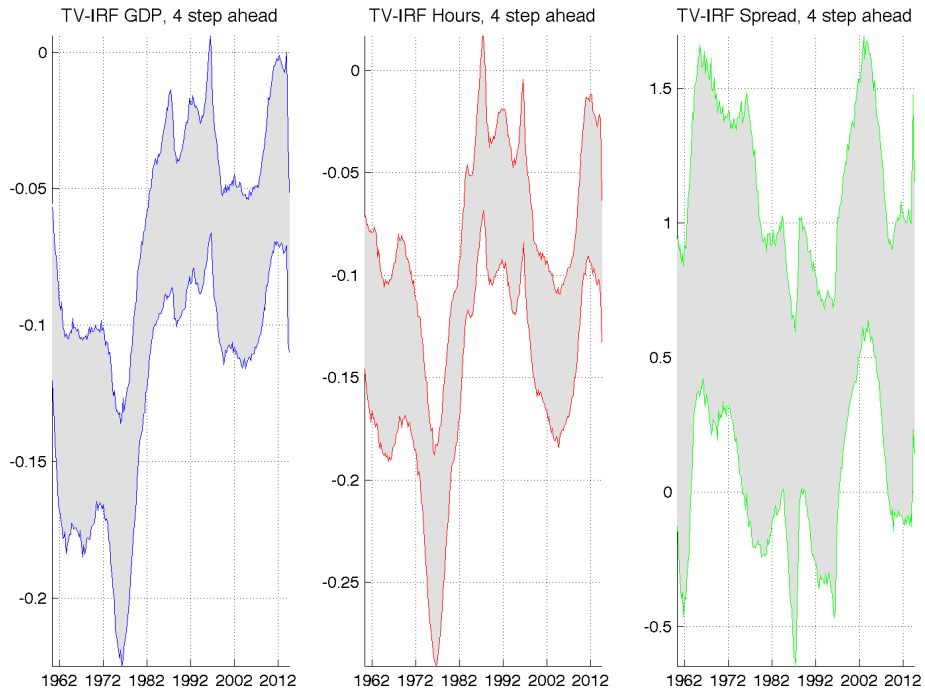
Need a litmus test for placing your model in the context of existing ones.
A Forecasting exercise?

Monte Carlo exercise

- Nice to see when the method works
- It would also be interesting to see when it does not work
- Delle Monche, Petrella, Venditti (2016): very challenging to track time variation when variances change in the transition equation
- In your model Q_t is time invariant by definition, but there are applications in TVP-BVARs by Benati where he also assumes stoch. volatilities on the coefficients
- Could therefore explore robustness to misspecification

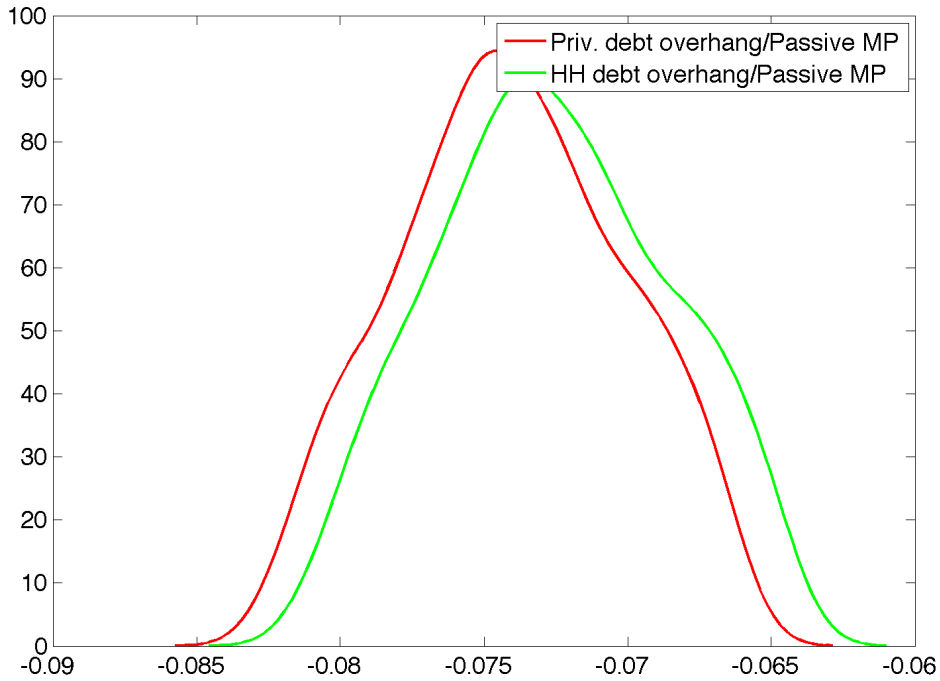
Empirical application

- What do we learn from structural analysis with TVP?
- Is description of changes over time enough?
- What drives changes in the IRFs to structural shocks?
- Barigozzi, Conti, Venditti (2017) 'Sentiments, Business Cycle and Financial Conditions'



Empirical application

- Regress TV-IRFs of GDP on indicator dummies of Debt-overhang/Passive Monetary policy



Conclusions

- An objective criterion to establish number of factors and discuss different way to restrict the number of 'static' parameters
- Need to convince bayesian that observation driven is worth pursuing
- Compare with recent developments in observation driven approaches in TVP-VARs in a forecasting context
- TVP-IRFs can be a dry object, they need to be interpreted