Discussion on “Large Time-Varying Parameter VARs: A Non-Parametric Approach” by George Kapetanios, Massimiliano Marcellino and Fabrizio Venditti

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Summary

- The paper introduces a nonparametric method for large VARs:
  - It does not impose a specific form of time-variation.
  - Estimators and asymptotic distributions are available in closed form.
  - It allows for several types of shrinkage.
  - Inference in terms of model selection criteria and pooling are provided.
- The paper studies the properties of the new estimator in a simulation exercise.
- Empirical applications:
  - Point forecasting with 78 time-series.
  - Response of industrial production indices to an unexpected increase in the price of oil.

Methodology

- In most of the paper, the proposed model assumes constant volatility.
- Clark (2011) and Clark and Ravazzolo (2015) show that a (small size) constant parameter VAR with SV produces accurate forecasts.
- Section 2.5 proposes a GLS estimator, but this is feasible only up to 20 variables.
- This is not so bad, in particular considering that medium size VARs are often the most accurate.
- Equation (31) requires the inversion of potentially large matrices ($nk \times nk$).
    - Block inversion.
    - GPU.

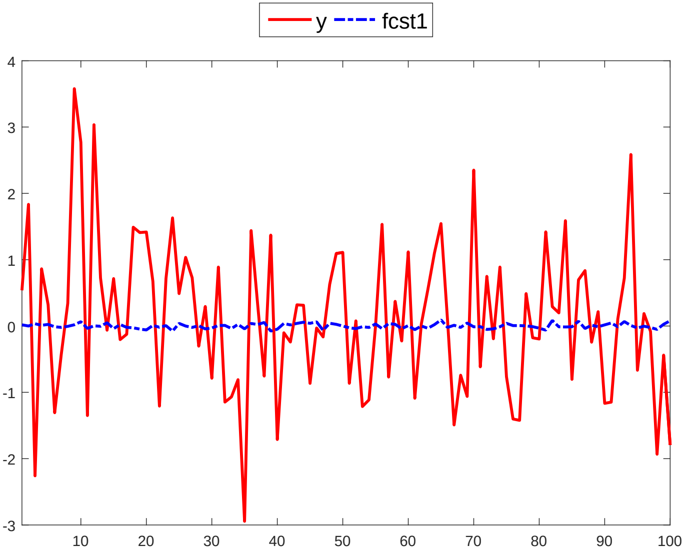
Simulation

1. The alternative model is the parametric model of Koop and Korobilis (2013).
    - Allow for time-varying coefficients and time-varying variance/covariance matrix.
    - Two further alternatives:
        - Time-varying coefficients but constant variance matrix (similar to the assumptions in the model presented in the paper).
        - Constant coefficients but time-varying volatility (Clark (2011), Clark and Ravazzolo (2015), Carriero, Clark and Marcellino (2016)).
2. Three DGPs:
    - Time-varying coefficients follow a random walk with bounds on the first autoregressive parameter.
    - Coefficients break only occasionally.
    - Coefficients evolve as a sine function.
    - All three cases assume stochastic volatility (and the nonparametric based model does not assume).
    - Consider a specification with constant parameters and time-varying volatility. Interesting to learn how the nonparametric estimator functions in a similar case of misspecification.

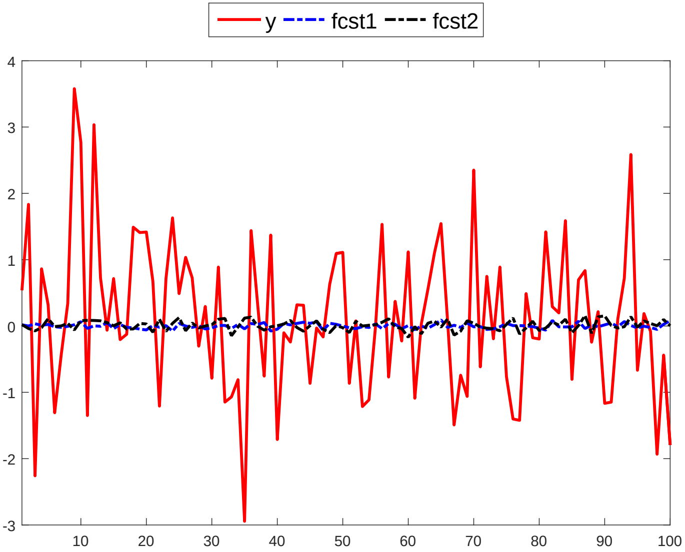
Empirical application

- The paper focuses on point forecasting (RSPE).
- These models can provide larger gains in density forecasting.

Point forecast



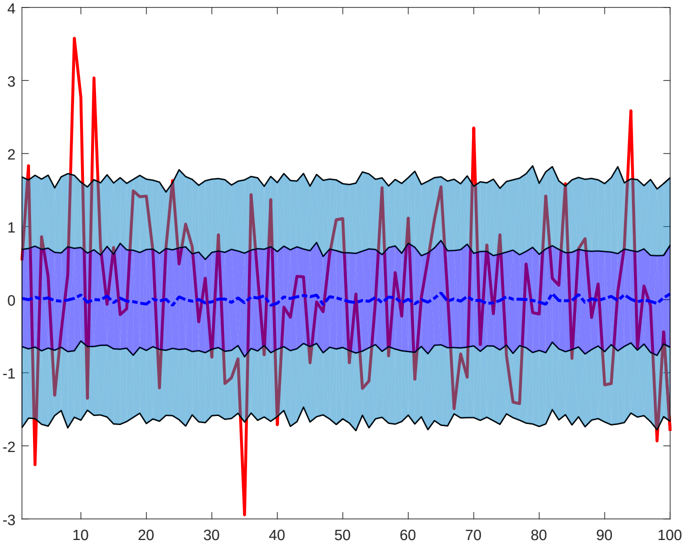
Point forecast



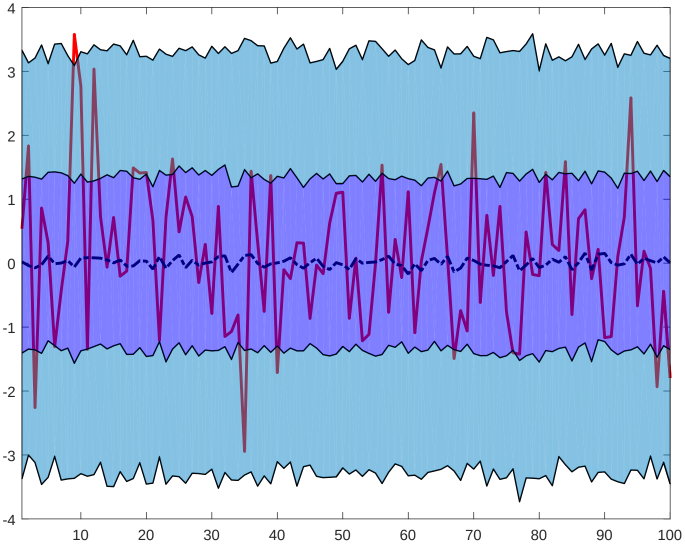
Mean square prediction analysis

	fcst1	fcst2
MSPE/Var(y)	1.000	1.013
VARIANCE	1.353	1.353
BIAS	0.001	0.003

Density forecast, model 1



Density forecast, model 2



Simulation example

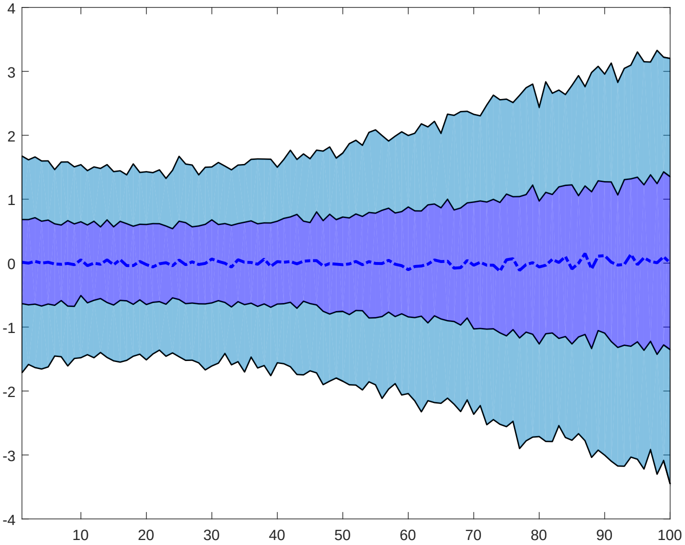
DGP:

$$y_t = N(\mu, \sigma),\ \mu = 0,\ \sigma = 1,\ t = 1, ..., T$$

Prediction models:

1. $\hat{y}_{t,1} = N(\mu_1, \sigma_1),\ \mu_1 = 0,\ \sigma_1 = 1$
2. $\hat{y}_{t,2} = N(\mu_2, \sigma_2),\ \mu_2 = 0,\ \sigma_2 = 2$

Density forecast, mixture



Structural analysis

- 28 variables VAR, 8 industrial production series.
- Response of the industrial production indices to an unexpected increase in the price of oil.
- Choleski decomposition (Edelstein and Kilian (2009)).
- No identification of oil supply and oil demand.
- Combination of identification strategies? Sign restriction for oil shocks only?

Minor comments

1. The L_{mse} criterion considers a short window and discard values before it.
   - Why not a discounting factor?
2. Figure 1 shows that the optimized λ hits the lower bound (1) in several occasions. Problems of convergence?