Discussion: Efficient estimation and forecasting in dynamic factor models with structural instability

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Overview of the paper

- Dynamic factor models where all model parameters are considered time-varying
- Mixture between observation driven and parameter driven approaches
- Variances are made TV using observation driven approach
- Loadings and VAR coefficients are made TV using parameter driven approach
- Two algorithms to approximate posterior mode: 1. filtering based, 2. simulation based
- Two applications: 1. macroeconomic forecasting, 2. yield-spread forecasting
- For the discussion I will focus on algorithm 1 and application 1

Equations

$$
\begin{aligned}
x_t &= \Lambda_t f_t + \epsilon_t & \epsilon_t &\sim N(0, V_t) \\
\lambda_t &= \lambda_{t-1} + \nu_t & \nu_t &\sim N(0, R_t) \\
f_t &= B_t f_{t-1} + \eta_t & \eta_t &\sim N(0, Q_t) \\
\beta_t &= \beta_{t-1} + \upsilon_t & \upsilon_t &\sim N(0, W_t)
\end{aligned}
$$

$$
\begin{aligned}
V_t &= \delta_1 V_{t-1} + (1 - \delta_1)\mathrm{diag}(\hat{\epsilon}_t \hat{\epsilon}_t') \\
R_t &= (\mu_1^{-1} - 1)\mathrm{Cov}(\lambda_{t-1} | x_1, \ldots, x_{t-1}) \\
Q_t &= \delta_2 Q_{t-1} + (1 - \delta_2)\hat{\eta}_t \hat{\eta}_t' \\
W_t &= (\mu_2^{-1} - 1)\mathrm{Cov}(\beta_{t-1} | x_1, \ldots, x_{t-1})
\end{aligned}
$$

Algorithm 1

1. Compute $\hat{f}^{\text{PCA}}$
2. Compute $\hat{\lambda}_t = \mathrm{E}(\lambda_t | X; \hat{f}^{\text{PCA}})$, for $t = 1, \ldots, T$
3. Compute $\hat{\beta}_t = \mathrm{E}(\beta_t | \hat{f}^{\text{PCA}})$, for $t = 1, \ldots, T$
4. Compute $\hat{f}_t = \mathrm{E}(f_t | X; \hat{\lambda}, \hat{\beta})$, for $t = 1, \ldots, T$

- Step (2); also gives V_t and R_t
- Step (3); also gives Q_t and W_t

General comments and questions

1. Ambitious paper!!!
2. Consistency of step (1) in algorithm 1? Bates, Plagborg-Moller, Stock & Watson (2013) give rates for $\lambda_{i,t}$? In addition B_t will also require some restrictions.
3. Imposing some structure on the loading matrix? Testing for parameter instability?
4. If forecasting and computational speed are the goals; why not entirely observation driven?
5. Reasoning the particular observation driven structure?

EWMA vs GAS update

- EWMA update per element

$$V_{i,t} = \delta_1 V_{i,t-1} + (1-\delta_1)\hat{\epsilon}_{i,t}^2$$

- GAS update per element

$$V_{i,t} = \delta_1 V_{i,t-1} + (1-\delta_1) S_t\left(-\frac{1}{2}F_{i,t}^{-1} + \frac{1}{2}\hat{\epsilon}_{i,t}^2 F_{i,t}^{-2}\right)$$

- where $\hat{\epsilon}_{i,t} = x_{i,t} - \hat{\lambda}_{t|t-1}\tilde{f}_t$ and $\tilde{f}_t$ is the current estimate for f_t
- and S_t is a scaling term, $F_{i,t} = \tilde{f}_t' \hat{P}_{i,t} \tilde{f}_t + V_{i,t-1}$
- Main difference is that GAS update also depends on predictive variance loadings
- Possible room for improvement see Blasques, Koopman & Lucas (2014)

Some further questions?

1. Are the variances in step (4) treated as known? if so why? Re-estimating V_t and Q_t is possible? When doing forecasting this will make a difference.
2. In general: how are the forecasts constructed?
3. Is it possible to estimate model parameters (μ's and δ's) in steps (ii) and (iii) using MLE? Similar as in Eickmeier, Lemke & Marcellino (2011). Not much work and saves grid-searches?
4. How do you initialize V_0 and Q_0 in general?

Table 2: Relative MSE for forecasting German GDP growth

Panel A: EWMA

		parameter specification					Relative MSE at horizon			
		r	δ_1	δ_2	μ_1	μ_2	1	2	3	4
1	TVP-DFM	2	0.83	0.83	1.00	1.00	0.77	0.95	0.98	1.08
2	TVP-DFM	3	0.83	0.83	1.00	1.00	0.77	0.95	0.98	1.09
3	TVP-DFM	2	0.87	0.83	1.00	1.00	0.77	0.95	0.98	1.08
4	TVP-DFM	3	0.87	0.83	1.00	1.00	0.77	0.95	0.98	1.09
5	TVP-DFM	2	0.99	0.83	1.00	1.00	0.76	0.96	1.00	1.10
6	TVP-DFM	3	0.99	0.83	1.00	1.00	0.77	0.96	1.00	1.12
7	TVP-DFM	2	0.83	0.99	1.00	1.00	0.82	1.04	1.09	1.10
8	TVP-DFM	3	0.83	0.99	1.00	1.00	0.83	1.06	1.10	1.20
9	TVP-DFM	2	0.99	0.99	1.00	1.00	0.82	1.07	1.12	1.24
10	TVP-DFM	3	0.99	0.99	1.00	1.00	0.83	1.08	1.13	1.24
11	TVP-DFM	2	0.99	0.99	0.98	0.98	0.82	1.07	1.12	1.24
12	TVP-DFM	3	0.99	0.99	0.98	0.98	0.83	1.08	1.13	1.24
13	PC	1	-	-	-	-	0.86	1.02	1.02	1.08
14	PC	2	-	-	-	-	0.87	1.01	1.01	1.09
15	PC	3	-	-	-	-	0.91	1.02	1.01	1.09
16	PC	4	-	-	-	-	0.94	1.06	1.08	1.15
17	AR	-	-	-	-	-	1.00	1.00	1.00	1.00

Comments

1. The PCA estimator is based on homoscedastic error-variances $V_t = I_n\sigma$. In the macro illustration V_t is initialized with $V_0 = I_N$. When $\delta_1 < 1$ *two* things change: (1) the variances become heteroskedastic and (2) the variances become time-varying. The improvement in forecasting is entirely attributed to the time-variation in the paper. A comparison with standard MLE would give more insight into the role for heterogeneous variances; see also Bai & Li (2012).
2. In the simulation study there is also a comparison w.r.t. two-step estimator of Doz, Giannone & Reichlin (2011), which shows that 4-steps improves two-step when time-variation in the loadings is large. Given that the loadings and factor coefficients are not time-varying in this application a comparison with two-step would be insightful.

Final remarks

- I enjoyed reading the paper.
- Thank you!