



Using Subspace Algorithms for the Estimation of Linear State Space Models in the Context of Approximate Dynamic Factor Models

Dietmar Bauer





1. Motivation



- Approximate dynamic factor models (aDFMs) are used for joint modelling of many time series, wherein the cross sectional dimension N is of the same size as the time series length T.
- In typical applications both range in the low hundreds.
- Classical joint models (like VAR) for such number of series necessarily contain many parameters.
- Factor models reduce the dimensionality:

$$y_{it} = \chi_{it} + \xi_{it} = \underbrace{\chi_i' F_t}_{ ext{factor component}} + \underbrace{\xi_{it}}_{ ext{diosyncratic component}}$$

for i = 1, ..., N, t = 1, ..., T...

- Factors and idiosyncratic component are assumed uncorrelated.
- In matrix notation: $Y_t^N = \Lambda_N F_t + \Xi_t^N \in \mathbb{R}^N$.
- I use asymptotic identification of factors and idiosyncratics as in Chamerblain and Rothschild (1983): $\lambda_{max}(\mathbb{E} \Xi_t^N(\Xi_t^N)') \leq M_{\Xi}$ and $\Lambda'_N \Lambda_N / N \stackrel{N \to \infty}{\longrightarrow} M_{\Omega}$, $\mathbb{E} F_t F_t' > 0$.





Assumption

- The processes $\Delta(F_t)_{t \in \mathbb{Z}}$, $(\Xi_t^N)_{t \in \mathbb{Z}}$ are wide sense stationary with mean zero for all N and possess spectral densities.
- For ΔF_t , Ξ_t^N , y_t^N we have uniform (in lag and in N) LIL rates $Q_T := \sqrt{\frac{(\log \log T)}{T}}$ for the estimation of covariances up to lag $H_T = O((\log T)^a)$ for some a > 1.
- Factor loadings λ_i are deterministic, $\frac{1}{N}\Lambda'_N\Lambda_N \to M_0 > 0$, $\sup_N \max_i \|\lambda_i\| \le M_\lambda$.
- $I_r' \Lambda_N = I_r$ for a selector matrix (other normalisations are possible.).
- $(F_t)_{t \in \mathbb{Z}}, F_t \in \mathbb{R}^r$, is a rational I(0) or I(1) process, i.e. it has a minimal state space representation as $(q \le r)$

$$F_t = \underbrace{\begin{pmatrix} C_1 & C_{\bullet} \end{pmatrix}}_{C} x_t + Du_t, x_{t+1} = \underbrace{\begin{pmatrix} I_c & 0 \\ 0 & A_{\bullet} \end{pmatrix}}_{A} x_t + \underbrace{\begin{pmatrix} B_1 \\ B_{\bullet} \end{pmatrix}}_{B} u_t, \quad \begin{matrix} u_t \in \mathbb{R}^q, \\ x_t \in \mathbb{R}^n. \end{matrix}$$

- $\lambda_{|max|}(A_{\bullet}) < 1$. $[I_q, 0]D$ is positive lower triangular; $\exists D^{\dagger} : D^{\dagger}D = I_q$ such that $A BD^{\dagger}C$ is stable with $\lambda_{|max|}(A BD^{\dagger}C) < \rho_{\circ} < 1$.
- $(u_t)_{t\in\mathbb{Z}}$ is a stationary, ergodic martingale difference sequence and has expectation zero, variance matrix $\Omega=I_q$ and finite fourth moments.



3. Estimation



Canonical Variate Analysis (CVA)

$$F_t = Cx_t + Du_t, \qquad x_{t+1} = Ax_t + Bu_t.$$

- \Rightarrow estimation could be done using OLS, if the state x_t and u_t were known!
 - 1. The state x_t can be approximated by past observations:

$$x_t(p) = \sum_{j=1}^p \mathcal{K}_j(p) F_{t-j} = \mathcal{K}_p F_t^{-p \to \infty} x_t$$

2. Predictions of F_{t+h} , $h \ge 0$, based on F_{t-1} , F_{t-2} ...:

$$F_t^+ = \mathcal{O}x_t + \mathcal{U}U_t^+ = \boxed{\mathcal{O}_f \mathcal{K}_p} F_t^- + \tilde{U}_t.$$
 (*)

Main idea:

- Apply CVA with PCA estimated common factors \hat{F}_t .
- lacksquare Estimate the state as $\hat{x}_t = \widehat{\mathcal{K}}_p \hat{\mathcal{F}}_t^-$ where $\widehat{\mathcal{K}}$ is obtained from RRR in (*).
- Different weights W_f^+ in the RRR step should be used (see paper)!



Theorem (Consistency)

- Let the data be generated according to the before mentioned Assumptions.
- Assume that $T/N^2 \to 0$, $T \to \infty$, such that $O(Q_T + 1/N) = O(Q_T)$.
- Let $p(T) \le H_T$, $f \ge n$, $p = p(T) \ge -\frac{e \log T}{\log n}$, e > 1, for $\rho_0 > 0$ and $p \ge p_0$ for $\rho_{\circ} = 0$.
- Further let $(\hat{A}, \hat{B}, \hat{C}, \hat{D})$ denote the CVA estimators with appropriate (see paper) weighting matrix W_f^+ in the RRR step based on the PCA estimates \hat{F}_t for given order n converted to an overlapping form.

Then

$$\max\{\|\hat{A} - A\|, \|\hat{B} - B\|, \|\hat{C} - C\|, \|\hat{D} - D\|\} = O(Q_T).$$

References:

- Bauer, D. (2025): Using Subspace Algorithms for the Estimation of Linear State Space Models in the Context of Approximate Dynamic Factor Models, working paper see: version on Github
- Chamberlain, G., Rothschild, M. (1983). Arbitrage, factor structure, and mean-variance analysis on large asset markets. Econometrica 51 (5), 1281-1304.

