Week 8 — Dynamic Factor Models

Dimension Reduction for Large Time-Series Panels

Dr Juan Zurita

Economic & Business Forecasting
The University of Edinburgh · School of Economics

Motivation

The Curse of Dimensionality

Central banks track hundreds of economic indicators.
How to use all this information for forecasting?

Solution: a small number of latent factors drive the co-movement.

$$y_{it} = \lambda_i' \mathbf{f}_t + e_{it}, \quad i = 1, \ldots, N$$

- $\mathbf{f}_t$: k-dimensional factor vector ($k \ll N$)
- λ_i: factor loadings for series i
- e_{it}: idiosyncratic component

Estimation

Principal Components

Static approach: extract factors via PCA on the $T \times N$ data matrix.

- Fast: eigenvalue decomposition
- Consistent as $N, T \to \infty$ (Stock & Watson, 2002)
- Scree plot determines k

Dynamic approach: specify factor dynamics

$$\mathbf{f}_t = \Phi_1 \mathbf{f}_{t-1} + \cdots + \Phi_s \mathbf{f}_{t-s} + \boldsymbol{\eta}_t$$

and estimate via Kalman filter (state space form).

How Many Factors?

- **Scree plot**: eigenvalues vs component number — look for the "elbow"
- **Bai-Ng criteria**: information criteria adapted for factor models
- **Proportion of variance**: retain components explaining $>$85–90%

Applications

Factor-Augmented Forecasting

Use extracted factors as additional predictors:

$$y_{t+h} = \alpha + \beta_1 y_t + \gamma' \hat{\mathbf{f}}_t + \varepsilon_{t+h}$$

Applications:

- **Nowcasting**: real-time GDP estimation (mixed frequencies)
- **Monetary policy**: summarising financial conditions
- **FAVAR**: factor-augmented VAR for structural analysis

Next week: machine learning methods.