

# Dynamic Factor Models

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# Survey Articles on Dynamic Factor Models

## Stock & Watson (2010)

Best general overview of dynamic factor models and applications.

## Bai & Ng (2008)

Comprehensive review of large-sample results for high-dimensional factor models estimated via PCA.

## Stock & Watson (2006)

Handbook chapter on forecasting with many predictors. One section is devoted to dynamic factor models.

## Breitung & Eickmeyer (2006)

Brief overview with an application to Euro-area business cycles.

# Why Factor Models?

1. Factors could be intrinsically interesting if they arise from a theoretical model (e.g. Financial Economics)
2. Many variables without running out of degrees of freedom
  - ▶ More information could improve forecasts/macro analysis
  - ▶ Mimic central banks “looking at everything”
3. Eliminate measurement error and idiosyncratic shocks to provide more reliable information for policy
4. “Remain Agnostic about the Structure of the Economy”
  - ▶ Advantages over SVARs: don't have to choose variables to control degrees of freedom, and can allow fewer underlying shocks than variables.

## Last Time: Classical Factor Analysis Model

$$\underset{(N \times 1)}{X_t} = \mu + \underset{(k \times 1)}{\Lambda} Z_t + \epsilon_t$$

$$\begin{bmatrix} Z_t \\ \epsilon_t \end{bmatrix} \stackrel{iid}{\sim} \mathcal{N} \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} I_k & 0 \\ 0 & \Psi \end{bmatrix} \right)$$

$\Lambda$  = matrix of factor loadings

$\Psi$  = diagonal matrix of idiosyncratic variances.

## Adding Some Dynamics

# Some (Confusing) Terminology

Static vs Dynamic, Exact vs Approximate

PCA stuff, when and why it works, what the basic conditions are, and when it fails.

Alternative ways of estimating: two-step, EM algorithm, Bayesian.



## Choosing the Number of Factors

Onatski paper: no one in the class listed it as a preference! Bai & Ng (2002).

# What Can We Do with Factors?

Among other possibilities:

1. Use them as Instrumental Variables
2. Use them to construct Forecasts
3. Use them to “Augment” a VAR

# Factors as Instruments – Bai & Ng (2010)

Endogenous Regressors  $x_t$

$$y_t = x_t' \beta + \epsilon_t \quad E[x_t \epsilon_t] \neq 0$$

Unobserved Variables  $F_t$  are Strong IVs

$$\underset{(k \times 1)}{x_t} = \underset{(r \times 1)}{\Psi' F_t} + u_t \quad E[F_t \epsilon_t] = 0$$

Observe Large Panel  $(z_{1t}, \dots, z_{Nt})$

$$z_{it} = \lambda_i' F_t + e_{it}$$

# Factors as Instruments – Bai & Ng (2010)

$$y_t = x_t' \beta + \epsilon_t, \quad x_t = \Psi' F_t + u_t, \quad z_{it} = \lambda_i' F_t + e_{it}$$

## Procedure

1. Calculate the PCs of  $Z$
2. Calculate  $\tilde{F}_t$  using the first  $r$  PCs of  $Z$
3. Use  $\tilde{F}_t$  in place of  $F_t$  for IV estimation

## Main Result

Under certain assumptions, as  $(N, T) \rightarrow \infty$  “estimation and inference can proceed as though  $F_t$  were known.” The resulting estimator is consistent and asymptotically normal.

# Forecasting with Dynamic Factors

Big literature on this and we'll talk more about it next time, but give an overview here.

# Factors as Instruments – Bai & Ng (2010)

## Why Might This be Helpful?

1. Avoid many instruments bias
2. Avoid bias from irrelevant instruments
3. Allow more observed instruments  $z_{it}$  than sample size  $T$
4. Provided that  $\sqrt{T}/N \rightarrow 0$ , all of the observed instruments  $z_{it}$  can be *endogenous* as long as  $F_t$  is exogenous

# FAVARs – Bernanke, Boivin & Elias (2005)

## Two Problems with Structural VARs

1. Number of parameters is *quadratic* in the number of variables. Unrestricted VAR infeasible unless  $T$  is large relative to  $N$ .
  - ▶ You've studied one solution to this problem already this semester: Bayesian Estimation with informative priors
2. To keep estimation tractable we typically use a small number of variables, but then the VAR innovations “might not span the space of structural shocks.”

# FAVARs – Bernanke, Boivin & Elias (2005)

## Factor-Augmented VAR Model

$$\begin{bmatrix} Y_t \\ F_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t$$

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t$$

$\begin{matrix} Y_t \\ (M \times 1) \end{matrix}$  = observable variables that “drive dynamics of the economy”

$\begin{matrix} F_t \\ (K \times 1) \end{matrix}$  = Small # of unobserved factors: “additional information”

$\begin{matrix} F_t \\ (N \times 1) \end{matrix}$  = Large # of observed “informational time series”



## FAVARs – Bernanke, Boivin & Elias (2005)

$$\begin{bmatrix} Y_t \\ F_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \quad X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t$$

### Consider Two Estimation Procedures

1. Two-step Procedure:
  - ▶ Estimate space spanned by factors using first  $K + M$  PCs of  $X$
  - ▶ Estimate VAR with  $\hat{F}_t$  in place of  $F_t$
2. Full Bayes (Gibbs Sampler)

### Empirical Application

Additional information contained in FVAR is “important to properly identify the monetary transmission mechanism.”