ALMA MATER STUDIORUM
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DEPARTMENT OF ECONOMICS

SECOND CYCLE DEGREE
IN
ECONOMICS AND ECONOMETRICS

Dynamic Matrix Factor Models and the EM Algorithm: A Nowcasting Framework for Mixed-Frequency Data in the Euro Area

Dissertation in Macroeconometrics

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Contents

General Overview

Research Focus:
Identify the causal effects of labor supply response to severe health shocks in the short and medium run

Fatal Health Shocks

- Significant increase in spousal labor supply.
- Result driven by significant income losses.

Nonfatal Health Shocks

- No significant effect on spousal labor supply.
- Result driven bu adequate social insurance coverage.

Key Implication:
Labor supply serves as a **self-insurance mechanism** for families.

Literature Review (I)
Models and Estimation Strategies

From DFM to DMFM

- Traditional DFMs extended to matrix-valued time series $\rightarrow$ Dynamic Matrix Factor Models (DMFM)
- DMFM captures both **cross-sectional** and **temporal** dependencies via matrix-valued latent factors

Estimation via EM Algorithm

- Quasi-Maximum Likelihood Estimation (QMLE) through the **EM algorithm**
- EM integrates **Kalman filtering** to handle missing data and mixed-frequency settings
- Initialization based on **Projected Estimators** (Yu et al. 2022)

Recent Advances in Factor Models

- Wang et al. (2019): Matrix Factor Models via long-run covariance
- Chen and Fan (2023): Projected estimators with autocorrelated errors
- Xu et al. (2025): QMLE with heteroskedastic idiosyncratic terms

Literature Review (II)

Dynamics and Forecasting Applications

Temporal Dynamics in DMFM

- MAR models (Chen et al. 2021): generalize VAR to matrix time series
- MMA models (Tsay 2024): better for seasonal structures
- State-space representation allows for dynamic modeling of latent matrix factors

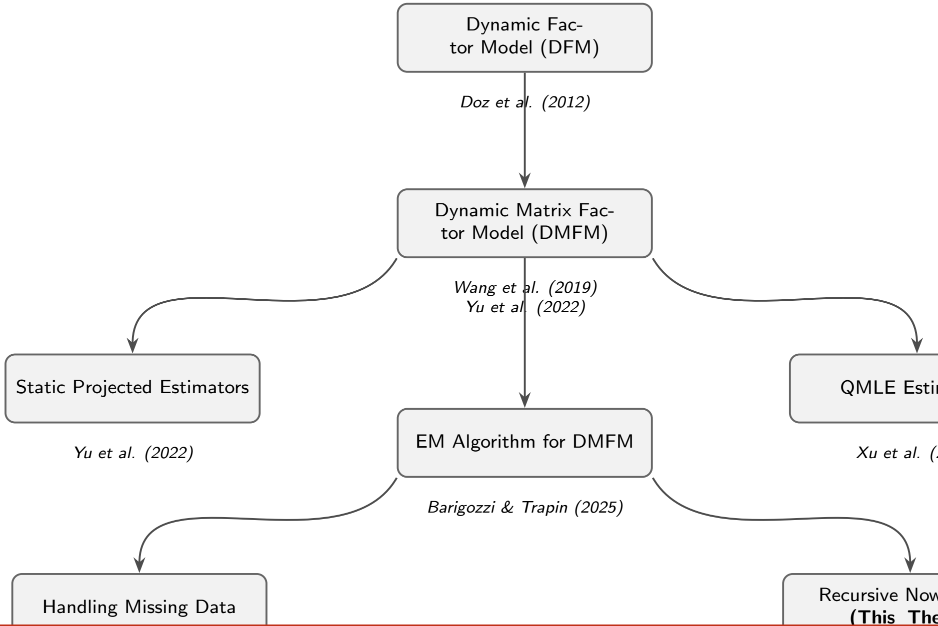
Nowcasting Framework

- EM-Kalman filtering approach for recursive nowcasting (Banbura and Modugno 2014)
- Flexible treatment of **missing data**, **publication delays**, and **mixed frequencies**
- Matrix formulation enables decomposition of revisions by **variable** and by **country**

Key Reference: Barigozzi and Trapin (2025)

- Full estimation of DMFM via adapted EM algorithm
- Initialization via Projected Estimators + imputation (Cen and Lam 2025)
- Quasi-likelihood inspired by Tipping and Bishop (1999)

Literature Review Diagram



The Model: State-Space Representations

Dynamic Matrix Factor Model (DMFM)

$$Y_t = RF_tC^\top + E_t \quad \text{(measurement equation)}$$
$$F_t = AF_{t-1}B^\top + U_t \quad \text{(transition equation)}$$

Dynamic Factor Model (DFM)

$$y_t = \Lambda F_t + \xi_t \quad \text{(measurement equation)}$$
$$F_t = AF_{t-1} + v_t \quad \text{(transition equation)}$$

Interpretation:
DMFM generalizes DFM by preserving the matrix structure of the data and latent factors, offering greater flexibility in modeling both cross-sectional and temporal dependencies.