

# CREST - GENES

## Cours doctoraux 2023 – 2024

### DYNAMIC FACTOR MODELS

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<b>SCHEDULE</b>	Monday	4th March 2024 11th March 2024	From 13:00 to 16:45	Room 2033
	Thursday	7th March 2024	From 13:00 to 16:15	Room 2033

#### Aims and objectives

The aim of this course is to provide an introduction to factor models in time series analysis by teaching students the basic theoretical foundations and by illustrating them some applications to macroeconomics and finance.

In the last years large datasets have become increasingly available to researchers and practitioners in many disciplines. In particular, during this *big data* revolution the analysis of high-dimensional time series has become one of the most active subjects of modern statistical methodology with applications in the most different areas of science including finance, econometrics, meteorology, genomics, chemometrics, complex physics simulations, biological and environmental research. Although the value of information is unquestionable, the possibility of extracting meaningful and useful information out of this large amount of data is also of great importance. To achieve such dimension reduction, several new analytical and computational techniques have been developed under the name of *machine learning* methods. Among these factor models not only are one of the pioneering methods in the field of unsupervised learning (dating back to Spearman, 1904), but up to these days have also been one of the most popular and most employed ones.

We start by discussing principal component analysis as a useful dimension reduction technique for large panels of time series. This is the most simple example of factor model (the static model) which we then generalize to include all temporal relations among the considered variables (the dynamic model). We then focus on the case in which the dynamic model can be re-written as a state space model and we present its estimation via Kalman filter and the Expectation Maximization algorithm. We then consider application of these models in two fields. First, in macroeconometrics for building indicators of the business cycle, for nowcasting, and for policy analysis problems. Related to these we briefly discuss how to deal with the issues of non-fundamentalness and cointegration. Second, in financial econometrics for volatility modelling and forecasting. Related to these we briefly discuss the complementarity of factor and network models and the issue of conditional heteroskedasticity. Real-data applications taken from existing papers are discussed during the lectures. Matlab or R code will be provided.

#### Outline

1. Introduction (2hrs).
  - o History.
  - o Taxonomy: static vs dynamic, exact vs approximate.
  - o Representation.
  - o Identification.
  - o Curse vs blessing of dimensionality.
2. Estimation (3hrs).
  - o Principal component analysis.

- Quasi maximum likelihood.
  - Expectation Maximization and Kalman smoother.
  - Dynamic principal component analysis.
  - Determining the number of factors.
3. Macroeconomic applications (2hrs).
    - Impulse response analysis.
    - Coincident indicators.
    - Nowcasting and forecasting.
    - The case of cointegrated factors.
  4. Financial applications (2hrs).
    - Networks.
    - Volatility measurement and forecasting.
    - The case of conditionally heteroskedastic factors.
  5. Extensions (1hr).
    - Non-stationary factor models.
    - Non-linear factor models.
    - Factor models for tensor data.

## Pre-requisites

Knowledge of stochastic processes and basics concepts of linear algebra are assumed, as in, e.g., Hamilton, J. D. (1994) Time Series Analysis.

## Some related literature (\*suggested before the course)

### Survey

\* Stock, J.H. and Watson, M.W., 2016. Dynamic factor models. In Oxford Handbook of Economic Forecasting, Clements, M. P. and Hendry, D. F. (eds), Oxford University Press.

Available at [http://www.princeton.edu/~mwatson/papers/dfm\\_oup\\_4.pdf](http://www.princeton.edu/~mwatson/papers/dfm_oup_4.pdf)

\* Stock, J.H. and Watson, M.W., 2016. Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. In Handbook of Macroeconomics (Vol. 2). Elsevier.

Available at [http://www.princeton.edu/~mwatson/papers/Stock\\_Watson\\_HOM\\_Vol2](http://www.princeton.edu/~mwatson/papers/Stock_Watson_HOM_Vol2)

\* Barigozzi, M., 2023. Quasi maximum likelihood estimation of high-dimensional factor models: A critical review.

Available at <https://doi.org/10.48550/arXiv.2303.11777>

### Applied papers

De Mol, C., Giannone, D. and Reichlin, L., 2008. Forecasting using a large number of predictors: Is Bayesian shrinkage a valid alternative to principal components?. *Journal of Econometrics*, 146, 318-328.

Giannone, D., Reichlin, L. and Small, D., 2008. Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, 55, 665-676.

Forni, M. and Gambetti, L., 2010. The dynamic effects of monetary policy: A structural factor model approach. *Journal of Monetary Economics*, 57, 203-216.

D'Agostino, A. and Giannone, D., 2012. Comparing alternative predictors based on large-panel factor models. *Oxford Bulletin of Economics and Statistics*, 74, 306-326.

Barigozzi, M., Conti, A.M. and Luciani, M., 2014. Do euro area countries respond asymmetrically to the common monetary policy?. *Oxford bulletin of economics and statistics*, 76(5), pp.693-714.

Barigozzi, M. and Hallin, M., 2017. A network analysis of the volatility of high dimensional financial series. *Journal of the Royal Statistical Society. Series C, Applied statistics*, 66, 581-605.

Forni, M., Gambetti, L., Marco, M. and Sala, L., 2020. Common component structural VARs.

Available at <http://pareto.uab.es/lgambetti/ceprdp.pdf>

Barigozzi, M. and Luciani, M., 2021. Measuring the output gap using large datasets. *The Review of Economics and Statistics*, pp.1-45.

Giovannelli, A., Lippi, M. and Proietti, T., 2023. Band-pass filtering with high-dimensional time series. Available at <https://doi.org/10.48550/arXiv.2305.06618>

#### Theory papers

Stock, J.H. and Watson, M.W., 2002. Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association*, 97, 1167-1179.

Bai, J., 2003. Inferential theory for factor models of large dimensions. *Econometrica* 71, 135– 171.

Bai, J. and Ng, S., 2006. Confidence intervals for diffusion index forecasts and inference for factor-augmented regressions. *Econometrica*, 74, 1133-1150.

Forni, M., Giannone, D., Lippi, M. and Reichlin, L., 2009. Opening the black box: Structural factor models with large cross sections. *Econometric Theory*, 25, 1319-1347.

Doz, C., Giannone, D. and Reichlin, L., 2011. A two-step estimator for large approximate dynamic factor models based on Kalman filtering. *Journal of Econometrics*, 164, 188-205.

Doz, C., Giannone, D. and Reichlin, L., 2012. A quasi maximum likelihood approach for large, approximate dynamic factor models. *Review of Economics and Statistics*, 94, 1014-1024.

Fan, J., Liao, Y. and Mincheva, M., 2013. Large covariance estimation by thresholding principal orthogonal complements. *Journal of the Royal Statistical Society. Series B, Statistical methodology*, 75, 603-680.

Hallin, M. and Lippi, M., 2013. Factor models in high-dimensional time series. A time domain approach. *Stochastic Processes and their Applications* 123, 2678–2695.

Forni, M., Hallin, M., Lippi, M. and Zaffaroni, P., 2017. Dynamic factor models with infinite-dimensional factor space: Asymptotic analysis. *Journal of Econometrics*, 199, 74-92.

Barigozzi, M. and Luciani, M., 2019. Quasi maximum likelihood estimation and inference of large approximate dynamic factor models via the EM algorithm.

Available at <https://doi.org/10.48550/arXiv.1910.03821>

Barigozzi, M., Lippi, M. and Luciani, M., 2021. Large-dimensional dynamic factor models: Estimation of impulse–response functions with I (1) cointegrated factors. *Journal of Econometrics*, 221, 455-482.

Barigozzi, M., 2022. On estimation and inference of large approximate dynamic factor models via the Principal component analysis and its equivalence with quasi maximum likelihood estimation.

Available at <https://doi.org/10.48550/arXiv.2211.01921>

Barigozzi, M., Cho, H. and Owens, D., 2022. FNETS: Factor-adjusted network estimation and forecasting for high-dimensional time series.

Available at <https://doi.org/10.48550/arXiv.2201.06110>