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Contents

Factor Extraction in Dynamic Factor Models: Kalman Filter Versus Principal Components

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ABSTRACT

This survey looks at the literature on factor extraction in the context of Dynamic Factor Models (DFMs) fitted to multivariate systems of economic and financial variables. Many of the most popular factor extraction procedures often used in empirical applications are based on either Principal Components (PC) or Kalman filter and smoothing (KFS) techniques. First, we show that the KFS factors are a weighted average of the contemporaneous information (PC factors) and the past information and that the weights of the latter are negligible unless the factors are close to the non-stationarity boundary and/or their loadings are pretty small when compared with the variance-covariance matrix of the idiosyncratic components. Note that the weight of the past can be large either because the cross-sectional dimension is small or because the magnitude of the factor loadings is small. Consequently, we are able to explain why, in practice, there is a general consensus about PC and KFS factors being rather similar when extracted from stationary

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systems of large dimensions. Second, we survey how PC and KFS deal with several issues often faced in the context of extracting factors from real data systems. In particular, we describe PC and KFS procedures to deal with mixed frequencies and missing observations, structural breaks, non-stationarity, Markov-switching parameters or multi-level factor structures. In general, we see that KFS is very flexible to deal with these issues.

Keywords: Markov-switching; missing observations; mixed-frequency; multi-level; non-stationarity; time-varying parameters; unobserved components.

1

Introduction

When dealing with large systems of economic time series, Dynamic Factor Models (DFMs), popularized by Geweke (1977) and Sargent and Sims (1977), assume the existence of a relatively small number of unobserved latent factors that capture the comovements in the variables. Note that DFMs were also the basis of the arbitrage pricing theory of Ross (1976). DFMs have been the main "big data" tool used in empirical macroeconomics and finance during the last 30 years; see Breitung and Eickmeier (2006), Bai and Ng (2008), Stock and Watson (2011), Barhoumi *et al.* (2013), Breitung and Choi (2013), Bai and Wang (2016), Doz and Fuleky (2020), Peña and Tsay (2021), Poncela *et al.* (2021) and Lippi *et al.* (in press) for some selected surveys carried out during the last two decades covering particular aspects of these models. In a very recent study, Goulet Coulombe *et al.* (2021) compare several Machine Learning procedures in terms of macroeconomic forecasting and conclude that "while Machine Learning methods can handle the high-dimensional X (both computationally and statistically), extracting common factors remains straightforward feature engineering that pays off".

Many of the most popular procedures often implemented in empirical applications to extract the underlying factors are based on either Principal Components (PC) or Kalman filter and smoothing (KFS), with prominent implementations of both techniques by leading central banks and public institutions.[1] PC-based procedures are non-parametric and, therefore, robust against misspecification of the dynamic evolution of the underlying factors and/or the idiosyncratic components. Furthermore, their computational simplicity allows them to extract factors in systems with rather large cross-sectional dimensions.[2] The alternative KFS-based procedures are parametric and require the estimation of a large number of parameters when dealing with large systems; see, for example, the very recent survey by Poncela *et al.* (2021) on KFS factor extraction. One of the advantages of KFS factor extraction is that it allows for Maximum Likelihood (ML) estimation of the DFM parameters with the corresponding extracted factors being efficient if their assumed specification is correct. However, when the cross-sectional dimension is large, the optimization of the log-likelihood may be problematic due to the large number of parameters that need to be estimated. Fortunately, Doz *et al.* (2012) soften the way to implement KFS in large systems with weakly correlated idiosyncratic noises by showing that, when both the cross-sectional and temporal dimensions diverge to infinity, the factors extracted assuming that the idiosyncratic noises are temporal and cross-sectionally uncorrelated (and, consequently, largely reducing the number of parameters to be estimated) are consistent, even if they are truly correlated in any of both directions. However, the KFS may not be efficient as, in this context, both the filters are run and the parameters are estimated in a misspecified model; see the asymptotic results by Barigozzi and Luciani (2020), who show that this lack of efficiency may be negligible in large samples.

[1] Although the focus in this survey is on economic and financial applications, there is an important literature using DFMs in many other areas as, for example, Psychology (Molenaar and Ram, 2009), Demography (French and O'Hare, 2013; Ortega-Osona and Poncela, 2005, and Shang *et al.*, 2011), environmetrics (Zuur *et al.*, 2003) or climate change (Diebold *et al.*, 2021).

[2] Fan *et al.* (2021a) also survey estimation based on low-rank regularization, which is an alternative to PC based on soft-thresholding instead of hard-thresholding.

In this survey, we look at the literature on PC and KFS factor extraction with a focus on how they compare and how they deal with several relevant issues often encountered when dealing with real systems of macroeconomic and financial time series. In particular, large systems of real macroeconomic and financial variables of interest are often characterized by missing observations, variables observed with mixed frequencies, structural changes, time-varying parameters, switching regimes and/or non-stationarity. Also, the structure of the factors could be multi-level as, for example, when there are global factors and factors affecting only subsets of the variables in the system, or the DFM could be defined for observations that are matrices instead of vectors. In empirical applications, there is a large number of authors who prefer the computational simplicity of PC-based methods while many others prefer the flexibility of KFS to deal with serially dependent unobserved factors. Both PC and KFS have been adapted to deal with the empirical characteristics mentioned above. However, their complexity and empirical performance could be different and, consequently, we also provide a comprehensive updated summary of the literature on the extensions of PC and KFS procedures proposed to extract the underlying factors in the context of the empirical characteristics often encountered in empirical applications.

A word of warning is due before the reader starts going through this survey. Due to the extremely large literature on DFMs and factor extraction, we have restricted ourselves to survey mostly published works, leaving out many interesting contributions that, we are sure, will be published in the near future. We have only cited working papers when they are crucial for our arguments. In any case, we want to apologize to the authors of many interesting works who have not been cited. It was an impossible mission trying to cover all contributions. In spite of this limitation, we still hope that this survey provides a broad vision of factor extraction and the advantages and limitations of the main two tools available for it.

The rest of this survey is organized as follows. Section 2 describes PC and KFS factor extraction and shows how they are related in the context of stationary static DFMs. Section 3 extends the description to non-stationary DFMs. Section 4 describes factor extraction in DFMs with time-varying parameters, structural breaks and Markov-switching parameters. Section 5 is a bird's eye view on how factors are extracted from multi-level DFMs while Section 6 deals with matrix-valued DFMs. Dealing with missing and mixed-frequency observations is considered in Section 7. Finally, Section 8 concludes.

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