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Forecasting macroeconomic variables using collapsed dynamic factor analysis

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ABSTRACT

We explore a new approach to the forecasting of macroeconomic variables based on a dynamic factor state space analysis. Key economic variables are modeled jointly with principal components from a large time series panel of macroeconomic indicators using a multivariate unobserved components time series model. When the key economic variables are observed at a low frequency and the panel of macroeconomic variables is at a high frequency, we can use our approach for both nowcasting and forecasting purposes. Given a dynamic factor model as the data generation process, we provide Monte Carlo evidence of the finite-sample justification of our parsimonious and feasible approach. We also provide empirical evidence for a US macroeconomic dataset. The unbalanced panel contains quarterly and monthly variables. The forecasting accuracy is measured against a set of benchmark models. We conclude that our dynamic factor state space analysis can lead to higher levels of forecasting precision when the panel size and time series dimensions are moderate.

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1. Introduction

The forecasting of economic growth is a challenging task, and requires a good understanding of both economic theory and dynamic econometric modeling of macroeconomic and financial time series. The methodological development of economic forecasting is therefore still in progress. In addition, the different crises since the collapse of Lehman Brothers in 2008 have provided policy makers with some incentive to review their methodology for forecasting macroeconomic time series. This paper aims to contribute to this debate by considering new methods for forecasting economic time series and presenting empirical evidence for the US economy.

We propose a collapsed dynamic factor analysis for the forecasting of a target variable vector using the information from many predictor variables. The dynamic factor model is collapsed by applying a dimension reduction to the high dimensional vector of predictors which we do not aim to forecast. A typical dimension reduction method, and the one which we use in this context, is the principal components technique. We then analyse the target variable jointly with the collapsed vector of predictors by means of the multivariate unobserved components time series model, which is framed as a linear Gaussian state space model. The required set of unobserved components is present in the observation equation for the target variable vector. A subset of these components is linked to the collapsed vector of predictors, which are typically the principal components. Hence, the model accounts for the information from the cross-section and time dimensions simultaneously. Due to the application of the dimension reduction technique, the collapsed model is far more parsimonious than the dynamic factor model specification for all series in the macroeconomic panel. Furthermore, it also allows for a flexible parametrization of the covariance structure in the idiosyncratic part of the target variable vector.

The unknown parameters can be estimated using the method of maximum likelihood, for which the loglikelihood function is evaluated by the Kalman filter. The proposed method can be implemented as a two-step

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procedure, where principal component analysis produces first-step factor estimates which are then modeled jointly with the target variable in the second step. It therefore combines principal component analysis and maximum likelihood estimation. The state space framework also allows for an unified and easy-to-implement treatment of time series analysis. Issues of practical relevance, such as forecasting with mixed data frequencies, nowcasting quarterly GDP from monthly macro panels, factor smoothing, and the treatment of so-called jagged edges, can then be dealt with in a straightforward manner.

Our modeling approach is related to several recent developments in dynamic factor analysis and in forecasting based on large panels of macroeconomic variables. The early contributions in the development of dynamic factor analysis have been reviewed recently by Bai and Ng (2008), Breitung and Eickmeier (2006) and Stock and Watson (2006a). Our approach is motivated by the diffusion indices of Stock and Watson (2002a,b). We adopt their use of principal components in the modeling of a vector of target variables. However, in our new modeling approach we analyse the target and the principal component variables simultaneously in a multivariate unobserved component time series model. A similar direction is taken by Doz, Giannone, and Reichlin (2011), who propose a two-step estimation method that is based on a dynamic factor model with the factor loadings set equal to the eigenvectors associated with a set of principal components. In the first step, the principal components are computed and its dynamic properties are estimated by means of a vector autoregressive model. In the second step, factor estimates and forecasts are obtained from Kalman filter methods applied to a model with the eigenvectors as factor loadings, and with the autoregressive coefficient matrices for the factors set equal to those estimated from the principal components. Doz et al. (2011) provide the asymptotic properties of the Kalman filter estimates and apply the model to nowcasting quarterly GDP using monthly variables that are released in a non-synchronized dating scheme. The Kalman filter estimates exploit the factor dynamics, and it is therefore expected that the resulting factor estimates will be more efficient than the principal components estimates.

Our approach differs from that of Doz et al. (2011) in that we adopt a simultaneous model for the target variable, the principal components and the unobserved dynamic factors, and estimate all parameters in this parsimonious model by the method of maximum likelihood. In this setting, we aim to capture all cross-sectional and time information in an optimal way. The idiosyncratic parts of the target vector series are specified explicitly and estimated jointly with the common factors. Hence, we avoid the problem that factors estimated from a large macroeconomic panel might be irrelevant to the forecasting target.

A Monte Carlo experiment illustrates the forecasting performance of the collapsed model, and compares it with forecasts from basic methods and from models that include principal components or other factor estimates as predictors. The basic methods include the random walk, autoregression and partially least squares methods, which are also considered in earlier studies, including those of Breitung and Eickmeier (2006), Groen and Kapetanios (2008) and Marcellino, Stock, and Watson (2003). We find that the collapsed factor model outperforms many earlier methods in terms of mean square forecast errors, particularly models where irrelevant factors for the target series are included and where macroeconomic panels have only small time and cross-sectional dimensions. These cases seem particularly relevant for small countries where the macro panels are less extensive, and for institutions where the means of maintaining large databases for forecasting are not available.

The remainder of the paper is organized as follows. In Section 2, our new method of a collapsed dynamic factor analysis is introduced. Its reliance on standard Kalman filter methods for moderate observation and state dimensions is highlighted. Issues related to mixed data frequencies for the forecasting of quarterly variables using panels of monthly macroeconomic time series are discussed in detail. The results of our Monte Carlo study are presented in Section 3. Empirical evidence is given in Section 4. From these two sections, we can conclude that our feasible methods do not compromise its forecasting performance relative to other methods; in most cases, the collapsed dynamic factor model outperforms the benchmark and competitor models. Finally, Section 5 concludes.

2. Collapsed dynamic factor analysis

2.1. The dynamic factor model

The observation x_{it} is for variable i at time t with $i = 1, \ldots, N$ and $t = 1, \ldots, T$. The time series in the vector $x_t = (x_{1t}, \ldots, x_{Nt})'$ can be analysed simultaneously by means of a dynamic factor model with $r \ll N$ latent components, which is given by

$$x_t = \Gamma_{xx} F_t + \varepsilon_{xt}, \quad \varepsilon_{xt} \sim \mathrm{N}(0, \Sigma_{xx}), \; t = 1, \ldots, T, \tag{1}$$

where Γ_{xx} is the $N \times r$ factor loading matrix with fixed coefficients, F_t is the r vector of r common dynamic factors, and ε_{xt} is a vector of normally distributed disturbances. The vector F_t with r latent components or dynamic factors can be specified as $F_t = Z_x \alpha_{xt}$, where Z_x is a fixed selection matrix and the state vector α_{xt} is modelled by a dynamic linear process. We can represent the dynamic factor model in a linear Gaussian state space form as

$$\begin{aligned} x_t &= \Lambda_{xx} \alpha_{xt} + \varepsilon_{xt}, \\ \alpha_{x,t+1} &= T_{xx} \alpha_{xt} + R_{xx} \eta_t, \quad \eta_t \sim \mathrm{N}(0, \Sigma_\eta), \end{aligned} \tag{2}$$

where $\Lambda_{xx} = \Gamma_{zz} Z_x$ is the state loading matrix, T_{xx} is the transition matrix, R_{xx} is a selection matrix, and η_t is a disturbance vector for which each element is independent of ε_{xs} for all possible values of t and s, with $t \neq s$. The system matrices Λ_{xx}, T_{xx}, R_{xx}, Σ_{xx} and Σ_η are fixed and their elements can rely partially on unknown parameters. Parameter estimation, diagnostic checking, factor extraction and forecasting can be based on the Kalman filter and related methods; see for example Durbin and Koopman (2012) and Harvey (1989) for textbook treatments. When the dimension N is large, Jungbacker and Koopman (2008) show that methods based on the Kalman filter remain computationally feasible.

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