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Dynamic factor models

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Abstract:

Factor models can cope with many variables without running into scarce degrees of freedom problems often faced in a regression-based analysis. In this article we review recent work on dynamic factor models that have become popular in macroeconomic policy analysis and forecasting. By means of an empirical application we demonstrate that these models turn out to be useful in investigating macroeconomic problems.

Keywords: Principal components, dynamic factors, forecasting

JEL Classification: C13, C33, C51

Non technical summary

In recent years, large-dimensional dynamic factor models have become popular in empirical macroeconomics. They are more advantageous than other methods in various respects. Factor models can cope with many variables without running into scarce degrees of freedom problems often faced in regression-based analyses. Researchers and policy makers nowadays have more data at a more disaggregated level at their disposal than ever before. Once collected, the data can be processed easily and rapidly owing to the now wide-spread use of high-capacity computers. Exploiting a lot of information can lead to more precise forecasts and macroeconomic analyses. A second advantage of factor models is that idiosyncratic movements which possibly include measurement error and local shocks can be eliminated. This yields a more reliable signal for policy makers and prevents them from reacting to idiosyncratic movements. In addition, the estimation of common factors or common shocks is of intrinsic interest in some applications. A third important advantage is that factor modelers can remain agnostic about the structure of the economy and do not need to rely on overly tight assumptions as is sometimes the case in structural models. It also represents an advantage over structural VAR models where the researcher has to take a stance on the variables to include which, in turn, determine the outcome, and where the number of variables determine the number of shocks.

In this article we review recent work on dynamic factor models and illustrate the concepts with an empirical example. We start by considering the traditional factor model. This model is designed to handle data sets which include only a small number of variables, and in this type of model, it is not allowed for serial and mutual correlation of the idiosyncratic errors. These fairly restrictive assumptions can be relaxed if it is assumed that the number of variables tends to infinity. Large data sets can be dealt with by the approximate factor model, which is outlined in this paper. We discuss different test procedures for determining the number of factors. Finally we present the dynamic factor model which allows the common factors to affect the variables not only contemporaneously, but also with lags. In addition, the factors may be described as a VAR model which is useful for structural macroeconomic analysis.

The article gives an overview of recent empirical work based on dynamic factor models. Those were traditionally used to construct economic indicators and to forecast. More recently, dynamic factor models were also employed to analyze monetary policy and international business cycles. We finally estimate a dynamic factor model for a large set of macroeconomic variables from European monetary union (EMU) member countries and central and eastern European countries (CEECs). We find that the variance shares of output growth explained by the common factors are larger in most EMU countries than in the CEECs. However, the variance shares associated with output growth in several CEECs exceed those associated with some peripheral EMU countries like Greece and Portugal, the latter being encouraging from the point of view of the prospective accession of the CEECs to EMU.

Nicht technische Zusammenfassung

In den letzten Jahren haben große dynamische Faktormodelle in der empirischen Makroökonomik an Bedeutung gewonnen. Sie weisen gegenüber anderen Methoden verschiedene Vorteile auf. Faktormodelle können viele Variablen einbeziehen, ohne dass das bei der Regressionsanalyse häufig auftretende Problem der unzureichenden Freiheitsgrade akut wird. Der Forschung und der Politik stehen heutzutage mehr und stärker disaggregierte Daten zur Verfügung als je zuvor. Die erhobenen Daten können aufgrund des inzwischen verbreiteten Einsatzes leistungsstarker Computer leicht und rasch bearbeitet werden. Auf der Grundlage umfangreicherer Datensätze lassen sich präzisere Prognosen und aussagefähigere makroökonomische Analysen erstellen. Ein zweiter Vorteil von Faktormodellen liegt darin, dass sich idiosynkratische, das heißt variablen-spezifische, Bewegungen herausrechnen lassen, die möglicherweise auf Messfehlern und lokalen Schocks beruhen. Damit erhalten die Politiker ein verlässlicheres Signal, und es kann verhindert werden, dass sie auf idiosynkratische Entwicklungen reagieren. Darüber hinaus ist die Schätzung gemeinsamer Faktoren oder Schocks für einige Anwendungen von eigenständigem Interesse. Ein dritter wichtiger Vorteil besteht darin, dass Faktormodelle eine agnostische Betrachtung der Wirtschaftsstruktur ermöglichen und keine zu strengen Annahmen erfordern, wie es zuweilen bei strukturellen Modellen der Fall ist. Außerdem besteht ein Vorteil gegenüber strukturellen VAR-Modellen, bei denen sich der Forscher für bestimmte Variablen entscheiden muss, deren Auswahl das Ergebnis beeinflusst und deren Anzahl die Zahl der Schocks vorgibt.

Das vorliegende Papier beschäftigt sich mit jüngeren Untersuchungen zu dynamischen Faktormodellen und veranschaulicht die Konzepte anhand eines empirischen Beispiels. Zunächst wird das klassische Faktormodell betrachtet. Dieses Modell dient der Analyse von Datensätzen, die nur wenige Variablen umfassen, und dieser Modelltyp schließt eine serielle und gegenseitige Korrelation der idiosynkratischen Fehler aus. Diese recht restriktiven Annahmen können gelockert werden, wenn angenommen wird, dass die Anzahl der Variablen gegen unendlich geht. Umfangreiche Datensätze können mithilfe des in diesem Diskussionspapier beschriebenen approximativen Faktormodells analysiert werden. Es werden unterschiedliche Testverfahren zur Bestimmung der Faktoranzahl diskutiert.

Schließlich wird ein dynamisches Faktormodell vorgestellt, bei dem die gemeinsamen Faktoren die Variablen nicht nur kontemporär, sondern auch verzögert beeinflussen können. Zudem lassen sich die Faktoren auch als VAR-Modell darstellen, was für die strukturelle makroökonomische Analyse nützlich ist.

Das vorliegende Papier gibt einen Überblick über neuere empirische Untersuchungen auf der Grundlage dynamischer Faktormodelle. Diese Modelle wurden in der Vergangenheit meist zur Konstruktion ökonomischer Indikatoren und zur Prognose verwendet. In jüngerer Zeit wurden dynamische Faktormodelle auch zur Analyse der Geldpolitik und internationaler Konjunkturzyklen herangezogen. In diesem Diskussionspapier wird ein dynamisches Faktormodell für eine große Anzahl makroökonomischer Variablen aus den Mitgliedstaaten der Europäischen Währungsunion (EWU) und der mittel- und osteuropäischen Länder (MOE) geschätzt. Wir kommen zu dem Ergebnis, dass die Varianzanteile des Produktionszuwachses, die von den gemeinsamen Faktoren erklärt werden, in den meisten EWU-Ländern größer sind als in den MOE. Allerdings sind die Varianzanteile des Produktionszuwachses in einigen mittel- und osteuropäischen Volkswirtschaften größer als in einigen peripheren EWU-Mitgliedstaaten (etwa Griechenland und Portugal), was für den angestrebten Beitritt der MOE zur EWU eine gute Voraussetzung ist.

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1 Introduction

In recent years, large-dimensional dynamic factor models have become popular in empirical macroeconomics. They are more advantageous than other methods in various respects. Factor models can cope with many variables without running into scarce degrees of freedom problems often faced in regression-based analyses. Researchers and policy makers nowadays have more data at a more disaggregated level at their disposal than ever before. Once collected, the data can be processed easily and rapidly owing to the now wide-spread use of high-capacity computers. Exploiting a lot of information can lead to more precise forecasts and macroeconomic analyses. The use of many variables further reflects a central bank's practice of "looking at everything" as emphasized, for example, by Bernanke and Boivin (2003). A second advantage of factor models is that idiosyncratic movements which possibly include measurement error and local shocks can be eliminated. This yields a more reliable signal for policy makers and prevents them from reacting to idiosyncratic movements. In addition, the estimation of common factors or common shocks is of intrinsic interest in some applications. A third important advantage is that factor modellers can remain agnostic about the structure of the economy and do not need to rely on overly tight assumptions as is sometimes the case in structural models. It also represents an advantage over structural VAR models where the researcher has to take a stance on the variables to include which, in turn, determine the outcome, and where the number of variables determine the number of shocks.

In this article we review recent work on dynamic factor models and illustrate the concepts with an empirical example. In Section 2 the traditional factor model is considered and the approximate factor model is outlined in Section 3. Different test procedures for determining the number of factors are discussed in section 4. The dynamic factor model is considered in Section 5. Section 6 gives an overview of recent empirical work based on dynamic factor models and Section 7

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presents the results of estimating a large-scale dynamic factor model for a large set of macroeconomic variables from European monetary union (EMU) member countries and central and eastern European countries (CEECs). Finally, Section 8 concludes.

2 The strict factor model

In an r-factor model each element of the vector $y_t = [y_{1t}, \ldots, y_{Nt}]'$ can be represented as

$$\begin{aligned} y_{it} &= \lambda_{i1} f_{1t} + \cdots + \lambda_{ir} f_{rt} + u_{it} \ , \quad t = 1, \ldots, T \\ &= \lambda_{i\cdot}' f_t + u_{it} \ , \end{aligned}$$

where $\lambda_{i\cdot}' = [\lambda_{i1}, \ldots, \lambda_{ir}]$ and $f_t = [f_{1t}, \ldots, f_{rt}]'$. The vector $u_t = [u_{1t}, \ldots, u_{Nt}]'$ comprises N idiosyncratic components and f_t is a vector of r common factors.

In matrix notation the model is written as

$$\begin{aligned} y_t &= \Lambda f_t + u_t \\ Y &= F\Lambda' + U, \end{aligned}$$

where $\Lambda = [\lambda_{1\cdot}, \ldots, \lambda_{N\cdot}]'$, $Y = [y_1, \ldots, y_T]'$, $F = [f_1, \ldots, f_T]'$ and $U = [u_1, \ldots, u_T]'$.

For the *strict factor model* it is assumed that u_t is a vector of mutually uncorrelated errors with $E(u_t) = 0$ and $E(u_t u_t') = \Sigma = \text{diag}(\sigma_1^2, \ldots, \sigma_N^2)$. For the vector of common factors we assume $E(f_t) = 0$ and $E(f_t f_t') = \Omega$.[1] Furthermore, $E(f_t u_t') = 0$. From these assumptions it follows that[2]

$$\Psi = E(y_t y_t') = \Lambda\Omega\Lambda' + \Sigma.$$

The loading matrix Λ can be estimated by minimizing the residual sum of squares:

$$\sum_{t=1}^{T} (y_t - Bf_t)'(y_t - Bf_t) \tag{1}$$

subject to the constraint $B'B = I_r$. Differentiating (1) with respect to B and F yields the first order condition $(\mu I_N - S)\hat{\beta}_k = 0$ for $k = 1, \ldots, r$, where $S =$

[1] That is we assume that $E(y_t) = 0$. In practice, the means of the variables are subtracted to obtain a vector of mean zero variables.

[2] In many applications the correlation matrix is used instead of the covariance matrix of y_t. This standardization affects the properties of the principal component estimator, whereas the ML estimator is invariant with respect to a standardization of the variables.

$T^{-1}\sum_{t=1}^{T} y_t y_t'$ and $\hat{\beta}_i$ is the i'th column of $\widehat{B}$, the matrix that minimizes the criterion function (1). Thus, the columns of $\widehat{B}$ result as the eigenvectors of the r largest eigenvalues of the matrix S. The matrix $\widehat{B}$ is the *Principal Components* (PC) estimator of Λ.

To analyse the properties of the PC estimator it is instructive to rewrite the PC estimator as an IV estimator. The PC estimator can be shown to solve the following moment condition:

$$\sum_{t=1}^{T} \widehat{B}' y_t \hat{u}_t' = 0, \tag{2}$$

where $\hat{u}_t = \widehat{B}_\perp' y_t$ and $\widehat{B}_\perp$ is an $N \times (N-r)$ orthogonal complement of $\widehat{B}$ such that $\widehat{B}_\perp' \widehat{B} = 0$. Specifically,

$$\widehat{B}_\perp = I_N - \widehat{B}(\widehat{B}'\widehat{B})^{-1}\widehat{B}' = I_N - \widehat{B}\widehat{B}'$$

where we have used the fact that $\widehat{B}'\widehat{B} = I_r$. Therefore, the moment condition can be written as $\sum_{t=1}^{N} \hat{f}_t \hat{u}_t'$, where $\hat{u}_t = y_t - \widehat{B}'\hat{f}_t$ and $\hat{f}_t = \widehat{B}' y_t$. Since the components of $\hat{f}_t$ are linear combinations of y_t, the instruments are correlated with $\hat{u}_t$, in general. Therefore, the PC estimator is inconsistent for fixed N and $T \to \infty$ unless $\Sigma = \sigma^2 I$.[3]

An alternative representation that will give rise to a new class of IV estimators is given by choosing a different orthogonal complement $\widehat{B}_\perp$. Let $\Lambda = [\Lambda_1', \Lambda_2']'$ such that Λ_1 and Λ_2 are $(N-r) \times r$ and $r \times r$ submatrices, respectively. The matrix $U = [u_1, \ldots, u_N]'$ is partitioned accordingly such that $U = [U_1', U_2']$ and U_1 (U_2) are $T \times (N-r)$ ($T \times r$) submatrices. A system of equations results from solving $Y_2 = F\Lambda_2' + U_2$ for F and inserting the result in the first set of equations:

$$\begin{aligned} Y_1 &= (Y_2 - U_2)(\Lambda_2')^{-1}\Lambda_1' + U_1 \\ &= Y_2\Theta' + V \end{aligned} \tag{3}$$

where $\Theta = \Lambda_1\Lambda_2^{-1}$ and $V = U_1 - U_2\Theta'$. Accordingly Θ yields an estimator for the renormalized loading matrix $B^* = [\Theta', I_r]'$ and $B_\perp^* = [I_r, \Theta']'$.

The i'th equation of system (3) can be consistently estimated based on the following $N - r - 1$ moment conditions

$$E(y_{kt} v_{it}) = 0, \quad k = 1, \ldots, i-1,\ i+1, \ldots, N-r \tag{4}$$

[3]To see that the PC estimator yields a consistent estimator of the factor space for $\Sigma = \sigma^2 I_N$ let B denote the matrix of r eigenvectors of Ψ. It follows that $B'\Psi B_\perp = B'\Lambda\Omega\Lambda' B_\perp$. The latter expression becomes zero if $B = \Lambda Q$, where Q is some regular $r \times r$ matrix.

that is, we do not employ y_{it} and $y_{n+1,t}, \dots, y_{Nt}$ as instruments as they are correlated with v_{it}. Accordingly, a GMM estimator based on $(N-r)(N-r-1)$ moment conditions can be constructed to estimate the $n \cdot r$ parameters in the matrix Θ. An important problem with this estimator is that the number of instruments increases rapidly as N increases. It is well known that, if the number of instruments is large relative to the number of observations, the GMM estimator may have poor properties in small samples. Furthermore, if $n^2 - n > T$, the weight matrix for the GMM estimator is singular. Therefore it is desirable to construct a GMM estimator based on a smaller number of instruments. Breitung (2005) proposes a just-identified IV etimator based on equation specific instruments that do not involve y_{it} and $y_{n+1,t}, \dots, y_{Nt}$.

In the case of homogeneous variances (i.e. $\Sigma = \sigma^2 I_N$) the PC estimator is the maximum likelihood (ML) estimator assuming that y_t is normally distributed. In the general case with $\Sigma = \mathrm{diag}(\sigma_1^2, \dots, \sigma_N^2)$ the ML estimator minimizes the function $\ell^* = tr(S\Sigma^{-1}) + \log|\Sigma|$ (cf. Jöreskog 1969). Various iterative procedures have been suggested to compute the ML estimator from the set of highly nonlinear first order conditions. For large factor models (with $N > 20$, say) it has been observed that the convergence of the usual maximization algorithms is quite slow and in many cases the algorithms have difficulty in converging to the global maximum.

3 Approximate factor models

The fairly restrictive assumption of the strict factor model can be relaxed if it is assumed that the number of variables (N) tends to infinity (cf. Chamberlain and Rothshield 1983, Stock and Watson 2002a and Bai 2003). First, it is possible to allow for (weak) serial correlation of the idiosyncratic errors. Thus, the PC estimator remains consistent if the idiosyncratic errors are generated by (possibly different) stationary ARMA processes. However, persistent and non-ergodic processes such as the random walk are ruled out. Second, the idiosyncratic errors may be weakly cross-correlated and heteroskedastic. This allows for finite "clusters of correlation" among the errors. Another way to express this assumption is to assume that all eigenvalues of $E(u_t u_t') = \Sigma$ are bounded. Third, the model allows for weak correlation among the factors and the idiosyncratic components. Finally, $N^{-1}\Lambda'\Lambda$ must converge to a positive definite limiting matrix. Accordingly, on average the factors contribute to all variables with a similar order of magnitude. This assumption rules out the possibility that the factors contribute only to a limited number of variables, whereas for an increasing number of remaining variables the loadings are zero.

Beside these assumptions a number of further technical assumptions restrict the moments of the elements of the random vectors f_t and u_t. With these assumptions Bai (2003) establishes the consistency and asymptotic normality of the PC estimator for Λ and f_t. However, as demonstrated by Bovin and Ng (2005a) the small sample properties may be severely affected when (a part of) the data is cross-correlated.

4 Specifying the number of factors

In practice, the number of factors necessary to represent the correlation among the variables is usually unknown. To determine the number of factors empirically a number of criteria were suggested. First, the eigenvalues of the sample correlation matrix R may roughly indicate the number of common factors. Since $tr(R) = N = \sum_{i=1}^{N} \mu_i$, where μ_i denotes the i'th eigenvalue of R (in descending order), the fraction of the total variance explained by k common factors is $\tau(k) = (\sum_{i=1}^{k} \mu_i)/N$. Unfortunately, there is no generally accepted limit for the explained variance that indicates a sufficient fit. Sometimes it is recommended to include those factors with an eigenvalue larger than unity, since these factors explain more than an “average factor”.

In some applications (typically in psychological or sociological studies) two or three factors explain more than 90 percent of the variables, whereas in macroeconomic panels a variance ratio of 40 percent is sometimes considered as a reasonable fit.

A related method is the “Scree-test”. Cattell (1966) observed that the graph of the eigenvalues (in descending order) of an uncorrelated data set forms a straight line with an almost horizontal slope. Therefore, the point in the eigenvalue graph where the eigenvalues begin to level off with a flat and steady decrease is an estimator of the sufficient number of factors. Obviously such a criterion is often fairly subjective because it is not uncommon to find more than one major break in the eigenvalue graph and there is no unambiguous rule to use.

Several more objective criteria based on statistical tests are available that can be used to determine the number of common factors. If it is assumed that r is the true number of common factors, then the idiosyncratic components u_t

should be uncorrelated. Therefore it is natural to apply tests that are able to indicate a contemporaneous correlation among the elements of u_t. The score test is based on the sum of all relevant $N(N-1)/2$ squared correlations. This test is asymptotically equivalent to the LR test based on (two times) the difference of the log-likelihood of the model assuming r_0 factors against a model with an unrestricted covariance matrix. An important problem of these tests is that they require $T >> N >> r$. Otherwise the performance of these tests is quite poor. Therefore, in typical macroeconomic panels which include more than 50 variables these tests are not applicable.

For the approximate factor model Bai and Ng (2002) have suggested information criteria that can be used to estimate the number of factors consistently as N and T tend to infinity. Let $V(k) = (NT)^{-1}\sum_{t=1}^{T}\hat{u}_t'\hat{u}_t$ denote the (overall) sum of squared residuals from a k-factor model, where $\hat{u}_t = y_t - \widehat{B}\hat{f}_t$ is the $N \times 1$ vector of estimated idiosyncratic errors. Bai and Ng (2002) suggest several variants of the information criterion, where the most popular statistic is

$$IC_{p2}(k) = \ln[V(k)] + k\left(\frac{N+T}{NT}\right)\ln[\min\{N,T\}].$$

The estimated number of factors ($\hat{k}$) is obtained from minimizing the information criterion in the range $k = 0, 1, \ldots, kmax$ where $kmax$ is some pre-specified upper bound for the number of factors. As N and T tend to infinity, $\hat{k} \xrightarrow{p} r$, i.e., the criterion is (weakly) consistent.

An alternative procedure to determine the number of factors based on the empirical distribution of the eigenvalues is recently suggested by Onatski (2005).

5 Dynamic factor models

The dynamic factor model is given by

$$y_t = \Lambda_0 g_t + \Lambda_1 g_{t-1} + \cdots + \Lambda_m g_{t-m} + u_t \tag{5}$$

where $\Lambda_0, \ldots, \Lambda_m$ are $N \times r$ matrices and g_t is a vector of q stationary factors. As before, the idiosyncratic components of u_t are assumed to be independent (or weakly dependent) stationary processes.

Forni, Giannone, Lippi and Reichlin (2004) suggest an estimation procedure of the innovations of the factors $\eta_t = g_t - E(g_t|g_{t-1}, g_{t-2}, \ldots)$. Let $f_t = [g_t', g_{t-1}', \ldots, g_{t-m}']'$ denote the $r = (m+1)q$ vector of "static" factors such that

$$y_t = \Lambda^* f_t + u_t\ , \tag{6}$$

where $\Lambda^* = [\Lambda_0, \ldots, \Lambda_m]$. In a first step the static factors f_t are estimated by PC. Let $\hat{f}_t$ denote the vector of estimated factors. It is important to note that a (PC) estimator does not estimate the original vector f_t but some "rotated" vector Qf_t such that the components of (Qf_t) are orthogonal. In a second step a VAR model is estimated:

$$\hat{f}_t = A_1 \hat{f}_{t-1} + \cdots + A_p \hat{f}_{t-p} + e_t \ . \tag{7}$$

Since $\hat{f}_t$ includes estimates of the lagged factors, some of the VAR equations are identities (at least asymptotically) and, therefore, the rank of the residual covariance matrix $\widehat{\Sigma}_e = T^{-1} \sum_{t=p+1}^{T} \hat{e}_t \hat{e}_t'$ is q, as $N \to \infty$. Let $\widehat{W}_r$ denote the matrix of q eigenvectors associated with the q largest eigenvalues of $\widehat{\Sigma}_e$. The estimate of the innovations of the dynamic factors results as $\hat{\eta}_t = \widehat{W}_r' \hat{e}_t$. These estimates can be used to identify structural shocks that drive the common factors (cf. Forni *et al.* 2004, Giannone, Sala and Reichlin 2002).

An important problem is to determine the number of dynamic factors q from the vector of r static factors. Forni et al. (2004) suggest an informal criterion based on the portion of explained variances, whereas Bai and Ng (2005) and Stock and Watson (2005) suggest consistent selection procedures based on principal components. Breitung and Kretschmer (2005) propose a test procedure based on the canonical correlation between $\hat{f}_t$ and $\hat{f}_{t-1}$. The i'th eigenvalue from a canonical correlation analysis can be seen as an R^2 from a regression of $\hat{v}_i' \hat{f}_t$ on $\hat{f}_{t-1}$, where $\hat{v}_i$ denotes the associated eigenvector. If there is a linear combination of $\hat{f}_t$ that corresponds to a lagged factor, then this linear combination is perfectly predictable and, therefore, the corresponding R^2 (i.e. the eigenvalue) will tend to unity. On the other hand, if the linear combination reproduces the innovations of the original factor, then this linear combination is not predictable and, therefore, the eigenvalue will tend to zero. Based on this reasoning, information criteria and tests of the number of factors are suggested by Breitung and Kretschmer (2005).

Forni *et al.* (2000, 2002) suggest an estimator of the dynamic factors in the frequency domain. This estimator is based on the frequency domain representation of the factor model given by

$$f_y(\omega) = f_\chi(\omega) + f_u(\omega),$$

where $\chi_t = \Lambda_0 f_t + \cdots + \Lambda_m f_{t-m}$ denotes the vector of common components of y_t, f_χ is the associated spectral density matrix, f_y is the spectral density matrix of y_t and u_t is the (diagonal) spectral density matrix of u_t. Dynamic principal components analysis applied to the frequencies $\omega \in [0, \pi]$ (Brillinger 1981) yields a consistent estimate of the spectral density matrix $f_\chi(\omega)$. An estimate of the common components χ_{it} is obtained by computing the time domain representation of the process from an inversion of the spectral densities. The frequency domain estimator yields a two-sided filter such that $\tilde{f}_t = \sum_{j=-\infty}^{\infty} \widehat{\Psi}'_j y_{t-j}$, where, in practice, the infinite limits are truncated. Forni, *et al.* (2005) also suggest a one-sided filter which is based on a conventional principal component analysis of the transformed vector $\tilde{y}_t = \widehat{\Sigma}^{-1/2} y_t$, where $\widehat{\Sigma}$ is the (frequency domain) estimate of the covariance matrix of u_t. This one-sided estimator can be used for forecasting based on the common factors.

6 Overview of existing applications

Dynamic factor models were traditionally used to construct economic indicators and for forecasting. More recently, they have been applied to macroeconomic analysis, mainly with respect to monetary policy and international business cycles. We briefly give an overview of existing applications of dynamic factor models in these four fields, before providing a macro analytic illustration.

Construction of economic indicators. The two most prominent examples of monthly coincident business cycle indicators, to which policy makers and other economic agents often refer, are the Chicago Fed National Activity Index[4] (CFNAI) for the US and EuroCOIN for the euro area. The CFNAI estimate, which dates back to 1967, is simply the first static principal component of a large macro data set. It is the most direct successor to indicators which were first developed by Stock and Watson but retired by the end of 2003. EuroCOIN is estimated as the common component of euro-area GDP based on dynamic principal component analysis. It was developed by Altissimo *et al.* (2001) and is made available from 1987 onwards by the CEPR.[5] Measures of core inflation have been constructed analogously (e.g. Cristadoro, Forni, Reichlin and Veronese (2001) for the euro area and Kapetanios (2004) for the UK).

Forecasting. Factor models are widely used in central banks and research institutions as a forecasting tool. The forecasting equation typically has the form

$$y^h_{t+h} = \mu + a(L)y_t + b(L)\hat{f}_t + e^h_{t+h} \ , \tag{8}$$

where y_t is the variable to be forecasted at period $t+h$ and e_{t+h} denotes the h-step ahead prediction error. Accordingly, information used to forecast y_t are

[4]See http://www.chicagofed.org/economic_research_and_data/cfnai.cfm.
[5]See http://www.cepr.org/data/eurocoin/.

the past of the variable and the common factor estimates $\hat{f}_t$ extracted from an additional data set.

Factor models have been used to predict real and nominal variables in the US (e.g. Stock and Watson (2002a,b, 1999), Giacomini and White (2003), Banerjee and Marcellino (2003)), in the euro area (e.g. Forni, Hallin, Lippi and Reichlin (2000, 2003), Camba-Mendez and Kapetanios (2004), Marcellino, Stock and Watson (2003), Banerjee, Marcellino and Masten (2003)), for Germany (Schumacher and Dreger (2004), Schuhmacher 2005), for the UK (Artis, Banerjee and Marcellino (2004)) and for the Netherlands (den Reijer 2005). The factor model forecasts are generally compared to simple linear benchmark time series models, such as AR models, AR models with single measurable leading indicators and VAR models. More recently, they have also been compared with pooled single indicator forecasts or forecasts based on "best" single indicator models or groups of indicators derived using automated selection procedures (PCGets) (e.g. Banerjee and Marcellino (2003)). Pooling variables versus combining forecasts is a particularly interesting comparison, since both approaches claim to exploit a lot of information.[6]

Overall, results are quite encouraging, and factor models are often shown to be more successful in terms of forecasting performance than smaller benchmark models. Three remarks are, however, in order. First, the forecasting performance of factor models apparently depends on the types of variable one wishes to forecast, the countries/regions of interest, the underlying data sets, the benchmark models and horizons. Unfortunately, a systematic assessment of the determinants of the relative forecast performance of factor models is still not available. Second, it may not be sufficient to include just the first or the first few factors. Instead, a factor which explains not much of the entire panel, say, the fifth or sixth principal component, may be important for the variable one wishes to forecast (Banerjee and Marcellino (2003)). Finally, the selection of the variables to be included in the data set is ad hoc in most applications. The same data set is often used to predict different variables. This may, however, not be adequate. Instead, one should only include variables which exhibit high explanatory power with respect to the variable that one aims to forecast (see also Bovin and Ng (2005b)).

Monetary policy analysis. Forni *et al.* (2004) and Giannone (2002, 2004)

[6]The models are further used to investigate the explanatory power of certain groups of variables, for example financial variables (Forni *et al.* (2003)) or variables summarizing international influences for domestic activity (see, for example, Banerjee *et al.* (2003) who investigate the ability of US variables or factors to predict euro-area inflation and output growth.

identify the main macroeconomic shocks in the US economy and estimate policy rules conditional on the shocks. Sala (2003) investigates the transmission of common euro-area monetary policy shocks to individual EMU countries. Cimadomo (2003) assesses the proliferation of economy-wide shocks to sectors in the US and examines if systematic monetary policy has distributional and asymmetric effects across sectors. All these studies rely on the structural dynamic factor model developed by Forni *et al.* (2004). Bernanke, Boivin and Eliasz (2005), Stock and Watson (2005) and Favero, Marcellino and Neglia (2005) use a different but related approach. The two former papers address the problem of omitted variables bias inherent in many simple small-scale VAR models. They show for the US that the inclusion of factors in monetary VARs, denoted by factor-augmented VAR (FAVAR) models, can eliminate the well-known price puzzle in the US. Favero *et al.* (2005) confirm these findings for the US and for some individual euro-area economies. They further demonstrate that the inclusion of factors estimated from dynamic factor models in the instrument set used for estimation of Taylor rules increases the precision of the parameters estimates.

International business cycles. Malek Mansour (2003) and Helbling and Bayoumi (2003) estimate a world and, respectively, a G7 business cycle and investigate to what extent the common cycle contributes to economic variation in individual countries. Eickmeier (2004) investigates the transmission of structural shocks from the US to Germany and assesses the relevance of the various transmission channels and global shocks, thereby relying on the Forni *et al.* (2004) framework. Marcellino, Stock and Watson (2000) and Eickmeier (2005) investigate economic comovements in the euro-area. They try to give the common euro-area factors an economic interpretation by relating them to individual countries and variables using correlation measures.

7 An Empirical Example

Our application sheds some light on economic comovements in Europe by fitting the large-scale dynamic factor model to a large set of macroeconomic variables from European monetary union (EMU) member countries and central and eastern European countries (CEECs). We determine the dimension of the euro-area economy, i.e. the number of macroeconomic driving forces which are common to all EMU countries and which explain a significant share of the overall variance in the set and we make some tentative interpretation. Most importantly, our application addresses the recent discussion on whether the CEECs should join the EMU. One of the criteria that should be satisfied is the synchronization of business cycles. In what follows, we investigate how important euro-area factors are for the CEECs compared to the current EMU members. In addition, the heterogeneity of the influences of the common factors across the CEECs is examined.[7]

Our data set contains 41 aggregate euro-area time series, 20 key variables of each of the core euro-area countries (Austria, Belgium, France, Germany, Italy, Netherlands, Spain), real GDP and consumer prices for the remaining euro-area economies (Finland, Greece, Ireland, Luxembourg, Portugal) and for eight CEECs (Czech Republic, Estonia, Hungary, Lithuania, Latvia, Poland, Slovenia, Slovak Republic) as well as some global variables.[8][9] Overall, we include $N = 208$ quarterly series. The sample ranges from 1993Q1 to 2003Q4. The factor analysis requires some pre-treatment of the data. Series exhibiting a seasonal pattern were seasonally adjusted. Integrated series were made stationary through differencing. Logarithms were taken of the series which were not in rates or negative, and we removed outliers. We standardized the series to have a mean of zero and a variance of one.

The series are collected in the vector $N \times 1$ vector y_t ($t = 1, 2, \ldots, T$). It is assumed that y_t follows an approximate dynamic factor model as described in Section 3. The r common euro-area factors collected in f_t are estimated by applying static principal component analysis to the correlation matrix of y_t. On the basis of the ICp_3 criterion of Bai and Ng (2002), we choose $r = 3$, although the other two criteria suggest $r = 2$ (Table 1). One reason is that factors are still estimated consistently if the number of common factors is overestimated, but not if it is underestimated (Stock and Watson (2002b), Kapetanios and Marcellino (2003), Artis *et al.* (2004)). Another reason is that two factors explain a relatively low share of the total variance (25 percent), whereas three factors account for 32 percent which is more consistent with previous findings for macroeconomic euro-

[7] A more comprehensive study based on a slightly different data set is provided by Eickmeier and Breitung (2005).

[8] Among the global variables are US GDP and world energy prices. Studies have shown that fluctuations in these variables may influence the euro area (see, for example, Jiménez-Rodríguez and Sánchez (2005), Peersman (2005)).

[9] The aggregate euro-area series are taken from the data set underlying the ECB's Area Wide Model (for a detailed description see Fagan, Henry and Mestre (2001)). The remaining series mainly stem from OECD and IMF statistics.

area data sets (Table 1).[10]

The common factors f_t do not bear a direct structural interpretation. One reason is that f_t may be a linear combination of the q "true" dynamic factors and their lags. Using the consistent Schwarz criterion of Breitung and Kretschmer (2005), we obtain $q = 2$, conditional on $r = 3$. That is, one of the two static factors enter the factor model with a lag. Informal criteria are also used in practice. Two dynamic principal components explain 33 percent (Table 1). This is comparable to the variance explained by the r static factors. The other criterion consists in requiring each dynamic principal component to explain at least a certain share, for example 10 percent, of the total variance. This would also suggest $q = 2$.

Even if the dynamic factors were separated from their lags, they cannot be given a direct economic meaning, since they are only identified up to a linear transformation. Some tentative interpretation of the factors is given nevertheless. In business cycle applications, the first factor is often interpreted as a common cycle. Indeed, as is obvious from Figure 1, our first factor is highly correlated with EuroCOIN and can therefore be interpreted as the euro-area business cycle. To facilitate the interpretation of the other factors, the factors may be rotated to obtain a new set of factors which satisfies certain identifying criteria, as done in Eickmeier (2005). Another possibility consists in estimating the common structural shocks behind f_t using structural vector autoregression (SVAR) and PC techniques as suggested by Forni *et al.* (2004). This would also allow us to investigate how common euro-area shocks spread to the CEECs.

Table 2 shows how much of the variance of output growth in CEECs and EMU countries is explained by the euro-area factors. On average, the common factors explain a larger part of output growth in EMU economies (37 percent) compared to the CEECs (7 percent). Interestingly, the shares of the peripheral countries (Greece and Portugal) are smaller than the corresponding shares in a number of CEECs. Of the latter, Hungary and Slovenia exhibit the largest variance shares explained by the euro-area factors. The dispersion across EMU countries is about four times as large as the dispersion across the CEECs. The difference is somewhat lower when Greece, Portugal and Ireland are excluded from the EMU group.[11]

[10] Those range between 32 and 55 percent (Marcellino *et al.* (2000), Eickmeier (2005), Altissimo *et al.* (2001)).

[11] These small peripheral countries were found to exhibit a relatively low synchronization with the rest of the euro area and are sometimes treated separately (e.g. Korhonen (2003)).

8 Conclusion

In this paper we have reviewed and complemented recent work on dynamic factor models. By means of an empirical application we have demonstrated that these models turn out to be useful in investigating macroeconomic problems such as the economic consequences for central and eastern European countries of joining the European Monetary Union. Nevertheless, several important issues remain unsettled. First it turns out that the determination of the number of factors representing the relevant information in the data set is still a delicate issue. Since Bai and Ng (2002) have made available a number of consistent information criteria it has been observed that alternative criteria may suggest quite different number of factors. Furthermore, the results are often not robust and the inclusion of a few additional variables may have a substantial effect on the number of factors.

Even if dynamic factors may explain more than a half of the total variance it is not clear whether the idiosyncratic components can be treated as irrelevant "noise". It may well be that the idiosyncratic components are important for the analysis of macroeconomic variables. On the other hand, the loss of information may even be more severe if one focuses on a few variables (as in typical VAR studies) instead of a small number of factors. Another important problem is to attach an economic meaning to the estimated factors. As in traditional econometric work, structural identifying assumptions may be employed to admit an economic interpretation of the factors (cf. Breitung 2005). Clearly, more empirical work is necessary to assess the potentials and pitfalls of dynamic factor models in empirical macroeconomic.

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Table 1: Criteria for selecting the number of factors

	Bai and Ng criteria			Variance shares of PCs	
r	IC_{p1}	IC_{p2}	IC_{p3}	Static PCs	Dynamic PCs
1	–0.096	–0.091	–0.109	0.159	0.211
2	–0.105*	–0.095*	–0.131	0.248	0.326
3	–0.100	–0.084	–0.138*	0.317	0.418
4	–0.082	–0.061	–0.133	0.371	0.494
5	–0.065	–0.039	–0.129	0.423	0.555
6	–0.037	–0.006	–0.114	0.464	0.608
7	–0.014	0.023	–0.103	0.504	0.656
8	0.012	0.054	–0.090	0.541	0.698
9	0.036	0.084	–0.078	0.575	0.734
10	0.066	0.118	–0.062	0.604	0.768

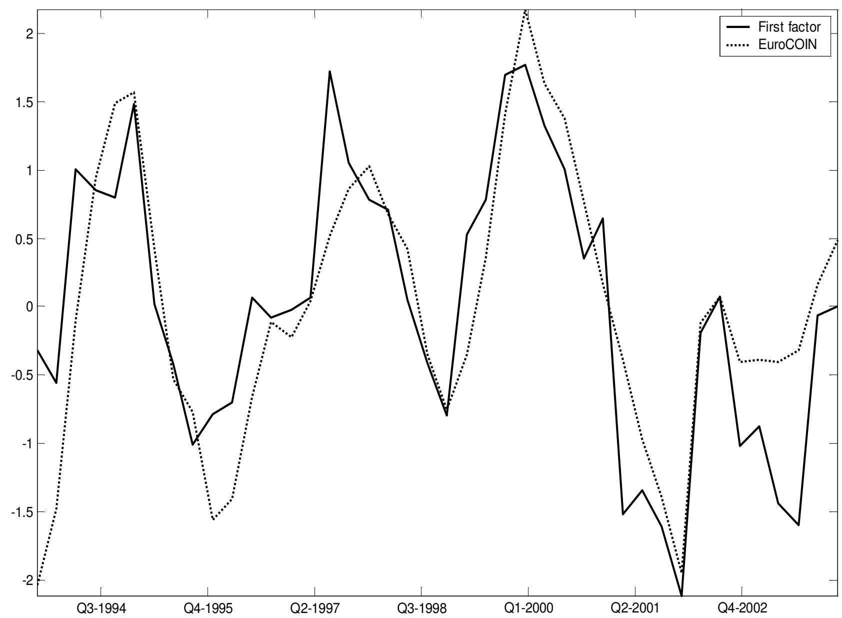
Note: The maximal number of factors for the Bai and Ng (2002) criteria is $r_{max} = 10$. The cumulative variance shares present the variance share explained by the first r principal components (PC). An asterisk indicates the minimum.

Table 2: Variance shares explained by the common factors

	Δ GDP		Δ GDP
AUT	0.42	CZ	0.03
BEL	0.60	ES	0.08
FIN	0.19	HU	0.18
FRA	0.66	LT	0.03
GER	0.60	LV	0.03
GRC	0.07	PL	0.07
IRE	0.27	SI	0.11
ITA	0.44	SK	0.05
LUX	0.44		
NLD	0.54		
PRT	0.09		
ESP	0.14		
Mean all countries	0.25	Std. all countries	0.22
Mean EMU	0.37	Std. EMU	0.21
Mean EMU - GPI	0.45	Std. EMU - GPI	0.18
Mean CEECs	0.07	Std. CEECs	0.05

Note: EMU - GPI denotes the Euro area less Greece, Portugal and Ireland.

Figure 1: Euro-area business cycle estimates



Note: The monthly EuroCOIN series was converted into a quarterly series. It was normalized to have a mean of zero and a variance of one.

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