DNB Working Paper

No. 415 / February 2014

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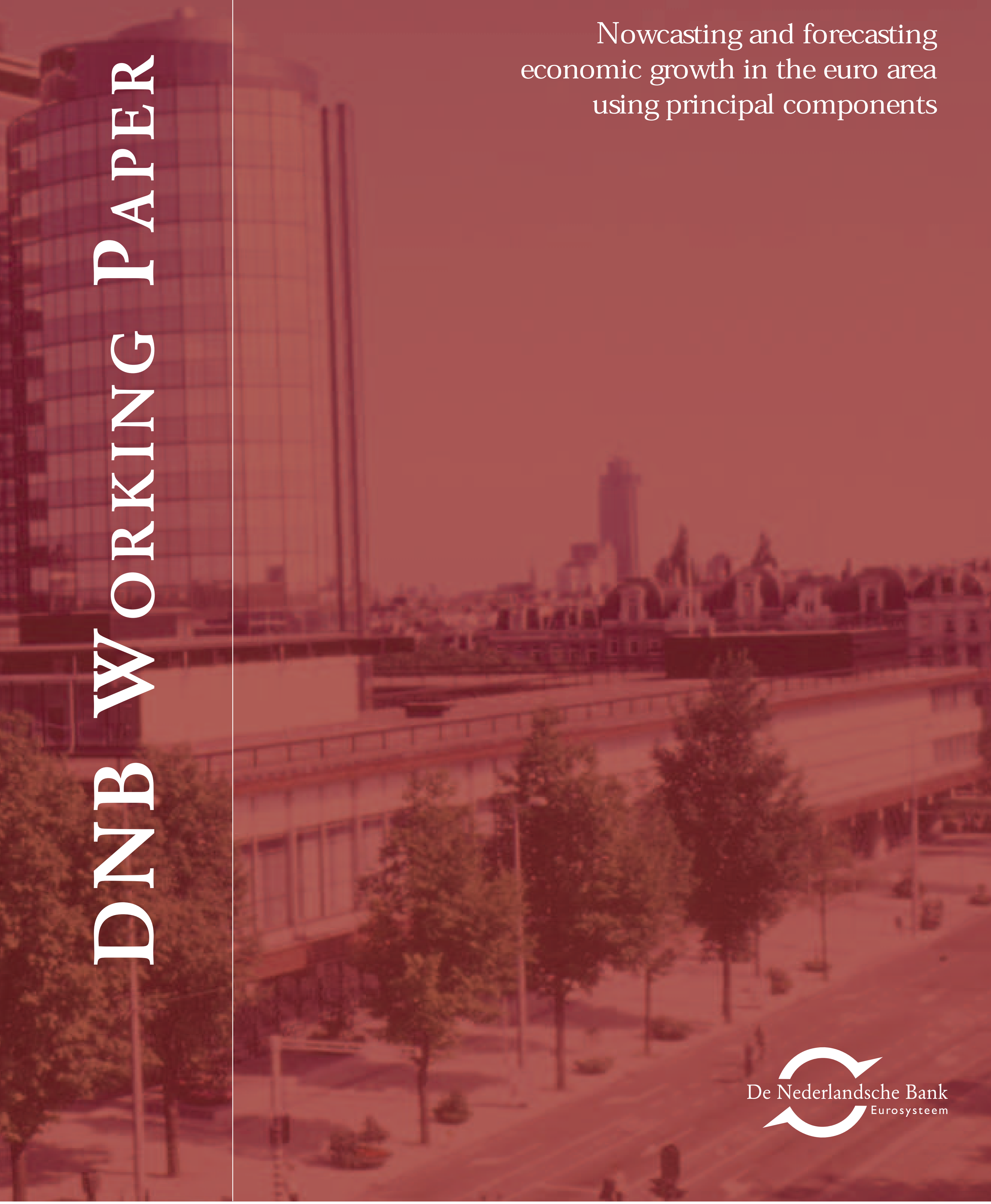
DNB WORKING PAPER



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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 415

February 2014

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Nowcasting and forecasting economic growth in the euro area using principal components

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February 14, 2014

Abstract

Many empirical studies show that factor models have a relatively high forecast compared to alternative short-term forecasting models. These empirical findings have been established for different data sets and for different forecast horizons. However, choosing the appropriate factor model specification is still a topic of ongoing debate. Moreover, the forecast performance during the recent financial crisis is not well documented. In this study we investigate these two issues in depth. We empirically test the forecast performance of three factor model approaches and report our findings in an extended empirical out-of-sample forecasting competition for the euro area and its five largest countries over the period 1992-2012. Besides, we introduce two extensions to the existing factor models to make them more suited for real-time forecasting. We show that the factor models were able to systematically beat the benchmark autoregressive model, both before as well as during the financial crisis. The recently proposed collapsed dynamic factor model shows the highest forecast accuracy for the euro area and the majority of countries we analyzed. The improvement against the benchmark model can range up to 77%, depending on the country and forecast horizon.

Keywords: Factor models, Principal component analysis, Forecasting, Kalman filter, State space method, Publication lag, Mixed frequency.

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1 Introduction

It is widely acknowledged that forecasting macro-economic time series is of key importance for economic policy makers but also for the general public. Reliable short-term forecasts are especially in high demand when the economic environment is uncertain. Many different methodologies exist for this purpose, ranging from simple bridge models to sophisticated dynamic factor models. Over the last decade the latter have become a popular tool for short-term forecasting amongst practitioners and econometricians. This is due to their good forecast performance as shown in amongst others Giannone et al. (2008) for the United States, Rünstler et al. (2009) and Angelini et al. (2011) for the euro area and Schumacher and Breitung (2008) for Germany. Despite the increasing attention for factor models, a number of specification issues are still not resolved. One of the issues is how to determine the optimal number of factors in the model, e.g. Bai and Ng (2002) and Bai and Ng (2007). Another issue of debate is the determination of the optimal size of the database to extract the factors from , e.g. Caggiano et al. (2011) and den Reijer (2013). A related issue that has attracted relatively little attention in the literature is the gain in forecast accuracy resulting from including autoregressive terms of the target variable in the model specification, i.e. including one or more lags of the targeted variable, in our case GDP, in the forecast equation. However, recent studies indicate this might be a promising extension in terms of forecast accuracy. Clements and Galvão (2008), Kuzin et al. (2011) and Jansen et al. (2012) find that the inclusion of an autoregressive term significantly improves the forecast accuracy of simple bridge equations, MIDAS as well as MFVAR models. It is an empirical question whether this conclusion also holds for factor models.

Our study compares the short-term forecast performance of different factor models for quarterly GDP growth for the euro area and its five largest countries before and during the financial crisis. We present a concise discussion of the literature on short-term forecasting using factor models and consider several recent developments. The earliest contributions on dynamic factor analysis have been recently reviewed by Stock and Watson (2006), Breitung and Eickmeier (2006) and Bai and Ng (2008). We concentrate on three factor models, i.e. the canonical factor model of Stock and Watson (2002) which started the current literature on factor models, the widely used dynamic factor model of Bańbura and Rünstler (2011) and the recently proposed collapsed dynamic factor model of Bräuning and Koopman (2014). The two dynamic factor models are siblings of the canonical factor model of Stock and Watson (2002) as the models are all built on the idea of using principal components to summarize the information in a large set of monthly indicators. However, in contrast to Stock and Watson (2002), both dynamic factor models analyze the target and the principal component variables simultaneously in a low-dimensional multivariate unobserved component time series model. This model setup allows for panels with mixed-frequencies and for the efficient handling of monthly series with different publication delays, and different starting dates. Because of these differences the matrix of monthly series contains so called "jagged" or "ragged" edges at the beginning and the end of the sample.

The econometric foundation of the Bańbura and Rünstler (2011) model is described in Doz et al. (2011). Doz et al. (2011) propose a two-step estimation method. 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, the factor estimates and forecasts are obtained from the Kalman filter and smoother. Doz et al. (2011) provide the asymptotic properties of the Kalman filter and smoother estimates and apply the model to forecast quarterly GDP growth with monthly variables containing jagged edges at the beginning and the end of the sample. Bańbura and Rünstler (2011) extend this approach by introducing quarterly GDP growth more explicitly allowing tracing back the contributions of individual variables to the factor model forecast, using an algorithm developed by Koopman and Harvey (2003).

The model of Bräuning and Koopman (2014) differs from Bańbura and Rünstler (2011) in the following respects: Firstly it adopts a low-dimensional unobserved components model for the target variable and a set of principal components from which the dynamic factors are extracted. The unknown parameters in this parsimonious model are jointly estimated by using maximum likelihood for which the loglikelihood function is evaluated using the Kalman filter and smoother. This model setup allows capturing all cross-sectional and dynamic time information in a transparent and optimal way. Secondly, the idiosyncratic part for the target vector series is modeled explicitly and estimated jointly with the dynamic factors. This mitigates the problem that the estimated factors in a large macroeconomic panel are not considering information from the forecasting target.

The main contributions of this paper are threefold. Firstly, we extend the approach of Bräuning and Koopman (2014) by proposing a more efficient way of handling the jagged edges in the collapsed dynamic factor model. We propose a three-step method. In the first step we analyze each univariate time series by an unobserved components model to extract the main signal for interpolating (or extrapolating) the jagged edges, in the second step we extract the principal components and in the third step we estimate all model parameters simultaneously. The efficient handling of the jagged edges significantly improves the forecast accuracy. Secondly, we extend the model of Bańbura and Rünstler (2011) by including autoregressive terms in the model, putting it on more equal footing with the models of Stock and Watson (2002) and Bräuning and Koopman (2014). This modification improves the forecast accuracy of the Bańbura and Rünstler (2011) model. Thirdly, we conduct a rigorous test of the forecast accuracy of factor models. We present a systematic comparison of the factor models for the euro area and its five largest countries (Germany, France, Italy, Spain and the Netherlands) utilizing the same information set across countries and the euro area. We show that the factor models were able to systematically beat the benchmark autoregressive model. The good performance of the factor models was not limited to the pre-crisis period, but the models also outperformed the benchmark model during the financial crisis. During the financial crisis the factor models were able to improve on the forecast accuracy of the benchmark model by up to 77%, depending on the factor model, country and forecast horizon. The recently proposed collapsed dynamic factor showed the highest forecast accuracy for the euro area and the majority of countries we analyzed, both before as well as during the financial crisis.

The remainder of the paper is organized as follows. Section 2 gives an overview of the factor models of Stock and Watson (2002), Bańbura and Rünstler (2011), and Bräuning and Koopman (2014) and introduces the modifications we propose for the Bańbura and Rünstler (2011) and Bräuning and Koopman (2014) models. Section 3 provides details on the construction of the database, the forecast setup and model specification issues (e.g. selection of the number of common factors and lags). Section 4 discusses the empirical results of our forecasting study. We summarize our findings in Section 5.

2 Factor models using principal components

This section describes the three factor models that are analyzed in our forecasting study: the principal components in an autoregressive model as proposed by Stock and Watson (2002), the high-dimensional dynamic factor model of Bańbura and Rünstler (2011), and the (collapsed) low-dimensional dynamic factor model of Bräuning and Koopman (2014). We focus on forecasting the quarterly GDP growth rate (quarter on quarter), denoted as $y_{t_q}^Q$, where $t_q = 1, \ldots, T_q$ is the quarterly time index. Following the usual statistical convention we express the quarterly GDP growth rate at the monthly frequency by defining y_t^Q such that it contains the quarterly GDP growth rate ($y_{t_q}^Q$) in the third month of each quarter ($t = 3t_q$), and missings otherwise, where $t = 1, \ldots, T$ is the monthly time index. The reverse relation is $T_q = \lfloor T/3 \rfloor$. We define y_t as the latent monthly GDP growth rate, i.e. the 3-month growth rate with respect to the corresponding month of the previous quarter. The notation y_t^* is used to indicate the mean-adjusted series of y_t, that is $y_t^* = y_t - \bar{y}$ where $\bar{y}$ is the sample mean of y_t.

The factor models that we describe in the remainder of this section all use principal component analysis to extract r monthly common factors, F_t, from a N-dimensional standardized stationary monthly time series of candidate predictors, X_t, for $t = 1, \ldots, T$. We denote the matrix of eigenvalues (or factor loadings) as Λ. We use notation $F_{t_q}^Q$ to indicate the r quarterly factors, that we calculate by taking 3-month averages of F_t.

2.1 Stock and Watson: autoregression with principal components

The Stock and Watson (2002) model aims at forecasting a single time series with length T, using a large number N of candidate predictor series, where typically $N >> T$. The high-dimensional problem is reduced to an autoregressive model for the key economic time series of interest and extended by a small number of principal components that are used as predictors. Forecasting is then carried out in a two-step procedure: first, a collection of factors is estimated from the candidate predictors; second, the relationship between the variable to forecast and the estimated factors is estimated by ordinary least squares (OLS) regression.

In our application we use the Stock and Watson (2002) model to forecast the quarterly GDP growth rate. We assume that $(X_t, y_{t_q+h}^Q)$ can be described as a factor model representation such that

$$X_t = \Lambda F_t + e_t, \qquad t = 1, \ldots, T, \tag{1}$$

and

$$y_{t_q+h}^Q = \alpha_h + \beta_h(L) F_{t_q}^Q + \gamma_h(L) y_{t_q}^Q + \varepsilon_{t_q+h}^Q, \qquad t_q = 1 \ldots, \lfloor T/3 \rfloor, \tag{2}$$

where e_t is a vector of idiosyncratic disturbances, h is the forecast horizon, α_h is the constant term, $\beta_h(L)$ and $\gamma_h(L)$ are finite order lag polynomials to give dynamics in the model. $y_{t_q+h}^Q$ is the variable to forecast using $(X_t, y_{t_q}^Q)$, and $\varepsilon_{t_q+h}^Q$ is the resulting forecast error. Note that the subscripts in the coefficients of the above forecast equation reflect the dependence of the projection on the forecast horizon. This means that we re-estimate the model coefficients for each forecast horizon h, holding the set of explanatory variables fixed. The matrix of factor loadings Λ in equation (1) is estimated from a static principal components analysis, applied to a balanced sub-sample of matrix X_t. The balanced sub-sample is obtained by discarding all of the rows containing missing values at the end of the estimation period. This typically only involves removing the last few rows that are not completely filled due to publication delays. The missing values at the beginning of the total sample are dealt with by using the Expectation Maximization (EM) algorithm as described in Stock and Watson (2002). We use a fixed lag structure equal to two for both lag-polynomials $\beta_h(L)$ and $\gamma_h(L)$. The parameters in forecast equation (2) are estimated by OLS.

2.2 Bańbura and Rünstler: high-dimensional dynamic factor model

The Bańbura and Rünstler (2011) model is based on the dynamic factor model of Giannone et al. (2008), which is given by

$$X_t = \Lambda F_t + e_t, \qquad e_t \sim N(0, \Sigma_e), \tag{3}$$

$$F_t = \sum_{j=1}^{p} \Phi_j F_{t-j} + \zeta_t, \qquad \zeta_t = B\eta_t, \qquad \eta_t \sim N(0, I_q), \tag{4}$$

where the latent factors F_t are assumed to be driven by a q-dimensional standardized white noise η_t, and where B is a $r \times q$ matrix with $q < r$, so that $\zeta_t = B\eta_t \sim N(0, BB')$. The stochastic process for F_t is assumed to be a stationary VAR(p) process. It is also assumed that the idiosyncratic disturbances e_t has a diagonal covariance matrix Σ_e.

The above specification differs from the presentation of Stock and Watson (2002) as the dynamics of the factors are modeled explicitly through equation (4) before entering the forecast equation. Moreover, the equations are cast in state space, enabling efficient handling of the jagged edges in the data and allow easy forecasting via the Kalman filter and smoother. Bańbura and Rünstler (2011) argue that exploiting the dynamics of the estimated latent factors can help to improve the accuracy.

The forecast equation is constructed by combining the monthly factor model in equations (3)-(4) with a forecast equation for mean-adjusted quarterly GDP growth in a mixed-frequency approach, see e.g. Mariano and Murasawa (2003), where the latent mean-adjusted monthly GDP growth rate y_t^* is introduced and is related to the common factors as follows,

$$y_t^* = \beta' F_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2), \qquad t = 1, \ldots, T. \tag{5}$$

The latent monthly variable y_T^* will be estimated via the Kalman filter. To complete the model, Bańbura and Rünstler (2011) assume that the innovations in (3)-(5) e_t, ζ_t and ε_t are mutually independent at all leads and lags.

The relationship between the observed quarterly GDP growth rate and the latent monthly GDP growth rate is introduced via a recursive latent cumulator variable y_t^{*C}, as introduced in Chapter 8 of Harvey (1989), where

$$y_{t+1}^{*C} = \delta_t y_t^{*C} + \frac{1}{3} y_{t+1}^*, \qquad \delta_t = \begin{cases} 0, & t = 3t_q, \\ 1, & \text{otherwise}, \end{cases} \tag{6}$$

for $t = 1, \ldots, T$ and $t_q = 1, 2, \ldots, \lfloor T/3 \rfloor$. To initialize the cumulator variable, it is assumed that $y_1^{*C} = \frac{1}{3} y_1^*$. The above rule implies that for $t = 3t_q$, y_t^{*C} is the average of the mean-adjusted latent monthly series within quarter t_q, which equals the observed mean-adjusted quarterly GDP growth.

Equation (3)-(6) are cast in state space form to enable straightforward forecasting. To illustrate, the observation equation for $r = 1$ and $p = 2$ is defined as:

$$\begin{pmatrix} X_t \\ y_t^Q \end{pmatrix} = \begin{pmatrix} 0 \\ \mu \end{pmatrix} + \begin{bmatrix} \Lambda & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} F_t \\ F_{t-1} \\ y_t^* \\ y_t^{*C} \end{pmatrix} + \begin{pmatrix} e_t \\ 0 \end{pmatrix}, \tag{7}$$

for $t = 1, \ldots, T$, where μ is the unconditional mean of the observed quarterly GDP growth rates. The transition equation is given by

$$\begin{bmatrix} I_r & 0 & 0 & 0 \\ 0 & I_r & 0 & 0 \\ -\beta' & 0 & 1 & 0 \\ 0 & 0 & -1/3 & 1 \end{bmatrix} \begin{pmatrix} F_{t+1} \\ F_t \\ y_{t+1}^* \\ y_{t+1}^{*C} \end{pmatrix} = \begin{bmatrix} \Phi_1 & \Phi_2 & 0 & 0 \\ I_r & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \delta_t \end{bmatrix} \begin{pmatrix} F_t \\ F_{t-1} \\ y_t^* \\ y_t^{*C} \end{pmatrix} + \begin{pmatrix} \zeta_t \\ 0 \\ \varepsilon_t \\ 0 \end{pmatrix}, \tag{8}$$

Bańbura and Rünstler (2011) estimate all parameters in equations (3)-(5) separately outside the state space model framework. The estimation of equation (3)-(4) and the statistical properties of the estimators are explained in detail by Doz et al. (2011). In summary, the matrix of factor loadings Λ in equation (3) is estimated from a static principal components analysis, applied to a balanced sub-sample of matrix X_t. The balanced sub-sample is obtained by discarding all of the rows that contain missing values at the end of the estimation period. This typically only involves removing the last few rows that are not completely filled due to publication delays. We deal with the missing values at the beginning of the sample by replacing these with the means of the predictors in X_t. Note that in our application these means are zero since the predictors in X_t are standardized. Principal component analysis, which was applied in equation (3), also gives the sample estimates of the common factors F_t, which are then plugged into equation (4). The estimation of parameters Φ_i is done by OLS and matrix B is estimated by another round of principal component analysis applied to the estimated residuals $\hat{\zeta}_t$. For the estimation of β' in equation (5), OLS is applied to the quarterly version of this equation, i.e.:

$$y_{t_q}^{*Q} = \beta' F_{t_q}^Q + \varepsilon_{t_q}^Q, \qquad t_q = 1, \ldots, T_q. \tag{9}$$

The disturbance variance σ_ε^2 in equation (5) is estimated as one-third of the sample variance of $\varepsilon_{t_q}^Q$. The estimated factor loadings and parameters are then used in the state space matrices together with the full matrix X_t, including the jagged edges at the end of the sample. Since the above model kept the estimated factor loadings $\hat{\Lambda}$ and diagonal covariance matrix $\hat{\Sigma}_e$ fixed in equation (7), the Kalman filter automatically reconstructs the unobserved common factors F_t.

2.3 Bańbura and Rünstler: an extension

Following literature studies and the results of Jansen et al. (2012), adding an autoregressive (AR) component into the forecast equation might significantly improve the accuracy of the GDP forecast. Therefore we add two autoregressive terms of y_t in equation (5) of Bańbura and Rünstler (2011). We call this model the augmented Bańbura and Rünstler factor model. The relationship between the latent monthly GDP growth rate and the common factor becomes,

$$y_t^* = \phi_1 y_{t-1}^* + \phi_2 y_{t-2}^* + \beta' F_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2), \tag{10}$$

for $t = 1, \ldots, T$, where ϕ_1 and ϕ_2 are the additional AR(2) coefficients. We then adjust the state space form accordingly. To illustrate, the observation equation for $r = 1$ and $p = 2$ is defined as:

$$\begin{pmatrix} X_t \\ y_t^Q \end{pmatrix} = \begin{pmatrix} 0 \\ \mu \end{pmatrix} + \begin{bmatrix} \Lambda & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} F_t \\ F_{t-1} \\ y_t^* \\ y_{t-1}^* \\ y_t^{*C} \end{pmatrix} + \begin{pmatrix} e_t \\ 0 \end{pmatrix}, \tag{11}$$

where μ is the unconditional mean of y_t^Q. The transition equation is given by:

$$\begin{bmatrix} I_r & 0 & 0 & 0 & 0 \\ 0 & I_r & 0 & 0 & 0 \\ -\beta' & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & -1/3 & 0 & 1 \end{bmatrix} \begin{pmatrix} F_{t+1} \\ F_t \\ y_{t+1}^* \\ y_t^* \\ y_{t+1}^{*C} \end{pmatrix} = \begin{bmatrix} \Phi_1 & \Phi_2 & 0 & 0 & 0 \\ I_r & 0 & 0 & 0 & 0 \\ 0 & 0 & \phi_1 & \phi_2 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & \delta_t \end{bmatrix} \begin{pmatrix} F_t \\ F_{t-1} \\ y_t^* \\ y_{t-1}^* \\ y_t^{*C} \end{pmatrix} + \begin{pmatrix} \zeta_t \\ 0 \\ \varepsilon_t \\ 0 \\ 0 \end{pmatrix}. \tag{12}$$

We estimate the parameters ϕ_1, ϕ_2 and β' in equation (12) by OLS on the quarterly version of equation (10), which is given by

$$y_{t_q}^{*Q} = \phi_1 y_{t_q-1}^{*Q} + \phi_2 y_{t_q-2}^{*Q} + \beta' F_{t_q}^Q + \varepsilon_{t_q}^Q, \qquad t_q = 1, \ldots, T_q. \tag{13}$$

2.4 Bräuning and Koopman: collapsed dynamic factor model

The collapsed factor model by Bräuning and Koopman (2014) is constructed in order to avoid the estimation of many unknown parameters due to the large dimensionality of matrix X_t. The Bräuning and Koopman (2014) model simultaneously estimates all model parameters and predicts the target variable simultaneously in one parsimonious framework. The state space framework enables easy estimation by using maximum likelihood, whilst the Kalman filter allows consistent forecasting. As illustration of the general modeling framework of Bräuning and Koopman (2014), we consider the following factor model to forecast the quarterly GDP growth rate with the help of its own dynamics and a set of latent factors,

$$\begin{aligned} X_t &= \Lambda F_t + e_t & e_t &\sim N(0, \Sigma_e), \\ y_t^Q &= \mu_t + \Gamma_\psi \psi_t + \Gamma_F F_t + \varepsilon_t, & \varepsilon_t &\sim N(0, \sigma_\varepsilon^2), \end{aligned} \tag{14}$$

for $t = 1, \ldots, T$ and where ψ_t is defined as the stochastic cyclical component, see Durbin and Koopman (2012). The interaction between X_t and y_t^Q can be specified in matrix form as follows,

$$\begin{pmatrix} y_t^Q \\ X_t \end{pmatrix} = \begin{pmatrix} \mu \\ 0 \end{pmatrix} + \begin{bmatrix} \Gamma_\psi & \Gamma_F \\ 0 & \Lambda \end{bmatrix} \begin{pmatrix} \psi_t \\ F_t \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ e_t \end{pmatrix}, \qquad t = 1, \ldots, T. \tag{15}$$

Bräuning and Koopman (2014) reduce the high dimensionality of X_t and its corresponding matrix of factor loadings Λ by pre-multiplying equation (15) by the transformation matrix P defined as

$$P = \begin{pmatrix} 1 & 0 \\ 0 & A_{PC} \end{pmatrix}, \tag{16}$$

where A_{PC} is an $r \times N$ matrix and r is the dimension of the numbers of latent factors in F_t. The matrix A_{PC} is based on the eigenvectors associated with the r largest eigenvalues of the $N \times N$ sample covariance matrix of X_t, such that the principal component estimates can be presented by:

$$\hat{F}_{PC,t} = A_{PC} X_t, \qquad\qquad t = 1, \ldots, T.$$

Further, it is assumed that $\hat{F}_{PC,t} = F_t +$ error by imposing $A_{PC}\Lambda = I_r$. Summarized, the collapsed dynamic factor model can be written as

$$\begin{pmatrix} y_t^Q \\ \hat{F}_{PC,t} \end{pmatrix} = \begin{pmatrix} \mu \\ 0 \end{pmatrix} + \begin{pmatrix} \Gamma_\psi & \Gamma_F \\ 0 & I_r \end{pmatrix} \begin{pmatrix} \psi_t \\ F_t \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ \tilde{e}_t \end{pmatrix}, \qquad t = 1, \ldots, T, \tag{17}$$

where $\tilde{e}_t = A_{PC}(e_t - [A'_{PC} - \Lambda]F_t)$. This error is expected to be small so that the disturbance $\tilde{e}_t$ has a zero mean and a diagonal variance matrix by construction. In the model, $\mathbb{V}\mathrm{ar}(\tilde{e}_t)$ is treated as an unknown variance matrix and is to be estimated.

The specification of latent variables ψ_t and F_t is given by AR(p_ψ) and VAR(p_F), respectively, with diagonal innovations variance matrix. Together with the cumulator variable y_t^{*C} in equation (6), the state space representation of the collapsed dynamic factor model for $p_\psi = p_F = 2$ and $r = 1$ is constructed as follows. The observation equation becomes,

$$\begin{pmatrix} y_t^Q \\ \hat{F}_{PC1,t} \end{pmatrix} = \begin{pmatrix} \mu \\ 0 \end{pmatrix} + \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{pmatrix} y_t^* \\ y_t^{*C} \\ \psi_t \\ \psi_{t-1} \\ F_{1,t} \\ F_{1,t-1} \end{pmatrix} + \begin{pmatrix} 0 \\ \tilde{e}_t \end{pmatrix}, \tag{18}$$

for $t = 1, \ldots, T$, and where μ is the unconditional mean of the observed quarterly GDP growth rate. The transition equation is given by

$$\begin{bmatrix} -1/3 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & -\Gamma_\psi & 0 & -\Gamma_{F_1} & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} y_{t+1}^* \\ y_{t+1}^{*C} \\ \psi_{t+1} \\ \psi_t \\ F_{1,t+1} \\ F_{1,t} \end{pmatrix} = \begin{bmatrix} 0 & \delta_t & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \phi_1 & \phi_2 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \tilde{\phi}_1 & \tilde{\phi}_2 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{pmatrix} y_t^* \\ y_t^{*C} \\ \psi_t \\ \psi_{t-1} \\ F_{1,t} \\ F_{1,t-1} \end{pmatrix} + \begin{pmatrix} 0 \\ \varepsilon_t \\ \kappa_t \\ 0 \\ \zeta_{1,t} \\ 0 \end{pmatrix}, \tag{19}$$

As summarized in Bräuning and Koopman (2014), the collapsed dynamic factor model procedure is a two-step process. The first step is to carry out a principal component analysis for dimension reduction of the large panel of indicators, equivalently to Stock and Watson (2002) and Bańbura and Rünstler (2011). In the second step, Bräuning and Koopman (2014) model the estimated principal components ($\hat{F}_{PC,t}$) jointly with the target variable (y_t^Q) in a state space model that includes a small number of parameters. The unknown parameters are then estimated simultaneously by maximum likelihood in a standard setting. This differs from the second step in the Bańbura and Rünstler (2011) model, where all model parameters are estimated separately outside the state space framework.

In the collapsed dynamic factor model it is crucial to pre-treat the jagged edges in the dataset before extracting the monthly factors. This contrasts with the Bańbura and Rünstler (2011) model, that include the jagged edges in the matrix X_t in the state-space framework. In that setup, the Kalman filter and smoother automatically deal with the missing values in the X_t matrix, using the specified parameters. The model of Bräuning and Koopman

(2014) does not include the jagged edges in X_t in the state-space setup, but only contains the estimated principal components $\hat{F}_{PC,t}$. If missing values in the matrix of candidate predictors X_t are ignored at the end of the sample, the model of Bräuning and Koopman (2014) is incapable of taking into account the latest information. To deal with the missing values at the beginning and the end of X_t we use a simple stationary ARMA(p, q) process, which is applied separately for each $X_{i,t}$, $i = 1, \ldots, N$. The parameters of the ARMA(p, q) specification are estimated by using maximum likelihood in a state space framework. The Kalman filter and smoother are used to obtain a balanced dataset. The size of the balanced dataset is determined by the series $X_{i,t}$ in X_t with the shortest publication lag. Note that all $X_{i,t}$ are standardized and rendered stationary before estimation (see section 3.1), so the use of an ARMA process is justified. To keep the process simple, we use an AR(2) model to deal with the jagged edges. The AR(2) process ensures that the variables return fairly quickly to their long-term trend. Figure 1 presents the idea for two variables j and k in our monthly dataset, where variable j contains missing values only at the beginning of the sample and variable k contains missing values only at the end of the sample. The x-axis shows the year and quarters and the y-axis shows the 3-month growth rate. The red dots show the realizations and the blue lines show the smoothed signal of the AR(2) process.

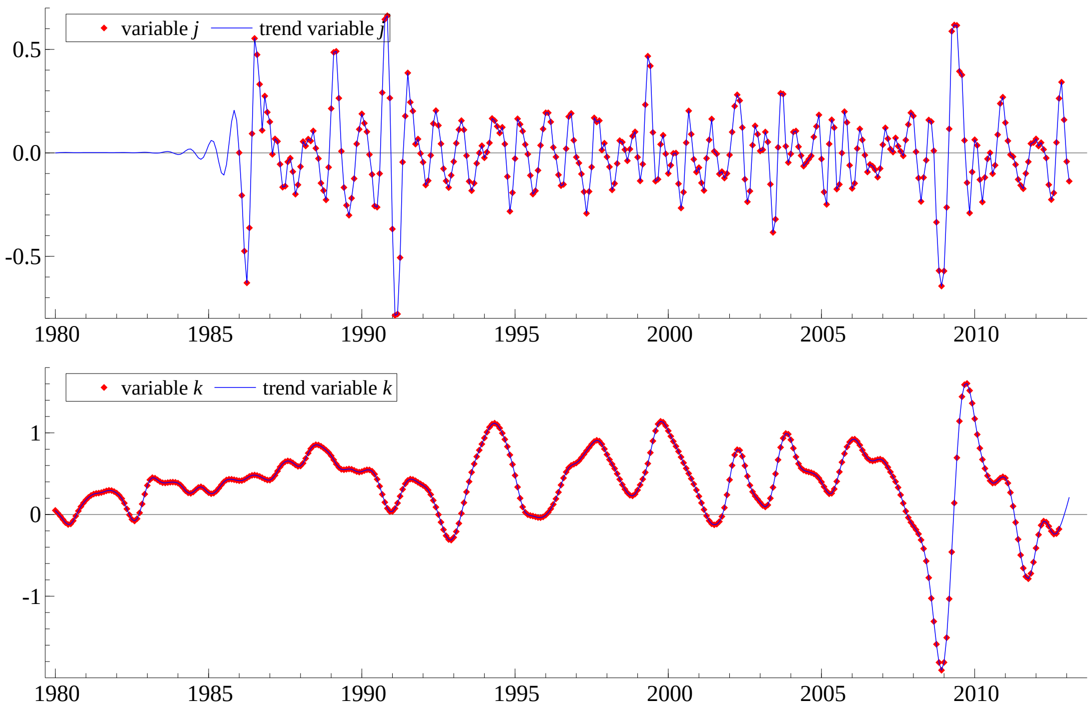

Figure 1: Dealing with the jagged edges of variables j and k using the smoothed signal of an AR(2).

3 Data, forecast design and specification issues

3.1 Dataset

Our monthly dataset of predictors consists of 52 monthly time-series, using harmonized definitions across countries. The monthly predictors fall into four predefined categories: production & sales, prices, monetary & financial indicators and surveys. Table IV in the

Appendix provides an overview of all variables, the applied transformations and the starting date of the monthly series for each country in our sample. Monthly data are usually available on a seasonally (and calendar effects) adjusted basis at the source. When necessary, raw data series are seasonally adjusted by the US Census X12-ARIMA-program. All monthly series are made stationary by differencing or log-differencing (in case of trending data, such as industrial production, retail sales and monetary aggregates). Thereafter, the variables are standardized by subtracting the mean and dividing them by their standard deviation. This standardization is necessary to avoid overweighting of large variance series in the extraction of common factors.

The primary source of the data is the ECB statistical data warehouse.[1] The world trade series are taken from the CPB world trade monitor.[2] Since the CPB world trade series only start in 1991 we backdated the series using world trade data from the IMF. Time series on industrial production for the United States are downloaded from the Board of Governors of the Federal Reserve System.[3] The Commodity prices and most financial market indicators are taken from Thomson Reuters Datastream. Survey data are taken from the European Commission[4] and the Purchasing Managers Indices for the United States and United Kingdom are from Markit.[5]

The quarterly GDP series for Italy, Spain and the Netherlands start in the first quarter of 1981.I, 2000.I and 1988.I, respectively. To backdate the GDP series to 1980.I we use the OECD release data and revisions database that contains historical GDP vintages.[6] The backdated GDP series were constructed by applying the quarter-on-quarter growth rates from the most recent OECD GDP vintages. In detail: for Italy we used the March 2013 and April 2006 vintages, for Spain the March 2013, November 2011, May 2005 and July 1999 vintages and for the Netherlands the March 2013 and July 2005 vintages. Quarterly GDP data for Germany were taken from the Deutsche Bundesbank[7] who constructed the GDP series using only GDP data for West Germany pre 1991.I and the re-unified Germany from 1991.I onwards. We constructed a synthetic GDP series for the euro area using the database underlying the ECB's Area Wide Model,[8] supplemented with data from the OECD database.

3.2 Pseudo real-time design

The forecast design aims to replicate the availability of the data at the time forecasts are made in order to mimic the real-time flow of information as closely as possible. To this end, we used a data set downloaded on March 4, 2013 and combined this with the typical data release calendar to reconstruct the available dataset on the 4^{th} of each month during the period January 1992 – December 2012. We construct the database such that the earliest starting date for the monthly series is January 1980, and the first quarter of 1980 for GDP. We thus employ a pseudo real-time design, which takes data publication delays into account, but ignores the possibility of data revisions for GDP and some indicators, such as industrial production. The latter implies that we might overestimate the forecast accuracy. However,

[1] `http://sdw.ecb.europa.eu`
[2] `http://www.cpb.nl/en/world-trade-monitor`
[3] `http://www.federalreserve.gov/releases/g17/Current`
[4] `http://ec.europa.eu/economy_finance/db_indicators/surveys/index_en.htm`
[5] `http://www.markit.com/en/products/research-and-reports/pmis/pmi.page`
[6] `http://stats.oecd.org/Index.aspx?querytype=view&queryname=206`
[7] `http://www.bundesbank.de/Navigation/EN/Home/home_node.html`
[8] `http://www.eabcn.org/data/awm/index.htm`

large real-time datasets for the countries we considered are not (yet) available. Moreover, the effects of data revisions on the forecasts of factor might largely cancel out, as has been documented by i.e. Bernanke and Boivin (2003) for the United States and Schumacher and Breitung (2008) for Germany.

We estimate the parameters of all models recursively, using only the information available at the time of the forecast, see Rünstler et al. (2009); Giannone et al. (2008); Kuzin et al. (2011), among others, for a similar approach. We construct a sequence of eleven forecasts for GDP growth in a given quarter, obtained in consecutive months. Table I explains the timing of the forecasting exercise, taking the forecast for the third quarter of 2012 as an example. We make the first forecast on January 4, 2012 which is called the two-quarter-ahead forecast in month one. We subsequently produce a monthly forecast for the next ten months, from February until November. The last forecast is made on November 4, 2012, approximately a week and a half before the flash release of GDP in mid-November. Following the conventional terminology, *forecasts* refer to one or two-quarter ahead forecasts, *nowcasts* refer to current quarter forecasts and *backcasts* refer to forecasts for the preceding quarter, as long as official GDP figures are not yet available. In our example, we make two-quarter ahead forecasts from January to March, one-quarter ahead forecasts from April to June, nowcasts from July to September, and backcasts in October and November.

Table I: Timing of forecast exercise (example: forecast for 2012.III)

Nr.	Name	Forecast made on the 4^{th} of
1		January
2	2Q ahead	February
3		March
4		April
5	1Q ahead	May
6		June
7		July
8	Nowcast	August
9		September
10		October
11	Backcast	November

3.3 Choosing the appropriate model specification

Estimation of the factor models requires explicit specification of the r factors (F_t). One approach is to determine the number of factors by applying information criteria. However, as noted in recent contributions, the application of information criteria might lead to inferior model specifications in terms of forecast accuracy, see Bernanke and Boivin (2003); Giannone et al. (2005); Boivin and Ng (2005). An alternative to using information criteria is to pool over different model specifications. In this paper we follow Kuzin et al. (2013), who conclude that taking the unweighted averaged forecast over all possible specifications of the factor models is superior to the use of information criteria or more complicated weighting schemes.

We limit our model specifications to models with two lags in the (vector) autoregressive dynamics and a maximum of four static factors. The upper bound of four was derived from the scree test of Cattell (1966) using normalized eigenvalues calculated from the set of

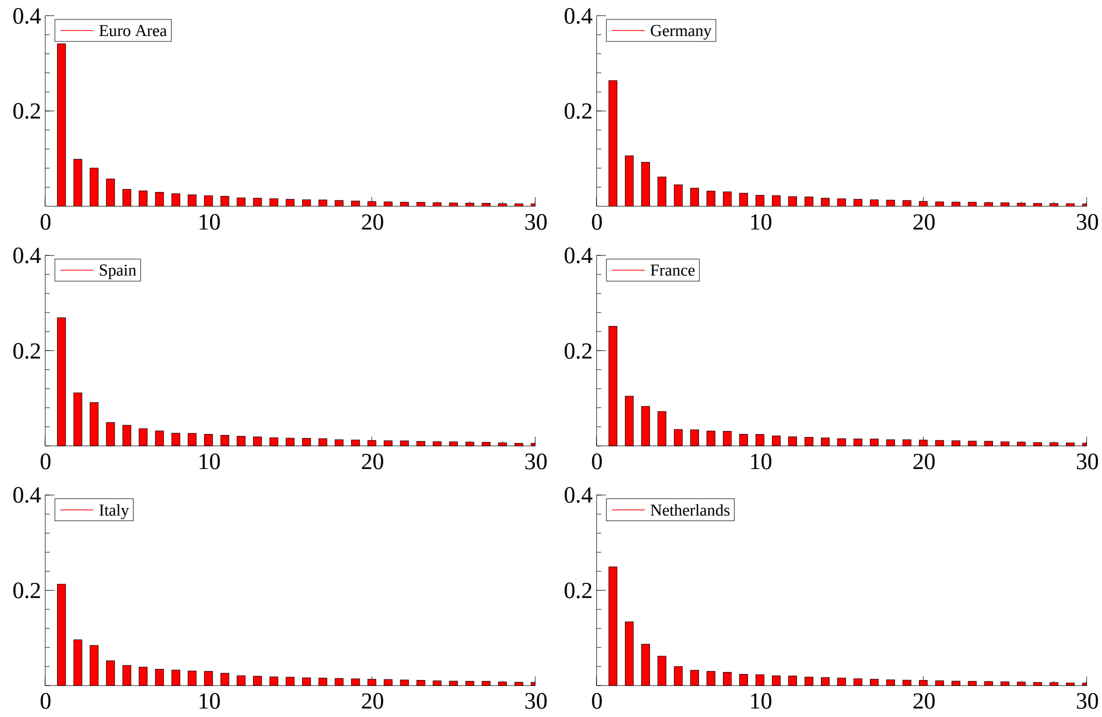

Figure 2: Scree plots of normalized eigenvalues computed from the set of candidate predictors (euro area and its five largest countries)

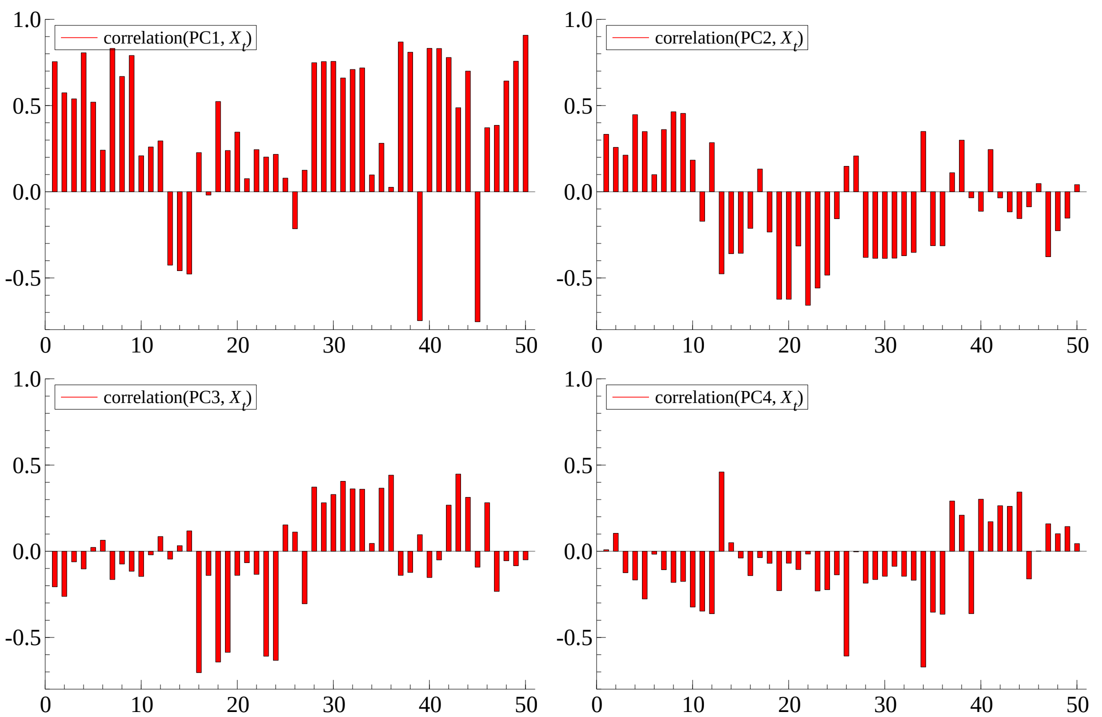

Figure 3: Correlation principal components (PCs) with the set of candidate predictors (euro area)

candidate predictors. Figure 2 shows the scree plots for the euro area and its five largest countries, where the normalized eigenvalues of the largest thirty principal components are presented. The plots show that the first principal component is able to explain between 20 and 30 percent of the comovement in the set of candidate predictors. Moreover, the explanatory power increases only very slightly after the fourth principal component. Figure 3 shows the correlation of the first four estimated principal components with the matrix of candidate predictors for the euro area.The x-axis shows the candidate variables that correspond to the numbers in Table IV in the Appendix, the y-axis shows the correlations in percent. The first principal component is strongly correlated with a broad range of variables apart from prices, which is in accordance with the high eigenvalue. This indicates that the bulk of the covariance of the candidate predictors can be explained by the first factor. The second and third principal components are strongly correlated with price variables, such as HICP, commodity prices and oil price, whilst the fourth principal component is highly correlated with financial variables, such as interest rates and exchange rates.

The factor model of Bańbura and Rünstler (2011) also requires a choice on the number of principal components to extract from the disturbance matrix in equation (4), the so called "dynamic" factors q. We followed a similar procedure as in Bańbura and Rünstler (2011) by imposing the restrictions $r \leq 4$ and $q \leq r$. The second restriction is motivated by the finding of D'Agostino and Giannone (2012) who stated that restricting the number of dynamic factors to be equal or less than the number of static factors does not hurt predictive power. Moreover, we need to choose between the original Bańbura and Rünstler (2011) and the augmented version of the model. Table IX in the Appendix compares the forecast accuracy of the original Bańbura and Rünstler (2011) model with the augmented version. We conclude that the forecast accuracy increases when the augmented version of the Bańbura and Rünstler (2011) model is used, though the differences are usually quite small. In the Tables in the remainder of this paper we will show the forecast accuracy of the augmented Bańbura and Rünstler (2011) model.

4 Empirical results

4.1 Forecast accuracy using the complete sample

This subsection describes the forecast accuracy of the factor models versus the benchmark model. The benchmark model is an autoregression of order 2. The factor models are the principal component model of Stock and Watson (SW), the augmented dynamic factor model of Bańbura and Rünstler (BR) and the collapsed dynamic factor model (CFM). In our analysis, we analyze the forecast performance for the euro area (EA) and its five largest countries, i.e.: Germany (DE), France (FR), Italy (IT), Spain (ES) and the Netherlands (NL). We measure forecast accuracy as the mean squared forecast error (MSFE).

Table II presents the forecast performance of the three factor models and the benchmark model for our five countries and the euro area for the complete length of the sample (1992.I–2012.IV). The underlying empirical analysis has been carried out on a monthly basis for eleven horizons. To keep the table parsimonious we only report the average forecast accuracy for the one and two quarter ahead forecast, the nowcast and the backcast.[9] Moreover, the presented MSFEs are averaged over model specifications with one to four factors. The rows labeled AR(2) report the MSFE of the benchmark model. For the three factor models, the entries

[9] The forecast for the months within the quarters are available from the authors upon request.

Table II: Forecast accuracy dynamic factor models (MSFE), 1992.I-2012.IV

	EA	DE	FR	IT	ES	NL
	Absolute					
AR(2)						
All horizons	*0.42*	*0.79*	*0.26*	*0.57*	*0.39*	*0.51*
2Q ahead forecast	*0.49*	*0.81*	*0.34*	*0.66*	*0.46*	*0.56*
1Q ahead forecast	*0.45*	*0.81*	*0.28*	*0.60*	*0.41*	*0.53*
Nowcast	*0.39*	*0.78*	*0.21*	*0.53*	*0.35*	*0.49*
Backcast	*0.32*	*0.76*	*0.16*	*0.47*	*0.31*	*0.45*
	Relative to AR(2) model					
BR						
All horizons	0.70	**0.81**	1.18	**0.74**	**0.93**	**0.76**
2Q ahead forecast	**0.79**	**0.93**	1.11	0.86	**0.99**	**0.92**
1Q ahead forecast	0.72	**0.85**	1.15	0.81	0.90	0.76
Nowcast	0.62	0.77	1.31	**0.63**	0.93	**0.65**
Backcast	0.57	**0.62**	1.23	0.57	0.83	**0.64**
CFM						
All horizons	0.60	0.78	0.86	0.68	0.84	0.70
2Q ahead forecast	0.74	0.85	0.89	0.77	0.94	0.85
1Q ahead forecast	0.62	0.83	0.86	0.73	**0.90**	0.69
Nowcast	0.51	**0.78**	0.85	0.63	0.75	0.60
Backcast	0.38	0.58	0.80	0.50	0.67	0.61
SW						
All horizons	0.87	1.04	**0.93**	0.85	**0.87**	0.88
2Q ahead forecast	0.94	1.18	0.99	0.85	1.03	1.00
1Q ahead forecast	0.92	1.12	**0.93**	0.88	**0.85**	0.94
Nowcast	0.82	0.95	**0.85**	0.87	**0.76**	0.78
Backcast	0.68	0.85	**0.87**	0.77	0.77	0.70

This table presents the MSFEs of backcasts, nowcasts, one quarter ahead forecasts and two quarter ahead forecasts as well as the average MSFE over all these horizons. The benchmark model is an autoregression of order 2 (AR(2)). The factor models are: the principal component model with diffusion index of Stock and Watson (SW), the augmented dynamic factor model of Bańbura and Rünstler (BR) and the collapsed dynamic factor model (CFM). The country codes are: Euro Area (EA), Germany (DE), France (FR), Italy (IT), Spain (ES) and the Netherlands (NL). The model forecasts are averaged over model specifications with **one to four factors**. The smallest MSFE for each horizon is highlighted. MSFEs that are at most 10% larger than the MSFE of the best model and also smaller than the MSFE of the benchmark model are in boldface.

refer to their MSFE relative to the benchmark model in order to improve comparability of the results across countries and horizons. Shaded areas indicate the model with the lowest MSFE for a particular forecast horizon and a particular country. Bold faced entries indicate models that have an MSFE that is less than 10% larger than that of the best model and also smaller than the MSFE of the benchmark model. The 10% threshold is meant as a rough assessment of the economic significance of differences in forecasting ability. We will call models that meet this condition "competitive models" as in terms of forecast performance they do no differ "too much" from the best model.[10] The outcomes in Table II point to several interesting results.

First, incorporating monthly information in a factor model pays off in terms of forecast accuracy, in particular for nowcasts and backcasts. Averaged over all horizons and countries, the improvement for the best models is around 26% on the benchmark AR(2) model, whilst the worst model still posts a gain of 9% on the benchmark. The results also indicate that predictions by the factor models deteriorate when the forecast horizon is longer. This is in line with previous research, that concludes that factor models are suitable for making nowcasts and backcasts but less suited for forecasting one and two quarters ahead, e.g. Giannone et al. (2008), Rünstler et al. (2009) and Bańbura and Rünstler (2011).

Second, the collapsed dynamic factor model displays the highest forecast accuracy. Looking across all countries and horizons, the collapsed dynamic factor model performs the best. The only exceptions are the nowcasts for Germany and the one quarter ahead forecast for Spain. However, in both cases the difference with the best model is negligible. The collapsed dynamic factor model post the highest gains in forecast accuracy on the benchmark model for the euro area, ranging from an average improvement of 26% for the two quarter ahead forecast to 62% for the backcasts.

Third, the collapsed dynamic factor model is the only model that beats the benchmark model by more than 10% or more across most countries and forecast horizons. The other two factor models have a less favorable forecast performance, i.e: the augmented Bańbura and Rünstler (2011) model fails to beat the benchmark model in France for all forecast horizons, whilst the Stock and Watson (2002) model is unable to outperform the benchmark model for Germany, Spain and the Netherlands when forecasting one or two quarters ahead.

The first result is yet another piece of empirical evidence that predictions by factor models are especially well suited for nowcasting and backcasting. The second result suggests that the collapsed dynamic factor model displays a significantly larger ability to absorb monthly information than the other two factor models we considered.

The relatively good forecast performance of the collapsed dynamic factor model is robust to model specification, as shown in Table V to VIII in the Appendix. The Tables show the forecast accuracy for model specifications with one to four factors respectively for all factor models.

4.2 Forecast accuracy during the Great Moderation and the Great Recession

Our sample includes the period of financial crisis. During this period there was a sharp drop in a broad range of indicators, including manufacturing, confidence indicators and exports. As a consequence real GDP growth sharply dropped across all industrialized countries. An interesting question is whether and to what extent the performance of the factor models

[10] We also conducted conventional statistical tests but -like other authors- we found these are not discriminating in practice. Details are available from the authors upon request.

differs between the volatile financial crisis and the years before, that can be characterized as a relatively stable period. Forecasting in times of crisis of course poses greater challenges, so the results of a comparative analysis might be more informative on the issue which factor model is best suited to forecast GDP growth. To determine the influence of the financial crisis on the forecast accuracy of the factor models we divide the sample into two periods, i.e. 1992.I-2007.IV and 2008.I-2012.IV. We call the latter period the "Great Recession" and the former the "Great Recession". Table III presents the outcome of the forecast performance of the three factor models and the benchmark model for our five countries and the euro area during both periods. The comparison of these two distinct periods points to some interesting results that we describe as follows.

First, predicting GDP growth during the Great Recession is more difficult than during the Great Moderation. Depending on the country analyzed, the MSFE of the benchmark model during the Great Recession is two to six times larger than during the Great Moderation. This deterioration is partly offset as the scope for improving forecast by using monthly information appears to be larger during the Great Recession, in particular for nowcasting and backcasting. For example, the relative MSFE of the collapsed dynamic factor model improves by 51% during the Great Recession, compared to 14% during the Great Moderation. This finding is consistent with the results of D'Agostino and Giannone (2012) and Jansen et al. (2012). Both studies show that the gain in forecast accuracy is especially sizeable in periods of large swings and high comovement in the monthly predictors, as was the case during the Great Recession.

Second, averaged over all horizons the collapsed dynamic factor model is the best or a competitive model during the Great Recession. This indicates that the model structure of the collapsed dynamic factor model is best suited to process monthly information in volatile times. This conclusion also holds for most countries when we analyze the forecast performance for each forecast horizon separately. The maximum gain in forecast accuracy against the benchmark model was 77%, recorded for the backcasts in the euro area. However, there are two exceptions. In Spain the collapsed dynamic factor model is not competitive when nowcasting and forecasting one quarter ahead, whilst in Germany the model is not competitive when backcasting and nowcasting.

Third, during the Great Moderation the collapsed factor model is still the best model for most of the countries, but not for all countries. Averaged across forecast horizon the collapsed dynamic factor model is the best model for the euro area and three out of the five countries we analyzed (Germany, Italy, Spain), but for the Netherlands the forecast accuracy of the Bańbura and Rünstler (2011) is higher for all horizons. In France, none of the factor models is able to beat the benchmark model.

Last, the low forecast accuracy of the Stock and Watson (2002) model during the Great Moderation is quite striking. The model is unable to beat the benchmark model for the majority of countries and forecast horizons.

Overall, splitting the total sample period into the volatile Great Recession and more tranquil Great Moderation enhances the understanding of the forecast accuracy of factor models. We show that for the euro area and three of our five countries the collapsed dynamic factor model is the best forecasting model during the Great Moderation as well as during the Great Recession. However, for France and the Netherlands, the high forecast accuracy of the collapsed dynamic factor model is limited to the Great Recession. This finding underlines the importance of continuous monitoring the forecast accuracy of the short-term forecasting models policy makers and econometricians use.

Table III: Forecast accuracy dynamic factor models (MSFE) during the Great Moderation and the Great Recession

	EA	DE	FR	IT	ES	NL	EA	DE	FR	IT	ES	NL
	Great Moderation (1992.I-2007.IV)						Great Recession (2008.I-2012.IV)					
	Absolute											
AR(2)												
All horizons	*0.20*	*0.44*	*0.15*	*0.28*	*0.27*	*0.32*	*1.12*	*1.93*	*0.60*	*1.51*	*0.77*	*1.13*
2Q ahead forecast	*0.23*	*0.44*	*0.18*	*0.31*	*0.30*	*0.35*	*1.32*	*2.01*	*0.83*	*1.77*	*0.96*	*1.23*
1Q ahead forecast	*0.21*	*0.44*	*0.15*	*0.29*	*0.28*	*0.32*	*1.23*	*1.98*	*0.68*	*1.60*	*0.84*	*1.18*
Nowcast	*0.19*	*0.44*	*0.13*	*0.27*	*0.25*	*0.30*	*1.03*	*1.89*	*0.47*	*1.39*	*0.67*	*1.09*
Backcast	*0.18*	*0.43*	*0.12*	*0.25*	*0.24*	*0.28*	*0.80*	*1.78*	*0.31*	*1.17*	*0.55*	*0.99*
	Relative to AR(2) model											
BR(2011)												
All horizons	0.86	0.99	1.37	**0.79**	0.93	0.83	0.60	0.68	1.03	0.72	0.92	0.70
2Q ahead forecast	0.80	**0.96**	1.09	**0.86**	0.96	0.88	0.79	0.91	1.13	0.85	1.01	0.97
1Q ahead forecast	0.78	**0.91**	1.32	**0.80**	0.87	0.82	0.68	**0.80**	1.03	0.81	0.93	0.71
Nowcast	0.97	1.11	1.72	**0.70**	**0.96**	0.81	0.41	0.52	0.95	0.59	0.90	0.50
Backcast	0.93	1.00	1.57	0.75	**0.91**	0.83	0.32	0.31	0.82	**0.45**	0.73	0.47
CFM(2013)												
All horizons	0.69	0.88	1.06	0.73	**0.98**	0.94	0.54	**0.71**	0.70	0.66	**0.69**	0.49
2Q ahead forecast	**0.83**	0.96	1.04	0.82	1.03	**0.95**	0.69	0.78	0.78	0.74	0.85	0.76
1Q ahead forecast	0.68	0.89	1.04	0.76	1.06	0.91	0.59	0.79	0.72	0.72	0.73	0.50
Nowcast	0.61	0.85	1.11	0.67	0.91	0.95	**0.44**	0.74	0.61	**0.61**	0.55	0.29
Backcast	0.59	0.78	1.07	0.60	0.86	0.99	0.23	0.43	0.46	0.44	0.42	0.27
SW(2002)												
All horizons	1.01	1.20	1.01	0.90	1.08	0.97	0.79	0.93	0.86	0.82	0.65	0.80
2Q ahead forecast	1.09	1.32	1.03	**0.87**	1.17	1.00	0.86	1.09	0.96	0.84	**0.90**	1.00
1Q ahead forecast	1.06	1.24	1.00	0.87	1.06	0.98	0.84	1.03	0.88	0.89	0.63	0.91
Nowcast	0.92	1.09	0.97	0.93	1.02	0.94	0.76	0.85	0.75	0.84	0.44	0.64
Backcast	0.88	1.12	1.05	0.95	1.02	0.98	0.53	0.63	0.65	0.65	**0.42**	0.45

This table presents the MSFEs of backcasts, nowcasts, one quarter ahead forecasts and two quarter ahead forecasts as well as the average MSFE over all these horizons. The benchmark model is an autoregression of order 2 (AR(2)). The factor models are: the principal component model with diffusion index of Stock and Watson (SW), the augmented dynamic factor model of Bańbura and Rünstler (BR) and the collapsed dynamic factor model (CFM). The country codes are: Euro Area (EA), Germany (DE), France (FR), Italy (IT), Spain (ES) and the Netherlands (NL). The model forecasts are averaged over model specifications with **one to four factors**. The smallest MSFE for each horizon is highlighted. MSFEs that are at most 10% larger than the MSFE of the best model and also smaller than the MSFE of the benchmark model are in boldface.

5 Conclusions

This paper makes three contributions to the existing empirical literature on forecasting GDP in the short-term. The first contribution is empirical. We present the outcome of a forecasting horse race of two popular factor models amongst policy makers and the recently developed collapsed dynamic factor model for the euro area and its five largest countries (Germany, France, Italy, Spain and the Netherlands), utilizing the same information set for all countries and the euro area. Our sample (1992.I-2012.IV) allows us to discriminate between the performance of the factor models during the volatile financial crisis and the more tranquil years before the crisis. Our second and third contribution are extensions to the existing factor models. First, we extend the model of Bańbura and Rünstler (2011) by introducing an autoregressive term of the target variable (GDP). Second, we extend the collapsed dynamic factor by proposing and efficient way to deal with jagged edges at the begin and the end of the estimation period.

We summarize our findings in four points. First, factor models can extract valuable information for short-term GDP forecasting, in particular as the forecast horizon shortens and more monthly information is processed. We find the largest gains in forecast accuracy for nowcasting and backcasting, suggesting that factor models are especially helpful when they are able to use information that pertains to the quarter of interest.

Second, during the Great Recession the gains in forecast accuracy against a simple benchmark model was much larger than during the Great Moderation. This finding underlines the importance of using factor models instead of simple benchmark models during volatile periods.

Third, measured over our sample, the collapsed dynamic factor model showed the highest forecast accuracy for the euro area and its five largest countries. For the euro area and three out of five countries (Germany, Italy and Spain) this result was driven by the high forecast accuracy during the Great Recession as well as the Great Moderation. However, for France and the Netherlands the higher forecast accuracy of the collapsed dynamic factor model is limited to the Great Recession.

Fourth, small changes in the structure of factor models can improve the forecast accuracy considerably. We show that the inclusion of an autoregressive term of the target variable (GDP) in the Bańbura and Rünstler (2011) model increases its forecast accuracy. Moreover, efficient handling of the jagged edges in the Bräuning and Koopman (2014) model is key to its good forecast performance.

The results of our large-scale comparative analysis may be useful to econometricians and policy makers who regularly use short-term forecasting models. An interesting topic for future research is how to trace back the contribution of the monthly indicators to the GDP forecast of the collapsed dynamic factor model. The competing Bańbura and Rünstler (2011) model does have this feature, and the collapsed dynamic factor model would probably gain in attractiveness for policy makers if this feature was incorporated as well.

Acknowledgments

The opinions expressed in this paper are personal views of the authors and do not necessarily reflect positions of De Nederlandsche Bank. We are grateful to seminar and conference participants at De Nederlandsche Bank and the Computational and Financial Econometrics Conference 2012 in Oviedo for their helpful comments. We are particularly indebted to Job Swank for his valuable comments and stimulating suggestions.

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A Appendix

A.1 Dataset

Table IV: Monthly series in uniform dataset

Nr.	Variable	Transformation			Country					
		sa	ln.	dif.	EA	DE	FR	IT	ES	NL
I. Production & sales (N=*15*)										
1	World Trade	1	1	1	‘77	‘77	‘77	‘77	‘77	‘77
2	Ind. prod. US	1	1	1	‘60	‘60	‘60	‘60	‘60	‘60
3	Ind. prod. UK	1	1	1	‘68	‘68	‘68	‘68	‘68	‘68
4	Ind. prod. (excl. constr.)	1	1	1	‘60	‘60	‘60	‘60	‘61	‘62
5	Ind. prod., consumer goods	2	1	1	‘80	‘80	‘63	‘60	‘65	‘90
6	Ind. prod., energy	2	1	1	‘80	‘91	‘63	‘80	‘80	‘00
7	Ind. prod., interm. goods	1	1	1	‘60	‘80	‘63	‘77	‘65	‘00
8	Ind. prod., capital goods	1	1	1	‘60	‘80	‘63	‘77	‘65	‘70
9	Ind. prod., manufacturing	2	1	1	‘60	‘78	‘60	‘71	‘80	‘70
10	Ind. prod., construction	2	1	1	‘85	‘78	‘85	‘95	‘88	‘85
11	Passenger car registration	1	1	1	‘77	‘77	‘77	‘77	‘77	‘79
12	Retail trade volume	2	1	1	‘70	‘68	‘70	‘90	‘95	‘60
13	Unemployment rate	1	0	1	‘83	‘62	‘83	‘83	‘86	‘83
14	Unemployment rate UK	1	0	1	‘83	‘83	‘83	‘83	‘83	‘83
15	Unemployment rate US	1	0	1	‘83	‘83	‘83	‘83	‘83	‘83
II. Prices (N=*9*)										
16	Total HICP-index	2	1	2	‘60	‘60	‘60	‘60	‘60	‘60
17	Core HICP-index	2	1	2	‘62	‘62	‘60	‘60	‘76	‘61
18	Producer prices	2	1	2	‘81	‘60	‘62	‘70	‘60	‘60
19	Commod. prices, tot.	2	1	2	‘60	‘60	‘60	‘60	‘60	‘60
20	Commod. prices, ind. mat.	2	1	2	‘60	‘60	‘60	‘60	‘60	‘60
21	Commod. prices, food-bev.	2	1	2	‘60	‘60	‘60	‘60	‘60	‘60
22	Commod. prices, metals	2	1	2	‘60	‘60	‘60	‘60	‘60	‘60
23	Commod. prices, energy	2	1	2	‘60	‘60	‘60	‘60	‘60	‘60
24	Oil price	2	1	2	‘85	‘85	‘85	‘85	‘85	‘85
III. Monetary & financial indicators (N=*14*)										
25	M1	2	1	1	‘70	‘80	‘80	‘80	‘80	‘80
26	M3	2	1	1	‘70	‘70	‘70	‘70	‘70	‘70
27	Int. rate mortgage	2	0	1	‘03	‘82	‘80	‘95	‘84	‘80
28	3 month interest rate	2	0	1	‘94	‘60	‘64	‘60	‘60	‘60
29	10 year gov. bond yield	2	0	1	‘70	‘60	‘70	‘60	‘80	‘60
30	Headline stock-index	2	1	1	‘73	‘73	‘73	‘73	‘87	‘73
31	Basic material-index	2	1	1	‘73	‘73	‘73	‘73	‘87	‘73
32	Industrials stock-index	2	1	1	‘73	‘73	‘73	‘73	‘87	‘73
33	Cons. goods stock-index	2	1	1	‘73	‘73	‘73	‘73	‘87	‘73
34	Cons. service stock-index	2	1	1	‘73	‘73	‘73	‘73	‘87	‘73
35	Financials stock-index	2	1	1	‘73	‘73	‘73	‘73	‘87	‘73
36	Loans to the private sector	2	1	1	‘80	‘80	‘80	‘83	‘80	‘82
37	Exchange rate, $ per EUR	2	1	1	‘74	‘74	‘74	‘74	‘74	‘74
38	Real eff. exchange rate	2	1	1	‘70	‘70	‘70	‘70	‘70	‘70
IV. Surveys (N=*14*)										
39	Ind. conf. - headline	1	0	1	‘85	‘85	‘85	‘85	‘87	‘85
40	Ind. conf. - orders	1	0	1	‘85	‘85	‘85	‘85	‘87	‘85

Continued on next page

Table IV – *Continued from previous page*

Nr.	Variable	Transformation			Country					
		sa	ln.	dif.	EA	DE	FR	IT	ES	NL
41	Ind. conf. - stocks	1	0	1	‘85	‘85	‘85	‘85	‘87	‘85
42	Ind. conf. - prod. expect.	1	0	1	‘85	‘85	‘85	‘85	‘87	‘85
43	Ind. conf. - empl. expect.	1	0	1	‘85	‘85	‘85	‘85	‘87	‘85
44	Cons. conf. - headline	1	0	1	‘85	‘85	‘85	‘85	‘86	‘85
45	Cons. conf. - exp. fin. sit.	1	0	1	‘85	‘85	‘85	‘85	‘86	‘85
46	Cons. conf. - exp. ec. sit.	1	0	1	‘85	‘85	‘85	‘85	‘86	‘85
47	Cons. conf. - exp. unemp.	1	0	1	‘85	‘85	‘85	‘85	‘86	‘85
48	Cons. conf. - exp. maj. pur.	1	0	1	‘85	‘85	‘85	‘85	‘86	‘85
49	PMI United States	1	0	1	‘60	‘60	‘60	‘60	‘60	‘60
50	OECD leading ind. UK	1	1	1	‘60	‘60	‘60	‘60	‘60	‘60
51	OECD leading ind. US	1	1	1	‘60	‘60	‘60	‘60	‘60	‘60
52	OECD comp. leading ind.	1	1	1	‘70	‘61	‘70	‘62	‘76	‘61

This table presents the starting year of the monthly series that were used for estimation. Series for which the time series starts later than 1986 are highlighted and excluded in the models because the series are too short. transform: sa: 1= seasonal adjustment at the source, 2= seasonal adjustment by US Census X12-method, log: 0=no logarithm, 1=logarithm, dif.: degree of differencing 1=first difference, 2=second difference

A.2 Number of factors in dynamic factor models

Table V: Forecast accuracy dynamic factor models (MSFE), 1992.I-2012.IV, one factor

	EA	DE	FR	IT	ES	NL
			Absolute			
AR						
All horizons	*0.42*	*0.79*	*0.26*	*0.57*	*0.39*	*0.51*
2Q ahead forecast	*0.49*	*0.81*	*0.34*	*0.66*	*0.46*	*0.56*
1Q ahead forecast	*0.45*	*0.81*	*0.28*	*0.60*	*0.41*	*0.53*
Nowcast	*0.39*	*0.78*	*0.21*	*0.53*	*0.35*	*0.49*
Backcast	*0.32*	*0.76*	*0.16*	*0.47*	*0.31*	*0.45*
			Relative to AR(2) model			
BR						
All horizons	0.73	0.80	1.18	0.81	1.04	0.85
2Q ahead forecast	**0.83**	**0.94**	1.15	**0.88**	1.05	0.99
1Q ahead forecast	0.78	0.86	1.21	0.87	1.03	0.87
Nowcast	0.64	0.70	1.24	0.75	1.11	0.77
Backcast	0.58	0.63	1.07	0.67	0.94	**0.71**
CFM						
All horizons	0.64	0.73	**0.95**	0.73	**0.91**	0.72
2Q ahead forecast	0.79	0.87	0.95	0.83	0.95	0.84
1Q ahead forecast	0.65	0.76	**0.92**	0.77	**0.92**	0.71
Nowcast	0.52	0.63	0.98	0.64	0.88	0.63
Backcast	0.49	0.57	0.97	0.58	**0.87**	0.65
SW						
All horizons	0.83	1.00	0.88	0.86	0.86	0.86
2Q ahead forecast	0.89	1.12	**0.98**	**0.88**	**0.98**	0.96
1Q ahead forecast	0.88	1.08	0.88	0.90	0.87	0.90
Nowcast	0.78	0.92	0.78	0.87	0.73	0.79
Backcast	0.64	0.79	0.77	0.72	0.83	0.74

This table presents the MSFEs of backcasts, nowcasts, one and two quarter ahead forecasts. The benchmark model is an autoregression of order 2 (AR(2)). The factor models are: the principal component of Stock and Watson model (SW), the augmented dynamic factor model of Bańbura and Rünstler (BR) and the collapsed dynamic factor model (CFM). The country codes are: Euro Area (EA), Germany (DE), France (FR), Italy (IT), Spain (ES) and the Netherlands (NL). The model forecasts are averaged over model specifications with **one to four factors**. The smallest MSFE for each horizon is highlighted. MSFEs that are at most 10% larger than the MSFE of the best model and also smaller than the MSFE of the benchmark model are in boldface.

Table VI: Forecast accuracy dynamic factor models (MSFE), 1992.I-2012.IV, two factors

	EA	DE	FR	IT	ES	NL
	Absolute					
AR						
All horizons	*0.42*	*0.79*	*0.26*	*0.57*	*0.39*	*0.51*
2Q ahead forecast	*0.49*	*0.81*	*0.34*	*0.66*	*0.46*	*0.56*
1Q ahead forecast	*0.45*	*0.81*	*0.28*	*0.60*	*0.41*	*0.53*
Nowcast	*0.39*	*0.78*	*0.21*	*0.53*	*0.35*	*0.49*
Backcast	*0.32*	*0.76*	*0.16*	*0.47*	*0.31*	*0.45*
	Relative to AR(2) model					
BR						
All horizons	0.73	0.97	1.26	0.76	1.03	0.72
2Q ahead forecast	0.81	1.03	1.12	0.87	1.01	0.88
1Q ahead forecast	0.74	0.97	1.21	0.81	0.99	0.70
Nowcast	0.66	1.01	1.48	0.64	1.12	0.61
Backcast	0.66	**0.79**	1.41	0.66	1.03	0.63
CFM						
All horizons	0.58	0.85	**0.91**	0.66	0.89	0.74
2Q ahead forecast	0.69	0.84	0.94	0.74	0.91	0.88
1Q ahead forecast	0.57	0.85	**0.91**	0.68	**0.90**	0.72
Nowcast	0.50	0.91	**0.90**	0.57	**0.86**	0.65
Backcast	0.49	0.76	0.86	0.59	0.84	0.65
SW						
All horizons	0.87	1.05	0.91	0.90	**0.91**	0.93
2Q ahead forecast	0.91	1.16	**0.98**	0.91	1.04	1.05
1Q ahead forecast	0.92	1.14	0.91	0.91	0.87	1.01
Nowcast	0.84	**0.97**	0.83	0.93	0.79	0.82
Backcast	0.73	0.85	**0.87**	0.80	**0.90**	0.73

This table presents the MSFEs of backcasts, nowcasts, one and two quarter ahead forecasts. The benchmark model is an autoregression of order 2 (AR(2)). The factor models are: the principal component of Stock and Watson model (SW), the augmented dynamic factor model of Bańbura and Rünstler (BR) and the collapsed dynamic factor model (CFM). The country codes are: Euro Area (EA), Germany (DE), France (FR), Italy (IT), Spain (ES) and the Netherlands (NL). The model forecasts are averaged over model specifications with **one to four factors**. The smallest MSFE for each horizon is highlighted. MSFEs that are at most 10% larger than the MSFE of the best model and also smaller than the MSFE of the benchmark model are in boldface.

Table VII: Forecast accuracy dynamic factor models (MSFE), 1992.I-2012.IV, three factors

	EA	DE	FR	IT	ES	NL
	Absolute					
AR						
All horizons	*0.42*	*0.79*	*0.26*	*0.57*	*0.39*	*0.51*
2Q ahead forecast	*0.49*	*0.81*	*0.34*	*0.66*	*0.46*	*0.56*
1Q ahead forecast	*0.45*	*0.81*	*0.28*	*0.60*	*0.41*	*0.53*
Nowcast	*0.39*	*0.78*	*0.21*	*0.53*	*0.35*	*0.49*
Backcast	*0.32*	*0.76*	*0.16*	*0.47*	*0.31*	*0.45*
	Relative to AR(2) model					
BR						
All horizons	0.75	0.85	1.21	0.78	0.92	**0.75**
2Q ahead forecast	**0.80**	**0.94**	1.12	0.87	**0.98**	**0.91**
1Q ahead forecast	0.76	0.88	1.16	0.83	0.85	**0.75**
Nowcast	0.75	0.86	1.36	**0.72**	**0.93**	**0.62**
Backcast	0.65	0.67	1.3	0.63	**0.89**	0.63
CFM						
All horizons	0.64	**0.87**	**0.94**	0.71	**0.92**	0.72
2Q ahead forecast	0.73	0.92	**0.98**	0.74	0.97	0.89
1Q ahead forecast	0.66	**0.92**	**0.94**	0.74	0.97	0.70
Nowcast	0.59	**0.90**	**0.91**	0.72	0.85	0.60
Backcast	0.48	**0.68**	0.86	0.56	0.82	**0.64**
SW						
All horizons	0.87	1.11	0.91	0.89	**0.99**	0.99
2Q ahead forecast	0.94	1.27	0.95	0.88	1.13	1.09
1Q ahead forecast	0.91	1.19	0.92	0.92	0.97	1.05
Nowcast	0.83	0.99	0.86	0.9	**0.88**	0.93
Backcast	0.72	0.92	**0.88**	0.81	**0.90**	0.81

This table presents the MSFEs of backcasts, nowcasts, one and two quarter ahead forecasts. The benchmark model is an autoregression of order 2 (AR(2)). The factor models are: the principal component of Stock and Watson model (SW), the augmented dynamic factor model of Bańbura and Rünstler (BR) and the collapsed dynamic factor model (CFM). The country codes are: Euro Area (EA), Germany (DE), France (FR), Italy (IT), Spain (ES) and the Netherlands (NL). The model forecasts are averaged over model specifications with **one to four factors**. The smallest MSFE for each horizon is highlighted. MSFEs that are at most 10% larger than the MSFE of the best model and also smaller than the MSFE of the benchmark model are in boldface.

Table VIII: Forecast accuracy dynamic factor models (MSFE), 1992.I-2012.IV, four factors

	EA	DE	FR	IT	ES	NL
	Absolute					
AR						
All horizons	*0.42*	*0.79*	*0.26*	*0.57*	*0.39*	*0.51*
2Q ahead forecast	*0.49*	*0.81*	*0.34*	*0.66*	*0.46*	*0.56*
1Q ahead forecast	*0.45*	*0.81*	*0.28*	*0.60*	*0.41*	*0.53*
Nowcast	*0.39*	*0.78*	*0.21*	*0.53*	*0.35*	*0.49*
Backcast	*0.32*	*0.76*	*0.16*	*0.47*	*0.31*	*0.45*
	Relative to AR(2) model					
BR						
All horizons	0.75	0.83	1.21	**0.76**	0.88	**0.78**
2Q ahead forecast	**0.81**	**0.92**	1.10	**0.87**	0.99	**0.95**
1Q ahead forecast	**0.73**	0.87	1.14	**0.85**	0.85	0.78
Nowcast	0.75	0.84	1.42	0.68	0.83	**0.64**
Backcast	0.65	0.62	1.35	0.52	**0.77**	**0.66**
CFM						
All horizons	0.67	**0.86**	0.80	0.75	**0.93**	0.71
2Q ahead forecast	0.79	0.86	0.82	0.81	1.10	0.87
1Q ahead forecast	0.69	**0.92**	0.80	0.80	0.99	0.68
Nowcast	0.62	0.95	0.78	0.75	0.75	0.61
Backcast	0.43	**0.65**	0.77	**0.53**	0.73	0.61
SW						
All horizons	1.01	1.15	1.12	0.87	0.97	0.99
2Q ahead forecast	1.13	1.33	1.13	**0.86**	1.18	1.12
1Q ahead forecast	1.08	1.17	1.13	**0.87**	**0.90**	1.06
Nowcast	0.95	1.04	1.12	0.90	0.84	0.88
Backcast	0.73	0.98	1.10	0.84	0.86	0.80

This table presents the MSFEs of backcasts, nowcasts, one and two quarter ahead forecasts. The benchmark model is an autoregression of order 2 (AR(2)). The factor models are: the principal component of Stock and Watson model (SW), the augmented dynamic factor model of Bańbura and Rünstler (BR) and the collapsed dynamic factor model (CFM). The country codes are: Euro Area (EA), Germany (DE), France (FR), Italy (IT), Spain (ES) and the Netherlands (NL). The model forecasts are averaged over model specifications with **one to four factors**. The smallest MSFE for each horizon is highlighted. MSFEs that are at most 10% larger than the MSFE of the best model and also smaller than the MSFE of the benchmark model are in boldface.

A.3 Adding an AR(2) term in Bańbura and Rünstler (2011)

Table IX: Sensitivity analysis (augmented) Bańbura and Rünstler model

	EA	DE	FR	IT	ES	NL
	Absolute MSFE					
Base BR model						
1 factor	0.56	**0.80**	0.61	**0.69**	**0.67**	**0.66**
2 factor	**0.57**	**0.91**	**0.60**	0.66	**0.66**	**0.61**
3 factor	**0.57**	**0.86**	**0.58**	0.67	**0.61**	**0.63**
4 factor	**0.58**	**0.84**	**0.58**	0.66	**0.60**	**0.63**
average 1-4 factors	**0.55**	**0.82**	**0.58**	0.65	**0.62**	**0.63**
Augmented BR model						
1 factor	**0.56**	0.80	0.55	0.68	0.64	0.66
2 factor	0.56	0.88	0.57	**0.66**	0.63	0.61
3 factor	0.56	0.82	0.55	**0.67**	0.60	0.62
4 factor	0.56	0.81	0.56	**0.66**	0.58	0.63
average 1-4 factors	0.54	0.80	0.55	**0.65**	0.60	0.62

This table presents the average MSFE over all forecast horizons (backcast, nowcast, one quarter ahead forecast and two quarter ahead forecast) for the Bańbura and Rünstler (2011) model and the augmented Bańbura and Rünstler (2011) model. The country codes are: Euro Area (EA), Germany (DE), France (FR), Italy (IT), Spain (ES) and the Netherlands (NL). Forecasts for specification with four static factors. The smallest MSFE for each horizon is highlighted. MSFEs that are at most 10% larger than the MSFE of the best model are in boldface.

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