EUROPEAN CENTRAL BANK

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ESTIMATING AND FORECASTING THE EURO AREA MONTHLY NATIONAL ACCOUNTS FROM A DYNAMIC FACTOR MODEL

by Elena Angelini, Marta Bańbura and Gerhard Rünstler

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In 2008 all ECB publications feature a motif taken from the €10 banknote.

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Abstract

We estimate and forecast growth in euro area monthly GDP and its components from a dynamic factor model due to Doz et al. (2005), which handles unbalanced data sets in an efficient way. We extend the model to integrate interpolation and forecasting together with cross-equation accounting identities. A pseudo real-time forecasting exercise indicates that the model outperforms various benchmarks, such as quarterly time series models and bridge equations in forecasting growth in quarterly GDP and its components.

Keywords: dynamic factor models, interpolation, nowcasting.

JEL Classification: E37, C53

Non-technical summary

Given the delays in the publication of macro-economic data, economic policy-making in real time faces the difficulty of uncovering the actual state of the economy. For the euro area, a flash estimate of GDP is available only about 6 weeks after the end of the respective quarter. The first estimate of the national accounts is released four weeks later. Meanwhile, when assessing the economic stance, participants have to rely on high-frequency indicators that arrive within the quarter, such as industrial production, surveys and financial market data. However, the large number of available indicators, the noise present in many of the series, and the different delays in their publication make the efficient exploitation of this information a difficult task. Under these circumstances, various approaches have been proposed to obtain measures of the economic stance from the monthly indicators. These include projections of quarterly GDP for the current and, possibly, next quarter, estimates of monthly GDP, and monthly coincident indicators of economic activity.

In this paper, we propose a unified approach for interpolation and forecasting of GDP and of its demand and value added components. The framework is based on a dynamic factor model for a large data set and is suitable for real-time application in which data arrive in an asynchronous manner. Our objective is to obtain estimates and forecasts that satisfy temporal aggregation identities with respect to the quarterly figures. We also show how to take into account relevant accounting identities.

One major advantage of our approach is being able to provide monthly estimates and predictions of quarterly GDP growth, which are mutually consistent. This greatly facilitates communicating the results to policy-makers, as it clarifies the implications of quarterly predictions for intra-quarter dynamics and vice versa. Our model can also deal with those irregular patterns of data availability at the end of the sample, which arise in real-time data sets due to differences in publication delays of individual monthly series. The model delivers efficient forecasts from such data sets and is therefore capable of exploiting the latest information.

We find that for GDP the factor model forecasts beat the forecasts from alternative models, such as quarterly models and bridge equations. The evidence is also encouraging for the demand components with the exception of private and public consumption, for which none of the models does well. The historical monthly interpolates of GDP delivered by our model are very similar to those obtained from standard interpolation methods based on small number of indicators. However we argue that this might not be the case for the real-time GDP interpolates of the most recent periods.

1 Introduction

Given the delays in the publication of macro-economic data, economic policy-making in real time faces the difficulty of uncovering the actual state of the economy. For the euro area, a flash estimate of GDP is available only about 6 weeks after the end of the respective quarter. The first estimate of the national accounts is released four weeks later. Meanwhile, when assessing the economic stance, participants have to rely on high-frequency indicators that arrive within the quarter, such as industrial production, surveys and financial market data. However, the large number of available indicators, the noise present in many of the series, and the different delays in their publication make the efficient exploitation of this information a difficult task. Under these circumstances, various approaches have been proposed to obtain measures of the economic stance from the monthly indicators. Those include projections of quarterly GDP for the current and, possibly, next quarter, estimates of monthly GDP, and monthly coincident indicators of economic activity.

In this paper, we investigate a unified approach for interpolation and forecasting of GDP and of its demand and value added components. The framework is based on a dynamic factor model for a large data set and is suitable for real-time application in which data arrive in an asynchronous manner. Our objective is to obtain estimates and forecasts that satisfy temporal aggregation identities with respect to quarterly figures as well as appropriate accounting constraints in an approximate way.

We build on the dynamic factor model due to Doz et al. (2005), which differs from other approaches (e.g. Stock and Watson, 2002; Forni et al., 2000) in modelling factor dynamics in an explicit manner. From a state-space representation of the model, forecasts are obtained through application of the Kalman smoother. As a consequence, the model can deal with those irregular patterns of data availability at the end of the sample, which arise in unbalanced real-time data sets due to differences in publication delays of individual monthly series (Giannone et al. 2008). In addition, the state-space framework allows for a comprehensive analysis of the contributions of individual data to the forecasts, which allows for a better understanding of the role of individual monthly series (Bańbura and Rünstler, 2007).

We combine the model with forecasting equations for monthly GDP and its demand components together with appropriate temporal aggregation rules and the relevant accounting identities. Hence, our approach provides monthly estimates and predictions of quarterly GDP growth and its components, which are mutually consistent. This greatly facilitates communicating the results to policy-makers, as it clarifies the implications of quarterly predictions for intra-quarter dynamics and vice versa.

In the empirical part of the paper we evaluate forecasts for GDP and its demand and value components in terms of out-of-sample forecast performance against various alternative models. As to euro area GDP, Banerjee et al. (2005), Bańbura and Rünstler (2007) and Angelini et al. (2008) report good forecasting performance of factor models. Alternatively, GDP growth has been forecast from bridge equations using a small set of selected monthly indicators, notably measures of production and sales (e.g. Rünstler and Sédillot, 2003; Baffigi et al., 2004; Diron, 2006).

Estimates of monthly GDP have so far mostly been derived from bottom-up approaches based on estimates of its monthly components (e.g. Mitchell et al., 2005a, 2005b; Proietti and Frale, 2007), which again are based on selected indicators. The latter suffers from the potential weakness that poor interpolates for certain components may hamper the aggregate GDP interpolate. One exception is Breitung and Schumacher (2006), which have employed a diffusion index model for estimating monthly GDP this purpose. In a recent paper, Proietti (2008) proposes an iterative non-linear estimator to interpolate the national accounts, which satisfies the national accounts constraints exactly and also allows for implementing exact (non-linear) temporal constraints for chain-linked data. The approach requires the data set to be balanced and, hence, is not applicable to forecasting in real time. By contrast, we implement these constraints directly in the state-space form and use log-linear approximisations, while ignoring issues related to chain-linking. This allows us to deal with unbalanced real-time data sets. Proietti and Frale (2007) have shown that ignoring chain-linking has only a very small impact on the interpolates.

We find that for GDP the factor model forecasts beat the forecasts from alternative models, such as quarterly models and bridge equations. The evidence is also encouraging for the demand components with the exception of private and public consumption, for which none of the models does well. Our conjecture is that for these specific series further research is required in order to choose optimal monthly indicators. We also compare the monthly interpolates of GDP delivered by our model to those obtained from standard interpolation methods based on small number of indicators. The resulting in-sample monthly estimates are very similar. However we argue that this might not be the case for real-time GDP interpolates of the most recent periods.

The paper is organised as follows. After a brief review of the DFM by Doz et al. (2005), the integrated DFM version to forecast and interpolate the national accounts is presented in section 2. Section 3 reports the results of a pseudo real-time exercise to compare the performance of the model with various alternative models. Section 4 shows estimates of monthly GDP and compares them to results from standard interpolation methods.

2 The model

2.1 A dynamic factor model

Dynamic factor models (DFMs) are designed to explain the dynamics in a panel of series by a few common sources of variation. Consider a vector of n stationary monthly series $x_t = (x_{1t}, \ldots, x_{nt})'$, $t = 1, \ldots, T$, which have been standardised to mean zero and variance one. The DFM by Doz et al. (2005) is given by the equations

$$x_t = \Lambda f_t + \xi_t, \qquad \xi_t \sim \mathbb{N}(0, \Sigma_\xi) \tag{1}$$

$$f_{t+1} = \sum_{i=1}^{p} A_i f_{t-i+1} + B\eta_t, \qquad \eta_t \sim \mathbb{N}(0, I_q). \tag{2}$$

through a matrix of factor loadings Λ, equation (1) relates the monthly series x_t to a $r \times 1$ vector of latent factors $f_t = (f_{1,t}, \ldots, f_{r,t})'$ plus an idiosyncratic component $\xi_t = (\xi_{1,t}, \ldots, \xi_{n,t})'$. The latter is assumed to be multivariate white noise with diagonal covariance matrix Σ_ξ. Equation (2) describes the law of motion for the latent factors f_t, which are driven by q-dimensional standardised white noise η_t, where B is a $r \times q$ matrix.

The fact that the dynamics of the latent factors is modelled explicitly, is a specific feature of this model against alternative DFM versions (e.g. Stock and Watson, 2002: Forni et al., 2000, 2005). Giannone et al. (2008) use a two-step approach to forecast quarterly GDP growth from the factor model. In a first step, they obtain forecasts of the latent factors as from the state-space model given by equations (1) and (2). In a second step, quarterly GDP is predicted from quarterly aggregates of forecasts by means of a static regression.

2.2 Interpolation and state space form

Following Bańbura and Rünstler (2007) we use a mixed frequency approach to combine the monthly factor model with equations to model monthly GDP growth within a single state space form. Consider the $m \times 1$ vector $y_t^Q = (y_{1t}^Q, \ldots, y_{mt}^Q)'$ of growth in quarterly GDP and its components, which satisfy the national accounts identity

$$\chi_{t-1}' y_t^Q = \kappa_t^Q. \tag{3}$$

with known, but possibly time-varying weights χ_{t-1}. The identity allows for an error term, κ_t^Q. Further, denote with $y_t = (y_{1t}, \ldots, y_{mt})'$ the month-on-month (m-o-m) growth rates in national accounts and with $y_t^{(3)} = (y_{1t}^{(3)}, \ldots, y_{mt}^{(3)})'$ the respective 3-month growth rates, i.e. growth rates vis-a-vis the same month of the previous quarter. Using logarithmic approximation, the aggregation rules to relate the latent monthly accounts to their observed quarterly counterparts are given by

$$y_t^Q = \frac{1}{3}(y_t^{(3)} + y_{t-1}^{(3)} + y_{t-2}^{(3)}) \tag{4}$$

$$y_t^{(3)} = y_t + y_{t-1} + y_{t-2} \tag{5}$$

where y_t^Q is to be understood as a monthly time series that contains the quarterly values in the 3^{rd} month of each quarter and and is otherwise not defined. Expression (4) applies then to the 3^{rd} month of the quarter. Combining the two rules gives

$$y_t^Q = \frac{1}{3}(y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4})$$

as derived e.g. by Mariano and Murasawa (2003) or Breitung and Schumacher (2006).

Monthly growth rates y_t are related to the common factors by the static equation

$$y_{t+1} = \mu + \Lambda_y f_{t+1} + \varepsilon_{t+1}, \qquad \varepsilon_{t+1} \sim \mathbb{N}(0, \Sigma_\varepsilon) \tag{6}$$

where μ is a $m \times 1$ constant term and Λ_y is the $m \times r$ matrix of factor loadings for the national accounts. The idiosyncratic component $\varepsilon_t = (\varepsilon_{1,t}, \ldots, \varepsilon_{m,t})'$ is again assumed to be multivariate white noise with diagonal covariance matrix Σ_ε. We also ensure that monthly national accounts satisfy constraint (3) by applying the monthly version

$$\chi'_{t-1} y_t = \kappa_t, \qquad \kappa_t \sim \mathbb{N}(0, \sigma^2_\kappa) \tag{7}$$

We assume that innovations $\xi_t, \eta_t, \varepsilon_t$,and κ_t are mutually uncorrelated.

Equations (1), (2), and (4) to (7) can be cast in one single state-space form, which is illustrated below for the case of $p = 1$. The transition equation contains the dynamic law of motion for the state vector $\alpha'_t = (f'_t, y'_t, y'_{t-1}, y_t^{(3)}, Q'_t)$ comprising the common factors (2), together with forecasting equations (6) for the unobserved monthly national accounts. In the below state space form, aggregation rule (4) is implemented in a recursive way from

$$Q_t = \Xi_{t-1} Q_{t-1} + \frac{1}{3} y_t^{(3)},$$

where $\Xi_{t-1} = 0_{m\times m}$ in the 1^{st} month and $\Xi_{t-1} = I_m$ otherwise (see Harvey, 1989, p. 309ff). As a result, expressions (4) hold in the 3^{rd} month of the quarter, with $y_t^Q = Q_t$. The transition equation is given by

$$\begin{bmatrix} I_r & 0 & 0 & 0 & 0 \\ -\Lambda_y & I & 0 & 0 & 0 \\ 0 & 0 & I & 0 & 0 \\ 0 & -I & -I & I & 0 \\ 0 & 0 & 0 & -\frac{1}{3}I & I \end{bmatrix} \begin{bmatrix} f_{t+1} \\ y_{t+1} \\ y_t \\ y_{t+1}^{(3)} \\ Q_{t+1} \end{bmatrix} = \begin{bmatrix} 0 \\ \mu \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} A_1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & I & 0 & 0 & 0 \\ 0 & 0 & I & 0 & 0 \\ 0 & 0 & 0 & 0 & \Xi_t \end{bmatrix} \begin{bmatrix} f_t \\ y_t \\ y_{t-1} \\ y_t^{(3)} \\ Q_t \end{bmatrix} + \begin{bmatrix} B\eta_t \\ \varepsilon_{t+1} \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

where I denotes the $m \times m$ identity matrix. The equation is to be pre-multiplied with the inverse of the left-hand matrix in the equation to achieve the standard state space form.

The observation equation is

$$\begin{bmatrix} x_t \\ 0 \\ y_t^Q \end{bmatrix} = \begin{bmatrix} \Lambda & 0 & 0 & 0 & 0 \\ 0 & \chi'_{t-1} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & I_m \end{bmatrix} \begin{bmatrix} f_t \\ y_t \\ y_{t-1} \\ \tilde{y}_t^{(3)} \\ Q_t \end{bmatrix} + \begin{bmatrix} \xi_t \\ \kappa_t \\ 0 \end{bmatrix}$$

The final row of the observation equation, related to y_t^Q, is defined only for the 3^{rd} month of the quarter and otherwise skipped in application.

2.3 Estimation, interpolation and forecasting

As shown by Giannone et al. (2008), under certain regularity conditions consistent estimates of the model parameters can be obtained as follows.

1. Apply principal components analysis to x_t to estimate the first r common factors $\widehat{f}_t$, together with factor loadings $\widehat{\Lambda}$, and variances of idiosyncratic components, $\widehat{\Sigma}_\xi$.
2. Estimate the VAR $\widehat{f}_t = \sum_{i=1}^p A_i \widehat{f}_{t-i} + \widehat{\zeta}_t$ to obtain estimates $\widehat{A}_i$ and $\widehat{\Sigma}_\zeta$. Further, apply principal components to the estimated covariance matrix $\widehat{\Sigma}_\zeta$ of residuals $\widehat{\zeta}_t$ and extract the first q components to obtain $\widehat{B}$.
3. Obtain quarterly aggregates $\widehat{f}_t^Q$ of estimates $\widehat{f}_t$ as from equations (4) and (5). Estimate a quarterly version of (6),

$$y_t^Q = \mu^Q + \Lambda_y \widehat{f}_t^Q + \varepsilon_t^Q, \qquad \varepsilon_t^Q \sim \mathbb{N}(0, \sigma_\varepsilon^Q),$$

   by OLS. As equation (6) is static, the quarterly aggregates give consistent estimates of Λ_y, $\sigma_\varepsilon = 3/\sqrt{19}\sigma_\varepsilon^Q$ and $\mu = 1/3\mu^Q$. Similarly, let $\sigma_\kappa = 3/\sqrt{19}\sigma_\kappa^Q$.[1]

We now turn to the application of the model to interpolation and forecasting in real-time. Real-time data sets typically contain missing observations at the end of the sample due to publication lags. Moreover, the number of missing data differs across series due to the different timing of data

[1] With ε_t being white noise, ε_t^Q follows an MA(1) process with coefficient 4/19. This does not affect the consistency of estimates from the quarterly version of equation (6). Doz et al. (2006) present an EM algorithm to obtain maximum likelihood estimates, but report little gains in forecasting performance.

releases. In our forecast exercise we will therefore apply *pseudo-real time* data sets $\mathcal{Z}_t$, which use the final data releases but take account of the timing of data releases. This is achieved by shifting the pattern of publication lags embodied in $\mathcal{Z}_T$ recursively back in time. That is, observation $z_{i,t-k}$, $k \geq 0$ is eliminated in $\mathcal{Z}_t$, if and only if observation $z_{i,T-k}$ is missing in $\mathcal{Z}_T$. The quarterly national accounts are treated in an equivalent way.

To obtain efficient estimates and forecasts of GDP growth from unbalanced data sets, Kalman filter and smoother recursions can be applied. For state-space form

$$\begin{aligned} z_t &= W_t \alpha_t + u_t & u_t &\sim \mathbb{N}(0, \Sigma_u) \\ \alpha_{t+1} &= c + T_t \alpha_t + v_t, & v_t &\sim \mathbb{N}(0, \Sigma_v) \end{aligned} \tag{8}$$

and any unbalanced data set $\mathcal{Z}_t$ the Kalman filter and smoother provide minimum mean square linear (MMSE) estimates $a_{t+h|t}$ of the state vector and their precision, $P_{t+h|t}$,

$$a_{t+h|t} = \mathbb{E}\left[\alpha_{t+h} | \mathcal{Z}_t\right] \tag{9}$$

$$P^j_{t+h|t} = \mathbb{E}\left[a^j_{t+h|t} - \alpha_{t+h}\right]\left[a^j_{t+h|t} - \alpha_{t+h}\right]', \tag{10}$$

for any $h > -t$. To handle missing observations, the rows in equation (8) corresponding to the missing observations in z_t are simply skipped when applying the Kalman filter recursions (Durbin and Koopman, 2003:92f). In the case of forecasting, $h > 0$, it is sufficient to run the Kalman filter, whereas ex-post estimates of monthly national accounts are derived from the smoother.

Finally, Bańbura and Rünstler (2007) have proposed to use an algorithm by Harvey and Koopman (2003) to obtain the Kalman filter and smoother weights of individual series in forecasts and monthly estimates of national accounts. This allows expressing estimates $a_{t+h|t}$ as

$$a_{t+h|t} = \sum_{k=0}^{t-1} \omega_k(h) z_{t-k} \ . \tag{11}$$

As data sets $\mathcal{Z}_t$ embody fixed data release patterns, the $1 \times n$ vector of weights $\omega_k(h)$ becomes independent of time t, once the Kalman filter approaches its steady state (see Bańbura and Rünstler, 2007). We will consider the cumulative smoother weights $\sum_{k=0}^{t-1} \omega_{k,i}(h)$ for series i, where $\omega_{k,i}(h)$ is the ith element of $\omega_k(h)$, $i = 1, \ldots, n$. The contribution of series i to estimate $a_{t+h|t}$ may be calculated as $\sum_{k=0}^{t-1} \omega_{k,i}(h) z_{i,t-k}$.

3 Forecast evaluation

In this section we present a forecast exercise to evaluate the historical forecast performance of the dynamic factor model against various rival models, including univariate time series models and bridge equations. We consider forecasts over the period of 2000 Q1 to 2006 Q2. We address the following questions. First, what is the forecastability of the components of GDP? While a number of studies have inspected forecasts for GDP, components have been neglected. Second, how does the DFM compare to benchmark models? Third, does constraint (3) help in forecasting?

3.1 Data, publication lags and forecast design

Our euro area data set ($\mathcal{Z}_T$) was downloaded on 20, February, 2007. It comprises 85 monthly series starting in January 1993.[2] Among official data on euro area economic activity, the monthly series contain components of industrial production (17), employment and unemployment data (5), extra euro area trade values from the balance of payments (4), and retail sales, new passenger car registrations. As to survey data, we use 24 series from the European Commission business, consumer, retail and construction surveys. Financial data comprise 17 series including exchange rates (6), interest rates (7), and equity price indices (4). In addition, the data contain monetary aggregates and loans (5) and 11 series on the international economy including raw material prices (5) and key macro-economic indicators for the U.S. (6). The series are given in annex A together with the data transformations that we use for all models in this study.

The monthly data are published with different delays. The survey and financial data and the raw material prices are available right at the end of the respective month. By contrast, most of the official data on euro area economic activity, such as industrial production, employment and retail sales are published with a delay of 6 to 8 weeks after the end of the month. The same applies to the euro area monetary aggregates. For our data set this implies that surveys, financial data and raw material prices are available for January, but most of the real activity data only for December 2006. Again, publication lags are listed in annex A.

[2] We are grateful to F. Altissimo and B. Roffia (ECB) for providing us with the original version of the data set.

Our euro area quarterly national accounts data include GDP and the major demand components with inventories being subsumed under the statistical discrepancy κ_t. In addition, we consider value added and its two major components, i.e. industry (incl. construction and agriculture) and services. The national accounts are published about 10 weeks after the end of the respective quarter, but a flash estimate of GDP is available about one month earlier. Hence, our data contain the GDP flash estimate for 2006 Q4, but first releases of the components only for 2006 Q3.

With our forecast design, we aim at replicating the real-time application of the models as closely as possible. We do not have real-time data sets at hand. However, following Rünstler and Sédillot (2003) and Giannone et al. (2008) we take account of publication lags in the series and use pseudo real-time data sets $\mathcal{Z}_t$ as defined in section 2.3. In addition, we re-estimate the models at each point in time based on the available data at the time the forecast is made.

Since our data have been downloaded on 20, February 2007, our forecasts will replicate the data availability situation on the 20^{th} day of the month.

We inspect *eight* forecasts for growth in GDP and its components in a certain quarter. These forecasts are obtained in consecutive months. We start with forecasting in the 1^{st} month of the previous quarter and stop in the 2^{nd} month of the subsequent (next) quarter, one month before the first estimate of national accounts is released by Eurostat. The design will be illustrated in more detail in section 3.2.

3.2 Forecast evaluation

The forecasts are evaluated over the period of 2000 Q1 to 2006 Q2, with recursive estimation starting in 1993Q1.[3] We consider the following models:

- As benchmarks we use naive (random walk) forecasts and first-order autoregressive processes (AR(1)) for quarterly GDP and its components. The naive forecast is simply the unconditional mean of the growth rate in each quarterly series, which amounts to a random walk

[3] Value added data start only in 1995 Q1. Hence, estimates of equation (6) for these series start in this period. We ignore the chain-linking issue and instead set $\sigma_\kappa > 0$ in equation (7) as from an estimate of the deviation from the idendity.

with drift forecast in the level of the series. Again, both forecasts are calculated recursively, i.e. each forecast being based on the available data at the time the forecast is made.

- As another model based on purely quarterly data, we consider vector autoregressions (VARs) that use the quarterly aggregates x_{jt}^Q of monthly indicators x_{jt}, $j = 1, \ldots, n$. Kitchen and Monaco (2006) have proposed to obtain forecasts for a quarterly series $y_{i,t}^Q$ from a set of monthly indicators $x_t = (x_{1t}, \ldots, x_{nt})'$ by averaging across bivariate models based on single indicators. For each component y_{it}^Q we run j bivariate VARs

$$A_{ij}(L) \begin{bmatrix} y_{it}^Q \\ x_{jt}^Q \end{bmatrix} = u_{ijt}^Q$$

to obtain forecasts $\widehat{y}_{i,t+h}^{Q,(j)}$. The lengths of lag polynomials $A_{ij}(L)$ are determined from the Schwartz information criterion (SIC). The final forecast $\widehat{y}_{i,t+h}^Q$ for component y_{it}^Q is found as a simple average across the forecasts from the j VARs,

$$\widehat{y}_{i,t+h}^Q = n^{-1} \sum_{j=1}^{n} \widehat{y}_{i,t+h}^{Q,(j)} \tag{12}$$

- Bridge equations are widely used for the short-term forecasting of GDP and its components (e.g., Baffigi et al., 2004; Rünstler and Sédillot, 2003; Diron, 2006), as they employ intra-quarter information from the individual indicators. We again follow the approach proposed by Kitchen and Monaco (2006). We, first, forecast the individual monthly indicators from monthly $AR(p)$ models, $\varphi(L)x_{jt}^{(3)} = e_{jt}$ over the desired horizon, where we use 3-month rates $x_{jt}^{(3)}$ as this tends to give better forecasts. Again, we use the SIC to determine lag length p. Second, forecasts $\widehat{x}_{jt+h}^{(3)}$ are aggregated to quarterly frequency, $\widehat{x}_{jt+h}^Q$ and the quarterly target series $y_{i,t}^Q$ is predicted from the 'bridge' equation

$$\widehat{y}_{i,t+h}^{Q,(j)} = c_{ij} + \beta_{ij} \widehat{x}_{j,t+h}^Q$$

We estimate parameters c_{ij} and β_{ij} by OLS. Third, the final forecast $\widehat{y}_{i,t+h}^Q$ is again obtained as the average of the forecasts as from equation (12).

- As to the DFM, we consider the multivariate model both with and without constraint (7).[4]

[4] The model without the constraint is equivalent to a running models, which contain single quarterly series (the case of $m = 1$.)

We apply the model to two sets of national accounts data. The first data set includes GDP and its demand components, i.e. private and public consumption, gross fixed capital formation (GFCF), export and imports and the statistical discrepancy. The second version contains total value added (VAD) plus its breakdown into VAD industry and VAD services.

As to the specification of the DFM, we determine the number of static factors r from the information criterion developed by Bai and Ng (2002), which gives $r = 4$, while the number of lags in factor dynamics is found from the SIC with $p = 3$. Studies have argued that two shocks are sufficient to model economic activity and we therefore set $q = 2$ (Giannone et al., 2008). Compared to specification selection based on forecast performance, this approach has the advantage that the specification choice is independent of the target series, as we want to evaluate our model across a set of target series.

Table 1 shows the RMSE from the naive forecast. The table also exemplifies the timing of the forecasts and data releases for the 2^{nd} quarter of the year. As noted above, we inspect *eight* forecasts for growth in GDP and its components in a certain quarter, which are obtained in consecutive months. We start with forecasting in the 1^{st} month of the previous quarter and stop in the 2^{nd} month of the subsequent (next) quarter, one month before the first estimate of national accounts is released by Eurostat. In our example of the 2^{nd} quarter of the year, we run the 1^{st} forecast on 20, January and the final (8^{th}) one on 20, August. Note that the last two 'forecasts' are actually a backcasts, whereas 'forecasts' 4 to 6 amount to nowcasting the current quarter.

Table 1: RMSE of naive forecast

Fcst	Example 2^{nd} quarter	GDP	Priv cons	Gov cons	GFCF	Export	Import	Stat discr	VAD total	VAD ind	VAD serv
8	August	.000	.314	.356	.798	1.509	1.438	.320	.364	.629	.301
7	July	.332	.314	.356	.798	1.509	1.438	.320	.364	.629	.301
6	June	.332	.314	.356	.798	1.509	1.438	.320	.364	.629	.301
5	May	.332	.316	.354	.807	1.526	1.460	.317	.372	.642	.307
4	April	.338	.316	.354	.807	1.526	1.460	.317	.372	.642	.307
3	March	.338	.316	.354	.807	1.526	1.460	.317	.372	.642	.307
2	Feb	.338	.317	.358	.819	1.538	1.474	.316	.380	.652	.314
1	Jan	.347	.317	.358	.819	1.538	1.474	.316	.380	.652	.314

Since, the naive forecast is based on the quarterly data, the RMSE measures shift only in 3-month terms. The timing of these shifts reflects the publication dates of the individual series. New observations for GDP become available in the 2^{nd} month of the quarter, while data for components are published only one month later.

Table 2: RMSE of benchmark models (relative to naive forecast)

	GDP	Priv cons	Gov cons	GFCF	Exp	Imp	Stat discr	VAD total	VAD ind	VAD serv
Quarterly AR(1)										
8		1.04	.97	1.10	.95	.91	.91	.89	.94	.96
7	.82	1.04	.97	1.10	.95	.91	.91	.89	.94	.96
6	.82	1.04	.97	1.10	.95	.91	.91	.89	.94	.96
5	.82	1.07	.96	1.01	1.00	1.01	1.01	.97	1.00	.97
4	.98	1.07	.96	1.01	1.00	1.01	1.01	.97	1.00	.97
3	.98	1.07	.96	1.01	1.00	1.01	1.01	.97	1.00	.97
2	.98	1.07	.99	1.03	1.01	1.05	1.01	1.02	1.01	1.03
1	1.03	1.07	.99	1.03	1.01	1.05	1.01	1.02	1.01	1.03
Quarterly VARs										
	GDP	Priv cons	Gov cons	GFCF	Exp	Imp	Stat discr	VAD total	VAD ind	VAD serv
8		1.05	.95	1.18	.92	.90	.95	.85	.88	.89
7	.82	1.05	.95	1.18	.92	.90	.95	.85	.88	.89
6	.82	1.05	.95	1.18	.92	.90	.95	.85	.88	.89
5	.82	1.07	.95	.99	.98	1.00	1.01	1.01	.96	.94
4	.98	1.07	.95	.99	.98	1.00	1.01	1.01	.96	.94
3	.98	1.07	.95	.99	.98	1.00	1.01	1.01	.96	.94
2	.98	1.09	.98	1.12	1.00	1.05	1.00	1.00	1.02	1.01
1	1.05	1.09	.98	1.12	1.00	1.05	1.00	1.00	1.02	1.01
Bridge equations										
	GDP	Priv cons	Gov cons	GFCF	Exp	Imp	Stat discr	VAD total	VAD ind	VAD serv
8		1.02	.97	1.06	.86	.94	.99	.80	.76	.83
7	.84	1.02	.97	1.06	.86	.94	.99	.80	.76	.83
6	.85	1.04	1.00	1.06	.87	.94	1.00	.81	.77	.84
5	.88	1.04	1.04	1.08	.87	.95	.99	.79	.79	.86
4	.87	1.04	1.01	1.09	.89	.96	.99	.79	.79	.87
3	.89	1.03	1.00	1.08	.92	.99	.99	.82	.82	.88
2	.93	1.03	1.00	1.10	.98	1.02	.99	.86	.87	.89
1	.95	1.04	.99	1.09	.99	1.02	.99	.85	.90	.88

Table 2 presents the results for the AR(1), VARs and bridge equations in terms of the RMSE relative to the RMSE of the naive forecast. For both the VARs and the bridge equations we construct the forecasts from a limited set of 8 series, which on average give smaller RMSE measures as compared to forecasts from the entire set of 87 series.[5]

As regards GDP, all 3 models improve upon the naive forecast for the very short horizons, i.e. forecasts 5 to 8 (the back- and late nowcasts). There, the gains in the RMSE are close to 20%. Forecast averages from VARs and bridge equations do not improve upon the AR(1). For the 1-quarter ahead forecasts (1 to 3) only bridge equations outperform the naive forecast, but the gains remain below 10%.

Similar patterns arise for the components of value added (VAD), but in this case the VARs and, in particular, the bridge equations beat the benchmark AR(1). Among demand components, some gains emerge for exports and imports, but these hardly ever exceed 10%. For private and public consumption as well as GFCF, the benchmark models give largely uninformative forecasts. Generally, with the exception of exports and the components of value added, the gains from the VARs and bridge equations upon the AR(1) are small.

The results for the DFM version without constraint (7) are shown in the upper panel of Table 3. The model shows substantial improvements upon the alternative models for GDP and many components. For the short horizons, the RMSE of the GDP forecast is now 30% lower as compared to the naive forecast. For the 1^{st} forecast, in particular, 8 months ahead of the data release, the improvement still amounts to 20%. Similar gains occur for gross fixed capital formation, exports and imports, and the components of value added. One exception of is VAD services, where the bridge equations also fare pretty well.

While the absence of any gains for private and public consumption may reflect a lack of forecastability of the series per se, it also may be a consequence of a lack of appropriate monthly indicators in our data set. It has been argued that private consumption follows a random walk

[5]The series are: industrial production in manufacturing, retail sales, new car registrations, the unemployment rate, and the European Commission business, consumer, building and retail confidence indices. They are used in bridge equations for euro area GDP proposed by Rünstler and Sédillot, 2003) and Diron (2006). We have also experimented with some of the equations used in these studies. They did not outperform our approach.

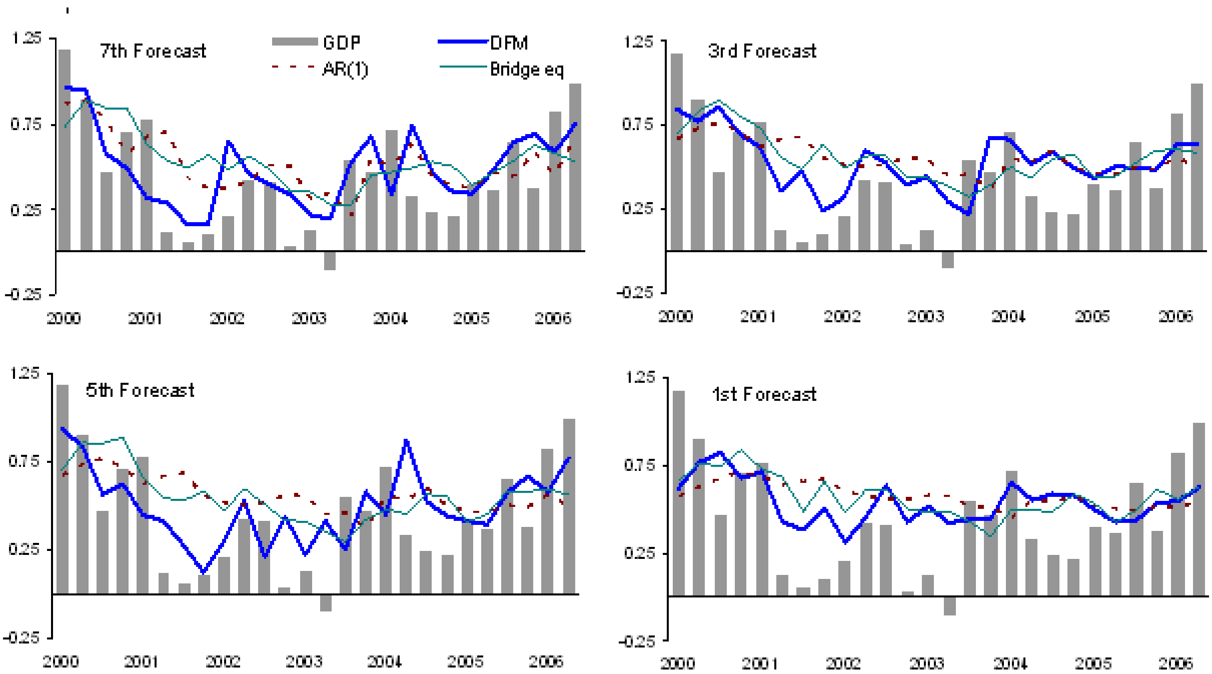
(Hall, 1988), and this also seems plausible for government consumption. However, the lack of forecastability does not necessarily preclude informative *nowcasts* of the series based on intra-quarter information.

Table 3: RMSE of dynamic factor models (relative to naive forecast)

	GDP	Priv cons	Gov cons	GFCF	Exp	Imp	Stat discr	VAD total	VAD ind	VAD serv
					w/o constraint (7)					
8		1.01	1.13	.81	.77	.69	1.13	.72	.64	.85
7	.70	.98	1.15	.81	.77	.72	1.13	.70	.64	.84
6	.72	.98	1.20	.84	.77	.70	1.11	.75	.70	.86
5	.74	.98	1.04	.81	.72	.74	.99	.75	.75	.86
4	.73	.97	1.02	.82	.70	.68	.98	.77	.76	.87
3	.73	.96	1.01	.81	.82	.80	.98	.76	.70	.88
2	.80	.96	1.01	.82	.86	.86	.99	.76	.77	.85
1	.81	.98	1.01	.86	.90	.90	.98	.80	.84	.86
					incl constraint (7)					
	GDP	Priv cons	Gov cons	GFCF	Exp	Imp	Stat discr	VAD total	VAD ind	VAD serv
8		.94	1.13	.78	.74	.69	1.20	.72	.62	.87
7	.67	.97	1.16	.82	.78	.72	1.13	.72	.63	.86
6	.70	.96	1.21	.85	.77	.70	1.12	.75	.68	.88
5	.76	.97	1.04	.78	.73	.74	.99	.76	.73	.87
4	.74	.96	1.03	.80	.70	.68	.99	.76	.73	.88
3	.73	.96	1.01	.78	.82	.80	.98	.74	.68	.87
2	.79	.95	1.02	.80	.85	.87	.99	.78	.77	.87
1	.79	.97	1.01	.84	.89	.91	.98	.84	.84	.91

Finally, the lower panel of Table 3 shows the results for the DFM using constraint (7). For the demand components, the inclusion of the constraint tends to slightly improve the RMSE in the very short-term, but to leave it unchanged thereafter. This appears to be related to the fact that the flash estimate of quarterly GDP is released about 4 weeks before the release of full national accounts. In this situation, the information contained in the flash estimate contributes to forecasting the demand components. For the components of value added, the inclusion of the constraint does not matter. Figure 1 shows forecasts from the DFM and the benchmarks. The graphs visualize the higher precision of the DFM forecasts compared to the AR(1) and the forecast averages from bridge equations.[6]

Figure 1: GDP forecasts



4 Estimates of the monthly national accounts

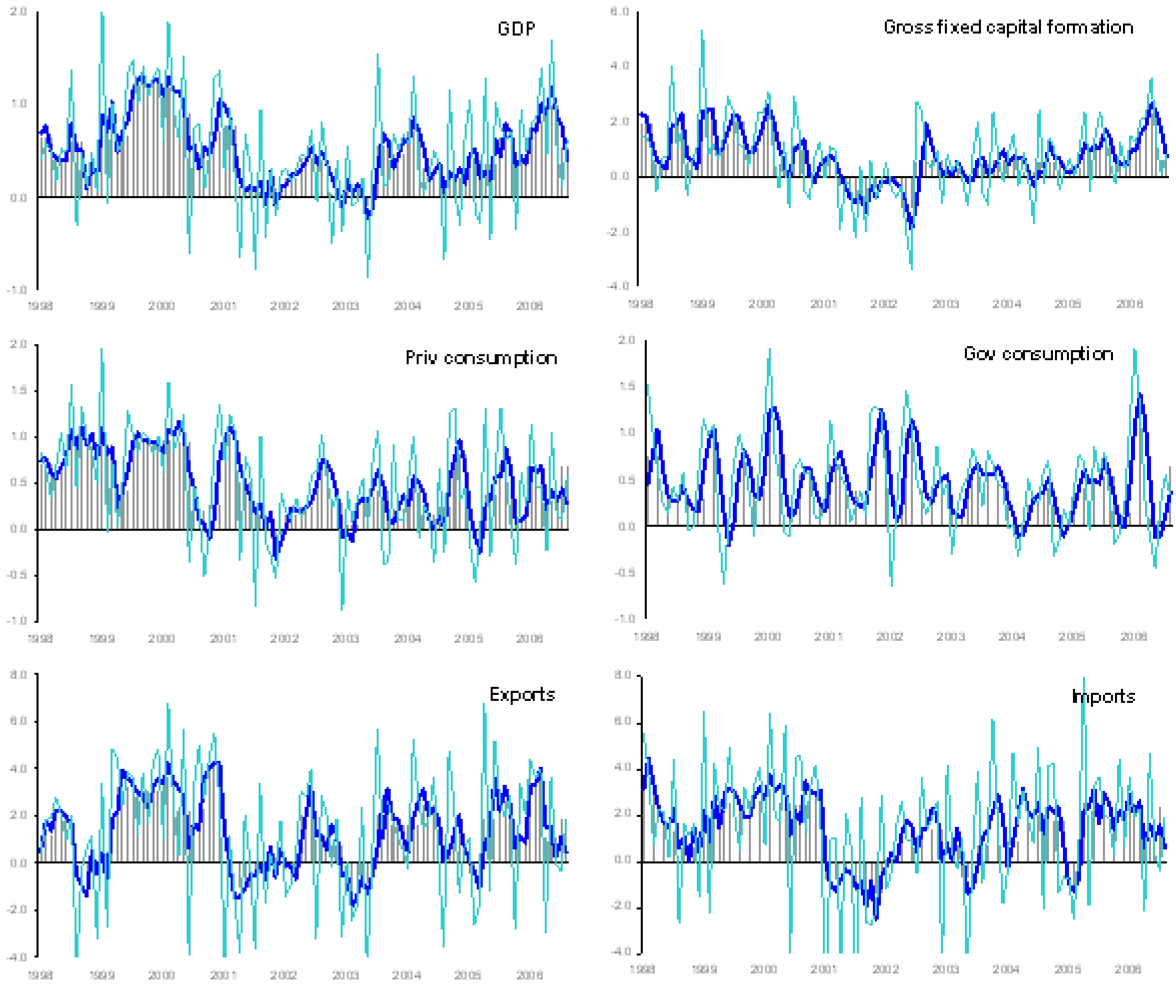
The smoothed estimates of growth in monthly GDP and its components from the DFM using constraint (7) are shown in Figure 2. The graph shows estimates of both 3-month and month-on-month rates, multiplied with 3, together with the observed quarterly rates. Note that these estimates are obtained from the Kalman smoother based on the entire data set $\mathcal{Z}_T$.

Angelini et al. (2005) compare factor-based interpolation methods with the traditional method by Chow and Lin (1971) and conclude that both methods fare well. We therefore also inspect estimates of monthly GDP growth from applying the Chow-Lin method to a single equation.

[6]Model versions that use 3-month growth rates of the indicators give a very similar forecast performance compared to to our baseline model. Results are obtainable upon request.

Following existing studies on estimating euro area monthly GDP (Mitchell et al., 2005a,2005b; Proietti and Frale, 2007), we choose euro area industrial production in manufacturing, total employment, the business confidence indicator, and retail sales as explanatory variables.[7]

Figure 2: Estimates of monthly growth in GDP and demand components

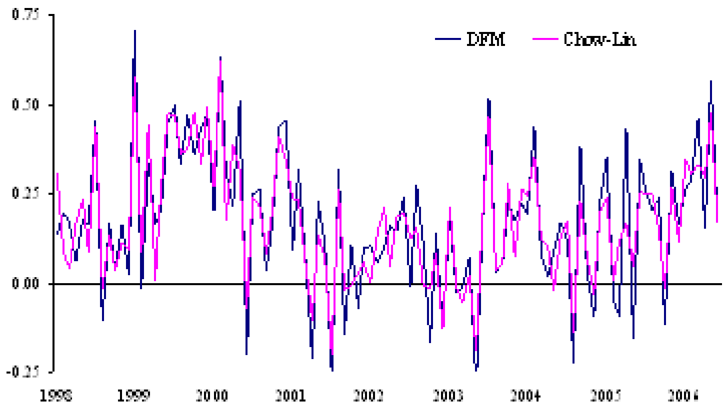


The grey bars show quarterly growth in the component, while the bold and thin lines show estimates of 3-month and month-on-month growth rates, respectively. The latter are multiplied with 3.

[7] It should also be noted that the aforementioned studies actually use more series as they derive monthly GDP as the sum of estimates of its value-added components. However, the estimates mostly use sectoral equivalents of these series. Other equations give very similar results, as long as major industrial production items are included.

Figure 3 demonstrates high correspondence among monthly growth estimates rates from the two methods with a contemporaneous correlation of 0.86 among the monthly series over the period of 1998 M1 to 2006 M6. This turns out to reflect the fact that the Kalman smoother attaches high weights to items of industrial production and, to a lesser extent, business surveys, when backcasting monthly growth rates. In this case, the DFM effectively uses very similar information to what has been chosen in the aforementioned studies.

Figure 3: Estimates of monthly GDP growth



Bańbura and Rünstler (2007) have however shown that the weights of individual series in quarterly GDP forecasts may change considerably with the forecast horizon. From contribution analysis as from equation (11) it can be shown that the same applies to estimates and forecasts of monthly growth. Table 4 presents the mean absolute contributions (MACs) of individual data groups to the forecasts of monthly GDP growth. Sample contributions have been estimated from the same pseudo real-time forecast design over the period 2000 Q1 to 2006 Q2 as used in section 3. Table 4 shows the mean absolute values of the contributions of data groups as defined in Table A.1.

The table demonstrates the shifts in the contributions of the individual data groups over the forecast horizon. 'Forecasts' 8 and 9 are actually estimates of monthly GDP, where quarterly GDP is already known. In this case, the model attaches very high weights to industrial production data. As the horizon increases, survey and financial data gain more weight relative to industrial production and (quarterly) GDP decline. This situation emerges already for nowcasts of monthly GDP in the current quarter.

Table 4: MAC to forecasts of monthly GDP growth

	Industr Prod	Surveys	Financial	Int'l	Labour	Money	GDP
9	85 %	18 %	18 %	2 %	1 %	0 %	18 %
8	90 %	18 %	19 %	2 %	0 %	0 %	18 %
7	90 %	22 %	30 %	5 %	1 %	0 %	11 %
6	44 %	63 %	35 %	6 %	1 %	0 %	11 %
5	21 %	32 %	33 %	10 %	1 %	0 %	11 %
4	10 %	21 %	20 %	4 %	0 %	0 %	0 %
3	5 %	14 %	21 %	3 %	0 %	0 %	0 %
2	6 %	7 %	12 %	5 %	0 %	0 %	0 %
1	4 %	11 %	10 %	2 %	0 %	0 %	0 %

Contributions are expressed in percentages of the mean absolute deviation of monthly GDP growth. Column 'GDP' shows the MAC of quarterly GDP growth. See Table annex A.1 for the definition of data groups.

Overall these findings parallel those of Bańbura and Rünstler (2007) for quarterly GDP forecasts. They indicate that equations that have been designed to estimate historical monthly growth in GDP and therefore rely heavily on industrial production data, are not necessarily optimal for the purpose of assessing the economic stance in real time.

5 Conclusions

The paper has combined a dynamic factor model due to Doz et al. (2005) with equations to simultaneously obtain both short-term forecasts and estimates of monthly growth in GDP and its components from a large monthly information set. Forecasts and monthly estimates are therefore consistent, which has advantages when the model is used for monitoring economic developments in real time.

We find that, for GDP and a number of components, the model beats forecasts from time series models based on quarterly data and from forecast averages from bridge equations. For public and private consumption, however, the forecasts remain uninformative. While these series are generally difficult to forecast given a lack of persistence, this not does preclude informative nowcasts.

Our findings therefore suggest that better monthly information on euro area consumption might be useful in the short-term forecasting of GDP. They also suggest that a bottom-up approach as used e.g. by Mitchell et al. (2005) suffers from the deficiency that poor estimates of certain components may translate into worsened estimates of overall GDP. An approach that achieves consistency by incorporating national accounts identities into the model may be preferable.

As to interpolation, ex-post estimates of monthly GDP growth are very similar compared to those derived from single equation methods that employ standard sets of monthly indicators, such as industrial production and confidence indicators, as the factor model attaches high weights to precisely those series used in the standard estimates. Weights change however substantially in forecasting. This suggests that equations that have been designed to estimate historical monthly growth in GDP and rely heavily on industrial production data, are not necessarily optimal for the purpose of assessing the economic stance in real time.

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Annex A: Data

No.	Series	Group	Publi-cation lag (months)	Trans-formation code
1	IP-Total industry	IndProd	3	2
2	IP-Total Industry (excl construction)	IndProd	2	2
3	IP-Manufacturing	IndProd	2	2
4	IP-Construction	IndProd	3	2
5	IP-Total Industry excl construction and MIG Energy	IndProd	2	2
6	IP-Energy	IndProd	2	2
7	IP-MIG Capital Goods Industry	IndProd	2	2
8	IP-MIG Durable Consumer Goods Industry	IndProd	2	2
9	IP-MIG Energy	IndProd	3	2
10	IP-MIG Intermediate Goods Industry	IndProd	2	2
11	IP-MIG Non-durable Consumer Goods Industry	IndProd	2	2
12	IP-Manufacture of basic metals	IndProd	2	2
13	IP-Manufacture of chemicals and chemical products	IndProd	2	2
14	IP-Manufacture of electrical machinery and apparatus	IndProd	2	2
15	IP-Manufacture of machinery and equipment	IndProd	2	2
16	IP-Manufacture of pulp, paper and paper products	IndProd	2	2
17	IP-Manufacture of rubber and plastic products	IndProd	2	2
18	Retail trade, except of motor vehicles and motorcycles	IndProd	2	2
19	New passenger car registrations	IndProd	1	2
20	Unemployment rate, total	Emp	2	3
21	Index of Employment, Construction	Emp	3	2
22	Index of Employment, Manufacturing	Emp	3	2
23	Index of Employment, Total Industry	Emp	3	2
24	Index of Employment, Total Industry (excluding construction)	Emp	3	2
25	Industry Survey: Industrial Confidence Indicator	Surveys	0	1
26	Industry Survey: Production trend observed in recent months	Surveys	0	1
27	Industry Survey: Assessment of order-book levels	Surveys	0	1
28	Industry Survey: Assessment of export order-book levels	Surveys	0	1
29	Industry Survey: Assessment of stocks of finished products	Surveys	0	1
30	Industry Survey: Production expectations for the months ahead	Surveys	0	1
31	Industry Survey: Employment expectations for the months ahead	Surveys	0	1
32	Industry Survey: Selling price expectations for the months ahead	Surveys	0	1
33	Consumer Survey: Consumer Confidence Indicator	Surveys	0	1
34	Consumer Survey: General economic situation over last 12 months	Surveys	0	1
35	Consumer Survey: General economic situation over next 12 months	Surveys	0	1
36	Consumer Survey: Price trends over last 12 months	Surveys	0	1
37	Consumer Survey: Price trends over next 12 months	Surveys	0	1
38	Consumer Survey: Unemployment expectations over next 12 months	Surveys	0	1
39	Construction Survey: Construction Confidence Indicator	Surveys	0	1
40	Construction Survey: Trend of activity compared with preceding months	Surveys	0	1
41	Construction Survey: Assessment of order books	Surveys	0	1
42	Construction Survey: Employment expectations for the months ahead	Surveys	0	1
43	Construction Survey: Selling price expectations for the months ahead	Surveys	0	1
44	Retail Trade Survey: Retail Confidence Indicator	Surveys	0	1
45	Retail Trade Survey: Present business situation	Surveys	0	1
46	Retail Trade Survey: Assessment of stocks	Surveys	0	1
47	Retail Trade Survey: Expected business situation	Surveys	0	1
48	Retail Trade Survey: Employment expectations	Surveys	0	1
49	Total trade - Intra Euro 12 trade, Export Value	Int'l	2	2
50	Total trade - Extra Euro 12 trade, Export Value	Int'l	2	2
51	Total trade - Intra Euro 12 trade, Import Value	Int'l	2	2
52	Total trade - Extra Euro 12 trade, Import Value	Int'l	2	2
53	US, Unemployment rate	Int'l	1	1
54	US, IP total excl construction	Int'l	1	2
55	US, Employment, civilian	Int'l	1	2
56	US, Retail trade	Int'l	1	2
57	US, Production expectations in manufacturing	Int'l	0	1
58	US, Consumer expectations index	Int'l	0	1
59	World market prices of raw materials in Euro, total, HWWA	Int'l	0	2
60	World market prices of raw materials in Euro, total, excl energy, HWWA	Int'l	0	2
61	World market prices, crude oil, USD, HWWA	Int'l	1	2
62	Gold price, USD, fine ounce	Int'l	0	2
63	Brent Crude, 1 month fwd, USD/BBL converted in euro	Int'l	0	2
64	ECB Nominal effective exch. rate	Financial	0	2
65	ECB Real effective exch. rate CPI deflated	Financial	0	2
66	ECB Real effective exch. rate producer prices deflated	Financial	0	2
67	Exch. rate: USD/EUR	Financial	0	2
68	Exch. rate: GBP/EUR	Financial	0	2
69	Exch. rate: YEN/EUR	Financial	0	2
70	Eurostoxx 500	Financial	0	2
71	Eurostoxx 325	Financial	0	2
72	US S&P 500 composite index	Financial	0	2
73	US, Dow Jones, industrial average	Financial	0	2
74	US, Treasury Bill rate, 3-month	Financial	0	1
75	US Treasury notes & bonds yield, 10 years	Financial	0	1
76	10-year government bond yield	Financial	0	1
77	3-month interest rate, Euribor	Financial	0	1
78	1-year government bond yield	Financial	0	1
79	2-year government bond yield	Financial	0	1
80	5-year government bond yield	Financial	0	1
81	Index of notional stock - Money M1	Money	2	2
82	Index of notional stock - Money M2	Money	2	2
83	Index of notional stock - Money M3	Money	2	2
84	Index of Loans	Money	2	2
85	Money M2 in the U.S.	Money	2	2

Transformation code: 1 = 3-month difference, 2 = 3-month growth rate

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