Short-term forecasts of euro area GDP growth.*

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Abstract

This paper evaluates models that exploit timely monthly releases to compute early estimates of current quarter GDP (now-casting) in the euro area. We compare traditional methods used at institutions with a new method proposed by Giannone, Reichlin, and Small (2005). The method consists in bridging quarterly GDP with monthly data via a regression on factors extracted from a large panel of monthly series with different publication lags. We show that bridging via factors produces more accurate estimates than traditional bridge equations. We also show that survey data and other 'soft' information are valuable for now-casting.

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1 Introduction

This paper evaluates different methods to construct early estimates and short term forecasts of quarterly GDP growth for the euro area, exploiting timely releases of monthly data.

Forecasting the present is an important task in Central Banks and, in particular, in the euro area. GDP data are published with a considerable delay. The first official release is the Eurostat's flash estimate of euro area GDP growth which is published six weeks after the end of the reference quarter). As a consequence, policy decisions have to rely on other information which is released in a more timely manner. More timely information have monthly or higher frequency and include "hard" indicators, like industrial production which is released six weeks after the end of the reference month, while "'soft" indicators such as survey data which are released at the end of, or few days after, the reference month.

Monthly indicators are routinely used in judgemental forecasting to form a view on current economic conditions before GDP data are made available. Statistical models which can perform this exercise and exploit timely information must deal with mixed frequency (using monthly data to nowcast quarterly GDP) and jagged edges (at the end of the sample, different variables will have missing points corresponding to different dates in accordance with their timeliness). In policy institutions models that have these characteristics go under the name of 'bridge equations'. These are predictive equations that bridge monthly information with quarterly ones.

More precisely, bridge equations are regressions of quarterly GDP growth on a small set of preselected key monthly indicators. This simple modelling strategy has been popular among policy institutions which commonly pooled several GDP forecasts from bridge equation models so as to consider information from a large number of predictors. In this paper we will focus on two main implementations of this technique: an approach, implemented at the ECB, that combines a number of selected bridge equations based on multiple regressors (see Diron, 2006; Rünstler and Sédillot, 2003) and an approach, which pools forecasts of GDP based on a large number of bridge equations with only one predictor each (see Kitchen and Monaco, 2003).

An alternative way to exploit large information to bridge monthly and quarterly variables has been proposed by Giannone, Reichlin, and Small (2005), first applied on US data at the Board of Governors of the Federal Reserve and now also regularly implemented at the ECB. This method consists in combining predictors in few common factors which are then used as regressors in bridge equation via the Kalman filter.

The first part of the paper will present an out-of-sample evaluation of the three methods, estimated with

different specification choices. The design of the experiment is pseudo-real time in the sense that we will replicate the data availability situation that is faced in real-time application of the models and that the models are re-estimated using only the information available at the time of the forecast. However, our design differs from a perfect real-time evaluation since we use final data vintages and hence ignore revisions to earlier data releases.

Although there is a large literature comparing the forecasting accuracy of factor models and forecast averaging,[1] no paper has focus on now-casting and therefore on forecasting combination and factor forecast with bridging. This is important since forecasting improvement of GDP with respect to naive models is mainly limited to current quarter (D'Agostino, Giannone, and Surico, 2006).[2]

We evaluate the impact of new data releases on current GDP nowcast throughout the quarter. We update the model two times per month, at the mid and at the end of the month and measure the accuracy of the forecasts computed using the information available at each date. This allows to understand the importance of different types of releases since the end of month update incorporates essentially the releases of 'soft' data while the mid of the month update incorporates mainly 'hard' data. Moreover, following Banbura and Rünstler (2007) we will study the weight the model attaches to 'soft' and 'hard' data to nowcast GDP. Both exercises will allow us to quantify the reliability of 'soft' data for the euro area case.

The paper is structured as follows. Section 2 describes the bridge techniques. Section 3 briefly reviews the alternative modelling strategy proposed in Giannone, Reichlin, and Small (2005) which relies on combining predictors in a few common factors. Section 4 provides an assessment on the empirical performance of these alternative methods. This section further reviews how to retrieve policy relevant information from the predictions of the 'bridging with factors' model, in effect rendering this model less mechanical in nature. Section 5 concludes.

2   Bridge equations (BE)

A traditional modelling strategy for obtaining an early estimate of quarterly GDP growth by exploiting information in monthly variables is based on the so-called 'bridge equations' (BE). 'Bridging' stands for linking

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[1]See for example Marcellino, Stock, and Watson (2003) for euro area data, Stock and Watson (2006) for the US, Camba-Mendez, Kapetanios, Smith, and Weale (2001) for major European countries, Artis, Banerjee, and Marcellino (2005) for the UK, Reijer (2007) for the Netherlands, Duarte and Rua (2007) for Portugal, Schumacher (2007) for Germany and Nieuwenhuyze (2005) for Belgium.

[2]A recent Euro-system project (see Rünstler, Barhoumi, Cristadoro, Reijer, Jakaitiene, Jelonek, Rua, Ruth, Benk, and Nieuwenhuyze (2008)) provides results from a streamlined version of this paper, but based on different country data-sets.

monthly data, typically released early in the quarter, with quarterly data, such as GDP and its components that are released late and are not available at monthly frequencies.

The bridge equations under regular use in several policy institutions, including the ECB, rely on selected indicators, which have been shown to contain some predictive content for quarterly GDP growth (see Baffigi, Golinelli, and Parigi, 2004; Diron, 2006; Kitchen and Monaco, 2003; Rünstler and Sédillot, 2003).

Let us denote quarterly GDP growth as y_t^Q and the vector of k selected stationary monthly indicators, for every bridge equation j, as $x_t^j = (x_{1,t}^j, \ldots, x_{k,t}^j)'$, $t = 1, \cdots, T$. The bridge equation is estimated from quarterly aggregates of the monthly data. Predictions of GDP growth are obtained in two steps. In a first step, the monthly indicators are forecast over the remainder of the quarter to obtain forecasts of their quarterly aggregates, x_{it}^{jQ}. The forecasts of the monthly predictors are typically based on univariate time series models.

In a second step, the resulting values are used as regressors in the bridge equation to obtain the GDP forecast. We have:

$$y_t^Q = \mu + \sum_{i=1}^k \beta_i^j(L) x_{it}^{jQ} + \varepsilon_t^{jQ} \tag{1}$$

where μ is an intercept parameter and $\beta_i^j(L) = \beta_{i0}^j + \ldots \beta_{is(i)}^j L^{s(i)}$ denote lag polynomials of length $s(i)$.

The models are designed to be used in real time and that at each date of the forecast some series, due to publication lags, will have missing data at the end of the sample. Moreover, due to the different timing of data releases, the number of missing data differs across series. Missing data are typically forecasted using *univariate* monthly autoregressive models.

Bridge equation can handle only a limited set of predictors. Information from many predictors is incorporated by *combining predictions* from many small models (see Diron, 2006; Kitchen and Monaco, 2003). An alternative route to incorporate large information consists in *combining the predictors* into few common factors.

3 Bridging with factors (BF)

In order to exploit information of many timely monthly releases to obtain an early estimate of quarterly GDP growth, an alternative to averaging many bridge equation, is to use estimated common factors as regressors. This idea was first introduced by Giannone, Reichlin, and Small (2005) and applied to US data.

In a nutshell, the idea of this approach is to compute factors from a large panel of monthly data. Factors are averaged so as to obtain quarterly series which are then used as regressors in the GDP equation; where time aggregation is such that the quarterly series corresponds to the third month of the quarter. Missing observations for the first and second quarter are computed via the Kalman filter.

Consider the vector of n stationary monthly series $x_t = (x_{1,t}, \ldots, x_{n,t})'$, $t = 1, \ldots, T$, which have been standardized to mean zero and variance one. The dynamic factor model considered by Giannone, Reichlin, and Small (2005) is then given by the equations

$$
\begin{aligned}
x_t &= \Lambda f_t + \xi_t, & \xi_t &\sim \mathbb{N}(0, \Sigma_\xi), & (2) \\
f_t &= \sum_{i=1}^{p} A_i f_{t-i} + \zeta_t, & & & (3) \\
\zeta_t &= B\eta_t, & \eta_t &\sim \mathbb{N}(0, I_q). &
\end{aligned}
$$

From an $n \times r$ matrix of factor loadings Λ, equation (2) 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 (3) describes the law of motion for the latent factors f_t, which are driven by q-dimensional standardized white noise η_t, where B is a $r \times q$ matrix, where $q \leq r$. Hence $\zeta_t \sim \mathbb{N}(0, BB')$. Finally, $A_1, \ldots, A_p$ are $r \times r$ matrices of parameters and it is further assumed that the stochastic process for f_t is stationary.

Let us now define quarterly GDP growth as the average of monthly latent observations: $y_t^Q = (y_t + y_{t-1} + y_{t-2})$ and obtain quarterly factors as $f_t^Q = (f_t + f_{t-1} + f_{t-2})$. The factors-based bridge equation is then defined as:

$$
\widehat{y}_t^Q = \beta' \widehat{f}_t^Q. \tag{4}
$$

where β is an $r \times 1$ vector of parameters. In the 3rd month of each quarter, we evaluate the forecast for quarterly GDP growth, $\widehat{y}_t^Q$, as the quarterly average of the monthly series:

$$
\widehat{y}_t^Q = \frac{1}{3}(\widehat{y}_t + \widehat{y}_{t-1} + \widehat{y}_{t-2}) \tag{5}
$$

and define the forecast error $\varepsilon_t^Q = y_t^Q - \widehat{y}_t^Q$. We assume that ε_t^Q is distributed with $\varepsilon_t^Q \sim \mathbb{N}(0, \sigma_\varepsilon^2)$. Innovations ξ_t, ζ_t, and ε_t^Q are assumed to be mutually independent at all leads and lags.

In order to insure consistency among monthly indicators and quarterly GDP, all monthly variables are transformed so as to insure that the corresponding quarterly quantities are given by $x_{it}^Q \sim (x_{it} + x_{it-1} + x_{it-2})$ where $t = 3k$ and $k = 1, \cdots, T/3$. This implies that series in differences enter the factor model in terms of 3

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month changes which is consistent with having defined quarterly GDP growth as the three month average of monthly latent observations.

Having specified the bridge equation we now have to deal with the fact that the monthly panel is unbalanced at the end of the sample due to different publication lags of the data. A key feature of the model by Giannone, Reichlin, and Small (2005) is that it deals easily with the unbalanced data set problem. From the state space form of the model, Kalman filter techniques can be easily applied. Precisely, to obtain efficient forecasts of GDP growth y_t^Q from the unbalanced data sets, the Kalman filter and smoother recursions is applied to the state space representation of this model.[3] The advantage of this framework over that of the simple bridge equations is that instead of forecasting missing values on the basis of a univariate autoregressive model, we obtain a forecast compatible with the model which exploits multivariate information.

Let us denote $z_t' = (x_t', y_t^Q)$ and consider a data set $\mathcal{Z}_T = \{z_s\}_{s=1}^T$ that has been downloaded on a certain day of the month and might contain missing observations for certain series at the end of the sample. Following Giannone, Reichlin, and Small (2005), a model-based measure for the uncertainty of forecasts from any data set $\mathcal{Z}_t$ can be easily computed by noting that the the variance of the forecast error for y_{t+h}^Q can be decomposed into

$$\mathrm{var}(\widehat{y}_{t+h|t}^Q - y_{t+h}^Q) = \pi_{t+h|t} + \sigma_\varepsilon^2 \tag{6}$$

where $\pi_{t+h|t} = \mathrm{var}(\widehat{y}_{t+h|t}^Q - \widehat{y}_{t+h}^Q)$ represents the effect stemming from the uncertainty in forecasts $f_{t+h|t}$ of the latent factors.[4] We denote $\pi_{t+h|t}$ as filter uncertainty, as opposed to residual uncertainty σ_ε^2.

Giannone, Reichlin, and Small (2005) have pointed that $\pi_{t+h|t}$ can be used for inspecting the information content of new data releases. Consider two data sets $\mathcal{Z}_t^{(date\ 1)}$ and $\mathcal{Z}_t^{(date\ 2)} \supseteq \mathcal{Z}_t^{(date\ 1)}$, hence $\mathcal{Z}_t^{(date\ 2)}$ is downloaded on a later date. With parameters θ being estimated from data $\mathcal{Z}_t^{(date\ 1)}$ in both cases, it can be shown that

$$\pi_{t+h|t}^{(date\ 1)} = \pi_{t+h|t}^{(date\ 2)} + \mathrm{var}\left[\widehat{y}_{t+h|t}^{Q,(date\ 1)} - \widehat{y}_{t+h|t}^{Q,(date\ 2)}\right]. \tag{7}$$

Hence, $\pi_{t+h|t}^{(date\ 1)} \geq \pi_{t+h|t}^{(date\ 2)}$ and filter uncertainty necessarily increases when information is withdrawn. Empirical results will be shown below.

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[3]See Appendixes A1 and A2 for further details.

[4]For the state space representation shown in the appendix, $\pi_{t+h|t}$ is obtained from the corresponding elements of matrix $P_{t+h|t}$ defined in equation A.5.

4   The models at work

In its regular monitoring of economic activity in the euro area, ECB staff uses a set of bridge equations that has gradually developed in recent years. This also includes equations to forecast the demand components of the national accounts and GDP of euro area member states, respectively (see Diron, 2006; Rünstler and Sédillot, 2003). The GDP forecast is derived as the simple average of the predictions from all the equations. In this paper we consider a *subset of these equations*, i.e. twelve bridge equations, which are designed to forecast euro area GDP directly, and derive the GDP forecast as the simple average of the predictions from these equations. They contain in various combinations, a small set of selected indicators for the euro area: industrial production, industrial production in construction, retail sales, new car registrations, the unemployment rate, money M1, the European Commission business and service confidence indices, and, among composite indicators, the OECD leading indicator, and the CEPR-Bank of Italy coincident indicator for the euro area 'EuroCoin'. The models used in each of the 12 individual equations are listed in Table 1. The GDP forecast is derived as the simple average of the predictions from such equations. In what follows we will refer to the method as BES model, standing for Bridge Equations based on Selected predictors.

Table 1: Bridge equations for euro area GDP growth-(*BES* model).

Explanatory variables	Equation											
	1	2	3	4	5	6	7	8	9	10	11	12
Industrial production (total)	*	*	*	*	*	*	*	*	*			
Ind productuion construction		*	*	*	*	*		*	*			
Retail sales		*	*	*	*	*	*	*	*			
New car registrations	*	*	*	*						*		
Service confidence				*	*		*		*			
Unemployment rate						*	*					
Money M1								*	*			
Business confidence										*		
EuroCoin (CEPR)											*	
OECD leading indicator												*

With the exception of EuroCoin and the service confidence index, the data have been transformed to represent monthly differences when expressed in rates (unemployment and business survey) and monthly growth rates otherwise. All series appear at lag 0 in the equations, i.e. $\beta_i^j(L) = 1$ with the exception of EuroCoin, which appears at lag 1, i.e $\beta_i^j(L) = L$, and real money, which appears at lag 2, i.e $\beta_i^j(L) = L^2$.

The factor model will be based of a larger information set incorporating a wide range of monthly indicator. The predictors include $n = 85$ monthly indicators. Among official data on euro area *economic activity*, the monthly series contain 19 series, i.e. components of industrial production (17), 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 22 series including exchange rates (6), interest rates (7), equity price indices (4), and raw material prices (5). As to the *international economy* the data contain 11 series including key macro-economic indicators for the US (7) and extra area trade volumes from the balance of payments statistics (4). In addition, the data set includes 5 series related to employment and 4 series on monetary aggregates and loans. We have transformed series to obtain stationarity. The series and their transformations are described in Appendix A3.

We will also produce early estimates of GDP growth averaging many bridge equations based on the same information set used for bridging with factor. We will assess the forecasting performance of an average of the predictions obtained by the eighty-five univariate bridge equations. Each equation j predicts quarterly GDP growth from the quarterly aggregate of stationary monthly indicator x_{1t}^{jQ} where:

$$y_t^Q = \mu_j + \beta_1^j(L)x_{1t}^{jQ} + \varepsilon_t^{jQ} \tag{8}$$

The idea of model averaging to combine information from large data-sets has been discussed largely in Hendry and Clements (2004). This method has been used for early estimates of GDP growth by the US Treasury (Kitchen and Monaco, 2003). In what follows we will refer to the method as BEA model, standing for Bridge Equations based on All predictors.

4.1 Design of the simulated pseudo out-of-sample exercise

We evaluate the forecasting accuracy of different methods under realistic informational assumptions. We design the forecasting evaluation exercise by mimic as closely as possible the real-time flow of information, by replicating the real time pattern of data availability. The parameters of the model are estimated recursively using only the information available at the time of the forecast. We do not have a real-time database for all the predictors considered, therefore we will not be able to take into account the real-time data revisions.

Taking into account the real time data flow is important to understand the marginal impact of blocks of releases since the latter depends on their order. The order of data arrival and the publication lag are particularly important when data are nearly collinear as it is the case for macroeconomics series. In this case, the block that is more timely has a larger information content since, by the time the later release is published, its informational content is already incorporated in the forecast.

In principle, the now-cast from each model can be computed whenever new data are released within the month. The Giannone, Reichlin, and Small (2005) factor model implemented at the Fed is updated once a week while

at the ECB the same model and the bridge equations are updated twice a month, in relation to data releases at the end of the month and the release of important 'hard' data such as industrial production in the middle of the month.

We will replicate this practice at the ECB and thus conduct two forecasts per month which replicate the data availability prevailing at the time of the two monthly updates. More precisely, we use a data set downloaded on 25 February 2008 and combine this with the typical data release calendar to re-construct data availability at the end of the month (*end*) and in the middle of the month (*mid*).

The data situation at the end of the month coincide with the release of financial market data and survey data for the previous month and retail trade turnover and monetary aggregates with a lag of one month. Around the middle of the month the bulk of 'hard' data on economic activity, including data on industrial production, external trade and new passenger car registrations are released. The attribution of releases to each update is described in the last column of the Table in appendix A3.[5]

For GDP of a certain quarter, we will produce a sequence of forecasts in seven consecutive months prior to the release.

Starting from these two data sets, $\mathcal{Z}_T^{(i)} = \{x_s\}_{s=1}^T$ for $i = \{end,\ mid\}$, we define a pseudo real-time data set $\mathcal{Z}_t^{(i)} = \{x_s\}_{s=1}^t$ as the observations from the original data set $\mathcal{Z}_T^{(i)}$ up to period t, but with observation $x_{i,t-h}$, $h \geq 0$, eliminated, if observation $x_{i,T-h}$ is missing in $\mathcal{Z}_T^{(i)}$.

Notice that, we could have updated the model more frequently throughout the month as done in the evaluation on US data by Giannone, Reichlin, and Small (2005). There use was made of a stylized calendar which allowed us to measure the marginal impact of the releases in that calendar on the now-cast. Such a detailed analysis is more difficult with European data since releases are clustered and the relative order of different data releases has changed over the evaluation period. Therefore, for this application, the model is updated only twice a month, in relation, roughly, to the release of 'soft' (end of month) and 'hard' (mid-month) data respectively. In this case the order of the stylized calendar is not far from reality since there are only two large groups and hence changes in the ordering over the evaluation sample are rather limited.

Therefore, the mid-of-month and the end-of-month updates reflect the incorporation of 'hard' and 'soft' data respectively, hence by looking at the evolution of the forecasts and its accuracy it is possible to assess the impact of hard and soft data on GDP.

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[5]The international data in our data set are published at various dates and we therefore attributed them accordingly.

4.2   Empirical specification of the models

There are several parameters to be specified: the number of lags for the bridge equations; the number of factors r, the number of shocks q and the lag length p of the VAR on the factors

Bridge equations.   Model specification is either based on information criteria or on the RMSE criteriun. The information criteria used is that proposed in Schwarz (1978) and will be referred to as SIC. For the *BEA* model, the lag length is chosen from the SIC for each equation individually at each point in time. We search lags in the range $[0, 4]$ and also consider the averages across this range. For the *BES* model the lag length is fixed ex-ante using the specification that is actually used at the ECB.[6] For the *BEA* model, parameters are also chosen on the basis of a recursive RMSE criterium. According to this criterion we chose the parametrization that, at each point in time, produces the minimum RMSE for the forecast computed up to that point. In addition, we will consider simple forecast averages across a range of specifications. For both BES and BEA, we use the autoregressive model on the monthly growth rates (or monthly difference) to forecast the missing observations for the predictors; lag length is selected by the SIC.

Bridging with factors.   Here use is made of both the RMSE and the information criteria, together with forecast averages across a range of specifications. For the RMSE we consider the lowest average RMSE over the entire forecast horizon. For instance, in 2003Q4, the available forecast errors are from 1999Q1 to 2003Q2 and this sample is used for model selection. As information criteria we use criterion IC_2 from Bai and Ng (2002) to determine r within a range of $[1, 8]$. Given r, we estimate equation (3) and determine lag length p from the SIC within a range of $[1, 4]$. Finally, we apply principal components analysis to the estimated residuals $\widehat{\zeta}_t$ and follow Bai and Ng (2007) in selecting q as the smallest value that satisfies the condition $\left(\sum_{i=q+1}^{r} \widehat{\lambda}_i \right) / \left(\sum_{i=1}^{r} \widehat{\lambda}_i \right) < q_{\mathrm{crit}}$, where $\widehat{\lambda}_i$ are the ordered eigenvalues from the sample covariance matrix of ζ_t and q_{crit} is an appropriate critical value.

For both information and RMSE criteria, the model is selected from the range $r = [1, 8]$, $q = [1, \min(5, r)]$, and $p = [1, 4]$. Forecast averages are also taken over this range.

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[6]The specification is based on the findings in Diron (2006) and Rünstler and Sédillot (2003), and mostly selects lag 0. This of course may bias results against them.

4.3 Forecasting performance

The models are evaluated by looking at the out-of-sample forecasting performances during the period 1999Q1 to 2007Q2. For GDP of a certain quarter, a sequence of forecasts in seven consecutive months prior to the release are computed. Furthermore, we conduct two forecasts per month, which replicate the data availability prevailing at the end of the month and in the middle of the month.

Figure 1: euro area GDP growth and model forecasts.
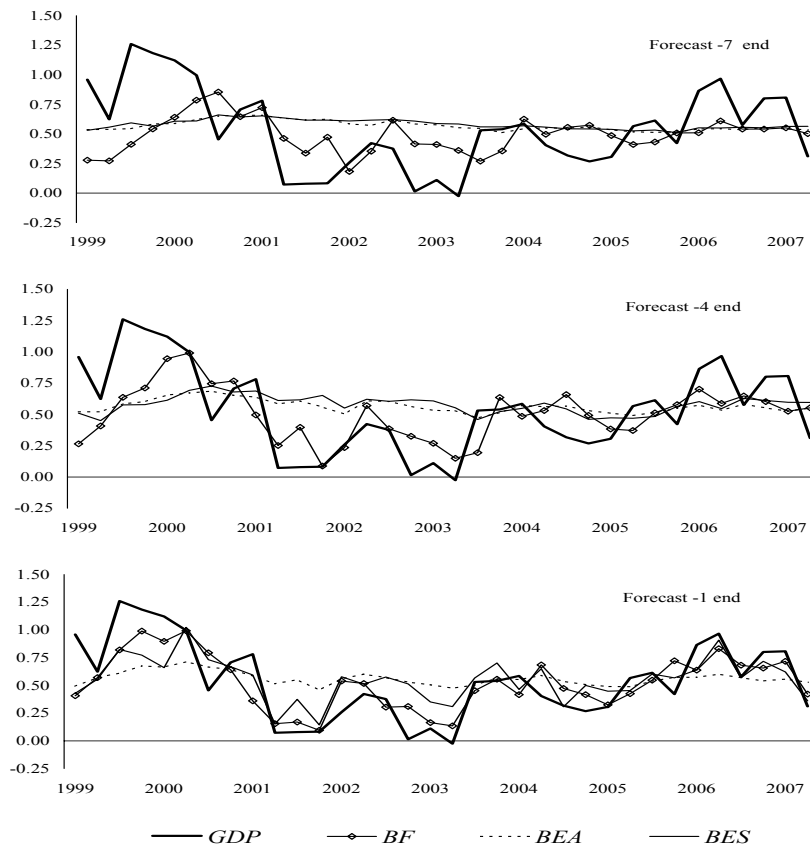
The figure reports the forecasts from the three models under study against the GDP numbers. For the *BF* and the *BEA* models the average performance across the diffeent specifications is reported. Values shown are the forecasts conducted at the *end* of months 7, 4, and 1, respectively, prior to the release of the GDP flash estimate.

Figure 1 shows the forecasts from the *BF* model and the two implementations of the bridge equation model, *BES* and *BEA* respectively. Results show that the factor model forecast tracks GDP more accurately, in particular during the pronounced slowdown in 2001-2003. The *BEA* produces forecasts which are rather flat.

Figure 2: RMSE from pseudo real-time exercise 1999Q1 - 2005Q4.
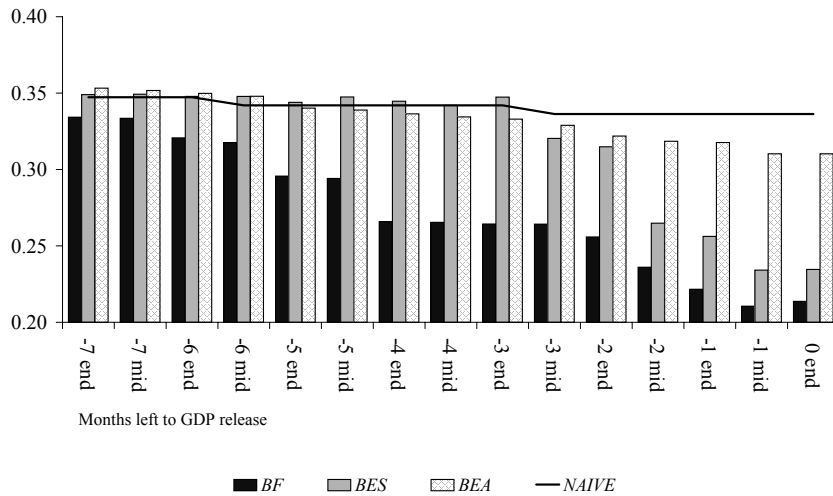
In the x-axis we write $-i\ end$ to indicate the forecasts conducted using information available at the end of i months ahead of the data release; we use $-i\ mid$ to indicate the forecast computed using information available in the middle of the month. See text for more details. For the BF and the BEA models the average performance across the different specifications is reported. The NAIVE forecast predicts GDP growth to be equal to the average of past GDP growth.

However, the BES starts tracking GDP dynamics one month before the first GDP release.

We compute out-of-sample measures for all models. Precisely, we look at the evolution of the RMSE for the now-casts computed after each data release within the quarter when GDP growth is projected on available monthly data series. Results are shown in Figure 2, which reports the RMSE for all models as well as for the naive constant growth forecast. For the BF model the Figure shows the RMSE derived from the average across specifications while detailed results for all parameterizations are reported in Table 2.

From both Figure 2 and Table 2 we can see that, for the BF model, there is a clear decline of the RMSE with the increase in monthly information. For the averages across different specifications, for instance, the RMSE declines steadily from .338 to .234, an improvement of around 30%. This feature is less clear for the bridge equations, especially the BEA specification whose performance does not improve over the quarter. Notice that the BES model becomes more accurate once there is less than 2 months to go for the release of GDP. This matches the time when industrial production for the current quarter is included for the first time. The result is not surprising as the BES makes extensive use of 'hard' data.

In general, we find that the BF model uniformly outperforms the AR(1) benchmark and the bridge equations

Table 2: Root mean squared error from short-term forecasts (1999Q1 - 2007Q2).

Quarter	Months to GDP release	Vintage	Benchmarks		BF Model				BE Models			
			NAIVE	AR(1)	RecRMS	Avg	IC	Best ex-post	BES	BEA		
										RecRMS	Avg	IC
Next	-7	-7 end	0.3473	0.3301	.3394	.3342	.3421	.3201	.3490	.3536	.3532	.3488
		-7 mid	0.3473	0.3301	.3440	.3335	.3392	.3208	.3493	.3511	.3517	.3473
Next	-6	-6 end	0.3473	0.3301	.3223	.3207	.3361	.3037	.3478	.3488	.3498	.3448
		-6 mid	0.3420	0.3446	.3195	.3176	.3293	.3016	.3478	.3462	.3479	.3423
Next	-5	-5 end	0.3420	0.3446	.3118	.2957	.3123	.2812	.3440	.3381	.3402	.3350
		-5 mid	0.3420	0.3446	.3125	.2941	.3063	.2805	.3475	.3363	.3389	.3331
Current	-4	-4 end	0.3420	0.3446	.2775	.2659	.2661	.2463	.3447	.3336	.3364	.3304
		-4 mid	0.3420	0.3446	.2740	.2654	.2616	.2447	.3420	.3322	.3344	.3281
Current	-3	-3 end	0.3420	0.3446	.2710	.2643	.2713	.2400	.3474	.3305	.3330	.3266
		-3 mid	0.3363	0.2955	.2600	.2642	.2662	.2338	.3204	.3264	.3289	.3224
Current	-2	-2 end	0.3363	0.2955	.2618	.2559	.2671	.2404	.3149	.3197	.3219	.3150
		-2 mid	0.3363	0.2955	.2299	.2360	.2370	.2119	.2649	.3159	.3185	.3116
Previous	-1	-1 end	0.3363	0.2955	.2172	.2216	.2277	.2052	.2562	.3152	.3177	.3111
		-1 mid	0.3363	0.2955	.1987	.2105	.2089	.1894	.2341	.3075	.3103	.3043
Previous	0	0 end	0.3363	0.2955	.2057	.2137	.2116	.2031	.2346	.3074	.3103	.3042

The table reports root mean square forecast errors from different models computed at the end of the month (*end*) or in the middle of the month (*mid*) as explained in the main text. The parameterizations for the *BF* model and the *BEA* model have been selected using three criteria. Namely, recursive mean square forecast error (*RecRMS*); averaging across all possible parameterizations (*Avg*); and applying recursively information criteria (*IC*). *Best ex−post* refers to the *BF* model with parameter settings $r = 5$, $p = 3$ and $q = 1$, which gave the lowest RMSE over the whole forecasting sample.

across all horizons and independently from the specification selection method. This is most likely a reflection of the fact that, contrary to the bridge equation model, the factor model exploits the information content of cross correlations across series. The major gains occur for the intermediate horizons, i.e. the forecasts made 3 to 5 months ahead of the release of the GDP flash estimate. For these forecasts, the RMSE is about 20% lower compared to the AR(1) benchmark. Among specification selection methods differences are small. This is in line with Rünstler, Barhoumi, Cristadoro, Reijer, Jakaitiene, Jelonek, Rua, Ruth, Benk, and Nieuwenhuyze (2008) who found that information and recursive RMSE criteria perform about equally well across nine data sets. Bridge equations do not uniformly beat the AR(1) and any gains upon the latter are small. Differences between the various specification selection methods are also very small for the bridge equation models.

Let us also remark that the best ex-post parameterizations on the entire exercise for the *BF* model is: $r = 5$, $q = 3$, and $p = 1$, shown in Table 2 under the heading 'Best ex-post'. Notice that this also corresponds to

Figure 3: Model based measure of uncertainty (Bridging with factors model).
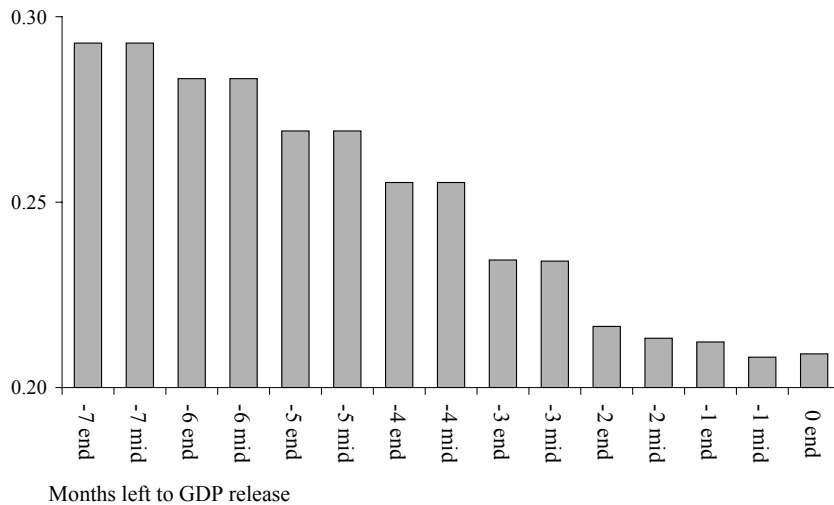
Months left to GDP release

the parameters chosen at the end of the evaluation sample using the recursive mean square forecast error criterion. This is the model selected for the last run at the end of the evaluation exercise from the recursive RMSE criterion. We use this parameterizations to compute the in-sample measure of uncertainty and also for the measures of contributions from economic indicators to the forecast reported below.

4.4 The marginal impact of data releases

From the factor model estimates, we can compute the marginal impact of data releases on the now-cast in two alternative ways.

First, following Giannone, Reichlin, and Small (2005), we can compute model based uncertainty as new data are published using equation (6). Results are reported in Figure 3 which illustrates that the general pattern of the out-of-sample measure is confirmed. Figure 3 further shows that the major reductions in model based uncertainty, reflected in the steps shown in the figure, come primarily with the releases of 'soft' data.

Second, following Banbura and Rünstler (2007), we can compute contribution (weight) of data releases to the forecast.

Figure 4: Contributions to GDP forecasts - (Bridging with Factors).
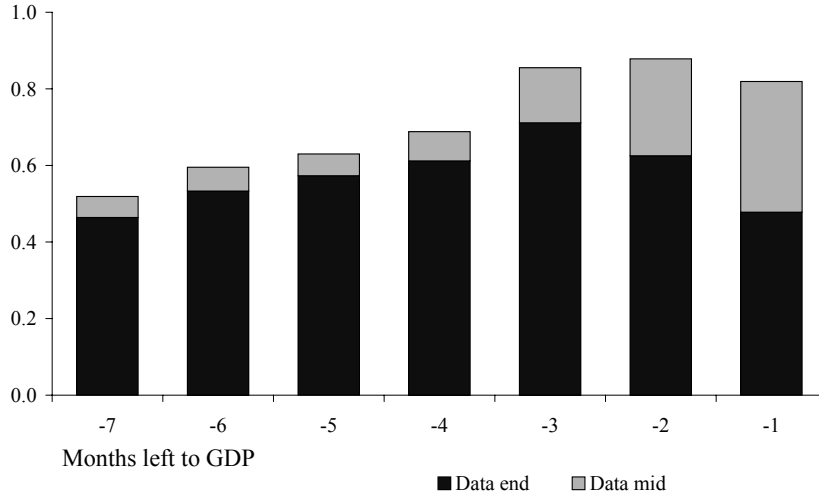
Values shown are mean absolute contributions of data groups, standardized by the standard deviation of GDP growth as explained in the text. 'Data end' and 'Data mid' refers to data availability at the end and in the middle of the month respectively. See appendix A3 for the precise definition of these two groups of data.

Since the pattern of data availability changes over time, the weight on each individual series changes throughout the quarter.[7] By looking at the magnitude of their weight in the forecasts, we can understand which variables are useful and when. Banbura and Rünstler (2007) have proposed to compute the weights of the individual observations in the estimates of the state vector using an algorithm developed by Harvey and Koopman (2003). Again, weights can be calculated for an arbitrary information set with those weights related to missing data being set to zero. This allows expressing forecasts as a weighted sum of available observations in $\mathcal{Z}_t$, i.e.

$$\widehat{y}_{t+h|t}^{Q} = \sum_{k=0}^{t-1} \omega_k(h) z_{t-k} \ , \tag{9}$$

From this expression the contribution of series i to the forecast can be computed as $c_{k,it} = \sum_{k=0}^{t-1} \omega_{k,i}(h) z_{i,t-k}$, where $\omega_{k,i}(h)$ is the ith element of $\omega_k(h)$, $i = 1, \ldots, n$. Results are reported in figure 4 which displays the mean absolute contribution, standardised with the sample standard deviation of GDP growth σ, namely $\sum_{t=1}^{T} |c_{k,it}| / \sigma$ and where time runs from 1999Q1 to 2007Q2, i.e. the evaluation sample.

Results show that the 'soft' data have most of the weight for earlier estimates. Later, when 'hard' data for

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[7]Notice that otherwise the filter is stationary and hence if it was unbalanced the weight of different blocks would not change.

the quarter are released, the weight on 'soft' information decreases in favor of the 'hard' data. Note that this is in line with the fact that, as shown by all results in this paper, the accuracy improves in earlier forecasts with the end-of-month update while for later forecasts it improves mainly with the mid-of-month release.

5   Conclusions

This paper evaluates pools of bridge equations and the 'bridging with factors' approach proposed by Giannone, Reichlin, and Small (2005) for the backcast, nowcast and short-term forecast of euro area quarterly GDP growth. This model provides a framework to exploit the data flow of monthly information during the quarter to forecast quarterly GDP and it allows to estimate the factors and compute missing observations due to publication lags within the same framework via the use of the Kalman filter.

In addition, we provide an out-of-sample evaluation of the models when updated at different dates of the month in relation with releases of 'soft' data and 'hard' data respectively.

Results indicate that the factor model improves upon the pool of bridge equations. In the case of the nowcast the root mean squared is lower by 10-15% and it is therefore a valid new tool to be used for short-term analysis.

We also show that, while the performance of bridge equations is fairly constant over the quarter, the RMSE of the factor model decreases with the arrival of new information. The advantage over bridge equations is particularly pronounced in the middle of the quarter, when it exploits a large number of early releases efficiently. Early in the quarters forecast errors decrease in relation to the release of 'soft' data since industrial production and 'hard' data in general are not yet available. At the end of the quarter, on the other hand, the decrease is marked in relation to the release of 'hard' data. This shows that timeliness is important and that, in order to evaluate the marginal improvement of groups of releases we need to condition on available information. The same point is shown by the fact that the contribution of the 'soft' data releases to the forecast is large at the beginning of the quarter and small at the end while the opposite is true for 'hard' data. Contrary to the bridge equations of the *BES* the bridging factor model makes use of a wide range of relevant 'soft' data. This translates into a better forecasting performance in particular at longer horizons, when the availability of 'hard' data for the reference quarter is scarce.

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A Appendix

A1 State Space representation of factor model

We cast equations (2) to (5) in state space form in the manner explained in Banbura and Rünstler (2007). We construct a series y_t^Q at monthly frequency such that it contains mean-adjusted quarterly GDP growth in the 3rd month of the respective quarter, whereas the remaining observations are treated as missing. The final row of observation equation (A.1), related to y_t^Q, is defined only for the 3rd month of the quarter and otherwise is skipped in application.

Aggregation rule (5) is implemented in a recursive way in equation (A.2), as from $\widehat{y}_t^Q = \Xi_t \widehat{y}_{t-1}^Q + \frac{1}{3}\widehat{y}_t$, where $\Xi_t = 0$ for t corresponding to the 1st month of the quarter and $\Xi_t = 1$ otherwise (Harvey, 1989:309ff). As a result, expression (5) holds in the 3rd month of each quarter. The inclusion of the GDP forecast in the state vector, $\alpha_t' = (f_t', \widehat{y}_t, \widehat{y}_t^Q)$, greatly facilitates the calculation of the various statistics discussed below.

$$
\begin{bmatrix} x_t \\ y_t^Q \end{bmatrix} = \begin{bmatrix} \Lambda & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} f_t \\ \widehat{y}_t \\ \widehat{y}_t^Q \end{bmatrix} + \begin{bmatrix} \xi_t \\ \varepsilon_t^Q \end{bmatrix} \tag{A.1}
$$

$$
\begin{bmatrix} I_r & 0 & 0 \\ -\beta' & 1 & 0 \\ 0 & -\frac{1}{3} & 1 \end{bmatrix} \begin{bmatrix} f_{t+1} \\ \widehat{y}_{t+1} \\ \widehat{y}_{t+1}^Q \end{bmatrix} = \begin{bmatrix} A_1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \Xi_{t+1} \end{bmatrix} \begin{bmatrix} f_t \\ \widehat{y}_t \\ \widehat{y}_t^Q \end{bmatrix} + \begin{bmatrix} \zeta_{t+1} \\ 0 \\ 0 \end{bmatrix} \tag{A.2}
$$

The estimation of the model parameters $\theta = (\Lambda, A_1, \ldots, A_p, \beta, \Sigma_\xi, B, \sigma_\varepsilon^2)$ is discussed in Giannone, Reichlin, and Small (2005). Briefly, Λ is estimated from static principal components analysis applied to a balanced sub-sample of data $\{x_s\}_{s=1}^T$. This also gives sample estimates of the common factors. The latter are used to estimate equation (3) and a quarterly version of (4) by standard regression techniques. Matrix B is estimated from principal components analysis applied to the estimated residuals $\widehat{\zeta}_t$.

Let us finally remark that (n, T) consistency of the factors for this two-step estimator whereby, in the first step, factors are estimated by principal component and, in the second step, they are re-estimated via the Kalman smoother, have been proven by Doz, Giannone, and Reichlin (2006b). The same authors, in a separate paper (Doz, Giannone, and Reichlin, 2006a), show that by iterating we obtain a quasi maximum likelihood estimator for the factors.

A2 Handling missing observations with the factor model

Let us denote $z_t' = (x_t', y_t^Q)$ and consider a data set $\mathcal{Z}_T = \{z_s\}_{s=1}^T$ that has been downloaded on a certain day of the month and might contain missing observations for certain series at the end of the sample. For the state space form

$$z_t = W(\theta)\alpha_t + u_t, \qquad u_t \sim N(0, \Sigma_u(\theta)) \tag{A.3}$$

$$\alpha_{t+1} = T_t(\theta)\alpha_t + v_t, \qquad v_t \sim N(0, \Sigma_v(\theta)),$$

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

$$a_{t+h|t} = \mathbb{E}\left[\alpha_{t+h}|\mathcal{Z}_t\right] \tag{A.4}$$

$$P_{t+h|t} = \mathbb{E}\left[a_{t+h|t} - \alpha_{t+h}\right]\left[a_{t+h|t} - \alpha_{t+h}\right]', \tag{A.5}$$

for $h > -t$.

To handle missing observations, the rows in equation (A.3) corresponding to the missing observations in z_t are simply skipped when applying the recursions, which is equivalent to setting to infinity the variance of the idiosyncratic noise related to the missing observations (on this point see Giannone, Reichlin, and Small (2005)).

A3   Data Appendix

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

The 'Publication lag' refers to the delay in months for releasing the data for a reference period. The date of release indicates if the release is included in the *end* or *mid* update of the model (see main text for further details). As for the transformation code is used to refer to differences while 2 is used when log differencing has been applied.