INTRODUCING THE EURO-STING: SHORT TERM INDICATOR OF EURO AREA GROWTH

2008

Maximo Camacho and Gabriel Perez-Quiros

Documentos de Trabajo
N.º 0807

BANCO DE ESPAÑA
Eurosistema

INTRODUCING THE EURO-STING: SHORT TERM INDICATOR OF EURO AREA GROWTH

INTRODUCING THE EURO-STING: SHORT TERM INDICATOR OF EURO AREA GROWTH (*)

Maximo Camacho (**)

UNIVERSIDAD DE MURCIA

Gabriel Perez-Quiros (***)

BANCO DE ESPAÑA AND CEPR

(*) We thank Francis Diebold, Simon van Norden, Ken Wallis, and the participants at the 5th Workshop on Forecasting Techniques, and at the internal seminar series of Banco de España, and European Central Bank for helpful comments and suggestions. We received extremely valuable research assistance from Camilo Ulloa. We are also thankful to the Euro-area division of the Banco de España for all the preliminary meetings that end up with this paper. Finally, we are thankful to Juan Ayuso for the clever idea for the name of the indicator. Remaining errors are our own responsibility. The paper was written when the first author was visiting the Banco de España. The views in this paper are those of the authors and do not represent the views of Banco de España or the EuroSystem.

(**) mcamacho@um.es.

(***) gabriel.perez@bde.es.

Documentos de Trabajo. N.º 0807
2008

ISSN: 0213-2710 (print)
ISSN: 1579-8666 (on line)
Depósito legal:
Unidad de Publicaciones, Banco de España

Abstract

We propose a model to compute short-term forecasts of the Euro area GDP growth in real-time. To allow for forecast evaluation, we construct a real-time data set that changes for each vintage date and includes the exact information that was available at the time of each forecast. In this context, we provide examples that show how data revisions and data availability affect point forecasts and forecast uncertainty.

Keywords: Business Cycles, Output Growth, Time Series.

JEL Classification: E32, C22, E27

1 Introduction

Early assessments of the ongoing evolution of the economic activity are of crucial interest for successful execution of economic agents decisions. In the Euro area, the lack of timely information associated with the publication of the macroeconomic variables, the presence of missing values in the historical time series, and the short length of the Euro-wide aggregates, make the day to day monitoring of the economic activity especially problematic. The objective of this paper is to provide a statistical method flexible enough to, dealing with these shortcomings, allow for the analysis of the short-term economic growth in the Euro area.

The generally accepted reference series to anticipate short-term economic developments is the Euro area GDP growth rate. However, the "final" estimates of GDP growth, the so called *second* release, is published with a delay of about 14 weeks after the end of the respective quarter. Given this publication delay, forecasters and researchers try to identify the current economic developments by using indicators which are more timely available although exhibit similar economic fluctuations than the reference series. Natural indicators are the two early announcements of the second release which are called *flash* and *first* releases, respectively. Other candidates are monthly indicators which are based on either economic activity data (*hard* indicators) or surveys (*soft* indicators) since they exhibit much shorter publishing delay than the second releases.

For this purpose, we use a coincident indicator approach which is based on an extension of the dynamic factor model described in Mariano and Murasawa (2003). Their baseline model is flexible enough to deal with temporal aggregation, and short samples. However, we extend the model in several directions in order to take into account the typical problems affecting the real-time economic analyses such as dealing with variable reporting lags or early announcements of the series of interest. In addition, since the original proposal was developed to construct in-sample economic indicators, we adapt the model to compute GDP growth rate forecasts in real time. Using these extensions, we examine the evolution of the model uncertainty as new data with more accurate information become available in real time since the model is updated each day that new data are released. Our proposed framework can also be viewed as a metric to measure the news associated with each realization of the indicators. This measure is based on the effect that new releases have on expected economic growth.

To understand how our proposal differs from the related literature it is worth emphasizing the double objective of our dynamic factor model. First, we construct the model with the aim of forecasting quarterly growth rate of GDP which simplify the evaluation (and accountability) of the forecasts versus other contributions, such as the (new) Eurocoin indicator advocated by Altissimo et al. (2006), which focus on narrower definitions of the "medium to long term" component of GDP growth whose forecasts are more difficult to evaluate. In this sense, our paper situates among those in the literature which try to use real-time data to continuosly update measurements and forecasts of lower frequency objects (as GDP). This approach is different from the one of those papers which try to measure high frequency objects (as real-time activity) on a daily or hourly bases. These papers try to measure a latent variable (real-time activity) related but distinct from the observed variable that we try to forecast (GDP). A good example of this approach is the contribution of Aruoba, Diebold and Scotti (2008).

The second objective of our model is to evaluate the impact that the information contained in the new releases of each indicator has on the short-term predictions of GDP growth rates. Hence, full dynamic forecasts of each indicator should be used to discriminate between the unpredictable and the predictable parts of the new data releases and therefore to change the forecast of growth accordingly. For this purpose, we need a fully specified dynamic factor model for all the variables included in the model. This requires that GDP forecasts must rely on a single specification that accounts for the full dynamic interactions among GDP, its announcements and the monthly indicators. Consequently, we are precluded from using the univariate bridge equations employed by Runstler and Sedillot (2003) and Dirhon (2006). Independent approaches to forecast Euro area GDP growth are Angelini et. al (2008) and Banbura and Runstler (2007) which employ large scale dynamic factor models to forecast European. However, in contrast to our specification, in these empirical applications they assume that the idiosyncratic components of all the indicators evolve as white noises. Additionally, none of them evaluate the forecasting accuracy in real time.

In the empirical analysis, we develop several exercises which lead to many interesting results. First, we accommodate the three Euro area GDP releases in a statistical model to examine the impact of preliminary announcements and data revisions in real time forecasting. We find that when all the information whiting each quarter is properly combined, the model improves upon the accuracy of preliminary announcements in forecasting GDP. Second, we illustrate the importance of relying on current-vintage as opposite to end-of-sample vintage data sets when analyzing forecasting accuracy in real time. The latter implicitly make the unrealistic assumption that data revisions are not important in real time which may lead to misleading results. Third, according to Banbura and Runstler (2007), we find that suitable treatment of publication lags may lead business surveys to provide important sources of information in predicting GDP beyond that of real activity data. Business surveys are especially relevant in the months previous to the publication of hard indicators. Fourth, we assess the evolution of forecast uncertainty in real time, showing that the uncertainty about the GDP forecast continuously decreases during the forecasting period. It falls about one third due to the publication of monthly indicators and falls again significantly with the flash releases. However, falls in uncertainty provided by first announcements are of much less importance.

Our final contribution has to do with the construction of the real-time data set that include the vintages that were available at the time of each forecast. The data refer to the piece of information that a forecaster would have had available at any given day in the past five years. This allow us to evaluate the relative relevance of our forecasts compared with some of the most popular Euro area GDP growth forecasts. Among them, we include the forecasts from the Eurocoin, the European Commission macroeconomic forecasts, the Euro area GDP growth projection of DG ECFIN, the IFO-INSEE-INSAE economic forecast, and the Projections of the OECD Economic Outlook. In terms of mean squared errors, we provide forecasts which are better than all of them for most of the forecasting horizons.

To sum up, in this paper we present a model which computes accurate short term forecasts of Euro area GDP growth in real time. The forecasts rely on the literature on coincident indicators which we extend to account for the specificities of real time forecasting and the full specification of the idiosyncratic component of each indicator. The name of the proposal is then based on these features: a model that combines the Short Term INdicators of Growth (STING).

The paper is organized as follows. Section 2 outlines the proposed methodology and analyzes how to deal with mixing monthly and quarterly frequencies of flow data, how to use early estimates of GDP growth and how to estimate the model. Section 3 evaluates the empirical reliability of our method. Section 4 concludes and proposes several research lines.

2 The model

In this section we develop a state space representation of a model to compute short term forecasts of Euro area GDP growth in real time from a data set that may include mixing frequencies and missing data.

2.1 Mixing frequencies

This paper deals with the problem of mixing monthly and quarterly frequencies of flow data by treating quarterly series as monthly series with missing observations. Let G_t be a quarterly series which is observable every third period and whose logs are integrated of order one. In this paper, series with these characteristics are the time series of GDP (second), its announcements (first and flash) and employment. These series are the quarterly aggregates of monthly series, X_t, which are assumed to be observable in this section. Accordingly, we can construct quarterly time series from monthly series by adding the monthly values of the corresponding quarter

$$G_t = 3\left(\frac{X_t + X_{t-1} + X_{t-2}}{3}\right), \tag{1}$$

which means that the quarterly levels are three times the arithmetic mean. However, handling with this definition would imply using non-linear state space models, which is rather troublesome. Mariano and Murasawa (2003) avoid this problem by approximating the arithmetic mean with the geometric mean. It is worth noting that if monthly changes are small the approximation error is almost negligible.[1] In practice, monthly changes of production and employment are small (less than a percentage point) so the geometric approximation is appropriate.

In this context, Proietti and Moauro (2006) and Aruoba, Diebold and Scotti (2008) propose dynamic factor models that permit exact filtering which avoids the approximation proposed by Mariano and Murasawa (2003). However, their proposals are not exempt of problems. The former authors develop an exact filter in a non-linear framework which involves approximations in its own. The latter authors propose a filter that is developed in a dynamic factor model where all the indicators used in the filter have to be assumed to have a polynomial trend.

Hence, we assume that the flow data at any quarter is three times the geometric mean of the monthly issues within the given quarter:

$$G_t = 3\left(X_t X_{t-1} X_{t-2}\right)^{1/3}, \tag{2}$$

which yields

$$\ln G_t = \ln 3 + \frac{1}{3}\left(\ln X_t + \ln X_{t-1} + \ln X_{t-2}\right). \tag{3}$$

Taking the three-period differences for all t and after some algebra, we can express the quarter-on-quarter growth rates (g_t) of the quarterly series as weighted averages of the monthly-on-monthly past growth rates (x_t) of the monthly series

$$g_t = \frac{1}{3}x_t + \frac{2}{3}x_{t-1} + x_{t-2} + \frac{2}{3}x_{t-3} + \frac{1}{3}x_{t-4}. \tag{4}$$

2.2 Flash, first and second GDP growth rates

Eurostat revises two times the GDP figures that correspond to a given quarter. The first estimate of GDP growth rate in the Euro area, y_t^f, is released about 45 days after the end of the respective quarter and this is the so-called flash estimate. Although it is very useful to have an early estimate of GDP, the disadvantage of this flash estimate is that it is based

[1] For example, even if we assume a high constant growth of 1% each month (annual growth rate of more than 12%), the difference between the arithmetic and the geometric means is less than 0.4 percentage points.

on incomplete information. Using more comprehensive information, the revision of this figure is published about 20 days after the flash and this is the so-called first estimate, y_t^{1st}. In addition, as new information is available, the second estimate of GDP growth rate, y_t^{2nd}, incorporates an additional revision about 40 days after the first and this is the so-called second estimate. According to this revision process, let us call e_1 the revision between the flash and the first, and e_2 the revision between the first and the second.

Due to data constraints (flash and first estimates are just available since 2003.1 and 1998.3, respectively), we are precluded from developing formal tests in order to discriminate between the news and noise versions of the revisions as described in Mankiw and Shapiro (1986). In spite of this limitation, we follow Evans (2005) to propose that

$$y_t^f = y_t^{2nd} + e_{1t} + e_{2t}, \tag{5}$$

$$y_t^{1st} = y_t^{2nd} + e_{2t}, \tag{6}$$

where e_{1t} and e_{2t} are independent mean zero revision shocks with variances and $\sigma_{e_1}^2$ and $\sigma_{e_2}^2$, respectively.[2]

2.3 State space representation

To consider the notion of comovements among the GDP series and the economic indicators, the time series are modelled as the sum of two orthogonal components. The first component is the common factor, f_t, and reflects the notion that the series dynamics are driven in part by common shocks. The second component captures the idiosyncratic behavior of each series.

For clarity in the exposition, let us start by assuming that all variables are always observed at a monthly frequency. Monthly growth rates of quarterly series and monthly growth rates of hard indicators are assumed to exhibit a direct relation with the common factor which measures the common component of the monthly growth rates of these series. However, the relation between the common factor and the soft indicators is treated in a

[2]For simplicity, we assume that e_{1t} and e_{2t} are uncorrelated. Adding correlation between errors is straightforward, but we think that the available sample of flashes and firsts is still too short to formulate elaborated models.

different manner. European Commission (2006) acknowledges that each confidence indicator is calculated as the simple arithmetic average of the balances of answers to specific questions chosen from the full set of questions in each individual survey. The selection of questions is guided by the aim of achieving an as high as possible coincident correlation of the confidence indicator with the reference series, such as year-on-year growth in industrial production, at euro-area level. Accordingly, we relate the level of soft indicators with the year-on-year common growth rate which can be written as the sum of current values of the common factor and its last eleven lagged values.

Let us collect the r_h hard indicators in the vector Z_t^h and the r_s soft indicators in the vector Z_t^s. Let l_t be the quarterly employment growth rate, and let u_{1t}, u_{2t}, U_t^h, and U_t^s be the scalars and r_h-dimensional and r_s-dimensional vectors which determine the idiosyncratic dynamics of GDP, unemployment and the economic indicators, respectively. The *measurement equation* can be defined as

$$\begin{pmatrix} y_t^{2nd} \\ Z_t^h \\ Z_t^s \\ l_t \\ y_t^{1st} \\ y_t^f \end{pmatrix} = \begin{pmatrix} \beta_1\left(\frac{1}{3}f_t+\frac{2}{3}f_{t-1}+f_{t-2}+\frac{2}{3}f_{t-3}+\frac{1}{3}f_{t-4}\right) \\ \beta_2 f_t \\ \beta_3\sum_{j=0}^{11} f_{t-j} \\ \beta_4\left(\frac{1}{3}f_t+\frac{2}{3}f_{t-1}+f_{t-2}+\frac{2}{3}f_{t-3}+\frac{1}{3}f_{t-4}\right) \\ \beta_1\left(\frac{1}{3}f_t+\frac{2}{3}f_{t-1}+f_{t-2}+\frac{2}{3}f_{t-3}+\frac{1}{3}f_{t-4}\right) \\ \beta_1\left(\frac{1}{3}f_t+\frac{2}{3}f_{t-1}+f_{t-2}+\frac{2}{3}f_{t-3}+\frac{1}{3}f_{t-4}\right) \end{pmatrix} +$$

$$\begin{pmatrix} \frac{1}{3}u_{1t}+\frac{2}{3}u_{1t-1}+u_{1t-2}+\frac{2}{3}u_{1t-3}+\frac{1}{3}u_{1t-4} \\ U_t^h \\ U_t^s \\ \frac{1}{3}u_{2t}+\frac{2}{3}u_{2t-1}+u_{2t-2}+\frac{2}{3}u_{2t-3}+\frac{1}{3}u_{2t-4} \\ \frac{1}{3}u_{1t}+\frac{2}{3}u_{1t-1}+u_{1t-2}+\frac{2}{3}u_{1t-3}+\frac{1}{3}u_{1t-4} \\ \frac{1}{3}u_{1t}+\frac{2}{3}u_{1t-1}+u_{1t-2}+\frac{2}{3}u_{1t-3}+\frac{1}{3}u_{1t-4} \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ e_{2t} \\ e_{1t}+e_{2t} \end{pmatrix}, \quad (7)$$

where $U_t^h = (v_{1t}, ..., v_{r_h t})'$, $U_t^s = (v_{r_h+1t}, ..., v_{rt})'$, and $r = r_h + r_s$. The factor loadings, $\beta = \begin{pmatrix} \beta_1 & \beta_2' & \beta_3' & \beta_4 \end{pmatrix}'$, measure the sensitivity of each series to movements in the latent factor and have dimensions that lead them to be conformable with each equation.

The dynamics of the model is achieved by assuming that

$$\begin{aligned} f_t &= a_1 f_{t-1} + ... + a_{m_1} f_{t-m_1} + \epsilon_t^f, && (8) \\ u_{1t} &= b_1 u_{1t-1} + ... + b_{m_2} u_{1t-m_2} + \epsilon_t^{u_1}, && (9) \\ v_{jt} &= c_{j1} v_{jt-1} + ... + c_{jm_3} v_{jt-m_3} + \epsilon_t^{v_j}, && (10) \\ u_{2t} &= d_1 u_{2t-1} + ... + d_{m_4} u_{2t-m_4} + \epsilon_t^{u_2}, && (11) \end{aligned}$$

where $\epsilon_t^f \sim i.i.d.N\left(0, \sigma_f^2\right)$, $\epsilon_t^{u_1} \sim i.i.d.N\left(0, \sigma_{u_1}^2\right)$, $\epsilon_t^{v_j} \sim i.i.d.N\left(0, \sigma_{v_j}^2\right)$, with $j = 1, ..., r$, and $\epsilon_t^{u_2} \sim i.i.d.N\left(0, \sigma_{u_2}^2\right)$. All the covariances are assumed to be zero. The identifying assumption implies that the variance of the common factor, σ_f^2, is normalized to a value of one.

More compactly, one can use the expression for the measurement equation

$$Y_t = Hh_t + w_t, \tag{12}$$

with $w_t \sim i.i.d.N\left(0, R\right)$. In addition, the *transition equation* can be stated as

$$h_t = Fh_{t-1} + \xi_t, \tag{13}$$

with $\xi_t \sim i.i.d.N\left(0, Q\right)$. An extensive description of how these equations look like for the empirical model has been stated in Appendix A.

To handle with missing observations, we substitute the missing observations with random draws θ_t from $N(0, \sigma_\theta^2)$ which are independent of the model parameters. The substitutions allow the matrices to be conformable but they have no impact on the model estimation since the Kalman filter uses for them the data generating process of the normal distribution. In that sense, the missing observations add just a constant in the likelihood function of the Kalman filter process. Let Y_{it} be the i-th element of the vector Y_t and R_{ii} be its variance. Let H_i be the i-th row of the matrix H which has α columns and let $0_{1\alpha}$ be a row vector of α zeroes. In this case, the measurement equation can be replaced by the following expressions

$$Y_{it}^{*} = \begin{cases} Y_{it} & \text{if } Y_{it} \text{ observable} \\ \theta_t & \text{otherwise} \end{cases}, \tag{14}$$

$$H_{it}^{*} = \begin{cases} H_{i} & \text{if } Y_{it} \text{ observable} \\ 0_{1\alpha} & \text{otherwise} \end{cases}, \tag{15}$$

$$w_{it}^{*} = \begin{cases} 0 & \text{if } Y_{it} \text{ observable} \\ \theta_t & \text{otherwise} \end{cases}, \tag{16}$$

$$R_{iit}^{*} = \begin{cases} 0 & \text{if } Y_{it} \text{ observable} \\ \sigma_\theta^2 & \text{otherwise} \end{cases}. \tag{17}$$

This trick leads to a time-varying state space model with no missing observations so the Kalman filter can be directly applied to Y_t^*, H_t^*, w_t^*, and R_t^*. Let $h_{t|\tau}$ be the estimate of h_t based on information up to period τ and let $P_{t|\tau}$ be its covariance matrix. With this notation, the *prediction equations* are

$$h_{t|t-1} = Fh_{t-1|t-1}, \tag{18}$$

$$P_{t|t-1} = FP_{t-1|t-1}F' + Q. \tag{19}$$

The prediction errors are $\eta_{t|t-1} = Y_t^* - H_t^* h_{t|t-1}$ with covariance matrix $\zeta_{t|t-1} = H_t^* P_{t|t-1} H_t^{*\prime} + R_t^*$. Hence, the log likelihood can be computed in each iteration as

$$l_t = -\frac{1}{2}\ln\left(2\pi\left|\zeta_{t|t-1}\right|\right) - \frac{1}{2}\eta_{t|t-1}'\left(\zeta_{t|t-1}\right)^{-1}\eta_{t|t-1}. \tag{20}$$

The *updating equations* are

$$h_{t|t} = h_{t|t-1} + K_t^* \eta_{t|t-1}, \tag{21}$$

$$P_{t|t} = P_{t|t-1} - K_t^* H_t^* P_{t|t-1}, \tag{22}$$

where the Kalman gain, K_t^*, is defined as $K_t^* = P_{t|t-1} H_t^{*\prime}\left(\zeta_{t|t-1}\right)^{-1}$. The initial values of $h_{0|0}$ and $P_{0|0}$ used to start the filter are a vector of zeroes and the identity matrix, respectively. Note that when at any date τ all the elements of the vector Y_τ are not observed, the updating equation is $h_{\tau|\tau} = h_{\tau|\tau-1}$ and time τ does not change the estimated dynamics of the model. This feature can be used to easily compute forecasts by adding missing data for all the variables in the model at the end of the sample.

It is worth noting that the Kalman filter allows for computing the contribution of each series to GDP forecasts. Substituting the prediction errors $\eta_{t|t-1}$ and (18) into the updating equation (21), one obtains

$$h_{t|t} = (I - K_t^* H_t^*) F h_{t-1|t-1} + K_t^* Y_t^*. \tag{23}$$

Now, when the Kalman filter is close to its steady state, this expression becomes

$$h_{t|t} = M_t^* (L) Y_t^*, \tag{24}$$

with the elements of the matrix of lag polynomial $M_t^* (L) = (I - (I - K_t^* H_t^*) FL)^{-1} K_t^*$ measuring the effects of unit changes in the lags of individual observations on the inference of the state vector $h_{t|t}$. Letting M_{jt}^* be each of these matrices, the inference on the state vector can be decomposed into a weighting sum of observations

$$h_{t|t} = \sum_{j=0}^{\infty} M_{jt}^* Y_{t-j}^*. \tag{25}$$

In this sense, $M_t^* (1) = (I - (I - K_t^* H_t^*) F)^{-1} K_t^*$ is a matrix that contains the cumulative impacts of the individual observations in the inference of the state vector.

Combining this relation with the first row of equation (7) which shows that GDP can be decomposed into the sum of its unobservable components, one can compute the cumulative impact of each indicator to the forecast of GDP growth. For the empirical illustration stated in Appendix A, this measure can be easily obtained as follows

$$\psi_t = \beta_1 \left(\frac{1}{3} m_{1t}^* + \frac{2}{3} m_{2t}^* + m_{3t}^* + \frac{2}{3} m_{4t}^* + \frac{1}{3} m_{5t}^* \right)' + \left(\frac{1}{3} m_{13t}^* + \frac{2}{3} m_{14t}^* + m_{15t}^* + \frac{2}{3} m_{16t}^* + \frac{1}{3} m_{17t}^* \right)', \tag{26}$$

where m_{it}^* is the i-th row of $M_t^* (1)$, and ψ_t is a vector which contains the cumulative forecast weight of each indicator.

3 Empirical results

3.1 Data description

The variables entering the proposed model are listed in Table 1 and plotted in Figure 1. For its interest in real time forecasts, the particular date on which these series are published and the samples that they cover are also shown in the figure. Note that the day on which the paper was written, 02/11/08, GDP growth and its announcements for the third quarter of 2007 are available, but none of these figures are available for the fourth quarter of 2007.

The list of indicators which are included in the dynamic factor model can be classified into three groups. The first group contains quarterly indicators. Apart from the second release of GDP and its early estimates (flash and first), the quarterly series of employment is included in this group. The second group of indicators is formed by monthly hard indicators which are based on economic activity data. In particular, they are the Euro area Industrial Production Index (IPI, excluding construction), the Industrial New Orders index (INO, total manufacturing working on orders), the Euro area total retail sales volume, and the extra-Euro area exports. Table 1 shows that these indicators exhibit large publication delays that range from 35 to 52 days. The last group of time series is constituted by soft indicators, which are based on survey data. The included soft indicators are the Euro-zone Economic Sentiment Indicator (ESI), the German business climate index (IFO), the Belgian overall business indicator (BNB), and the Euro area Purchasing Managers confidence Indexes (PMI) in the services and manufactures sectors. The main characteristic of soft indicator is that they are promptly available and can be observed in Table 1 since these indicators are available timely within the reference month.

To consider the full dynamic specification of all the variables included in the model, we deal with a relatively reduced number of indicators. However, it is not necessarily a disadvantage compared with large scale models. The problem of a prior selection of variables is not fully solved in the generally proposed large scale models for the Euro area, because none of them use all the information available in real time at all levels of disaggregation for all the countries and regions used in the analysis. Hence, prior to constructing the forecasts, the exercise of selecting the indicators used in the analysis have to be developed in any case. In addition, the level of complexity that large scale models incorporates to real time analysis is not always justified. In the context of forecasting, Boivin and Ng (2006) have recently suggested that the forecast accuracy does not necessarily increase with the number of series included in the model and Banbura and Runstler (2007) find that most of the predictive content of their large scale model is contained in a small set of variables.

In this paper, the selection of indicators is based on the advice of professional forecasters. Once we defined a set of core variables which were chosen by most of forecasters, we decided to include an additional variable when it increases the percentage of variance explained by the common factor. In that sense, we declined the inclusion of different financial indicators such as term premium and risk premium and other commonly used real variables such as registration of vehicles.

Depending on the nature of the data, these time series are transformed in different ways.[3] GDPs and employment are used in quarterly growth rates. Hard indicators are transformed by taking monthly growth rates. However, soft indicators are included in levels. In addition, to be included in the dynamic factor model, all of these series have been normalized to have zero mean and unit variance.

Following the method outlined in Section 2, missing data are conveniently replaced by random numbers which have been generated from $N(0,1)$. Figure 2 provides a clear outlook of the importance of missing data in the Euro area forecasting exercises. First, many series start too late. Retail sales, industrial new orders, exports, employment, BNB and PMI start in the second half of the nineties, and flash and first are just available for the last four and nine years, respectively. Second, hard indicators exhibit a publication delay of one or two months which leads to missing data at the end of the sample. Finally, quarterly series do not contain monthly issues and, apart from the standard publication delays, they are available just the third month of each quarter.

3.2 In-sample analysis

The in-sample analysis have been carried out with the most updated data set available on February, 11th 2008. To facilitate the reader inspection of the differences in release dates, the last rows of the data set have been reported in Table 2. In this table we can observe the particularities of real-time forecasting. Data for quarterly series appear just in the third month of each quarter and, although the vintage refer to 2008, their figures for the

[3] These transformations imply that although some series are integrated they are not cointegrated.

fourth quarter of 2007 are not available yet. Soft indicators contain data until January 2008 while hard indicators exhibit their typical publication delays of one and two months. In the next forecasting dates but not in this vintage, preliminary advances of GDP growth (flash and first) will be available for the last quarter of 2007.

To understand how our proposed method predicts, recall that our interest is on short term forecasting. For this purpose, the model has been developed to forecast a rolling window of nine months that are moving according to the publication date of the second estimates. The day we wrote the paper, the last available second release of GDP was the third quarter of 2007 which was released on January, 9th 2008. Hence, from this date until April, 9th 2008 (the release date for GDP second of the last quarter of 2007) the forecast of GDP that our model produces include the period from October 2007 to June 2008 (fourth quarter of 2007, first quarter of 2008 and second quarter of 2008). From April 9th 2008 the previsions will cover the nine months from January 2008 to September 2008 (first three quarters of 2008). Since second estimates are part of the observed variables in the measurement equation, these nine-month forecasts can be obtained directly from the Kalman filter iterations by imposing nine months of missing observations after the last figure that is available for second releases. Accordingly, the in-sample vintage of data reported in Table 2 shows missing observations for GDP growth from October 2007 to June 2008.

The model adopted in this paper is based on the notion that comovements among the macroeconomic variables have a common element, the common factor, that moves according to the Euro area business cycle dynamics. To check if the estimated factor agrees with the Euro area business cycle, Figure 2 plots the factor (left scale) and the Eurocoin (right scale) published by the CEPR which is probably the leading coincident indicator of the euro area business cycle. The similarities between their business cycle dynamics are striking suggesting that they track the same business cycle pattern.

The maximum likelihood estimates of the factor loadings, which reflect the degree to which variation in each observed variable can be explained by the latent series, are reported in Table 3.[4] In all cases, the estimates are positive and statistically significant,

[4] Other maximum likelihood estimates are available from the authors upon request.

indicating that these series are procyclical, i.e., positively correlated with the common factor.[5] Although all the series contain incremental information about the Euro area business cycle pattern, there are some differences in the absolute sizes of the corresponding factor loadings. Our estimates show that real activity data exhibit the highest loading factors. In particular, the highest impact of the common component is on industrial production (0.21), closely followed by industrial new orders (0.19) and second (0.12). However, loading factors of soft indicators tend to be lower than those of real activity data and all of them are below 0.07. As we will examine later on, this result does not necessarily should be interpreted as evidence in contrast to survey data. These in-sample estimates may reflect the fact that ignoring the timely advantages of soft indicators would diminish their role in factor models when hard indicators are available.

Second GDP forecasts can be examined in Figure 3 and Table 4. Figure 3 plots the monthly estimates of GDP quarterly growth rates along with their actual values. According to the methodology employed in this paper, the Kalman filter anchors monthly estimates to actual whenever GDP is observed. Hence, for those months where GDP is known, actual and estimates coincide. Table 4 (Panel A) shows how our proposal anticipates the next future issues of the Eurostat data release process. The key issues are the second GDP growth rates for quarters 2007.4, 2008.1 and 2008.2, which we call lagged, current and future forecasts, respectively. In addition, this table presents the predicted values for the next three quarters of flash and first estimates and their standard deviations.

In addition, recall that one of the differential advantage of our model is that it proposes a complete dynamic specification for all the indicators. This allows us to compute accurate forecasts not only for GDP but also for the whole set of indicators that are used to estimate the dynamic factor model. These forecasts are crucial for forecasting exercises about the expected changes in second predictions against different possible next values of these indicators.[6] Table 4 (Panel B) shows the forecasts for the next unavailable month of each indicator.

[5] This is not surprising and is in agreement with conventional views of the business cycle.

[6] Imposing white noise idiosyncratic dynamics will produce very naive forecasts since it would restrict them to be proportional among the set of indicators, with constants of proportionality equal to the factor loadings.

Let us move to examine the cumulative forecast weights of each indicator. Table 5 shows the evolution of the last months of cumulative forecast weights (normalized to add one) on GDP growth. Firstly, we concentrate on quarterly series. According to the anchoring characteristic of our proposal, rows labelled as 2007.06 and 2007.09 reveal that, when second is published, the cumulative forecast weights of all the indicator series on GDP forecasts are zero.[7] In addition, cumulative weights for quarterly series are zero for the first two months of each quarter since they are missing observations and do not add any information to the Kalman filter. It is important to notice that, using this specific data set, flash, first and employment have always weights zero. These series only have weights during the periods in which they are available but the corresponding GDP second is not.[8]

Secondly, note that the last four rows of Table 5 are rows of zeroes and that they refer to missing data in all the series included in the model. In these cases, GDP predictions are computed from dynamic projections since no new data is incorporated in the model. Then, the cumulative forecast weights of all the indicators fall to zero.

Finally, the evolution of the weights of monthly indicators dramatically depends on the nature of the indicators and the date on which they are computed. Cumulative weights to forecast second values up to 2007.11 are high and concentrated on hard indicators, basically IPI and INO. However, the reported weights for soft indicators are typically smaller for those forecasts. In line with the results of Banbura and Runstler (2007), this should not be interpreted as a failure of soft indicators to incorporate useful forecast information about GDP growth. It just means that they contain limited information beyond the real activity data when the latter are already published. Once their more timely publication takes place in short term forecasts, business surveys gain importance. Accordingly, the table reports significant improvements in the cumulative weights of soft indicators in the forecast of GDP growth for 2007.12. In this month, IPI, INO and Exports are not available and the two highest weights refer to soft indicators (weights of PMIs are 0.30 and 0.21 for manufactures and services, respectively) followed by Sales (weights of 0.19). In 2008.01,

[7] The intuition behind this result is that once GDP is available, its figure is a sufficient statistic to forecast GDP.

[8] In these cases flash and first cumulative weights are about 0.8.

hard indicators are no longer available so only survey data exhibit positive weights to forecast GDP.[9]

Figure 4 illustrates how the model can be used to evaluate the reaction of GDP forecasts to different next issues of the indicators. The ESI indicator was lastly updated on 01/31/08, the expected value of ESI for that date was 104.2, and the estimate of GDP growth rate for 2008.1 which was associated to this expected value was 0.47. The day before the ESI realization, we call the Kalman filter with the last vintage of ESI but where the observation of January 2008 was filled in with simulated with values from about -15 to 220. The figure plots the GDP forecasts associated to these simulated values of ESI and shows the GDP forecast changes due to potential ESI departures from its expected value. The actual realization of ESI was 101.7 which implied a decrease in the predicted GDP growth of about 0.06.

It is worth noting the logistic shape of GDP responses in Figure 4. The intuition behind these responses is simple. Recall that the state vector updates according to two sources of variation, the prediction error and the Kalman gain which decreases as the variance of the state vector increases. As the generated values of ESI separates from the expected value, the forecast error increases but, for extreme departures of the indicator simulations from its expected value, the Kalman gain becomes negligible and the state vector remains almost unchanged so the forecasts of GDP growth become flat.

3.3 Real-time analysis

As Croushore and Stark (2001) pointed out, developing a real-time data set is simple in concept. However, producing real-time data require a great amount of effort in practise since one has to handle with old and physical sources of data. In addition, the data set should always follow the principle of plugging what data were available at what time in the corresponding cell in order to use each day of the forecast just the time series information available at those days. According to this principle, we have constructed a data set that gives the forecasters a picture of the data that were available at any given day in the past four years (2004-2008).

[9] We will come back to the role of soft indicators in real-time forecasting in the next section.

Each day that a particular series of our data set was updated, we collect the whole set of time series available at this moment in "vintages" that were called vint-mm/dd/yy. These vintages were kept fixed until the day that a new series was updated. Hence, we compile different vintages which contain just the information that was available at the days of the vintages so we can mimic the forecasting procedure that a forecaster would have done during the last years. The first vintage for which we could collect data for all indicators was vint-01/02/04 therefore we start the real-time analysis with the forecast of GDP growth in the last quarter of 2003, which was still not available at that time. We end up with 424 different vintages for the period 01/02/04 to 02/05/08.

Using the first vintage of our data set, called vint-01/02/04, we estimate the model and compute the nine-months forecasts of GDP that include lagged (2003.3), current (2004.1) and future (2004.2) forecasts as described in the in-sample exercise. In order to keep the exercise feasible, we use the estimated parameter in the next 28 vintages until the second release for the last quarter of 2003 is published on 04/16/04. The model is then re-estimated and the procedure is then recursively repeated until the last vintage of our data set, vint-02/05/08, that was also used to perform the in-sample analysis.

To illustrate how the real-time forecasting exercise is developed in each forecasting period that includes the nine-months forecasts, we plot in Figure 5 the real time forecasts that were made each day of two different forecasting periods. The chart on the top includes all the last forecasts of GDP growth for 2007.4, i.e., forecasts made from 07/12/07 (publication day of 2007.1 GDP) to 02/11/08 (today). To evaluate uncertainty, the figure also displays the associated one standard deviation error bands. With this chart we can examine the model's reactions to the financial turbulences that took place during the summer of 2007. PMI services and manufactures were the first series to incorporate in our model information about the business climate. In September 2007, these series fell about -3.82 and -1.13 points, with the former figure representing the larger decline in the history of PMI services. In addition, BNB, IFO and ESI also exhibited strong declines of about -1.8, -1.6, -3.1, respectively. As can be observed in the figure, the declines in GDP growth forecasts came soon after. As soon as these data were introduced in the model, GDP forecast falls 0.3 percentage points. After one month of low forecasts, the recovery of most of the survey data and the relatively better news that came from real activity data (especially from IPI which grew about 0.5% in August) let GDP forecasts up to partially compensate the summer's falls.

The bottom chart of Figure 5 plots the forecasts of the second forecasting exercise. The figure shows the real time forecasts of GDP for 2006.3 over the period from 04/12/06 to 01/10/07. This period is particularly interesting since, being a recent period, reflects the revisions process suffered by second GDP growth. The revision of this quarter appears in the difference between the data that has actually been published as it was available in real-time (bottom horizontal line) and the data as it appears in the current revision (top horizontal line). Although both flash and first were about 0.52 which roughly coincides with the figure issued on 01/11/07, we were forecasting almost a second growth of 0.58 for 2006.3. However, Eurostat has revised up this figure to 0.58 in the GDP time series published on 01/09/08. This example is very illustrative to show the importance of truly real-time exercises by using current-vintage data sets instead of end-of-sample vintage data sets to asses real-time forecasting performance.[10] In addition, the exercise illustrates that, as suggested by Orphanides and van Norden (2002), real-time forecasts must be compared with the last vintage as *final* data in the measurement of output.

The relation between the incoming of new and updated information and the forecast error is examined in Figure 6. This figure plots the sample average of the standard errors associated to each GDP forecast of any of the 275 days that last each forecasting exercise. Although the standard errors may vary somewhat from quarter to quarter, on average the uncertainty about the GDP forecast continuously decreases during the forecasting period. The forecast uncertainty falls about one third during the first 200 days as information from the indicators become available to compute the forecasts. The variance then falls significantly following the flash releases. However, the falls in uncertainty provided by the first releases are of much less importance. This pattern indicates that the first releases provides less new information about GDP growth beyond that already contained in the flash estimates.

One additional interesting exercise is to examine the forecasting accuracy of our model

[10] The out-of-sample data sets are based on final data that are cut in some date and sequentially enlarged.

with respect to the preliminary announcements of GDP growth. For this purpose, we report in Table 6 the Mean Squared Errors (MSE) which refer to forecast comparisons among the preliminary announcements and the revised values of second GDP (vintage 01/09/08) along with the MSE from Euro-STING forecasts which were made on different days of the forecasting process: the days before and after flash and first releases. According to this table, the Euro-STING forecasting accuracy on the days before flash releases (MSE of 0.027) is similar but slightly worse than that of the preliminary announcements (MSE of 0.024 and 0.025).[11] However, the MSE of the Euro-STING forecast on the day on which the flash is released is 0.022 which reduces the MSE of the flash estimates themselves. Something similar happens with the first releases. But in this case, incorporating the information of first releases in the model leads to dramatic reductions in MSE which falls to 0.014. Accordingly, preliminary announced GDP cannot be considered as the most accurate forecasts of the revised GDP figures. Using the upcoming information from all the indicators is important to improve upon the forecasting accuracy in real time.

Before ending the real time forecasting section, let us take up again the issue of the importance of the timely information contained in soft indicators. Figure 7 plots the relative cumulative forecast weights of all the observations corresponding to the first quarter of 2007 on the forecast of GDP for that current quarter.[12] As we can observe, on the publication day of BNB for January (01/24/07) it was the only indicator available in that quarter to infer the GDP growth of that period. Accordingly, BNB receives the 100% of the relative forecast weight. As new information from other indicators is available, the relative forecast weights decrease until BNB is published in February (02/24/07) when there is a new peak. The intuition for this peak is that there are two values of the BNB that affect the inference of GDP for that quarter but only at most one issue for the rest of the monthly indicators. Following the same reasoning, BNB weights decrease until the new

[11] It is worth pointing out that the main gain of flash releases comes only from just one quarter, 2005.4. Taking out this quarter, there is no additional information in the flash which is not already contained in the Euro-STING model.

[12] We use 2007.1 because we wanted to analyze the weights evolution of a single series and after this date, PMI were released before BNB. Weights for PMI are more difficult to interpret since they refer to manufactures and services.

peak corresponding to March 2007. After this peak, there is a long decline in BNB weights as hard indicators become available. The last dramatic decline refer to the publication of the flash estimate for this quarter on 05/15/07. Finally, weights collapse to 0 when second GDP growth for 2007.1 is published on 7/12/07. This real-time exercise reinforces the previous results that survey data contain valuable information to forecast GDP growth apart from that contained in real activity data once their more timely publication is taken into account.

3.4 Forecasting accuracy

Figure 8 provides a visual inspection of the good real-time forecast accuracy of our model. This figure plots the forecasts for the most immediate quarter of GDP growth of our nine-month forecasting exercise which were predicted every day of the real-time forecasting period. The figure also displays the last available GDP growth figures (vintage vint-02/05/07) which include the data revisions. In general, final values of GDP growth become within the two-standard errors bands that appear in shaded areas.

To asses the relative forecasting accuracy of the real-time forecasts, we show in Table 7 the mean squared errors of our forecast and those of a list of well-known forecasts of Euro-area GDP growth rate. Among them, we include the Eurocoin forecasts, the IFO-INSEE-INSAE economic forecasts, the European Commission macroeconomic forecasts, the projections of the OECD Economic Outlook, and the Euro-area GDP growth projection of DG ECFIN.[13]

The Euro-STING forecasts are updated daily and that each of these days the model computes GDP growth forecasts of the next nine months. However, its competitors publish the forecasts with lower frequency and only some of them compute forecasts at different horizons. For this reason, the first three columns of this table refer to forecast comparisons which are made with different leads and lags with respect to the GDP figure that the competitors are trying to forecast. It is worth noting that forecast comparisons have been made carefully in the sense of comparing forecasts that refer to the same forecasting horizon and that are available on the same day in which the competitor publishes its

[13] See Appendix B for a description of these forecasts.

release. Note that this framework goes against our interest because the Euro-STING could obtain better forecasts since it is updated daily and could use more updated information than its competitors which do not change the forecasts during a whole month or even a quarter.

In terms of mean squared forecast error, our simple and automatized model beats most of its competitors. As shown in Table 7, the Euro-STING model outperforms the Eurocoin forecasts, the IFO-INSEE-INSAE economic forecasts and the European Commission macroeconomic forecasts. Relative to the projections of DG ECFIN, the Euro-STING shows better forecasting performance as the forecasting horizon increases. The Euro-STING forecasts are also comparable with those of the best of its competitors, the projections of the OECD Economic Outlook.

In spite of the good forecasting performance, we are precluded from computing pairwise comparison with the standard statistical tests due to data constraints. However, we are in the condition to affirm that the Euro-STING forecasting performance is as good as that of most familiar Euro area GDP growth forecasts in the forecasting arena. One significant advantage of the Euro-STING forecasts relies on its promptly publication. Forecasts are updated daily as new information become available which permits the day to day monitoring in the Euro area.

4 Conclusion

Monitoring the Euro area economic developments in real time has been, continues to be, and will be the source of many debates. How to deal with lacks of timely information associated with the publication of the macroeconomic variables, how to fill in missing values in the time series, how to use short Euro-wide aggregates, and how to open some of the black-box proposals is still an open question. Our paper contributes to this literature by providing a method that handles with all of these problems but keeping the model sufficiently tractable to develop economic analyses in real time.

Using this model, we elaborate several empirical contributions. First, we construct a new coincident indicator of the Euro area economy that evolves according to the Euro area business cycle dynamics. Second, we put some examples to illustrate that the analysis of the forecasting accuracy in real time should rely on current-vintage data sets and not on end-of-sample vintage data sets which may lead unrealistic results. Third, we show that monthly indicators and flash announcements contain valuable information to reduce forecast uncertainty. Finally, we find that once the timely publication of survey indicators takes place in short term forecasts, business surveys gain importance with respect to economic activity data.

We consider that the construction of a real-time data base is also a useful contribution. The data base contains 424 different vintages which collect just the information that was available to construct real time forecasts each day of the last five years. With this data base we evaluate the forecasting accuracy of our model in a horse-race analysis against the most familiar forecasts of the Euro area GDP growth rate. We find empirical support in favor of our proposal.

The model developed in this paper provides a solid ground to take into account (at least) two natural extensions. The former has to do with the pre-seasonally adjustment of the series that is made by Eurostat. The usefulness of extending the baseline model to handle with non seasonally adjusted series, which would follow the lines suggested by Harvey and Shephard (1993), is twofold. First, it would allow researchers to examine how different procedures handling with seasonality may affect forecast performance in real time. Second, it would constitute an unified model for forecasting macroeconomic series in those countries that produce non seasonally adjusted aggregates.

The latter extension has to do with anticipating changes on business cycle regimes. Dynamic factors models are probably the most appropriate framework to combine the two key features of the business cycle: the idea of comovements among macroeconomic aggregates and the dichotomy between expansions and recessions. Following the economic arguments suggested by Diebold and Rudebusch (1996), the extension would try to unify the linear dynamic factor model proposed in this paper and the non-linear Markov-switching methodology.

To sum up, we thing that the model presented in this paper, which describes and evaluates what we call Euro-STING forecasts, is a good forecasting tool. It has good forecasting record, it is automatically updated when new information become available, it constitutes a way of measuring the effects of news in the indicators on GDP growth rate, and it allows for extensions that could embrace in the same framework several problems such as seasonality and non-linearities that historically have been analyzed separately from the forecasting exercise.

Appendix A

To illustrate how the matrices stated in the measurement and transition equations look like, let $0_{i,j}$ be a matrix of $(i \times j)$ zeroes, I_r be the r-dimensional identity matrix, and $\otimes$ be the Kronecker product. According to the empirical application, let us assume that $m_1 = m_2 = m_4 = 6$, $m_3 = 2$, $r_h = 4$, and $r_s = 5$. For simplicity, let us assume that all variables are always observed at a monthly frequency.

In this example, the measurement equation, $Y_t = Hh_t + w_t$, with $w_t \sim i.i.d.N\left(0, R\right)$, can be expressed as

$$
\begin{aligned}
Y_t &= \begin{pmatrix} y_t^{2nd} & Z_t^{h'} & Z_t^{s'} & l_t & y_t^{1st} & y_t^f \end{pmatrix}', & (27)\\
w_t &= 0_{1,r+4}, & (28)\\
R &= 0_{r+4,r+4}, & (29)
\end{aligned}
$$

$$
h_t = \left(f_t, ..., f_{t-11}, u_{1t}, ..., u_{1t-5}, v_{1t}, v_{1t-1}, ..., v_{rt}, v_{rt-1}, u_{2t}, ..., u_{2t-5}, e_{1t}, e_{2t}\right)'. \quad (30)
$$

The matrix H is in this case

$$
H = \begin{pmatrix}
H_{11} & 0_{1,6} & H_{12} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 0 \\
H_{21} & 0_{r_h,6} & 0_{r_h,6} & H_{22} & 0_{r_h,10} & 0_{r_h,6} & 0_{r_h,1} & 0_{r_h,1} \\
H_{31} & H_{31} & 0_{r_s,6} & 0_{r_s,8} & H_{32} & 0_{r_s,6} & 0_{r_s,1} & 0_{r_s,1} \\
H_4 & 0_{1,6} & 0_{1,6} & 0_{1,8} & 0_{1,10} & H_{12} & 0 & 0 \\
H_{11} & 0_{1,6} & H_{12} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 1 \\
H_{11} & 0_{1,6} & H_{12} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 1 & 1
\end{pmatrix}, \quad (31)
$$

where

$$
\begin{aligned}
H_{11} &= \begin{pmatrix} \frac{\beta_1}{3} & \frac{2\beta_1}{3} & \beta_1 & \frac{\beta_1}{3} & \frac{2\beta_1}{3} & 0 \end{pmatrix}, & (32)\\
H_{12} &= \begin{pmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{1}{3} & \frac{2}{3} & 0 \end{pmatrix}, & (33)\\
H_{22} &= I_{r_h} \otimes \begin{pmatrix} 1 & 0 \end{pmatrix}, & (34)\\
H_{32} &= I_{r_s} \otimes \begin{pmatrix} 1 & 0 \end{pmatrix}, & (35)\\
H_4 &= \begin{pmatrix} \frac{\beta_4}{3} & \frac{2\beta_4}{3} & \beta_4 & \frac{\beta_4}{3} & \frac{2\beta_4}{3} & 0 \end{pmatrix}, & (36)
\end{aligned}
$$

H_{21} is a $(r_h \times 6)$ matrix of zeroes whose first column is β_2, and H_{31} is a $(r_s \times 6)$ matrix whose columns are β_3.

Using the assumptions of the underlying example, the transition equation can be stated as follows. Let Q be a diagonal matrix in which the entries inside the main diagonal are determined by the vector

$$q = \begin{pmatrix} \sigma_f^2 & 0_{1,11} & \sigma_{u_1}^2 & 0_{1,5} & \sigma_{v_1}^2 & 0 & ... & \sigma_{v_r}^2 & 0 & \sigma_{u_2}^2 & 0_{1,5} & \sigma_{e_1}^2 & \sigma_{e_2}^2 \end{pmatrix}', \tag{37}$$

The matrix F becomes

$$F = \begin{pmatrix} a & 0_{12,6} & 0_{12,8} & 0_{12,10} & 0_{12,6} & 0 & 0 \\ 0_{6,12} & b & 0_{6,8} & 0_{6,10} & 0_{6,6} & 0 & 0 \\ 0_{8,12} & 0_{8,6} & c_h & 0_{8,10} & 0_{8,6} & 0 & 0 \\ 0_{10,12} & 0_{10,6} & 0_{10,8} & c_s & 0_{10,6} & 0 & 0 \\ 0_{6,12} & 0_{6,6} & 0_{6,8} & 0_{6,10} & d & 0 & 0 \\ 0_{1,12} & 0_{1,6} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 0 \\ 0_{1,12} & 0_{1,6} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 0 \end{pmatrix}, \tag{38}$$

where

$$a = \begin{pmatrix} a_1 & ... & a_6 & ... & 0 & 0 \\ 1 & ... & 0 & ... & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & ... & 0 & ... & 1 & 0 \end{pmatrix}, \tag{39}$$

$$b = \begin{pmatrix} b_1 & ... & b_5 & b_6 \\ 1 & ... & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & ... & 1 & 0 \end{pmatrix}, \tag{40}$$

$$c_i = \begin{pmatrix} c_{11} & c_{12} & ... & 0 & 0 \\ 1 & 0 & ... & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & ... & c_{r1} & c_{r2} \\ 0 & 0 & ... & 1 & 0 \end{pmatrix}, \tag{41}$$

$$
d = \begin{pmatrix} d_1 & ... & d_5 & d_6 \\ 1 & ... & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & ... & 1 & 0 \end{pmatrix}. \tag{42}
$$

Appendix B

All the indicators used in the forecasting analysis can be found at the following links:

1. EuroCoin:

   http://www.cepr.org/data/eurocoin/

2. DG_ECFIN:

   http://ec.europa.eu/economy_finance/indicators/euroareagdp_en.htm

3. EC_Macroeconomic_Forecast:

   http://ec.europa.eu/economy_finance/about/activities/activities_keyindicatorsforecasts_en.htm

4. IFO_INSEE_ISAE:

   http://www.cesifo-group.de/portal/page/portal/ifoHome/a-winfo/d2kprog/30kprogeeo

5. OCDE:

   http://www.oecd.org/department/0,3355,en_2649_34109_1_1_1_1_1,00.html

References

[1] Altissimo, F., R. Cristadoro, M. Forni, M. Lippi and G. Veronese (2006). *New Eurocoin: Tracking economic growth in real time,* CEPR discussion paper No. 5633.

[2] Aruoba, B., F. Diebold and C. Scotti (2008). *Real-time measurement of business conditions,* PIER Working Paper No. 08-011, Department of Economics, University of Pennsylvania.

[3] Banbura, M., and G. Runstler (2007). *A look into the model factor black box. Publication lags and the role of hard and soft data in forecasting GDP,* ECB working paper No. 751.

[4] Boivin, J., and S. Ng (2006). "Are more data always better for factor analysis?", *Journal of Econometrics,* 132, pp. 169-194.

[5] Croushore, D., and T. Stark (2001). "A real time data set for macroeconomists", *Journal of Econometrics,* 105, pp. 111-130.

[6] Diebold, F., and R. Mariano (1995). "Comparing predictive accuracy", *Journal of Business and Economic Statistics,* 13, pp. 253-263.

[7] Diebold, F., and G. Rudebusch (1996). "Measuring business cycles: A modern perspective", *Review of Economics and Statistics,* 78, pp. 67-77.

[8] Diron, M. (2006). *Short-term forecasts on Euro area real GDP growth. An assessment of real-time performance based on vintage data,* ECB working paper No. 622.

[9] European Commission (2006). *The joint harmonized EU programme of business and consumer surveys,* Special Report No. 5/2006.

[10] Evans, M. (2005). "Where are we now? Real time estimates of the macroeconomy", *International Journal of Central Banking,* 1, pp. 127-175.

[11] Giannone, D., L. Reichlin, and D. Small (2006). *Nowcasting GDP and inflation. The real-time informational content of macroeconomic data releases,* ECB working paper No. 633.

[12] Harvey, A., and N. Shephard (1993). "Structural Time Series Models", in G S Maddala et. al., *Handbook of Statistics,* Volume 11, Elsevier Science Publishers.

[13] Mankiw, G., and M. Shapiro (1986). "News or noise? Analysis of GNP revisions", *Survey of Current Business,* 66, pp. 20-25.

[14] Mariano, R., and Y. Murasawa (2003). "A new coincident index of business cycles based on monthly and quarterly series", *Journal of Applied Econometrics,* 18, pp. 427-443.

[15] Orphanides, A., and S. van Norden (2002). "The unreliability of output-gap estimates in real time", *The Review of Economics and Statistics,* 4, pp. 569-583.

[16] Proietti, T., and F. Moauro (2006). "Dynamic factor analysis with nonlinear temporal aggregation constraints", *Applied Statistics,* 55, pp. 281-300.

[17] Runstler, G., and F. Sedillot (2003). S*hort-term estimates of Euro area real GDP by means of monthly data,* ECB working paper No. 276.

Table 1. Data description

	Euro Area Indicators Variables (a) (b)			
	Name	Definition	Observations	Reporting lag (c)
Quarterly Hard Indicators	Flash GDP	Euro Area GDP	19	45 days
	First GDP	Euro Area GDP	37	60 days
	Second GDP	Euro Area GDP	66	102 days
	Employment	Euro Area Total Employment	66	102 days (d)
Monthly Hard Indicators	IPI	Euro Area Industrial Production Index (excluding construction)	200	42 days
	Sales	Euro Area Total Retail Sales Volume	155	35 days
	INO	Industrial New Orders Indices. Total manufacturing working on orders	154	52 days
	Exports	Extra- Euro Area Exports	200	45 days
Monthly Soft Indicators	BNB	Belgium Overall Business Indicator	202	-8 days
	ESI	Euro-Zone Economic Sentiment Indicator	202	0 days
	IFO	Germany IFO Business Climate Index	202	-8 days
	PMI Manufactures	Euro Area Manufacturing Purchasing Managers Index	128	1 day
	PMI Services	Euro Area Services Purchasing Managers Index	115	5 days

Notes:
(a) All hard indicators data (indicators of real activity) are growth rates of the seasonally adjusted series.
Soft Indicators (based on opinions surveys) are first differences of the seasonally adjusted series.
(b) Euro area refers to EMU-12 until december 2006 and EMU-13 (includes Slovenia) after that date.
(c) Aproximately. It can marginally change as a function of weekends or number of days of the month.
(d) Starting in 2007.1 the reporting lag is 45 days

Table 2. Data set available on 02/11/08

	Second	IPI	Sales	INO	Export	ESI	BNB	IFO	PMIM	PMIS	Employment	First	Flash
2007.06	0.31	0.01	0.67	4.41	2.52	111.10	5.50	107.00	55.56	58.33	0.58	0.35	0.34
2007.07	na	0.65	0.35	-3.09	-0.57	110.40	4.20	106.40	54.90	58.34	na	na	na
2007.08	na	1.15	-0.03	0.92	2.73	109.40	3.30	105.70	54.34	58.04	na	na	na
2007.09	0.76	-0.86	0.17	-1.17	-1.35	106.30	1.50	104.10	53.21	54.22	0.33	0.71	0.71
2007.10	na	0.54	-0.64	2.54	1.22	105.40	-0.10	103.90	51.52	55.81	na	na	na
2007.11	na	-0.45	-0.66	2.72	0.26	104.10	1.40	104.20	52.80	54.14	na	na	na
2007.12	na	na	-0.09	na	na	103.40	-1.90	103.00	52.56	53.14	na	na	na
2008.01	na	na	na	na	na	101.70	-0.80	103.40	52.77	50.56	na	na	na
2008.02	na	na	na	na	na	na	na	na	na	na	na	na	na
2008.03	na	na	na	na	na	na	na	na	na	na	na	na	na
2008.04	na	na	na	na	na	na	na	na	na	na	na	na	na
2008.05	na	na	na	na	na	na	na	na	na	na	na	na	na
2008.06	na	na	na	na	na	na	na	na	na	na	na	na	na

Notes. See Table 1 for acronyms. Figures labelled as “na” refer to either missing data or data that are not available on 02/11/08.

Table 3. Factor loadings

Second	IPI	Sales	INO	Exports	ESI	BNB	IFO	PMIM	PMIS	Employment
0.15	0.21	0.06	0.19	0.12	0.05	0.06	0.05	0.07	0.07	0.10
(0.03)	(0.04)	(0.03)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.02)	(0.04)

Notes. See Table 1 for acronyms. Standard errors are in parentheses. Data set ends on 02/11/08.

Table 4. Last day forecast (February 11th 2008)

Panel A

Series	2007.4	2008.1	2008.2
FLASH	0.40	0.38	0.38
	(0.05)	(0.06)	(0.07)
FIRST	0.39	0.36	0.36
	(0.07)	(0.07)	(0.08)
SECOND	0.41	0.37	0.37
	(0.10)	(0.11)	(0.14)

Panel B

Series	Next month
IPI	0.41
Retail Sales	0.247
INO	-1.825
Exports	0.716
ESI	100.712
BNB	-2.978
IFO	102.565
PMI Man	52.567
PMI Serv	50.844
Employment	0.194

Notes. See Table 1 for acronyms. Standard errors are in parentheses. Data set ends on 02/11/08.

Table 5. Cumulative weights

	Second	IPI	Sales	INO	Exports	ESI	BNB	IFO	PMIM	PMIS	Employment	First	Flash
2007.06	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2007.07	0.00	0.32	0.06	0.29	0.09	0.04	0.04	0.02	0.09	0.06	0.00	0.00	0.00
2007.08	0.00	0.32	0.06	0.29	0.09	0.04	0.04	0.02	0.09	0.06	0.00	0.00	0.00
2007.09	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2007.10	0.00	0.32	0.06	0.29	0.09	0.04	0.04	0.02	0.09	0.06	0.00	0.00	0.00
2007.11	0.00	0.32	0.06	0.29	0.09	0.04	0.04	0.02	0.09	0.06	0.00	0.00	0.00
2007.12	0.00	0.00	0.19	0.00	0.00	0.13	0.12	0.05	0.30	0.21	0.00	0.00	0.00
2008.01	0.00	0.00	0.00	0.00	0.00	0.15	0.15	0.06	0.37	0.27	0.00	0.00	0.00
2008.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2008.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes. See Table 1 for acronyms. Data set ends on 02/11/08.

Table 6. Accuracy of preliminary announcements

Indicator	Day of the forecast	MSE
Flash estimators		0.024
First Estimators		0.025
Euro-STING	Day before Flash	0.027
Euro-STING	Day after Flash	0.022
Euro-STING	Day before First	0.022
Euro-STING	Day after First	0.014

Note. Entries are mean squared errors in forecasting the last revised values of second GDP (vintage 01/09/08). First two rows refer to preliminary announcements and last four rows are forecasts from the Euro-STING model which are computed the days before and after flash and first releases.

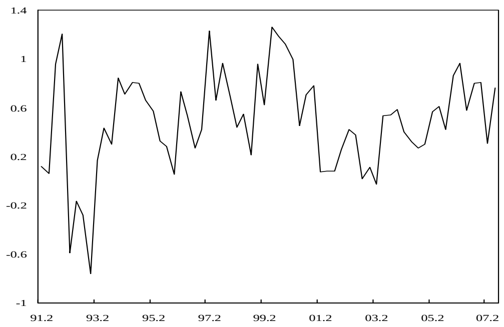
Table 7. Real-time forecasting evaluation

	1 Month lag	2 Month lag	3 Month lag	Total
Eurocoin	0.083	0.046	0.042	0.057
Euro-Sting	0.075	0.030	0.016	0.040
	1 Months lag	2 Months lead	5 Months lead	Total
IFO-INSEE-ISAE	0.060	0.071	0.069	0.067
Euro-Sting	0.044	0.048	0.037	0.043
	3 Months lead	6 Months lead	9 Months lead	Total
European Commission	0.055	0.086	0.068	0.070
Euro-Sting	0.028	0.071	0.033	0.044
	3 Months lag	0 Months	3 Months lead	Total
OECD	0.019	0.049	0.036	0.035
Euro-Sting	0.019	0.048	0.037	0.034
	1 Month Lag	2 Months lead	5 Months lead	Total
DG ECFIN	0.045	0.044	0.107	0.065
Euro-Sting	0.046	0.033	0.052	0.044

Notes. Entries are mean squared errors. Forecasting period refer to 2003.4 to 2007.3. Last column is the simple average. See Appendix B for data description.

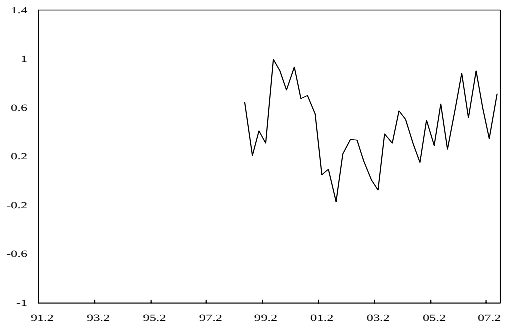
Figure 1. Time series used in the model

GDP second growth rate



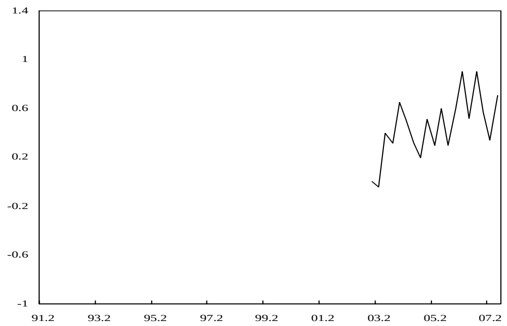
Sample 91.2-07.3. Vintage 01/09/08

GDP first growth rate



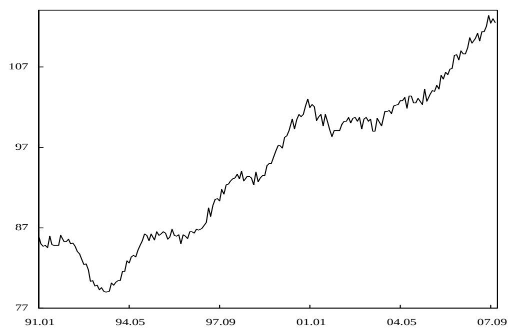
Sample 98.2-07.3. Vintage 11/30/07

GDP flash growth rate



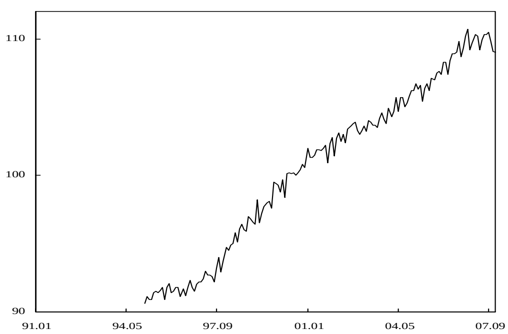
Sample 03.1-07.3. Vintage 11/14/07

Industrial production



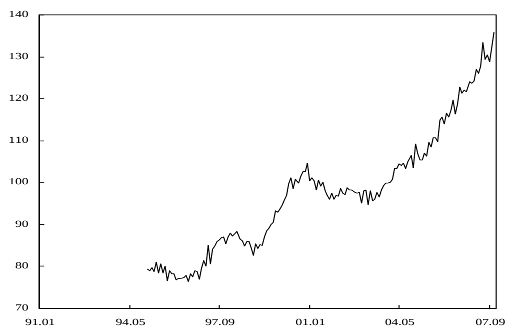
Sample 91.01-07.11. Vintage 01/14/08

Retail Sales



Sample 95.01-07.12. Vintage 02/05/08

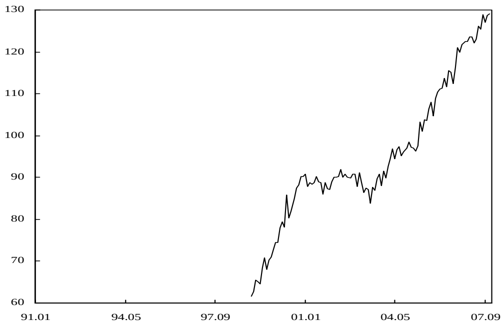
Industrial new orders



Sample 95.01-07.11. Vintage 01/23/08

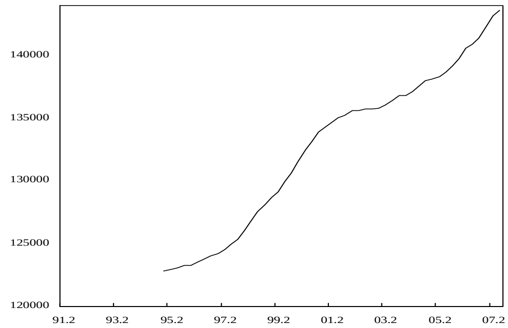
Figure 1. Time series used in the model (continued)

Exports



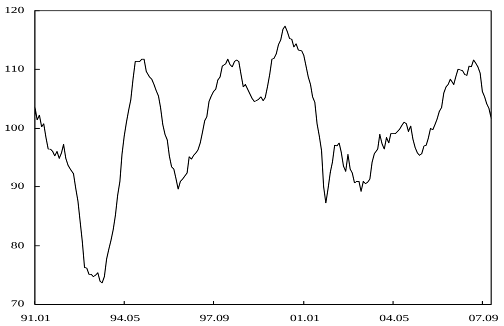
Sample 99.01-07.11. Vintage 01/17/08

Employment



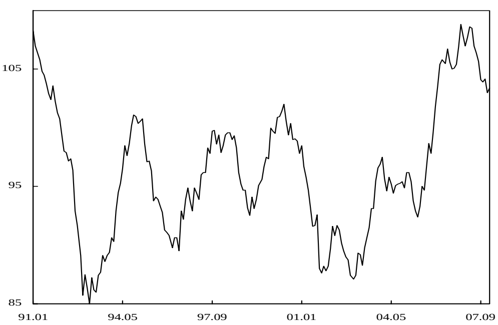
Sample 95.1-07.3. Vintage 01/09/08

ESI



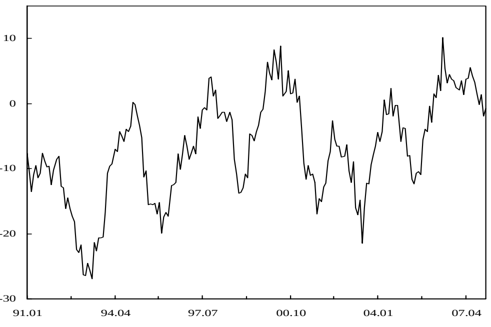
Sample 91.01-08.01. Vintage 01/31/08

IFO



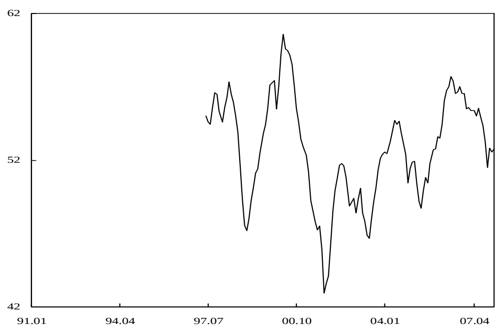
Sample 91.01-08.01. Vintage 01/24/08

BNB



Sample 91.01-08.01. Vintage 01/24/08

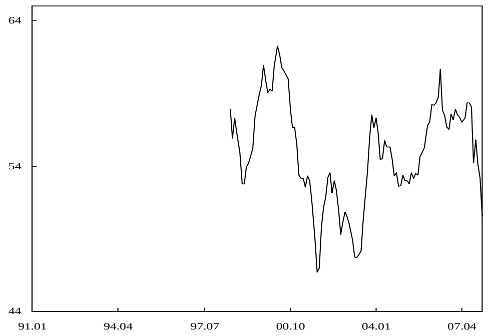
PMI Manufactures



Sample 97.06-08.01. Vintage 02/01/08

Figure 1. Time series used in the model (continued)

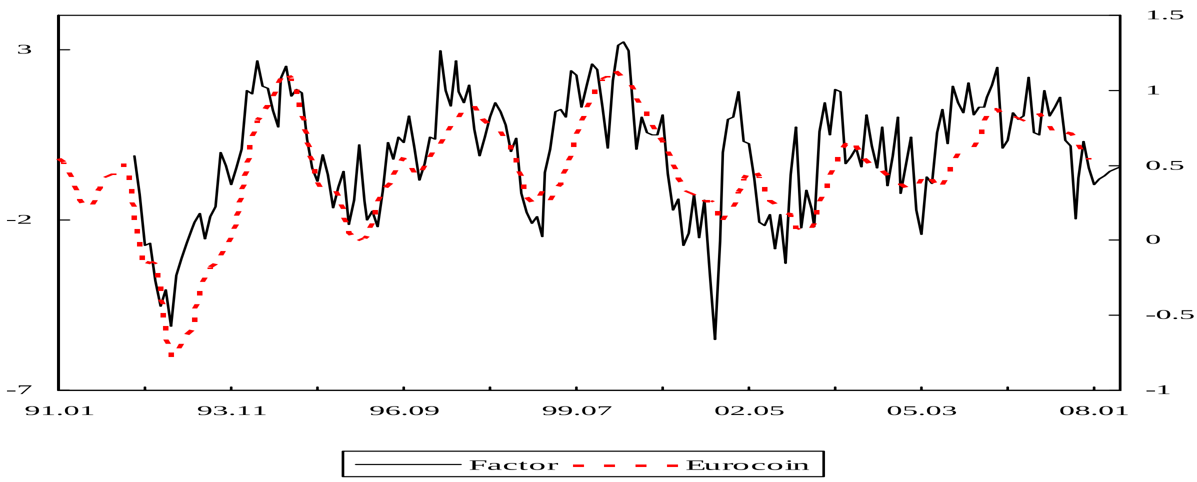
PMI Services



Sample 97.06-08.01. Vintage 02/05/08

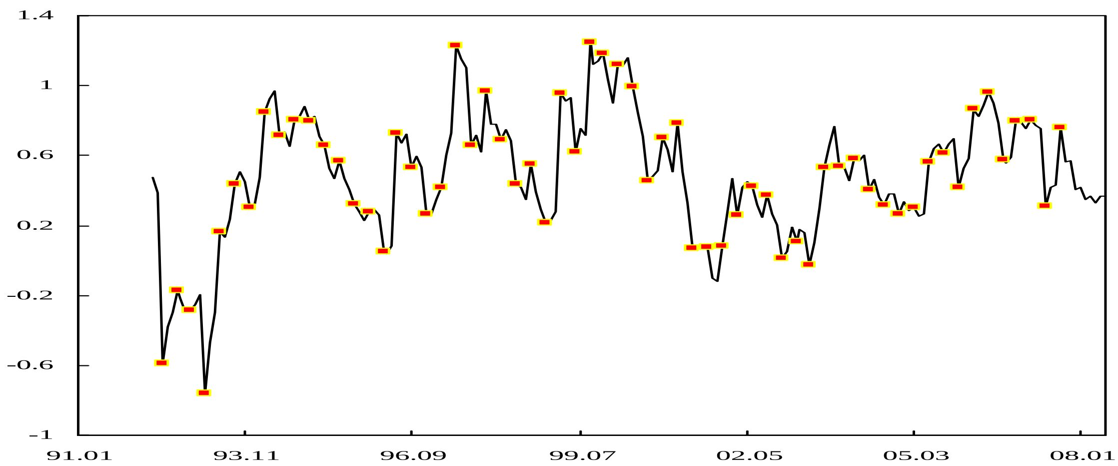
Notes. See Table 1 for acronyms. Charts refer to data available on 02/11/08.

Figure 2. Common factor and Eurocoin



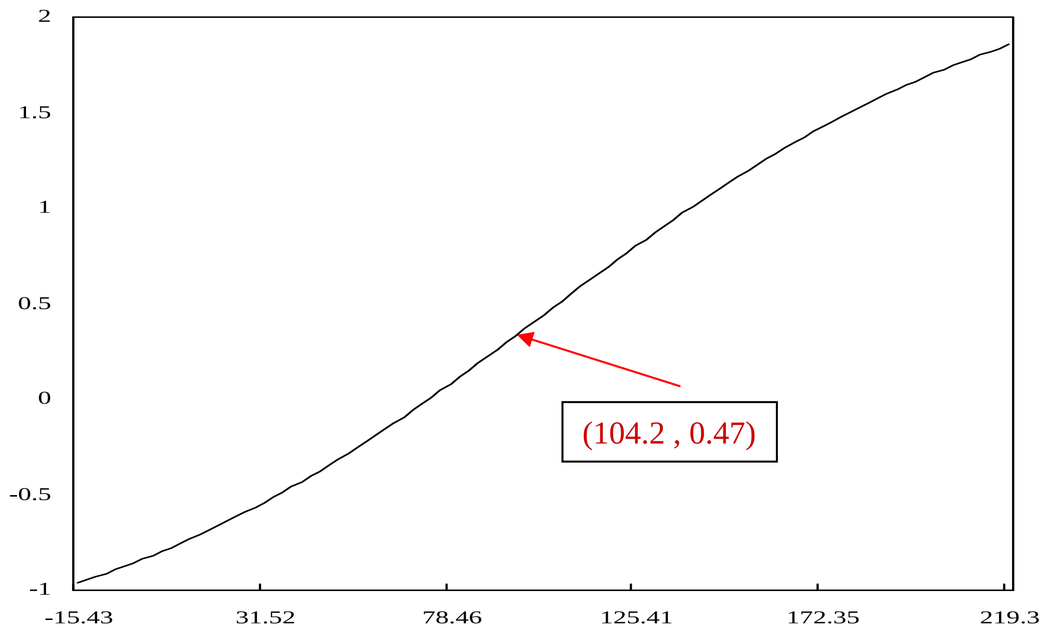
Notes. The factor is estimated from 92.04 to 08.06 with information on 02/11/08. The last vintage for the Eurocoin contains data until 07.12.

Figure 3. GDP second growth rate: actual and estimates



Notes. GDP growth rates are estimated from 1992.04 to 2008.06 with information on 02/11/08. Dots over the line refer to actual data (third month of each quarter; last one in 2007.3).

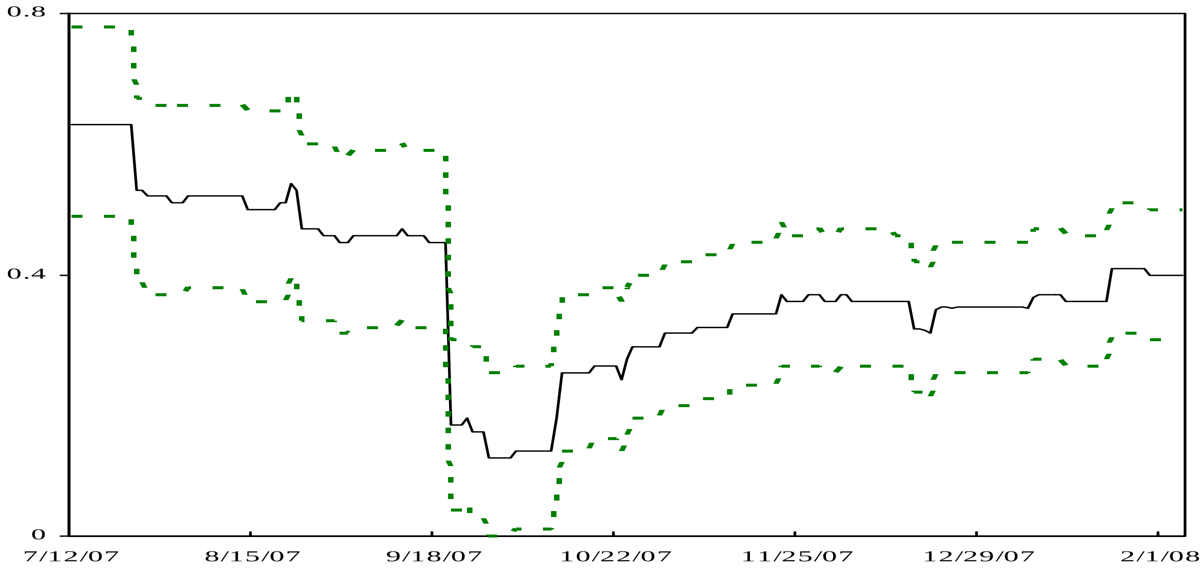
Figure 4. GDP forecast in 2008.1 and ESI potential releases



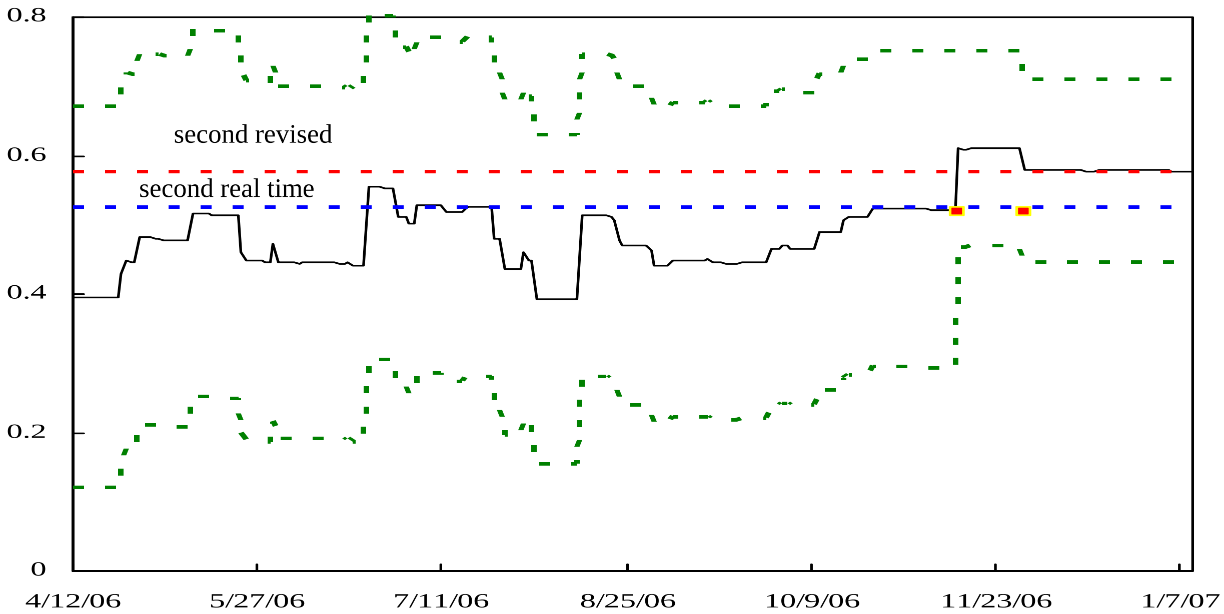
Notes. Expected ESI values and growth rates before the last ESI updates are inside the box.

Figure 5. GDP second growth rate in real-time

GDP second forecasts for 2007.4

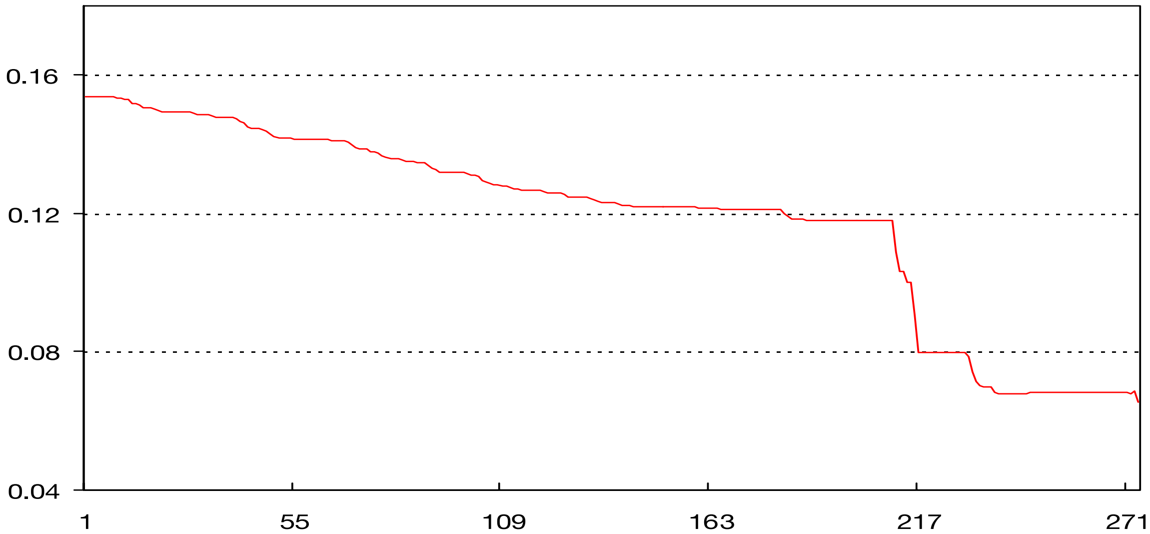


GDP second forecasts for 2006.3



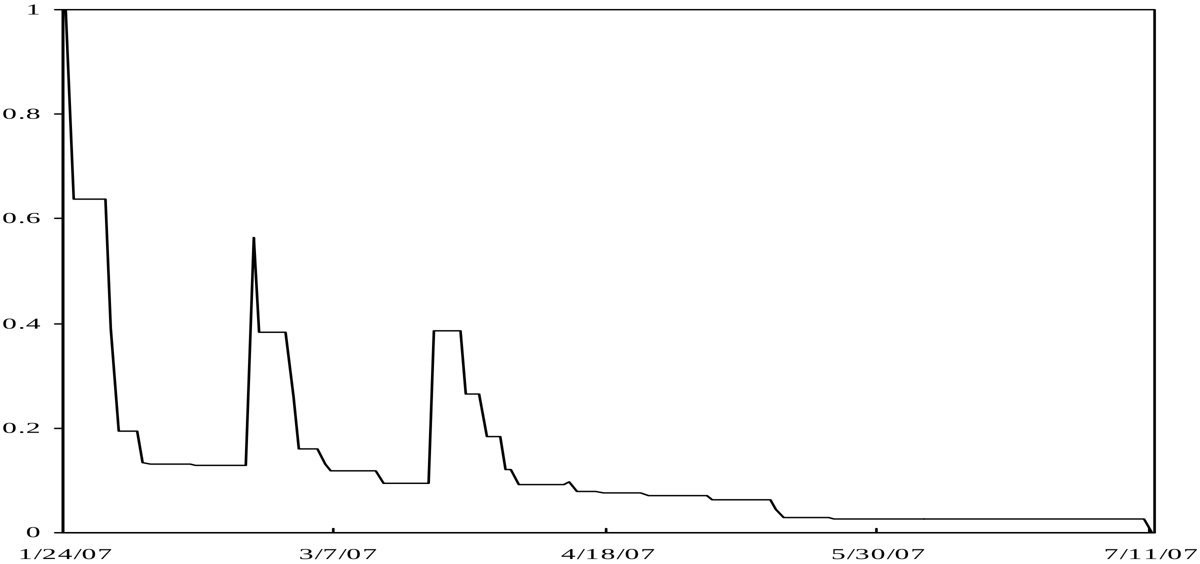
Notes. Floating points refer to flash and first announcements. They are calculated for the nine-month forecasting periods described in the text.

Figure 6. Averaged standard errors over the days of the forecasting period



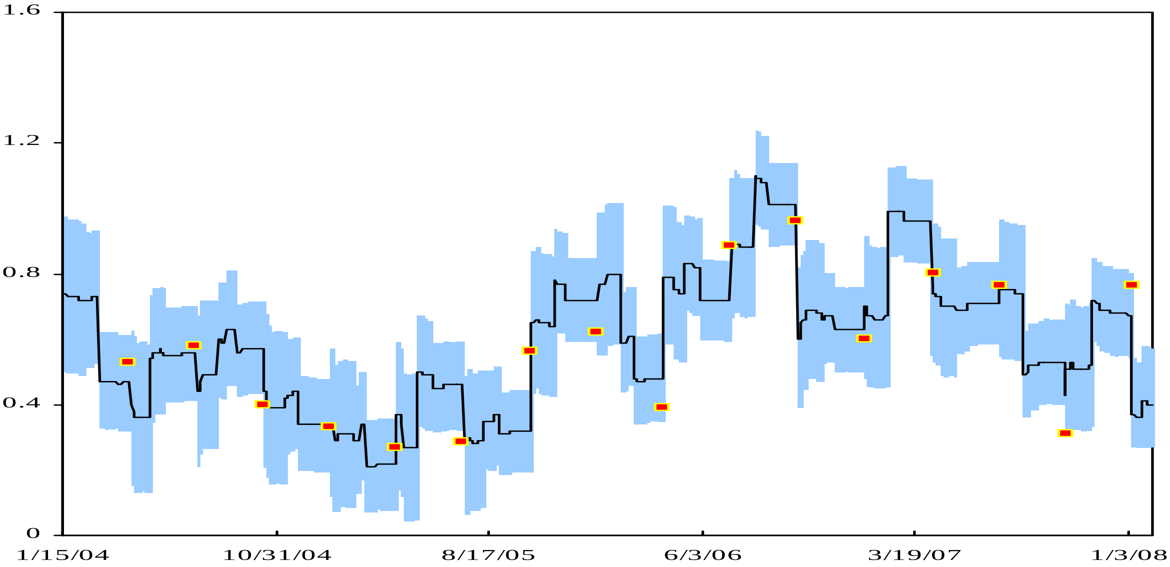
Notes. Real time sample covers from 01/15/04 to 02/11/08.

Figure 7. Cumulative forecast weights for BNB in real-time



Notes. Weights are computed daily from 01/24/07 to 07/12/07 and refer to GDP forecasts for the first quarter of 2007.

Figure 8. Real-time lagged forecasts of GDP



Notes. Real time sample covers from 01/15/04 to 02/11/08. Shaded area refers to plus and minus two standard error bands. Floating points refer to revised values of second GDP (Vintage 01/09/08) which are dated on their real-time announcements.

BANCO DE ESPAÑA PUBLICATIONS

WORKING PAPERS[1]

0701 PRAVEEN KUJAL AND JUAN RUIZ: Cost effectiveness of R&D and strategic trade policy.
0702 MARÍA J. NIETO AND LARRY D. WALL: Preconditions for a successful implementation of supervisors' prompt corrective action: Is there a case for a banking standard in the EU?
0703 PHILIP VERMEULEN, DANIEL DIAS, MAARTEN DOSSCHE, ERWAN GAUTIER, IGNACIO HERNANDO, ROBERTO SABBATINI AND HARALD STAHL: Price setting in the euro area: Some stylised facts from individual producer price data.
0704 ROBERTO BLANCO AND FERNANDO RESTOY: Have real interest rates really fallen that much in Spain?
0705 OLYMPIA BOVER AND JUAN F. JIMENO: House prices and employment reallocation: International evidence.
0706 ENRIQUE ALBEROLA AND JOSÉ M.ª SERENA: Global financial integration, monetary policy and reserve accumulation. Assessing the limits in emerging economies.
0707 ÁNGEL LEÓN, JAVIER MENCÍA AND ENRIQUE SENTANA: Parametric properties of semi-nonparametric distributions, with applications to option valuation.
0708 ENRIQUE ALBEROLA AND DANIEL NAVIA: Equilibrium exchange rates in the new EU members: external imbalances vs. real convergence.
0709 GABRIEL JIMÉNEZ AND JAVIER MENCÍA: Modelling the distribution of credit losses with observable and latent factors.
0710 JAVIER ANDRÉS, RAFAEL DOMÉNECH AND ANTONIO FATÁS: The stabilizing role of government size.
0711 ALFREDO MARTÍN-OLIVER, VICENTE SALAS-FUMÁS AND JESÚS SAURINA: Measurement of capital stock and input services of Spanish banks.
0712 JESÚS SAURINA AND CARLOS TRUCHARTE: An assessment of Basel II procyclicality in mortgage portfolios.
0713 JOSÉ MANUEL CAMPA AND IGNACIO HERNANDO: The reaction by industry insiders to M&As in the European financial industry.
0714 MARIO IZQUIERDO, JUAN F. JIMENO AND JUAN A. ROJAS: On the aggregate effects of immigration in Spain.
0715 FABIO CANOVA AND LUCA SALA: Back to square one: identification issues in DSGE models.
0716 FERNANDO NIETO: The determinants of household credit in Spain.
0717 EVA ORTEGA, PABLO BURRIEL, JOSÉ LUIS FERNÁNDEZ, EVA FERRAZ AND SAMUEL HURTADO: Update of the quarterly model of the Bank of Spain. (The Spanish original of this publication has the same number.)
0718 JAVIER ANDRÉS AND FERNANDO RESTOY: Macroeconomic modelling in EMU: how relevant is the change in regime?
0719 FABIO CANOVA, DAVID LÓPEZ-SALIDO AND CLAUDIO MICHELACCI: The labor market effects of technology shocks.
0720 JUAN M. RUIZ AND JOSEP M. VILARRUBIA: The wise use of dummies in gravity models: Export potentials in the Euromed region.
0721 CLAUDIA CANALS, XAVIER GABAIX, JOSEP M. VILARRUBIA AND DAVID WEINSTEIN: Trade patterns, trade balances and idiosyncratic shocks.
0722 MARTÍN VALLCORBA AND JAVIER DELGADO: Determinantes de la morosidad bancaria en una economía dolarizada. El caso uruguayo.
0723 ANTÓN NÁKOV AND ANDREA PESCATORI: Inflation-output gap trade-off with a dominant oil supplier.
0724 JUAN AYUSO, JUAN F. JIMENO AND ERNESTO VILLANUEVA: The effects of the introduction of tax incentives on retirement savings.
0725 DONATO MASCIANDARO, MARÍA J. NIETO AND HENRIETTE PRAST: Financial governance of banking supervision.
0726 LUIS GUTIÉRREZ DE ROZAS: Testing for competition in the Spanish banking industry: The Panzar-Rosse approach revisited.
0727 LUCÍA CUADRO SÁEZ, MARCEL FRATZSCHER AND CHRISTIAN THIMANN: The transmission of emerging market shocks to global equity markets.
0728 AGUSTÍN MARAVALL AND ANA DEL RÍO: Temporal aggregation, systematic sampling, and the Hodrick-Prescott filter.
0729 LUIS J. ÁLVAREZ: What do micro price data tell us on the validity of the New Keynesian Phillips Curve?
0730 ALFREDO MARTÍN-OLIVER AND VICENTE SALAS-FUMÁS: How do intangible assets create economic value? An application to banks.

---

1. Previously published Working Papers are listed in the Banco de España publications catalogue.

0731 REBECA JIMÉNEZ-RODRÍGUEZ: The industrial impact of oil price shocks: Evidence from the industries of six OECD countries.

0732 PILAR CUADRADO, AITOR LACUESTA, JOSÉ MARÍA MARTÍNEZ AND EDUARDO PÉREZ: El futuro de la tasa de actividad española: un enfoque generacional.

0733 PALOMA ACEVEDO, ENRIQUE ALBEROLA AND CARMEN BROTO: Local debt expansion… vulnerability reduction? An assessment for six crises-prone countries.

0734 PEDRO ALBARRÁN, RAQUEL CARRASCO AND MAITE MARTÍNEZ-GRANADO: Inequality for wage earners and self-employed: Evidence from panel data.

0735 ANTÓN NÁKOV AND ANDREA PESCATORI: Oil and the Great Moderation.

0736 MICHIEL VAN LEUVENSTEIJN, JACOB A. BIKKER, ADRIAN VAN RIXTEL AND CHRISTOFFER KOK-SØRENSEN: A new approach to measuring competition in the loan markets of the euro area.

0737 MARIO GARCÍA-FERREIRA AND ERNESTO VILLANUEVA: Employment risk and household formation: Evidence from differences in firing costs.

0738 LAURA HOSPIDO: Modelling heterogeneity and dynamics in the volatility of individual wages.

0739 PALOMA LÓPEZ-GARCÍA, SERGIO PUENTE AND ÁNGEL LUIS GÓMEZ: Firm productivity dynamics in Spain.

0740 ALFREDO MARTÍN-OLIVER AND VICENTE SALAS-FUMÁS: The output and profit contribution of information technology and advertising investments in banks.

0741 ÓSCAR ARCE: Price determinacy under non-Ricardian fiscal strategies.

0801 ENRIQUE BENITO: Size, growth and bank dynamics.

0802 RICARDO GIMENO AND JOSÉ MANUEL MARQUÉS: Uncertainty and the price of risk in a nominal convergence process.

0803 ISABEL ARGIMÓN AND PABLO HERNÁNDEZ DE COS: Los determinantes de los saldos presupuestarios de las Comunidades Autónomas.

0804 OLYMPIA BOVER: Wealth inequality and household structure: US vs. Spain.

0805 JAVIER ANDRÉS, J. DAVID LÓPEZ-SALIDO AND EDWARD NELSON: Money and the natural rate of interest: structural estimates for the United States and the euro area.

0806 CARLOS THOMAS: Search frictions, real rigidities and inflation dynamics.

0807 MAXIMO CAMACHO AND GABRIEL PEREZ-QUIROS: Introducing the EURO-STING: Short Term INdicator of Euro Area Growth.

BANCO DE ESPAÑA
Eurosistema

Unidad de Publicaciones
Alcalá, 522; 28027 Madrid
Telephone +34 91 338 6363. Fax +34 91 338 6488
e-mail: publicaciones@bde.es
www.bde.es