Forecasting the Euroarea GDP in real time*

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Abstract

We propose a model to compute short-term forecasts of the Euro area GDP growth and probabilities of recession 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. We provide examples showing how data revisions and data availability affect point forecasts and forecast uncertainty.

Keywords: Business Cycles, Output Growth, Time Series.

JEL Classification: E32, C22, E27

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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 economic monitoring activities especially problematic. The objective of this paper is to provide a statistical method being flexible enough to, dealing with these shortcomings, allow for the analysis of the short-term economic situation in the Euro area. For this purpose we combine the two key features of the business cycle: the idea of comovements among macroeconomic agganalysis of the current economic situation and for the anticipation of economicregates and the dichotomy between expansions and recessions.

In the Euro area, the reference series to develop the analysis of the current economic situation and for the anticipation of short-term economic developments is the Euro area GDP growth. However, the Eurostat publishes the official estimate of the Euro area GDP, called *second* release, with a delay of about 14 weeks after the end of the respective quarter. The coincident indicator approach that uses time series with shorter publication delay but that exhibit the same economic fluctuations than GDP growth has been the most extended solution to this problem. Possible candidates are early announcements of GDP growth, called *flash* and *first* releases, *hard indicator*s that are based on economic activity data, and especially *soft indicators*, that are based on survey since all of them exhibit much shorter publishing delay.

The coincident indicator approach used in this paper is based on an extension of the common factor model described in Mariano and Murasawa (2003). Their model accounts for the typical problems affecting the real-time economic analysis as variable reporting lags, temporal aggregation, and short samples. Hoiwever, we have extended their baseline model in two directions. First, we incorporate preliminary advances of GDP growth and quarterly series as indicators. Second, we accomodate the nonlinear pattern of business cycle phases by assuming that the common factor is governed by a Markov-switching process. For this purpose, we the follow the lines suggested by Chauvet (1998) to construct a coincident indicator for the US economy.

With respect to other models to forecast GDP growth, our proposal shows some advantages. First, while Evans (2005) focuses on the daily contribution to GDP growth within each quarter, we focus on quarterly growth rate directly but our inferences may change daily as new information becomes available. This allows to skip the unrealistic smoothness assumptions incorporated in his model. Second, although the (new) Eurocoin indicator advocated by Altissimo et al (2006) incorporates the information of many indicators it exhibits the trade off of not being able to produce daily forecast updating easily. Some authors as Giannone et al (2006) evaluate the models that include large number of indicators by constructing pseudo intra-month vintages, so their results cannot be considered as truly real-time forecasting exercises. In addition, the Eurocoin focuses on medium to long term component of GDP growth rate which reduces the model's results repeatability and the possibility of finding responsabilities when forecast accuracy falls. Third, contrary to Mitchell et al. (2005) our forecasts are derived from a single fully specified econometric model.

Finally, we construct a real-time data set that include vintages that were available at the time of each forecast giving the picture of the data that a forecaster would have been available at any given day in the past four years. This allow us to compare our forecasting performance against those of the most popular forecasts made for the Euro area GDP growth. Among them, we include the forecasts from the Eurocoin, the European Comission macroeconomic forecasts, the Euro area GDP growth projection of the DG ECFIN of the European Comission, the IFO-INSEE-INSAE Economic Forecast, and the Projections of the OECD Economic Outlook. Overall, we provide forecasts that are at least comparable (and better in many cases) to all of them in any forecasting horizon.

The paper is organized as follows. Section 2 outlines the proposed methodology and analyzes how to deal with mixing monthly and quarterly frequencies, how to use early estimates of GDP growth and how to estimate the model. Section 3 evaluates the empirical reliability of our method and extend the model to capturing nonlinear business cycle features. Section 4 concludes.

2 The model

In this section we develop a state space representation of a model that deals with those problems stated in the introduction. Summing up, the model allows us to compute short term forecasts of the Euro area GDP growth in real time from a data set that may include mixing frequencies and missing data. The model also captures both comovements among economic indicators and business cycle asymmetries.

2.1 Mixing frequencies

This paper deals with the problem of mixing monthly and quarterly frequencies by treating quarterly series as monthly series with missing observations. Let G_t be a quarterly series that is observable every third period and whose logs are integrated of order one. In this paper, examples of these series are the time series of flashes, firsts, seconds and employment. These series are the quarterly aggregates of monthly series, X_t, that we are going to assume as being observable. Accordingly, we can construct monthly time series from quarterly series by adding the 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 arithmetic mean which, if monthly changes are small compared with the monthly average in each quarter, the approximation error should not be almost negligible. In practice, monthly changes of production and employment are less than a percentage point so the geometric approximation should be appropriate Hence, we can state that

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

which yields

$$\ln G_t = \ln X_t + \ln X_{t-1} + \ln X_{t-2}. \tag{3}$$

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 in economic practise, the disadvantage of this fast estimate is that it is based on incomplete information (see European Commission, 2004). Using more representative information, the revision of this figure is published in the press notice of quarterly first GDP growth rate, y_t^{1st}, about 20 days after the flash and this is the so-called first estimate. In addition, as updated 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 e_2 the first and the revision between the first and the second.

Due to data constraints (flash and first estimates are just available since 2003.I and 1998.III, respectively), we could not develop formal tests in order to discriminate between the news and noise versions of revisions described in Mankiw and Shapiro (1986). In spite of this limitation, we obtain some results for revisions from first to second releases that lead us to consider that the Eurostat's revision process may reflect measurement errors in the preliminary estimates.[1] If the provisional estimate differs from the revised value by a measurement error, then the revision should be uncorrelated with the revised value and correlated with the provisional estimate itself. Figure 1, which displays scatter plots of second and first GDP growth figures against revisions, offers an informal look at the informational content of the revisions. The plots point out a negligible relationship between revised data and revisions (correlation of 0.02) in the left-hand chart and a negative

[1] We do not replicate the exercise for the revisions from flash to second releases since we have just 15 observations.

relationship between announcements and revisions (correlation of -0.16) in the right-hand chart. It seems that the Eurostat tends to be conservative in its raw announcements in the sense that preliminary GDP releases tend to be revised downward and low preliminary numbers tend to be revised upwards.

Being consequent with the assumption that flash and first estimates represent noisy signals of second estimates, we follow Evans (2005) to propose that

$$\begin{aligned} y_t^f &= y_t^{2nd} + e_{1t} + e_{2t}, && (5) \\ y_t^{1st} &= y_t^{2nd} + e_{2t}, && (6) \end{aligned}$$

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.

2.3 State space representation

In order 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 one is the common factor, f_t, and reflects the notion that the series dynamics are driven in part by common shocks. The second one captures the idiosyncratic behavior of each series.

For clarity in the exposition, let us assume that all variables are always observed and that there are no preliminary estimates of GDP within each quarter. Let x_t^{2nd} and x_t^e be the monthly GDP and employment growth rates, respectively. Let's collect the r monthly indicators in the vector z_t. Let u_{1t}, u_{2t}, and U_t be the scalars and r-dimensional vector that determine the idiosyncratic dynamics of GDP, unemployment and the economic indicators, respectively. Hence model can be stated as:

$$\begin{pmatrix} x_t^{2nd} \\ z_t \\ x_t^e \end{pmatrix} = \beta f_t + \begin{pmatrix} u_{1t} \\ U_t \\ u_{2t} \end{pmatrix}, \qquad (7)$$

where β is the $r+2$ vector of factor loadings, which measure the sensitivity of each series to movements in the common factor, and $U_t = (U_{1t}, ..., U_{rt})'$.[2]

[2] According to the empirical analysis, GDPs and hard indicators are in growth rates whereas soft indi-

The dynamics of the model is achieved by assuming that

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

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

It is convenient to write the model in state space form in order to estimate it by using the Kalman filter. Let μ_t be the employment growth rate, and $\beta = \begin{pmatrix} \beta_1 & \beta_2' & \beta_3 \end{pmatrix}'$ be the vector of factor loadings of GDP, the r monthly indicators and the employment growth rate, respectively. The *measurement equation* can be defined as

$$
\begin{pmatrix} y_t^{2nd} \\ z_t \\ \mu_t \\ y_t^{1st} \\ y_t^f \end{pmatrix} = \begin{pmatrix} \beta_1\left(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4}\right) \\ \beta_2 f_t \\ \beta_3\left(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4}\right) \\ \beta_1\left(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4}\right) \\ \beta_1\left(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4}\right) \end{pmatrix} +
$$

$$
\begin{pmatrix} \frac{1}{3}u_{1t} + \frac{2}{3}u_{1t-1} + u_{1t-2} + \frac{2}{3}u_{1t-3} + \frac{1}{3}u_{1t-4} \\ U_t \\ \frac{1}{3}u_{2t} + \frac{2}{3}u_{2t-1} + u_{2t-2} + \frac{2}{3}u_{2t-3} + \frac{1}{3}u_{2t-4} \\ \frac{1}{3}u_{1t} + \frac{2}{3}u_{1t-1} + u_{1t-2} + \frac{2}{3}u_{1t-3} + \frac{1}{3}u_{1t-4} \\ \frac{1}{3}u_{1t} + \frac{2}{3}u_{1t-1} + u_{1t-2} + \frac{2}{3}u_{1t-3} + \frac{1}{3}u_{1t-4} \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 0 \\ e_{2t} \\ e_{1t} + e_{2t} \end{pmatrix} \quad (12)
$$

More compactly, one can use the expression

$$
Y_t = Hh_t + w_t, \quad (13)
$$

with $w_t \sim i.i.d.N(0, R)$. To illustrate how these matrices 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.

cators are in first differences and all of them have been standardized. Hence, the model reflects that the time series of the analysis are integrated but not cointegrated.

Assuming $m_1 = m_2 = m_4 = 6$ and $m_3 = 2$, this can be expressed as

$$
\begin{aligned}
Y_t &= \begin{pmatrix} y_t^{2nd} & z_t' & \mu_t & y_t^{1st} & y_t^f \end{pmatrix}', && (14)\\
w_t &= 0_{1,r+4}, && (15)\\
R &= 0_{r+4,r+4}, && (16)
\end{aligned}
$$

$$h_t = (f_t, ..., f_{t-5}, u_{1t}, ..., u_{1t-5}, U_{1t}, ..., U_{1t-1}, ..., U_{rt}, ..., U_{rt-1}, u_{2t}, ..., u_{2t-5}, e_{1t}, e_{2t})' \quad (17)$$

$$H = \begin{pmatrix} H_1 & 0 & H_2 & 0 & & & & & & & ... & & 0 \\ \beta_2 & 0_{r,1} & & & H_3 & 0_{r,1} & & & & & ... & & 0_{r,1} \\ 0 & & ... & & & 0 & H_4 & 0 & H_2 & 0 & ... & & 0 \\ H_1 & 0 & H_2 & 0 & & & ... & & & 0 & ... & 0 & 1 \\ H_1 & 0 & H_2 & 0 & & & ... & & & & ... & 1 & 1 \end{pmatrix}, \quad (18)$$

where

$$
\begin{aligned}
H_1 &= \begin{pmatrix} \frac{\beta_1}{3} & \frac{2\beta_1}{3} & \beta_1 & \frac{\beta_1}{3} & \frac{2\beta_1}{3} \end{pmatrix}, && (19)\\
H_2 &= \begin{pmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{1}{3} & \frac{2}{3} \end{pmatrix}, && (20)\\
H_3 &= I_r \otimes \begin{pmatrix} 1 & 0 \end{pmatrix}', && (21)\\
H_4 &= \begin{pmatrix} \frac{\beta_3}{3} & \frac{2\beta_3}{3} & \beta_3 & \frac{\beta_3}{3} & \frac{2\beta_3}{3} \end{pmatrix}. && (22)
\end{aligned}
$$

In addition, the *transition equation* can be stated as

$$h_t = F h_{t-1} + v_t, \quad (23)$$

with $v_t \sim i.i.d.N\,(0, Q)$. Using the assumptions of the underlying example, the matrix Q is a diagonal matrix in which the entries inside the main diagonal are

$$\begin{pmatrix} \sigma_f^2 & 0_{1,4} & \sigma_{u_1}^2 & 0_{1,4} & \sigma_{U_1}^2 & 0 & ... & \sigma_{U_r}^2 & 0 & \sigma_{u_2}^2 & 0_{1,4} & \sigma_{e_1}^2 & \sigma_{e_2}^2 \end{pmatrix}, \quad (24)$$

and the matrix F becomes

$$F = \begin{pmatrix} a & & & & & & 0 & 0 \\ M_1 & & & & & & 0_{4,1} & 0_{4,1} \\ 0 & b & & & & & 0 & 0 \\ 0_{4,1} & M_1 & & & & & 0_{4,1} & 0_{4,1} \\ 0 & & c_1 & & & & 0 & 0 \\ 0 & & M_2 & & & & 0 & 0 \\ \vdots & & & \ddots & & & \vdots & \vdots \\ 0 & & & & c_r & & 0 & 0 \\ 0 & & & & M_2 & & 0 & 0 \\ 0 & & & & & d & 0 & 0 \\ 0_{4,1} & & & & & M_1 & 0_{4,1} & 0_{4,1} \\ 0 & & & & & & 0 & 0 \\ 0 & & & & & & 0 & 0 \end{pmatrix}, \tag{25}$$

where

$$a = \begin{pmatrix} a_1 & \dots & a_5 & 0 \end{pmatrix}, \tag{26}$$

$$M_1 = \begin{pmatrix} 1 & & 0 & 0 \\ & \ddots & & \vdots \\ 0 & & 1 & 0 \end{pmatrix}, \tag{27}$$

$$b = \begin{pmatrix} b_1 & \dots & b_5 & 0 \end{pmatrix}, \tag{28}$$

$$c_j = \begin{pmatrix} c_{1j} & c_{2j} \end{pmatrix}, \; j = 1, ..., r, \tag{29}$$

$$M_2 = \begin{pmatrix} 1 & 0 \end{pmatrix}, \tag{30}$$

$$d = \begin{pmatrix} d_1 & \dots & d_5 & 0 \end{pmatrix}. \tag{31}$$

In order to handle with missing observations we put zeroes for missing observations, and rewrite the measurement equation as if they are random draws θ_t from $N(0, \sigma_\theta^2)$ independent of the model parameters, so that the Kalman filter "skips" missing. In this case, the measurement equation should be replaced by the following expressions

$$Y_t^* = \begin{cases} Y_t & \text{if observable} \\ 0 & \text{otherwise} \end{cases}, \tag{32}$$

$$H_t^* = \begin{cases} H & \text{if observable} \\ 0 & \text{otherwise} \end{cases}, \tag{33}$$

$$w_t^* = \begin{cases} 0 & \text{if observable} \\ \theta_t & \text{otherwise} \end{cases}, \tag{34}$$

$$R_t^* = \begin{cases} R & \text{if observable} \\ R_2 & \text{otherwise} \end{cases}, \tag{35}$$

where R_2 is a diagonal matrix with variances σ_θ^2 in its main diagonal.

This trick leads to a time-varying state space model with no missing observations so the Kalman filter can be applied. The filter consists of two set of equations, the prediction and updating equations. 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

$$h_{t|t-1} = H_t^* h_{t-1|t-1}, \tag{36}$$

$$P_{t|t-1} = H_t^* P_{t-1|t-1} H_t^{*\prime} + Q. \tag{37}$$

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

$$l_t = -\frac{1}{2}\ln\left(2\pi\left|F_{t|t-1}\right|\right) - \frac{1}{2}\eta_{t|t-1}'\left(F_{t|t-1}\right)^{-1}\eta_{t|t-1}. \tag{38}$$

The *updating equations* are

$$h_{t|t} = h_{t|t-1} + K_t \eta_{t|t-1}, \tag{39}$$

$$P_{t|t} = P_{t|t-1} - K_t H_t^* P_{t|t-1}, \tag{40}$$

where the Kalman gain, K_t, is defined as $K_t = P_{t|t-1} H_t^{*\prime}\left(H_t^* P_{t|t-1} H_t^{*\prime} + R_t^*\right)^{-1}$. The initial values of $h_{0|0}$ and $P_{0|0}$ used to start the filter are zeroes. Note that when at any date τ all elements of the vector Y_τ are not observed, the updating equations are skip and time τ does not contribute to the log likelihood at all. 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.

An interesting additional tool of analysis that can be obtained from this filter is the response of the Euro area GDP growth to an unanticipated change in any indicator. Following Stock and Watson (1991) this measure can be easily obtained as

$$R_t = \beta_1 \left(\frac{1}{3}\lambda_{1t} + \frac{2}{3}\lambda_{2t} + \lambda_{3t} + \frac{2}{3}\lambda_{4t} + \frac{1}{3}\lambda_{5t} \right) + \left(\frac{1}{3}\lambda_{7t} + \frac{2}{3}\lambda_{8t} + \lambda_{9t} + \frac{2}{3}\lambda_{10t} + \frac{1}{3}\lambda_{11t} \right), \tag{41}$$

where λ_{it} is the i-th row of the matrix

$$W_t = \left(I - \left(I - K_t^* H_t^*\right) F\right)^{-1} K_t^*. \tag{42}$$

3 Empirical results

3.1 Data description

The variables entering the proposed model are listed in Table 1 and plotted in Figure 2. For its interest in real time forecasts, the particular date on which these series are published and the sample that they cover is also shown in the figure. Note that the second estimate for the first quarter of 2007 is no longer available but the preliminary announcements, flash and first, were already published on 04/12/07 and 06/01/07. The monthly hard indicators, that are based on economic activity data, are the Euro area industrial production index (excluding construction), the Industrial New Orders Indices (INO, total manufacturing working on orders), the Euro area total retail sales volume, and the extra-Euro area exports. The quarterly employment that refer to the first semester was already published. The soft indicators, that are based on survey data, 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

Figure 2 provides a clear outlook of the importance of missing data in the Euro area forecasting exercise. 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, the hard indicators exhibit a publication delay of one or two months. Finally, quarterly series do not contain monthly issues. To facilitate the reader the inspection of all of these data irregularities, the last rows of this data set have been summarized in Table 2. Note that the most updated time series is employment (last vintage on June, 13th 1997) and marks the data set that has been used in the in-sample analysis.

Preliminary data analysis, based on Dickey-Fuller tests and not included to save space, suggested modeling hard indicators in growth rates and soft indicators in first differences. 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 that have been generated from $N(0,1)$.

3.2 In-sample analysis

The in-sample analysis have been carried out with the most updated data set available on June, 13th 1997. To understand how our proposed method predicts, recall that our interest is on short term forecasts, so 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 last second release was for the fourth quarter of 2006 and was released on April, 12th 1997. Hence, from these date until July, 12th 1997, the release date for GDP second of the first quarter of 2007, the previsions of GDP are from June 2007 to September 2007. From July, 13th 1997 the previsions will cover the nine months from April 2007 to December 2007. Accordingly, our in-sample analysis ends in September 2007.

The model adopted in this paper is based on the notion that comovements between the macroeconomic variables have a common element, the common factor, that moves according to the Euro area business cycle dynamics. In order to check if the estimated factor agrees with the Euro area business cycles, Figure 3 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 are reported in Table 3.[3] In all cases the estimates are positive and statistically significant, indicating that these series are procyclical, that is, positively correlated with the common factor.[4] Although all the series contain incremental information about the Euro area business cycle pattern, soft indicators tend exhibit higher loading factors.

Figure 4 plots the estimated series of GDP quarterly growth rates along with the actual data. Note that, according to the methodology employed in this paper, the Kalman filter anchor estimates to actuals whenever GDP is observed. Hence, for those months where GDP is known, actual and estimates coincide. In addition, Table 4 shows the main in-sample output of this procedure, the second forecasts for the nine months from January 2007 to September 2007. This anticipates three future issues of the Eurostat data releases process: the GDP growth rates for first, second and third quarters of 2007. In the table, these figures appear in the second column of rows labelled as 2007.03, 2007.06 and 2007.09 that we call lagged, current and future forecasts, respectively.

Table 5 shows the impacts (normalized to add one) on GDP estimates from unexpected shock in the indicator series. According to the anchoring procedure, rows labelled as 2006.09 and 200.12 reveal that, once the second is published, the impact of unexpected changes in the indicator series on GDP are zero. Row labelled as 2007.03 points out that flash and first are obviously the indicators with highest impact on GDP growth. However, the weight of the flash estimate is zero once the first is published. Since no hard indicator contain data referred to May, row labelled as 2007.05 reveals that the response of GDP growth to unexpected changes on the soft indicators is equally shared (adding the response to changes in both PMIs). Finally, last four rows indicate that for those months where no data is available, GDP predictions just depend on the series dynamics and the weights fall to zero.

To illustrate how the weights can be used to anticipate forecast changes, we show in Figure 5 the GDP predicted values for the second quarter of 2007 against different values of IFO that will be updated on 06/22/07. Recall (Table 4) that our forecast for 2007.06

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

[4] Sales are just marginally significant. This series is still included in the analysis since it is a key series in monitoring the Euro area economy.

was 0.57 (horizontal dotted line) and that the predicted value for IFO in 2007.06 is 0.2 (vertical dotted line). Obviously, if the IFO changes 0.2 in June with respect to its value in May, the prediction of GDP growth for 2007.06 is unaltered. In addition, the logistic shape of the GDP response function indicates that the highest changes in the GDP predictions occur in changes of IFO around its expected value. However, atypical changes of IFO are interpreted as misleading values so the impact on GDP forecasts decrease when IFO changes increase in absolute value.

3.3 Real-time analysis

In concept, developing a real-time data set is simple. However, producing real-time data require a great amount of effort in practise, including handling with old and physical sources of data 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.

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. n sum, we have 346 different vintages and they contain just the information that was Iavailable 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-11/24/03 so we start the real-time analysis with the vintage called vint-01/15/04 that is the first vintage that allows us to initiate the analysis of a complete quarter.[5]

Using the first vintage of our data set, called vint-01/15/04, we estimate the model and compute the nine-months forecasts of GDP that include the lagged (2003.IV), current (2004.I) and future (2004.II) 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 for the last quarter of 2003 is published on 04/16/04. The model is then re-

[5] We failed to obtain the time series of Industrial New Orders prior to 11/24/03.

estimated and procedure is then recursively repeated until the last vintage of our data set, vint-06/13/07, 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 6 the real time forecasts made each day of two forecasting periods. The first one (top chart) includes all the forecasts of GDP growth for the first quarter of 2007, i.e., from 10/11/06 (publication day of 2006.II GDP) to 06/14/07 (today). At the beginning of the forecasting period, the forecasts for 2007.I refer to true forecasts, after the publication day of 2006.III GDP (01/11/07) they are current forecasts, and from the publication day of 2006.IV GDP (04/12/07) they are lagged forecasts. Note that the two standard error bands become narrowed as the time is going on since the forecasts are made with more information. In particular, GDP forecasts especially reacts to flash and second releases, plotted as floating spots in the graph. In these days, the distance between the two standard error bands is reduced the most.

The forecasts for the second example of the forecasting exercise made in real time appears in the bottom chart of Figure 6 which shows the real time forecasts of GDP over the period from 04/12/06 to 01/10/07. This period is particularly interesting since, being a recent period, the second for 2006.III has actually been published as it was available in real-time (bottom horizontal line) and as it appears in the current revision (top horizontal line). Both flash and first was about 0.52 and roughly coincides with the figure issued on 01/11/07 while we were forecasting almost 0.58. However, the Eurostat has revised up this figure to 0.58 in the GDP time series published on 04/1207. This example is perfect to illustrate forecasting exercise should relay on truly real-time by using current-vintage data sets instead of end-of-sample vintage data sets. The out-of-sample are usually based on final data that are cut in some date and sequentially enlarged with data obtained at the end of the sample that include data revisions. These exercises implicitly rely on the assumption that data revisions are not important in real-time but, as we have shown in this example, the assumption may be far from reality leading to misleading and unrealistic results.

The relation between the incoming of new and updated information and the forecast error is examined in Figure 7. This figure plots the sample average of the standard errors associated to each GDP forecast that is associated to any of the 275 days that last each forecasting exercise. Although the standard errors may very 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.

Figure 8 provides a visual inspection of the good real-time forecast accuracy of our model. This figure plot the lagged GDP forecast computed each day of the real-time forecasting period along with the real-time GDP figures (blue line) and the last GDP figures available that includes the data revisions. In sum, both the GDP figures in real-time and their the revised versions are included within the two-standard errors bands that appear in shaded areas.

3.4 Forecasting accuracy

In order to address the performance of our indicator, we compare our out of sample forecast with a list of well-known forecast for the Euro-area GDP. Even though we beat, in terms of smaller mean squared forecast error, most of our competitors, we do not interpret this result as evidence of improving the forecast because the small sample for the out-of-sample predictions makes impossible to statistically test for gains, in pairwise comparisons, between any of the forecast.

We have daily forecast of next three quarters of the second revision of the GDP growth after the latest release. None of the competitors have daily forecast of the GDP and only some of them have at different horizons. Then, when we compare our forecast with the competitors, we are careful to compare our forecast for the GDP at the same horizon that our competitor on the same day in which the competitor publishes its release. The framework that we adopt goes against our interest because, when comparing forecast, the competitor does not change during a whole month or even a quarter its release while we change it everyday, being able to adapt better than any competitor to the new available information.

We use as competitors the releases of five different popular forecast. The Eurocoin, the European Comission Macroeconomic forecasts, the Euro-area GDP growth projection of the DG ECFIN of the European Comission, the IFO_INSEE_INSAE Economic Forecast, and the Projections of the OECD Economic Outlook.[6]

As shown in Table 6, our forecast are in line with the rest of the popular macroeconomic forecasts. We beat, the Eurocoin at the three horizons for which we have the same forecast, the European Comission macroeconomic forecast at two of the three horizons, the DGECFIN, the IFO_INSEE_INSAE Economic Forecast at two of the three horizons and we beat the OECD at one horizon. In general, as stated before, we understand that we can not test the significativity of these gains, but at least, informally, we can affirm that we do as well as anybody else in the forecasting arena.

3.5 Markov-switching analysis

In the previous section we model the comovements among the Euro area economic aggregates by assuming that these series share an unobserved common factor that represents the business cycle dynamics. A different problem is to infer (in real time) the phase of the cycle from this baseline model. This requires reformulating the model in order to provide inferences about probabilities of recessions and expansions.

For this purpose, we assume that the common factor is driven by an unobservable state variable that evolves according to the business cycle dynamics:

$$f_t = \alpha_{s_t} + a_1 f_{t-1} + ... + a_{m_1} f_{t-m_1} + \epsilon_t^f. \quad (43)$$

[6] All the indicators can be found at the following links:

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

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

EC_Macroeconomic_Forecast:

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

IFO_INSEE_ISAE:

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

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

In this paper, s_t is assumed to evolve according to an irreducible 2-state Markov process whose transition probabilities are defined by

$$p\left(s_t = j | s_{t-1} = i, s_{t-2} = h, ..., \chi_{t-1}\right) = p\left(s_t = j | s_{t-1} = i\right) = p_{ij}, \tag{44}$$

where $i, j = 1, 2$, and $\chi_t = (Y_t, , Y_{t-1}, ...)$. Within this framework, we can label $s_t = 0$ and $s_t = 1$ as the expansion and recession states at time t if $\alpha_0 > 0$ and $\alpha_0 < 0$. Hence, the common factor is expected to exhibit positive rates of growth in expansions and negative rates of growth in recessions.

Maximizing the exact log likelihood function of the associated nonlinear Kalman filter is computational burdersome. However, Kim (1994) proposes an approximate maximum likelihood estimation based on the collapsing technique that overcome this problem. Using the notation $Z_{t|t-1}^{(i,j)}$ to denote the variable Z conditional on the information available up to $t-1$ and the realized states $s_{t-1} = i$ and $s_t = j$, the prediction equations become

$$h_{t|t-1}^{(i,j)} = \Lambda_j + H_t^* h_{t-1|t-1}^i, \tag{45}$$

$$P_{t|t-1}^{(i,j)} = H_t^* P_{t-1|t-1}^i H_t^{*\prime} + Q, \tag{46}$$

where $\Lambda_{s_t} = \begin{pmatrix} \alpha_{s_t} & 0_{1,n-1} \end{pmatrix}'$, $s_t = i, j$, and n is the dimension of the state vector h_t. The updating equations become

$$h_{t|t}^{(i,j)} = h_{t|t-1}^{(i,j)} + K_t^{(i,j)} \eta_{t|t-1}^{(i,j)}, \tag{47}$$

$$P_{t|t}^{(i,j)} = P_{t|t-1}^{(i,j)} - K_t^{(i,j)} H_t^* P_{t|t-1}^{(i,j)}. \tag{48}$$

Each iteration, the nonlinear filter computes produces a 2-fold increase in the number of cases to consider. Kim (1994) approximates $h_{t|t}^j$ and $P_{t|t}^j$ by weighted averages of the updating equations where the weights are given by the probabilities of the Markov state:

$$h_{t|t}^j = \frac{\sum_{s_{t-1}=0}^{1} p\left(s_t = j, s_{t-1} = i | \chi_t\right) h_{t|t}^{(i,j)}}{p\left(s_t = j | \chi_t\right)} \tag{49}$$

$$P_{t|t}^j = \frac{\sum_{s_{t-1}=0}^{1} p\left(s_t = j, s_{t-1} = i | \chi_t\right) \left(P_{t|t}^{(i,j)} + \left(h_{t|t}^j - h_{t|t}^{(i,j)}\right)\left(h_{t|t}^j - h_{t|t}^{(i,j)}\right)'\right)}{p\left(s_t = j | \chi_t\right)}. \tag{50}$$

Let us move to the empirical illustration of this extension. Following the results of Camacho and Perez-Quiros (2005) we consider that the dynamics of a nonlinear model can be alternatively captured either by autoregressive parameters or by a Markov switching process that governs the business cycle patterns. For this reason, we set $m_1 = 0$. In addition, we choose $m_2 = m_3 = m_4 = 2$.

Regarding the model's accuracy in forecasting GDP growth the nonlinear model exhibit similar predictive power than the linear model so we skip the analysis of forecasting GDP and concentrate on the analysis of the identification of the Euro area business cycle phases.

The maximum likelihood estimates that describe the nonlinear nature of this process reveal that on average the cyclical comovements among the series, that is represented by the common factor, is positive within state $s_t = 0$ ($\widehat{\alpha}_0 = 1.07$) and negative within state $s_t = 1$ ($\widehat{\alpha}_0 = -1.32$). This indicates that the states can be identifies as expansions and recessions, respectively. In addition, the estimates of the transition probabilities are $\widehat{p}_{00} = 0.93$ and $\widehat{p}_{11} = 0.91$, which indicates that both phases of the business cycle are highly persistent. The expected duration of a typical Euro area expansion is $(1 - \widehat{p}_{00})^{-1}$ or 14 months, and the expected duration of recession is likewise $(1 - \widehat{p}_{11})^{-1}$ or 11 months.

Figure 9 provides a visual inspection of the in-sample probabilities of state 1 (right scale) inferred from our model. For comparison purposes, the figure also plots the Euro area GDP growth (left scale) and highlights the CEPR recessions with shaded gray areas. Over the sample period, high probabilities of state $s_t = 1$ correspond closely with the CEPR recessions. In a first look of this graph it may seem that our recessionary indicator identifies the business cycle turning points too late. However, a deeper look inside the picture reveals that the CEPR business cycle chronology dated peaks in moments of positive high GDP growth rates and dated throughs in moments of negative GDP growth rate. Our business cycle chronology is much more in relation with GDP growth rate.

The last part of the sample is of special interest, highlighted in green. Although the CEPR dated the last peak on November 1999, they have not dated the through yet. Our recessionary indicator does not show clear signals of turning points on November since the quarterly GDP growth rate was greater that one but reveals that this expansion lasts until the third quarter of 2000. In addition, the inferred probabilities reveal that the last months can be identified as a moment of great uncertainty.

Finally, Figure 10 shows how the estimated probabilities of recession can be updated in real time. Following the same notation used to identify lagged, current and future GDP forecasts, this figure plots the lagged probabilities computed each day of the real-time forecasting period along with the Euro area GDP growth rate. As expected, high probabilities correspond to period of low GDP growth.

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 black-box proposals is still an open question.

In this paper we contribute 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. In addition, our proposal is able to compute short term forecasts of the probabilities of Euro area recessions. This makes the real time economic outlook much easily to interpret by all readers, including non economists.

Using this model, we elaborate several empirical contributions. First, we construct a new coincident indicator of the Euro area economy that allows us to date the Euro area business cycle turning points. 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, monthly indicators and flash announcements contain valuable information to predict and to reduce forecast uncertainty. It seems that first announcements do not contain much additional information about the second releases.

We consider that the construction of a real-time data base and a toolkit to obtain easily the information from it is a contribution itself. The data base contains 346 different vintages that collect just the information that was available to construct real time forecasts each day of the last four years. With this data base and the proposed model we evaluate its forecasting accuracy in a horse-race analysis against the most known forecasts of the Euro area GDP growth rate. We find empirical support in favor of our proposal.

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Table 1. Data description

	Euro Area Indicators Variables (a) (b)			
	Name	Definition	Observations	Reporting lag (c)
Quarterly Hard Indicators	Flash GDP	Euro Area GDP	17	45 days
	First GDP	Euro Area GDP	35	60 days
	Second GDP	Euro Area GDP	63	102 days
	Employment	Euro Area Total Employment	64	102 days (d)
Monthly Hard Indicators	IPI	Euro Area Industrial Production Index (excluding construction)	193	42 days
	Sales	Euro Area Total Retail Sales Volume	147	35 days
	INO	Industrial New Orders Indices. Total manufacturing working on orders	147	52 days
	Exports	Extra- Euro Area Exports	193	45 days
Monthly Soft Indicators	BNB	Belgium Overall Business Indicator	149	-8 days
	ESI	Euro-Zone Economic Sentiment Indicator	194	0 days
	IFO	Germany IFO Business Climate Index	195	-8 days
	PMI Manufactures	Euro Area Manufacturing Purchasing Managers Index	119	1 day
	PMI Services	Euro Area Services Purchasing Managers Index	106	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 14/06/07

	Second	First	Flash	IPI	Sales	INO	ESI	BNB	IFO	PMIM	Exports	PMIS	Employment
2006.09	0.58	0.52	0.52	-0.97	-0.79	-0.94	1.50	1.40	0.00	0.09	2.58	-0.80	0.26
2006.10	na	na	na	0.11	0.20	0.60	1.10	-0.70	0.40	0.36	-0.34	-0.16	na
2006.11	na	na	na	0.23	0.49	0.65	-0.10	-0.30	1.50	-0.44	1.51	1.06	na
2006.12	0.89	0.90	0.90	1.24	0.46	1.70	-0.10	-1.00	1.80	-0.04	1.88	-0.37	0.31
2007.01	na	na	na	-0.62	-0.94	-0.02	-0.60	-0.40	-0.80	-1.02	-0.65	0.70	na
2007.02	na	na	na	0.46	0.40	-0.64	0.50	1.40	-0.90	0.12	-0.04	-0.37	na
2007.03	na	0.60	0.57	0.54	0.43	2.68	1.40	-2.10	0.70	-0.21	1.17	-0.16	na
2007.04	na	na	na	-0.82	0.18	na	-0.10	2.40	0.90	-0.03	na	-0.36	na
2007.05	na	na	na	na	na	na	0.90	0.10	0.00	-0.37	na	0.27	na
2007.06	na	na	na	na	na	na	na	na	na	na	na	na	na
2007.07	na	na	na	na	na	na	na	na	na	na	na	na	na
2007.08	na	na	na	na	na	na	na	na	na	na	na	na	na
2007.09	na	na	na	na	na	na	na	na	na	na	na	na	na

Table 3. Factor loadings

Second	IPI	Sales	INO	ESI	BNB	IFO	PMIM	Exports	PMIS	Employment
0.04	0.06	0.01	0.06	0.13	0.09	0.10	0.14	0.04	0.10	0.02
(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.01)	(0.03)	(0.01)

Table 4. In-sample second forecasts

	Actuals	Forecast	se
2006.09	0.58	0.58	0.00
2006.10	na	0.62	0.08
2006.11	na	0.61	0.09
2006.12	0.89	0.89	0.00
2007.01	na	0.67	0.08
2007.02	na	0.67	0.09
2007.03	na	0.67	0.07
2007.04	na	0.74	0.09
2007.05	na	0.63	0.10
2007.06	na	0.57	0.11
2007.07	na	0.58	0.11
2007.08	na	0.63	0.12
2007.09	na	0.64	0.13

Table 5. Weights

	Second	First	Flash	IPI	Sales	INO	ESI	BNB	IFO	PMIM	Exports	PMIS	Employment
2006.09	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0000
2006.10	0.00	0.00	0.00	0.16	0.03	0.15	0.15	0.15	0.14	0.11	0.04	0.07	0.0000
2006.11	0.00	0.00	0.00	0.17	0.04	0.16	0.13	0.15	0.14	0.09	0.04	0.06	0.0000
2006.12	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0000
2007.01	0.00	0.00	0.00	0.16	0.03	0.15	0.15	0.15	0.14	0.11	0.04	0.07	0.0000
2007.02	0.00	0.00	0.00	0.17	0.04	0.16	0.13	0.15	0.14	0.09	0.04	0.06	0.0000
2007.03	0.00	0.87	0.00	0.02	0.01	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.0006
2007.04	0.00	0.00	0.00	0.21	0.04	0.00	0.18	0.19	0.17	0.13	0.00	0.09	0.0000
2007.05	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.26	0.24	0.16	0.00	0.11	0.0000
2007.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0000
2007.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0000
2007.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0000
2007.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0000

Table 6. Real-time forecasting evaluation

Forecasting period 2003.4-2007.1

Mean Squared Error

	1 Months Lag	**2 Months Lag**	**3 Months lag**
Eurocoin	0.79	0.62	0.58
CPQ	0.75	0.28	0.14
	3 Months Lead	**1 Month Lead**	**1 Month Lag**
Ecomission (a)	0.38	0.35	0.38
CPQ	0.43	0.25	0.02
			1 Month Lag
DGECfin			0.80
CPQ			0.71
	5 Months Lead	**3 Months Lead**	**1 Month Lag**
IFO_INSEE-INSAE	0.63	0.66	0.63
CPQ	0.58	0.68	0.45
	3 Months Lead	**Current Month**	
OECD (b)	0.31	0.28	
CPQ	0.12	0.41	

(a) The sample comprises only 2006 for which we have the interim forecasts
(b) We only cover half of the sample because we do not have coincident forecast for all the periods. The interim forecast are irregular. We also do not have a specific date of release for all of them. We use the forecast at the midpoint between one release and the next.

Figure 1. First and second estimates against revisions 1998.III-2006.IV

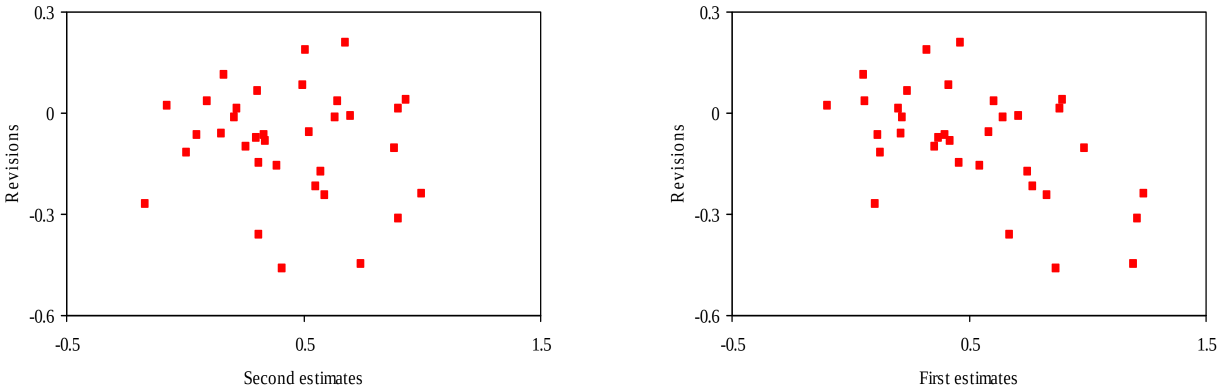
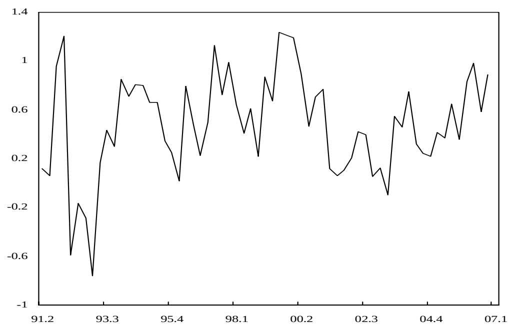


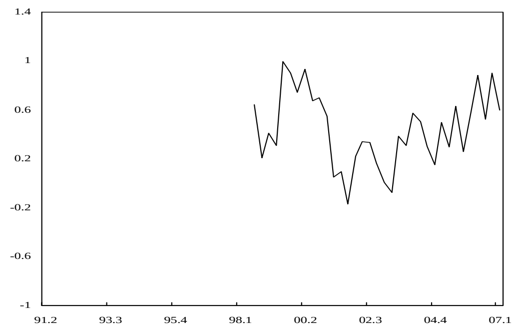
Figure 2. Time series used in the model

GDP second growth rate



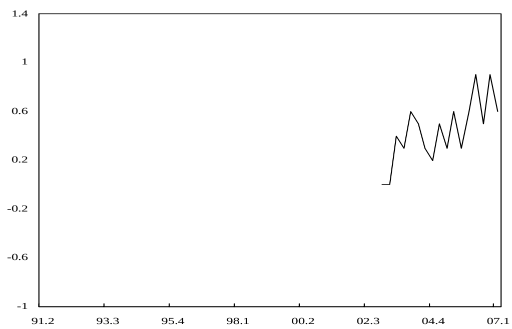
Sample 91.II-06.IV. Vintage 04/12/07

GDP first growth rate



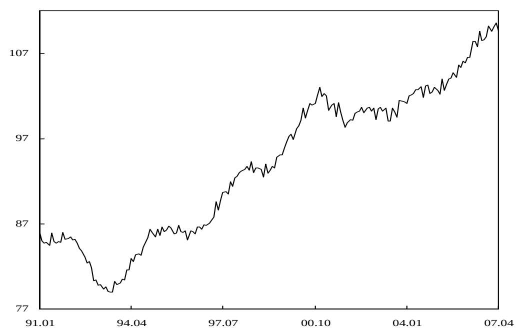
Sample 98.II-07.I. Vintage 06/01/07

GDP flash growth rate



Sample 03.I-07.I. Vintage 04/12/07

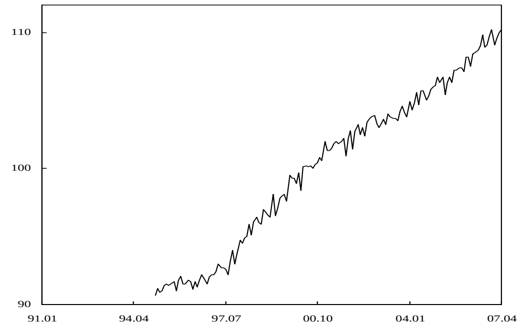
Industrial production



Sample 91.01-07.04. Vintage 06/12/07

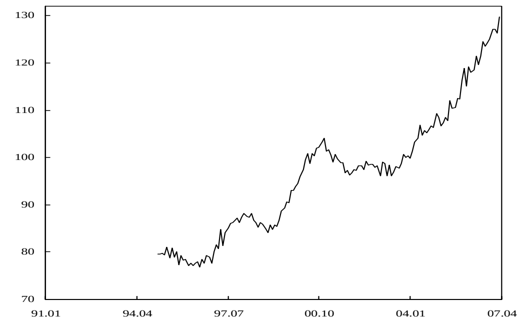
Figure 2. Time series used in the model

Retail Sales



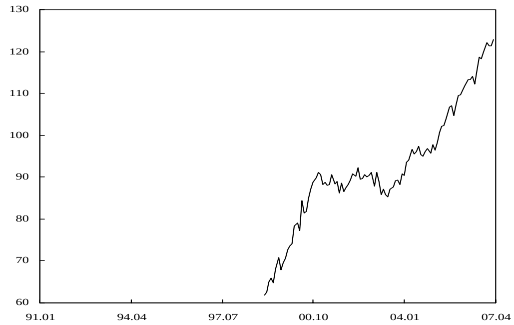
Sample 95.01-07.04. Vintage 06/05/07

Industrial new orders



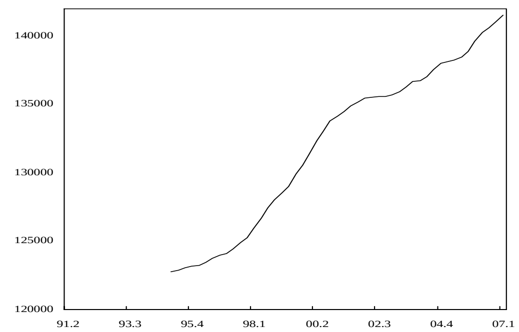
Sample 95.01-07.03. Vintage 05/23/07

Exports



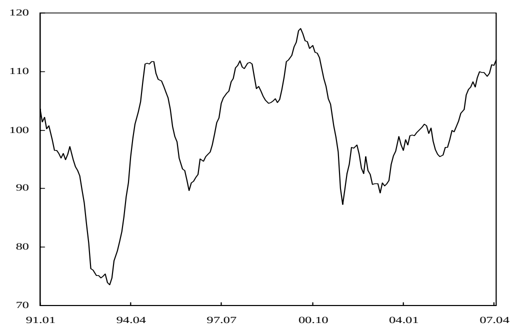
Sample 99.01-07.03. Vintage 05/22/07

Employment



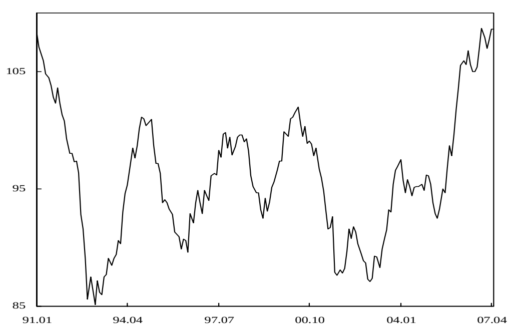
Sample 95.I-07.I. Vintage 06/13/07

ESI



Sample 91.01-07.05. Vintage 05/31/07

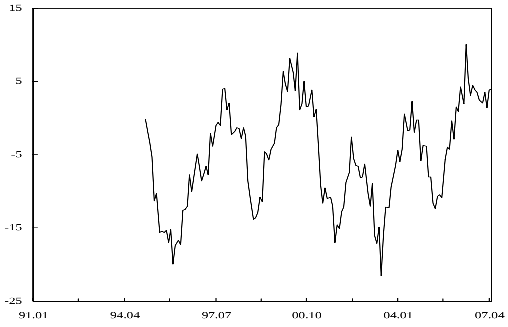
IFO



Sample 91.01-07.05. Vintage 05/24/07

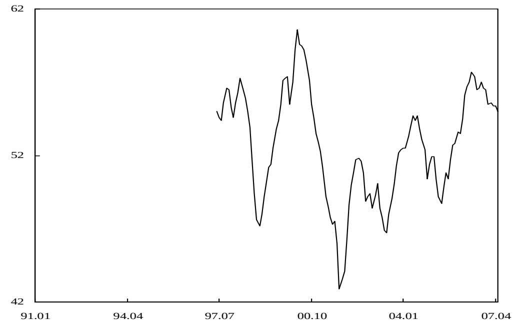
Figure 2. Time series used in the model

BNB



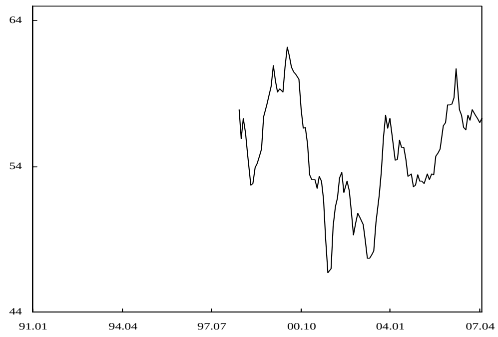
Sample 95.01-07.05. Vintage 05/24/07

PMI Manufactures



Sample 97.06-07.05. Vintage 06/01/07

PMI Services



Sample 97.06-07.05. Vintage 06/05/07

Figure 3. Common factor and Eurocoin

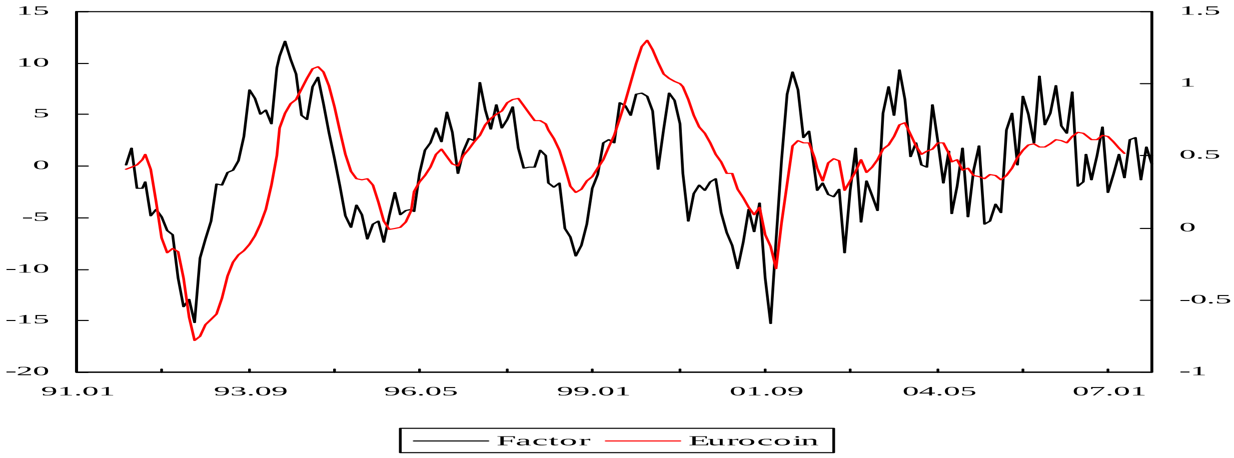


Figure 4. GDP second growth rate: actuals and estimates

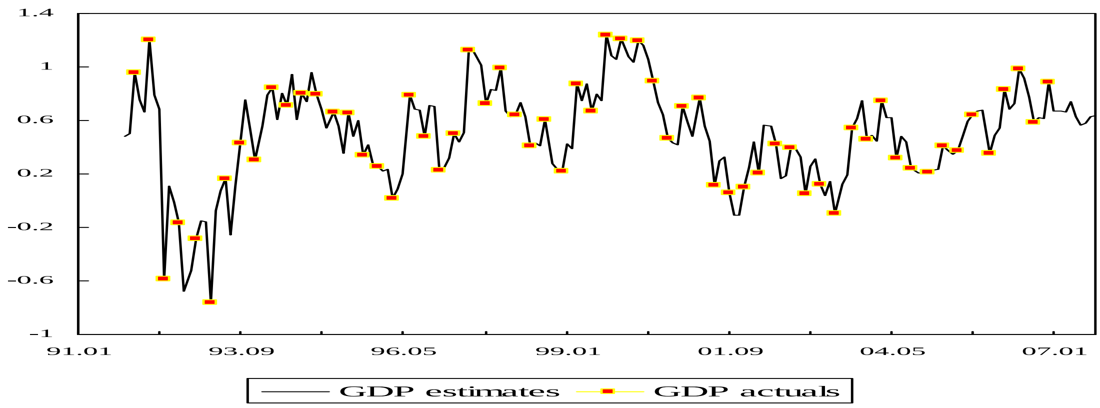


Figure 5. GDP forecast in 2007.06 and IFO releases

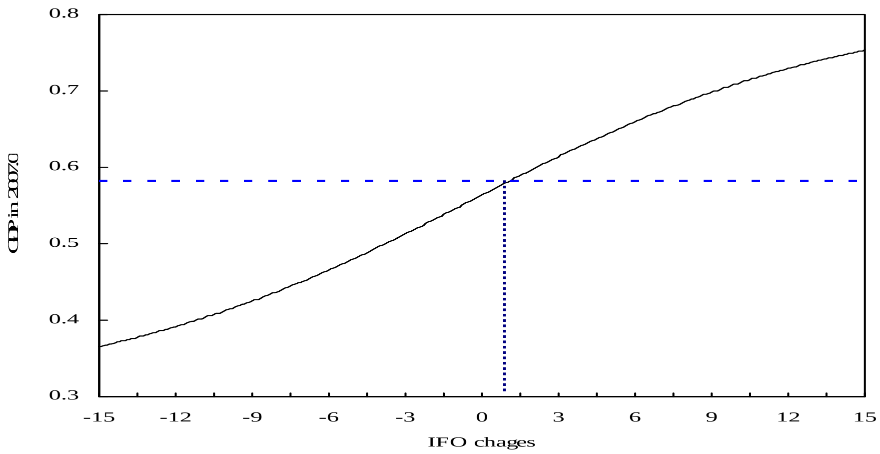
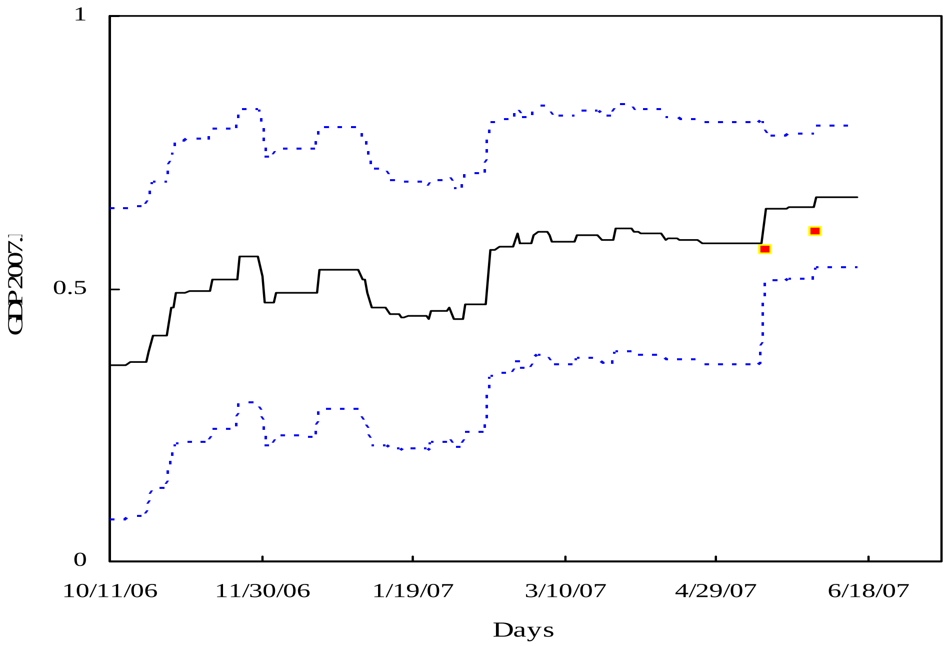


Figure 6. GDP second growth rate in real-time



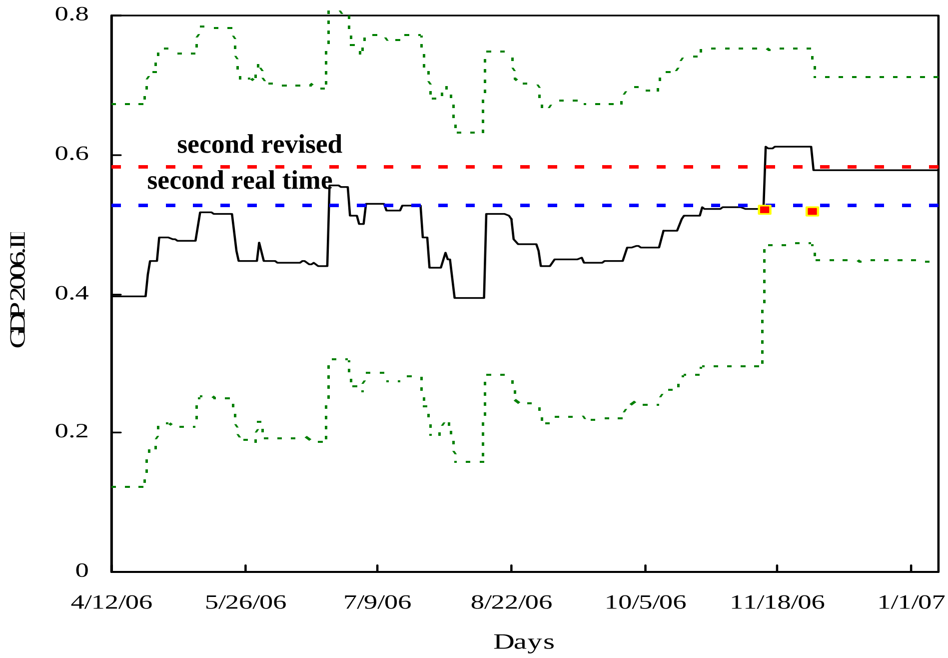


Figure 7. Averaged standard errors over the forecasting period

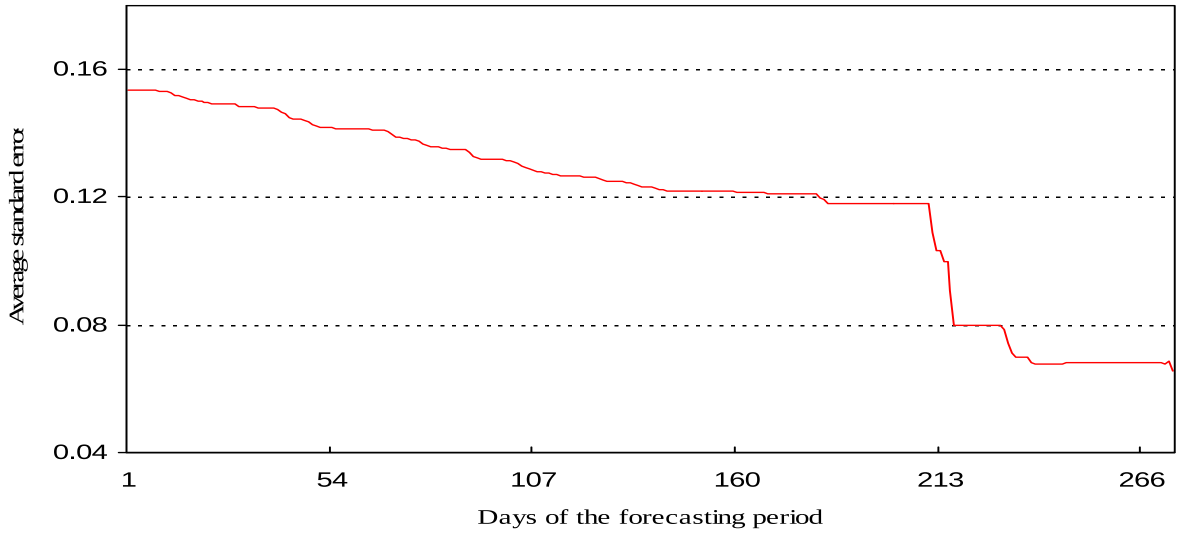


Figure 8. Real-time lagged forecasts of GDP

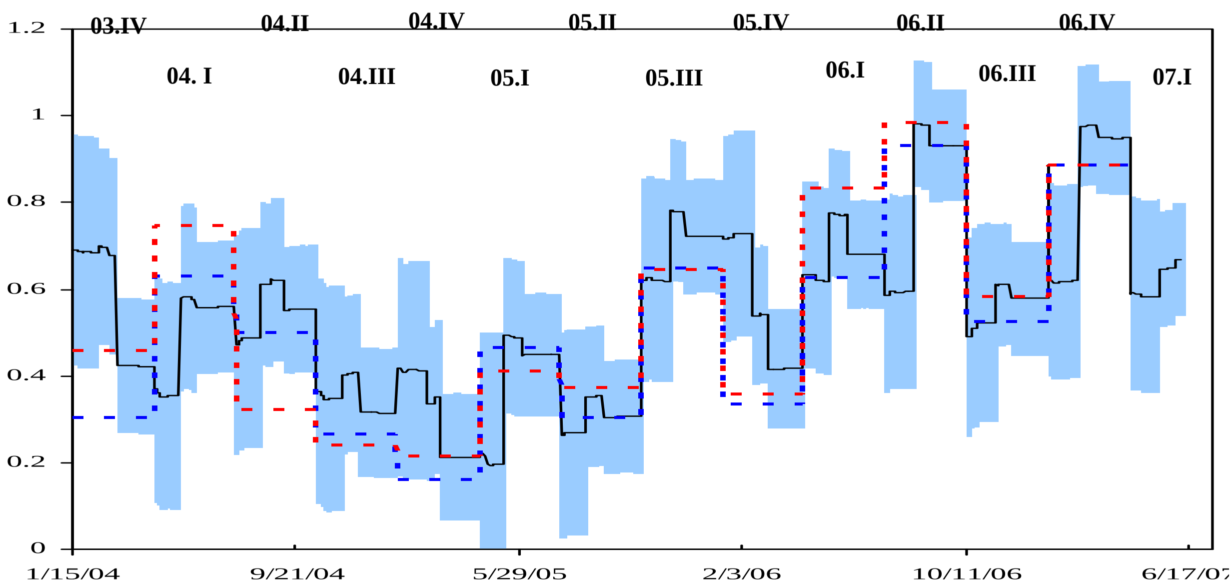


Figure 9. In-sample probabilities of recession

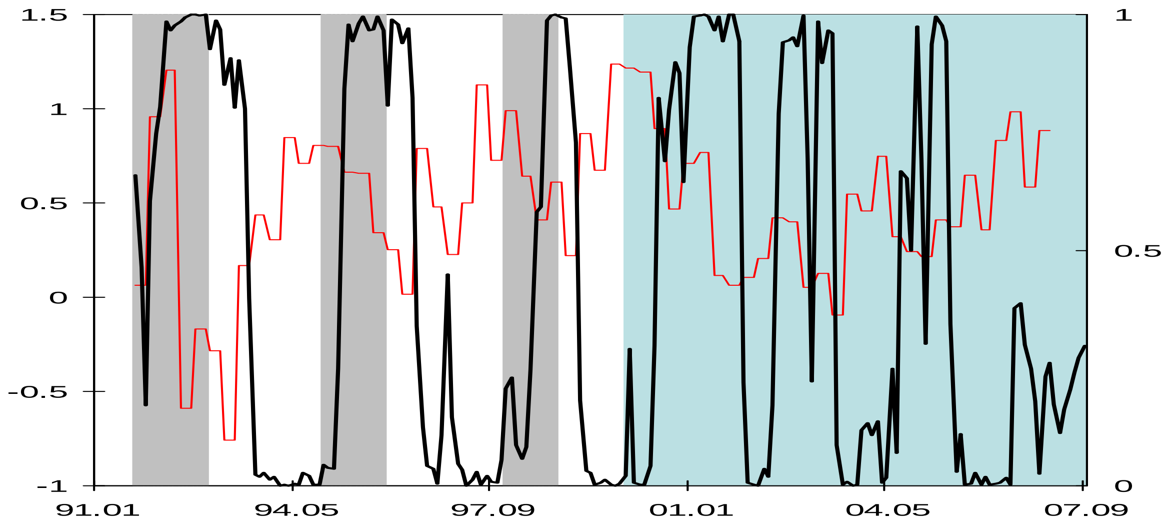


Figure 10. Real-time probabilities of recession