Green shoots in the Euro area. A real time measure*

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Abstract

We show that an extension of the Markov-switching dynamic factor models that accounts for the specificities of the day to day monitoring of economic developments such as ragged edges, mixed frequencies and data revisions is a good tool to forecast the Euro area recessions in real time. We provide examples that show the nonlinear nature of the relations between data revisions, point forecasts and forecast uncertainty. According to our empirical results, we think that the real time probabilities of recession are an appropriate statistic to capture what the press call *green shoots*.

Keywords: Business Cycles, Output Growth, Time Series.

JEL Classification: E32, C22, E27

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1 Introduction

Business cycles as we know them today exhibit two key insights. The first basic feature of the business cycle is the presence of comovements across economic indicators. Burns and Mitchell (1946) stated that a reference scale of business cycles must be extracted from the fallible indications provided by time series for varied economic activities. In the same spirit, the NBER business cycle dating committee, defines a recession as a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in production, employment, real income, and other indicators. The second key feature of the business cycle dynamics is the recurrence of two separate business cycle phases, recessions and expansions, which are clearly distinguishable with different dynamics. Burns and Mitchell (1946) stressed that a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle.

There are several approaches in the literature aiming to simultaneously deal the two business cycles features. Firstly, Diebold and Rudebusch (1996) suggested a two-step unified procedure. In the first step, they model comovements among individual economic indicators by using the linear coincident indicator approach described in Stock and Watson (1991). In the second step, they model the existence of two separate business cycle regimes by using the univariate Markov-switching specification advocated by Hamilton (1989) to the factor that has been estimated in the first step. Secondly, Kim and Yoo (1995), Chauvet (1998) and Kim and Nelson (1998) proposed a one-step Markov-switching dynamic factor model to consider both comovements and regime shifts. Recently, Chauvet and Hamilton (2006) and Chauvet and Piger (2008) showed the excellent performance of this model when computing real-time inference of the US business cycle states. Thirdly, Camacho, Perez Quiros and Poncela (2010) extended the Markov-switching dynamic factor model to deal with the typical difficulties of the timely day to day monitoring of the economic activity such as mixing frequencies, ragged ends and data revisions. They examined the accuracy of a very stylized version of the model to account for the US business cycles.

Following the third proposal, this paper describes and evaluates a method that computes real-time recession probabilities in the Euro area. The baseline framework is the linear Euro-STING dynamic factor model suggested by Camacho and Perez Quiros (2010) which has already been validated as a useful model to compute short term forecasts of the Euro area GDP growth rates in real time. Using the techniques suggested by the previous literature on business cycles, we incorporate Markov-switching dynamics in the Euro-STING model. With a real-time Euro area dataset, we develop several forecasting exercises that lead to some interesting results. First, we show evidence in favor of the nonlinear nature of the data generating process. Second, we date the Euro area business cycle turning points since 1990. Using the NBER dates as reference, we find that the US and the Euro area business cycles are becoming more synchronous in the last years. Third, we show that the model provides a significant improvement in the speed with which the Euro area business cycle turning points can be identified.

Overall, our results suggest that the Markov-switching dynamic factor model proposed in this paper is a very useful tool to monitor the day to day economic activity in the Euro area economy. This is of special importance due to the explosive interest on business cycle turning points identification emerged since the 2008-2009 recession. Analysts, policy makers, and journalists, have extensively used the term *green shoots* to refer to signals of the end of the recession period. Needless is to say that this term is far from following scientific criteria since it is very imprecise and it leaves the users to identify recoveries depending on their own beliefs, specially when the cost of checking in real time the publication calendar of many indicators is costly. Our real-time recession probabilities overcome these drawbacks since they provide economic agents with a statistical definition of the term green shoots which is very easy to interpret for the general public. When is a green shoot really green? When the probability of recession becomes sufficiently low.

The structure of this paper is organized as follows. Section 2 outlines the model and discusses some econometric details regarding the extension of Markov-switching dynamic factor models to account for some particularities of real time forecasting. Section 3 evaluates the empirical reliability of the model in within sample and real time exercises. Section 4 concludes.

2 The model

In this section, we briefly describe a model in which the business cycle indicators depend on a common factor, which evolves according to Markov-switching dynamics, and individual idiosyncratic components. The model is flexible enough to account for mixing frequencies, data revisions, different samples and unsynchronized data releases.[1]

2.1 Mixing frequencies

The fact that some economic indicators are available monthly while others are available quarterly raises the question of how to combine them into a unified forecasting model. Quarterly series which refer to stocks can be converted easily in monthly observations since they simply refer to quantities which are measured at a particular time and do not require any time restriction. Accordingly, these series can be treated as observed the month that they are issued and as unobserved otherwise. However, flow variables are measured during some time periods and must be temporally aggregated. Mariano and Murasawa (2003) describe a time aggregation which is based on the notion that quarterly time series can be viewed as sums of underlying monthly series in the corresponding quarter. Assuming that arithmetic means can be approximated by geometric means, quarter-on-quarter growth rates (g_t) of quarterly series are weighted averages of the monthly-on-monthly past growth rates (x_t) of the (assumed to be known) monthly underlying series

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

Recently, the pros and cons of using approximate filters instead of exact filters have been evaluated by Camacho and Perez Quiros (2010). In this context, it is worth mentioning that although the influential proposal of Aruoba, Diebold and Scotti (2009a) early used polynomial detrending series to avoid approximations, they recently acknowledge in Aruoba, Diebold and Scotti (2009b) that this leads to undesirable time series characteristics.

[1] Further theoretical results in favor of the model can be found in Camacho, Perez Quiros and Poncela (2010).

2.2 Data revisions

The fact that economic data are frequently revised complicates the day to day monitoring of the economic activity since revisions change the data input into forecasting models. In the Euro area, Eurostat revises twice the GDP growth figures in its official data release process.[2] The flash estimate, y_t^f, appears about 45 days after the end of the respective quarter. Since it is based on preliminary information, Eurostat publishes the first estimate about 20 days after which relies in more complete data. Finally, the second estimate of GDP growth rate, y_t^{2nd}, incorporates an additional revision about 40 days after the first. 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.

In this paper, we follow Evans (2005) and Coenen, Levin, Wieland (2005) to consider that preliminary advances are noisy signals of revised data:

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

$$y_t^{1st} = y_t^{2nd} + e_{2t}, \tag{3}$$

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.[3] Camacho and Perez Quiros (2010) show empirical evidence to be confident that this specification is a reasonable representation of the data revision process.

2.3 Ragged edges

In addition to the technical difficulties associated to the real time assessments of the economic activity that have been discussed below, forecasters have to deal with the typical lack of synchronicity in data publication. Usually, monthly indicators are published much more timely than quarterly series. In addition, indicators based on surveys (soft indicators) are more promptly issued than economic activity indicators (hard indicators) and their samples are usually longer. This implies that forecasters need a model to compute forecasts from unbalanced sets if they do not want either to loose valuable information at the time

[2] Other major revisions can also be modeled. However, in this paper we only consider the official GDP release calendar.

[3] For simplicity, we assume that e_{1t} and e_{2t} are uncorrelated.

of the forecast or to wait until balanced panels become available. This difficulty is the easiest to address in the context of dynamic factor models. As documented in Giannone, Reichlin and Small (2008), the Kalman filter frequently used in the estimation of dynamic factor models may be used to fill in the gaps of the non-synchronous flow of data releases.

Following Mariano and Murasawa (2003), missing data which comes from mixing frequencies and ragged edges are replaced by random draws θ_t from $N(0, \sigma_\theta^2)$ which must independent of the model parameters. The substitutions allow the matrices of the Kalman filter to be conformable but they have no more impacts on the model estimation than adding a constant in the likelihood function. This leads the forecasting procedure to become an extremely easy exercise. Computing h-period ahead forecasts reduces to add h rows of missing data at the end of the dataset which will automatically be replaced by forecasts inside the model.[4]

2.4 Specification of the model

The Markov-switching dynamic factor model consists of a factor model which decomposes the joint dynamics of the business cycle indicators into two components. The first component is a common factor which captures the occasional discrete variations in the dynamic features of the business cycle indicators. The second component refers to the idiosyncratic dynamics of each indicator and is modelled by using the standard techniques of linear autoregressive time series.

To be specific, in this specification the common factor, f_t, is driven by an unobservable state variable s_t:

$$f_t = \alpha_{s_t} + a_1 f_{t-1} + ... + a_{m_1} f_{t-m_1} + \epsilon_t^f. \tag{4}$$

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

$$p\left(s_t = j | s_{t-1} = i, s_{t-2} = h, ..., \chi_{t-1}\right) = p\left(s_t = j | s_{t-1} = i\right) = p_{ij}, \tag{5}$$

where $i, j = 0, 1$, and χ_t refer to the information set up to period t.

[4] Camacho, Perez Quiros and Poncela (2010) showed that this method remains valid in Markov-switching specifications.

In the related literature, several specifications of the nonlinear dynamics of the common factor have been suggested. Kim and Yoo (1995) and Chauvet (1998) allowed the intercept term to be regime dependent. In the specification of Kim and Nelson (1998) it is the mean instead of the intercept what is allowed to exhibit regime shifts.[5] In this paper, we follow Camacho and Perez Quiros (2007) to assume that the factor dynamics can be captured by shifts between the business cycle states and we set the autoregressive coefficients equal to zero. 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 $\alpha_1 < 0$. Hence, the common factor is expected to exhibit positive growth rates in expansions and lower (usually negative) growth rates in recessions.

To specify the dynamic factor model of flash, first, second, employment, hard and soft indicators, let us first assume that missing data do not appear in the dataset so that quarterly series are observed monthly and the corresponding vintage panels are balanced. We assume that the factor captures the common dynamics in the growth rates of real activity data. However, since survey indicators in Europe are designed to capture annual growth rates of the reference series (see European Commission, 2006), we impose that the levels of soft indicators depend on the sum of current values of the common factor and their 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 in the model. The dynamic of the business cycle indicators can be

[5] Our empirical results suggest that the performance of switching mean and switching intercept is similar.

stated as

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

$$\begin{pmatrix} \frac{1}{3}u_{1t} + \frac{2}{3}u_{1t-1} + u_{1t-2} + \frac{2}{3}u_{1t-3} + \frac{1}{3}u_{1t-4} \\ U_t^h \\ U_t^s \\ \frac{1}{3}u_{2t} + \frac{2}{3}u_{2t-1} + u_{2t-2} + \frac{2}{3}u_{2t-3} + \frac{1}{3}u_{2t-4} \\ \frac{1}{3}u_{1t} + \frac{2}{3}u_{1t-1} + u_{1t-2} + \frac{2}{3}u_{1t-3} + \frac{1}{3}u_{1t-4} \\ \frac{1}{3}u_{1t} + \frac{2}{3}u_{1t-1} + u_{1t-2} + \frac{2}{3}u_{1t-3} + \frac{1}{3}u_{1t-4} \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ e_{2t} \\ e_{1t} + e_{2t} \end{pmatrix}, \quad (6)$$

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 complete dynamics of the model is achieved by assuming that

$$u_{1t} = b_1 u_{1t-1} + ... + b_{m_2} u_{1t-m_2} + \epsilon_t^{u_1}, \quad (7)$$

$$v_{jt} = c_{j1} v_{jt-1} + ... + c_{jm_3} v_{jt-m_3} + \epsilon_t^{v_j}, \quad (8)$$

$$u_{2t} = d_1 u_{2t-1} + ... + d_{m_4} u_{2t-m_4} + \epsilon_t^{u_2}, \quad (9)$$

where $\epsilon_t^f \sim i.i.d.N\left(0, \sigma_f^2\right)$, $\epsilon_t^{u_1} \sim i.i.d.N\left(0, \sigma_{u_1}^2\right)$, $\epsilon_t^{u_2} \sim i.i.d.N\left(0, \sigma_{u_2}^2\right)$, and $\epsilon_t^{v_j} \sim i.i.d.N\left(0, \sigma_{v_j}^2\right)$, with $j = 1, ..., r$. All the covariances are assumed to be zero and we set the variance of the noise associated to the common factor, σ_f^2, equal to one.[6]

Consider the following state space representation of the Markov-switching dynamic factor model

$$Y_t = H h_t + w_t, \quad (10)$$

$$h_t = \Lambda_{s_t} + F h_{t-1} + \xi_t, \quad (11)$$

[6] This identifying assumption is standard in dynamic factor models.

where $\Lambda_{s_t} = \begin{pmatrix} \alpha_{s_t} & 0_{1,n-1} \end{pmatrix}'$, $s_t = i, j$, and

$$\begin{pmatrix} w_t \\ \xi_t \end{pmatrix} \tilde{}\, iidN\left(0, \begin{pmatrix} R & 0 \\ 0 & Q \end{pmatrix}\right). \tag{12}$$

The Appendix provides more details on the model structure and the specific forms of these matrices.

Let us now describe how to handle missing data. For this purpose, we follow Mariano and Murasawa (2003) and substitute missing observations with random draws θ_t from $N(0, \sigma_\theta^2)$. This implies replacing the i-th row of Y_{it} H_{it} w_t and the i-th element of the main diagonal of R_t, by Y_{it}^*,H_{it}^*, w_{it}^*, and R_{iit}^*. The starred expressions are Y_{it}, H_{it}, 0, and 0 if variable Y_{it} is observable at time t, and θ_t, 0_{1p}, θ_t, and σ_θ^2 in case of missing data, where p is the dimension of the state vector h_t. Accordingly, this transformation converts the model in a time-varying state space model with no missing observations and the nonlinear version of the Kalman filter can be directly applied to Y_t^*, H_t^*, w_t^*, and R_t^*.

To describe how the model can be estimated, let $h_{t|\tau}^{(i,j)}$ be the forecast of h_t based on information up to period τ and the realized states $s_{t-1} = i$ and $s_t = j$, and let $P_{t|\tau}^{(i,j)}$ be its covariance matrix. The prediction equations become

$$h_{t|t-1}^{(i,j)} = \Lambda_j + H_t^* h_{t-1|t-1}^i, \tag{13}$$

$$P_{t|t-1}^{(i,j)} = H_t^* P_{t-1|t-1}^i H_t^{*\prime} + Q, \tag{14}$$

where $h_{t-1|t-1}^i$ is the estimation of h_t at time $t-1$ with information up to time $t-1$ if $s_{t-1} = i$ and $P_{t-1|t-1}^i$ its mean squared error matrix defined in (18) and (19), respectively. The conditional forecast errors are $\eta_{t|t-1}^{(i,j)} = Y_t^* - H_t^* h_{t|t-1}^{(i,j)}$ and $\zeta_{t|t-1}^{(i,j)} = H_t^* P_{t|t-1}^{(i,j)} H_t^{*\prime} + R_t^*$ is its conditional variance. Hence, the log likelihood given $s_{t-1} = i$ and $s_t = j$ can be computed at each t as

$$l_t^{(i,j)} = -\frac{1}{2}\ln\left(2\pi\left|\zeta_{t|t-1}^{(i,j)}\right|\right) - \frac{1}{2}\eta_{t|t-1}^{(i,j)\prime}\left(\zeta_{t|t-1}^{(i,j)}\right)^{-1}\eta_{t|t-1}^{(i,j)}. \tag{15}$$

The updating equations become

$$h_{t|t}^{(i,j)} = h_{t|t-1}^{(i,j)} + K_t^{(i,j)}\eta_{t|t-1}^{(i,j)}, \tag{16}$$

$$P_{t|t}^{(i,j)} = P_{t|t-1}^{(i,j)} - K_t^{(i,j)} H_t^* P_{t|t-1}^{(i,j)}, \tag{17}$$

where the Kalman gain, $K_t^{(i,j)}$, is defined as $K_t^{(i,j)} = P_{t|t-1}^{(i,j)} H_t^{*\prime} \left(\zeta_{t|t-1}^{(i,j)}\right)^{-1}$.

Maximizing the exact log likelihood function of the associated nonlinear Kalman filter is computational bourdersome since at each iteration, the filter produces a 2-fold increase in the number of cases to consider. Two solutions have been proposed in the literature. The first solution, which is based on collapsing some terms of the former filter was proposed by Kim (1994) and used by Kim and Yoo (1995) and Chauvet (1998). The second solution, which is based on Bayesian estimation methods of Gibbs sampling, was proposed by Kim and Nelson (1998) and gets approximation-free inference at the cost of being computationally harder. Based on the results of Chauvet and Piger (2005), who show that the approximated method works very well in practice, we use Kim's algorithm to compute inference in the nonlinear Kalman filter.[7]

In particular, the proposal of Kim (1994) is based on collapsing the posteriors $h_{t|t}^{(i,j)}$ and $P_{t|t}^{(i,j)}$ at the end of each iteration by using the their weighted averages where the weights are given by the probabilities of the Markov state:

$$h_{t|t}^{j} = \frac{\sum_{s_{t-1}=0}^{1} p\left(s_t = j, s_{t-1} = i|\chi_t\right) h_{t|t}^{(i,j)}}{p\left(s_t = j|\chi_t\right)} \tag{18}$$

$$P_{t|t}^{j} = \frac{\sum_{s_{t-1}=0}^{1} p\left(s_t = j, s_{t-1} = i|\chi_t\right) \left(P_{t|t}^{(i,j)} + \left(h_{t|t}^{j} - h_{t|t}^{(i,j)}\right)\left(h_{t|t}^{j} - h_{t|t}^{(i,j)}\right)'\right)}{p\left(s_t = j|\chi_t\right)}. \tag{19}$$

To conclude this section, let us point out one additional advantage of this proposal against standard Markov-switching dynamic specifications applied to balanced datasets: our model can easily compute GDP growth forecasts. Recall that our method mixes frequencies and fills in outliers following the rule of replacing missing by random numbers which allows us to include GDP growth as an additional business cycle indicator. In this context, if we call T the last month for which we have observed GDP growth, we call $h_{T+1|T}^{(j)}$ the collapsed version of $h_{T+1|T}^{(i,j)}$, and we call $h_{T+1|T}^{(j)}(k)$ the k-th element of $h_{T+1|T}^{(j)}$,

[7] Using 2^{12} states (some indicators depend on 12 lags of the factor) leads to intractable specifications. In the empirical analysis we tried with 2^5 and 2^2 and we obtain similar model accuracy.

the forecasts for month $T+1$ when $s_{T+1}=j$ can be computed by the model as

$$y^{2nd,j}_{T+1/T}=\beta_1\left(\frac{1}{3}h^{(j)}_{T+1|T}(1)+\frac{2}{3}h^{(j)}_{T+1|T}(2)+h^{(j)}_{T+1|T}(3)+\frac{2}{3}h^{(j)}_{T+1|T}(4)+\frac{1}{3}h^{(j)}_{T+1|T}(5)\right)+$$
$$\left(\frac{1}{3}h^{(j)}_{T+1|T}(13)+\frac{2}{3}h^{(j)}_{T+1|T}(14)+h^{(j)}_{T+1|T}(15)+\frac{2}{3}h^{(j)}_{T+1|T}(16)+\frac{1}{3}h^{(j)}_{T+1|T}(17)\right). \quad (20)$$

Using the matrix of transition probabilities, one can easily obtain $p\left(s_{T+1}=j,s_T=i|\chi_t\right)$ which can be used to compute $p\left(s_{T+1}=j|\chi_t\right)=\sum_i p\left(s_{T+1}=j,s_T=i|\chi_t\right)$ and the unconditional forecats of GDP

$$y^{2nd}_{T+1/T}=\sum_j p\left(s_{T+1}=j|\chi_t\right)y^{2nd,j}_{T+1/T}. \quad (21)$$

It is worth noting that these forecasts are easily computed in practice by including a missing observation y^{2nd}_{T+1} in the dataset since the model will automatically replace the missing by a dynamic forecast. Following the same reasoning, forecasts for longer horizons and forecasts for other indicators can be automatically computed.

3 Empirical results

3.1 Data description

The empirical analysis focuses on the thirteen business cycle indicators used in the linear Euro-STING model of Camacho and Perez Quiros (2010). The set of business cycle indicators include: (1) four quarterly series, second GDP growth releases, its two preliminary announcements flash and first, and employment, all of them in quarterly growth rates; (2) four monthly hard indicators, 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 extra-Euro area Exports, all of them in monthly growth rates; and (3) five soft indicators, 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 services and manufactures sectors, which are loaded in levels. The effective sample goes from April 1991 to January 2010. In the empirical analysis, data are firstly standardized by substracting the sample mean from each variable and dividing by its standard deviation.[8]

3.2 In-sample analysis

The in-sample analysis was carried out with the vintage data set that was available on January, 15th 2010. The unsynchronized way on which data are published is illustrated in Table 1 which reports the latest available figures of each indicator. Since GDP and Employment releases appear quarterly, the two first months of each quarter are treated as missing data. In some forecasting dates (not in this vintage), preliminary advances of GDP growth (flash and first) could be available before the publication of second GDP. Survey data have very short publishing delay of one (or even less) month while hard data are released with a relatively longer delay of about two months.

The last feature illustrated in Table 1 is the forecasting schedule followed in this paper. Forecasts for a particular quarter of GDP growth spread over a period of nine months. Accordingly, the nine months of missing data after the last GDP growth observation (October 2009 to June 2010) will be replaced by short-term dynamic forecasts by the model. Hence, in the forecasting period the model will end up with backcasts (2009.4), nowcasts (2010.1) and forecasts (2010.2). As soon as the GDP figure for the last quarter of 2009 becomes available, the nine-moth forecasting horizon will be moved forward conveniently.

The model specification has proceeded under several assumptions regarding regime switching. We need to perform several exercises to provide suggestive evidence as to whether the model accords to the model assumptions. First, we assumed that the positive autocorrelation of the common underlying economic activity can be captured by regime switching rather than by autoregressive parameters.[9] To provide evidence that this assumption is realistic, we estimated the linear Euro-STING by using the same datasets and we obtained that the sample correlation between both factors was 0.97.[10] This result

[8] According to Camacho and Perez Quiros (2010) the indicators have been selected from successive enlargements of the model proposed by Stock and Watson (1991) following two criteria. First, data (basically soft indicators) should be early available. Second, a new indicator is included whenever the proportion of GDP explained by the factor is increased.

[9] Hence, we imposed $m_1 = 0$ in (4).

[10] Factors extracted from linear and nonlinear filters lead to very similar graphs. They have been omitted

is not surprising. Camacho and Perez Quiros (2007) show that there are identification problems when the persistence in a time series can be captured by both Markov-switching dynamics and linear autoregressive methods.

The second exercise to assess the robustness of our assumptions has to do with showing that the factor exhibits business cycle dynamics. The maximum likelihood estimates of parameters show that the factor is expected to be significantly positive (value of 0.37 with standard deviation of 0.10) in the state $s_t = 0$ while it is significantly negative (-2.04 with standard deviation of 0.31) in the state $s_t = 1$. Accordingly, we can associate these states as expansions and recessions. In addition, each regime is highly persistent, with estimated probabilities of one regime to be followed by the same regime of 0.97 in the case of expansions and 0.93 in the case of recessions (standard deviations of 0.02 and 0.06, respectively). Finally, another interesting business cycle implication of the Markov framework is that one can derive the expected number of quarters that the business cycle phases prevail. Conditional on being in state 0, the expected duration of a typical expansion in the Euro area is $(1 - \widehat{p}_{00})^{-1}$ or 33.33 months, and the expected duration of recession is likewise $(1 - \widehat{p}_{11})^{-1}$ or 14.28 months. These estimates agree with the well-known fact that expansions are longer than contractions on average.

Although the scope of this paper is more ambitious than simply constructing a coincident index, we must additionally check if the dynamics of the common factor are consistent with the Euro area business cycles since the model was constructed under the assumption that the indicators share the underlying aggregate economic activity dynamics whose pattern is captured by the common factor. For this purpose, the switching factor coincident index estimated in this paper is compared with the Eurocoin which is published each month by CEPR and is considered the leading coincident indicator of the euro area business cycle. A visual inspection of Figure 1 suggests that the common factor and the Eurocoin move together synchronously. Although the Eurocoin moves very smoothly since it is designed to track the medium term trend (by removing short-run fluctuations from a large dataset), the sample correlation between these two series is about 0.7. Remarkably, there seems to be high commonality among their switching times. While both indicators

to save space.

fluctuate around their respective means, the broad changes of direction in the series seem to mark quite well the same cycles. In particular, they exhibit periods of pronounced drops in dates for which GDP growth rates deteriorate significantly: 1992-1993, 2001 and 2008. Of special interest is the most recent period for which both indicators reached a peak in the beginning of 2008 and have declined since then until the recovery in the summer 2009.

To examine the correlation of the business cycle indicators and the factor, Table 2 reports the maximum likelihood estimates of the factor loadings (standard errors within parentheses). The estimates are always positive and statistically significant, which agrees with the standard view that the indicators are procyclical. With respect to the size of the correlations, the economic indicators with larger factor loadings are those corresponding to IPI (0.36), INO (0.33) and GDP (0.29). Soft indicators exhibit much lower factor loadings, with a maximum of 0.11 in the case of PMI in manufactures. This result could be an indication against the inclusion of the surveys as coincident indicators. However, Camacho and Perez Quiros (2010) show that the in-sample estimates of the factor loadings do not reflect the timely advantages of survey data that are observed in real time exercises.

Table 3 shows some of the key outputs of the model: forecasts of GDP growth and the corresponding inferences about the business cycle provided by the Markov-switching specification. The forecasts were computed from a vintage dataset dated on May 13, 2009 which allows the reader to check for the accuracy of the day to day economic monitoring of the model since the final estimates are already available. According to our nine-moth forecasting procedure, the table shows the forecasts of flash, first and second for quarters 2009.1, 2009.2 and 2009.3 (we call them backcasting, nowcasting and forecasting figures, respectively) along with their final estimates in parentheses. Overall, the table suggests that the forecasts of GDP growth are quite accurate. In addition, the Markov-switching dynamics of the model allow us to compute probabilities of recessions for these quarters. They fall from 0.99 in the first quarter to 0.35 in the second quarter and to 0.05 in the third quarter which reveals that the through in the Euro area business cycle occurred within this forecasting period. Finally, this table shows the forecasts for each of the business cycle indicators used in the model and their final estimates in parentheses.

One additional application of the Markov-switching dynamic factor specification developed in this paper is that the model provides the framework to date the historical Euro area business cycle phases. For this purpose, we show in Figure 2 the monthly full sample smoothed inferences that the economy is in recession. To confront them with the data, this figure adds the quarterly GDP growth estimates which are estimated at monthly frequency from the model.[11] For international comparisons, the US recessions dated by the NBER are included in the graph as shaded areas.[12] From this figure, we observe that the inferred probabilities create clear signals about the business cycle states. High probabilities of recessions appear in 1992-1993, 2001 and 2008 which correspond to low (or even negative) growth. The figure also shows that the business cycle concordance between the Euro area and the US has increased significantly during the last two decades. While US clearly leads the 1991 recession, the 2001 and 2008 recessions are highly synchronized.

Since we are interested in obtaining specific turning point dates, we will require a rule to convert the recession probabilities into a dichotomous variable which signals whether the economy is in an expansion or a recession. A simple rule used by Hamilton (1989) is based on whether one would expect that the Euro are is more likely than not to be in a recession. Accordingly, we require that the probability of recession moves from above 0.5 to consider a through and from below 0.5 to consider a peak. The specific inference about the historical turning points generated by the Markov-switching dynamic factor model appears in Table 4. For comparison purposes, the NBER official dates are also shown in the table. In relation with the US, the recession in the early nineties clearly finishes later in the Euro area, but the historical turning points dates in 2001 and 2008 recessions roughly coincide. According to this exercise, we could see that discrepancies in business cycle synchronicity between the US and the Euro seem to have diminished.

When a business cycle indicator is published, the statistical agency that updates the figures tries to provide the economic agents with an outlook of the economy which is supposed to be contained in the indicator release. However, inferring the state of the economy from the data publication is not easy. Therefore, the Markov-switching dynamic factor model facilitates this interpretation since it becomes a filtering rule which extracts

[11] According to the model, GDP monthly estimates equal to the actual figures in the third month of each quarter.

[12] Note that the NBER has not dated the last through yet.

the indicator's information about the state of the economy, by transforming the indicator release into probabilities of recession which are much easier to interpret. To illustrate the usefulness of Markov-switching models to transform the information about the economic evolution that is contained in business cycle indicators, we do the following exercise.

Suppose that we were in January 2006 and we had information about indicators up to December 2005. This month was clearly part of an expansion period. Now, we simulate the possible outcomes of the following BNB release (from about -32 to 2) for January 2006, the first available indicator with current information about the first quarter of 2006. Using these potential outcomes, we infer the probability of recession for that month which is obtained from data vintages that contains each of these outcomes. Figure 3 (bottom line) displays the predicted probability of recession, associated to each BNB potential issue. We now repeat the exercise for January 2009, a clear recession month, and we also plot the recession probabilities in Figure 3 (top line). The nonlinear features that are accounted for by the model can be clearly detected by examining the inferred probabilities of recessions in January 2006 and January 2009.[13] As we can observe from the pictures, the curve associated to 2006 is clearly shifted down. This implies that the same BNB value contains very different information about the probability of an imminent recession depending on the period that it is considered. Specifically, in 2009, a BNB value of -20 would be associated with a probability of recession of almost 0.8. However, in 2006, the same value of BNB would implied a recession probability next period close to 0.3. The intuition is clear. In order to predict that a recession is coming, we need stronger evidence in the BNB behavior in expansions than in recessions to infer that a recession is imminent. Even for no experts in economics, our nonlinear proposal facilitates the task of interpreting new releases of the main economic indicators in the Euro area by converting them into probabilities of recesion.

The Markov-switching behavior assumed in this specification also implies richer relationships between the business cycle indicators and GDP previsions than those suggested by linear dynamic factor models. The intuition behind the nonlinear responses is also

[13] It is worth recalling that we are using exclusively the datasets that were available at the dates of the forecasts.

clear: New releases are converted into inferences about the state of the business cycle which are used in computing output predictions by the model. To illustrate this nonlinear effect, we plot in Figure 4 the expected GDP growth rates that would be forecasted from different potential realizations of BNB in January 2009. For this purpose, we call the Kalman filter with the historical time series of all the data but enlarged with each of these simulated values of BNB and we plot in the figure the forecasts of the different expected values of output growth. For extreme negative values of the indicator, the model would infer probabilities of recession close to one and GDP which are used to forecast growth rates values that are close to -1.5. As the values of BNB increase, the model predicts relatively better values of GDP growth which increase almost linearly with BNB since then until values of the indicator of about -20. Around this value, which corresponds to the values for which Figure 4 showed a substantial decline in the inferred probability of recession, the expected responses of GDP to BNB values dramatically increase. As documented in Figure 3, for values of BNB about -9, the inferred probabilities of recession become very low indicating that the economy would be in the expansionary phase. Since then, the expected GDP growth to BNB becomes quasi linearly trended again.

3.3 Real-time analysis

In this section, we examine the real time performance of the model in predicting turning points in the last 2008-2009 recession. In the search of a benchmark model to compare the predictive accuracy of the one proposed in this paper, it is worth noting that Camacho and Perez Quiros (2010) documented that the linear Euro-STING is able to forecast the euro area GDP growth in real time as well as professional forecasters such as the European Commission's 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. Hence, we consider that the linear Euro-Sting model is an appropriate benchmark to examine the forecasting accuracy of the Markov-switching model.

To allow for this 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 of any given day in the period 2004.01-2010.01. In this context, for each day on which a particular series of our data set was updated, we collect the whole set of time series available at that moment. These vintages are kept fixed until the day that a new series was updated. Hence, we have compiled 597 different vintages for the real-time forecasting period. In Table 5, we measure the accuracy of the linear and Markov-switching specifications in forecasting growth by using Mean Squared Errors (MSE) which are the average of the deviations of the predictions from the real-time (labeled as *real*), the first release of the second estimate of GDP published for a particular quarter and from the final (labeled as *final*) releases of GDP available in the most updated dataset. To test whether the differences between the models are significant, we use the test proposed by Diebold and Mariano (1995), henceforth DM. Results for backcasts, nowcasts and forecasts appear horizontally. According to the table, in backcasting, forecasts from the nonlinear model outperform those from the linear model although the accuracy in nowcasting and forecasting reverses. Remarkably, according to the p-values of the DM tests the hypothesis of equal predictive accuracy cannot be rejected at conventional levels. This notably implies that the nonlinear model is not a statistically significantly worse predictor of the Euro area GDP growth than the linear model.

Despite the comparable accuracy in forecasting growth from the linear and nonlinear models, the main contribution of the latter is its ability to compute timely inferences about the Euro area business cycles.[14] Figure 5 shows the probabilities of recessions that would be inferred daily by a forecaster who used the information available at the day of the forecast from January, 1st 2008 to January, 15th 2010.[15] According to this figure, in mid-July 2008 the probability of recession increased up to values that are very close to one. It is worth noting that this promptly signal of bad news about the state of the Euro area economy represents a great improvement in the timing of turning points identifications with respect to other standard dating methods such as the two consecutive falls in GDP. In July, the latest available figure of second GDP was for 2008.1 (released July 9th) and it was still a positive and very high number (0.72) while the probability of recession reached

[14] In addition, Perez Quiros and Timmermann (2001) show that the main forecasting gains from Markov-switching specifications rely on the forecasts of higher moments of the data, asymmetric risks and extreme values.

[15] This period includes the 2008-2009 Euro area recession.

a high record of 0.98. Since the GDP figures for the second and third quarters of 2008 were negative, if one considered that two consecutive falls of GDP growth mark the peak, the recession would not be formally identified before the publication day of the third quarter GDP, November 15th 2008. However, Figure 6 shows that both soft and hard indicators started the falls in early summer: the growth rates of IPI, INO and Exports were -1.69, -4.69 and -3.98 in May, IFO lost 3.8 points in June, and ESI and PMIM lost 5.1 and 1.78 points in July.

In addition, Figure 5 helps us to examine to what extent the Euro area recession is over at the end of 2009 and when the through was detected by our model. This exercise can be interpreted as a real-time search for the famous green shoots. About mid-April 2009, the probability of recession dramatically dropped from values of about 0.8 to values close to zero. As in the case of the peak, we find evidence of a trough that marks the end of the recession before other standard dating methods since the latest available figure of GDP growth was still very negative (-1.57% for the last quarter of 2008). Even later (15th of May 2009), the first quarter of 2009 was published with an even more negative number (-2.55% for the flash of 2009.1).

Which are the mechanics behind these good signals that mark the changes in probabilities? When the probabilities of recession were still high at the beginning of April, the values of some soft indicators such as ESI and PMIM were 64.6 and 33.9, respectively. However, the following realizations since that date were 67.3 and 36.9 which implied significant improvements after several months of consequtive falls. In addition, the good news were confirmed by the hard indicators when they became available: IPI and INO increased from -0.46 and 0.10 in April to 1.64 and 1.42 in May, and Sales and Exports raised from -0.52 and -1.37 in May to 0.01 and 1.08 in June. Therefore, the Markov switching dynamic factor model had unequivocally signaled in April 2009 that the through in the euro area had occurred. [16] After a long winter, the green shoots of economic recovery in the Euro area sprang up in May 2009.[17]

[16] Interestingly, the number of searches of the term "green shoots" in Google trends shows a peak in May, a few days after the sharp reduction in the probability of recession.

[17] Much later, on November 13th, Eurostat published a positive and strong GDP growth rate (0.37) for the third quarter of 2009 which implied that the end of the recession became official.

4 Conclusion

Markov-switching dynamic factor models are becoming very popular in empirical analyses. In a recent proposal, Camacho, Perez Quiros and Poncela (2010) extend the models to account for some specificities of real time forecasting exercises: mixing frequencies, data revisions and ragged edges. In this paper, we document the usefulness of accounting for these data problems to be used in the day to day monitoring of the Euro area economy. We show that the model gave early signals of the beginning of the 2008-2009 recession in early July 2008 and of the end of the recession, around April 2009.

The usefulness of this analysis is more evident when one interprets the real-time recession probabilities obtained in the paper as a statistical definition of the term green shoots. Over the year 2009 this expression has been highly popularized as a term that represents the beginnings of economic recoveries after a recession. But the term is very imprecise and has not been defined in economically meaningful ways. It leaves the users of the term to identify when the recovery comes depending basically on their own beliefs. In addition, since the signals of recoveries do not appear in all the economic indicators with the same intensity, the skeptical users will be inclined to accentuate the negative signals of some indicators while the optimistic users will be tempted to stress the positive signals of some others. Needless is to say that monitoring the latest releases of the relevant economic indicators for no experts in economics is quite high. Using the real-time probabilities which can be daily updated from our computationally simple algorithm would facilitate the analysis of the day to day economic developments.

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 $m_1 = 0$, $m_2 = m_4 = 6$, $m_3 = 2$, $r_h = 4$, 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 $w_t \sim i.i.d.N(0, R)$, can be expressed as

$$
\begin{aligned}
Y_t &= \begin{pmatrix} y_t^{2nd} & Z_t^{h'} & Z_t^{s'} & l_t & y_t^{1st} & y_t^{f} \end{pmatrix}', && (22)\\
w_t &= 0_{r+4,1}, && (23)\\
R &= 0_{r+4,r+4}, && (24)
\end{aligned}
$$

$$
h_t = (f_t, ..., f_{t-11}, u_{1t}, ..., u_{1t-5}, v_{1t}, v_{1t-1}, ..., v_{rt}, v_{rt-1}, u_{2t}, ..., u_{2t-5}, e_{1t}, e_{2t})'. \quad (25)
$$

The matrix H is in this case

$$
H = \begin{pmatrix}
H_{11} & 0_{1,6} & H_{12} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 0 \\
H_{21} & 0_{r_h,6} & 0_{r_h,6} & H_{22} & 0_{r_h,10} & 0_{r_h,6} & 0_{r_h,1} & 0_{r_h,1} \\
H_{31} & H_{31} & 0_{r_s,6} & 0_{r_s,8} & H_{32} & 0_{r_s,6} & 0_{r_s,1} & 0_{r_s,1} \\
H_4 & 0_{1,6} & 0_{1,6} & 0_{1,8} & 0_{1,10} & H_{12} & 0 & 0 \\
H_{11} & 0_{1,6} & H_{12} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 1 \\
H_{11} & 0_{1,6} & H_{12} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 1 & 1
\end{pmatrix}, \quad (26)
$$

where

$$
\begin{aligned}
H_{11} &= \begin{pmatrix} \frac{\beta_1}{3} & \frac{2\beta_1}{3} & \beta_1 & \frac{\beta_1}{3} & \frac{2\beta_1}{3} & 0 \end{pmatrix}, && (27)\\
H_{12} &= \begin{pmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{1}{3} & \frac{2}{3} & 0 \end{pmatrix}, && (28)\\
H_{22} &= I_{r_h} \otimes \begin{pmatrix} 1 & 0 \end{pmatrix}, && (29)\\
H_{32} &= I_{r_s} \otimes \begin{pmatrix} 1 & 0 \end{pmatrix}, && (30)\\
H_4 &= \begin{pmatrix} \frac{\beta_4}{3} & \frac{2\beta_4}{3} & \beta_4 & \frac{\beta_4}{3} & \frac{2\beta_4}{3} & 0 \end{pmatrix}, && (31)
\end{aligned}
$$

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, $h_t = \Lambda_{s_t} + Fh_{t-1} + \xi_t$, can be stated as follows. Let Q be a diagonal matrix in which the entries inside the main diagonal are determined by the vector

$$q = \begin{pmatrix} \sigma_f^2 & 0_{1,11} & \sigma_{u_1}^2 & 0_{1,5} & \sigma_{v_1}^2 & 0 & ... & \sigma_{v_r}^2 & 0 & \sigma_{u_2}^2 & 0_{1,5} & \sigma_{e_1}^2 & \sigma_{e_2}^2 \end{pmatrix}', \tag{32}$$

The matrix F becomes

$$F_{s_t} = \begin{pmatrix} a & 0_{12,6} & 0_{12,8} & 0_{12,10} & 0_{12,6} & 0 & 0 \\ 0_{6,12} & b & 0_{6,8} & 0_{6,10} & 0_{6,6} & 0 & 0 \\ 0_{8,12} & 0_{8,6} & c_h & 0_{8,10} & 0_{8,6} & 0 & 0 \\ 0_{10,12} & 0_{10,6} & 0_{10,8} & c_s & 0_{10,6} & 0 & 0 \\ 0_{6,12} & 0_{6,6} & 0_{6,8} & 0_{6,10} & d & 0 & 0 \\ 0_{1,12} & 0_{1,6} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 0 \\ 0_{1,12} & 0_{1,6} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 0 \end{pmatrix}, \tag{33}$$

where

$$a = \begin{pmatrix} 0 & ... & 0 & ... & 0 & 0 \\ 1 & ... & 0 & ... & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & ... & 0 & ... & 1 & 0 \end{pmatrix}, \tag{34}$$

$$b = \begin{pmatrix} b_1 & ... & b_5 & b_6 \\ 1 & ... & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & ... & 1 & 0 \end{pmatrix}, \tag{35}$$

$$c_s = \begin{pmatrix} c_{11} & c_{12} & ... & 0 & 0 \\ 1 & 0 & ... & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & ... & c_{r1} & c_{r2} \\ 0 & 0 & ... & 1 & 0 \end{pmatrix}, \tag{36}$$

$$d = \begin{pmatrix} d_1 & ... & d_5 & d_6 \\ 1 & ... & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & ... & 1 & 0 \end{pmatrix}. \tag{37}$$

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Table 1. Data set available on January 15, 2010

	Second	IPI	Sales	INO	Exports	ESI	BNB	IFO	PMIM	PMIS	Employment	First	Flash
2009.06	-0.12	0.96	0.02	2.79	1.08	73.20	-23.60	86.00	42.62	44.65	-0.48	-0.12	-0.11
2009.07	na	0.42	0.02	4.44	4.47	76.00	-22.80	87.40	46.25	45.69	na	na	na
2009.08	na	1.14	-0.22	0.50	-4.11	80.80	-18.20	90.50	48.24	49.92	na	na	na
2009.09	0.42	0.30	-0.41	1.66	4.49	82.80	-17.80	91.40	49.29	50.86	-0.49	0.38	0.37
2009.10	na	-0.28	0.33	-2.23	-0.09	86.10	-14.20	92.00	50.73	52.58	na	na	na
2009.11	na	1.02	-1.19	na	-0.42	88.80	-8.80	93.90	51.20	53.04	na	na	na
2009.12	na	na	-0.09	na	na	91.30	-7.90	94.70	51.59	53.63	na	na	na
2010.01	na	na	na	na	na	na	na	na	na	na	na	na	na
2010.02	na	na	na	na	na	na	na	na	na	na	na	na	na
2010.03	na	na	na	na	na	na	na	na	na	na	na	na	na
2010.04	na	na	na	na	na	na	na	na	na	na	na	na	na
2010.05	na	na	na	na	na	na	na	na	na	na	na	na	na
2010.06	na	na	na	na	na	na	na	na	na	na	na	na	na

Notes. See the text for acronyms. Figures labelled as “na” refer to either missing data or data that are not available on the day of the forecast.

Table 2. Factor loadings

Second	IPI	Sales	INO	Exports	ESI	BNB	IFO	PMIM	PMIS	Employment
0.29	0.36	0.10	0.33	0.20	0.08	0.10	0.08	0.11	0.10	0.13
(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)

Notes. See the text for acronyms. Standard errors are in parentheses.

Table 3. Forecasts from data set available on May 13, 2009

	GDP and announcements			Indicators		
	2009.1	2009.2	2009.3	Series	Forecasts	
FLASH	-2.01	-0.28	0.34	IPI	-0.63	(-0.46)
	(-2.50)	(-0.11)	(0.36)	Sales	0.61	(-0.18)
				INO	-3.12	(-0.46)
FIRST	-1.67	-0.16	0.39	Exports	1.02	(-1.57)
	(-2.50)	(-0.12)	(0.38)	ESI	68.21	(70.20)
				BNB	-28.91	(-27.6)
SECOND	-1.83	-0.14	0.47	IFO	84.13	(84.40)
	(-2.53)	(-0.18)	(0.42)	PMIM	36.85	(40.68)
				PMIS	43.10	(44.62)
	Recession probabilities			Employment	-0.44	(-0.72)
PROB	0.99	0.35	0.05			

Notes. See the text for acronyms. Actual realizations are in parentheses.

Table 4. Dating of business cycle turning points

Business cycle reference dates		Duration in months			
peak	trough	Peak to trough	Trough to peak	Peak from previous	Trough from previous
Euro area					
---	1993.04		95		
2001.04	2001.10	7	77		103
2008.03	2009.04	13		85	90
US (NBER)					
1990.07	1991.03		120		
2001.03	2001.11	8	73	128	81
2007.12	---				

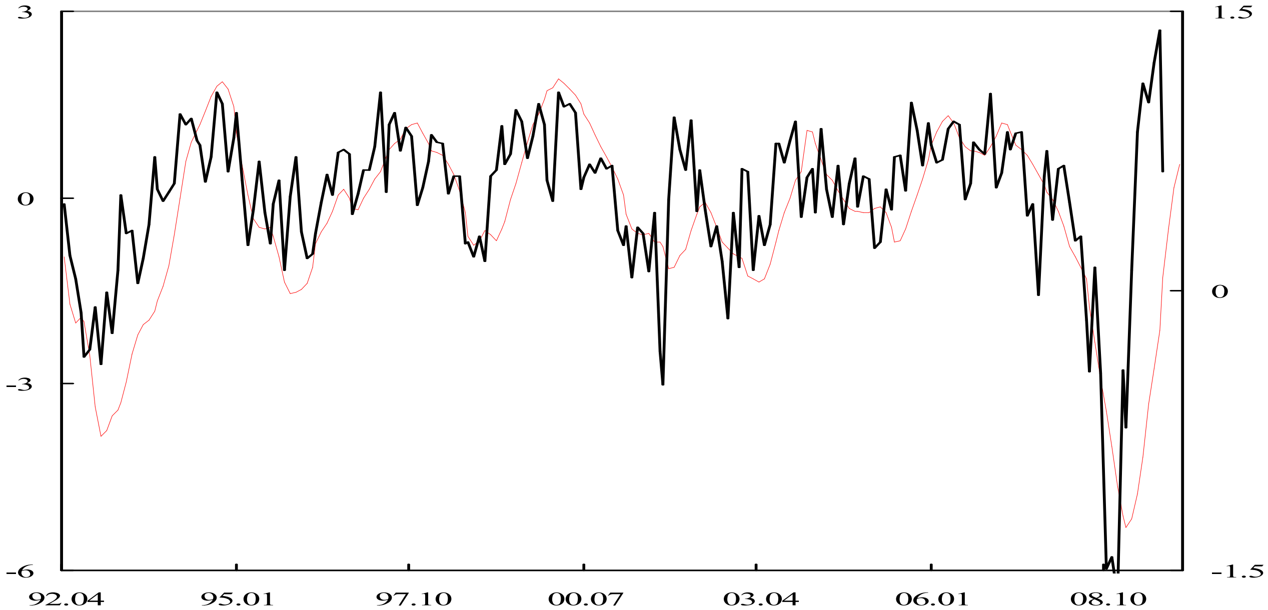
Notes. In the Euro area, peaks and troughs are dated at t by using 0.5 as the threshold for smoothed recession probabilities. Last through has not been dated by the NBER yet.

Table 5. Comparing the predictive accuracy

		Linear model	Markov-switching	DM
Backcasting	MSE-real	0.095	0.084	0.596
	MSE-final	0.101	0.094	0.710
Nowcasting	MSE-real	0.243	0.298	0.201
	MSE-final	0.258	0.332	0.100
Forecasting	MSE-real	0.335	0.445	0.229
	MSE-final	0.400	0.519	0.176

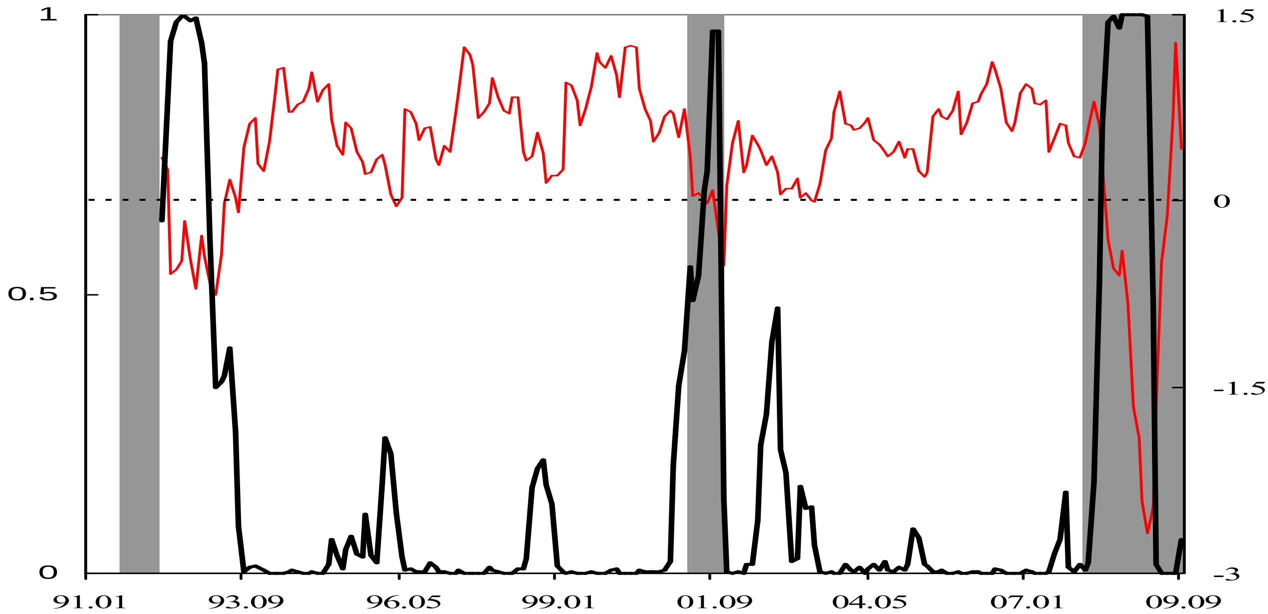
Notes. DM refers to p-values from Diebold and Mariano (1995) test. Mean squared errors are computed by comparing real time final revised GDP growth figures.

Figure 1. Common factor and Eurocoin



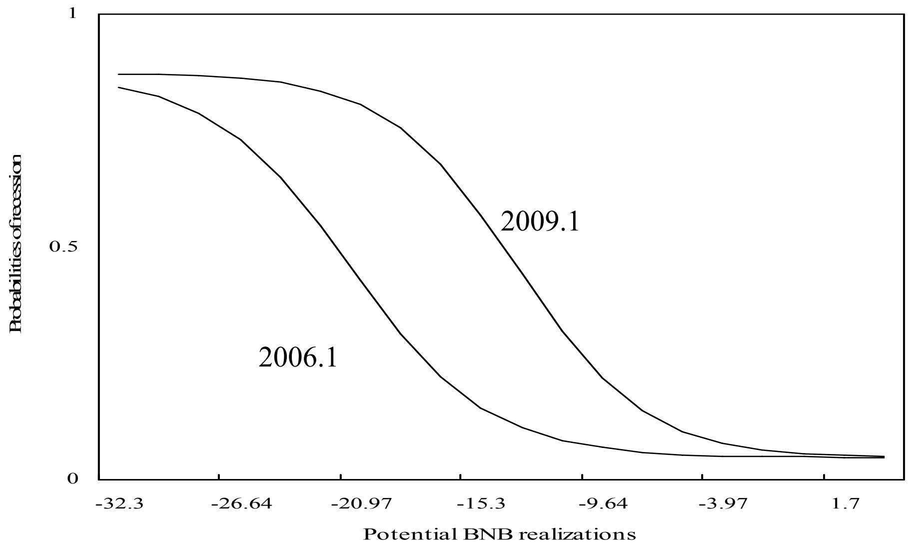
Notes. Black line (left scale) refers Euro area coincident indicators computed from our model while red line (right scale) refers to Eurocoin. The effective sample is 92.04-09.12.

Figure 2. In-sample GDP and recession probabilities



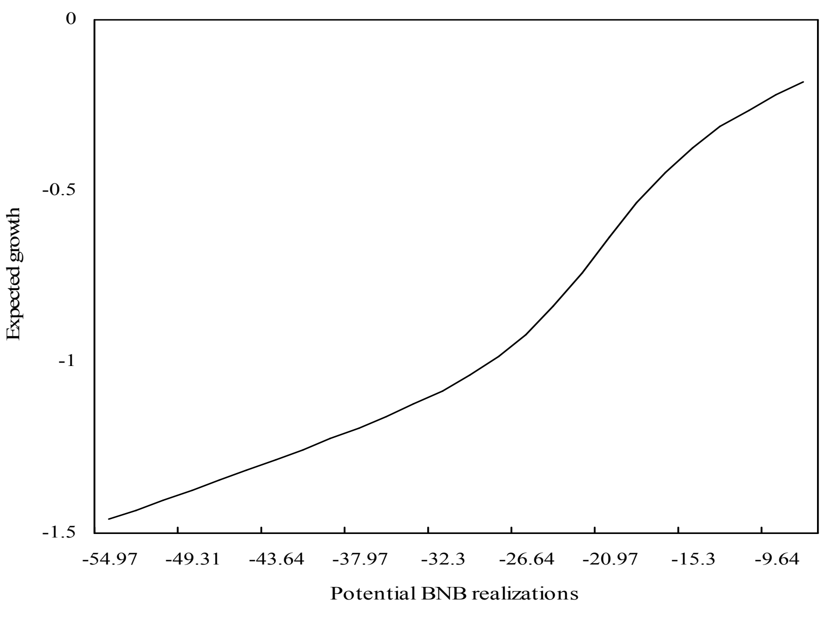
Notes. Black line (left scale) refers Euro area smoothed recession probabilities. Red line (right scale) refers to Euro area quarterly GDP at monthly frequency (third months of each quarter are actual figures). Shaded areas corresponds to the NBER recessions for US.

Figure 3. Probabilities of recession on BNB.



Notes. The graph plots the probability of recession for different values of the next variable to be released (BNB) at two different points, 2006.1 and 2009.1

Figure 4. GDP growth forecast on 01/17/09



Notes. The graph plots GDP forecasts which are computed from linear and Markov-switching dynamic factor models for different potential values of BNB.

Figure 5. Real-time recession probabilities 2008.01-2010.01

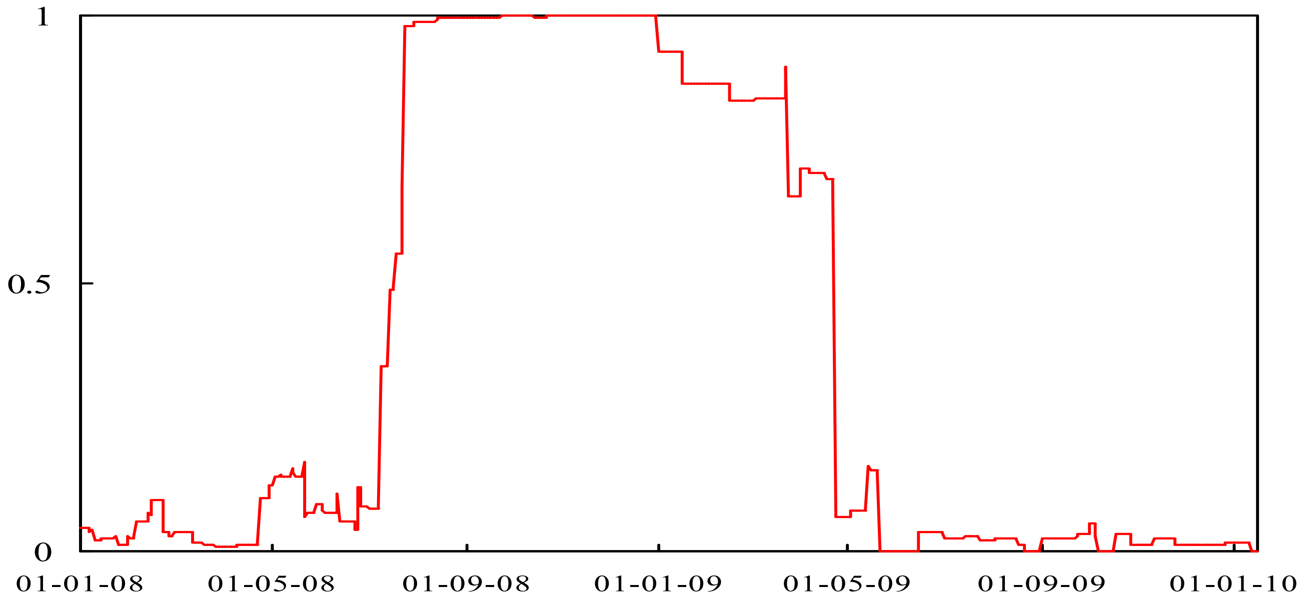
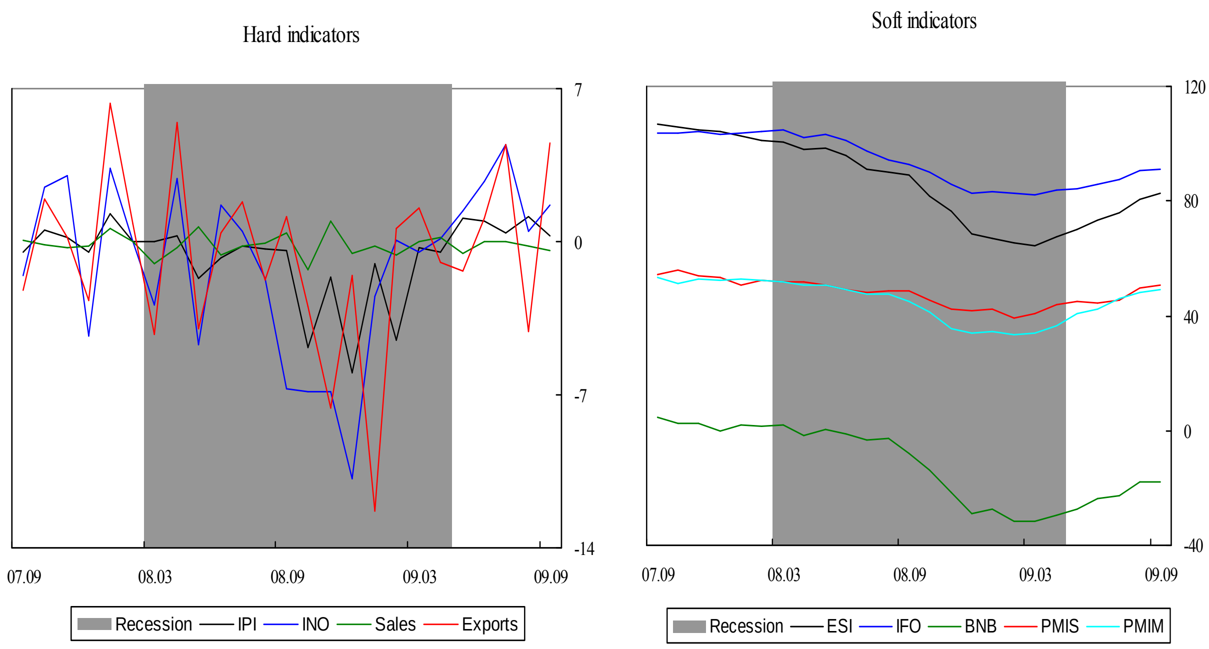


Figure 6. Evolution of indicators 2007.09-2009.09



Notes. Hard indicators are in growth rates while soft indicators are in levels. The shaded area refer to the recession marked by the peck and through of Table 4.