The Euro-STING in forecasting the state of the business cycle*

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Abstract

We extend the Markov-switching dynamic factor models to account for the specificities of the day to day monitoring of economic developments such as ragged edges, mixed frequencies and data revisions. The model is used to compute inferences of the percentage chance that the Euro area economy will face a recession in the short term. Applied to a real time dataset, we provide examples which show the nonlinear nature of the relations between data revisions, point forecasts and forecast uncertainty.

Keywords: Business Cycles, Output Growth, Time Series.

JEL Classification: E32, C22, E27

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1 Introduction

Diebold and Rudebusch (1996) were the first to suggest a unified explanation of the two business cycle features, comovements of economic aggregates and business cycle asymmetries, which were embedded in the seminal description developed by Burns and Mitchell (1946). They argued that comovements among individual economic indicators can be modelled by using the linear coincident indicator approach described in Stock and Watson (1989), while the existence of two separate business cycle regimes can be modelled by using the Markov-switching specification advocated by Hamilton (1989). Integrating these suggestions, Kim and Yoo (1995), Chauvet (1996) and Kim and Nelson (1998) combined the dynamic-factor and Markov-switching frameworks to propose different versions of statistical models which capture both comovements and regime shifts. Recently, Chauvet and Hamilton (2006) and Chauvet and Piger (2008) examine the empirical reliability of these models in computing real time inferences of the US business cycle states.

We consider that Markov switching dynamic factor models, which are originally designed to deal with balanced panels of business cycle indicators, exhibit several drawbacks when applied to the (timely) day to day monitoring of the economic activity. The first drawback has to do with mixing frequencies. Some of the typical economic indicators that are observed to infer business cycle states are available monthly while others are available quarterly. For example, the National Bureau of Economic Research (NBER) dating committee acknowledges that recessions are defined as significant declines in economic activity normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales, which are clearly available at different frequencies. The second drawback refers to data revisions. Statistical agencies in most of the industrialized economies establish release calendars in which dates of preliminary announcements and their subsequent revisions are announced in advance. Although these revisions change the data input into forecasting models, the standard Markov switching dynamic factor models proposed in the literature are no longer accounting for data revisions yet. The third drawback is related to the ragged edges of real time datasests due to the typical lack of synchronicity that characterizes the daily flow of macroeconomic information. Not accounting for this publication pattern would imply that forecasters using traditional Markov-switchcing dynamic factor models to develop early assessments of the economic evolution can involve substantial costs since forecasters are restricted either to loose valuable information at the time of the forecast or to wait until balanced panels become available.

In this context, this paper shows how to adapt Markov-switching dynamic factor models to account for all the specificities associated to real time forecasting. Our proposal allows forecasters to use whatever business cycle economic indicator regarding their publication delays, frequency in publications, and potential revisions. In particular, the model allows for mixed frequencies, by bridging monthly indicators with quarterly series as in Mariano and Murasawa (2003). In addition, the model accounts for data revisions for GDP growth, by assuming that preliminary estimates are equal to the true data plus an uncorrelated noise as in Evans (2005). Finally, the model handle ragged edges in order to take into account all the available information which is released in a non-synchronous way by filling in missing data with factors as in Giannone, Reichlin and Small (2008). For these purposes, we follow the strategy of allowing for Markov-switching nonlinearities in the baseline linear framework of Camacho and Perez Quiros (2008).

In the empirical section, we apply the model to a real time Euro area dataset and develop several exercises which lead to some interesting results. First, we show evidence to consider 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. Third, we show in a real time experiment that the model provides a significant improvement in the speed with which business cycle turningg points can be identified. Overall, these results suggest that the Markov-switching dynamic factor model proposed in this paper is a potentially very useful tool to be used in the day to day monitoring of the Euro area economy.

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 propose modeling business cycle indicators as a function of a common factor which evolves according to a Markov-switching dynamics and individual idiosyncratic components. The model is flexible enough to account for mixing frequencies, data revisions, different samples and unsynchronized releases.

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.[1] To deal with this data problem, this section describes a method to weight monthly observations to form quarterly predictions and compares the method with other proposals in the literature.

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. In this paper, we follow Mariano and Murasawa (2003) to 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

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

[1] Aruoba, Diebold and Scotti (2009) describe a linear model to combine time series which are available at higher-than-monthly frequencies.

In empirical applications, the underlying monthly series are not usually available but can be treated as missing and estimated by using an appropriate specification of the Kalman filter.

It is worth mentioning that the performance of the filter relies on the accuracy of geometric means to approximate arithmetic means. In practice, it is hard to believe that monthly changes of quarterly series could be high enough to invalidate the approximation, however. For example a constant growth of 1% each month in a particular quarter (annual growth of more than 12%), would imply a difference between arithmetic and geometric means of less than 0.4 percentage points. In addition, other approaches in the literature which try to skip the approximation are not exempt of problems. The exact nonlinear filter of Proietti and Moauro (2006) involves approximations in its own and the exact linear filter of Aruoba, Diebold and Scotti (2009) assumes all indicators to be polynomial trends.

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:

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

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

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

where e_{1t} and e_{2t} are independent mean zero revision shocks with variances and $\sigma^2_{e_1}$ and $\sigma^2_{e_2}$, respectively.[3] Camacho and Perez Quiros (2008) show empirical evidence to be confident that this specification is a reasonable representation of the data revision process.[4]

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 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 $N(0, \sigma^2_\theta)$ which must independent of the model parameters.[5] 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.

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

[4] To account for revisions in of all the indicators is out of the scope of this paper. Altavilla and Ciccarelli (2007) is a good reference for interested readers.

[5] Fill in missing observations with means, medians or zeroes would also be valid.

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 $i, j = 1, 2$, and χ_t refer to the information set up to period t.

In the related literature, several specifications of the nonlinear dynamics of the common factor dynamics have been suggested. Kim and Yoo (1995) and Chauvet (1998) allowed 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. In this paper, we follow Camacho and Perez Quiros (2007) to assume that the factor dynamics can 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 rates of growth in expansions and negative rates of growth 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 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 its last eleven lagged values.

Let us collect the r_h hard indicators in the vector Z_t^h and the r_s soft indicators in the vector Z_t^s. Let l_t be the quarterly employment growth rate, and let u_{1t}, u_{2t}, U_t^h, and U_t^s be the scalars and r_h-dimensional and r_s-dimensional vectors which determine the idiosyncratic dynamics of GDP. The dynamic of the business cycle indicators can be 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 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 $\epsilon_t^f \sim i.i.d.N\left(0, \sigma_f^2\right)$, $\epsilon_t^{u_1} \sim i.i.d.N\left(0, \sigma_{u_1}^2\right)$, $\epsilon_t^{v_j} \sim i.i.d.N\left(0, \sigma_{v_j}^2\right)$, with $j = 1, ..., r$, and $\epsilon_t^{u_2} \sim i.i.d.N\left(0, \sigma_{u_2}^2\right)$. All the covariances are assumed to be zero and we set the variance of the common factor, σ_f^2, equal to one.[6]

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

$$\begin{aligned} Y_t &= Hh_t + w_t, & (10) \\ h_t &= \Lambda_{s_t} + Fh_{t-1} + \xi_t, & (11) \end{aligned}$$

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, $0_{1\alpha}$, θ_t, and σ_θ^2 in case of missing data. 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

$$\begin{aligned} h_{t|t-1}^{(i,j)} &= \Lambda_j + H_t^* h_{t-1|t-1}^i, & (13) \\ P_{t|t-1}^{(i,j)} &= H_t^* P_{t-1|t-1}^i H_t^{*\prime} + Q. & (14) \end{aligned}$$

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 can be computed in each iteration as

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

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

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 filter former was proposed by Kim (1994) and used by Kim and Yoo (1995) and Chauvet (1995). The second solution, which is based on and 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 the Kim's algorithm to compute inference in the nonlinear Kalman filter.

In particular, Kim (1994) approximates $h_{t|t}^j$ and $P_{t|t}^j$ by the weighted averages of the updating equations where the weights are given by the probabilities of the Markov state:

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

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

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 and $h_{T+1|T}^{(i,j)}(j)$

the j-th element of $h_{T+1|T}^{(i,j)}$, forecasts for month $T+1$ can be computed by the model as

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

It is worth noting that including a missing observation y_{T+1}^{2nd} in the dataset, 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 thirteen business cycle indicators covering the period April 2004 to January 2009. According to Camacho and Perez Quiros (2008), the set of business cycle indicators include: (1) three quarterly series, second GDP growth releases, its two preliminary announcements flash and first, and employment, all of them in quarterly growth rates, (2) monthly hard indicators, Euro area Industrial Production Index (IPI, excluding construction), the Industrial New Orders index (INO, total manufacturing working on orders), the Euro area total retail sales volume, and the extra-Euro area exports, 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 the services and manufactures sectors, which are loaded in levels. In the analysis, data are standardized by substracting the sample mean from each variable and dividing by its standard deviation.

Table 1, which reports the last figures of the time series, illustrates the main characteristic of how the flow of macroeconomic information may affect real time forecasting. Since GDP and Employment releases appear quarterly, the two first months of each quarter are treated as missing data. Surveys have very short publishing delays of one (or even less) months while hard data are released with a relatively longer delay of about two months.

Finally, forecasts for particular quarters of GDP spread over a period of nine months. Accordingly, the nine months of missing data after the last GDP growth observation (October 2008 to January 2009) will be replaced by short-term forecasts by the model. As soon as the GDP figure for the last quarter is available, the nine-moth forecasting horizon will be moved forward conveniently.

3.2 In-sample analysis

The in-sample analysis was carried out with the vintage dataset that was available on January, 21th 2009. The unsynchronized way on which data are published is illustrated in Table 1. In this table we can observe the particularities of real-time forecasting. Data for quarterly series appear just in the third month of each quarter and, although the vintage refer to 2008, their figures for the fourth quarter of 2007 are not available yet. Soft indicators contain data until January 2008 while hard indicators exhibit their typical publication delays of one and two months. In the next forecasting dates but not in this vintage, preliminary advances of GDP growth (flash and first) were already available for the last quarter of 2008.

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 parameter. To provide evidence that this assumption is realistic, we estimate the linear version of the common factor model of Camacho and Perez Quiros (2008) using the same data set and we obtain that the sample correlation between both factors is 0.97.[7]

The second exercise to assess the robustness of our assumptions has to do with the view that the factor exhibits a business cycle dynamics. To evaluate the extent to which data reinforce this thesis we examine the factor dynamics. The maximum likelihood estimates of parameters show that 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

[7] Normalizing linear and nonlinear factors leads to very similar graphs.

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 and 0.93 (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 1, the expected duration of a typical US expansion is $(1 - \widehat{p})^{-1}$ or 32.33 months, and the expected duration of recession is likewise $(1 - \widehat{q})^{-1}$ or 14.28 months. These estimates accord with the well-known fact that expansions are longer than contractions on average.

The last exercise is related to the statistical significance of the nonlinear model. Applied to the same dataset, the log likelihood rises from -178.10 to -128.27 when nonlinearities are accounted for in the dynamic factor model so that the likelihood ratio test statistics would be about 100. Although standard econometrics cannot be employed in this context, we consider that the increases in likelihood are significant enough to be confident that nonlinearities appear to be part of data generating process.

Although the scope of this paper is more ambitious than constructing a coincident index, we must check if its dynamics is 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 is designed to track the medium term trend by removing short-run fluctuations from a large dataset (so that the index moves smoothly), the sample correlation between these two series is about 0.7. Remarkably, there seems to be commonality among switch times. While the indicators fluctuate around their respective means, the broad changes of direction in the series seem to mark quite well the 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 for nowcasting is the most recent period for which both indicators reached a peak in the begining of 2008 and have declined since then.

To examine the correlation of these 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 loading factors are those corresponding to IPI (0.36), INO (0.33) and GDP (0.29). Soft indicators exhibit much lower loading factors, with a maximum of 0.11 in the case of PMI in manufactures. This results is tempted to be interpreted in contrast to using surveys as coincident indicators. However, Camacho and Perez Quiros (2008) show that the in-sample estimates of the loading factors do not reflect the timely advantages 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 for quarters 2008.4, 2009.1 and 2009.2. We call them backcasting, nowcasting and forecasting figures, respectively. In line with to the current pessimism about the short term evolution of the underlying economic activity, this table suggests that output is expected to fall in the next quarter although the intensity of the falls are expected to decline from -1.23 in backasting to -0.07 in forecasting. According to these estimates, the expected probability of staying in recession in the next future is very high. Finally, this table shows the forecasts for each of the business cycle indicators used in the model.

One additional application of the Markov-switching dynamic factor specification developed in this paper is that the model provides an ideal framework to date the historical Euro area business cycle phases. For this purpose, we show in Figure 3 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 equal to the actual figures in the third month of each quarter. For international comparisons, the US recessions dated by the NBER are included in the graph as shaded areas. 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. They also reveal one episode of uncertainty in the economy in 2002. This figure reveals that the Euro area economy suffers in 2002 from great uncertainty in the economy since recession probabilities rise up to 0.7 in this year. Finally, the figure 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. Following Chauvet and Piger (2008), we take a conservative approach.[8] To establish a peak (trough) at time t, we require that the probability of recession moves from above 0.8 (below 0.2) and remains above (below) this threshold for three consecutive months. Table 3 reports the turning points derived from this criterion. 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, but the historical turning points dates in 2001 and 2008 recessions roughly coincide. According to this exercise, we conclude that discrepancies in business cycle synchronicity between the US and the Euro area have been recently diminished.

To illustrate the usefulness of Markov-switching models to transform the information about the economic evolution that is contained in business cycle indicators, we develop the following exercise. When a business cycle indicator is published, the statistical agency in church of its release tries to provide the economic agents with an outlook of the economy which is supposed to be contained in the indicator release. However, the intuition behind the indicator releases are not so easy since they are no more than numbers. The Markov-switching dynamic factor model becomes a filtering rule which extracts the indicator's information about the state of the economy, by transforming the indicator release into probabilities of recession which are much easy to interpret.

Suppose we are in the January 2006 which was a year that can be considered as an economic expansion, and we simulate the possible outcomes of the following BNB release

[8] Applying the second step in the procedure described by these authors does not change our turning point dates.

from about -32 to 2. Using these potential outcomes, we infer which is the probability of recession for that month. Figure 4 (bottom line) displays the predicted probability of recession, associated to each BNB potential issue growth. In addition, we present in tins figure the results of a similar analysis, but applied to the probability of recessions for January 2009, which can be considered as an economic recession. It is worth mentioning that we are using exclusively the information available at the dates of the forecasts. As we can see 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 we consider. 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 have 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 that in recessions to believe that a recession is imminent.

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 intition behind the nonlinear responses is clear: new releases are be 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 5 the expected GDP growth rates that would be forecasted from different potential realizations of BNB. For this puspose, we call the Kalman filter with the historical time series of BNB which is enlarged with each of these simulated values and we plot in the graph the forecasts of the different expected values of output growth. For extreme negative values of the indicator, the model would inferred probabilities of recession close to one and GDP which are used to forecast growth rates values which 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 the indicator of about -20. Around this value, which correspond to the values for which Figure 4 showed a substantial decline in the inferred probability of recession, the line suddenly increases its shape and the responses of expected GDP to BNB values dramatically increase. As documented in Figure 4, for values of BNB about -9, the infered probabilities of recession become very low indicating that the economy would be in the expansionary phase. Since then, the expected growth to BNB become quasi linearly trended again.

3.3 Real-time analysis

We examine the real time performance of the model in predicting turning points in the last 2008 recession.

Figure 3 shows the probabilities of recessions that would be inferred daily by a forecaster who used the information available at the day of the forecast. Although we dated the last peak in February 2008 by using the full sample estimated probabilities, in the beginning of the year the probability of recession is almost zero and remains negligible until Summer. The five-month lag in identify the peak reflects the typical uncertainty regarding real time analyses. However, this lag is reasonably short if we recall that the NBER waited one year in dating the last peak. Since bad news had been accumulated in that period, on the 9th of July the probability of recession has a pronounced increase to 0.34 due to the negative figure of Industrial Production. One of the worse historical records of Exports let the recession probability to reach the phycological threshold of 0.5 on the 18th of July. At the end of this month, the data that were published were among the worse in the history of almost all the business indicators which implied that the probability of recession became greater than 0.9. Consecutive good news were not observed since then so that the probability of recession remained around this value until the last vintage. Hence, the Markov switching dynamic factor models had unequivocally signaled in July 2008 that a peak in the euro area had occurred.

4 Conclusion

Markov-switching dynamic factor models are becoming very popular in empirical analyses. However, they fo not account for some specificities which are typical of real time forecasting exercises. They do not mixes frequencies, do not model data revisions and do not account for ragged edges. Not accounting for these publication patterns would imply that forecasters using traditional Markov-switchcing dynamic factor models to develop early assessments of the economic evolution can involve substantial costs since forecasters are restricted either to loose valuable information at the time of the forecast or to wait until balanced panels become available. We propose a model in this paper which is able to deal with all of them and we show that it is a potentially very useful tool to be used in the day to day monitoring of the Euro area economy

Appendix A

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

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

$$
\begin{aligned}
Y_t &= \begin{pmatrix} y_t^{2nd} & Z_t^{h'} & Z_t^{s'} & l_t & y_t^{1st} & y_t^f \end{pmatrix}', && (21)\\
w_t &= 0_{1,r+4}, && (22)\\
R &= 0_{r+4,r+4}, && (23)
\end{aligned}
$$

$$h_t = (f_t, ..., f_{t-11}, u_{1t}, ..., u_{1t-5}, v_{1t}, v_{1t-1}, ..., v_{rt}, v_{rt-1}, u_{2t}, ..., u_{2t-5}, e_{1t}, e_{2t})'. \quad (24)$$

The matrix H is in this case

$$
H = \begin{pmatrix}
H_{11} & 0_{1,6} & H_{12} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 0 \\
H_{21} & 0_{r_h,6} & 0_{r_h,6} & H_{22} & 0_{r_h,10} & 0_{r_h,6} & 0_{r_h,1} & 0_{r_h,1} \\
H_{31} & H_{31} & 0_{r_s,6} & 0_{r_s,8} & H_{32} & 0_{r_s,6} & 0_{r_s,1} & 0_{r_s,1} \\
H_4 & 0_{1,6} & 0_{1,6} & 0_{1,8} & 0_{1,10} & H_{12} & 0 & 0 \\
H_{11} & 0_{1,6} & H_{12} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 1 \\
H_{11} & 0_{1,6} & H_{12} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 1 & 1
\end{pmatrix}, \quad (25)
$$

where

$$
\begin{aligned}
H_{11} &= \begin{pmatrix} \frac{\beta_1}{3} & \frac{2\beta_1}{3} & \beta_1 & \frac{\beta_1}{3} & \frac{2\beta_1}{3} & 0 \end{pmatrix}, && (26)\\
H_{12} &= \begin{pmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{1}{3} & \frac{2}{3} & 0 \end{pmatrix}, && (27)\\
H_{22} &= I_{r_h} \otimes \begin{pmatrix} 1 & 0 \end{pmatrix}, && (28)\\
H_{32} &= I_{r_s} \otimes \begin{pmatrix} 1 & 0 \end{pmatrix}, && (29)\\
H_4 &= \begin{pmatrix} \frac{\beta_4}{3} & \frac{2\beta_4}{3} & \beta_4 & \frac{\beta_4}{3} & \frac{2\beta_4}{3} & 0 \end{pmatrix}, && (30)
\end{aligned}
$$

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

$$q = \begin{pmatrix} \sigma_f^2 & 0_{1,11} & \sigma_{u_1}^2 & 0_{1,5} & \sigma_{v_1}^2 & 0 & ... & \sigma_{v_r}^2 & 0 & \sigma_{u_2}^2 & 0_{1,5} & \sigma_{e_1}^2 & \sigma_{e_2}^2 \end{pmatrix}', \tag{31}$$

The matrix F becomes

$$F_{s_t} = \begin{pmatrix} a & 0_{12,6} & 0_{12,8} & 0_{12,10} & 0_{12,6} & 0 & 0 \\ 0_{6,12} & b & 0_{6,8} & 0_{6,10} & 0_{6,6} & 0 & 0 \\ 0_{8,12} & 0_{8,6} & c_h & 0_{8,10} & 0_{8,6} & 0 & 0 \\ 0_{10,12} & 0_{10,6} & 0_{10,8} & c_s & 0_{10,6} & 0 & 0 \\ 0_{6,12} & 0_{6,6} & 0_{6,8} & 0_{6,10} & d & 0 & 0 \\ 0_{1,12} & 0_{1,6} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 0 \\ 0_{1,12} & 0_{1,6} & 0_{1,8} & 0_{1,10} & 0_{1,6} & 0 & 0 \end{pmatrix}, \tag{32}$$

where

$$a = \begin{pmatrix} 0 & ... & 0 & ... & 0 & 0 \\ 1 & ... & 0 & ... & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & ... & 0 & ... & 1 & 0 \end{pmatrix}, \tag{33}$$

$$b = \begin{pmatrix} b_1 & ... & b_5 & b_6 \\ 1 & ... & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & ... & 1 & 0 \end{pmatrix}, \tag{34}$$

$$c_i = \begin{pmatrix} c_{11} & c_{12} & ... & 0 & 0 \\ 1 & 0 & ... & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & ... & c_{r1} & c_{r2} \\ 0 & 0 & ... & 1 & 0 \end{pmatrix}, \tag{35}$$

$$d = \begin{pmatrix} d_1 & ... & d_5 & d_6 \\ 1 & ... & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & ... & 1 & 0 \end{pmatrix}. \tag{36}$$

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Table 1. Data set available on January 21, 2009

	Second	IPI	Sales	INO	Exports	ESI	BNB	IFO	PMIM	PMIS	Employment	First	Flash
2007.06	-0.18	-0.27	-0.84	-0.17	0.34	94.80	-5.90	101.00	49.16	49.13	0.17	-0.20	-0.20
2007.07	na	-0.42	0.30	2.06	2.65	89.50	-7.60	97.3	47.38	48.32	na	na	na
2007.08	na	0.65	0.09	-1.60	-2.23	88.50	-5.90	94.7	47.55	48.46	na	na	na
2007.09	-0.19	-1.81	0.23	-5.40	1.24	87.50	-14.40	92.80	44.97	48.44	-0.07	-0.20	-0.19
2007.10	na	-1.59	-1.04	-4.71	-2.78	80.00	-14.80	90.1	41.10	45.76	na	na	na
2007.11	na	-1.56	0.62	2.72	-4.70	74.90	-23.70	85.8	35.58	42.47	na	na	na
2007.12	na	na	-0.09	na	na	67.10	-31.30	82.60	33.90	42.10	na	na	na
2008.01	na	na	na	na	na	na	na	na	na	na	na	na	na
2008.02	na	na	na	na	na	na	na	na	na	na	na	na	na
2008.03	na	na	na	na	na	na	na	na	na	na	na	na	na
2008.04	na	na	na	na	na	na	na	na	na	na	na	na	na
2008.05	na	na	na	na	na	na	na	na	na	na	na	na	na
2008.06	na	na	na	na	na	na	na	na	na	na	na	na	na

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

Table 3. Last in-sample forecasts

	GDP and announcements			Indicators	
	2008.4	2009.1	2009.2	Series	Forecasts
FLASH	-0.86	-0.33	0.00	Second	?
	(0.07)	(0.08)	(0.11)	IPI	?
				Sales	?
FIRST	-0.9	-0.34	0	INO	?
	(0.07)	(0.09)	(0.11)	Exports	?
				ESI	?
SECOND	-1.23	-0.52	-0.07	BNB	?
	(0.09)	(0.13)	(0.18)	IFO	?
				PMIM	?
	Recession probabilities			PMIS	?
PROB	0.99	0.82	0.68	Employment	?

Notes. See the text for acronyms. Standard errors 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			
---	1993.06		90		
2000.12	2001.10	9	76		100
2008.02	---			85	
		US (NBER)			
1990.07	1991.03		120		
2001.03	2001.11	8	73	128	81
2007.12	---				

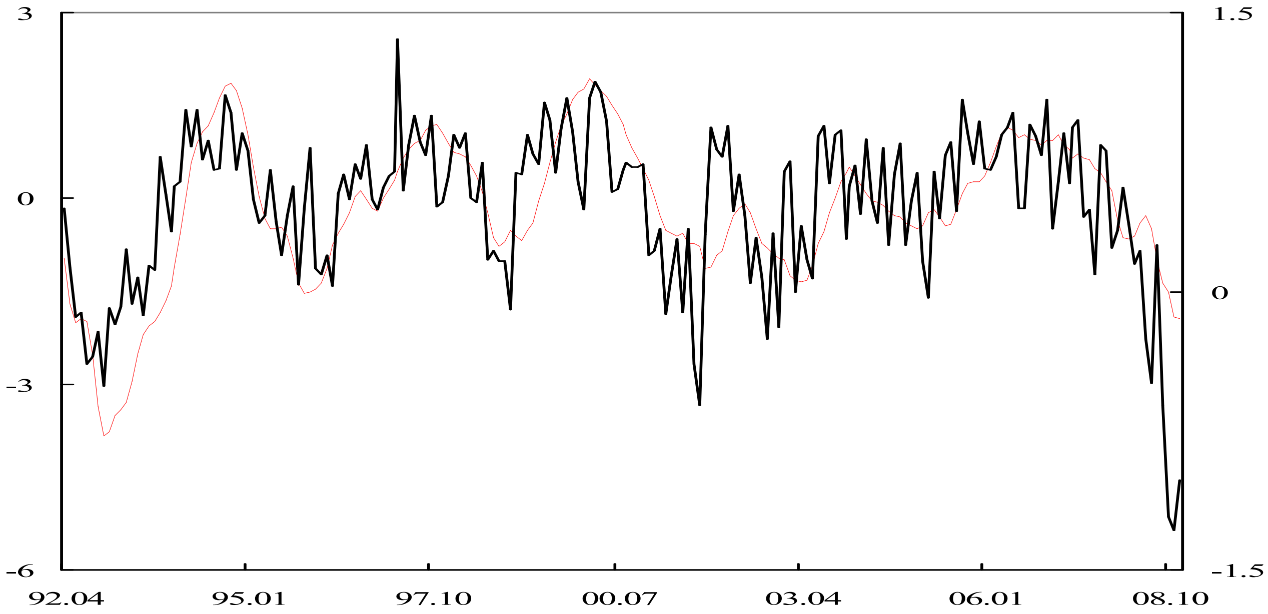
Notes. In the Euro area, peaks and troughs are dated at t using 0.8 and 0.2 thresholds for smoothed recession probabilities, respectively.

Table 5. Comparing the predictive accuracy

		Linear model	Markov-switching	DM
Backcasting	MSE-real	0.032	0.029	0.053
	MSE-final	0.022	0.022	0.867
Nowcasting	MSE-real	0.070	0.056	0.040
	MSE-final	0.063	0.061	0.830
Forecasting	MSE-real	0.094	0.101	0.607
	MSE-final	0.082	0.103	0.123

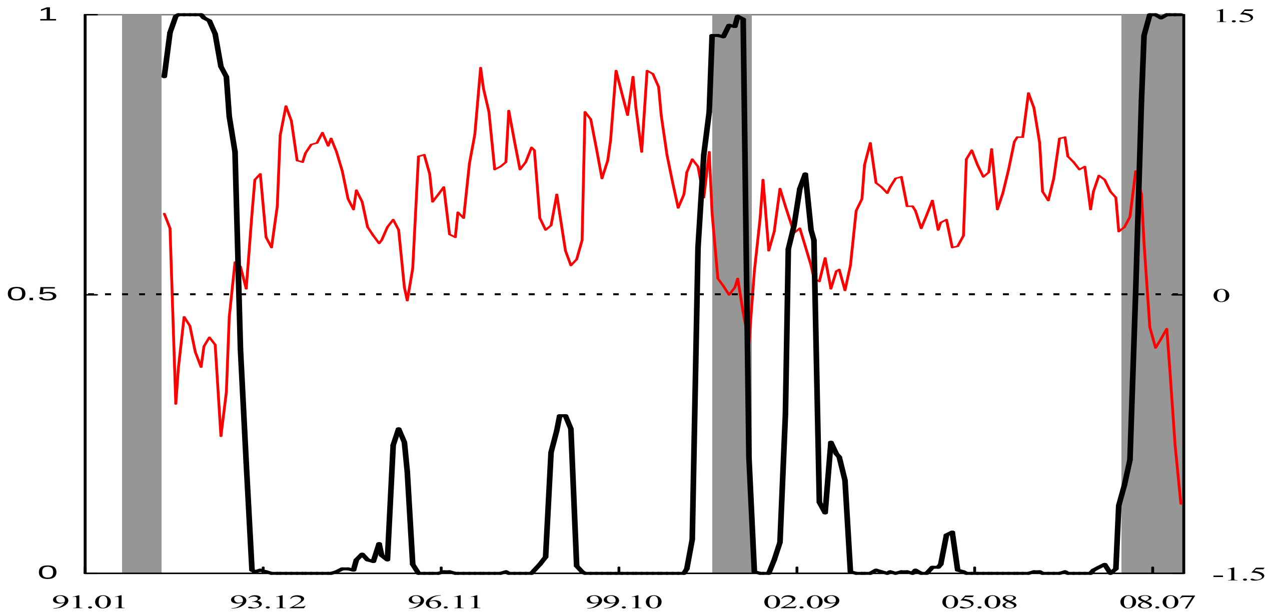
Notes. DM refers to p-values from Diebold and Mariano (1995) test. Mean squared errors are computed by comparing real time final revised GDP growth figures.

Figure 1. Common factor and Eurocoin



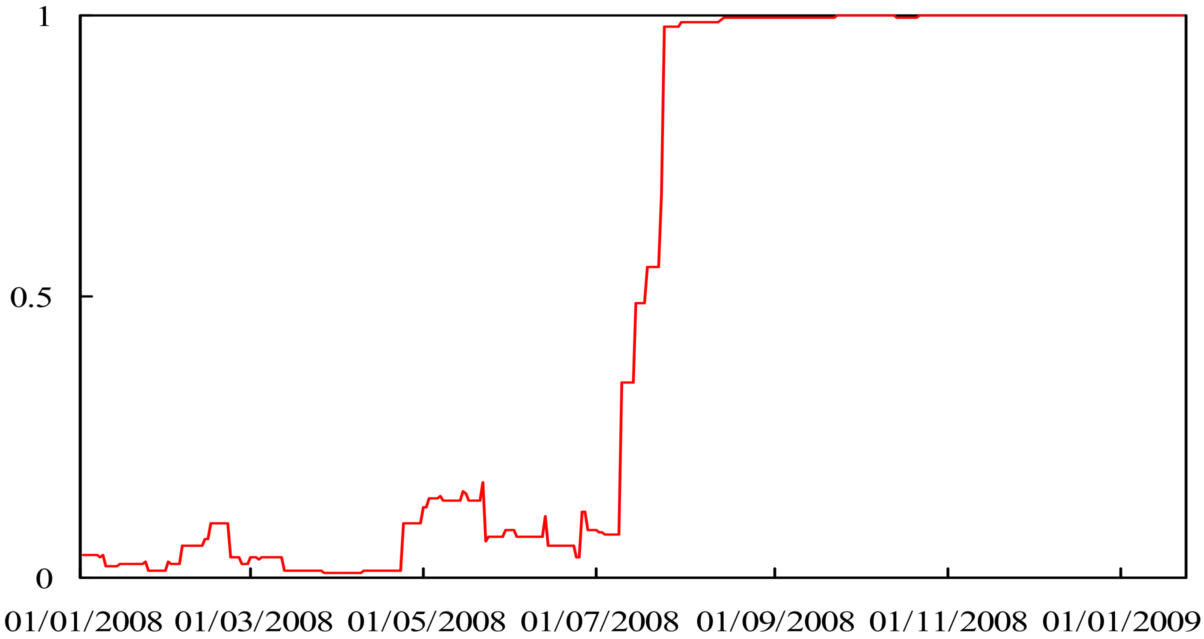
Notes. Black line (left scale) refers Euro area coincident indicators computed from our model while red line (right scale) refers to Eurocoin. The sample is 92.04-08.12.

Figure 2. In-sample GDP and recession probabilities



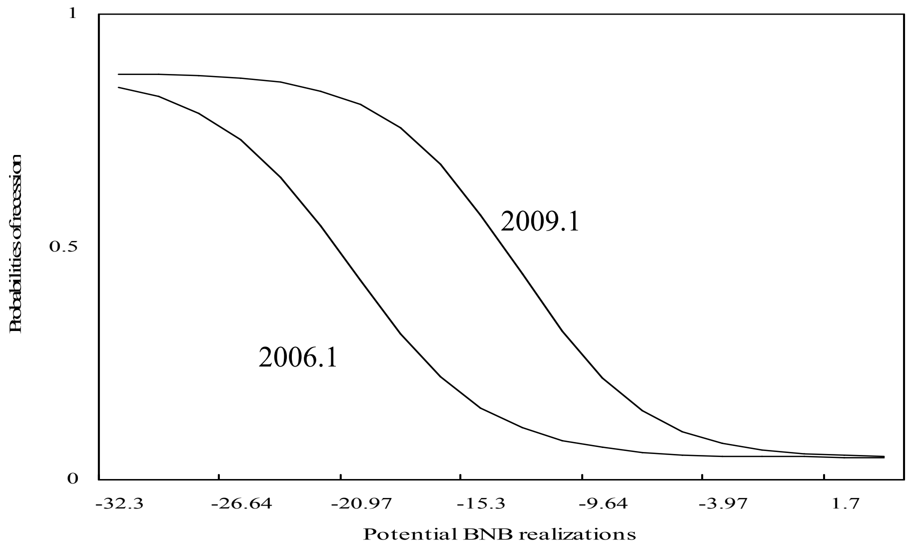
Notes. Black line (left scale) refers Euro area recession probabilities. Red line (right scale) refers to Euro area quarterly GDP at monthly frequency (third months of each quarter are actual figures). Shaded areas corresponds to the NBER recessions for US.

Figure 3. Real-time recession probabilities



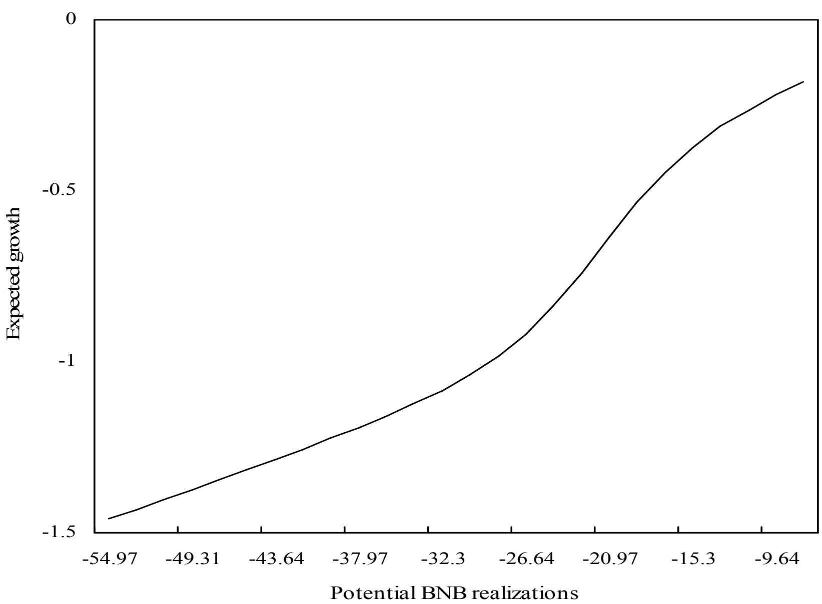
Notes. Backcasting recession probabilities

Figure 4. 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 5. 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.