A useful tool to forecast the Euro-area business cycle phases*

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Abstract

Based on a novel extension of existing multivariate Markov-switching models, we provide the reader with a useful tool to analyze current business conditions and to make predictions about the future state of the Euro-area economy in real time. Apart from the Industrial Production Index, we find that the European Commission Industrial Confidence Indicator, that is issued with no delay, is very useful to construct the real-time predictions.

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1 Introduction

A common feature of industrialized economies is that economic activity moves between periods of expansion, in which there is economic boom, and periods of recession in which there is economic contraction. Understanding these phases, collectively called the business cycle, has been the focus of much research over the past century. A further issue is whether one should look at fluctuations in the level of economic activity or fluctuations around some trend. Some researchers examine *classical cycles*, which concern turning points in the level of real economic activity. Other researchers study *growth cycles*, in which case expansions and recessions refer to periods of increasing and decreasing growth, typically defined after detrending output series. Both are important for economic agents who require acceptable knowledge of current and future states of the economy at adopting their economic decisions.

The introduction of the common European currency has increased the interest and the need for business cycle analysis at the level of the Euro zone. Although there is no consensus on how representative this common Euro-area cycle is of the business cycle of the individual members, it is a reference for economic agents due to its influence on monetary policy decisions. Special attention deserves the effort done by the Center for Economic and Policy Research (CEPR) with the creation of a group of experts to date the Euro-area business cycle. However, this group concentrates on describing the past, not analyzing the current state or predicting the future. For instance, at identifying classical cycles, they define the period since 2001 as a "prolonged pause in aggregate economic activity" with no statement towards one or the other state of the cycle. At identifying growth cycles, they acknowledge that "these turning points can only be identified with a lag".[1]

The purpose of this paper is to find a useful tool to identify and forecast the Euro-area business cycles. The main contribution to the literature can be summarized in the word "useful". Our goal is to find an algorithm that can be, and that has already been, easily incorporated by practitioners in a computer program. With a minimum of information, our algorithm delivers every month inference about the current state of the business cycle and forecasts the probability of future economic states. We consider that the appropriate framework for this business cycle analysis is the Markov-switching model (MS) proposed by Hamilton (1989). This approach is not new in the related literature. Examples of recent papers that use Markov-switching models to examine the Euro-area business cycle are Krolzig (2001), Massman and Mitchell (2003), Artis, Marcellino and Proietti (2003), Artis, Krolzig and Toro (2004), Harding (2004), Krolzig (2004), Mitchell and Mouraditis (2004), and Krolzig and Toro (2005). However, our paper presents several contributions

[1] Details of the CEPR business cycle dating can be found on the web page www.cepr.org.

to the Euro-area business cycle literature that overcome some drawbacks that are presented in those papers.

First, most of the previous papers use Gross Domestic Product (GDP) as the reference series to make inference about the business cycle state of the economy. We think that the use of the Euro-area GDP series presents serious problems. The published statistics are too short to make inference and the estimated series are subject to some aggregation and standardization caveats that make the link with the official series problematic. By contrast, we consider that using the Industrial Production Index (IPI) series as reference for the Euro-area cycle is more appropriate. Even though it only refers to the manufacturing sector, the series is more homogeneous across economies, and therefore, the aggregation is a minor problem. Moreover, the IPI is one of the most important series used when obtaining the GDP quarterly data from annual European national accounts. In addition, manufacturing is the sector that is more affected by business cycle fluctuations.

Second, a subset of these papers use the official seasonally adjusted IPI series. But, prior to be used in their studies, the series is corrected by outliers and smoothed using a seven-month moving average. We think that transforming the data as they do reduces the usefulness of the Markov-switching approach to identify the current state of the economy and to forecast future states. In addition, the results will depend on the smoothing technique selected by the researcher.

Third, none of the previous works addresses the "usefulness" of the proposed tool at all. Even though the MS approach allows econometricians to make inference about historical sequence of business cycle states, the typical delay of two months that characterizes the IPI releases reduces to the minimum the MS ability to generate reliable predictions in real time. In order to avoid the problems associated with the publication lags of the series of reference, we look for series that, being closely linked to the IPI series, are reported without delay. In line with Oller and Tallbom (1996), Kauppi, Lassila and Terasvirta (1996), and Garcia-Ferrer and Bujosa-Brun (2000), we examine the information about the future state of the economy contained in indicators based on survey data. In particular, we consider the European Commission Industrial Confidence Indicator (ICI), that is closely related with industrial activity. Those papers concentrate on dating the cycle and on how the survey data precede with some lead the turning points of the series of interest. However, we focus on integrating both the IPI and ICI series in a multivariate algorithm that generates forecasts of the Euro-area business cycle phases in real time. In our in-sample analysis, we show that the inference about the Euro area business cycles has gained valuable insights using the indicator series. More importantly, in our out-of-sample and real-time exercises, we show that the ICI series helps us to correct the systematic delay in the one month ahead inference about the state of the Euro economy that characterizes the univariate forecasts.

Finally, an additional methodological contribution of the paper, comes from the particular form of mixing the information of IPI and ICI to obtain business cycle probabilities. In the standard bivariate Markov-switching specifications, two extreme cases are presented in the literature. The first one is the case of complete independent business cycle, where there are two independent hidden Markov processes in the bivariate specification. The second one is the case of perfect synchronization, where there is only one Markov process that is shared by both variables. We think that in most real cases, the dynamics of these series describe a situation that is somehow in between. Hence, we model the data generating process as a linear combination of these two extreme situations, where the parameters of the linear combination are estimated from the data. To our knowledge, we are the first in the literature proposing a mixture of these two extreme cases to capture the dynamics of two macroeconomic series. In particular, we obtain that the IPI and ICI series are neither independent nor do they completely share the state of the economy. We show that they present slightly different information about the business cycle.

The paper is organized as follows. Section 2 describes the data. Section 3 presents the forecasts developed with univariate models of IPI. Section 4 shows how to use the CLI information to update the forecasts about the state of the economy by using an extension of the existing bivariate Markov-switching model. Section 5 concludes.

2 Preliminary analysis of data

2.1 The Euro area Industrial Production Index

The data used for our empirical analysis are the natural logarithms of the seasonally adjusted Euro-area Industrial Production Index (IPI) which is published by Eurostat. These data are monthly and the sample period goes from 1980.01 to 2004.11.[2] To study the usefulness of any inference about the current and future states of the Euro economy inferred from this series, it is crucial to realize that the series is published with a delay of two months. That is, the information about the IPI in period t is not known until two months later. For example, although the real-time releases of the IPI series are available since 2001.06, the sample period of the first real-time issue just goes from 1980.01 to 2001.04.

As we mentioned in the introduction, we understand that choosing the industrial production index as a measure of aggregate economic activity versus the obvious choice of analyzing GDP

[2] The latest data published by Eurostat do not go back that far. The problem is that France has changed the base for their IPI series. However, the differences between the previously released series and the new one are so small that the old and the new series can be linked without major problem.

could be controversial. However, in addition to the reasons stated above, for most of the Euro economies the quarterly GDP series are not calculated from national accounts on a quarterly basis but constructed from annual series that are converted to quarterly using indicators.[3]

In order to facilitate a visual inspection of our data set, Figure 1 plots the level of the IPI series. This figure shows the original data, with a clear outlier in 1984.06. This implies a monthly decrease of more than 3%, that corresponds to a decrease of 42% on annualized rates. The outlier leads only to a very noisy signal in that particular date. Consequently, the atypical data was replaced by a simple linear interpolation from the values of IPI for the previous and following months. It is worthy of remark that this interpolation leads to a negligible impact in our empirical exercise.

2.2 The Euro area Industrial Confidence Indicator

Since the Index of Consumer Sentiment was introduced in 1953 by Katona (1951) in the US, the usefulness of sentiment indicators to forecast economic activity has been the subject of many studies. Although data series derived from business surveys have received less attention as leading indicators of recessions than the ones derived from consumer surveys, they also have a long tradition of being used as indicators.

The National Association of Purchasing Managers (NAPM) survey of manufacturers goes back to 1931. In Europe, the first business survey dates back to the late 1940s (IFO in Germany in 1949) and early 1950s (INSEE in France and ISCO in Italy, 1951). In the framework of the harmonized EU programme of business and consumer surveys, data series from industry surveys are available for the Euro area since 1980. Industry surveys have played a prominent role in the assessment of the business cycle after a large decline in industrial confidence indicator of the Euro area in the early nineties that coincided with the deep recession that finished in 1993. This coincidence was interpreted as a strong evidence that industrial confidence indicators could be a useful indicator to predict recessions and expansions in the Euro area.

The existence of a long series can make it a useful tool for analyses at Euro area level. The Commission calculates and publishes this composite indicator, named the Industrial Confidence Index (ICI), using every month data for the current month for the Euro area. The ICI is defined as the arithmetic mean of the answers (seasonally adjusted balances) to the questions on production expectations, order books and stocks (the latter with its sign inverted). The choice of these

[3] Only UK relies on the quarterly national accounts as the main building blocks for the annual account. Other countries (for example France, Italy and Spain) rely on annual accounts and use mathematical and statistical methods to estimate quarterly series. Germany produces annual accounts separately and integrates the quarterly data with the annual estimates.

variables and the linear combination that is used in calculating the indicator is justified by the Commission as the most appropriate way to summarize accurately the industrial climate.

The two latter series (order books and stocks) have been considered to be very useful to identify periods of expansion and recession in the production growth of the Euro area. These two indicators show the same developments but inverted. When order books go up, stocks of finished products go down. In a cyclical trough the distance between two series is at maximum while in a cyclical peak, it is at minimum. The production expectations series has been used in the applied literature to forecast future movements of industrial production index.

Figure 2 plots (black line) the Industrial Confidence Index. Contrary to the systematic delay of two months with which the IPI series is published, the ICI series does not exhibit any publication delay. As we show below, the availability of the ICI series in real time will be key to solve the problems of the IPI series to compute real-time inferences about the Euro-area business cycle phases.

2.3 Comovements between IPI and ICI

The performance of the ICI series has been evaluated by its ability to track the evolution of the Euro area industrial production annual growth rates (see for example, EC, 1997). This relationship has been obtained by examining the time cross-correlation coefficients between the ICI and the growth rate of the IPI. Cross-correlation is a measure of how closely aligned the timing of cyclical fluctuations are for two indicators over their cycles. We can examine the dynamic synchronicity of these series in Table 1 and Figure 2. They show that there is a strong concordance between the ICI series (black line) and the annual growth rate of the IPI series (red line). In addition, they reveal that the ICI series is a coincident indicator of the annual growth rate of the industrial production index of the Euro area.

The explanation of these findings could be that respondents seem to relate the concept of a normal level of their order books to the one observed in the previous year, behaving as if a comparison had been asked between the current level of order books and the level in the same month of the previous year. In this sense, the ICI series could be considered as a backward-looking indicator. These high correlations, suggest that we may have reliable information about the industrial production index two months in advance, that coincides with the difference in publication time between the IPI and ICI series. However, we will explore other relations across these variables that will go beyond this simple relationship.

3 Forecasting with univariate models

3.1 The model

Hamilton (1989) proposed an algorithm that allows to make inference and forecast the state of the business cycle from an economic time series. His proposal is based on the fact that the expected value of the series of interest is different from recession versus expansion periods. However, his filter is just defined on stationary series. In this respect, the Phillips-Perron unit root tests reveals that the log of IPI data present a unit root (p-value of 0.07) while their differences are stationary (p-value of 0.00). Consequently, letting Y_t be the IPI series, and defining $y_t = 100 \ln(Y_t/Y_{t-1})$, we consider that the conditional expectations of the series growth rates are

$$\begin{aligned} E(y_t) &= \mu_1, \text{ if the economy is in expansion, and} \\ E(y_t) &= \mu_2, \text{ if the economy is in recession,} \end{aligned} \tag{1}$$

with $\mu_1 > \mu_2$. These two expected values can be rewritten in equation form as follows:

$$y_t = \mu_{s_t} + u_t, \tag{2}$$

where s_t is an unobservable latent variable that takes on values 1 and 2. Obviously, these two different expected values are not the only forces driving the dynamic behavior of the series. There is autocorrelation in the dynamics of the series that may be captured by allowing u_t to follow a general autoregressive process of order p. Therefore, we consider that

$$u_t = \sum_{i=1}^{p} \phi_i u_{t-i} + \epsilon_t, \tag{3}$$

with ϵ_t following a standard independent and identically distributed Gaussian white noise with zero mean and variance σ^2.

Plugging (3) in (2) we get

$$y_t = \mu_{s_t} + \sum_{i=1}^{p} \phi_i u_{t-i} + \epsilon_t, \tag{4}$$

and substituting u_{t-i} by its value defined in (1), we obtain

$$y_t = \mu_{s_t} + \sum_{i=1}^{p} \phi_i (y_{t-i} - \mu_{s_{t-i}}) + \epsilon_t \tag{5}$$

Equation (5) is known in the Kalman filter literature as the observation equation. In this expression, the estimated value of the series y_t is a function of the unobservable variable, s_t, which represents the state of the economy. It is relevant to show that, although we have only two basic states of the economy, recessions and expansions, the autoregressive components imply that more states of the economy that just the ones corresponding to period t are important for describing the law of motion of y_t. In particular, Hamilton (1994) shows that we will have $k = 2^{p+1}$ states of the economy that are usually collected in a new state variable s_t^*, that summarizes the k different states in the convenient way.

In addition, to estimate the model we need to propose the law of motion for the unobservable variable. Following Hamilton (1989), we assume that s_t evolves as a Markov chain of order one. This type of assumption implies that the transition probabilities exhibit the property

$$Pr[s_t = j|s_{t-1} = i, |\Omega_{t-1}] = Pr[s_t = j|s_{t-1} = i] = p_{ij}, \tag{6}$$

where Ω_{t-1} represents all the available information in period $t-1$, and $i, j = 1, 2$. Hamilton (1994) shows that s_t^* also presents the properties of a Markov chain with transition probabilities p_{lm}^*, with $l, m = 1, 2, ...k$, that may be derived from p_{ij}. These probabilities are usually collected in transition matrices P and P^*, whose columns sum to unity.

Before getting into details on how the model can be estimated, it is convenient to relate our work with previous papers in the literature that deals with the Euro-area business cycle in the Markov switching context. In our opinion, two major concerns arise from these papers. The first one is that some of these papers consider that the rate of growth of the seasonally adjusted IPI series is too noisy. Accordingly, these authors smooth the series by using a seven-month moving average. In this respect, we understand that the industrial production growth rate is noisy and consequently difficult to estimate with a parsimonious model (see Figure 3). However, smoothing the series with a moving average representation generates all kinds of misspecifications. Firstly, the estimated model needs at least as many lags as the number of elements used in the smoothing. Secondly, the changes in regimes are more difficult to interpret due to the smoothing filter. Hence, a change in regime in period t will come from the influence of changes from $t - r$ to $t + r$, where the amplitude $2r$ represents the order of the moving average. It is convenient to point out that this concern also affects all the papers that deal with the series in annual rates of growth that are computed as differences of order 12, since these differences are a moving average of differences of order 1. Finally, these additional filters reduce the ability to predict the movements of the series of interest in real time. At any point in time, the model uses information of the future, not available until r periods ahead. Unfortunately, it is likely that, in period $t + r$, the prediction about the state of the economy in period t is no longer a relevant question.[4]

[4] We are aware that using seasonally adjusted series implies some smoothing. However, the seasonally adjusted series is an official series and it does not depend on the filter used for the specific research. In practice, this reasoning is similar to assume that our series of interest is the seasonally adjusted version of IPI.

There exists a second mayor concern that arises from the standard Markov-switching literature applied to deal with the Euro-area business cycles. Many of these papers estimate what is called a Markov-switching process in the intercept. This model implies the specification

$$y_t = \mu_{s_t} + \sum_{i=1}^{p} \phi_i y_{t-i} + \epsilon_t. \tag{7}$$

Even though this expression leads to a sharp reduction in the number of different states, we think that it could potentially contain serious misspecifications. To see why, let us illustrate the problem with an example. Assume that the series of interest takes on the value 0.2 in expansions and -0.2 in recessions. In addition, assume that $p = 1$, and that the value of ϕ is about one. Let us consider that there is a change in regime in period t, for example the beginning of a recession. The data in period $t-1$ (still an expansion) is around the level of the expansions, 0.2. In period t, the intercept term in state 2, μ_2, has to bring down the series to the recession levels, so it should take on the value -0.4. However, in period $t+1$, when the data in period t is already around the recessions level, the intercept does not necessarily has to bring the series to a lower level and the value of -0.4 is (in absolute value) too high. Hence, the model is then misspecified exactly in the most interesting periods, the turning points.

Coming back to the original Markov-switching specification, our target consists on maximizing the log-likelihood function

$$L = \sum_{t=1}^{T} \ln f(y_t|\Omega_{t-1}), \tag{8}$$

where $f(y_t|\Omega_{t-1})$ represents the conditional density function of y_t given the information available in $t-1$. Applying the total probability theorem and knowing that the states of the economy have no intersection, the conditional density may be decomposed into

$$f(y_t|\Omega_{t-1}) = \sum_{i=1}^{k} f(y_t|s_t^* = i, \Omega_{t-1}) P(s_t^* = i|\Omega_{t-1}), \tag{9}$$

where k refers to the 2^{p+1} different states of the economy.

Given that ϵ_t follows a Gaussian process, $f(y_t|s_{t-1}^* = i, \Omega_{t-1})$ follows a Gaussian distribution, with mean given by (5) and variance given by the variance of ϵ_t. The other term of (9) requires some additional decomposition. Again, applying the total probability theorem:

$$\begin{aligned} P(s_t^* &= i|\Omega_{t-1}) = \sum_{j=1}^{k} P(s_t^* = i|s_{t-1}^* = j, \Omega_{t-1}) P(s_{t-1}^* = j|\Omega_{t-1}) \\ &= \sum_{j=1}^{k} p_{ij}^* P(s_{t-1}^* = j|\Omega_{t-1}). \end{aligned} \tag{10}$$

These probabilities are usually collected in a $(k \times 1)$ vector $\xi^*_{t|t-1}$. Now, applying Bayes theorem one can make inference about the current state of the economy as follows:

$$\begin{aligned} P(s^*_{t-1} &= j|\Omega_{t-1}) = P(s^*_{t-1} = j|y_{t-1}, \Omega_{t-2}) \\ &= \frac{f(y_{t-1}|s^*_{t-1} = j, \Omega_{t-2})P(s^*_{t-1} = j|\Omega_{t-2})}{\sum_{i=1}^{k} f(y_{t-1}|s^*_{t-1} = i, \Omega_{t-2})P(s^*_{t-1} = i|\Omega_{t-2})}. \end{aligned} \tag{11}$$

These probabilities are usually collected in a $(k \times 1)$ vector $\xi^*_{t-1|t-1}$. As we can observe, equation (11) is basically a function of $P(s^*_{t-1} = i|\Omega_{t-2})$, which is the left hand side of equation (10) lagged one period. Therefore, iterating in (10) and (11), we get the log-likelihood function as a function of just the parameters to estimate and the initial conditions on the state of the economy in the initial period, which can also be expressed as a function of the parameters to estimate.[5]

Finally, the optimal m-period-ahead forecast about the regime for some future period, conditional on the information available at date t, is

$$\xi^*_{t+m|t} = P^* \cdot \xi^*_{t|t}. \tag{12}$$

As described in Hamilton (1994), the inference about the value of s_t can be obtained by summing together the relevant probabilities for s^*_t.

3.2 Empirical results

We estimate model (5) with lag length selected by the Schwarz criterion, equals to one. Maximum likelihood estimates of parameters, reported in Table 3, show that in regime represented by $s_t = 1$, the average growth rate is positive ($\widehat{\mu}_1 = 0.22$), so we can interpret this regime as the expansion period. By contrast, the average is negative ($\widehat{\mu}_2 = -0.24$) in regime represented by $s_t = 2$, so we can interpret this regime as the recession period. In addition, each regime is highly persistent, with estimated probabilities of one regime to be followed by the same regime of 0.98 and 0.94, respectively.[6]

Figure 4 plots the so-called filtered probabilities of recession, that is, the probabilities of being in a recession at each period of time conditional on the information up to that period of time.

[5] Although, from the derivations, it seems that there are many different transition probabilities p^*_{lm}, they are much simpler. For many cases the transition probabilities are zero because some transitions are, by definition, impossible. In other cases, they are just a function of two parameters, p_{11} (the probability of going from expansion to expansion) and p_{22} (the probability of a recession following a recession). For a detailed explanation, see Hamilton (1994).

[6] With respect to the nonlinear numerical algorithms, we always use the default values of the BFGS routine. Starting points are the estimates from the linear version of the alternative nonlinear specifications. We always check the robustness of our results with respect to a broad range of reasonable start-up values.

As we can see, a simple Markov-switching specification without any kind of data transformation, allows us to differentiate the specific business cycle phases at each period. They correspond to probabilities of being in recession close to 1 or 0, respectively.

In the empirical analyses that use US data, it is standard to corroborate that the unobserved state variable s_t actually refers to the business cycle phases by comparing the filtered probabilities with the official business cycle chronology provided by the National Bureau of Economic Research (NBER). However, dealing with other countries' business cycles, this approach is not straightforward since there is no widely accepted business cycle chronology being updated timely for those countries. In order to provide a basis for comparison, we use the well-known Bry-Boschan business cycle dating procedure for identifying classical turning points from the levels of IPI.[7] This method has come widely used to infer the business cycle turning points from time series. However, it cannot be used to develop real-time confident statements towards one or the other state of the cycle in the last six months of the sample since algorithm imposes that a phase must last at least six months. This makes impossible to use this procedure to identify the current state of the economy or to forecast future business cycle developments in real time.

Figure 4 shows that the Bry-Boshan classical business cycles recessions (represented by shaded areas) and those periods of high probability of negative IPI growth rates are in close agreement. Consequently, we can consider that states one and two represent periods of classical business cycle expansions and recessions, respectively. However, although the univariate Markov-switching specification of IPI is useful to describe past Euro-area business cycles, we will show that it cannot be used to form timely updated forecasts.

Its major inconvenience comes from the delay with which the IPI series is published. The real-time issues of the IPI series are provided with a delay of two months. Hence, the information about IPI in period t is not known until 2 months later. The problems associated with this statistical delay can be clearly shown in the following out-of-sample exercise. Let us consider the case of a hypothetical forecaster who, at each month t, needs a forecast of the probability of recession at $t+1$, with t going from 1991.12 to 2004.10. In order to make the first forecast, the portion of the IPI series that the forecaster would know goes from the beginning of the sample until 1991.10. Due to the two-months delay on which the series of IPI is issued, the forecaster does not know this series until 1991.12. Then, the forecaster could estimate the univariate Markov-switching model and could compute, using (12), the three periods ahead forecast for 1992.01 that is his/her first out-of-sample prediction.[8] Then, when a new observation of the IPI series is added, the reestimation of

[7] For a details on the Bry-Boschan procedure and its relation with the NBER dating procedures, see Artis, Kontolemis and Osborn (1997).

[8] We select 1992.01 as the first out-of-sample forecast because we want to combine having enough observations

the model would be necessary with the computation of the next prediction, 1992.02. The process is iterated recursively until the last out-of-sample prediction, 2004.11.

Note that these three periods ahead forecasts represent the forecasted probability of being in a recession in period $t+1$ with the information available in period t, which is dated in $t-2$. This is the probability of interest for us, namely the probability that somebody doing the forecast in period t would assign to having a recession in $t+1$. In Figure 5, we plot these out-of-sample probabilities (red line) along with the in-sample probabilities (black line) already shown in Figure 4. As we can observe, the model predicts systematically late. Even if the model were correct and described the historical states of the economy perfectly, the filter would be useless for prediction because it predicts late the future state. Therefore, the statistical delay matters a lot when the purpose is more than just describing the past of the series.

Following Diebold and Rudebusch (1991), we try to corroborate the out-of-sample findings, by performing a real-time exercise that mimics the information sets that were actually available at the historical date of each forecast. The first issue of IPI that is available in real-time is 2001.06 whose last figure corresponds to 2001.04. With this series, we estimate the corresponding MS model and compute our first real-time forecast for 2001.07. To compute the next prediction, we consider the next data for the IPI series, issued in 2001.07 that includes the real-time revisions of IPI, apply the MS methodology and compute the forecast for the 2001.08. Accordingly, we repeat the process until the last real-time forecast, 2004.11. In Figure 5, we plot these real-time forecasted probabilities (blue line). As shown in the graph, the univariate MS model of IPI also predicts systematically late in real time. This leads us to look for a more appropriate alternative method to construct real-time predictions of the Euro-area business cycles.

4 Forecasting with bivariate models

4.1 The model

To overcome the previous problem in forecasting the Euro-area states of the economy by using just the IPI series, we propose to make use of the business cycle information that is contained in the ICI series. In order for the ICI to be useful to describe the business cycle properties of the IPI series, the cyclical movements of ICI must be a good predictor of the IPI changes. The ICI series should increase when IPI exhibits recessions although the business cycle dating of both series would be uncorrelated. At the same time, the probabilities of recession for these two series, could exhibit a

to estimate the model and capturing at least part of the recession of the early 90s.

non-linear relationship. Therefore, the simple correlation might not be the best approach to test how appropriate one variable is to predict nonlinear changes of the other.

In this respect, we propose the following criteria. The ICI series will be useful to predict the IPI changes of regime if the probabilities of these changes are affected by the movements of ICI. The most popular way of specifying this type of dependence in the literature would be to use the ICI index as an explanatory variable for the transition probabilities of IPI. However, this was not a successful strategy with our series, perhaps because of the high volatility of our left-hand side variable, the IPI series. We then try a multivariate Markov-switching approach. The intuition behind this approach is very simple. We think that IPI and ICI could share part of the state of the business cycle but that this common state explains only part of the movements in the realizations of the two series. We need an appropriate filter to find this business cycle relationship.

According to the preliminary unit root tests, we propose a bivariate Markov switching model for IPI growth rate (labelled as y_t) and ICI first differences (labelled as x_t). In addition to the statistical reasons for differentiation, with the unit root tests already pointed out, there are economic reasons behind this differentiation. We have seen that the ICI series in levels is correlated with the annual differences of the series of the log of IPI. Therefore, the level of the ICI series contains information about the past of the IPI series. In order to predict the future, variation of these series should have information about the IPI growth rates that we want to predict.

We then estimate the following model. Let the latent variable of IPI be the previous unobserved variable s_t, that takes on value 1 if y_t is in an expansion and 2 if y_t is in a recession, and whose transition probabilities are p_{ij}. Let v_t denote the latent variable of ICI. This variable takes on value 1 if x_t is in an expansion and 2 if x_t is in a recession, and its transition probabilities are q_{ij}. Using this notation, our final specification is:[9]

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \mu_{s_t} + \sum_{i=1}^{p_1} \phi_i (y_{t-i} - \mu_{s_{t-i}}) \\ \gamma_{v_t} + \sum_{i=1}^{p_2} \theta_i (x_{t-i} - \gamma_{v_{t-i}}) \end{pmatrix} + \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix}, \tag{13}$$

where $(\epsilon_{1t}, \epsilon_{2t})'$ follows the Gaussian i.i.d. bivariate process

$$\begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix} \right]. \tag{14}$$

In this paper, we propose two extensions of this baseline framework. The first extension has to do with the analysis of the degree of business cycle synchronization that may appear between the

[9] This specification is simpler than a standard vector autoregressive model. However, in the empirical analysis, we check that y_t is not significant in the equation of x_t and vice versa.

unobserved state variables that govern the business cycle movements of IPI and ICI. Two extreme cases are presented in the literature. The first one refers to the case of complete independence of their cycles. That is, in the bivariate specification, their hidden Markov processes evolve independently. The second one refers to the case of perfect synchronization in which there is only one Markov process for the business cycles of both variables. We think that in most of the real cases, the degree of business cycle synchronization is somewhere in between, so our proposal has to do with a linear combination of these two extreme situations, where all parameters of the linear combination are estimated from the data.

Skipping the technical details that can be found in Camacho and Perez-Quiros (2006), this novel specification allows us to examine the degree of business cycle interdependence between the individual series. On the one hand, under the assumption that IPI and ICI are governed by two independent Markov switching processes, we will have four basic states with the conditional probability of being in each state being equal to the product of the probabilities of being in each of the individual states.[10] That is, the conditional probabilities are

$$\xi^{I}_{t|t-1} = \begin{pmatrix} P\left(s_t = 1, v_t = 1|\Omega_{t-1}\right) \\ P\left(s_t = 2, v_t = 1|\Omega_{t-1}\right) \\ P\left(s_t = 1, v_t = 2|\Omega_{t-1}\right) \\ P\left(s_t = 2, v_t = 2|\Omega_{t-1}\right) \end{pmatrix} = \begin{pmatrix} P(s_t = 1|\Omega_{t-1})P(v_t = 1|\Omega_{t-1}) \\ P(s_t = 2|\Omega_{t-1})P(v_t = 1|\Omega_{t-1}) \\ P(s_t = 1|\Omega_{t-1})P(v_t = 2|\Omega_{t-1}) \\ P(s_t = 2|\Omega_{t-1})P(v_t = 2|\Omega_{t-1}) \end{pmatrix}, \tag{15}$$

where the superscript I refers to the case of independent cycles. On the other hand, under the assumption that both series share the state of the economy, we could rewrite the conditional probabilities of each basic state as

$$\xi^{D}_{t|t-1} = \begin{pmatrix} P(s_t = 1, v_t = 1|\Omega_{t-1}) \\ P(s_t = 2, v_t = 1|\Omega_{t-1}) \\ P(s_t = 1, v_t = 2|\Omega_{t-1}) \\ P(s_t = 2, v_t = 2|\Omega_{t-1}) \end{pmatrix} = \begin{pmatrix} P(s_t = 1|\Omega_{t-1}) \\ 0 \\ 0 \\ P(s_t = 2|\Omega_{t-1}) \end{pmatrix}, \tag{16}$$

where the superscript D refers to the case of fully dependent cycles. Obviously, given that they share the state of the business cycle, in this case is impossible to be in state 1 for one variable and state 2 for the other or vice versa.

Stated like we did above, we can see that the only difference between sharing or not the state of the economy refers to the form of their transition probabilities. We do not know which is the best model for the data. In fact, the true data generating process can be a point between these two

[10] For presentation purposes we forget about the need of 2^{p+1} states. However, we are careful of taking all these technicalities into account in the estimation.

extreme assumptions. In order to find this intermediate point, we consider that actual business cycle synchronization is δ times the case of independence and $(1-\delta)$ times the case of perfect dependence, where $0 \leq \delta \leq 1$. The weight δ may be interpreted as a measure of business cycle desynchronization between these variables since it evaluates the proximity of their business cycles to the case of complete independence. Consequently, we propose the following transition process:

$$\xi_{t|t-1} = (1-\delta)\xi^D_{t|t-1} + \delta\xi^I_{t|t-1}. \tag{17}$$

The second extension to the existing literature on multivariate Markov-switching models deals with the reduction in the systematic delay in the prediction of business cycle probabilities that has been detected in the univariate case. Out of the multivariate framework, we can obtain the joint probabilities of recession for the series of IPI and ICI. As stated in the univariate model, the Markov-switching specification allows us to provide statistical inference about the in-sample probabilities of occurrence of each state of the cycle. However, the bivariate specification has an important advantage with respect to the univariate model for IPI. In the univariate case, at any period t we had to make inference about period $t+1$ with information up to $t-2$, due to the delay of two months with which the IPI series is issued. In the bivariate specification, we can use the timely issues of ICI (that is reported without delay) to update the forecasts about the business cycle probabilities in $t-1$ and t. With the bivariate specification in mind, we propose the following scheme for predicting probabilities of recession in the Euro area.

1) Compute filtered probabilities $P(s_{t-2} = i, v_{t-2} = j|\Omega_{t-2})$. In period t, estimate the bivariate model for the sample for which we have available information for both series. This will imply estimating the model for both variables up to period $t-2$.

2) Forecast the probabilities $P(s_{t-1} = i, v_{t-1} = j|\Omega_{t-2})$. With the probabilities of recession and expansion estimated for the last period of estimation (period $t-2$) and the transition probabilities stated above, use (10) to predict the probabilities of being in recessions and expansions in $t-1$.

3) Update the filtered probabilities $P(s_{t-1} = i, v_{t-1} = j|\Omega_{t-1})$. This can be done by using the data for ICI in $t-1$ in (11).

4) Forecast the probabilities $P(s_t = i, v_t = j|\Omega_{t-1})$. Using updated filtered probabilities and the transition probabilities in (10), compute the probabilities of recession and expansions in t.

5) Update the filtered probabilities $P(s_t = i, v_t = j|\Omega_t)$. Update those probabilities using the data for ICI in period t in (11). These last probabilities are our proposed best inference about the current state of the economy.

6) Compute predictions $P(s_{t+1} = i, v_{t+1} = j|\Omega_t)$. At each time period t, updated forecasts of the business cycle probabilities for the next month can be obtained using (10).

4.2 Empirical results

Let us first start with the standard bivariate Markov-switching model stated in (13). Maximum likelihood parameter estimates of this specification are displayed in the first column of the Table 3, labelled as Model 1.

As a first step, we are interested in examining the comovements among their respective business cycle dynamics. The first interesting question is to test the null hypothesis that the series have the same inertia in terms of probabilities of staying in recession of expansion. For this attempt, we estimate (13) under the assumption that the two variables share the probability of staying in expansions or recessions. The resulting parameter estimates appear in the second column of Table 3, labelled as Model 2. We cannot reject the null that these series share the probabilities of staying in the each of the business cycle phases, with a p-value of 0.62.

Out of the previous exercise, we have learned that the two series share the transition probabilities. However, a more restrictive question should be tested. Do these series share the state of the economy in each period of time? In terms of our proposed notation, the question can be stated as: Is $s_t = v_t$ for each t? If this is the case, we do not need two Markov processes to describe the data because both series move with the same unobserved variable. The model estimated under this assumption is displayed in the third column of Table 3, labelled as Model 3. The problem with this test is that, given that the two models are not nested, there is no standard formal way in the literature to test this hypothesis.

Our proposal for testing this assumption consists on assuming that the business cycle synchronization between IPI and ICI is an average between the case of perfect synchronization and the case of complete independence. As stated in (17), parameter δ determines the proximity to the case of independent cycles. Maximum likelihood estimates for this specification are displayed in the fourth column of Table 3, labelled as Model 4. Looking at this table, we can see that the estimated δ is 0.20, which is close to zero. Hence, the assumption that they share the business cycle is closer to reality than the independence of the business cycles. However, the data generating process is something between Model 2 and Model 3.

Looking at these estimates, the first regime in IPI and ICI (represented by $s_t = 1$ and $v_t = 1$, respectively), is characterized by positive IPI growth rate ($\widehat{\mu}_1 = 0.28$) and positive differences of ICI ($\widehat{\gamma}_1 = 0.63$) so we can interpret this regime as the expansion period. By contrast, the in second regime (represented by $s_t = 2$ and $v_t = 2$, respectively) the average IPI growth rate is negative ($\widehat{\mu}_2 = -0.20$) and the average ICI differences are also negative ($\widehat{\gamma}_1 = -1.19$), so we can interpret this regime as the recession period. In addition, each regime is highly persistent, with (shared) estimated probabilities of one regime to be followed by the same regime of 0.96 and 0.91, respectively.

It is now time to examine if the dynamics of the unobserved state variables match with the European business cycles. Figure 6 reports the filtered probabilities of both series being in state two obtained from Model 4. Looking at this figure, it seems clear that they do not match well with the classical business cycles outlined in Figure 4. Relating these probabilities with the IPI series showed on Figure 1, there exist episodes with high probability of state two that are characterized by low, but not negative growth rates of the IPI series. Examples are the period of high probabilities of state two that appears in the middle of the eighties and the last two periods of high probability of state two in the end of the nineties. The fact that we are finding "too many recessions" compared with the classical dating could be an indication that the unobserved state variables of the bivariate model may refer to growth rate cycles instead of classical cycles.

In order to confirm this fact, we compute the dating of the growth rate cycles. For this attempt, we apply the Bry-Boschan procedure to the industrial production gap, that is obtained by the difference between IPI and its standard Hodrick-Prescott trend. Figure 6 indicates that there is a strong concordance between the growth rate recessions of IPI (shaded areas) and the periods of high filtered probability of both IPI and ICI being at state two. In this case, the bivariate model does not generate false growth rate cycles.

While Figure 6 suggests that the historical inferences of cycle probabilities generated by the Markov-switching filter correspond closely to the sequence of IPI growth rate cycles, this is not enough to validate the utility of ICI to develop business cycle forecasts in real time. We have first to examine wether the CLI issues help the forecasters to palliate the systematic delay in the forecasts that we have detected in the univariate proposal.

In order to address the out-of-sample performance of the bivariate specification, we repeat the same exercise that we did in the univariate case. We estimate the model recursively and compute out-of-sample forecasts using the proposed filter (the one that updates the business cycle probabilities with the ICI series) for the period 1992.01-2004.11. The results are plotted in Figure 7 (red line), along with the in-sample filtered probabilities that had already been plotted in Figure

6 (black line). Both series are much closer to each other than the ones presented in Figure 5. Hence, the systematic delay in the prediction of the future state of the business cycle has been corrected.

Finally, as in the univariate case, we perform a real-time forecasting exercise for the period 1992.01-2004.11. In this scenario, instead of using portions of the last issues of IPI and ICI, we use just the information sets that were actually available at the historical date of each forecast by following the rules proposed in the previous section. As shown in Figure 6 (blue line), the delay in the real-time forecasts of the probabilities of recession that characterized the univariate predictions is also corrected. This result may be interpreted as an empirical support in favor of our proposed filter to forecast probabilities of recessions in the Euro area in real time.

5 Conclusions

For different reasons that go from the need to smooth the data to publication lags, the literature on business cycle analysis has found important difficulties to shed light to identify and forecast the Euro-area business cycle phases in real time. We show that to compute up-to-date forecasts of classical business cycles from the Euro-area Industrial Production series, the major difficulty comes from the fact that this series is issued with a systematic delay of two months. This leads to probability forecasts that come too late to be useful for any real-time forecaster.

In this paper, we propose a novel methodology that overcomes these difficulties. We show that the European Commission Industrial Confidence Indicator, that is closely related with industrial activity, is useful to identify and to forecast the state of the Euro area growth rate cycles. In particular, using the information available up to period t, the indicator allows us to examine the likelihood of the state of the economy in that period and to make reliable forecasts for period $t+1$.

From a methodological point of view, we propose a twofold extension of existing Markov-switching models. First, our method allows us to examine the degree of business cycle synchronization between the industrial production series and the confidence indicator. Second, our proposal allows us to update the filtered probabilities of recession with the timely information contained in the confidence indicator, that is issued with no time delay.

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Table 1. Cross-correlation annual growth rates of IPI and ICI.

	IPI leads-lags						
	-3	-2	-1	0	1	2	3
ICI	0.80	0.83	0.84	0.85	0.82	0.78	0.72

Table 2. Univariate Markov-switching model.

Parameters	Estimates
μ_1	$\underset{(0.05)}{0.22}$
μ_2	$\underset{(0.13)}{-0.24}$
ϕ_1	$\underset{(0.05)}{-0.45}$
σ^2	$\underset{(0.06)}{0.72}$
p_{11}	$\underset{(0.01)}{0.98}$
p_{22}	$\underset{(0.05)}{0.94}$

Notes. Entries refer to estimates and standard errors (in parenthesis) that correspond to the Markov-switching model in Section 4. Sample: 1980.01-2004.11.

Table 3. Bivariate Markov-switching models.

	Model 1	Model 2	Model 3	Model 4
μ_1	0.21 (0.05)	0.22 (0.05)	0.27 (0.06)	0.28 (0.05)
μ_2	-0.21 (0.12)	-0.20 (0.13)	-0.18 (0.08)	-0.20 (0.09)
ϕ_1	-0.45 (0.05)	-0.45 (0.05)	-0.46 (0.05)	-0.47 (0.05)
p_{11}	0.98 (0.01)	0.97 (0.01)	0.95 (0.02)	0.95 (0.02)
p_{22}	0.95 (0.04)	0.92 (0.04)	0.91 (0.04)	0.91 (0.04)
γ_1	0.58 (0.23)	0.53 (0.23)	0.62 (0.20)	0.63 (0.20)
γ_2	-1.15 (0.43)	-1.21 (0.33)	-1.19 (0.25)	-1.19 (0.26)
θ_1	0.20 (0.07)	0.20 (0.07)	0.20 (0.07)	0.20 (0.06)
θ_2	0.21 (0.07)	0.21 (0.07)	0.22 (0.07)	0.21 (0.07)
q_{11}	0.96 (0.02)			
q_{22}	0.91 (0.04)			
σ_{11}	0.72 (0.06)	0.72 (0.06)	0.70 (0.06)	0.69 (0.06)
σ_{22}	1.43 (0.14)	1.45 (0.14)	1.40 (0.13)	1.40 (0.13)
σ_{21}	0.07 (0.07)	0.07 (0.07)	0.03 (0.06)	0.05 (0.06)
δ				0.22 (0.24)
L	-334.37	-334.84	-325.38	-325.04

Notes. These models are different bivariate Markov-switching specifications for IPI and ICI, 1980.01-2004.11. Model 1 assumes two independent Markov-switching models as the underlying law of motion of the data. Model 2 specifies two independent Markov-switching models but sharing the transition probabilities. Model 3 presents the results assuming both series are determined just by one unobserved Markov-switching component. Model 4 assumes that the data generating process is a mixture of Model 2 and Model 3. Last row refers to the log-likelihood. Standard errors are in parentheses.

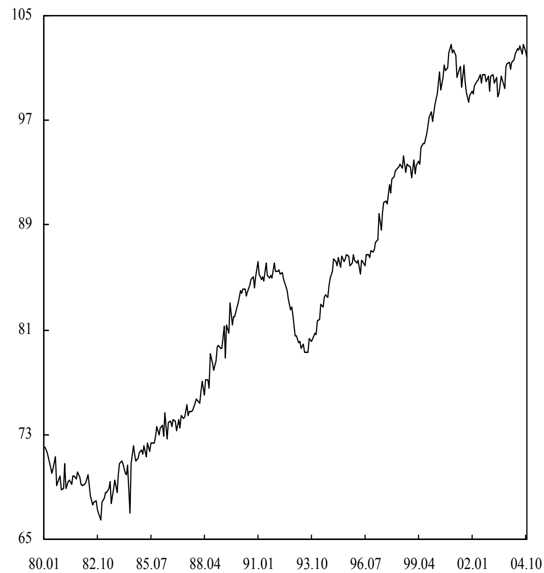

Figure 1: Euro-area Industrial Production Index (IPI), 80.01-04.11.

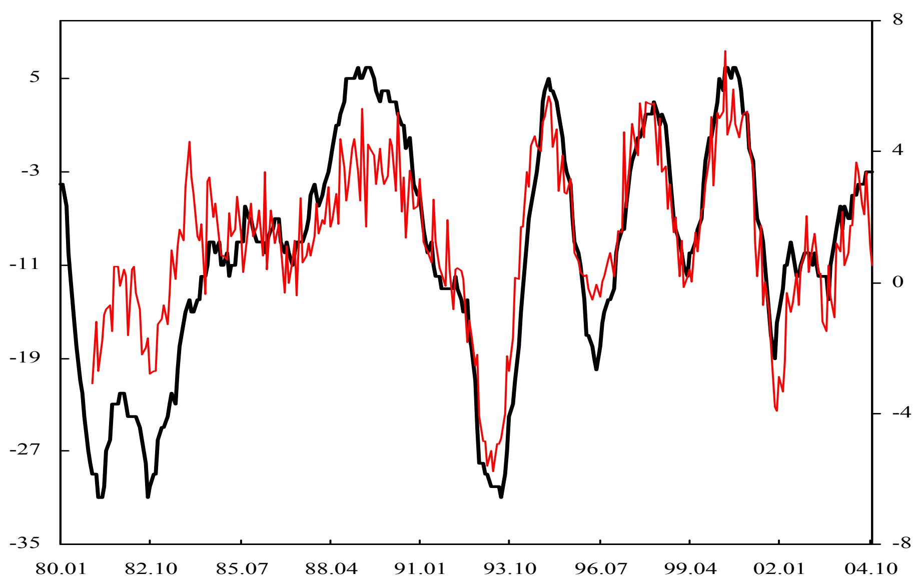

Figure 2: Levels of ICI (black line) and annual growth rates of IPI (red line), 80.01-04.11.

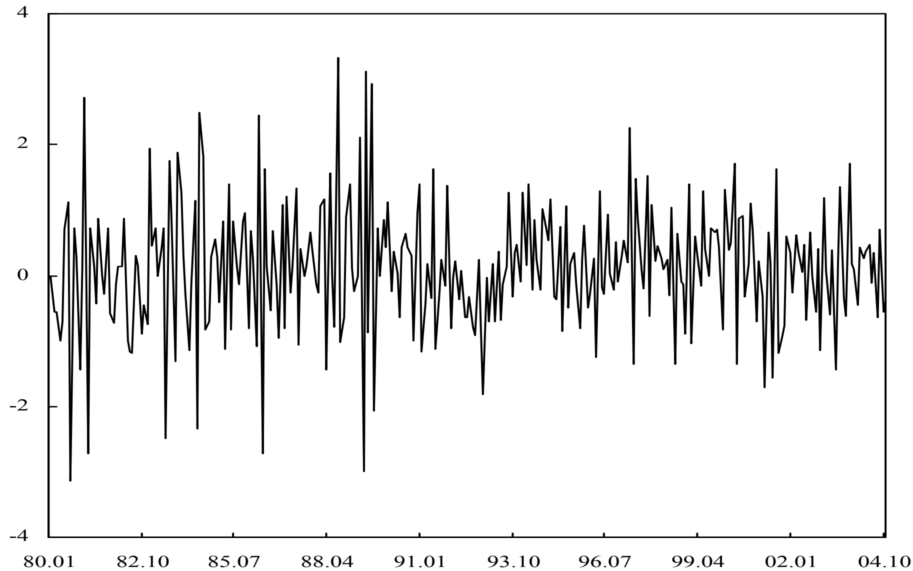

Figure 3: Monthly growth rates of IPI, 80.01-04.11.

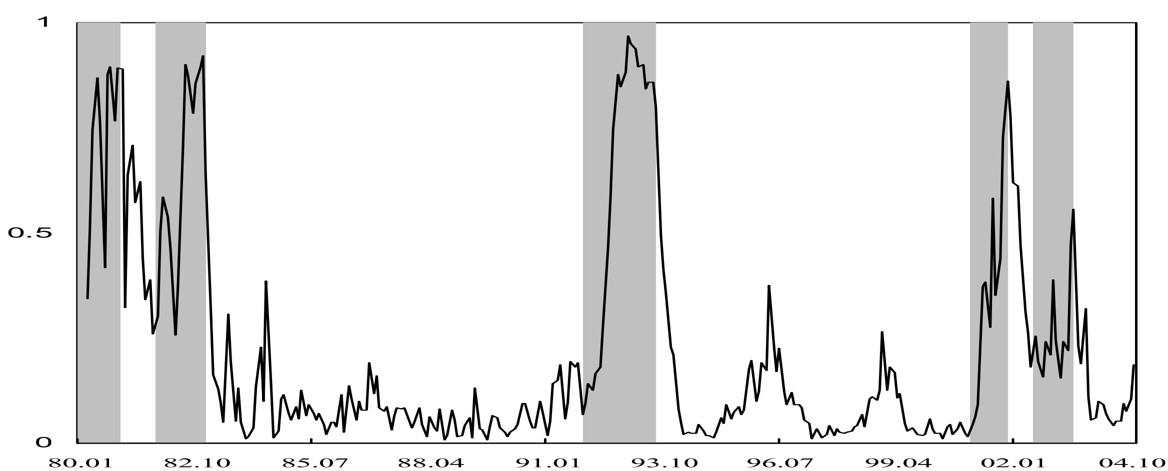

Figure 4: Filtered probabilities of recessions from univariate Markov-switching model applied to IPI. Shaded areas represent classical recessions obtained by applying Bry-Boschan to IPI. Sample: 80.01-04.11.

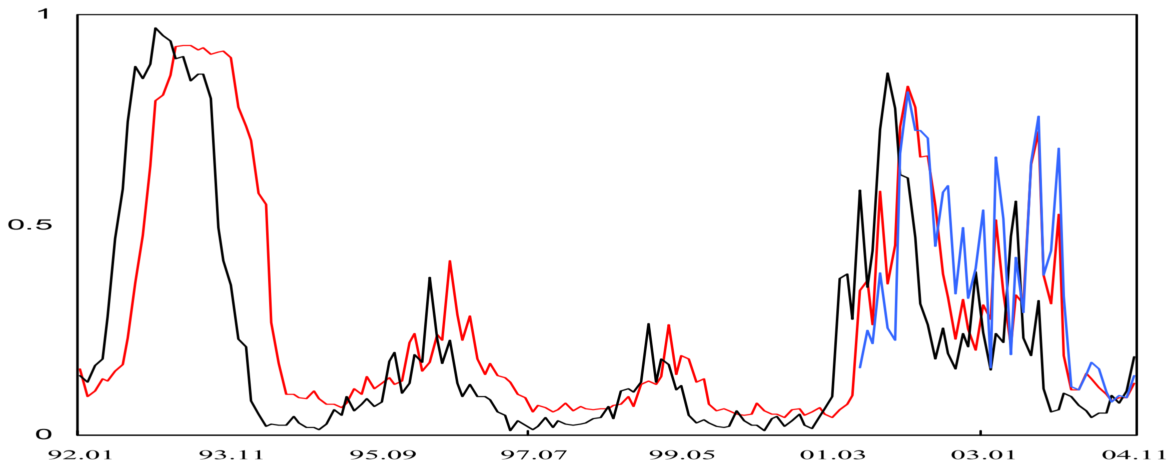

Figure 5: In-sample (black line), three-months-ahead out-of sample forecasts (red line) and three-months-ahead real-time forecasts (blue line) filtered probabilities of recessions from the univariate Markov-switching model applied to IPI. In-sample and out-of-sample probabilities: 92.01-04.11. Real-time probabilities: 01.07-04.11.

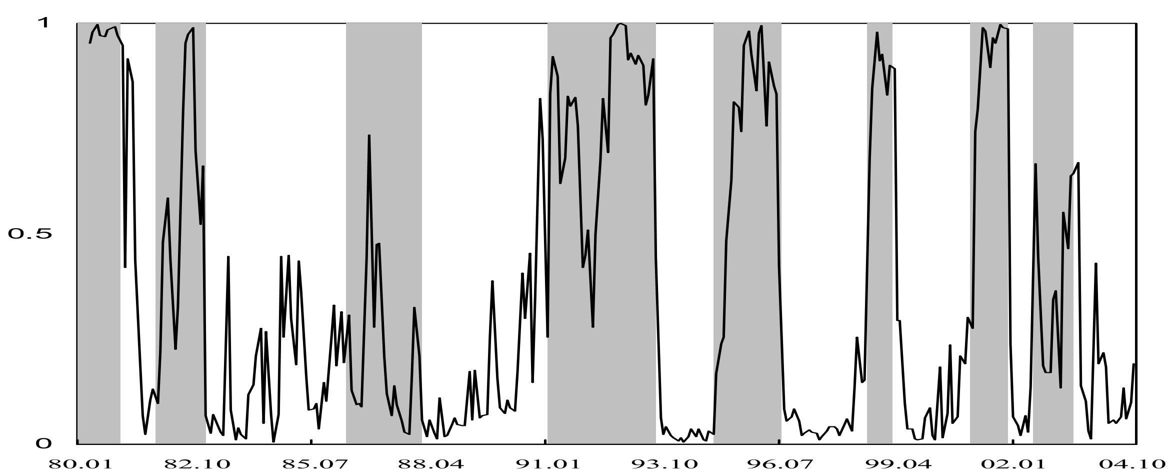

Figure 6: In-sample filtered probabilities of recessions from bivariate Markov-switching model applied to IPI and ICI. Shaded areas represent growth cycle recessions obtained by applying Bry-Boschan to the Hodrick-Prescott cycle of IPI. Sample: 80.01-04.11.

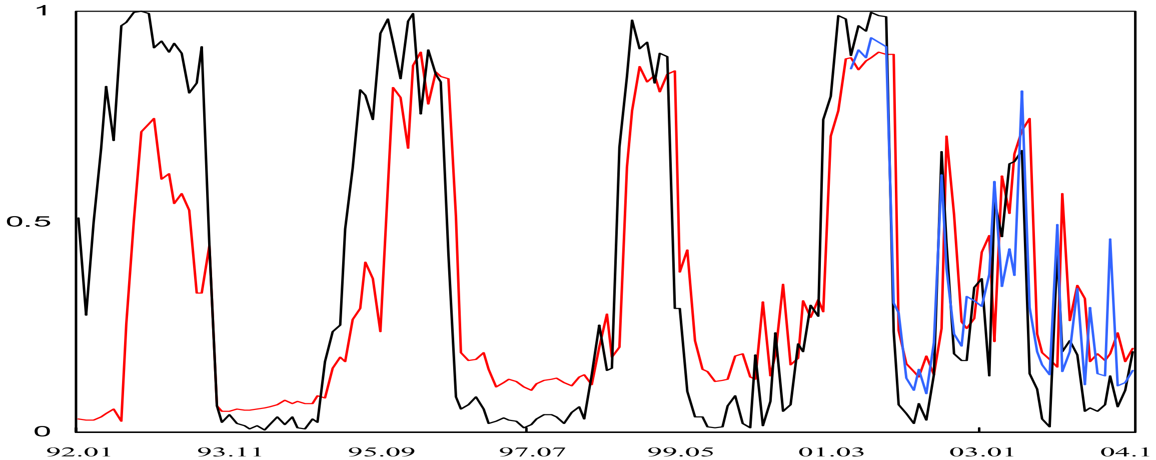

Figure 7: In-sample (black line), three-months-ahead out-of sample forecasts (red line) and three-months-ahead real-time forecasts (blue line) filtered probabilities of recessions from the bivariate Markov-switching model applied to IPI and ICI. In-sample and out-of-sample probabilities: 92.01-04.11. Real-time probabilities: 01.07-04.11.