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Detecting cyclical turning points: the ABCD approach and two probabilistic indicators

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Abstract

The intricate issue of detecting and forecasting turning points of macroeconomic cycles has been one more time well illustrated recently with the global downturn experienced by most countries around the world in 2000-2001. Governments and Central Banks are very sensitive to economic indicators showing signs of deterioration in order to adjust their policies sufficiently in advance to avoid more deterioration or a recession. These indicators require at least two qualities: they must be reliable and they must provide a readable signal as soon as possible.

In this paper we first discuss the concept of detection and propose the ABCD strategy of the COE to identify the relevant cyclical turning points. Second, we introduce a couple of indicators able to nowcast and to forecast those turning points. Both indicators are probabilistic and are based on two different approaches. The first one is computed by using the turning point detection algorithm of Neftçi (1984) and aims at forecasting the fluctuations of the growth cycle. The second one is grounded on the Markov-Switching model proposed by Hamilton (1989) and is used to detect peaks and troughs of the classical cycle in real time. The paper will review the performance of those indicators which have been disseminated into the public by the COE since 1996. The analysis of those leading and coincident indicators will focus particularly on the United States and the Eurozone cyclical turning points.

Key Words: turning point, ABCD approach, probabilistic indicators, forecasting, nowcasting, cycle.

JEL Classification: C32, C51, E32

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Introduction

There is a long tradition of analysis and identification of economic cycles, mainly in the United States, including the analysis and identification of turning points since the seminal work of Burns and Mitchell (1946). Governments and Central Banks are very sensitive to economic turning points indicators showing signs of deterioration in order to adjust their policies sufficiently in advance to avoid more deterioration or recession. Also, private actors are sensitive to early signals of economic upturns or downturns in order to improve decision making.

The detection of turning points faces the problem of using data in real time with the difficult issues of edge effects and data revision. It can be thought of as a nowcasting challenge. A turning point may be considered as an event modeled as a binary variable. In this sense, the detection is the probability estimation of the event with an attached decision rule. In this paper, we introduce a couple of indicators able to nowcast and to forecast those turning points. Those indicators require at least two qualities: they must be reliable and they must provide a readable signal as soon as possible.

The first section discusses some useful concepts in the study of macroeconomic cycles and introduces the ABCD approach used by the Centre d'Observation Economique (COE). The second section presents two probabilistic indicators developed by the COE[1] in order to detect in real time the different points of the ABCD approach. In the last section, those methods are applied to the detection of the US and the Eurozone cyclical turning points.

1 Detecting cyclical turning points: the ABCD approach

1.1 The concept of detection

The concept of detection is not commonly used in statistics or in economics. It relates etymologically to the research of an object or a phenomena which is "hidden", like the use of a Geiger device to detect radioactivity. This definition can be generalized to statistics: the detection relates to the research or estimation of a "hidden" event. Under this definition, the detection of a turning point (TP hereafter) is strictly the research and the identification of a TP which has just occurred or which is happening in the present time. However, a wider vision of the TP detection issue may include, besides the TP identification in real time, the *ex post* dating since, in the past, TPs,

[1] These indicators are released monthly on the COE web site (www.coe.ccip.fr)

even not “hidden”, are not clearly observable and need to be estimated. Also, a more general definition could include the detection of coming TPs, *i.e.* the predictions of TPs in the short term. The present document will focus on the two last aspects: TPs detection and prediction. Let us review some specific issues when successively identifying past, present and future TPs:

1.1.1 Detecting past turning points: dating the cycles (turning points chronology)

In the United States, the National Bureau of Economic Research’s Business Cycle Dating Bureau’s Committee[2] is widely recognized as the authority for determining the peaks and troughs of the classical business cycle. However, there is a substantial delay before the announcement of those dates. For example, the July 1990 peak was announced in April 1991 and the March 1991 trough only in December 1992. More recently, the March 2001 peak was announced in November 2001.

In other countries, there is no official dating of the classical business cycle. The main issue is the definition of criteria used to recognize an economic fluctuation as a cycle. The Conference Board[3] refers to the 3D’s rule (diffusion, deepness, duration). If dating the classical business cycle is not so easy, then dating the growth cycle is even more difficult since the series must first be de-trended. Moreover, the way the series is seasonally adjusted (directly or indirectly for geographic aggregates like Eurozone indicators) and previously adjusted for calendar effects may impact on the datation (see for example Astolfi *et al.*, 2001 and Lommatzsh and Stephan, 2001). It may therefore happen that different estimates are available on the market: we refer, for instance, to Anas (2000), Krolzig (2001) or Artis *et al.* (2002) for Eurozone business cycle datations.

There have been many attempts to create an algorithm which would establish the TPs dates. The most famous one is the Bry and Boschan (1971) procedure still in use in many countries in order to estimate TPs of a series (see, for example, Kim, Buckle and Hall, 1995). Apart from those non parametric approaches, a great number of parametric models has been developed lately, which could be useful to date the TPs of the classical business cycle, based mainly on the Hamilton’s (1989) Markov-Switching model. But a decision rule is still needed to identify the TPs as discussed by Harding and Pagan (2001a, 2001b). In the case of switching regime models, the identification is undertaken with a “natural” decision rule made on estimated smoothed probabilities of the “hidden” regimes (probability higher than 50%). In this respect, a controversy has recently emerged between Hamilton and Harding and Pagan regarding the usefulness of using those sophisticated models *versus* more transparent and simple methods for dating cycles (see also Anas and Ferrara, 2002b, for an empirical comparison of parametric and non-parametric dating methods).

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[2] www.nber.org/cycles

[3] www.conference-board.org

1.1.2 Detecting present turning points: real time detection

If the use of quarterly GDP series may be sufficient to provide a dating of the past TPs, it is clearly not operational in real time. GDP is only available on a quarterly basis with a delay of one to three months, sometimes with significant revisions. Thus, GDP is not a good candidate to assess TPs in real time and the use of other series is unavoidable. A solution is to use a GDP proxy commonly called a coincident index (estimated by use of diverse linear methods). Stock and Watson (1989) were the first to revive consideration on comovement of variables along the cycle by introducing a dynamic factor model in order to extract a common factor. In this case, methods have to be determined to estimate the probability of a TP of this common factor. In this respect, Diebold and Rudebush (1996) proposed to mix together dynamic factor models and regime switching (see also Kim and Nelson, 1998). If no coincident indices are used, other generally non linear methods may directly produce the probability of a TP in real time. For example, the multivariate Markov-Switching Vector Autoregressive (MS-VAR) model proposed by Krolzig (1997) or the univariate Markov-Switching model combined with a probability aggregation method proposed by the COE and developed in this document (see section 2 and Anas and Ferrara, 2002a).

1.1.3 Detecting future turning points: predicting turning points

The timing of the prediction is very important. It is quite difficult to predict TPs in the medium or long term (over 9 months). Even if economic imbalances sometimes make an adjustment plausible or necessary in the future, it is difficult or even impossible to predict when this adjustment will occur. In the short term, however, the TP prediction is, or should be, easier, except for important and sudden external shocks (like, for instance, the September 11th terrorist attack in New-York). Indeed, foreseeable changes in economic policies should not reverse the course of economic development due to the impact delay of these measures and the inertia of economic evolution. This is why it may be useful to complement macroeconomic modeling with short-term leading or coincident indicators.

We may distinguish two different ways to predict a TP:

1. A leading index is elaborated based on various leading series through simple linear transformations (for example, indices computed by the OCDE or by the Conference Board) or through more sophisticated methods (for example, indices computed by Stock and Watson (1993) by using dynamic factor models). Then, a method is applied either to compute a turning point probability (Stock and Watson (1993) algorithm or Markov-Switching models) or to emit an *ad-hoc* signal (for example, the Conference Board). However, the average lead has to be known.

2. A second approach consists in detecting the TPs of various leading economic time series and aggregating the corresponding probabilities in order to provide a signal for a future TP (Anas, 1997, and Anas and Nguiffo-Boyom, 2001). As an

alternative, a multivariate Markov-Switching model could be applied directly to the set of leading time series.

1.2 The ABCD approach

First, there is a question of definition. In particular, the « business cycle » may either be the « generic » term for economic fluctuations or refer to the fluctuations of the level of the series. In the academic literature, this difference is rarely made. In the present study we will distinguish the classical business cycle from the growth cycle (the deviation from trend) and we refer to Figure 1 for the three possible representations: classical cycle (in level), growth cycle (deviation to trend) and growth rate cycle. Various TPs are associated with those cycles with an automatic chronology. Points α and β are the extrema of the growth rate cycle. Points B and C are the extrema of the classical cycle, while points A and D are the extrema of the growth cycle.

Our ABCD approach is based on the two following principles:

a. The TP detection issue must be considered as the progressive follow-up of the cyclical movement. Instead of concentrating on one TP (a peak for example), it is more informative to consider that the downwards movement will first materialise in a peak of the growth rate (point α), then, if the slowdown gains in intensity, the growth rate will decrease below the trend growth rate (point A) and finally, if it is really getting worse, the growth rate will become negative (point B) provoking a recession.

b. We consider that the cycle in growth rates is not a good indicator of future economic cycles. First, it is subject to erratic movements as well as to very short-live fluctuations due to transitory events (strikes for example) producing false alarms and making the peak lead extremely unstable, which remove any practical interest for the signal. This is why we consider that the detection of α and β is not always useful and neither informative, even if practitioners, market economists or officials often use it for their diagnosis. We prefer to detect points A and B which announce respectively downward phases of growth cycle and classical cycle. However, if the slowdown does not gain in intensity to become a recession, then point A will not be followed by point B. We call the follow-up of those points (A and B for peaks and C and D for troughs) the ABCD strategy for TPs analysis. We will concentrate on the detection and prediction of those TPs.

As an illustration, we present in Figure 2 the TPs chronology during the US 1990-91 recession. It is worthwhile to observe that point α is reached at the end of 1987, two years before point A. This large advance proves that this kind of TP is not reliable to predict cyclical movements. Figure 3 presents the TPs chronology during the 1992-93 recession in the Eurozone. We observe here the difficulty to locate the point α.

Figure 1 - Evolution of cycles and ABCD approach

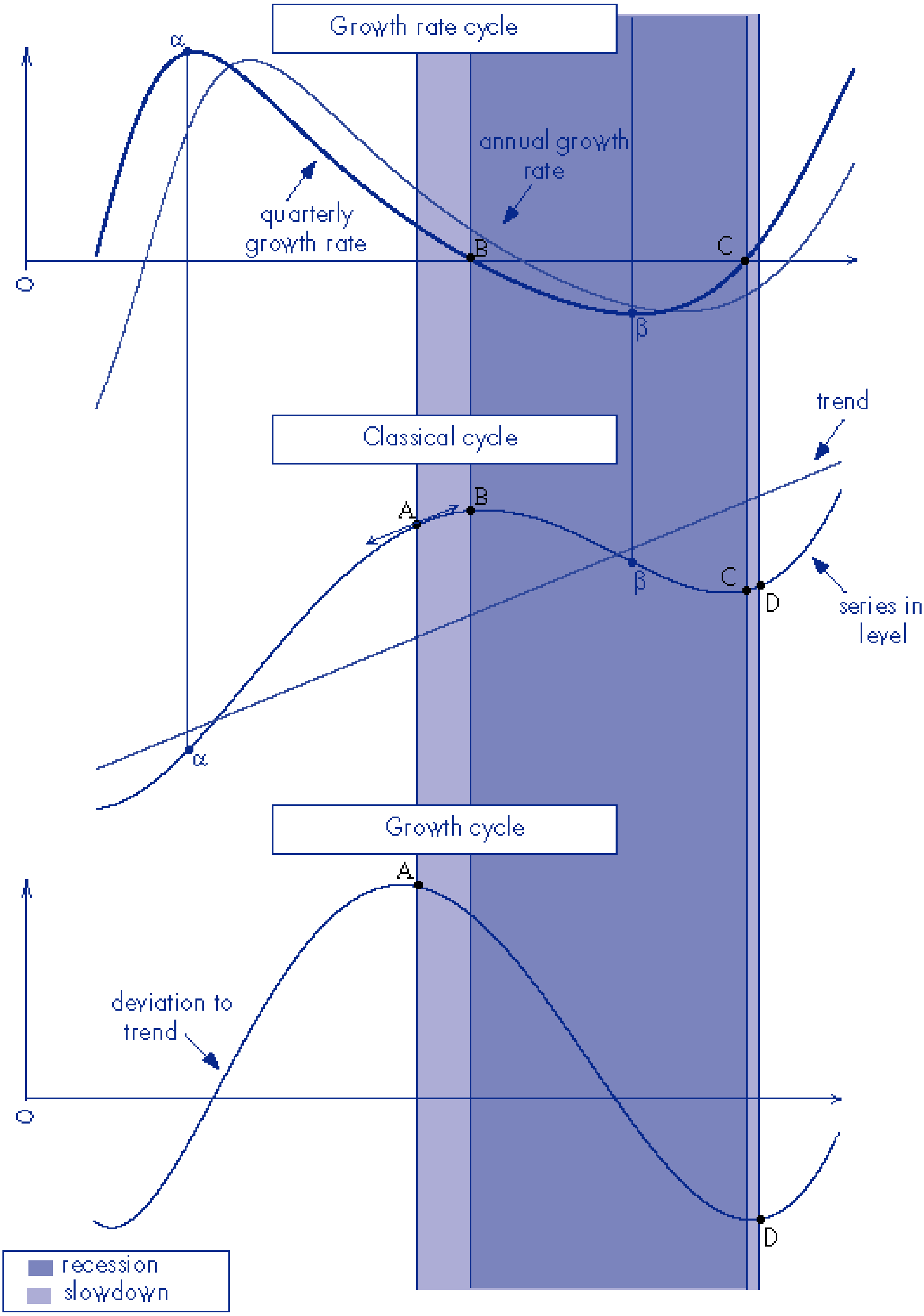


Figure 2 - Evolution of the US cycle over the 1986-1992 period and the ABCD approach

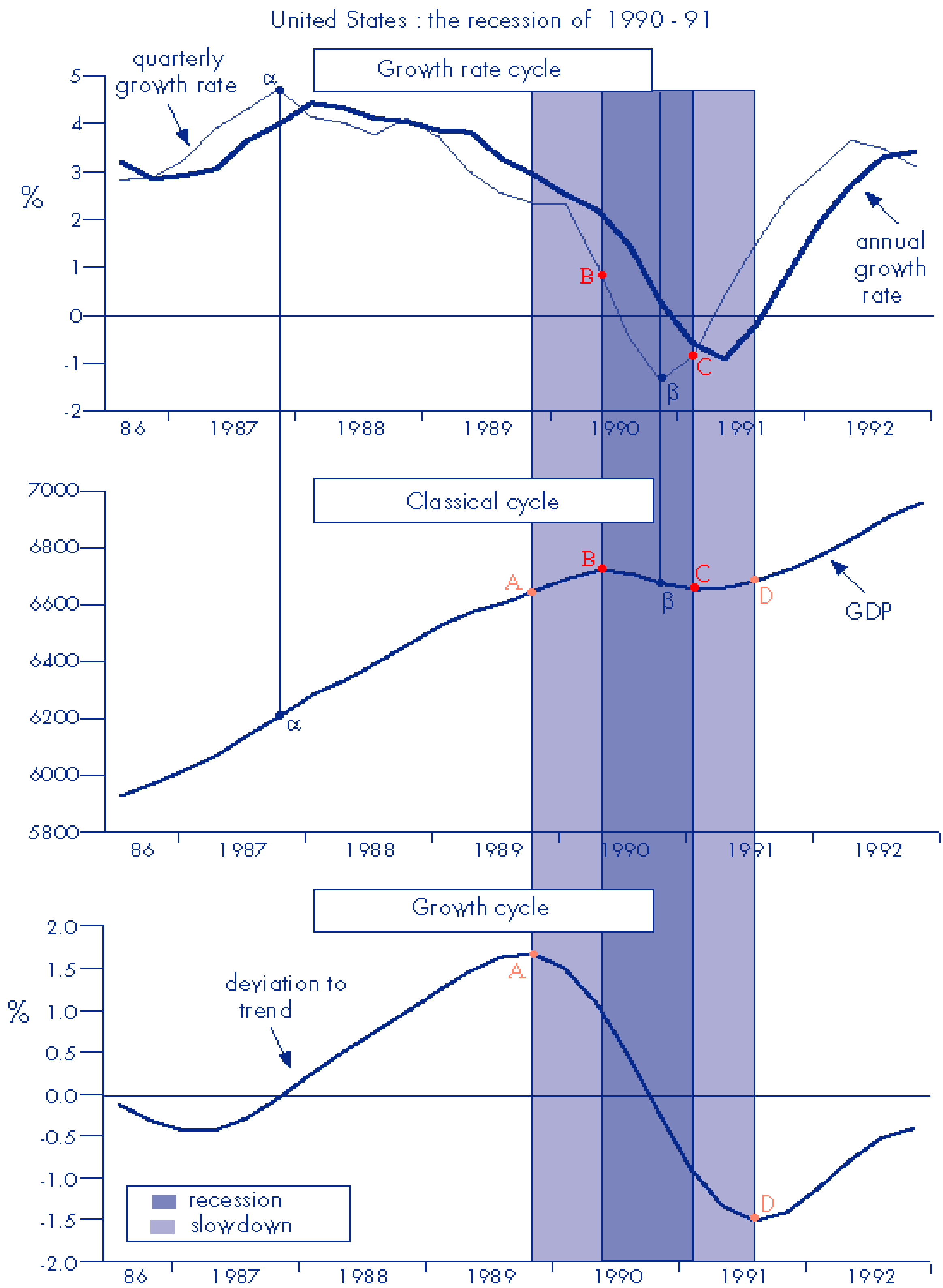
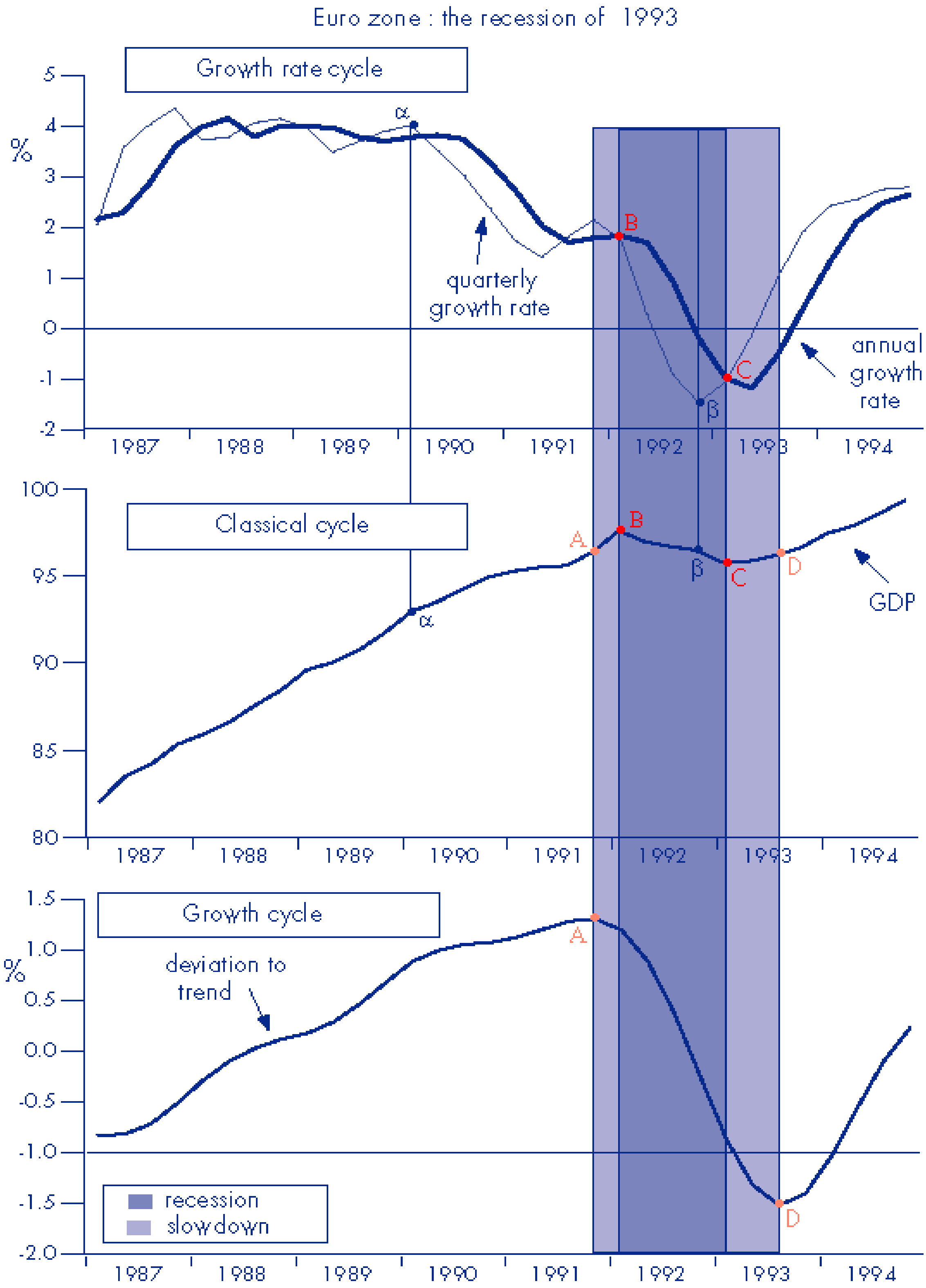


Figure 3 - Evolution of the Eurozone cycle over the 1987-1994 period and the ABCD approach



2 A couple of probabilistic indicators

This section introduces a couple of original economic indicators able to detect in real time and predict macroeconomic TPs. Both indicators are probabilistic and based on two different approaches. We first introduce a leading probabilistic indicator of the growth cycle TPs (points A and D) based on the Neftçi's (1982) approach, then a coincident probabilistic indicator of the business cycle TPs (points B and C) based on the univariate Markov-Switching model proposed by Hamilton (1989). In both cases, an aggregation method has been developed by the COE to combine the probabilities given by the various components of these probabilistic composite indicators.

The distinction between real-time detection and prediction is somewhat arbitrary. Let's take the example of a hiker in a mountain. If he hikes at night, he will never know when he reaches the peak of the mountain until he sufficiently walks down. It is exactly the same question for an economic peak. The probability of a peak will reach a significant level well after the effective occurrence of this peak. The delay will be short if the indicators we used to detect the peak are reactive to a turning point or even lead the global turning point.

If we can find stable leading indicators for the growth cycle TPs, we are not sure that we can find stable and reliable indicators for business cycle TPs, at least for the peaks. We are never sure that a slowdown will turn into a recession because quick and adequate policy measures, mostly fiscal and monetary, may be sufficient to avoid a recession. This is why it is so difficult to predict recessions, as underlined in many studies. What is however possible is to quickly detect the recession by means of quasi-coincident indicators. It is less difficult to predict the exit of a recession, maybe because of the property of duration-dependence pointed out by Diebold *et al.* (1993).

The choice of the right method is a tricky question. Many studies have tried to compare the performance of Probit models, Markov-Switching models and linear models. We think that a method which is appropriate for the detection of points A and D of our ABCD approach, may not be efficient for the detection of points B and C. This is related to the degree of volatility and smoothness of the cycle. We found that Markov-Switching models work better on classical than on growth cycles. On the contrary, the Neftçi's approach seems more indicated for the growth cycle.

2.1 A leading probabilistic indicator of the growth cycle

This leading probabilistic indicator is computed by using the turning point detection algorithm of Neftçi (1982) applied to a set of leading time series and aims at forecasting the fluctuations of the growth cycle. First, we present the Neftçi's sequential algorithm.

2.1.1 The Neftçi turning point detection method

The aim of this algorithm is to detect cyclical turning points in real time, which mark the beginning or end of a cyclical downturn. For this purpose, Neftçi (1982) developed a stochastic model for macroeconomic time series, based on the ingenious work of Shiryayev (1978), to detect probability changes over processes. It is based on the assumption that the series behaves differently depending on the downward or upward regime in which it evolves.

The sequential algorithm

Let us consider the stochastic process $(X_t)_t$, where, for all t, X_t represents the observation on increments of the macroeconomic time series considered. According to the finite sample $(x_t)_{t=1,\ldots T}$, we will infer the occurrence or non-occurrence of a change in the economic regime. Let Z (respectively Z') be an integer-valued random variable denoting the date following a peak (respectively trough)[4]. Let us suppose $Z = i$ (or $Z' = i$), for $i = 2,\ldots,t$, with *T ³ t ³ 2*, which means that a turning point has appeared between dates i-1 and i. With the two following assumptions, we will be able to characterize the cumulative distribution function.

- *Assumption 1*. The probability distribution of $(X_{i+j})_{j=0,1,2,\ldots}$ is different and independent of the distribution of $(X_{i-j})_{j=1,2,\ldots}$.
- *Assumption 2*. The realizations of the stochastic process $(X_t)_t$ between and within regimes are independent.

If we consider that a peak appeared between dates i-1 and i, *i.e.* $Z = i$, with *T ³ t > i ³ 2,* then we get:

$$P(X_1 \le x_1, \ldots, X_i \le x_i, \ldots, X_t \le x_t) = F^1(x_1, \ldots, x_{i-1}) F^0(x_i, \ldots, x_t)\,, \quad (1)$$

where $F^1(.)$ and $F^0(.)$ are the two cumulative distribution functions for the upward and downward regime respectively. Generally, $F^1(.)$ and $F^0(.)$ are chosen to be Gaussian cumulative distribution functions. The variable Z is not directly observable. Based on historical values of $(X_t)_t$, we intend to determine, at any date t, whether a turning point has already occurred $(Z \le t)$ or not $(Z > t)$.

Suppose that the practitioner has gathered some experience from the study of past turning points and has subjectively defined *a priori* probabilities. Let T_t be the *a priori* transition probability of the change from upward to downward regime, *i.e.*

[4] We suppose that Z refers to the date of peaks, but the results are diametrically symmetric for troughs.

$$T_t = P(Z = t \mid Z > t-1)\ , \tag{2}$$

and T_t' the *a priori* probability of the change from downward to upward regime, *i.e.*

$$T_t' = P(Z' = t \mid Z' > t-1)\ , \tag{3}$$

Let us note $\bar{x}_t = (x_1, \ldots, x_t)$ the historical values of *(X_t)* since the last trough. Given $\bar{x}_t$, let us evaluate at any date *t* the probability of occurrence of a turning point in the recent past. Let $P_t\,(P_t')$ denote the *a posteriori* probability of occurrence of a peak (trough) at or before date *t* based on observations $\bar{x}_t$, i.e:

$$P_t = P(Z \le t \mid \bar{x}_t)\ , \tag{4}$$

Thus, using Bayes' rule, we get:

$$P_t = \frac{P(\bar{x} \mid Z \le t)P(Z \le t)}{P(\bar{x}_t)}\ . \tag{5}$$

and by extension:

$$P_t = \frac{P(\bar{x}_t \mid Z \le t)P(Z \le t)}{P(\bar{x}_t \mid Z \le t)P(Z \le t) + P(\bar{x}_t \mid Z > t)P(Z > t)}\ . \tag{6}$$

Thus, by using this previous equation, the following Neftçi's formula is recursively derived (for peaks $(t \ge 1)$):

$$P_t = \frac{\left[P_{t-1} + (1 - P_{t-1})T_t\right] f^{\,0}(x_t)}{\left[P_{t-1} + (1 - P_{t-1})T_t\right] f^{\,0}(x_t) + \left[(1 - P_{t-1})(1 - T_t)\right] f^{\,1}(x_t)}\ , \tag{7}$$

where $f^{\,0}(.)$ is the density function of *(X_t)$_t$* during a downward regime and $f^{\,1}(.)$ during an upward regime, and where $P_1 = 0$.

We can see from equation (7) that Neftçi's formula allows to compute the *a posteriori* probability of occurrence of a turning point, incorporating current information into the posterior probabilities estimated over previous periods. As described in Niemira (1991): "(...) *the Neftçi method accumulates probabilities from the start of the previous turning point. This particular dynamic characteristic of the Neftçi method is a major improvement over its predecessors*." This is an advantage over, for instance, a Probit approach which has poor dynamic contents and may therefore be less powerful if the lead times are unstable.

The transition probabilities T_t and T'_t in the Nefçi formula indicate the degree of persistence of the process. For instance, Hamilton (1989) assumes that these probabilities are constant overtime. However, recent works (see, for instance, Filardo, 1994 or Diebold, Lee and Weinbach, 1994) propose time-varying transition probabilities as a function of the phase age or based on a leading indicator. Neftçi (1982) considers that the transition probabilities are non constant and estimates them from past experience.

Parameter estimation

The parameters of the probability distribution function of $(X_t)_t$ are estimated over samples made of upward and downward regimes. The *a priori* transition probabilities denoted T_t' and T_t must also be estimated.

The first step consists in an *a priori* dating of the cycle peaks and troughs (classical business cycle or growth cycle) of $(X_t)_t$. The data are split into upward and downward regimes in order to obtain two separate samples made respectively of observations belonging to upward and downward regimes. This *ex-ante* determination of peaks and troughs is done visually or by using automatic techniques based on *ad-hoc* rules. For example, in Artis *et al.* (1995a), a method called ALT is designed and applied to the reference series to verify its performance. In Artis *et al.* (1995b), a variant of the maximum distance criterion used in discriminant analysis is developed. Those techniques of « dating » a cycle are numerous (see, for example, Harding and Pagan (2001a) for an extensive review).

In the second step, the parameters of the probability density functions $f^0(X_t)$ and $f^1(X_t)$ and the *a priori* probabilities (T_t' and T_t) must be estimated. A few assumptions are needed to estimate these parameters.

The probability density functions are estimated using an empirical distribution of $(X_t)_t$ or by fitting a tabulate density function to observations of $(X_t)_t$ in each regime. In Neftçi's paper (1982), the density functions $f^0(X_t)$ and $f^1(X_t)$ are estimated by using the empirical frequency distribution of (X_t) during upward and downward periods. On the contrary, in the papers of Diebold and Rudebush (1989, 1991), Artis et *al.* (1995a) and Anas (1997) a Normal distribution is fitted. In Diebold and Rudebush, the densities are calculated first in a static way (1989) then dynamically (1991) to have an *ex ante* or real-time evaluation of the performance of the famous CLI index. In Artis *et al.* (1995b) a similar rolling-estimation technique is used.

Concerning *a priori* transition probabilities T_t' and T_t, we may suppose that the probability of a turning point is an increasing function of the age of the regime. In this case, *a priori* transition probabilities are duration-dependent, as supposed in the paper of Neftçi (1982). However, in Diebold and Rudebush (1989, 1991), evidence was presented that expansions and contractions in postwar US were not characterized by duration dependence. In our study, the assumption of overtime constant transition probabilities is used, as is the case in most of applied studies. Thus, the *a priori* estimation of transition probabilities is done by using the average duration of upward and downward regimes in the past.

Lastly, P_t (respectively P'_t) is initialized to 0 for the first observation, and more generally when a downward (respectively upward) regime ends.

2.1.2 Construction of the leading probabilistic indicator

Classical leading composite indices are often constructed as a weighted average of normalized leading indicators. The COE approach is different (see Anas (1997) and Anas and Nguiffo-Boyom (2001)). We start with the idea that the combination of statistical information is easier to perform in the space of probabilities than in the space of time series. Time series are often difficult to compare because of their different nature (opinion surveys and real values or rates and levels) and of their different frequencies. We therefore prefer to compute the probability of a future signal by using a set of leading indicators and find a way to aggregate the probabilities of their signals.

Aggregation procedure

Suppose we select N leading time series $(X^k_t)_t$ for $k=1,\ldots,N$ (see the next subsection for the choice of the series). For $k=1,\ldots,N$, we associate a latent variable $(S^k_t)_t$ such that, for all t, $S^k_t = 1$ if a turning point of the series (X^k_t) has occurred before date t and $S^k_t = 0$ otherwise. Moreover, consider a forecast horizon h, we note $(R_t)_t$ the variable such that $R_t = 1$ if a cyclical turning point of the global economy occurs between t and $t+h$ (a peak for example) and $R_t = 0$ otherwise. We want to estimate the value $P(R_t = 1)$, for all t.

For each leading time series $(X^k_t)_t$ the probability of an upcoming cyclical turning point can be developed by using the bayesian formula as follows:

$$P(R_t = 1) = P(R_t = 1 | S_t^k = 1) P(S_t^k = 1) + P(R_t = 1 | S_t^k = 0) P(S_t^k = 0)\,. \quad (8)$$

The two risks[5] associated with this approach are, first a_t^k the risk of a false signal (or type I error), defined as:

$$a_t^k = P(R_t = 0 | S_t^k = 1)\,, \quad (9)$$

[5] Both risks are widely discussed in the seminal article of Okun (1960).

and second, b_t^k the risk of missing the cyclical turning point[6] (or second type error), defined as:

$$b_t^k = P(R_t = 1 \mid S_t^k = 0) \,. \tag{10}$$

We assume that both risks are constant overtime, *i.e.* for all *t;* $a_t^k = a^k$ and $b_t^k = b^k$. An estimate of $P(R_t = 1)$ is $P_k(R_t = 1)$ defined by:

$$P_k(R_t = 1) = (1 - a^k)P_t^k + b^k(1 - P_t^k) \,, \tag{11}$$

$$= b^k + (1 - a^k - b^k)P_t^k \,, \tag{12}$$

where a^k and b^k are empirical estimates and where P_t^k is the *a posteriori* probability of an upcoming cyclical turning point given by the Nefçi's formula (equation (7)) applied to the variable $(X^k{}_t)_t$.

In the same way the diffusion indices are computed, we may consider a kind of diffusion index of these probability estimates $P_k(R_t = 1)$ given by equation (12) through an aggregation procedure over the *k* leading series:

$$\frac{1}{N}\sum_{k=1}^{N}\left[P_k(R_t = 1)\right] = \frac{1}{N}\sum_{k=1}^{N} b^k + (1 - a^k - b^k)P_t^k \,, \tag{13}$$

$$= \overline{b} + \sum_{k=1}^{N} \frac{\left(1 - a^k - b^k\right)}{N} P_t^k \,. \tag{14}$$

Lastly, we decide to normalize the formula (14) so that it would equal 1 as soon as all *a posteriori* probabilities equal 1. The final index we use, called IARC (in French : “Indicateur Avancé de Retournement Conjoncturel”), which is an estimate of $P(R_t = 1)$ for all *t*, is such that:

$$IARC = \frac{\overline{b}}{1 - \overline{a}} + \sum_{k=1}^{N}\left[\frac{\left(1 - a^k - b^k\right)}{\sum_{k=1}^{N}\left(1 - a^k\right)}\right]P_t^k \,, \tag{15}$$

where $\overline{a}$ and $\overline{b}$ are the averages of the type I and type II risks.

6 Either because the leading indicator missed the general economic TP or because the signal was too late.

Note that the minimum value of the IARC indicator is not 0 but $\bar{b}$ / (1 - $\bar{a}$), because there always exist a risk of missing the turning point. For communication purposes, the IARC indicator is put negative when in search for a trough (see section 3).

Choice of the series

We use several criteria to select the leading components of the IARC indicator. As outlined by the OECD, an economic rationale is needed to avoid taking only the statistical performance into account over a period of time. Also, the series need to be available for a long period of time to allow for estimation. But the main selection criterion relates to the length and degree of stability of the operational lead as well as to the intensity of first and second type risks. There is generally a trade-off: when the lead increases, the risks increase at the same time.

2.2 A coincident probabilistic indicator of the business cycle

The coincident indicator of the business cycle we propose is grounded on the Markov-Switching model proposed by Hamilton (1989) and is used in order to detect peaks and troughs of the classical cycle in real time, that is the start and the end of a recession.

2.2.1 The Markov-Switching model of Hamilton (1989)

Markov-Switching models have been introduced in the statistical literature by Hamilton (1989) in order to take into account in modelling a certain type of non stationarity, inherent to some economic or financial time series, that cannot be caught by classical linear models. Having observed that such time series frequently exhibit shifts in mean, the original idea of Hamilton (1989) was to model these non stationary time series by using a piecewise stationary linear process. Precisely, it is often assumed that the observed time series can be approximated by an autoregressive process whose parameters evolve over time. Moreover, the evolution of these parameters is governed by an unobservable variable which in turn follows a first order K-state Markov chain that is independent of past observations on the observed time series. In economics, this unobservable variable, denoted $(S_t)_t$, is often supposed to represent the current state of the economy. Thus, a 2-state Markov chain is generally used in applications, that is, for all t, the time series S_t takes the value 1 when the economy is in expansion and takes the value 2 when the economy is in contraction. We only consider this special case $K=2$ in the remaining and we refer, for instance, to Sichel (1994), Layton and Smith (2000) or Ferrara (2003) for further discussions on the number of regimes.

Specification of the model

The Hamilton Markov-Switching process, $(X_t)_t$, in the case of an AR(p) process, can be given by the following equation:

$$X_t = a_{0,St} + a_{1,St} X_{t-1} + \ldots + a_{p,St} X_{t-p} + \varepsilon_t, \tag{16}$$

where, for $k=0,\ldots,p$, $a_{k,St} = a_{k,1}$ when $S_t = 1$, and $a_{k,St} = a_{k,2}$ when $S_t = 2$ and where $(e_t)_t$ is a white noise process with finite variance s^2.

Moreover, the whole specification of the Markov-Switching model needs the specification of $(S_t)_t$, as a 2-state first order Markov chain. That is, the value of the time series S_t, ,for all t, depends only on the last value S_{t-1}, *i.e.,*for $i,j=1,2,$:

$$P(S_t = j \mid S_{t-1} = i, S_{t-2} = i, \ldots) = P(S_t = j \mid S_{t-1} = i) = p_{ij}. \tag{17}$$

Obviously, the probabilities $(p_{ij})_{i,j=1,2}$ are the *transition probabilities* of moving from one state to the other. In the remaining of this paper, the AR(p) 2-state Markov-Switching model of Hamilton (1989), given by equations (16) and (17), will be denoted a MS(2)-AR(p) process. Interest is also given to the computation of unconditional probabilities of being in a specific state. It can be shown that (see for instance Hamilton (1994)) for $j=1,2,$:

$$P(S_t = j) = (1-p_{jj}) / (2-p_{11}-p_{22}). \tag{18}$$

Lastly, it can be shown that the average length L_j of both regimes, for $j=1,2$, is given by:

$$L_j = 1 / (1-p_{jj}). \tag{19}$$

Parameter estimation

We are now interested in parameter estimation of a MS(2)-AR(p) process defined by equations (16) and (17). Let $(x_1, \ldots, x_T)^t$ be an observed time series with finite sample size T generated by a MS(2)-AR(p) process. We assume that the parameter q to be estimated belongs to a compact space included in R^{2p+5} and q is equal to:

$$\theta = (a_{0,1}, a_{1,1}, \ldots, a_{p,1}, a_{0,2}, a_{1,2}, \ldots, a_{p,2}, \sigma^2, p_{11}, p_{22})^t. \tag{20}$$

The parameter estimation method generally used is the classical maximum likelihood estimation (MLE hereafter) method, based on the assumption that the white noise process $(e_t)_t$ in equation (16) is a Gaussian process. Furthermore, the Markov chain $(S_t)_t$ is supposed to be independent of $e_{t'}$, for all t and t'. The MLE method is somewhat classical in the statistical literature, but in this case the main difficulty stems from the fact that the latent process S_t cannot be observed and has therefore to be estimated, for all dates t. The MLE method aims at finding the parameter q so that the conditional log-likelihood $L(q)$ is maximum, with $L(q)$ expressed as :

$$L(q) = \sum_{t=1}^{T} \log f(x_t / F_{t-1}, q)\,, \tag{21}$$

where, for all t, F_t denotes the vector of observations obtained through date t and where $f(x_t / F_{t-1}, q)$ is the conditional density of the MS(2)-AR(p) model, which can be written as :

$$f(x_t / F_{t-1}, q) = \sum_{i=1}^{2} f(x_t / S_t = i, F_{t-1}, q) P(S_t = i / F_{t-1}, q)\,, \tag{22}$$

where $f(x_t / S_t = i, F_{t-1}, q)$ is the conditional density of x_t, assuming the current state is known for each date t, given by, under the Gaussian assumption, :

$$f(x_t / S_t, F_{t-1}, q) = \frac{1}{\sqrt{2p}\,s} \exp[(x_t - a_{0,St} - \sum_{k=1}^{p} a_{k,St} x_{t-k})^2 / 2s^2]\,, \tag{23}$$

Thus, by using equations (21) to (23), the log-likelihood $L(q)$ can be evaluated for a given parameter q. However, according to equation (22), the evaluation of the conditional log-likelihood $L(q)$ asks for the knowledge of $P(S_t = i / F_{t-1}, q)$, for $i=1,2$. This estimation is computed by using properties inherent to Markov chains: this is the forecast of being in the state i given the information through date $t-1$. This estimated probability $P(S_t = i / F_{t-1}, q)$, for $i=1,2$, is referred to as the *filtered probability* of being in state i. This filtered probability will be saved in output to build our coincident business cycle indicator. Also note that another conditional probability of being in the state i can be computed, given all the available information through date T. This probability $P(S_t = i / F_T, q)$, for $i=1,2$, is referred to as the *smoothed probability* of being in state i, often used in recession dating procedures.

Model extensions

In view of the extensive practical use of Markov-Switching models, more advanced specification of the basic MS-AR process have been developed. For instance, in the classical specification of the model proposed by Hamilton (1989) the transition probabilities are supposed to be constant overtime. That is, in the business cycle framework, as the current phase of the growth cycle ages, the probability of moving to the other phase of the cycle remains the same. However, some authors (Filardo and Gordon (1994), Filardo (1994), Durland and McCurdy (1994) or Diebold, Lee and Weinbach (1994)) pointed out the lack of flexibility of this assumption and proposed an extended Markov-Switching model in which the transition probabilities are allowed to fluctuate over time, referred to as time-varying transition probability (TVTP) Markov-Switching model. In such models, the transition probabilities are supposed to change along the current phase of the growth cycle, according to information variables, such as the age of the current phase of the cycle (duration dependence) or exogenous leading indicators. Moreover, as another extension of this feature, Lam (1997) allows both the mean and the transition probabilities to depend upon the age of the current phase of the business cycle. Beside the papers already quoted, we also refer to Filardo (1998) regarding parameter estimation considerations for TVTP Markov-Switching models.

As another example, multivariate generalisations of the basic MS-AR model have recently been proposed by Krolzig (1997), who introduces vectorial MS-VAR processes, where the conditional stochastic processes are Gaussian classical VAR(p) and the regime-generating process is a Markov chain. Furthermore, Krolzig (1997) allows the observed process to be cointegrated, by considering Markov-Switching vector equilibrium correction models referred to as MS-VECM models.

As a further extension to the multivariate framework, we can also quote the work of Diebold and Rudebush (1996) who aims at modeling simultaneously the main two stylized facts of the business cycle as defined by Burns and Mitchell (1946), namely (i) comovements among economic variables through the cycle, and (ii) non linearity in the evolution of the business cycle. To reach that goal, Diebold and Rudebush (1996) developed a multivariate dynamic factor with regime-switching (see also Kim and Nelson (1998) for parameter estimation issues).

2.2.2 Construction of the coincident probabilistic indicator

We now describe the way used to build our coincident probabilistic indicator, starting from the filtered probabilities given by the Markov-Switching model applied to the increments of diverse carefully chosen time series (see also Anas and Ferrara, 2002a).

Aggregation procedure

The aggregation procedure is basically the same as the one developed to build the leading probabilistic IARC indicator in section 2.1.2. Let us assume we select N coincident time series $(X^k_t)_t$, for $k=1,\dots,N$ (see the next subsection for the choice of the series). For $k=1,\dots,N$, we associate a latent variable $(S^k_t)_t$ so that, for all t, $S^k_t = 1$ if the series X^k_t belongs to a low regime corresponding to a recession regime and $S^k_t = 0$ otherwise. Moreover, we define the variable $(R_t)_t$ so that $R_t = 1$ if the economy is in recession and $R_t = 0$ otherwise. We want to estimate $P(R_t = 1)$, for all t, which will constitute our recession indicator.

Just as in subsection 2.1.2, for each coincident time series $(X^k{}_t)_t$, the probability of a recession can be developed by using the bayesian formula given by equation (8). The two risks a^k and b^k associated with this approach are respectively the risk of a false signal (type I error) and the risk of missing the business cycle turning point (type II error), given respectively by equations (9) and (10). However, in this case, we generally get $P(R_t = 1 / S^k{}_t = 0) = 0$, *i.e.* recessions are never missed. This is understandable insofar as a recession is a main macroeconomic event widely diffused all over the series. Thus, we estimate $P(R_t = 1)$ by $P_k(R_t = 1)$, for all t, defined by :

$$P_k\,(R_t = 1) = (1 - a^k)\,P_t^k\ , \tag{24}$$

where a^k is an empirical estimate of the type I error supposed to be constant overtime and where P_t^k is the filtered probability of being in recession provided by the Markov-Switching model applied to the variable $(X^k{}_t)_t$.

Lastly, just as for the IARC indicator, we aggregate the probabilities estimates $P_k(R_t = 1)$ given by equation (24) and we normalize the resulting index in order to get our final index (called “Start-End Recession Index”, or SERI), given by:

$$SERI = \sum_{k=1}^{N}\left[\frac{\left(1 - a^k\right)}{\sum_{k=1}^{N}\left(1 - a^k\right)}\right]P_t^k\ . \tag{25}$$

Choice of the series

One of the main issues of this kind of indicator is the way to choose the different components to be included. Indeed, we search for series with a strong persistence, because volatility can lead unreliable signal, as well as an ability of reaction in case of recession, to provide a signal as soon as possible. For instance, regarding the United States, the series considered by the Business Cycle Dating Committee of the NBER (industrial production, employment, real income and wholesale-retail sales) seem to be potential candidates. These latter series are also integrated in some other economic composite indicators (see for instance Stock and Watson (1993)). Moreover, as our aim is to develop a monthly indicator to detect recession, the series considered have to be sampled on a monthly basis. Therefore, series such as GDP or Eurozone employment cannot be included in the indicator.

In order to discriminate among the huge set of economic monthly time series available in data bases, we considered a criterion able to measure the goodness of recession real-time detection of the series. The chosen criterion is the quadratic probability score (QPS) of Brier (1950), suggested for example by Diebold and Rudebusch (1989), and defined as follows:

$$QPS = \frac{1}{T}\sum_{t=1}^{T}(R_t - P_t)^2 \ , \qquad (26)$$

where, for $t=1,\ldots,T$, $(P_t)_t$ is the estimated filtered probability to be in recession stemming from the Markov-Switching model applied to a given variable and $(R_t)_t$ takes for value 1 during recession phases and 0 during expansion phases, according to a reference datation chronology. Regarding the United States, we refer to the well known NBER datation chronology provided by the Business Cycle Dating Committee. Regarding other countries, we establish our own reference datation by examining peaks and troughs of the business cycle and by summing up various studies on the topic.

It is worthwhile to note that macroeconomic series linked with employment are the most informative in terms of recession detection. For instance, regarding our US indicator, two series out of four are related to employment: the unemployment rate and the help-wanted advertising index released by the Conference Board. This is coherent with the observation made by Hall (2002), chairman of the Business Cycle Dating Committee, who notes that “employment is probably the single most reliable indicator” of recession.

However, it turns out that employment-related series are often lagged versus the reference business cycle. In order to reduce this lag, we add other components to our indicator, such as the industrial production index, which is more advanced but provides some false signals. Indeed, the industrial production index is indicative of an industrial recession which occurs more often than a global recession. However, this phenomenon is taken into account by the aggregation procedure which gives less weight to these series.

3 Detection of the US and Eurozone cyclical turning points

In this section, we apply both our indicators, IARC and SERI, for leading and real-time turning points detection to the US economy, then to the Eurozone economy. For each zone, we validate the indicators through an historical analysis over the past, then, we present the results on the last cycle. But first, let us precise the decision rules associated with both indicators and how the given signals have to be interpreted by practitioners.

3.1 Decision rules and signals interpretation

A decision rule is important to decide whether a turning point has occurred or not. *Ad-hoc* rules are often used to signal a turning point expressed as a criterion to be satisfied (for example, the Conference Board rule). In our case, the decision rule is the determination of a threshold over which the probability of a turning point is understood as a signal. For example, in the case of Markov-Switching models with 2 regimes, the "natural" 50% threshold is recommended by Hamilton (1989). However, it does not generally allow to avoid false signals. If we use a higher threshold for detecting recessions, the signal will be more reliable but also more lagged. In the case of the US GDP series over the period 1952-84 studied by Hamilton (1989), this problem was not apparent because of the low GDP volatility and the quasi absence of growth cycles. Therefore, the question of the definition of a statistically robust threshold is still open. In the Neftçi approach a 90% or 95% threshold is recommended.

These decisions imply first and second type risks and should be constructed in view of the costs generated by these errors. Unfortunately, the latter are difficult to assess, so that, in practice, no decision rule is associated to the computed probabilities. For example, the various recession indices computed by Stock and Watson and released monthly on their web site[7] are raw probabilities without decision rules associated to them. Therefore, when the recession probability reached 73 % (as was the case in June 2001[8]), what conclusion can be drawn ?

Observe that it is possible to directly evaluate the performance of the probabilistic indicator without using any decision rule. For example, Diebold and Rudebush (1989) evaluate turning point forecasts on a number of attributes such as accuracy, calibration, resolution and sharpness, based on the works of Winkler (1969). The accuracy statistics is the Brier's (1950) QPS, analogous to the mean square error, given by equation (26).

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[7] see James Stock's web site : http://ksghome.harvard.edu/~.JStock.Academic.Ksg/

[8] this filtered probability has been revised by a smoothed probability of 94 % a year later

In the COE approach, an empirical threshold is determined on the aggregated probability, based on past performances comparatively to reference datations, in order to make the understanding of the signal easier for decision-makers.

First, regarding the leading IARC index, a threshold has to be defined. We decided to take two empirically estimated thresholds into account over the period 1972 - 1997. Thus, we get the following two decision rules:

- A peak (resp. a trough) may occur in the next nine months when the IARC index reaches 60% (resp. –60%).
- A peak (resp. a trough) will most probably occur in the next three months when the IARC index reaches 80% (resp. –80%) and remains over (under) it (persistence of the signal).

Second, regarding the coincident SERI index, a signal of the recession start is given when the SERI crosses the natural value of 50% and stays over this threshold, and, symmetrically, a signal of the recession end is given when the SERI crosses the natural value of 50% and stays below this threshold.

3.2 Performance of the probabilistic indicators over the US cycle

3.2.1 Historical review of past cycles

An historical dynamical analysis of both IARC and SERI indicators performance is carried out on US data, over the period January 1972 - December 2000. Over this period of time, apart from the most recent one starting in 2000, the US economy experienced six growth cycles (see Figure 5). Four of those six slowdowns turned into a recession (see Figure 4). Only the growth cycle peaks of 1984 and 1994 (points A in the ABCD approach) were not followed by business cycle peaks (points B in the ABCD approach). The average delay between points A and B is 7 months. Regarding the troughs, the delay between troughs of the business cycle (point C) and troughs of the growth cycle (point D) is only one month for the first three recessions (1973, 1980, 1981), because the recovery of the economy was characterised by a sharp slope. Regarding the 1990 recession, the recovery was pretty sluggish, thus the delay between points C and D was of around six months.

Figure 4 – US GDP business cycle from Q1 1972 to Q4 2000

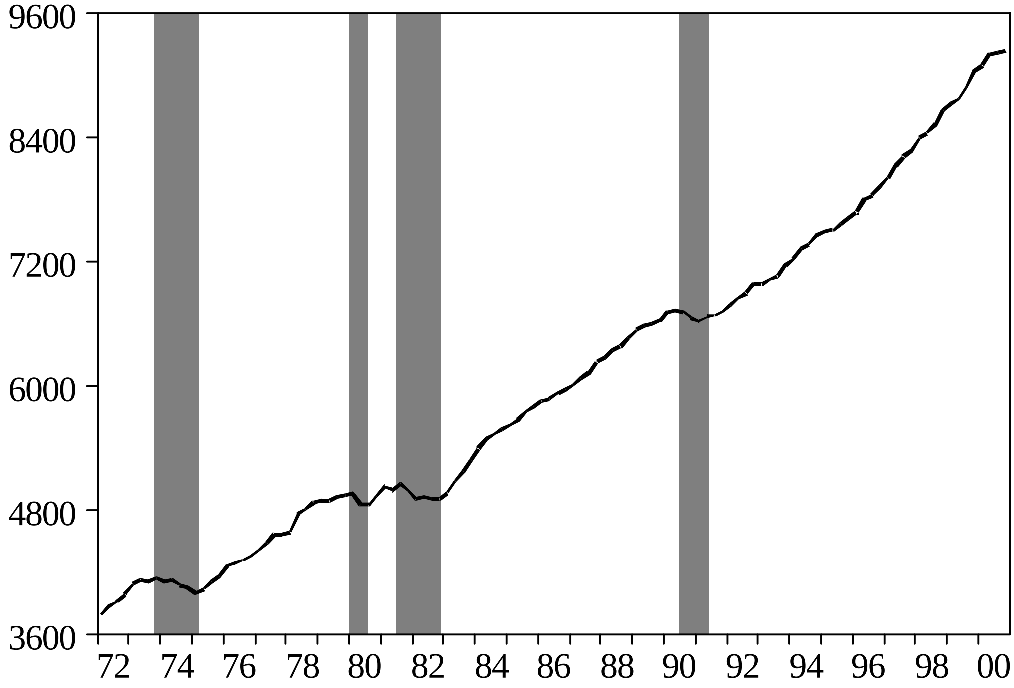
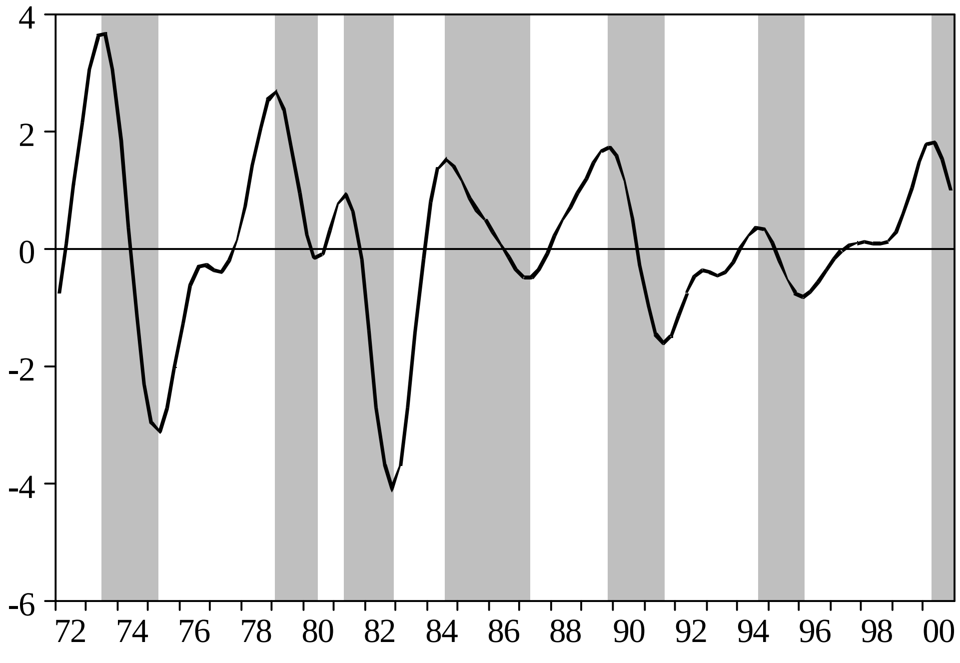


Figure 5 – US GDP growth cycle from Q1 1972 to Q4 2000



3.2.2 Validation stage

Let us first focus on the start-end recession index (SERI). Over the January 1972 - December 2000 period, the automatic selection procedure based on the QPS criterion and on an economic consideration lead us to keep the following four series:

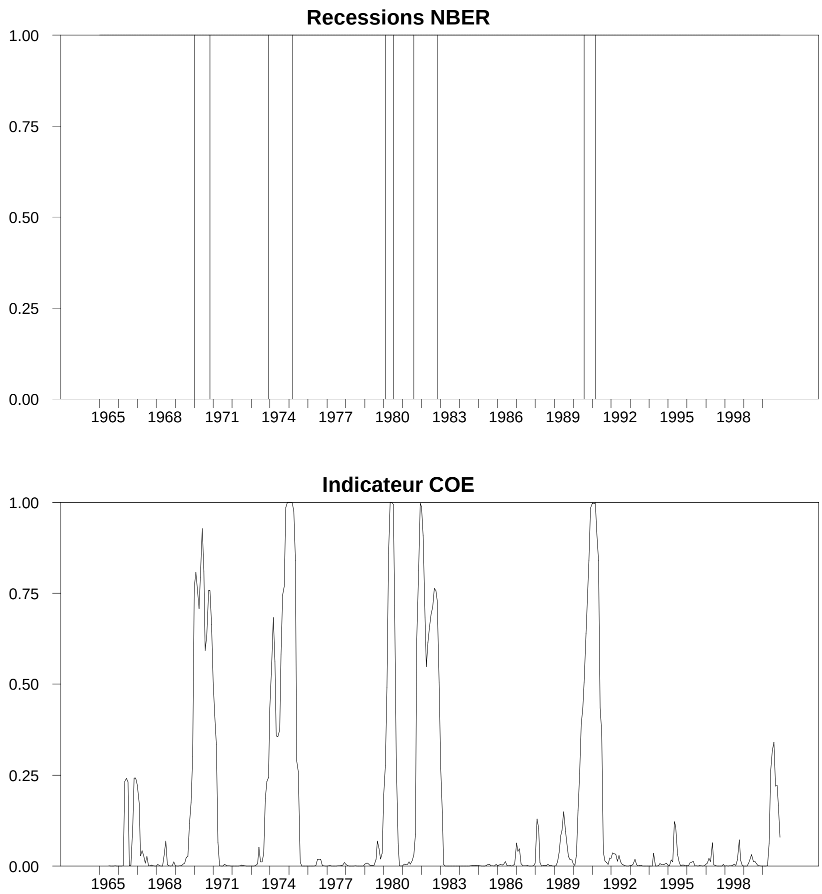
- Unemployment rate of civilian workers
- Manufacturing industrial production index
- The Conference Board's Help-Wanted Advertising Index
- Construction spending for the private sector

Many other series have been rejected by the automatic selection, because of their high degree of type I and type II errors, such as : household confidence index, ISM index, real income or wholesale-retail sales. It is also worthwhile to note that the selected series must not be strongly revised from one month to the other. However, from time to time, series may be significantly revised over a long period of time. For instance, in May 2002, revisions on the construction spending series were made back to January 1998.

We consider that a series gives a recession signal when the filtered probability crosses the threshold value of 50%. None of the signals provided by these four series miss a recession, but the signals are slightly lagged (around 1 month), except for the one stemming from construction spending which is advanced. Indeed, as a recession is a main economic event resulting in a significant decline widely diffused over the whole economy, all series considered always react when a recession occurs. In fact, these four series present a high degree of persistence. However, they sometimes send false signals. Especially, the IPI series send three false signals of classical cycle troughs. Therefore, the latter series has the weakest weight in the composite indicator, according to the aggregation procedure. The most reliable component is the unemployment rate, which never gives a false signal. However, this series is the most lagged towards the reference business cycle. This phenomenon illustrates well the trade-off between lead and reliability. According to our experience, it is extremely difficult to develop a reliable indicator able to predict when recessions will begin within a reasonable horizon. The prediction of the end of a recession should be easier, insofar as the economy presents the property of duration-dependence during this phase (see Diebold *et al.*, 1993). This means that the probability of a recovery increases as the recession phase ages. In that case, a TVTP Markov-Switching model could be fruitfully used.

The results provided by the SERI indicator are strongly coherent with the reference recession dates given by the NBER (see Figure 6). The average lag over a recession start is 1.4 month, varying between 0 and 2 months, and the average lag over a recession end is 1.6 months, varying between 1 and 2 months. We note that lags are stable overtime. The SERI never emits a false signal of a recession start, but a false signal of a recession end has been given during the 1974 recession, where all the series switched almost simultaneously to a non-recession regime. Note that, by incorporating a censoring rule of minimum duration for the signal, we may avoid having such false signal.

Figure 6 – Evolution of the SERI indicator and the NBER recession datation from January 1965 to December 2000



Let us now consider the IARC index. The components have been chosen by examining a set of series commonly considered as leading series, according to their advance and their correlation with the reference growth cycle. We selected the following six series:

- S&P's 500 stock index
- Yield curve

- ISM (ex-NAPM) survey
- Consumers expectations
- Stocks in the manufacturing industry
- New construction permits

Over the considered period, these series present cyclical evolutions in advance over the GDP growth cycle, with an average lead of ten months, but with a detection delay varying between four and seven months. All six growth cycles have been experienced by the series, although the movement is sometimes lagged. The financial components and consumers expectations exhibit a large advance along with a high volatility, thus generating some false signals. On the opposite, the other three components are less advanced, but have a higher coefficient of correlation with the reference growth cycle. In comparison with the series used in the SERI indicator, these series present a higher degree of volatility.

The IARC indicator possesses an average lead of 2.5 months over the reference growth cycle, but the signal is lagged at three times. Especially, the 1994-95 cycle is not correctly anticipated by the components. At the 80% level, the IARC does not provide any false signal.

3.2.3 Real-time results on the last US cycle

We are now interested in the last US cycle and in how the IARC and SERI indicators helped to detect in real time and predict TPs of the growth and classical cycles.

We first focus on the US growth cycle, that is the detection of points A and D of the ABCD approach. In April 2000, the IARC crossed the 80% value, which means that a turning point of the growth cycle, a peak A in this case, would probably occur in the next three months (see Table 1). Indeed, by using the most up-to-date GDP data, the US growth cycle, estimated by applying a classical Baxter-King filter, shows a peak in May 2000. When the peak was announced, it meant that the US growth rate would decrease below its trend growth rate estimated at more than 3% at this time.

Knowing that a point A had been detected, we then focussed on the search of a peak of the classical cycle, *i.e.* the detection of point B of the ABCD approach. In November 2001, the NBER Datation Commitee officially determined that a peak in business activity occurred in March 2001, ending a period of 10 years of expansion beginning in March 1991. This latter period is the longest expansion period identified by the NBER and has been characterized by strong growth rates (around 3.5% on average).

Table 1 - Evolution of the IARC leading indicator in search for a peak of the growth cycle from January 1999 to May 2000

janv-99	0.14
févr-99	0.16
mars-99	0.22
avr-99	0.26
mai-99	0.24
juin-99	0.22
juil-99	0.23
août-99	0.38
sept-99	0.5
oct-99	0.59
nov-99	0.5
déc-99	0.42
janv-00	0.44
févr-00	0.52
mars-00	0.68
avr-00	0.82
mai-00	0.85

Source: COE, May 2002

The signal provided by the SERI indicator was clear (see Table 2). In March 2001 the SERI reached the value of 60% and thus crossed the threshold value of 50%. This signal, which happened to be highly persistent, meant that the estimated peak in business activity (point B) occurred in January 2001, taking into account the average delay of 1.4 month. This signal has been confirmed the month after, in April 2001. This result is close to the NBER datation, however the March 2001 SERI index was released in April 2001, 7 months before the NBER announcement. We do not point out the lack of swiftness of the NBER, which only aims at dating and which has strong political and public implications, but this result underlines the reliability and the timeliness of our indicator.

The various series which compose the indicator provide signals at different times. First, the industrial production index crossed the threshold value of 50% in January 2001, which is not surprising insofar as the IPI is known as a leading indicator of the classical cycle. Then, the two series related to employment indicated the start of recession in March and April 2001, which points out that employment is coincident with the classical cycle. Lastly, the construction spending series reached 55% in July 2001 and did not stay long in a recession regime. This phenomenon partly reflects the resilience of the American households to decrease their spending during this recession, which avoided a deeper crisis.

Table 2 - Evolution of the dynamical probability of being in recession for each component of the SERI indicator and evolution of the indicator from January 2001 to May 2002

	Unemployment	IPI	Help-Wanted	Construction	SERI
janv-01	0,00	**0,87**	0,03	0,00	0,20
févr-01	0,05	0,99	0,05	0,00	0,24
mars-01	0,45	0,98	**1,00**	0,00	**0,60**
avr-01	**0,98**	0,94	1,00	0,00	0,74
mai-01	0,99	0,95	1,00	0,04	0,76
juin-01	0,97	0,99	1,00	0,11	0,78
juil-01	0,96	0,98	1,00	**0,55**	0,88
août-01	1,00	0,99	1,00	0,94	0,98
sept-01	0,99	0,99	1,00	0,97	0,99
oct-01	1,00	1,00	1,00	0,50	0,88
nov-01	1,00	0,99	1,00	**0,53**	0,89
déc-01	1,00	0,98	**1,00**	0,08	**0,78**
janv-02	1,00	0,93	0,14	0,03	0,48
févr-02	0,99	**0,60**	0,00	0,01	0,42
mars-02	0,93	0,01	0,01	0,00	0,27
avr-02	**0,95**	0,00	0,00	0,00	0,27
mai-02	0,21	0,00	0,02	0,02	0,07

Source: COE, May 2002

This latter recession has been characterized by an unusual divergent behavior in timing of the main macroeconomic indicators which caused some difficulties for most economists to clearly detect this episode as a recession. Indeed, it took experts a long time to recognize that the US recession started in March 2001. Only just after the terrorist attacks on New York in September 2001, a consensus emerged among the economists to argue in favor of a recession. According to our indicator, it is noteworthy that the peak of the classical cycle happened prior to the terrorists attacks in September 2001. Thus, we argue that the US economy was already in recession before the September 11 attack, and that this attack has only lengthened the recession by two or three months.

This US recession can be qualified as mild, especially if we look at the GDP growth rate which has been negative only during the third quarter of 2001. However, there is a substantial probability that the sequence of GDP growth rates will be significantly revised in the coming years[9].

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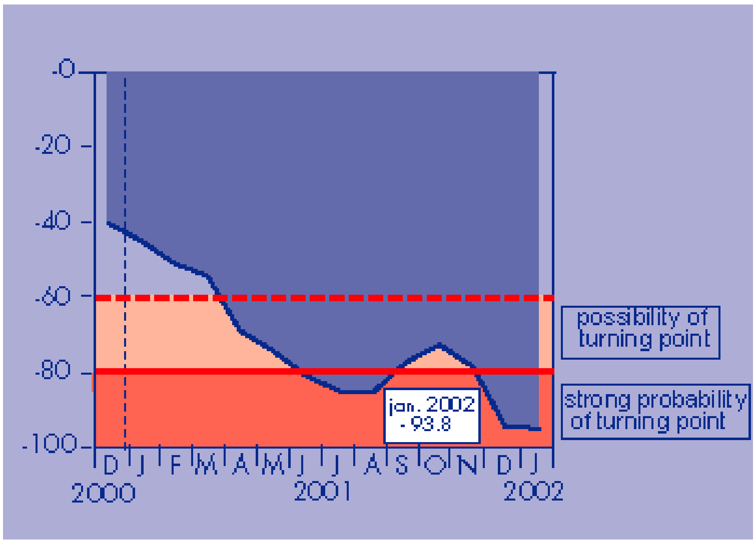
[9] Indeed, in 2003, the GDP figures have been revised and show now a decrease in activity from the first to the last quarter of 2001

Once point B was detected, we were looking for point C, that is the end of the recession period. The SERI crossed the 50% value in January 2002, which meant that the trough of the classical cycle would have happened in November 2001. Assuming this date will be confirmed later by the NBER[10], it implies that this recession would have lasted 9 months, a length close to the average length over the last four recessions (11 months). The US recession length is lying between 6 (in 1980) and 16 (in 1974) months.

At the same time, the IARC was used to anticipate point D, *i.e.* the trough of the growth cycle (see Figure 7). A signal was emitted in July 2001 (the IARC crossed the threshold value of -80%), implying a trough in the next three months. This signal was cancelled out by an unpredictable shock: the September 11th terrorist attack. As a result, the values of the IARC from September to November 2001 declined under -80%. Finally, the signal of a trough was emitted by the IARC with the data of December 2001, thus implying that point D would occur during the first quarter of 2002. Indeed, if we look at the most up-to-date data concerning the US growth rate, it seems that the trough of the US growth cycle could be dated to the first quarter of 2002.

Figure 7 - Evolution of the IARC leading indicator for the US in search for a trough (point D) from January 2001 to January 2002



Source: COE, May 2002

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[10] In its latest memo released in April 2003, the business cycle dating committee of the NBER had not yet officially recognise this trough

3.3 Performance of the probabilistic indicators over the Eurozone cycle

3.3.1 Historical review of past cycles

In the case of the Eurozone area, the datation of the business cycle (points B and C) is not easy for various reasons.

- For some countries of the Eurozone, homogeneous series of quarterly GDP are not available for a long period of time. The German GDP series was starting in 1992 because of the reunification but a retropolation should soon be available.
- In some series, the methodology has been changing overtime; for example GDP for France is corrected for trading days since 1995. With new base years, estimates are not strictly comparable along time.
- The method for seasonal adjustment or correction of trading days is not homogeneous across countries. The adjustment may be done before or after the aggregation (indirect versus direct method)

In order to date the growth cycle (points A and D), there is a need to select the de-trending method and to perform it before or after the aggregation over the countries (indirect *versus* direct approach). We do not want to discuss those issues here. Let us mention the recent work of the Conference Board (see Zarnowitz and Ozyildirim, 2001) showing that the TPs identification shows great similarity when using the PAT approach or the Hodrick-Prescott or band-pass (like Baxter-King) filtering methods, at least for the United States.

In this paper, we will use a datation on a direct GDP aggregate for the Eurozone derived from Eurostat data for the period starting in 1995 and using COE's calculations before. This series is thus provisional. In order to estimate the growth cycle, we will use both above mentioned filtering methods. Different turning points datation techniques are available. An easy one is the Bry and Boschan (1971) approach, directly applicable on the classical cycle or on the estimated growth cycle. The dating of the last growth cycle is never easy because of edge effects. If we locate the peaks and troughs of the cycles graphically, criteria of length, intensity and "trend crossing" should be used. The mid-80's and the 1998-99 cycle are mild ones because they do not cross the trend. In their study, Zarnowitz and Ozyildirim (2001) indicated that the 1998-99 cycle was identified by the Bry and Boschan algorithm but not accepted by them because they were uncertain that it could be qualified as a growth cycle contraction. Therefore, we could also consider that the ascending phase lasted from the end of 1997 to mid-2001 without a real slowdown due to the Asian countries. In fact, the growth cycle is clearly detected in Italy and in Germany, while it is not in France, where it is known as a "trou d'air".

Figure 8 – Eurozone GDP business cycle from Q1 1972 to Q4 2000

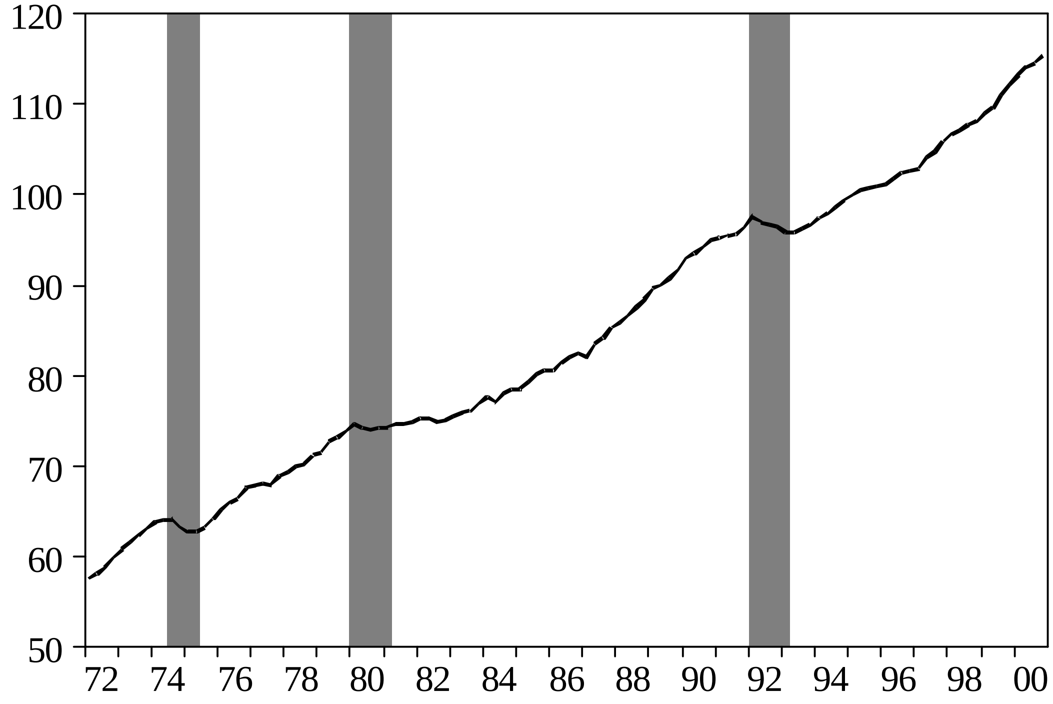
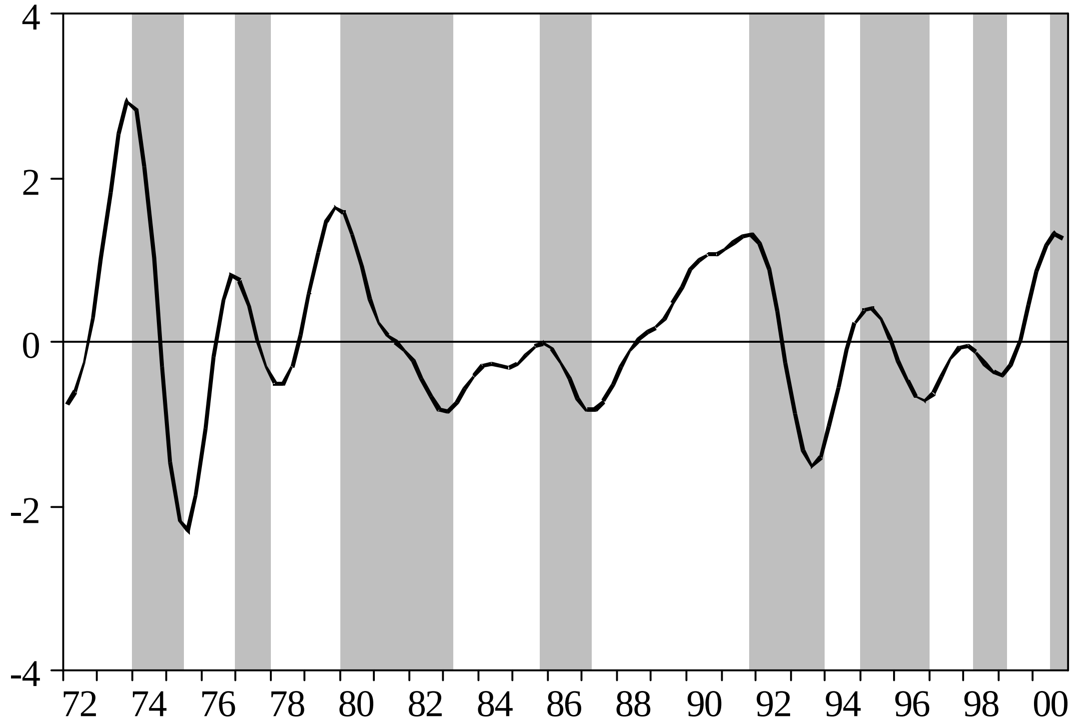


Figure 9 – Eurozone GDP growth cycle from Q1 1972 to Q4 2000



Over the period January 1972 – March 2002 the Eurozone economy experienced eight growth cycles (see Figure 9). Three of them were followed by a business cycle (see Figure 8). The growth cycle peaks of 1977, 1986, 1995, 1998 and 2000 (points A in the ABCD approach) were not followed by business cycle peaks (points B in the ABCD approach). The average delay between points A and B was about 3 quarters in the first recession (first oil shock) and around one quarter in the following two recessions starting in 1980 and 1992. Regarding the last cycle, the peak may be located in the third quarter of 2000 while the trough is not established yet. Despite a decrease of GDP in the last quarter of 2001 (quarterly growth rate of -0.2 %), there was no recession in the Eurozone during that period.

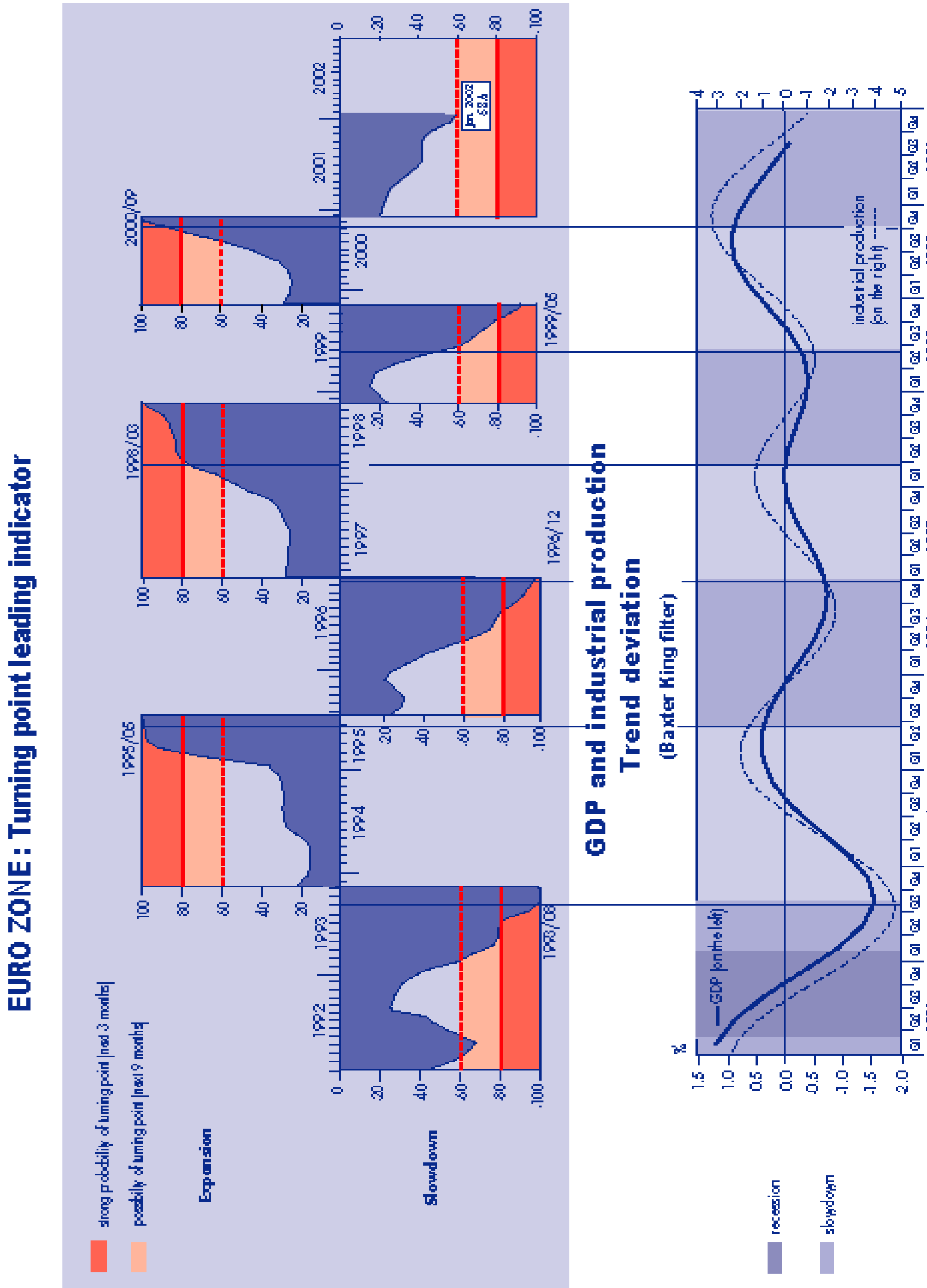
3.3.2 Detecting the Eurozone growth cycle

We need first to select the leading economic time series. Each leading series used for the detection of the Eurozone turning points growth cycle is a weighted average of member countries leading series. We selected five leading series:

- a Eurozone stock market index computed by the COE
- the spread between long and short term interest rates
- the first factor of a principal component analysis of business survey results in the intermediate goods industry in the Eurozone
- manufacturer prices expectations concerning wholesale trade in the Eurozone
- the COE leading indicator IARC of the American growth cycle.

For each series, a calculation of the operational mean lead has been performed over the 1990-1999 period. The 1980's do not provide a good period for estimating the performance of indicators because of the relative heterogeneity of economic growth cycles in the zone. The performance can be evaluated in Figure 10: a strong signal is always emitted in the three months before the turning point.

Figure 10 – Historical performance of the IARC leading indicator for the Eurozone



Source: COE, May 2002

The Eurozone growth cycle upward phase ended at the end of the last quarter 2000. Actually, the peak can be found in the third quarter of 2000 according to the last estimate of the cycle done in May 2002 (because of edge effect it takes at least one year to locate a peak). A strong signal was given by the COE leading indicator in October 2000 (see Figure 10), anticipating a peak in the three next months. This was quite a good performance since at that time most economists were rather optimistic about economic growth in 2001 and did not anticipate any peak in the growth cycle.

More recently, in February 2002, the COE leading indicator for the Eurozone entered the range indicating a strong recovery probability within the next three months, meaning that the Eurozone growth rate should be above its trend now assessed at 2% in the third quarter of 2002 (see Figure 10). According to the methodology used to build this indicator, it means that, if the signal is persistent, the centred three quarters moving-average of quarterly changes should overpass 2% in annual terms in the third quarter of 2002.

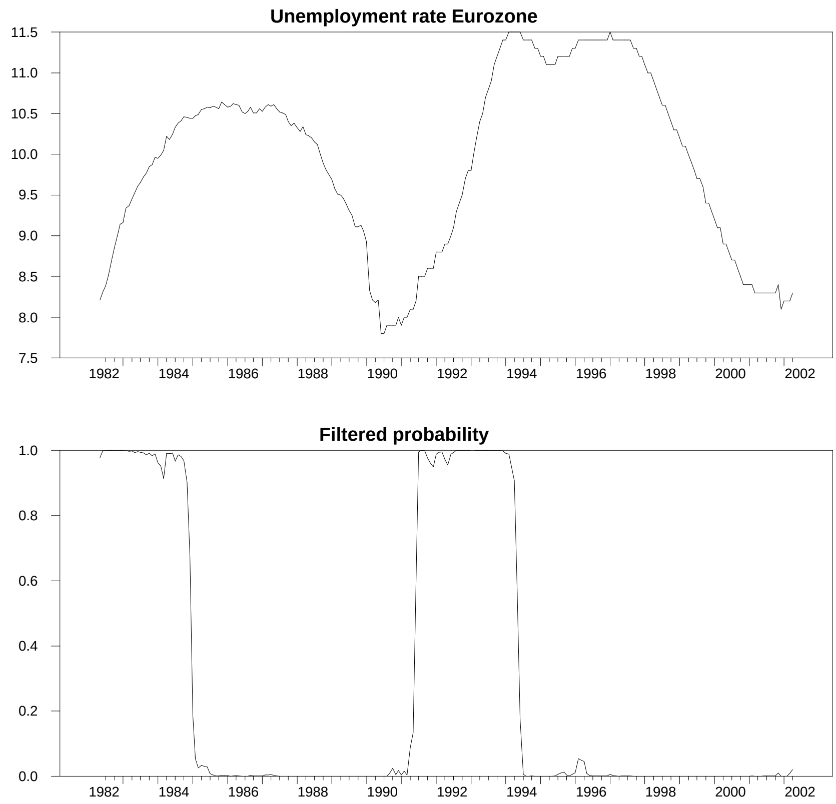
3.3.3 Detecting the Eurozone classical cycle

The direct use of GDP to detect the turning points of the classical cycle is not operational because of the availability delay and the degree of revisions of GDP data. We must therefore use a GDP proxy. We want to use a set of coincident series to get a coincident signal of recession. The idea is to develop a Eurozone coincident probabilistic indicator similar to the one developed by the COE for the American business cycle (see section 3.2). The series to be included in the indicator must have an economic meaning. But other statistical restrictions also have to be mentioned, such as fast availability, weak revisions, long enough history, etc...

As mentioned earlier before, the employment series is a widely recognised coincident indicator. The Eurozone employment series does not provide any false signal. However, the signal is given with a certain delay. An inconvenient is the quarterly frequency of the series and its publication delay. Monthly series are available only for some European countries.

Another series of interest, close to the employment series, is the unemployment rate series. This series appears to give the same results than the employment series. The advantage is its monthly availability and the reasonable delay of publication. Two periods of low regimes for the unemployment series have been identified by the MS model since 1982 (see Figure 13). It seems that unemployment rate is a reliable indicator to detect the peaks of the business cycle but is to persistent during the low phases of the cycle to detect the troughs.

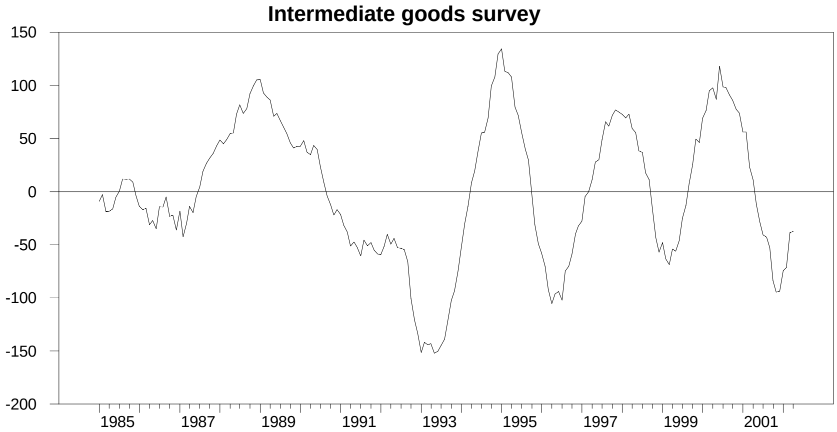
Figure 11 - Eurozone unemployment rate from January 1982 to April 2002 and filtered probability of a low regime



We also tried other series derived from some European surveys. Below are presented the filtered probabilities of a low regime, stemming from a MS model for the industrial survey restricted to the intermediate goods sector (see Figure 12), and for the construction sector (see Figure 13). Regarding the first survey, a common factor has been derived from a principal component analysis on major questions (tendency, orders and stocks). As regards the construction sector, the synthetic index calculated by the European commission has been used.

We observe that those surveys are very reactive to the economic climate. However, regarding the classical cycle, these series provide too many false recession signals (type I error). In fact, the surveys are more linked to the growth cycle.

Figure 12 - Survey on the Eurozone production of intermediate goods from January 1985 to April 2002 and filtered probability of a low regime (MS(2)-AR(0) model)



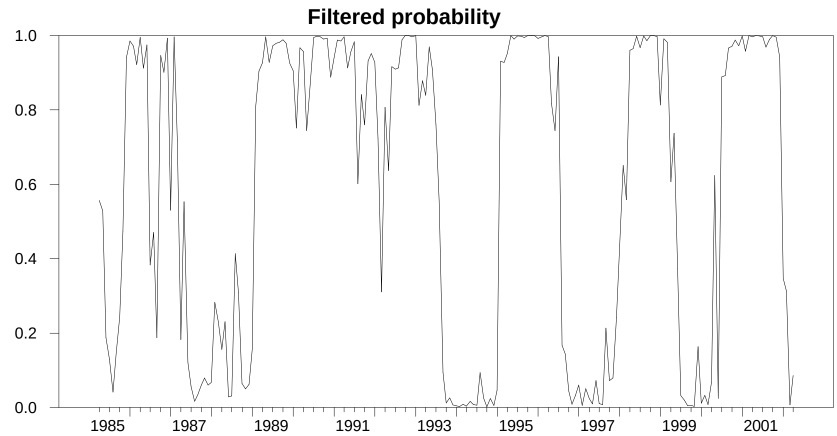
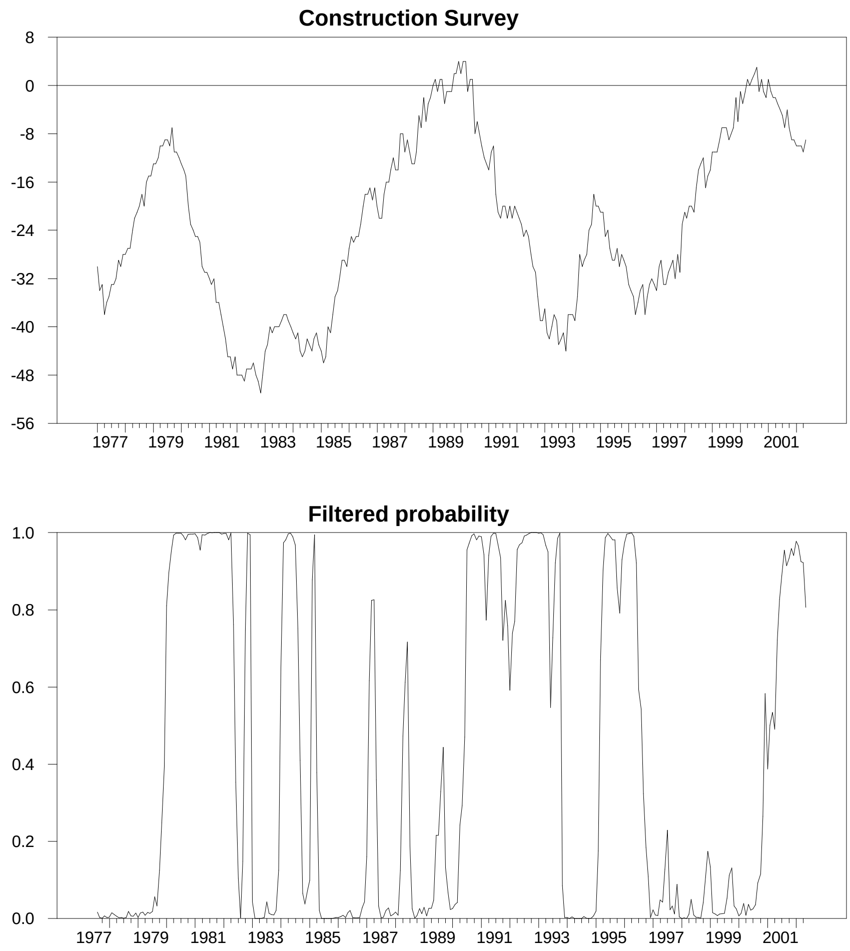


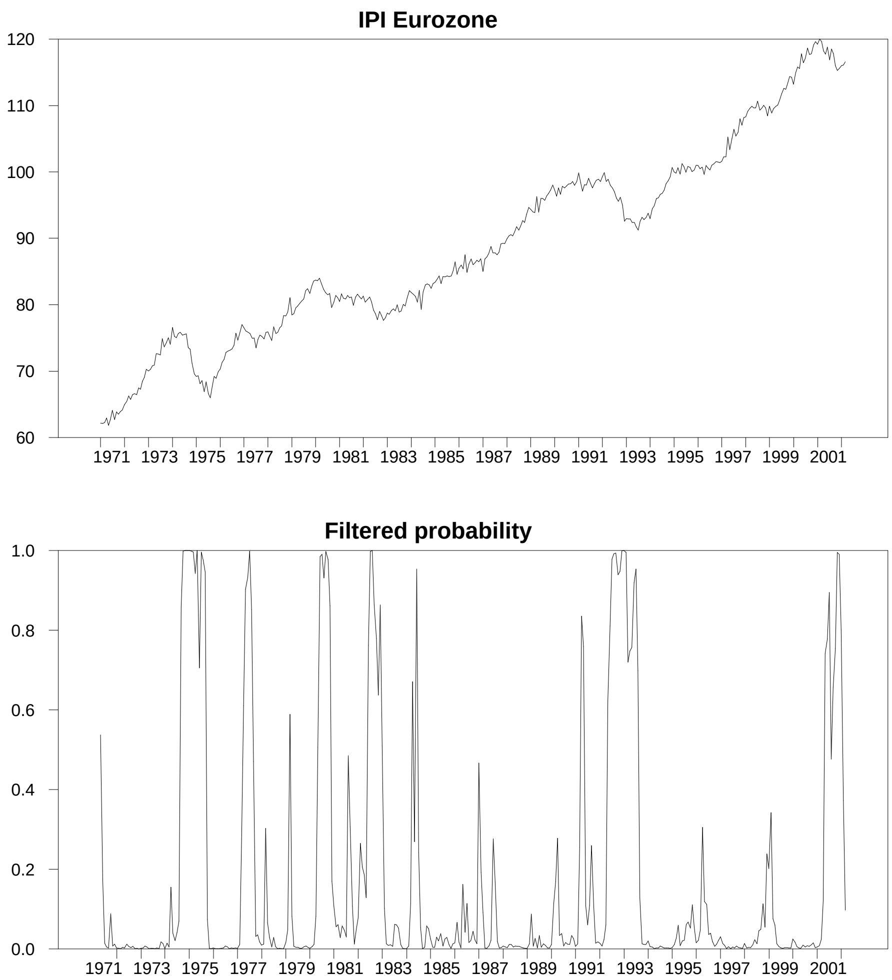
Figure 13 - Survey on Eurozone construction from January 1977 to May 2002 and filtered probability of being in a low regime (MS(2)-AR(0) model)



We finally tried to use the industrial production index as a coincident indicator. The results are sensitive to the selected frequency (monthly or quarterly), to the degree of smoothing and to the choice concerning the length of the variation taken into account. Depending on those choices, the MS model exhibits more or less signals. For example, we could use a variation over 18 months on the monthly series to avoid any false signals. But in this case, the signal would be very late (more than one year on average). The industrial index shows several industrial recessions (see Figure 14), the number of which depends on the criteria used to define a recession. We observe that the index has been decreasing for several months in 2001, therefore showing an industrial recession. What could be planned is to design a model with three regimes. The low regime would correspond to recessions (negative growth rates), the medium regime would be the low-growth regime (positive growth but below the trend growth rate) and an expansion phase where the growth rate is above the trend growth rate.

Finally, more series should be added to those series in order to produce an aggregated signal. The aggregation rule described in section 2.2.2 will be applied. The Eurozone coincident probabilistic indicator is currently under development by the COE.

Figure 14 - Industrial production index from January 1971 to March 2002 and filtered probability of a low regime (MS(2)-AR(0) model)



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