



Detecting cyclical turning points:

the ABCD approach and
two probabilistic indicators -
26th CIRET Conference,
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Session:

Composite and leading Indicators / New methods

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

Jacques ANAS and Laurent FERRARA*

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 be able to adjust their policies sufficiently in advance to avoid more deterioration or a recession. Those 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 to forecast 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 in real time peaks and troughs of the classical cycle. 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 particularly focus on the United States and the Eurozone cyclical turning points.

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

JEL Classification:

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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 be able 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 for improving decision making.

The detection of turning points, which is our main objective in this paper, faces the problem of using data in real time with the difficult issues of edge effects and data revision. It can be thought 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 in order to detect 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, 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.

But let us review some specific issues when identifying successively past, present and future TPs:

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

In the United States, the NBER's Business Cycle Dating Bureau's Committee is widely recognized as the authority for determining the peaks and troughs of the classical business cycle (points B and C). 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 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) or Krolzig (2001) 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 a series' TPs (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 (2001). 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 with Hamilton regarding the usefulness of using those sophisticated models *versus* more transparent and simple methods for dating cycles.

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) recently 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).

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 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 three different ways to predict a TP:

1. A coincident index is elaborated and then projected through different techniques (for example, VAR models in the Stock and Watson approach, comovement in dynamic factor models). A method and a rule to detect the TPs of the projected coincident indicator have then to be used: probit, Hamilton, Neftçi or ad-hoc rules are possible candidates.
2. A leading index is elaborated and a method and a rule are applied to detect the TP of that leading indicator. In this case, however, the average lead has to be known.
3. A third approach consists in using multivariate models: detecting the TPs of various leading indicators and aggregating the corresponding probabilities in order to provide a signal for a future TP (Anas, 1997, and Anas and Nguiffo-Boyom, 2001).

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). 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 a 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 tendencial 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 lead of the peaks extremely unstable, which remove any practical interest for the signal. This is why we do not consider that the detection of α and β is useful and informative even if practitioners, market economists or officials often use it for their diagnosis. We prefer to detect A and B which announces respectively downwards phases of growth cycle and classical cycle. However, If the slowdown does not gain in intensity to become a recession, then A will not be followed by point B. The follow-up of those points (A and B for peaks and C and D for troughs) is called the ABCD strategy for TP analysis. We will concentrate in this document 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 the point α is reached at the end of 1987, that is two years before point A. This pretty large advance proves that this kind of TP does not seem 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

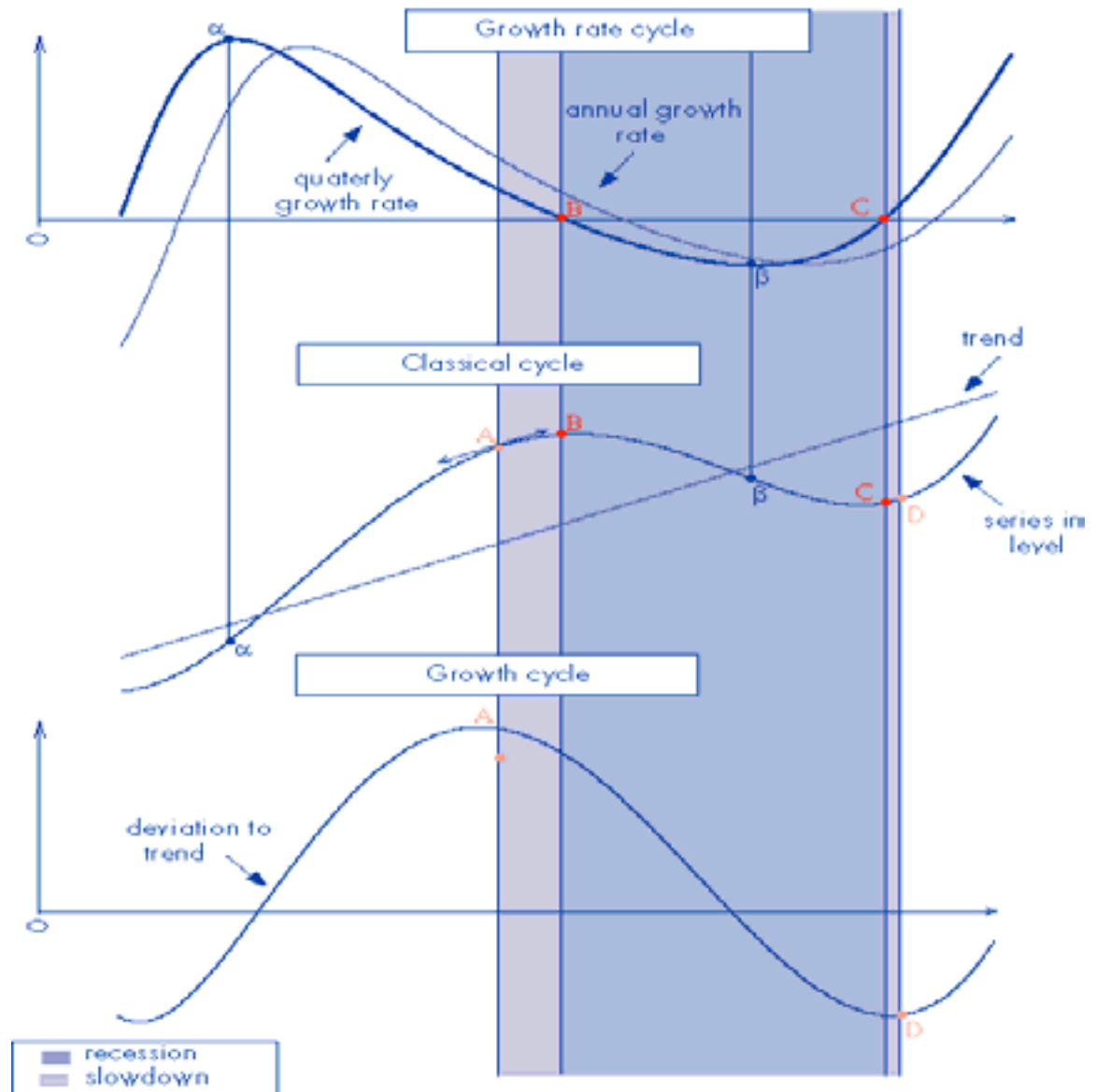


Figure 2 - Evolution of the US cycle over the 1986-1992 period and the ABCD approach

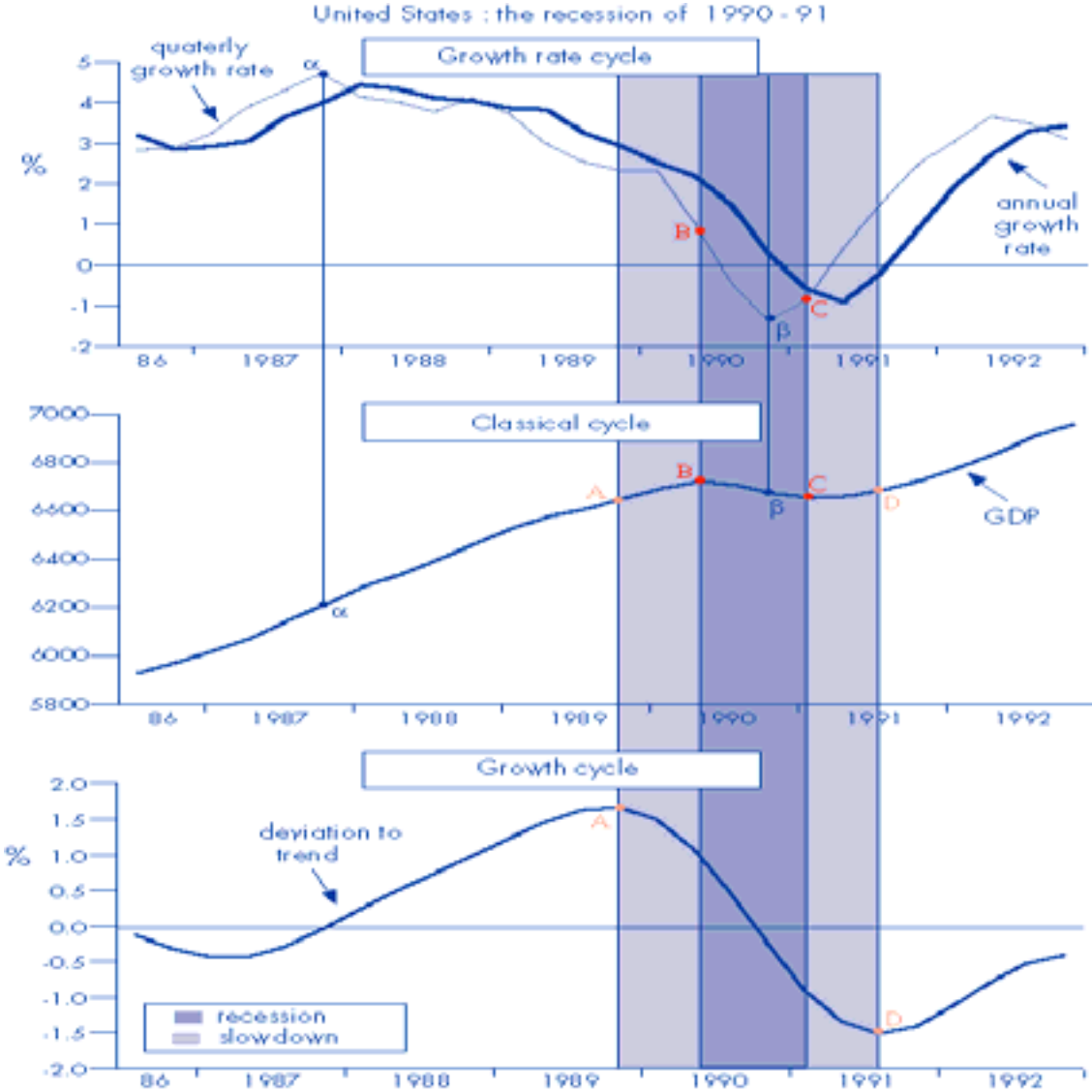
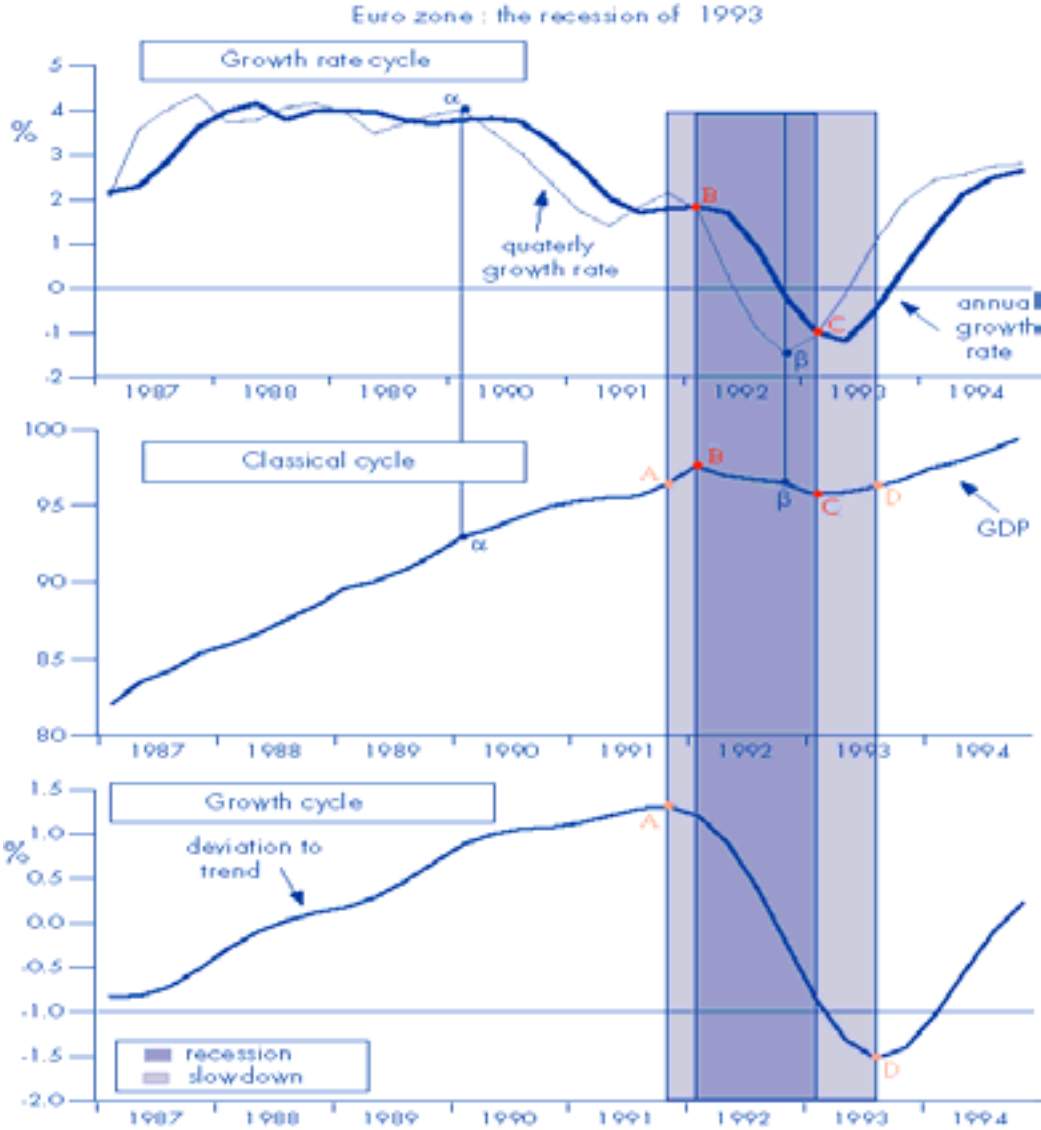


Figure 3 - Evolution of the Eurozone cycle over the 1987-1994 period and the ABCD approach



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 are 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 diverse 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 goes down afterwards. It is exactly the same question for an economic peak. The probability of a peak will reach a significative level well after the effective occurrence of this peak. If this delay is short, it is because the indicators we have used to detect the peak are very reactive to a turning point or even somewhat leading 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 reliable indicators for business cycle TP, 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. It is why it is so difficult to predict recessions, like it has been underlined in so many studies. What is however possible is to detect quickly 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 cycles 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 to

forecast 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 Shirayayev (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 $(x_t)_{t=1,\dots,T}$, 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)¹. Let us suppose $Z = i$ (or $Z' = i$), for $i = 2, \dots, t$, with $T \geq t \geq 2$, 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 $(X_{i+j})_{j=0,1,2,\dots}$ is different and independent of the distribution of $(X_{i-j})_{j=1,2,\dots}$.
- *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 $T \geq t > i \geq 2$, then we get:

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

where $F^1(\cdot)$ and $F^0(\cdot)$ are the two cumulative distribution functions for the upward and downward regime respectively. Generally, $F^1(\cdot)$ and $F^0(\cdot)$ 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 ($Z \leq t$) or not ($Z > t$).

¹ We suppose that Z refers to the date of peaks, but the results are diametrically symmetric for troughs.

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.*

$$T_t = P(Z = t | Z > t - 1), \quad (2)$$

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

$$T_t' = P(Z' = t | Z' > t - 1). \quad (3)$$

Let us note $\bar{x}_t = (x_1, \dots, x_t)$ 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 , that is:

$$P_t = P(Z \leq t | \bar{x}_t). \quad (4)$$

Thus, using Bayes' rule, we get:

$$P_t = \frac{P(\bar{x}_t | Z \leq t) P(Z \leq t)}{P(\bar{x}_t)}, \quad (5)$$

and by extension:

$$P_t = \frac{P(\bar{x}_t | Z \leq t) P(Z \leq t)}{P(\bar{x}_t | Z \leq t) P(Z \leq t) + P(\bar{x}_t | Z > t) P(Z > t)}, \quad (6)$$

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

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

where $f^0(\cdot)$ is the density function of $(X_t)_t$ during a downward regime and $f^1(\cdot)$ 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 Neftçi's formula indicate the degree of persistence of the process. For instance, Hamilton (1989) assumed 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) considered that the transition probabilities were non constant and estimated 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 (2001) 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 the paper of Neftçi (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 it 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 or values, rates or levels, different frequencies and volatility. 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 selected N leading 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 $(S^k_t)_t$ 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 risks² associated with this approach are, first α_t^k the risk of a false signal (or type I error), defined as:

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

² Both risks are widely discussed in the seminal article of Okun (1960).

and second, β_t^k the risk of missing the cyclical turning point³ (or second type error), defined as:

$$\beta_t^k = P(R_t = 1 | S_t^k = 0). \quad (10)$$

We assume that both risks are constant overtime, *i.e.* for all t : $\alpha_t^k = \alpha^k$ and $\beta_t^k = \beta^k$. An estimate of $P(R_t = 1)$ is $P_k(R_t = 1)$ defined by:

$$P_k(R_t = 1) = (1 - \alpha^k)P_t^k + \beta^k(1 - P_t^k) \quad (11)$$

$$= \beta^k + (1 - \alpha^k - \beta^k)P_t^k, \quad (12)$$

where α^k and β^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 $(X_t^k)_t$.

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:

$$\frac{1}{N} \sum_{k=1}^N [P_k(R_t = 1)] = \frac{1}{N} \sum_{k=1}^N \beta^k + (1 - \alpha^k - \beta^k)P_t^k, \quad (13)$$

$$= \bar{\beta} + \sum_{k=1}^N \frac{(1 - \alpha^k - \beta^k)}{N} P_t^k. \quad (14)$$

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, that we call IARC (in French : "Indicateur Avancé de Retournement Conjoncturel"), which is an estimate of $P(R_t = 1)$ for all t , is such that:

$$IARC = \frac{\bar{\beta}}{1 - \bar{\alpha}} + \sum_{k=1}^N \left[\frac{(1 - \alpha^k - \beta^k)}{\sum_{k=1}^N (1 - \alpha^k)} \right] P_t^k, \quad (15)$$

where $\bar{\alpha}$ and $\bar{\beta}$ are the averages of the type I and type II risks.

³ 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 $\bar{\beta} / (1 - \bar{\alpha})$, 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 for selecting the leading components of the IARC indicator. As outlined by the OECD, an economic rationale is needed to avoid taking only the statistical performance over a period of time into account. Also, the series need to be available for a long period of time to allow for estimation. But the main selection criteria relates to the degree and stability of the operational lead as well as to the low degree 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

This coincident indicator of the business cycle is grounded on the Markov-Switching model proposed by Hamilton (1989) and is used in order to detect in real time peaks and troughs of the classical business cycle, 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 through 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.

Specification of the model

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

$$X_t = a_{0,S_t} + a_{1,S_t} X_{t-1} + \dots + a_{p,S_t} X_{t-p} + \varepsilon_t, \quad (16)$$

where, for $k=0, \dots, p$, $a_{k,S_t} = a_{k,1}$ when $S_t = 1$, and $a_{k,S_t} = a_{k,2}$ when $S_t = 2$ and where $(\varepsilon_t)_t$ is a white noise process with finite variance σ^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 $i, j=1, 2$:

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

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 equation (16), will be denoted a MS(2)-AR(p) process. Interest is also given in applications to unconditional probabilities of being in a specific state. It can be shown that (see for instance Hamilton (1994)) for $j=1, 2$:

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

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

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

Parameter estimation

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

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

The parameter estimation method generally used is the classical maximum likelihood estimation (MLE hereafter) method, based on the assumption that the white noise process $(\varepsilon_t)_t$ in equation (16) is a Gaussian process. Furthermore, the Markov chain $(S_t)_t$ is supposed to be independent of $\varepsilon_{t'}$, 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 date t . The MLE method aims to find the parameter θ such that the conditional log-likelihood $L(\theta)$ is maximum, with $L(\theta)$ expressed as :

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

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

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

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

$$f(x_t / S_t = i, F_{t-1}, \theta) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{(x_t - a_{0,S_t} - \sum_{k=1}^p a_{k,S_t} x_{t-k})^2}{2\sigma^2}\right], \quad (23)$$

Thus, by using equations (21) to (23) the log-likelihood $L(\theta)$ can be evaluated for a given parameter θ . However, according to equation (22), the evaluation of the conditional log-likelihood $L(\theta)$ asks for the knowledge of $P(S_t = i / F_{t-1}, \theta)$, 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 $P(S_t = i / F_{t-1}, \theta)$, 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. Note also that another conditional probability of being in the state i can be computed, given all the available information through date T . This probability $P(S_t = i / F_T, \theta)$, for $i=1,2$, is referred to as the *smoothed probability* of being in state i , often used for 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 given by equation (16) have been developed. For instance, in the classical specification of the model proposed by Hamilton (1989) (equation (16)) 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 (1993), 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. Besides the papers already quoted, we refer also to Filardo (1998) regarding parameter estimation considerations for TVTP Markov-Switching models.

As another example, multivariate generalisations of the basic MS-AR model have been recently proposed by Krolzig (1997), who introduces vectorial MS-VAR processes, where the conditional stochastic processes is a 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 further extension to the multivariate framework, we can also quote the work of Diebold and Rudebush (1996) who aims to model simultaneously the two main 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 describe now 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 time series carefully chosen.

Aggregation procedure

The aggregation procedure is basically the same as the one developed to build the leading probabilistic indicator IARC in the section 2.1.2. Assume we selected N coincident time series $(X^k)_t$, 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 $(S^k)_t$ such 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 $(R)_t$ such 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.

Similarly as in the subsection 2.1.2, for each coincident time series $(X^k)_t$ the probability of a recession can be developed by using the bayesian formula given by equation (8). The two risks α^k and β^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 $P(R_t = 1 / S_t^k = 0) = 0$, that is 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 :

$$P_k(R_t = 1) = (1 - \alpha^k) P_t^k, \quad (24)$$

where α^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 $(X^k)_t$.

Lastly, similarly 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 to get our final index (called Start-End Recession Index, or SERI), given by:

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

Choice of the series

One of the main issue of this kind of indicator is the way to choose the different components to include. Indeed, we search for series with a pretty strong persistence, because volatility can lead unreliable signal, as well 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 considered series have, of course, to be sampled on a monthly basis. Therefore, series such as GDP or Eurozone employment cannot be included in the indicator.

To discriminate among the huge set of economic monthly time series available in data bases, we consider 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), defined as follows:

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

where, for $t=1, \dots, T$, $(P_t)_t$ 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's datation chronology provided by the Business Cycle Dating Committee⁴. Regarding other countries, we establish our own reference datation by examining peaks and troughs of the business cycle and by summing up diverse studies on this 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 Board⁵. 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 into our indicator other components such as the industrial production index, more advanced but providing some false signals. Indeed, industrial production indexes are indicative of industrial recession which occur more often than global recession. However, this phenomenon is taken into account by the aggregation procedure which gives less weight to these series.

⁴ See www.nber.org/cycles

⁵ see www.conference-board.org

3 Detection of the US and Eurozone cyclical turning points

In this section, we apply our both indicators, IARC and SERI, for real-time turning points detection to the US economy, then to the Eurozone economy. For each zone, we validate in a first step the indicators through an historical analysis over the past, then, in a second step, we present the results on the last cycles. First, we 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. 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 and must be therefore under-evaluated. Obviously, the signal is thus more reliable but also more lagged. In the case of the US GDP series over the period 1952-84 studied by Hamilton (1989), the low GDP volatility and the quasi absence of growth cycles in the USA avoid this problem. Therefore, the question of the definition of a statistically robust threshold is still open. In the Neftçi approach, a threshold of 90% or 95% is recommended.

These decisions imply first and second type risks and they should be constructed in view of the costs generated by these errors. Unfortunately, these errors are difficult to assess so that, in practice, no decision rule is determined. It may be possible to directly evaluate the probability estimates without using any decision rule. For example, Diebold and Rudebush (1989) evaluate turning point forecasts on a number of attributes like accuracy, calibration, resolution and sharpness, based on the works of Winkler (1969). The accuracy statistics is the Brier’s (1950) QPS, analog to the mean square error, given by equation (26). As another example, the diverse recession indexes computed by Stock and Watson, and released monthly on their web site⁶, are raw probabilities without decision rules associated with. Therefore, when the recession probability reached 73% (as it was the case in June 2001), what is the conclusion to draw ? 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.

⁶ see Jame’s Stock web site : <http://ksghome.harvard.edu/~Jstock.Academic.Ksg/>

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 two following 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 probably occur in the next three months when the IARC index reaches 80% (resp. -80%).

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.

Lastly, note that ad-hoc rules are often used to signal a turning point expressed as a criterion to be satisfied. The most famous example is the Conference Board rule. Ad-hoc rules may also be devised in non linear approaches. For example, in Markov-Switching models, the crossing of the mean value (called demarcation line) of a regime may be used as a decision rule (Amstad and Etter, 2000).⁷

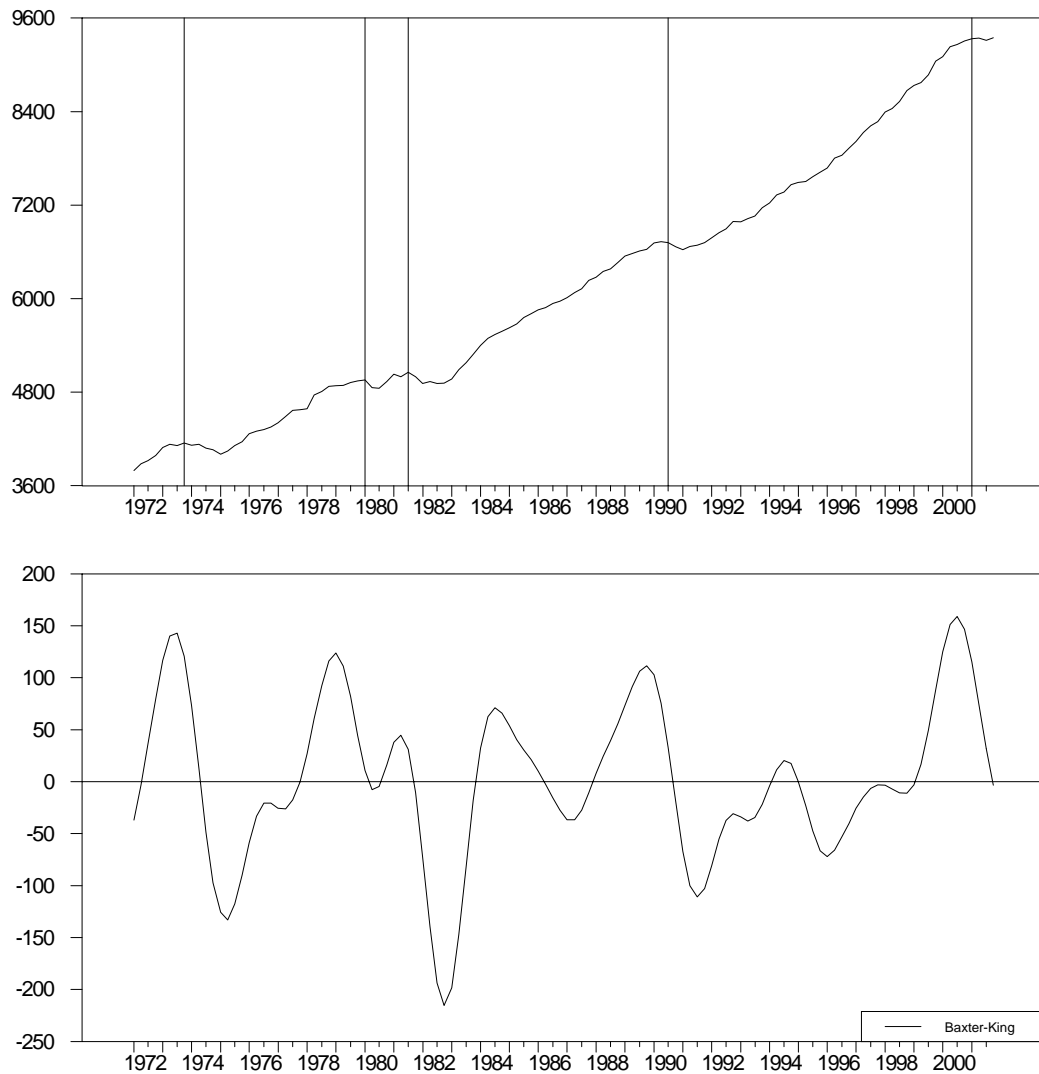
3.2 Performance of the probabilistic indicators over the US cycle

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 2001. Over this latter period, the US economy experienced six growth cycles (excepted the most recent one beginning in 2000). Four of those six slowdowns turn into a recession (see Figure 4). Only the growth cycle peaks of 1984 and 1994 (points A in the ABCD approach) have not been 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 three first 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 about six months.

⁷ These crossings are interpreted as a signal of overheating or excessive slowdown.

Figure 4 – US GDP and growth cycle from Q1 1972 to Q4 2001



3.2.2 Validation stage

Let's first focus on the start-end recession index (SERI). Over the period January 1972 – December 2000, the automatic selection procedure based on the QPS criterion and an economic consideration lead us to keep the four following 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 : households confidence index, ISM index, real income or wholesale-retail sales. It is also worthwhile to note that retained series are not strongly revised from one month to the other. However, from time to time, series are significantly revised over a long period. For instance, in May 2002 revisions, on the construction spending series were made back to January 1998.

We consider that a series gives a signal of recession 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), excepted 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 the series considered always react when a recession occurs. In fact, these four series present a high degree of persistence. However, they send sometimes false signals. Especially, the IPI series send three false signals of business cycles troughs. Therefore, this latter series possesses 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 existing between the lead and the reliability. According to our experience, it appears extremely difficult to develop a reliable indicator able to predict with a reasonable horizon when recessions will begin. 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. The average lag over a recession start is 1.4 months, lags varying between 0 and 2 months, and the average lag over a recession end is 1.6 months, lags 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.

Let's 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 six following series:

- S&P's 500 stock index

- Yield curve
- ISM 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 the 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 three other 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 1994-1995 cycle is badly anticipated by the components. At the 80% level, the IARC do 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 how the IARC and SERI indicators have helped to detect in real time and to predict TPs of the growth and classical cycles.

We focus first 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 has been detected, let's focus now on the peak of the classical cycle, that is the detection of point B of the ABCD approach. In November 2001, the NBER Datation Committee determined officially 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 the average over this period).

Table 1 - Evolution of the IARC indicator in the 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	0,50
oct-99	0,59
nov-99	0,50
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 very clear (see Table 2 and Figure 5). In March 2001, the SERI reached the value of 60% and thus crossed the threshold value of 50%. This signal meant that the estimated peak in business activity (point B) occurred during January 2001, taking into account the average delay of 1.4 months. This signal has been confirmed the month after, in April 2001. This result is very close to the NBER datation, however the SERI index of March 2001 has been released in April 2001, thus 7 months before the NBER announcement. Of course, we do not pretend to point out the lack of swiftness of the NBER, which aims to date and not to detect in real time and which is under strong political and public pressures, but this result underlines the reliability and the timeliness of our indicator.

The various series which compose the indicator provided 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 well known as a leading indicator of the classical cycle. Then, the two series related to employment have indicated the start of the recession in March and April 2001, which points out that employment is coincident with the classical cycle. Lastly, the construction spending series attained 55% in July 2001 and did not stay a long time in a recession regime. This phenomenon reflects partly the resilience of the American households to decrease their spending during this recession, which avoided a deeper crisis.

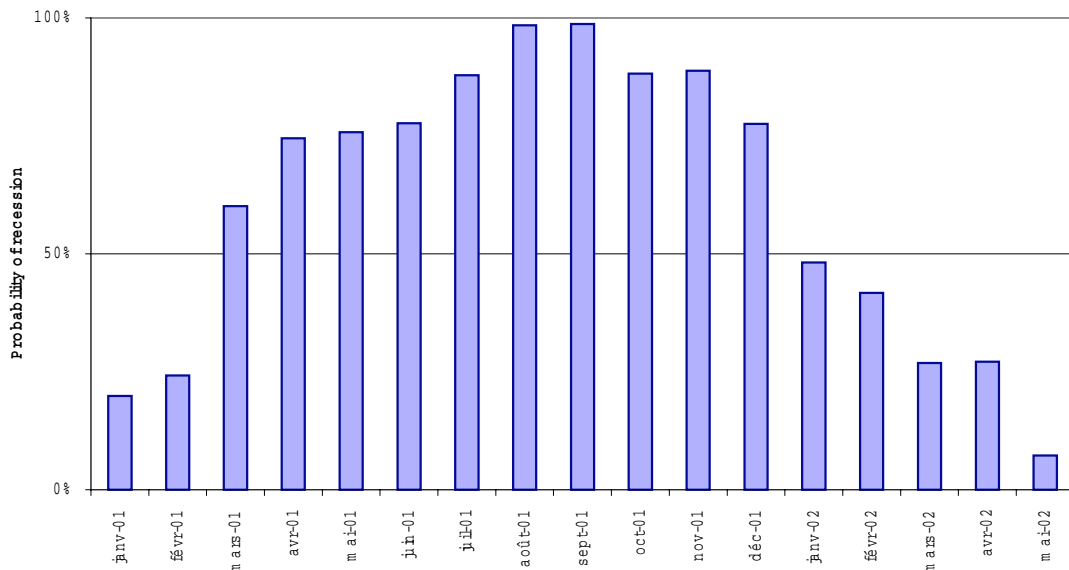
Table 2 - Evolution of the dynamical probability of being in recession for each component of the SERI indicator and evolution of the indicator itself from January 2001 to May 2002

	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

The unusual divergent behavior in timing of the SERI components is characteristic of this latter recession and has been the cause of the difficulty for most economist to detect clearly this episode as a recession. Indeed, it took a long time for the experts 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 estimated peak of the classical business cycle is 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 this attack has just lengthen this recession of two or three months.

This latter US recession can be qualified as a mild recession, especially if we look at the GDP growth rate which has been negative only during one quarter (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.

Figure 5 - Evolution of the SERI indicator from January 2001 to May 2002

Once the point B was detected, we were looking for the 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 can be estimated to be in November 2001. Assuming this date will be confirmed later by the NBER, this implies that this recession lasted 9 months, a length close to the average length over the eight last recessions (11 months). The US recessions length is lying between six (in 1980) and sixteen (in 1974) months.

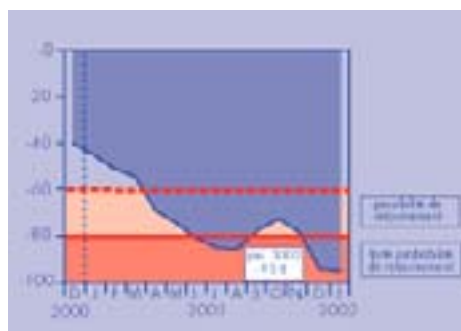
In parallel, the IARC was used to detect the point D, *i.e.* the trough of the growth cycle (see Table 3 and Figure 6). A signal was emitted in July 2001 (the IARC crossed the threshold value of 80%), implying a trough in the next three months. This signal was cancelled out by an unpredictable shock : the September 11th terrorists attack. As a result, the values of the IARC from September to November 2001 declined under 80%. Finally, a signal of a trough was emitted by the IARC with the data of December 2001, implying thus that the 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 can be dated to the first quarter of 2002.

Table 3 - Evolution of the IARC indicator in the search for a trough of the growth cycle from January 2001 to December 2001

janv-01	-0,44
févr-01	-0,50
mars-01	-0,53
avr-01	-0,68
mai-01	-0,73
juin-01	-0,80
juil-01	-0,84
août-01	-0,84
sept-01	-0,76
oct-01	-0,72
nov-01	-0,77
déc-01	-0,94

Source: COE, May 2002

Figure 6 - Evolution of the IARC indicator in the search for a trough (point D) from January 2001 to December 2001



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 different reasons.

- For some countries of the Eurozone, homogeneous series of quarterly GDP are not available for a long period of time. The series of german GDP was starting in 1992 because of the reunification but a repotation should be soon available.

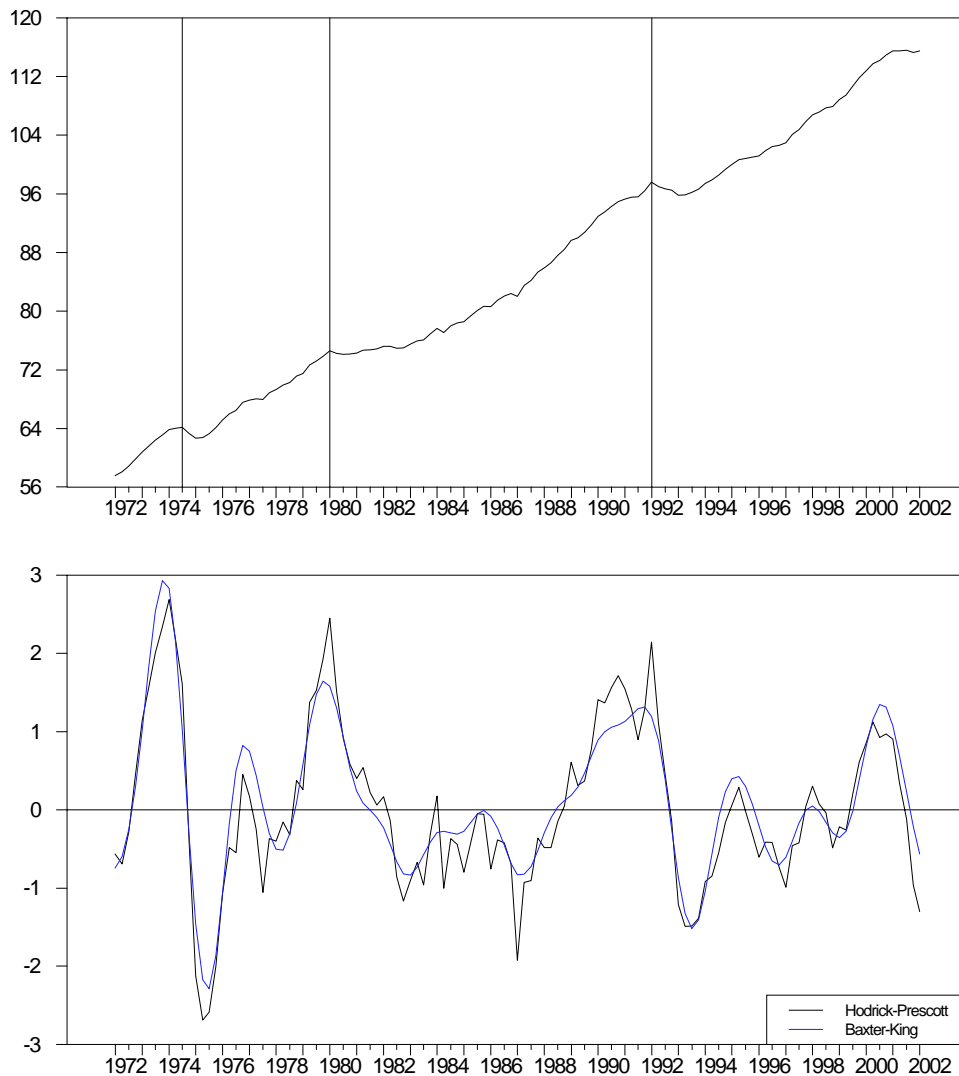
- In some series, the methodology has been changing overtime; for example GDP for France is corrected for trading days since 1995. With new base years, estimates are not strictly comparable along time.
- The method for seasonal adjustment or correction of trading days is not homogeneous across countries. The adjustment may be done before or after the aggregation (indirect versus direct method)

For dating 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 here to discuss those issues. Let mention the recent work of the Conference Board (see Zarnowitz and Ozyildirim, 2001) showing that the TPs identification show 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. Therefore, this series is quite provisional. For estimating the growth cycle, we use both above mentioned filters. Different turning points datation techniques are available. An easy one is the Bry and Boschan (1971) approach, applicable directly 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 graphically the peaks and troughs of the cycles, 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. Zarnowitz and Ozyildirim (2001) indicated in their study 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 also could 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 the "trou d'air".

Over the period January 1972 – March 2002, the Eurozone economy experienced eight growth cycles (see Figure 7). Three of them have been followed by a business cycle. The growth cycle peaks of 1977, 1986, 1995, 1998 and 2000 (points A in the ABCD approach) have not been 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 two following 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 yet clearly established but, according to our projections, should have occurred in the second quarter of 2002. Despite a decrease of GDP in the last quarter of 2001, there was no recession in the Eurozone during that period of time.

Figure 7 – Eurozone GDP and growth cycle from Q1 1972 to Q4 2001



3.3.2 Detecting the Eurozone growth cycle

We first need 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 have selected five leading series:

- a Eurozone stock market index
- the spread between long and short term interest rates

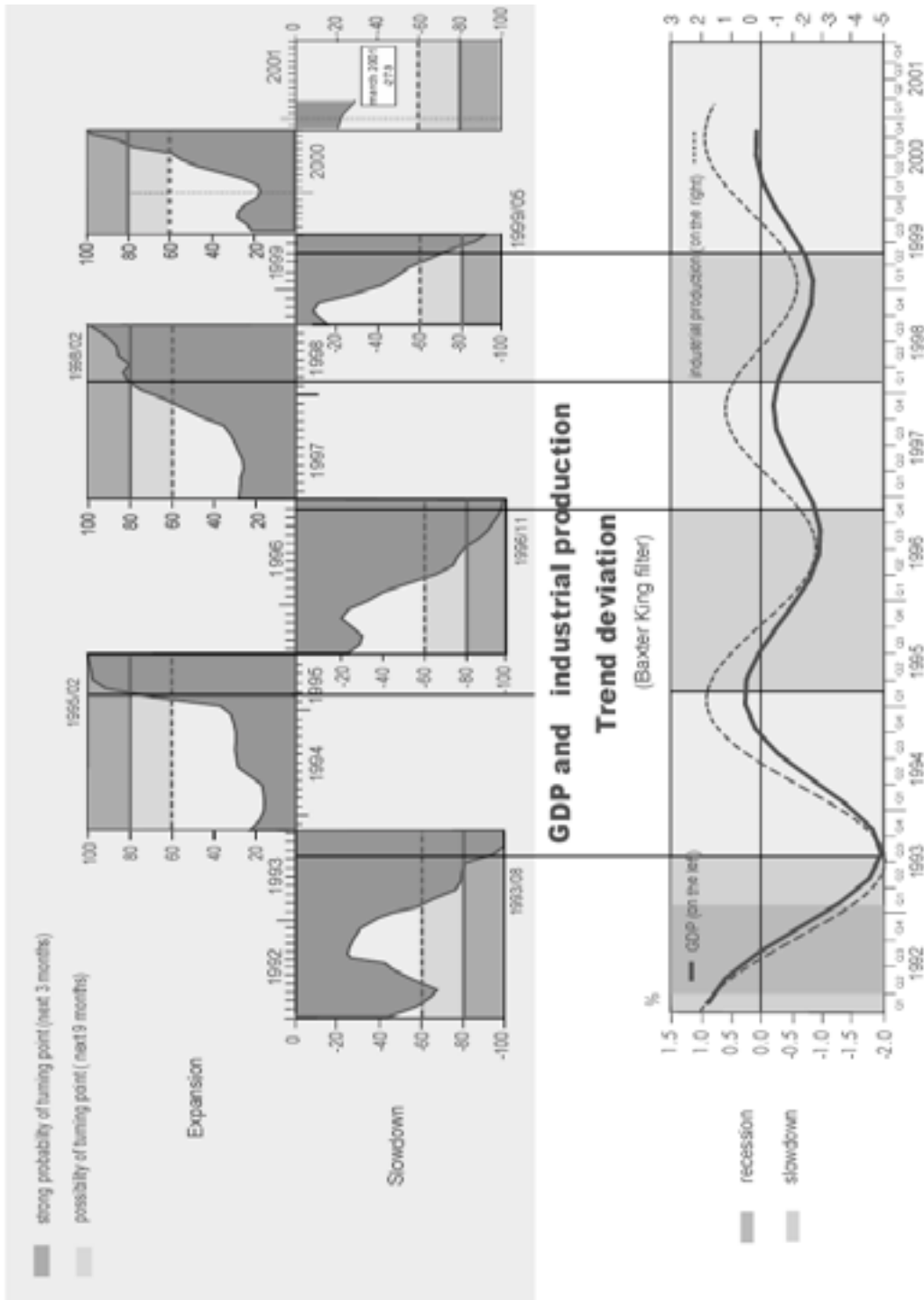
- the first factor of a principal component analysis of business survey results in the intermediate goods industry in the Eurozone
- manufacturer prices expectations concerning wholesale trade in the Eurozone
- the COE leading indicator of the American growth cycle.

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 8: a strong signal is always emitted in the three months before the turning point.

Figure 8 - Performance of the COE leading indicator for the Eurozone

EURO ZONE : Leading indicator of turning points



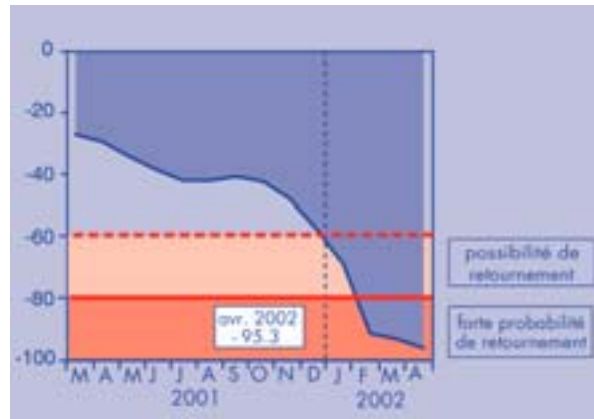
The Eurozone growth cycle upward phase ended at the end of the last quarter 2000. Actually, the peak can be found in the third quarter of 2000 according to the last estimate of the cycle done in May 2002 (because of edge effect it takes at least one year to locate a peak). A strong signal was given by the COE leading indicator in October 2000 (see Figure 9), 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.

Figure 9 - COE leading indicator for the Eurozone: search for the next peak in December 2000



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

Figure 10 - COE leading indicator for the Eurozone: search for the next trough in April 2002



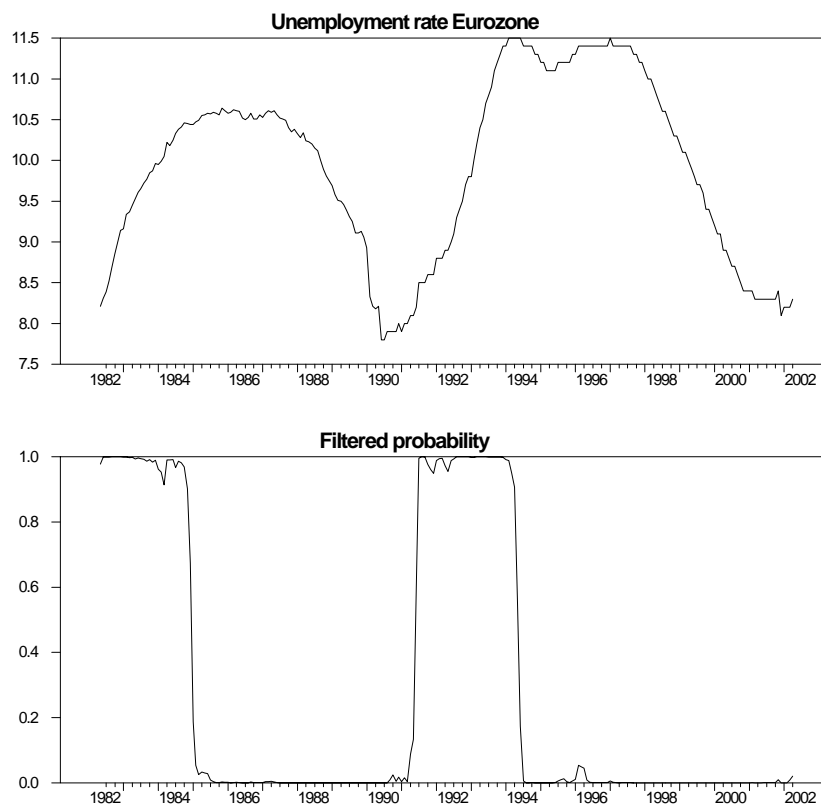
3.3.3 Detecting the Eurozone classical cycle

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. Therefore, we must 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 coincident indicator which was 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 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 delay of publication. Monthly series are only available for some European countries.

Another series of interest, close to the employment series, is the unemployment rate series. This series appears to give more or less 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 are identified by the MS model since 1982 (see Figure 11).

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



We also have tried other series derived from some European surveys. Below are presented the filtered probabilities of being in 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 concerns 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 business cycle, these series provide too much false signals of recession. Actually, they are informative of the growth cycle.

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

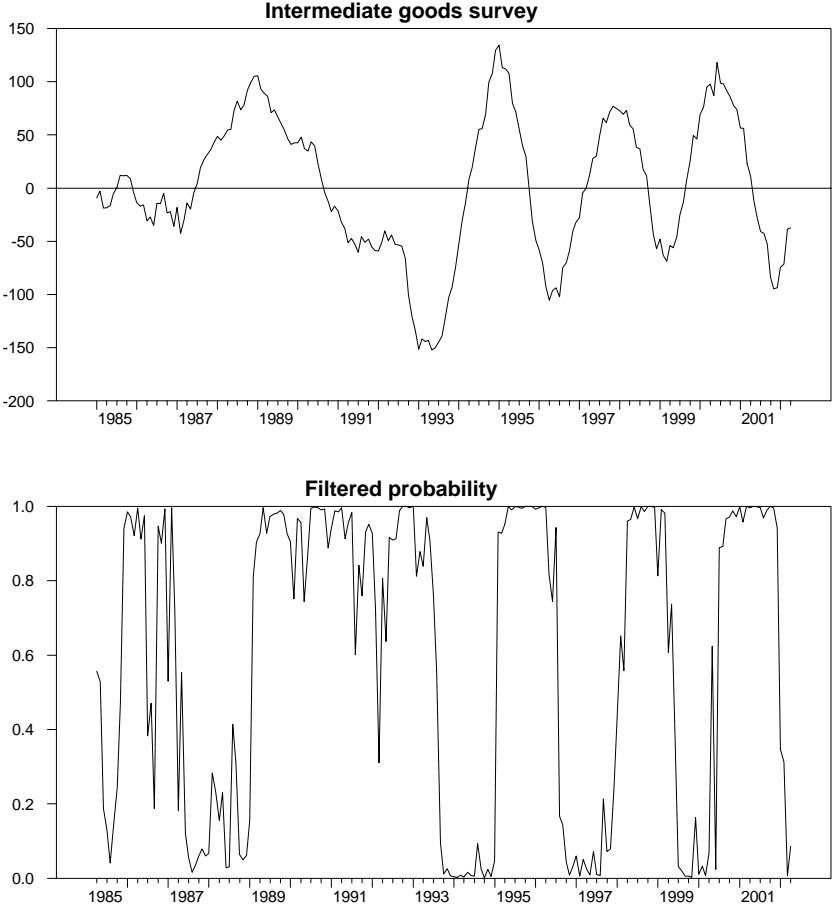
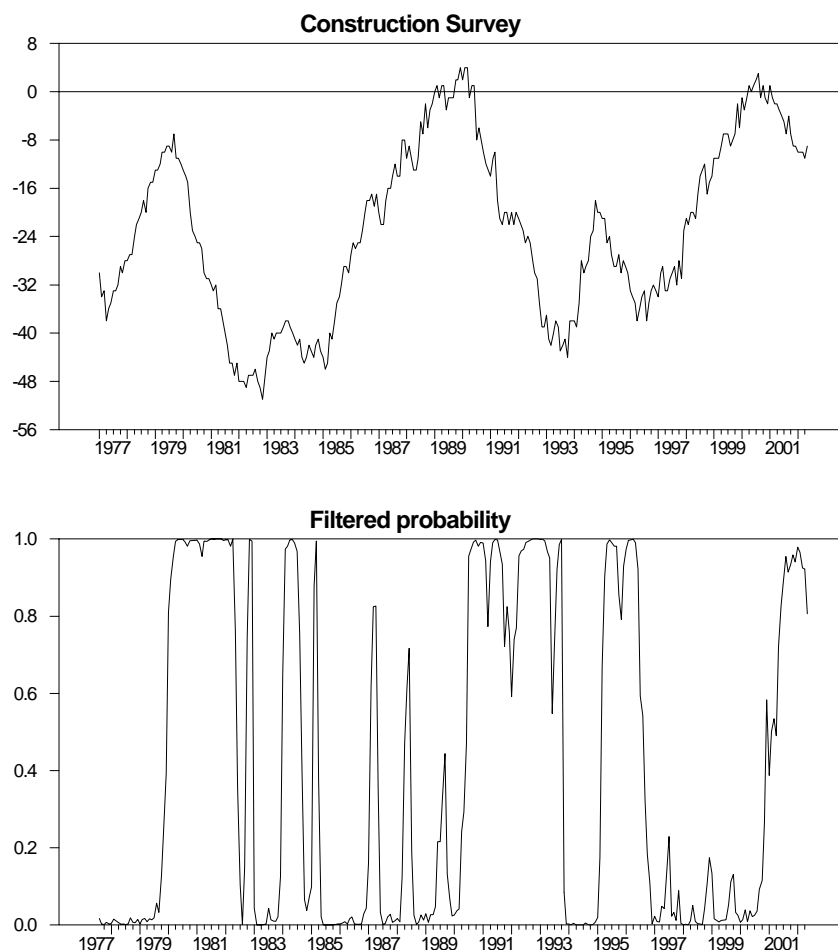


Figure 13 - Survey on Eurozone construction from January 1977 to May 2002 and filtered probability of being in a low regime (MS(2)-AR(0) model)

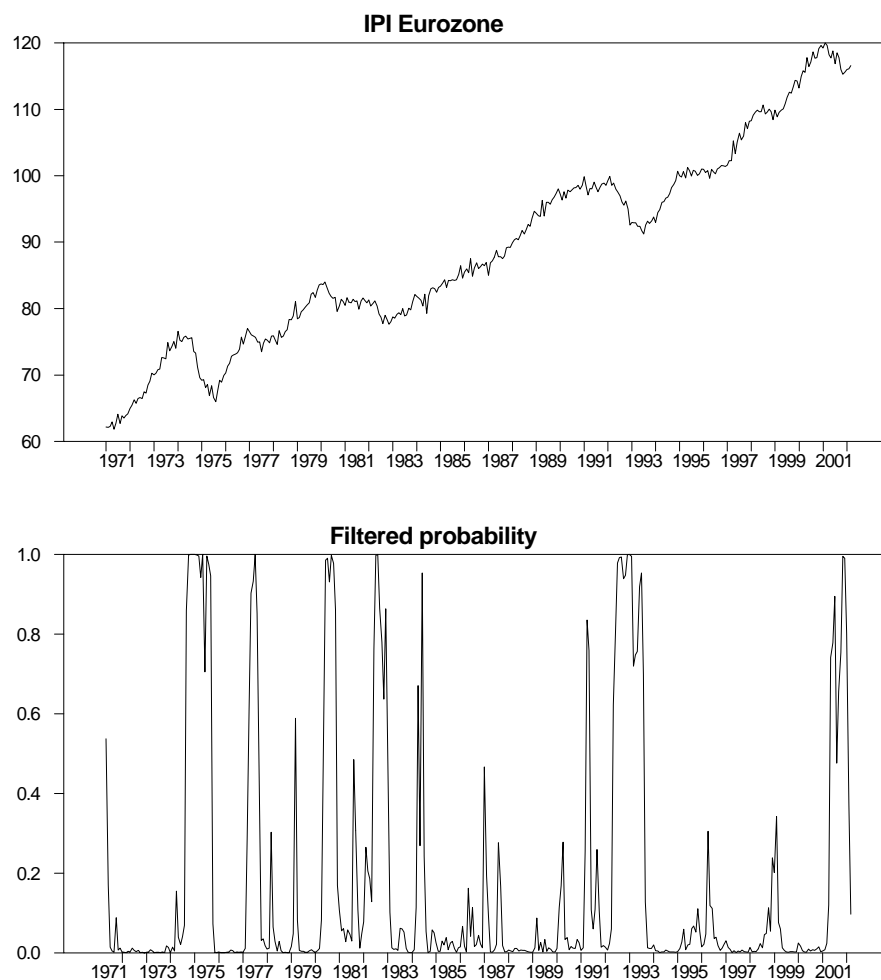


We finally tried to use the industrial production index as a coincident indicator. The results are sensitive to the selected frequency (monthly or quarterly), to the degree of smoothing and to the choice concerning the length of the variation taken into account. Depending on those choices, the MS model exhibits more or less signals. For example, we could use a variation over 18 months on the monthly series to avoid any false signal. But in this case, the signal would be very late (more than one year on average). Actually, the industrial index shows several industrial recessions (see Figure 14) which number depends on the criteria used to define a recession. We observe that the index has been decreasing for several months in 2001, showing therefore a 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, under development in the COE, should be soon available.

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



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