A system for dating and detecting turning points in the euro area[1]

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Abstract

In the paper we aim to introduce a statistical dating and detection of turning points giving them a first economic interpretation. The main advantage of the proposed approach is represented by the fact that classical and growth cycles are jointly considered both in the dating and in the detecting stage. A key result of this choice is a better description of different economic phases as well as a more accurate investigation of the economic cyclical behaviour. The proposed approach considerably improves the relevance of information delivered to users in comparison with a standard analysis based only on classical or growth cycle component.

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1. Introduction

The main aims of business cycle analysis are to detect, in real-time, and anticipate, as far as possible, economic fluctuations with a particular attention paid to the turning points. The achievements of such goals strongly depend on the availability of a reliable historical analysis of main cyclical events. The accurate dating of past turning points as well as a detailed description of cyclical movements (length, deepness, symmetry, etc.) are essential elements of this historical analysis. Moreover, a detailed comparison of convergence and synchronisation of cyclical fluctuations among sectors and countries constitute a useful complement to the previous analysis in order to identify common and idiosyncratic behaviours. The dating and detection processes are not considered as easy tasks for several reasons.

First of all we have to clarify to which cycle definition we refer to, classical cycle, growth cycle or acceleration one, because distinct definitions will tackle different features. Each characterization of cyclical movements has obviously advantages and drawbacks, and relates to specific aspects of economic fluctuations.

Second, the dating exercise has to be based on sufficiently long time-series covering several cycles. Unfortunately this requirement is difficult to fulfil because statistics can be affected by a several methodological changes, evolving statistical aggregates and classifications etc., which will inevitably shorten their length (or cause breaks). Finally, in the process of dating and detecting turning points, statistical findings need to be interpreted and validated from an economic and even more, from a political point of view.

The objective of this paper is to define a framework for dating and detection of turning points for the euro area as a whole. As regards to the kind of cycle we have to deal with, we have decided to develop an integrated approach allowing us to date and detect in a consistent way both the classical and the growth cycle, while the acceleration cycle has been excluded due to its volatility.

Concerning the availability of long time-series for the euro area this has been one of the major problems which we have been confronted to. The empirical part of the paper is based mainly on provisional back-calculations of euro area aggregates available at Eurostat - and currently under assessment.

In this paper we introduce a statistical dating and detection of turning points giving them a first economic interpretation. A full validation from an economic and political point of view of the proposed chronology has to be considered out of the scope of this paper.

The main advantage of the proposed approach, from the authors' point of view, is -that classical and growth cycles are jointly considered both in the dating and in the detecting stage. A key result of this choice is a better description of different economic phases as well as a more accurate investigation of the economic cyclical behaviour. The proposed approach considerably improves the relevance of information delivered to users in comparison with a standard analysis based only on classical or growth cycle component.

The structure of the paper is the following: Section 2 presents a synthetic comparative analysis of existing chronologies, focusing either on classical or growth cycle chronologies. Section 3 describes the methodological framework of the paper. Section 4 introduces a simultaneously dating of turning points presenting a first chronology as well as the results of a diffusion and synchronisation analysis based on six main euro area countries. Section 5 is devoted to the construction of two coincident indicators for the real-time detection of turning points: we present the methodology for the construction of both indicators and compare four alternative approaches. Furthermore, we show the results for a coincident indicator of the classical cycle and briefly discuss alternatives for a release policy of the two indicators. Section 6 presents some conclusions and lines for further research.

2. Overview of existing chronologies

There are a great number of papers on national chronology dating (i.e. Belgium, United Kingdom, Canada, Austria, and Australia), however very few countries have official dating procedure (among them US (NBER), Japan (EISR) and Italy since 1999 (ISAE)). Since the establishment of the euro area several papers have been devoted to its cyclical dating. Moreover, an academic Dating Committee has been set up by the CEPR to validate the observed turning points.

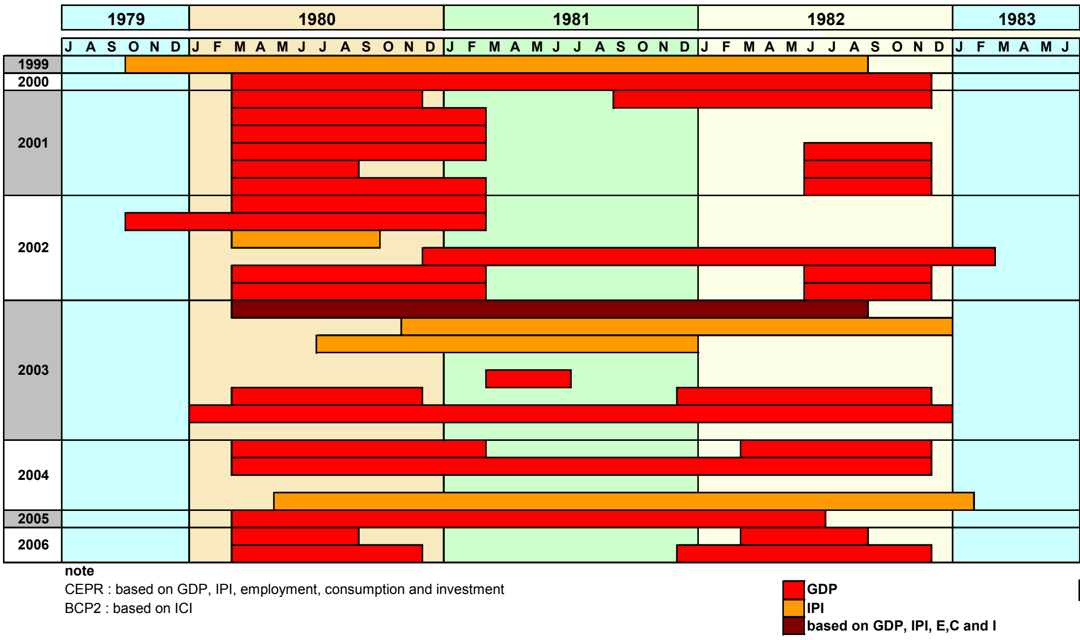
2.1 Business Cycle turning points dating

As regards the business cycle turning point dating, although this list is not exhaustive, we refer to the following twenty papers: Artis, Krolzig and Toro (1999, AKT), Krolzig and Toro (2000, KT), Lommatzch and Stephan (2001, LS), Krolzig (2001, K1,K2) and (2002, K1,K2, K3), Harding and Pagan (2001, HP, 2004, HP), Fagan, Henry and Mestre (2001, FHM), Beyer, Dornik and Hendry (2001, BDH), Harding (2002, H), Artis, Marcellino and Proietti (2002, AMP1, AMP2), CEPR (2003, CEPR), Bengoechea, Camacho and Perez-Quiros (2003, BCP1, BCP2), McAdam (2003, M1, M2), Kaufmann (2003, KA1, KA2), Anas and Ferrara (2003, AF), Artis, Krolzig and Toro (2004, AKT), Bengoechea and Perez-Quiros (2004, BP1, BP2), Artis, Marcellino and Proietti (2004, AMP), Mönch and Uhlig (2005, MU), Benalal et al. (2006, BA), and Anas and Ferrara (2006, AF). Some authors are repeated because they may change their turning points estimates over time. The consensus chronology may be summarized as follows:

- One recession in 1975 (first oil shock) with a peak between 1974Q1 and 1974Q3. The trough is mainly located in 1975Q1 or 1975Q3;
- One recession in 1980-1982 or a double-dip (second oil shock and US double dip recession). The full-fledge recession is mentioned by Artis, Krolzig, Bengoechea and Mönch. There is an agreement on the termination in 1982Q3 or 1982Q4;
- One recession in 1993. The peak is located in 1992Q1 generally, sometimes in 1992Q2. The location of the trough lies between 1993Q1 and 1993Q3, with a majority however in 1993Q1.
- An industrial recession in 2001 and another in 2003 are identified by Bengoechea (2003 and 2004) while the beginning of a further global recession in 2001Q1 is mentioned by Krolzig (Nov. 2002).

The various dating have more or less the same quality since they are converging generally towards the same dating. There is however an uncertainty of around one semester about the location of the turning points. The question of a double-dip or a full-fledge recession in 1981-83 is still open. As an example, Figure 1 shows the convergence for the 1980-82 recession.

Figure 1: Convergence of business cycle turning points dating of the euro area (1980-82 recession)



Duration

AKT		35		
KT	33			
LS			9	15
K1	12			
K2	12			
HP			12	6
FHM			6	6
BDH	12		6	
H	12			
K1	16			
K2		7		
K3	27			
AMP1			12	6
AMP2			12	6
CEPR	30			
BCP1		26		
BCP2		18		
M1				
M2	4			
AF			9	12
KA1				
KA2				
HP			12	9
AKT	33			
BP1				
BP2		33		
MU	28			
BA			6	6
AF			9	12
Mean	18.8	23.8	9.3	8.7

2.2 Growth Cycle turning points dating

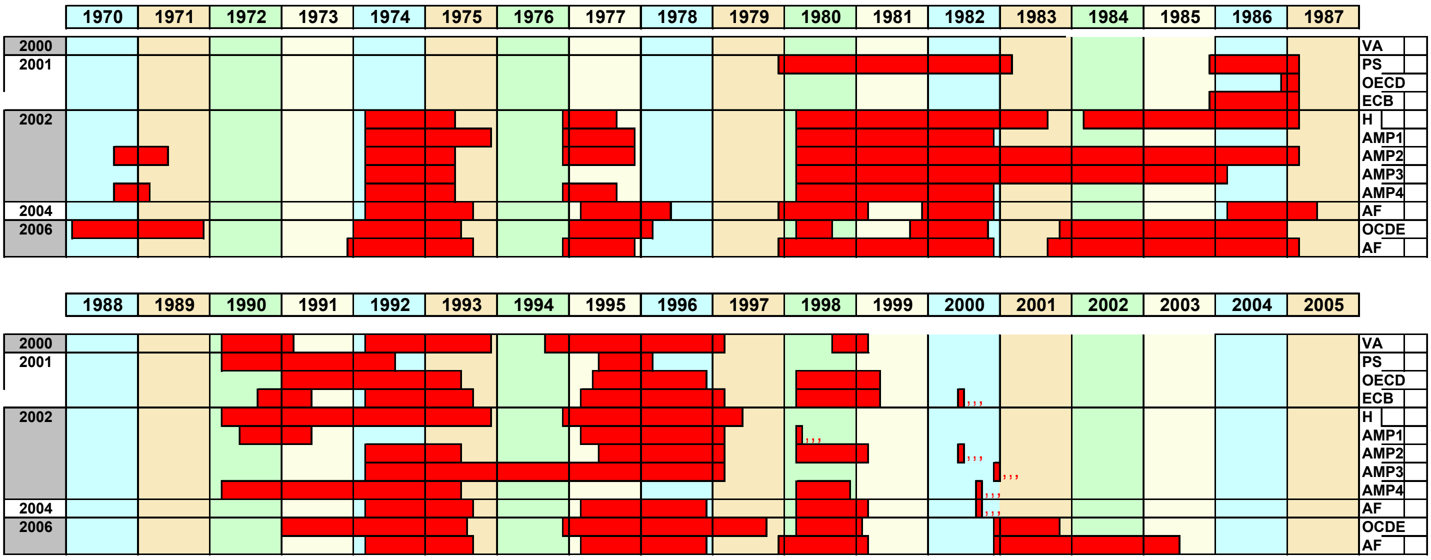
As regards the growth cycle turning point dating, we found only seven sources, but once again this list is not exhaustive: Vanhaelan et al. (2000, VA), Peersman and Smets (2001, PS), European Central Bank (2001, ECB), Harding (2002, H), Artis, Marcellino and Proietti (2002, AMP1, AMP2, AMP3, AMP4) Anas and Ferrara (2000, 2004 and 2006, AF), OECD (recurrent) (OECD). Most of the dating was done in the early 2000's. The scarcity of dating in the last years is probably a consequence of the greater instability in the euro area and the questionable convergence which emerged in many recent articles. A comparison for all mentioned sources could be undertaken since 1980, which is the most common and reasonable starting date for dating. The main findings of this comparison can be synthesized as follows:

- The authors agree on the occurrence of a peak (the onset of the second oil shock) in the 1979Q4-1980Q1 period. There is also a clear agreement on the occurrence of a trough in the 1982Q4-1983Q1 period (except for Harding: 1983Q3).
- Two authors include an intermediate cycle in 1981, linked probably to the idiosyncratic economic rebound in France due to the new economic policy entailed by the socialist party victory: Anas and Ferrara (in 2004 but not anymore in 2006) and OECD (until now).
- Another cycle is identified around 1986 by some authors.
- There is a general agreement on the trough of 1987Q1.
- For the subsequent peak, there is an uncertainty due to the German reunification. There is a majority of peaks in 1992Q1 (except the OECD mentioning 1991M1). Other authors mention 1990Q1. The following trough is located between 1993Q2 and 1993Q3.
- A peak is often mentioned in early 1995 with a subsequent trough in 1996Q4 or 1997Q1. The OECD is the exception with 1997M10.
- The Asian crisis related cycle is also mentioned in most dating with a peak commonly in 1998Q1 (except Vanhealan: 1998Q3) and a trough in 1999Q1
- For the most recent cycle, the studies are generally too old to identify them. The last identified peak is located between 2000Q2 and 2000Q4. The most recent trough is only identified by the OECD (2001M11) and Anas-Ferrara (2003Q2)

Finally, we can say that there is a general agreement on the number of cycles (see Figure 2 for the convergence of Growth Cycle turning points dating) with a discrepancy of one semester on the location of turning points, while disagreements mainly concern:

- the effect of the reunification on the location of the peak in the early 90's;
- the identification of a first mini-cycle in 1986 and a second one in 1998.

Figure 2: Convergence of growth cycle turning points dating of the euro area



3. Cyclical framework

From the previous section, it appears evident that the authors have concentrated their attention mainly on the classical business cycle, whilst the growth cycle has been treated only by a few of them. At the same time, looking at the whole period covered by the dating exercise, we can observe that only three, or maybe four recessions have been identified, with only one between the second half of the 1980's and the end of the 1990's. This evidence, together with the business cycle high degree of asymmetry, can be considered as a drawback of an analysis based only on classical cycle both for its limited informative power as well as for its relevance for policy making purposes.
On the other hand, despite the limited attention of academics, it is well known that central banks, financial market analysts and policy makers look at the behaviour of the growth cycle with particular attention. The main disadvantage of an approach based on growth cycle is due to the fact that it strongly depends on the underlying detrending approach. The separation between trend and cycles is conceptually correct and useful but empirically difficult to carry out because of their interaction. In this section we present an approach to business cycle analysis integrating classical and growth cycles. This will allow us to identify, in a common framework, both classical and growth cycle turning points giving a more accurate description and follow-up in real time of the economic global cyclical fluctuations.
In order to achieve this objective, we refer here to the so-called "ABCD approach" originally proposed by Anas and Ferrara (2004). The ABCD approach is not developed in details in this paper and we refer to the paper by Anas and Ferrara (2004) for further discussion on this approach. Briefly, the main idea is that there exists a chronology in the sequence of the turning points of the business and growth cycles. In order to assess and understand the ABCD approach we have to

clearly identify what kind of turning points we are dating and detecting. The business cycle is made up of expansions and recessions, i.e. the fluctuations of the level of the series. The growth cycle instead (the deviation from trend and sometimes called deviation cycle) seeks to represent the fluctuations around the trend. Therefore its identification implies the previous delicate task of estimating the trend, which is rather difficult especially in real time[6]. However, it is a quite useful tool for describing and analysing historical fluctuations. The growth rate cycle (sometimes called acceleration cycle) seems easy to compute but the underlying pace, i.e. free of irregular movements, is not so obvious to estimate[7].
Specific turning points (TPs) are associated with those three cycles. Points B and C will be the extreme points of the classical cycle, while points A and D will be those of the growth cycle. The ABCD approach is based on the two following principles:

- The TP dating or detection issue must be considered as a progressive follow-up of the cyclical movement. Even if no cycle is similar to the previous one, the sequence of turning points is always respected in practice. A slowdown movement will first materialise in a peak in the growth cycle (point A) and if it is getting worse, the growth rate will become negative (point B) determining a recession. For an upward movement, the sequence will be a trough of the business cycle (point C) and a recovery of the growth rate above the trend growth rate (point D).

- However, if the slowdown does not gain in intensity to become a recession, then point A will not be followed by point B. In other words, the economy can experience a descending phase of the growth cycle (peak A and trough D) without going through a recession (peak B and trough C). We call the monitoring of the temporal sequencing of those points (A and B for peaks and C and D for troughs) the ABCD strategy for TPs analysis.

- It is worth noticing that the ABCD approach is an empirical one. The empirical analysis we propose does not rely on a theoretical approach of the nature and the causes of the cycles. Therefore, it is not a proposal of a unified theory that applies to business cycles and growth cycles alike. This is rather a data-driven approach that provides successive real-time signals to decision-makers in terms of turning points. There are different patterns of cyclical development. A recession may occur suddenly so that A and B would coincide. Symmetrically, in a rapid exit of a recession, C and D would coincide. As regards the CD phase, the economy can go from C to D either with a fast pace (V-shaped exit, the dates of C and D are close) or with a slow pace (e.g. “jobless” recovery, the dates of C and D are distant), but D will always be the date where the deviation to trend reaches a minimum.

- In the estimation part, the business and growth cycles are treated separately. For the dating exercice, we propose two separate turning point chronologies: one for the business cycle and one for the growth cycle. Of course, the ABCD chronology has to be respected. In the detection process, we also propose two separate indicators: one for detecting the business cycle TP’s and one for the growth cycle TP’s. Therefore, while the ABCD approach proposes an interpretation and an integrated analysis of the cycles, those cycles are estimated and detected separately. An improvement of this research could be to assess simultaneously both cycles by using a parametric model with three regimes as in Ferrara (2003).

4. Dating euro area business and growth cycles

[6] This is why the ECRI decided to abandon the using of the growth cycle after having using it for twenty years (Achuthan and Banerji, 2004).
[7] The Eurocoin indicator is an attempt to measure this underlying growth at the level of the euro area.

In this section, we describe the methodology we developed to estimate euro area turning points chronologies for both business and growth cycles. Clearly, we assume the existence of a meaningful euro area aggregate for which we assess the cyclical fluctuations. Therefore, the dating will be made directly on euro aggregates. More precisely, the dating of the euro area cycles is derived from a direct approach based on aggregate GDP and IPI on which we measure the amplitude and the duration of the movements. In a second step, we assess the geographical diffusion and synchronisation through an indirect approach based on country-specific GDP and IPI. The coherence between direct and indirect approaches is thus ensured. We see the indirect approach as a check for robustness of the direct approach. Similarly, the detection is based on euro area aggregated variables, implying no mismatch between dating and detecting. Results are presented at the end of this section.

Business and growth cycles are distinct concepts. As the growth cycle is defined by the deviation from the trend, once the trend has been extracted, the peaks A and troughs D of the ABCD approach are not so difficult to locate because of the quasi-symmetry of the growth cycle. In this paper, we consider the "two-stages" Hodrick-Prescott filter (HP2 hereafter, see Artis et al., 2002) which allows to design a band-pass filter as the difference of two Hodrick-Prescott low-pass filters, the first one working on higher frequencies (we choose 1.5 years) and the second one on lower frequencies (we choose 8 years).

The business cycle is non-linear and strongly asymmetric, insofar as expansion and recession periods do not present the same stylised facts as regards, for instance, duration, persistence or volatility (see for example Clements and Krolzig, 2003, for a discussion on business cycle asymmetries). Therefore, points B and C are more difficult to locate: the business cycle requires further concepts to be measured. We assume the description of Burns and Mitchell (1946) of the business cycle into two regimes: expansions and recessions.
For both cycles, we assess the occurrence of a phase by measuring the criteria of duration and deepness. Starting from a set of candidate turning points provided by the non-parametric algorithm described below, we will give a measure of these criteria and say that the euro area is in a given phase if these criteria are simultaneously fulfilled. Duration and deepness are measured starting from the euro area aggregated time series (direct approach). Diffusion and synchronisation are also estimated starting from specific country variables (indirect approach). It is noteworthy that our methodology is a general-to-specific one, insofar as we consider all the candidate turning points provided by the non-parametric procedure and we eliminate them progressively when they do not verify one of the criteria.

4.1 A non-parametric algorithm

According to the results of Anas and Ferrara (2004) and Anas et al. (2006), we are in favour of non-parametric procedures instead of parametric ones in the framework of turning points dating chronology. Indeed, it has been shown that the model specification step is an intricate issue and can lead to inappropriate results. Moreover, if the model is not stable, adding a new point to the series can change dramatically the chronology, which is not desirable. For the real-time assessment of turning points, parametric models are preferred (see Section 5).

We describe below the procedure for the business cycle, but we have to mention that the same procedure applies in the case of the growth cycle. The term "recession" has just to be replaced by the term "low phase of the growth cycle".

In the first step, a set of candidate periods of recession has to be selected on the aggregated series, through the dating procedure. The non-parametric procedure, considered to obtain a dating chronology on a univariate aggregated time series, is based on the following algorithm:

1. Outliers are disregarded in the seasonal adjustment step executed by either Tramo-Seats or Census-X12-Arima.
2. For monthly data, irregular movements in the series are excluded in the seasonal adjustment step executed by the procedure. We focus on the Trend-Cycle series. In the case of GDP quarterly data the SA-WDA series are not smoothed out.
3. The identification of a first candidate set of turning points on the time series of interest (y_t) is determined by using the following rule, which is the heart of the Bry and Boschan (1971) algorithm:
   Peak at t : $\{ y_t > y_{t-k} , y_t > y_{t+k} , k=1,\ldots, K \}$
   Trough at t : $\{ y_t < y_{t-k} , y_t < y_{t+k} , k=1,\ldots, K \}$,
   where $K=2$ for quarterly time series and $K=5$ for monthly time series.
4. Turning points within six months of the beginning or end of the series are disregarded.
5. A procedure for ensuring that peaks and troughs alternate is developed by using the following rule:
   - in the presence of a double through, the lowest value is chosen.
   - in the presence of a double peak, the highest value is chosen.

This algorithm allows the selection of a first set of candidate turning points.

4.2 Deepness and duration assessment

Once the candidate periods have been retained by the non-parametric algorithm on the aggregated series, we assess the criteria of duration and deepness. The duration means that the phase must last "more than a few months", as noted by the NBER in its seminal definition of a recession, but there is no reference minimum duration. We use the following criteria:

1. a phase of the cycle must last at least 6 months for the business cycle and 9 months for the growth cycle;
2. a complete cycle must have a minimum duration of 15 months for the business cycle and 18 months for a growth cycle.

The deepness refers to the amplitude of the phase. As noted by the NBER, a recession is a "significant decline in activity". Obviously, the practical difficulty is to assess when the fall of the economy is "significant" enough. To measure this amplitude, we use the following value of deepness, for a recession:

$$Deepness = |X_P - X_T| / X_P, \tag{3.1}$$

where X_P and X_T are respectively the values of the series at the peak and trough of the business cycle to be considered. In the case of normalised indexes, such as the Industrial Production Index, we simply look at the difference between the values of the series at peak and trough. Moreover, concerning the growth cycle, because of its symmetry, we simply consider the absolute difference for each phase.
To summarise the information on both duration and deepness we assess the measure of, what we call, severity (denoted S) of a recession defined by:

$$S = 0.5 \times Deepness \times Duration. \tag{3.2}$$

This measure is in fact the percentage of loss during the phase of the cycle[8]. This severity measure is also referred in the literature as the *"triangle approximation" to the cumulative movements* (see for example Harding and Pagan, 1999). Note that there is a wide literature concerned with the concept of "cycle shape"; we refer for example to the paper of Clements and Krolzig (2003).

4.3 Diffusion and synchronisation assessment

Once duration and deepness have been estimated for each candidate cycle through the severity index, we assess their diffusion and synchronisation over the countries by considering an indirect analysis. The spatial diffusion means that almost all countries have to be affected by the exogenous shock in the case of a recession while the concept of synchronisation refers to the timing of the impact of the exogenous shock which creates leads and lags in cyclical movements of different countries. For instance, the industrial growth cycle in 1995 did not turn into a recession because it was not synchronised. Indeed, Italy and the Netherlands were in industrial recession later than the other countries. As another example, the 1998 impact of the Asian crisis was not diffused to all the countries in the euro area, only Italy and Belgium were affected by an industrial recession.

In this section, we introduce a version of the simultaneous measure of diffusion and synchronisation between N cycles introduced by Boehm and Moore (1984) and revisited in Harding and Pagan (2002). Actually, Boehm and Moore (1984) developed an algorithm which seeks to reproduce the NBER dating procedure by identifying clusters of turning points and apply it to the Australian economy. One of the advantages of this method is to provide as a by-product a dating chronology of the business cycles, that we call in the remaining *indirect dating*.
First, we compute a dating chronology for each country i, for $i=1,\ldots,N$, according to the method described in the previous subsection 4.1. Then, we define τ_{ij}^{P} (respectively τ_{ij}^{T}) as the observation date of the j^{th} peak (respectively trough) in the country i. We define $d_i^P(t)$ (respectively $d_i^T(t)$) as the distance in time from t to the nearest peak (respectively trough) in the country i. That is, for $i=1,\ldots,N$ and for $t=1,\ldots,T$:

$$d_i^P(t) = \underset{j}{Min}\left|t - \tau_{ij}^{P}\right| . \tag{3.3}$$

In order to aggregate the information relative to the countries, we consider the following statistics, which are the distances to cycle peaks and troughs for the euro area as a whole:

$$d^P(t) = \sum_{i=1}^{N} \omega_i d_i^P(t), \tag{3.4}$$

and

$$d^T(t) = \sum_{i=1}^{N} \omega_i d_i^T(t), \tag{3.5}$$

where $(\omega_i)_i$ are the weights of the countries in the euro area according to a given economic aggregate. We can consider the GDP of the country or the weights given in the national account statistics or in the short term business statistics[9].
Dates at which $d^P(t)$ and $d^T(t)$ achieve their local minima can be assumed to be the dates of the centres of a cluster of, respectively, peaks and troughs for the euro area. Thus, we obtain a set of dates t_j^P and t_j^T defined as the estimated indirect dates of peaks and troughs for the euro area.

[8] In fact, the « real » loss would rather be the surface lying below the trend.
[9] See for example the Annex 1 of the third progress report on the implementation of the Monetary Committee's report on information requirements in EMU (note EFC/ECFIN/610/02 of 15 January 2003).

As a measure of the diffusion/synchronisation (DS, hereafter), we choose the following statistic, for peaks (respectively trough), when $d^P(t_j^P) \neq 0$, :

$$DS_j = \frac{1}{d^P(t_j^P)} \times 100. \tag{3.6}$$

High values of this statistics will indicate that the turning point is well diffused and synchronised. When *DS* statistics retains small values, the turning point is neither diffused nor synchronised and when DS has an intermediate value, it means that the cycle is either not enough diffused or not enough synchronised. This *DS* measure can be seen as an estimate of the certainty around the turning point. As we do not know anything about the probability distribution of these measures of severity and diffusion/synchronisation, it is difficult to make statistical inference. In this study, the *DS* values serve only as a basis to compare different periods of time.

4.4 Results

We provide a dating chronology for both the business and growth cycles. The definite chronology is based on a direct approach applied to the euro area GDP and IPI.

According to the ABCD approach coherence between growth cycle and business cycle turning points has to be fulfilled. Namely, the sequence of turning points has to be respected. Second, we must check if there is coherence between direct and indirect dating. That is, the turning points estimated during the deepness and duration assessment step has to match with the ones estimated during the diffusion and synchronisation assessment step. A lack of coherence would mean a failure of the dating procedure. Actually, we see the indirect approach as a check for robustness of the direct approach.

According to this methodology, Anas et al. (2007) propose a turning points chronology for both cycles presented in Table 1 and Table 2. In this section, we update this chronology until the last quarter of 2006, by using the latest data stemming from the Euroind[10] database of Eurostat. The time coverage of Euroind-series has been completed by some euro area and Member States back-calculations which are still provisional and not yet official.

According to those dating chronologies, from 1970, it appears that the euro area economy has experienced seven growth cycles, three of them containing a business cycle. The growth cycle peaks of 1977, 1986, 1995 and 1998 (points A of the ABCD approach) were not followed by business cycle peaks (points B of the ABCD approach). The euro area has experienced four economic recessions since 1970:

- the first oil shock (1974 Q2 – 1975 Q1, 3 quarters);
- the second oil shock double-dip (1980 Q1 – 1980 Q4, 3 quarters, and 1981 Q4 – 1982 Q4, 4 quarters);
- the 1992-93 recession (1992 Q1 – 1993 Q1, 4 quarters).

The average time-lag between points A and B was of about 3 quarters in the first recession (first oil shock) and around one quarter in the following two recessions starting in 1980 and 1992.

[10] The Euroind database (European and national short-term indicators is a database containing infra-annual statistics available on the Eurostat website, within the Euro-indicators special topic).

Table 1: Business cycle chronology for the aggregated euro area

Dates	Peak B	Trough C
1974-75	Q2 1974	Q1 1975
1980	Q1 1980	Q4 1980
1982	Q4 1981	Q4 1982
1992-93	Q1 1992	Q1 1993

Table 2: Growth cycle chronology for the aggregated euro area

Dates	Peak	Trough
1974-75	Q1 1974	Q3 1975
1977-78	Q1 1977	Q2 1978
1979-81	Q4 1979	Q1 1981
1981-82	Q4 1981	Q4 1982
1986-87	Q1 1986	Q2 1987
1991-93	Q1 1992	Q3 1993
1995-96	Q1 1995	Q4 1996
1998-99	Q1 1998	Q1 1999
2000-2003	Q4 2000	Q2 2003

As new results, we focus now on the update of the chronologies. As regards the growth cycle, we focus only on data since 1995, estimated by the HP2 method. By applying the non-parametric algorithm on the growth cycle, we retain three peaks and four troughs, implying thus four descending candidate phases of the growth cycle since 1995. Concerning the last candidate phase, with a peak in Q2 2004 and trough in Q2 2005, the amplitude is rather short (equal to 0.26), with a duration of four quarters. Thus, the severity index of this phase is of 0.52, which is very weak in comparison with the severity indexes of previous descending phases (5.27 in 1995-1997, 1.58 in 1997-1999 and 8.86 in 2001-2003). When completing the study with an indirect approach, by computing the *DS* statistics, we show evidence of a local maximum for the troughs, implying the presence of a through in the growth cycle, located in Q4 2004. Thus this trough estimated from the indirect approach is quite different from the one estimated by the direct approach (in Q2 2005). Moreover, when focusing on peaks, we observe that the local maximum is less marked than the previous ones. This rather smooth shape of the local maximum is due to a lack of synchronisation among the countries. In conclusion, we do not accept this last candidate phase as a phase of the growth cycle.

As regards the business cycle, recently, the question arose about evidence of a recession during the last low phase of the growth cycle from Q4 2000 to Q2 2003. Over this period, it is clear that an industrial recession occurred, with a peak B in December 2000 and a trough D in November 2001. However, we did not find any evidences of a global recession on the GDP series. Indeed, the non-parametric algorithm did not detect any recession phase on the aggregated euro area GDP. Therefore, there is no severity measure associated. In the indirect approach, the *DS* measures do not present any significant local maxima, for both peaks and troughs between 2000 and 2006, in comparison with previous recession periods. In fact, four of the six main countries have experienced at least one recession phase between 2000 and 2006 (Germany, Italy, Belgium and the Netherlands). But it turns out, that those phases were neither enough diffused across the countries of the area nor synchronized. Consequently, we decided not to conclude to the occurrence of a recession over the last few years. This result must be carefully interpreted because GDP figures may still be revised, implying thus different results on the countries and on the euro aggregate.

5. Early detection system

The real-time detection of turning points faces the problem of using data in real time with the difficult issues of end-point effects (whenever filters are used to detrend the series) and of data revision. It can be considered as a nowcasting challenge. Real-time detection thus requires methods with a strong statistical content taking into account the non-linearity of the cycles in a parametric way. In this respect, many non-linear models have been proposed in the literature since the early 80`s, often based on regime-switching approaches. Probabilistic composite indicators based on such non-linear models are therefore very useful for the real-time analysis of economic cycles.

In the recent years a lot of attention has been paid to methods based on likelihood or posterior distributions - and there are proofs for their optimality properties (see e.g. Shiryaev, 1963, and Frisén and de Maré, 1991). Many of the suggested methods and most part of the applied literature on real time detection are based on Hidden Markov models or Markov Switching models. In fact, a turning point may be considered as an event modeled as a binary variable and thus these models best capture the idea of the change in the economic activity and are flexible enough to describe its dynamics. In this sense, the real-time detection may be seen as the probability estimation of the event with an attached decision rule.

In particular, Chauvet and Hamilton (2005) discuss formal quantitative algorithms that can be used to identify business cycle turning points. They also provide the intuition and detailed description of these algorithms for both simple parametric univariate inference as well as latent-variable multiple-indicator inference using a state-space Markov Switching approach. To convert the probabilities produced by the switching models into turning point dates they follow Hamilton (1989) and classify a turning point as occurring when the filtered probabilities move from below 50 percent to above 50 percent or vice versa. This approach has the intuitive appeal as it separates phases where an expansion state is more likely from those where a recession state is more likely[11].

Regime switching models popularized by Hamilton (1989) are thus empirically proved to be efficient tools for detecting turning points and in the following we propose two probabilistic coincident indicators based on Markow Switching models.

5.1 The proposed methodology

Turning point real-time indicators have to fulfil two main requirements: they must be reliable and provide a readable signal as soon as possible. The system of coincident indicators we propose may be qualified as “early detection system” since it aims at minimizing the delay with which a turning point will be “detected” (signalled) in real time. The reliability assessment of the occurrence of turning points is done by computing different scores (such as quadratic Brier’s scores) measuring the distance between “true” and “detected” turning points in real time.

Beyond the quantitative value of the real-time indicator, we try to provide a decision rule to help the practitioner to decide between the two alternatives at each date *t:*

“H0: Recession at date t” versus “H1: no recession at date t”

Therefore, two underlying non-symmetric risks appear, namely:

[11] They also discuss the possibility of rendering quasi-official pronouncements based on their index and thus recommend being prudent to build it in a bit of conservatism.

type I risk of error = risk to incorrectly announce a recession,
type II risk of error = risk to incorrectly miss a recession.

Both risks are also non-symmetric in terms of communication. To our opinion, it seems preferable to minimize the type I risk of error with this new start-end recession indicator. Indeed, we are in favour of announcing a recession with a lag rather than to announce a wrong recession but with a strong lead. We point out here the classical trade-off between timeliness and reliability of an indicator, well known by statisticians and analysts.

Thus, according to the various methodologies based on Markov-Switching models, proposed in Krolzig (1997), Kim and Nelson (1999), Anas and Ferrara (2002, 2004) and Ferrara (2006), we propose two probabilistic composite coincident indicators based on regime-switching models to detect in real-time the turning points of both growth and business cycles. In this respect, we propose to select N coincident variables among monthly PEEIs to be included as components in the indicator. These variables are chosen by optimization of the Brier's criteria by reference to the defined chronology. According to our experience, it seems preferable to deal with a value of N not too high ($N < 10$), in opposition to some indicators based on big-data models involving more than 1000 variables.
To model the coincident variables, we consider Markov Switching models. In particular, the process $(Y_t)_t$ is said to be a MSI(K)-AR(p) process if it verifies the following equation:

$$Y_t = \mu(S_t) + \sum_{j=1}^{p} \phi_j(S_t) Y_{t-j} + \varepsilon_t$$

where $(\varepsilon_t)_t$ is a Gaussian white noise process with finite variance, where ϕ_j are the AR coefficients, for $j=1,\dots,p$, and where the unobservable discrete variable $(S_t)_t$ is supposed to represent the current state of the economy (for all t, $S_t \in \{1,\dots, K\}$, K being the number of regimes). In the MSI(K)-AR(p) the intercept and the AR coefficients switch according to a discrete regime variable $(S_t)_t$.
Finally, the whole specification of the model needs the specification of $(S_t)_t$ as a K-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 $i,j=1,\dots,K$:

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

The probabilities $(p_{ij})_{i,j=1,\dots,K}$ are the *transition probabilities* of moving from one state to the other, which completely describe the Markov chain. Obviously, we get:

$$p_{11}+ p_{12}+ \dots + p_{1K} =1.$$

For each regime, p_{ii} is a measure of the persistence of the regime i. For further details, we refer to Hamilton (1994).

Regarding the parameter estimation issue, from an observed trajectory $(y_1, \dots, y_T)$, the maximum likelihood method is used in connection with the Expectation-Maximization (EM) algorithm, which has been proved to be more robust to the starting parameters values. As a by-product of the estimation step, we get the estimated conditional probabilities of being in the state i, for $i=1,\dots,K$, $P(S_t = i / y_{t-1},\dots,y_1, \theta)$, referred to as the *filtered probability*, and $P(S_t = i / y_T,\dots,y_1, \theta)$, referred to as the *smoothed probability*. Both probabilities may be used, respectively, to detect in real time and to date *ex post* the turning points of the economic cycles.

Regarding the choice of the number of regimes K, we compare many series with a 2-regime specification and a 3-regime specification in terms of growth cycle replication measured by the *QPS* index. That is, if we note $(P_t)_t$ is the filtered probability of being in the low regime of the growth cycle stemming from the MS model, the objective is to minimize the following value:

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

where, for $t=1,\ldots,T$, $(R_t)_t$ equals 1 during low phases of the growth cycle according to the reference dating. Moreover, we also test the models with a different variance in each regime (heteroscedastic hypothesis).

A choice has to be made to aggregate the selected variables. We estimate filtered TP's probabilities associated with each variable and then aggregate the probabilities. This approach allows a better understanding of the variations of the estimated index through the analysis of each component. Moreover, this way to aggregate information, by taking the risk of false signal inherent to each component, is original and appears to be well appropriate to this kind of topic. It could be an option to aggregate first the information, for example by estimating a composite index by using a factor model as proposed by Stock and Watson and then to estimate a MS model on the univariate composite index. Another procedure could be to fit a multivariate MS-VAR model to all the components to estimate the common cycle.

In the following we present the detailed methodology we developed to construct two original indicators:

1) a probabilistic coincident indicator to detect in real-time the peaks and troughs of the business cycle. We call this new indicator the **BCCI** (Business Cycle Coincident Indicator);
2) a probabilistic coincident indicator to detect in real-time the peaks and troughs of the growth cycle. We call this new indicator the **GCCI** (Growth Cycle Coincident Indicator).

5.1.1 Business Cycle Coincident Indicator (BCCI)

In this subsection, we describe the monthly coincident indicator of the business cycle BCCI to assess each month the occurrence of turning points B and C in the ABCD approach.
Concerning the choice of the components, we focus preferably on some key economic indicators available on the Euroind data base, aggregated at the euro area level. As our aim is to construct an indicator on a monthly basis since 1980, we focus only on monthly time series, which strongly limits - our research. Indeed, the number of available euro-aggregates monthly series, generally considered as descriptive of the business cycle, is quite low. For instance, series of employment or capacity utilization rate are only available on a quarterly basis. Another difficulty inherent to the euro area is that most of the potentially interesting data, contained for example in the Euroind database, only starts in 1991, just after the German reunification. Yet, since 1991, the euro area experienced only a single recession, which implies that the statistical inference is going to be a hard job. The learning set is thus considerably narrow in comparison with the one for the US.
Among the series of interest, two of them seem to be particularly well appropriated: the industrial production index (IPI) and the unemployment rate. Indeed, the study carried out by Anas et al. (2007) proved empirically a full equivalence between industrial and global recessions, for the euro area on the period 1970-2000. Thus, the information conveyed by the IPI appears to be useful to detect recessions in real-time. Moreover, series related to the employment have been proved to be very useful to characterize global recessions. It is noteworthy that both series are used by the Dating Committee of the NBER to date the US recessions (see NBER, 2003) and are used in other papers

aiming either at dating the business cycle (see for example Anas et al., 2007, or Mönch and Uhlig, 2005) or at detecting it in real-time (see for example Anas and Ferrara, 2002, 2004).
In the Euroind data base, the official euro area IPI starts in January 1990, while the unemployment rate begins only in January 1993. Thus, we use an IPI series provided by Eurostat from January 1971 and we rigorously back-calculated the unemployment series since 1971 by using unemployment rates in France, Germany and Italy.
We consider also the monthly series of new passenger car registrations in the euro area released each month by the association of European automobile manufacturers (ACEA[12]). This series is of great interest for short-term economic analysis because it reflects, on a monthly basis, information on manufacturing goods consumption, only available on a quarterly frequency through the official quarterly accounts. Therefore, economists and market analysts follow carefully the evolution of this series to have a first monthly opinion on household consumption in the euro area. This series is also integrated in large macroeconomic models in order to predict the euro area growth (see, for instance, the European Commission DG-Ecfin model developed by Grassmann and Keereman, 2001). However, it is well known among practitioners that, due to its high volatility, the extraction of a clear economic signal from this series is not an obvious task.
The final selection of the variables to be included in the indicator has been done by using the classical QPS index, defined by:

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

where, for $t=1,\ldots,T$, $(P_t)_t$ is the filtered probability of being in the low regime of the business cycle stemming from the MS model and $(R_t)_t$ equals 1 during the low phase of the business cycle according to the reference dating.
We considered the information conveyed by many series to construct our indicator, specifically opinion surveys in diverse sectors. But, we reach the conclusion that most of the opinion surveys are describing the growth cycle instead of the business cycle.

Data transformation

All the classical stationarity tests, like the Augmented Dickey-Fuller, point out the non-stationarity of the IPI, unemployment rate and new cars registrations, although it is not possible, for a finite sample, to discriminate between a DS-type (*Difference Stationary*) and a TS-type non-stationarity (*Trend Stationary*). Thus, we are transforming the series to achieve stationarity - by taking their growth rate over a given lag. This lag is chosen by minimizing the QPS criterion. Consequently, we choose the growth rate over 12 months for the IPI and the new cars registrations and the inverted growth rate over 3 months for the unemployment rate.
Two of the three components of the indicator have been statistically treated. First a Perron test (1997) on the unemployment rate shows evidence of a break in the series, estimated in July 1984. An intervention analysis (Box and Tiao, 1975) on the differenced series allows estimating a persistent impact of 0.1704. The definitive stationary series is thus corrected from this impact before this date. Second, the new car registrations series has been corrected from the "catalytic converters" effect, obligatory on new vehicles since January 1993, through an intervention analysis. This law implied a strong increase in the sales at the end of 1992, followed by a significant drop in January 1993, implying thus a break in the series, with a persistent effect. The impact has been estimated at around 100 000 vehicles. We correct thus the series from this effect before this date to have a coherent time series.

Finally, we retain the following three components:

[12] See the website www.acea.be for further details.

X^1: Industrial Production Index, Total except construction (Source: Eurostat (since January 1990) completed by provisional back-calculated values until January 1977; Unit: Index of Volume, 2000=100; Statistical treatment: Seasonally and Trading day adjusted; Data transformation: Growth rate over 12 months)

X^2: Unemployment rate (Source: Euroind (since January 1993) completed by provisional back-calculated values until January 1975; Unit: Percent; Statistical treatment: Seasonally and Trading day adjusted; Data transformation: Inverted differentiation over 3 months)

X^3: New car registrations (Source: ACEA; Starting date: January 1978; Unit: Volume; Statistical treatment: Seasonally adjusted with X11 by Coe-Rexecode / GRETA; Data transformation: Growth rate over 12 months and non-centered moving average over 6 months)

Note that, due to the various lags involved in the data transformation, the starting date of the BCCI is set to June 1979. For each component k, $k=1,\ldots,N$, we associate a latent variable $(S^k_t)_t$ such that, for all t values, $S^k_t = 1$ if the time series (X^k_t) belongs to the low regime corresponding to the recession phase and $S^k_t = 0$ otherwise. Regarding the choice of the number of regimes K, instead of using statistical tests, which are not proven to be powerful, we use the 3-regime approach advocated in Ferrara (2003) which seems suitable for euro area data. In fact, we compare many series with a 2-regime specification and a 3-regime specification in terms of business cycle replication measured by the QPS. Moreover, we also test the models with a different variance in each regime (heteroscedastic hypothesis). It turns out that we retain the same model for each component, namely a 3-regime Markov Switching model with the same variance in each regime.
We also note R_t a binary variable so that $R_t = 1$ if the economy is in recession at date t and $R_t = 0$ if the economy is in expansion. We use the reference dating to estimate R_t. Our aim is to estimate $P(R_t = 1)$, that is the probability that the economy is in recession at date t, according to the N filtered probabilities $P^k(S_t = 1 / F_{t-1}),\ k=1,\ldots,N$, stemming from the MS models applied to each component.

The final issue is how to aggregate the N filtered probabilities $P^k(S_t = 1 / F_{t-1})$. We consider an aggregation procedure based on the number of missed and extra cycles.
If we note $P(R_t = 1)$ the probability that the economy is in recession at date t, we can thus write that:

$$P(R_t = 1) = P(R_t = 1 | S_t^k = 1) P(S_t^k = 1 / F_{t-1}) + P(R_t = 1 | S_t^k = 0) P(S_t^k = 0 / F_{t-1})$$

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

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

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

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

We assume that both risks are constant in time, *i.e.* for all t values; $\alpha_t^k = \alpha^k$ and $\beta_t^k = \beta^k$. For each component k, an estimate of $P(R_t = 1)$ is given by $P^k(R_t = 1)$ defined by:

$$\begin{aligned} P^k(R_t = 1) &= (1 - \alpha^k) P_t^k + \beta^k (1 - P_t^k), \\ &= \beta^k + (1 - \alpha^k - \beta^k) P_t^k . \end{aligned}$$

Our idea is to give more weight to a component allowing us to reproduce the number of total cycles and give less weight to a component providing extra-cycles or missing cycles. To estimate the weights, we count the number of missed cycles and extra-cycles. Thus, if a given component describes perfectly the euro area business cycle since 1979, the number of signals emitted by the component is three. To estimate empirically both risks, we count the number of false signals and missed signals emitted by the variable, by comparison with the number of referenced low phase of the growth cycle. Thus, the weight of each component, $(X^k_t)_t$, for $k=1,\dots,N$, is given by:

$$\omega_k = \frac{3}{3 + \alpha_k + \beta_k}$$

which are then normalized by taking:

$$\varpi_k = \frac{\omega_k}{\sum_{k=1}^{N} \omega_k}$$

Thus, BCCI is given by, for each date t:

$$BCCI = \sum_{k=1}^{N} \varpi_k P(S_t^k = 1 / F_{t-1})$$

Results related to estimated models for each of the components are presented in Table 3.

Table 3: Parameter estimation and standard errors for the MS models and averaged duration for the regimes (in months) for each of the 3 components (data until October 2006)

	IPI	Unemployment	Registrations
Starting date	Jan 1978	Jan. 1976	Jun. 1979
Parameters			
P_{11}	0.9071	0.9250	0.9086
P_{22}	0.9108	0.9243	0.9349
P_{33}	0.9372	0.9596	0.9205
μ_1	-3.3418 (0.2390)	-0.2958 (0.0141)	-5.2168 (0.6038)
μ_2	0.9254 (0.2068)	-0.0474 (0.0092)	1.1557 (0.3094)
μ_3	4.3791 (0.2038)	0.1486 (0.0071)	8.8413 (0.3877)
σ	1.3513	0.0809	2.9776
Average duration			
Low regime	11	13	11
Intermediate regime	11	13	15
High regime	16	25	13

We observe that average durations of the recession regime (around one year) are close and coherent with benchmark durations. Average duration of recessions is around two times lower than the sum of the other two regimes. We retain as real-time recession probability the filtered probability of being in the low regime. In order to transform the quantitative information provided by each component, we have to choose a threshold over which a signal of peak or trough is given. We choose the natural threshold of 0.50 recommended by Hamilton (1989).

The unemployment rate component describes exactly the three recession phases experienced by the euro area since 1980, which is a strong proof of its reliability. The total IPI does not miss any cycles, but produces an extra-cycle at the end of 2001, indicating thus an industrial recession in the euro area. The new cars registrations series allows reproducing only two of the three recessions, the second dip of the double-dip recession in early eighties is not detected. Otherwise, this component provides three false signals of recessions.

Concerning the weights of each component in the BCCI, we get the following results:

$$\omega_1 = 3/(3+1+0) = 0.75$$
$$\omega_2 = 3/(3+0+0) = 1.00$$
$$\omega_3 = 3/(3+3+1) = 0.43$$

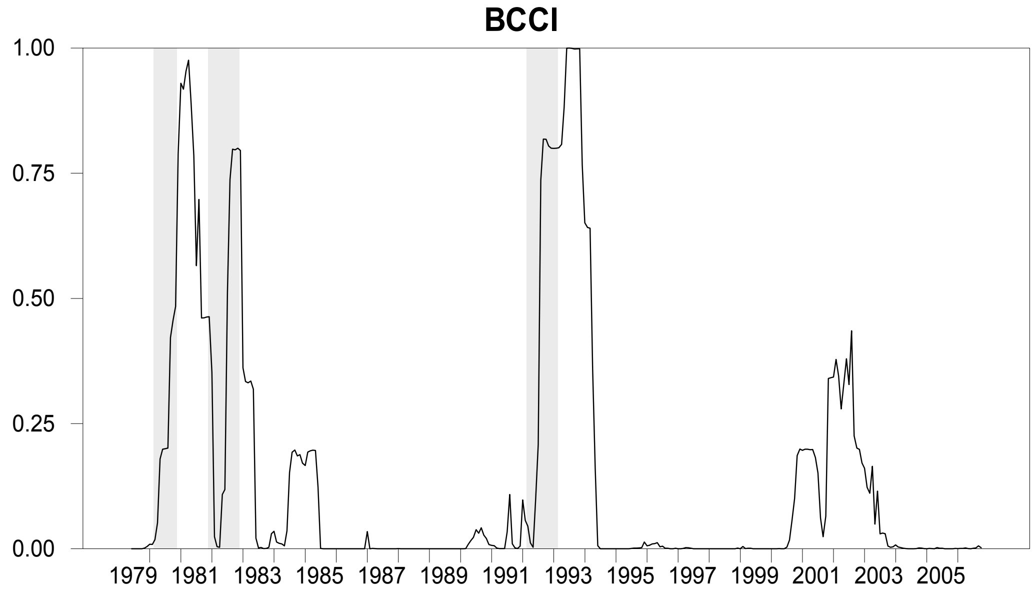
thus:

$$\varpi_1 = 0.34; \varpi_2 = 0.46; \varpi_3 = 0.20$$

Note that the normalized weights are not uniform. The highest weight was attributed to the unemployment rate due to its very strong reliability. This component does not provide false signal and never misses a recession.

The BCCI is presented in the Figure 3, along with the benchmark recession phases. At the level of each component, we saw that the 0.5 threshold corresponds to the value where the probability of one event becomes greater than the probability of the alternative event. As the weights are normalized, there is no scale effect when aggregating. This property is particularly true when the weights are chosen in an optimal way.

Figure 3: BCCI and recession phases



5.1.2 Growth Cycle Coincident Indicator (GCCI)

In this subsection, we describe the monthly coincident indicator of the growth cycle GCCI to assess each month the occurrence of turning points A and D in the ABCD approach. The methodology we propose is to detect coincident turning points of the cycles. With a coincident indicator, we do not have to wait for the quarterly national accounts and the GDP release to assess the cyclical situation.

Concerning the choice of the series, we focus on some key economic indicators available on the Euroind database, aggregated at the euro area level. Several set of data have been considered: opinion surveys, real economic data and financial series. A pre-selection of the series has been done according to our experience on growth cycle turning points, according to the availability of the series on a monthly frequency and according to their long historical existence. For example, we focus only on DG-Ecfin opinion surveys for industry, building, consumer and retail trade, at the euro area level. The services survey is only available since April 1995 and has been consequently disregarded. Concerning real data, we pre-selected the components of the industrial production index and the components of imports and exports. For example, the retail trade series has not been pre-selected because it only starts in January 1995. We also consider unemployment, total and for young workers (less than 25 years old). As regards financial data, we pre-selected the Euro-dollar exchange rate, the interest rate spread (10 years minus 3 months), several monetary aggregates, the EuroStoxx index and loans to the private sector. We have considered seasonally adjusted data for business and consumer surveys and seasonally and calendar adjusted data for real sector variables, while financial data are generally raw data. The final selection of the variables to be included in the indicator has been done by minimizing the QPS criterion defined previously.

As regards stationary data, like the opinion surveys, we consider their growth in order to detect the turning points where the growth becomes negative or positive. Thus we have to differentiate the original series to underline the phases of low and high pace of growth. To find the appropriate differentiation lag, we consider a grid-search procedure over different lags and we find that the appropriate lag is of 6 months. This lag results from the classical trade-off between reliability and advance. Indeed, it turns out that a lag of 3 months produces less reliable results while a lag of 9 months provides better results but lagged. As regards real data, we consider the growth rate over one year and we observe that peaks and troughs seem to be generally coincident with the reference growth cycle. Thus, we decide to consider the differentiation of the growth rate, namely an acceleration estimator, to assess the phases of the growth cycle. Here again, we show that a 6-months lag minimizes the *QPS*, while keeping the coincident property. Last, we observe that financial variables do not provide interesting results. It turns out that those series are generally leading the growth cycle, but with a great number of extra-cycles. Moreover, the lead *viz* peaks and troughs of the growth cycle are not stable overtime. Consequently, no financial series are introduced in the indicator.

We thus retain the following five components:

X^1: Employment expectations for the months ahead in the industry survey (Source: DG-EcFin; Starting date: January 1985, Unit: Balance of opinions; Statistical treatment: Seasonally adjusted; Data transformation: Differentiation over 6 months)

X^2: Construction Confidence Indicator (Source: DG-EcFin; Starting date: January 1985; Unit: Balance of opinions; Statistical treatment: Seasonally adjusted; Data transformation: Differentiation over 6 months)

X3: Financial situation over the last 12 months in the consumer survey (Source: DG-EcFin; Starting date: January 1985; Unit: Balance of opinions; Statistical treatment: Seasonally adjusted; Data transformation: Differentiation over 6 months)

X^4: Industrial Production index, Total except construction (Source: Eurostat; Starting date: January 1990; Unit: Index of Volume, 2000=100; Statistical treatment: Seasonally and Trading day adjusted; Data transformation: Growth rate over 12 months and differentiation over 6 months)

X^5: Imports of intermediate goods from outside euro area (Source: Eurostat; Starting date: January 1989; Unit: Index of Volume, 2000=100; Statistical treatment: Seasonally and Trading day adjusted; Data transformation: Growth rate over 12 months and differentiation over 6 months)

By taking the various lags into account, note that the starting date of the indicator will be July 1991. For each component of the growth cycle coincident indicator k, $k=1,...,N$, we associate a latent variable $(S^k_t)_t$ such that, for all t values, $S^k_t = 1$ if the time series (X^k_t) belongs to the low regime corresponding to the low phase of the growth cycle and $S^k_t = 0$ otherwise. In fact, it turns out that we retain the same model for each component, namely a 2-regime Markov Switching model with the same variance in each regime.

As for the BCCI, we note R_t a binary variable so that $R_t = 1$ if the economy is in the low phase of the growth cycle at date t and $R_t = 0$ if the economy is in the high phase of the growth cycle. We use the reference dating to estimate R_t . Our aim is to estimate $P(R_t = 1)$, that is the probability that the economy belongs to the low phase of the growth cycle at date t, according to the N filtered probabilities $P^k(S_t = 1 / F_{t-1})$, $k=1,...,N$, stemming from the MS models applied to each component (we note F_{t-1} the information contained in the vector $(X^k_1, ..., X^k_{t-1})$).

The issue is then to decide the way to aggregate the N various filtered probabilities $P^k(S_t = 1 / F_{t-1})$. We focused our attention on four different aggregation procedures[13] and compared the results in terms of turning point detection. Considering its simplicity, readability and overall results, we decided to use a simple average over the N filtered probabilities stemming from the components. This simple average is the Growth Cycle Coincident Indicator. We consider the indicator as a diffusion index, without giving a weight to the components.

$$GCCI = \frac{1}{N}\sum_{k=1}^{N} P(S_t^k = 1/F_{t-1}) \,,$$

Table 4: Parameter estimation and standard errors for the MS models and average duration (in months) for the regimes for each of the 5 components (data until November 2006)

	IND.EA.7	BUI.EA.99	CONS.EA.1	IPI	IMPORT.INTER
Starting date	1985-7	1985-7	1985-7	1991-7	1990-7
Parameters					
P_{11}	0.9362	0.9649	0.9352	0.9323	0.8923
P_{22}	0.9539	0.9809	0.9698	0.9371	0.9278
μ_1	-4.9962	-4.8926	-2.7238	-2.1448	-4.5644
μ_2	4.2707	4.3701	1.3075	2.3181	3.0820
σ	3.5315	3.9633	1.6427	1.6646	4.1711
Average duration					
Low regime	16	29	15	15	9
High regime	22	52	33	16	14

Table 5: Monthly dating chronologies for the euro area stemming from each indicator

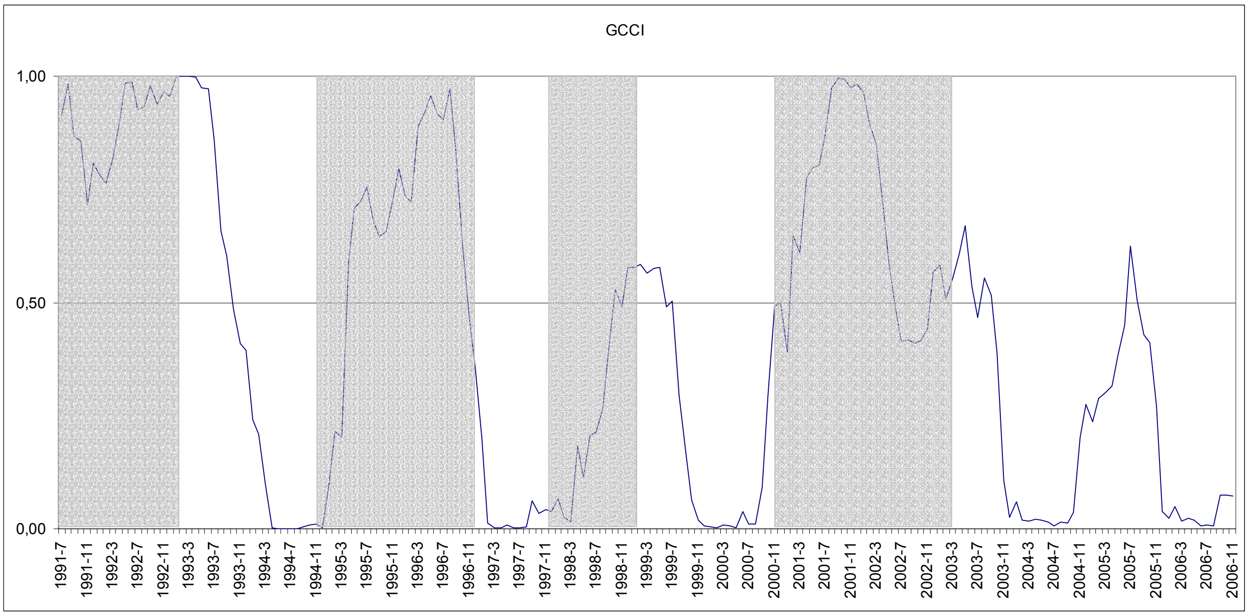
	Reference	**GCCI**
Peak A	M2 1986	
Trough D	M5 1987	
Peak A	M2 1991	M7 1991 (*)
Trough D	M8 1993	M9 1993

[13] We tested weights based on both type I and type II risks for each component and weights based on a normalized concordance index between the filtered probabilities from each component and the reference dating.

Peak A	M2 1995	M4 1995
Trough D	M11 1996	M10 1996
Peak A	M2 1998	M10 1998
Trough D	M5 1999	M7 1999
Peak A	M11 2000	M11 2000
		M5 2002
		M12 2002
Trough D	M5 2003	M9 2003

(*) starting date of the indicator

Figure 4: GCCI and low phases of the growth cycle



5. 2 Real-time publication

Given the early detection nature of the two indicators, it is important to discuss their publication delays.

5.2.1 Growth Cycle Coincident Indicator

According to the official calendars, the usual release dates for each component of the indicator GCCI are:
- Employment expectations for the months ahead in the industry survey: usually released by the end of referring month;
- Construction Confidence Indicator: usually released by the end of referring month;
- Financial situation over the last 12 months in the consumer survey: usually released by the end of referring month;
- Industrial Production Index, Total except construction: usually released around 43 days after the referring month;
- Imports of intermediate goods from outside euro area: usually released around 48 days after the referring month.

Therefore, waiting 48 days after the end of the month, all the information regards the 5 components of the GCCI would be available. We could reduce this delay releasing the GCCI as soon as the survey figures appear. We would thus use incomplete information, representing 60% of the total GCCI variance. So, forecasting the filtered probability that the IPI and Imports belong to the first regime, it would be possible to release a Growth Cycle Coincident Indicator at the beginning of the month following the referring one, based on the surveys and the estimates of the two other time series (IPI and Imports).

5.2.2 Business Cycle Coincident Indicator

According to the official calendar released by Eurostat it turns out that the IPI and unemployment rate are respectively released around 43 days and 32 days after the end of the reference month. Moreover, the ACEA releases the number of new cars registrations around 15 days after the end of the reference month. Therefore, if we wait 43 days after the end of the month, we will have exhaustive information as regards the three components of the BCCI. We could reduce this delay if we released the BCCI as soon as the unemployment rate figure appears. We would thus have incomplete information, representing 67 % of the total BCCI variance. It would be possible to gain 11 days in the publication process if the filtered probability that the IPI belongs to the first regime were forecasted. Supposing this choice for both indicators, it would be possible to release simultaneously both indicators GCCI and BCCI, although with respect to different reference months (GCCI possesses an advance of one month over BCCI).

Alternative release strategies could also be evaluated on the basis of an in depth simulation exercise, principally in order to avoid any risk of delivering false signals.

6. Conclusion

This paper has presented an application to the euro area economy of an integrated framework for dating and detecting both classical and growth cycle turning points. This framework is mainly based on the so-called ABCD approach (proposed by Anas and Ferrara in 2004). Concerning the dating process we can observe that the derived chronology is in line with the already existing ones, both for classical and growth cycles, with a few discrepancies of minor relevance. Some slight inconsistencies emerged in the period from the beginning of 2000, but it is clear that this part of the chronology cannot yet be considered as definitive due to the fact that the main macro-economic variables involved are still under revision. Moreover, it has to be noted that for the first time, in the year 2000 we have experienced an industrial recession which was not reflected at a macro-economic level. Concerning the detecting stage, the two proposed indicators performed in a satisfactory way with a higher reliability of the coincident growth cycle indicator with respect to the coincident business cycle one. By the way this is a quite expected result due to the fact that the growth cycle is usually more easily forecastable than the classical one. Even if we found very encouraging results, the proposed framework needs to be better analysed in order to become a fully operational tool, regularly used in the assessment of the euro area business cycle situation.

Future improvement activities will mainly focus on:

- finalisation of the back-calculation exercise in Eurostat which will be an essential pre-requirement for the assessment of a final chronology;
- investigation of the effects of alternative seasonal adjustment methods on dating and detecting turning points: it is well known that Tramo-Seats usually produces smoother seasonally adjusted series than X-12 ARIMA with relevant differences especially in the recent values of the series;

- further investigation on alternative detrending filters in order to identify the most suitable one in terms of reliability of the cyclical estimates especially at the end of the sample;
- improvement of the coincident indicators, especially the classical cycle one, in order to reduce the existing reliability gap.

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