DISCUSSION PAPER SERIES

No. 7376
CEPR/EABCN No. 42/2009

**IDENTIFICATION OF SLOWDOWNS
AND ACCELERATIONS FOR THE
EURO AREA ECONOMY**

Olivier Darné and Laurent Ferrara

INTERNATIONAL MACROECONOMICS

€ABCN

Euro Area Business Cycle Network
WWW.EABCN.ORG

Centre for Economic Policy Research

www.cepr.org

IDENTIFICATION OF SLOWDOWNS
AND ACCELERATIONS FOR THE
EURO AREA ECONOMY

**Olivier Darné, Banque de France, DGEI-DCPM and
University of Nantes, LEMNA**
Laurent Ferrara, Banque de France, DGEI-DCPM

This Discussion Paper is issued under the auspices of the Centre's research programme in **INTERNATIONAL MACROECONOMICS**. Any opinions expressed here are those of the author(s) and not those of the Centre for Economic Policy Research. Research disseminated by CEPR may include views on policy, but the Centre itself takes no institutional policy positions.

The Centre for Economic Policy Research was established in 1983 as an educational charity, to promote independent analysis and public discussion of open economies and the relations among them. It is pluralist and non-partisan, bringing economic research to bear on the analysis of medium- and long-run policy questions.

These Discussion Papers often represent preliminary or incomplete work, circulated to encourage discussion and comment. Citation and use of such a paper should take account of its provisional character.

ABSTRACT

Identification of slowdowns and accelerations for the euro area economy

In addition to quantitative assessment of economic growth using econometric models, business cycle analyses have been proved to be helpful to practitioners in order to assess current economic conditions or to anticipate upcoming fluctuations. In this paper, we focus on the acceleration cycle in the euro area, namely the peaks and troughs of the growth rate which delimitate the slowdown and acceleration phases of the economy. Our aim is twofold: First, we put forward a reference turning point chronology of this cycle on a monthly basis, based on gross domestic product and industrial production index. We consider both euro area aggregate level and country specific cycles for the six main countries of the zone. Second, we come up with a new turning point indicator, based on business surveys carefully watched by central banks and short-term analysts, in order to follow in real-time the fluctuations of the acceleration cycle.

Olivier Darné
University of Nantes
IEMN-IAE
Chemain de la Censive du Tertre
44322 Nantes
FRANCE

Email: Olivier.Darne@univ-nantes.fr

Laurent Ferrara
Banque de France
46-1383 DCPM-Diaconj
31 rue Croix des Petits Champs
75049 Paris Cedex 01
FRANCE

Email:
laurent.ferrara@banque-france.fr

Submitted 10 July 2009

1   Introduction

Economic diagnosis and forecasting tools used by central banks in their periodic assessment of macroeconomic conditions are often based on quantitative econometric methods. For example, when one is trying to forecast the quarterly gross domestic product [GDP] growth rate of a given country, practitioners search for correlations between leading or coincident economic variables and figures provided by the quarterly national accounts. However, over the past, quantitative methods have led to significative forecast errors, especially just before turning points in the business cycle. For some years, several econometric tools have been proposed in the literature with the aim to provide with qualitative information on the current and future evolution of economic cycles. Those tools are complementary to classical quantitative forecasting tools in the sense that they timely provide with the direction of the growth rate and with the assessment of current cyclical conditions. Such qualitative information may be used by forecasters in order to weight various forecasting scenarii.

Placing the cycle in the heart of the conjunctural economic analyses is not a recent idea. The first cyclical analyses at a large scale are due to the works of Wesley Mitchell and Arthur Burns at the NBER in early 1920s and have been prolonged in many economic institutes like The Conference Board, the Economic Cycle Research Institute (ECRI) or OECD. The renewal of cyclical approaches is mainly linked to the recent development of non-linear econometric models flexible enough to take certain stylized facts of the business cycle into account, such as asymmetries in the phases of the cycle. In this respect, emphasis has been put on the class of models that allows for regimes switching. Especially, Markov-Switching models popularized by Hamilton (1989) have been widely used in business cycle analysis in order to describe economic fluctuations (e.g., Chauvet and Piger, 2003, 2008; Ferrara, 2003; Clements and Krolzig, 2003; Anas and Ferrara, 2004; Artis, Krolzig and Toro, 2004; Bengoechea *et al.*, 2006; Anas *et al.*, 2007 or Layton and Smith, 2007).

The popularity of the work of Hamilton is mainly grounded on the ability of the model to reproduce the NBER business cycle dating estimated by expert claims within the Dating Committee. However, when dealing with economic cycles some confusion appears as regards the definition of those cycles. In the empirical literature on economic cycles, we can distinguish between three kinds of cycles: the business cycle, the growth cycle and the acceleration cycle whose characteristics differ. Basically, the business cycle refers the (log-)level of the series, as defined by Burns and Mitchell (1946). Turning points of the business cycle delimitate periods of recessions (negative growth rate) and expansions (positive growth rate). The business cycle is characterized by strong asymmetries in its phases, concerning for example durations or amplitudes. For example, since 1970, the average duration of an expansion phase in the euro area varies between 8 and 11 years according to the studies while the average duration of a recession is only of one year. It seems also that only recessions possess the property of duration-dependence implying thus that the probability of switching to the regime of expansion increases with time. The growth cycle, introduced by Mintz (1969), is the cycle of the deviation to the long-term trend, which can be seen as the potential or tendencial growth. This cycle is sometimes referred to as the output gap. Last, the acceleration cycle is the cycle described by increases and decreases in the growth rate of economic activity. A turning point of this cycle occurs when a local extremum is reached. This cycle is thus a sequence of decelerating and accelerating phases. Such a cycle is very interesting for the short-term analysis of the euro area, not often affected by recessions, because of its high frequency. However, its more pronounced volatility implies a more complex real-time detection.

We refer for example to Anas and Ferrara (2004) or Zarnowitz and Ozyldirim (2006) for a more detailed description of the stylized facts of those various types of cycles.

When dealing with turning point indicators, it is necessary to possess a benchmark turning point chronology of the cycle we aim at tracking. Only the US have a well known benchmark turning point chronology of the business cycle established by the Dating Committee of the NBER. As regards the euro area, European institutes, such as the CEPR (CEPR, 2003, 2009) or Eurostat (Mazzi and Savio, 2007), have proposed a reference dating for the business cycle. Moreover, the OECD updates regularly a monthly chronology for the growth cycle of the euro area, as well as for its members, available on the institution web site [1]. Otherwise, several academic studies have also developed dating chronologies for both the business and growth cycles, see for example Artis, Marcellino and Proietti (2004), Artis, Krolzig and Toro (2004), Anas and Ferrara (2004), Mönch and Uhlig (2005), Anas, Billio, Ferrara and LoDuca (2007) or Anas, Billio, Ferrara and Mazzi (2008). A review of the various turning point chronologies can be found in the paper of Anas, Billio, Ferrara and Mazzi (2008). However, a historical turning point chronology of the euro area acceleration cycle has never been proposed, except in Harding (2004) but his analysis ends in 1998.

The innovation in this paper is twofold. First, we propose a monthly turning point chronology for the euro area acceleration cycle through a non-parametric approach from January 1987 to September 2007. Second, we develop a probabilistic coincident indicator to track in real-time the euro area acceleration cycle, based on well known economic soft indicators carefully watched by central banks and economic analysts in their short-term economic monitoring. This indicator is computed from the estimation of multivariate linear models whose parameters evolve according to a Markov chain, in the vein of the works of Krolzig (1997) or Kim and Nelson (1998).

2 A turning point chronology of the euro area acceleration cycle

In this section we propose a monthly chronology of turning points for the euro area acceleration cycle. We use the basic version of the non-parametric dating algorithm proposed by Bry and Boschan (1971) and modified by Harding and Pagan (2002). This approach is very simple to handle and has been used in several empirical papers dealing with business cycles analysis (see, for example, Harding, 2004, Engel *et al.*, 2005, Anas *et al.*, 2007 or Demers and MacDonald, 2007). We apply this methodology to the broadest measure of economic activity, that is euro area GDP. In order to have a monthly dating, we replicate the same approach to the euro area industrial production index [IPI] and we propose a rule to translate the quarterly dates into monthly dates. From this aggregated dating, some stylized facts of the cycle (duration, amplitude, geographical diffusion ...) are measured to validate this turning point chronology and a comparison with other existing chronologies is carried out.

2.1 Dating

Assume $(Y_t)_t$ is the series of interest (GDP or IPI), seasonally adjusted and corrected from trading days and outliers. The basic Bry-Boschan algorithm detects a peak at date t if the following condition is verified:

$$\{(\Delta_k Y_t, \ldots, \Delta Y_t) > 0, (\Delta Y_{t+1}, \ldots, \Delta_k Y_{t+k}) < 0\} \tag{1}$$
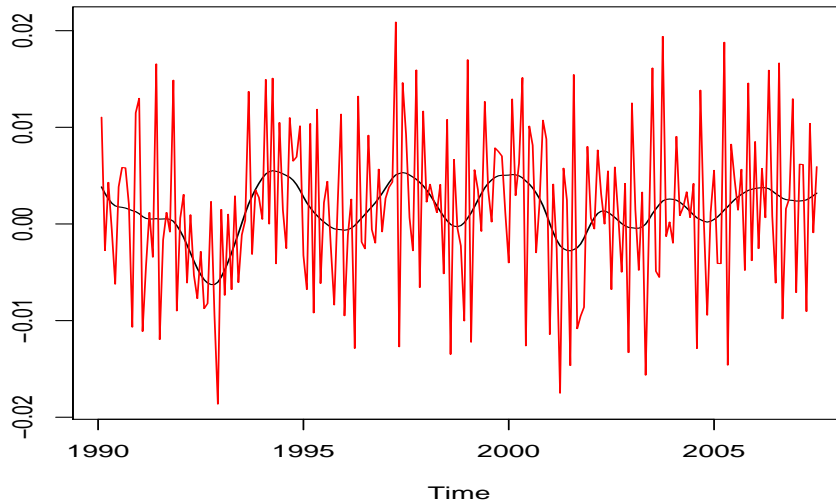
---

[1] www.oecd.org

4

Figure 1: Monthly IPI growth rate and smoothed IPI growth rate by removing high frequencies with a low-pass filter (Jan. 1990 - Sep. 2007).

and detects a trough at date t if the following condition is verified :

$$\{(\Delta_k Y_t, \dots, \Delta Y_t) < 0, (\Delta Y_{t+1}, \dots, \Delta_k Y_{t+k}) > 0\}, \tag{2}$$

where the operator Δ_k is defined such as $\Delta_k Y_t = Y_t - Y_{t-k}$. Harding and Pagan (2002) suggest $k = 2$ for quarterly data and $k = 5$ for monthly data. Generally, turning points within six months of the beginning or end of the series are disregarded. Last, a procedure for ensuring that peaks and troughs alternate is developed, for example by imposing that in the presence of a double through, the lowest value is chosen and that in the presence of a double peak, the highest value is chosen. Censoring rules related to the minimum duration of phases are also imposed in the original algorithm specifying that a phase must last at least six months and that a complete cycle (from peak to peak) must last at least 15 months. In fact, this censoring rule applies for the business cycle because, as noted by the NBER in its seminal definition, a recession must last *more than a few months*, but there is no reference minimum duration. In this paper, as we focus on the acceleration cycle, we apply the Bry-Boschan algorithm to the series $(Y_t)_t$ defined as the quarterly GDP growth rate or monthly IPI growth rate.

First, we choose the widest measure of economic activity of the zone, namely the aggregated GDP at the euro area level. Due to the need of a long historical series, we report our attention to the euro area GDP series estimated by Fagan, Henry and Mestre (2005, FHM hereafter) available through the EABCN web site [2]. This series ranges from Q1 1970 to Q4 2005 and is therefore more interesting for an historical analysis than the official series stemming from Eurostat that only starts in 1995. However, as regards the quarterly GDP growth rate, both series match on the common period Q1 1995 - Q4 2005. The average difference between FHM and Eurostat data [3] growth rate is only of -0.006 points. Therefore, we consider the GDP growth rate series constructed by taking the FHM series from Q1 1970 to Q4 1994 and the Eurostat series from Q1

---

[2]www.eabcn.org

[3]We use Eurostat data as published November 14, 2007.

1995 to Q3 2007. We apply the simplified Bry-Boschan algorithm to the growth rate series to identify peaks and troughs of the GDP acceleration cycle. It is noteworthy that we consider the Q4 1991 and Q1 1992 jumps and the consequent Q2 1992 strong dip as outliers. Those points are linked to the German reunification and trouble the cyclical diagnosis around this period. Estimated dates of turning points since 1987 until 2007 are reported in the first column of Table 1. Second, we consider the IPI (global except construction) for the euro area. The official series computed by Eurostat starts in January 1990 and we use the information until September 2007. We first filter the IPI monthly growth rate series by eliminating the fluctuations with a frequency higher than one year by using a low-pass filter [4]. This filtering step is necessary to remove the noise due to short-term fluctuations (see Figure 1). Then, we apply the same procedure as for GDP. The results are presented in the second column of Table 1.

It is noteworthy that both chronologies indicate the same number of cycles underlying thus the major role of the industrial sector in the global acceleration cycle. To provide with the final monthly dating, we propose the following *ad hoc* rule: We say that if, for a given peak (or trough), the month belongs to the quarter, then we keep the monthly date. Otherwise, we pick up the month within the quarter that is the closest to the monthly date. The final proposed dating is presented in the third column of Table 1. The decelerating phase starts just after the peak and finishes at the date of the trough and the accelerating phase starts just after the trough and ends at the date of the peak.

	GDP	IPI	Dating	Duration	Amplitude	Excess
peak	1987 Q2	NA	1987 M5			
trough	1993 Q1	1992 M11	1993 M1	68	2.4	-0.18
peak	1994 Q1	1994 M3	1994 M3	14	1.6	0.10
trough	1996 Q1	1996 M2	1996 M2	21	0.9	-0.04
peak	1997 Q2	1997 M4	1997 M4	16	1.2	-0.14
trough	1998 Q4	1998 M10	1998 M10	15	1.0	0.07
peak	1999 Q3	1999 M9	1999 M9	11	1.0	0.03
trough	2001 Q3	2001 M9	2001 M9	24	1.2	-0.09
peak	2002 Q2	2002 M4	2002 M4	7	0.4	-0.05
trough	2003 Q2	2003 M4	2003 M4	12	0.4	0.04
peak	2004 Q1	2003 M10	2004 M1	9	0.6	0.17
trough	2004 Q4	2004 M11	2004 M11	10	0.3	0.04
peak	2006 Q2	2006 M4	2006 M4	17	0.7	-0.05

Table 1: Turning points chronologies for acceleration cycles for GDP and IPI, as well as the proposed dating (third column). Durations are in months and amplitudes are in points of percentage. *NA* stands for non-available information.

2.2 Characteristics of the cycle

Three main characteristics are often invoked in order to identify the phases of a cycle, namely the 3D's (duration, depth and diffusion) or, as in Banerji (1999), the 3P's (persistent, pronounced and pervasive). Persistence (or duration) means that the phase must last more than a few months. Generally, starting from the Bry and Boschan (1971) rule, empirical studies consider that a phase of the cycle must last at least five months. A pronounced phase of a cycle is a phase with a

---

[4]As low-pass filter, we use the Hodrick-Prescott filter with the appropriate tuning parameter ($\lambda = 13.9$) to eliminate fluctuations with a frequency higher than one year. The fact that the Hodrick-Prescott filter behaves like a low-pass filter has been proved by Gomez (2001) and it used for example in Artis et al. (2004)

sufficient amplitude (depth) from the peak to the trough and conversely. Last, to be recognized as a phase of the cycle, the cycle must be diffused either across the sectors or across the various countries of an economic zone.

Assume that the previous step has produced the same number J of accelerating and decelerating phases. For $j = 1, \ldots, J$, we note D_j^a and D_j^d the durations in months of the jth accelerating and decelerating phases, respectively. The amplitude of a descending (or ascending) phase is measured by the absolute distance between the peak and the trough (or the trough and the peak). We note $A_j = |Y_{t_P} - Y_{t_T}|$ the amplitude of a given phase j, where Y_{t_P} is the growth rate at the date of peak and Y_{t_T} is the growth rate at the date of trough. To sum up duration and amplitude of a phase j, an index of severity, noted S_j, is often used. The severity is sometimes referred to as the *triangle approximation to the cumulative movements* (Harding and Pagan, 2002, p. 370) and is defined by:

$$S_j = 0.5 \times D_j \times A_j. \tag{3}$$

The severity index measures the area of the triangle with length D_j and height A_j. In fact, the actual measure of cumulative movements, which may be substantially different from S_j in case of departure from linearity, is given by:

$$C_j = \left| \sum_i^{D_j} (Y_i - Y_0) \right| - 0.5 \times A_j, \tag{4}$$

where Y_0 is the value of the variable at the date of peak, Y_{t_P}, for a decelerating phase (or at the date of trough, Y_{t_T}, for an accelerating phase). The term $0.5 \times A_j$ removes the bias due to thepproximation of a triangle by a sum of rectangles. Consequently, for a given phase j, the difference between the observed growth and a linear growth can be measured by the *excess cumulated movements* index defined by:

$$E_j = (C_j - S_j)/D_j. \tag{5}$$

This excess index E_j can be seen as a measure of the departure to the linearity for the growth rate of a given phase. The excess index is divided by the duration so that phases can be compared, independently from their duration. A null excess index implies a linear growth within a phase (decreasing or increasing growth), thus a constant acceleration (negative or positive). For a descending phase, a positive excess index means that the loss of growth is greater than it would be with a linear growth and a negative index indicates that the loss is lower. For an increasing phase, a positive excess index means that the gain of growth is greater than it would be with a linear growth and a negative index indicates that the gain is lower. We can also refer to Camacho *et al.* (2008) for a description of the measures of duration, depth and excess and for a bootstrap approach to evaluate the uncertainty associated to these measures.

We measure those three characteristics on the GDP quarterly growth rate series of the euro area, displayed in the last three columns of Table 1. From the peak located in May 1987, the euro area experienced 6 acceleration cycles (from peak to peak), the last peak located in April 2006 being provisional. The first decelerating phase was exceptionally long (68 months), mainly because of the economic recession experienced by the zone in 1992-93. Moreover, the German reunification generated a low growth rate during this period. Except this latter phase, the average durations of acceleration and deceleration phases are, respectively, of 12 and 16 months. This rather symmetric average duration of both phases is a stylized fact of the acceleration cycle

that differs strongly from the business cycle, for which durations of phases are clearly different, recessions being shorter than expansions. The relatively high frequency of this cycle suggests that its analysis may be very fruitful for short-term economic analysis.

We focus now on the amplitude of the cycle. Average amplitude of an acceleration phase is of 0.9 percentage point of growth and, if we exclude the first decelerating phase of the analysis, exceptionally long, the average amplitude of a deceleration phase is of 0.7 percentage point. Here again, we point out the symmetry of the phases in terms of amplitude. However, we observe also that the amplitude of the phases tend to decay. We do not have enough data to carry out a dynamic analysis, but it will be interesting to follow this stylized fact in the future. Several studies have already underlined the decreasing amplitude of economic cycles since the eighties – mainly in the US business cycle (see Sensier and van Dijk, 2004, among others). This phenomenon is often referred to as the 'Great Moderation' and is generally explained by more efficient monetary policies or by a better management of inventories (see Summers, 2005). However according to the latest macroeconomic fluctuations that occurred in 2008, it seems that that this theory has to be revisited.

As regards excess indexes, we note that three out of the six decelerating phases possess a negative index implying thus a loss of growth lower than expected with a linear growth. The decelerating phase due to the Asian crisis in 1997-98 has an positive index (0.07), as well as the second decelerating phase of the double-dip in 2003 (0.04) and the 2004 deceleration (0.04), although close to zero. Concerning the accelerating phases, only two phases have a strong positive index indicating a gain of growth by comparison with a linear growth within the phase (in 1993-94 and 2003-04). Those phases start with a negative growth rate implying thus a sharp recovery. The acceleration before the Asian crisis presents a negative index indicating a loss of growth by comparison with a linear rate. Otherwise, other accelerating phases exhibit an index close to zero.

We focus now on the cross-country diffusion of the phases for both GDP and IPI series. We consider the six main countries of the euro area, namely Germany, France, Italy, Spain, Belgium and the Netherlands, that cover around 90 % of the added value of the whole area. Series are official data stemming from Eurostat web site, from 1995 Q1 to 2007 Q3 for GDP and from January 1990 to September 2007 for IPI. For each country, we apply the Bry-Boschan approach on both GDP and IPI. Estimated turning points dates are presented in Table 2 for GDP and

	Euro	Germany	France	Italy	Spain	Belgium	Netherlands
Trough	1996q1	1996q1	1996q4	1996q2		1996q1	1996q1
Peak	1997q2	1997q2	1998q2	1997q2	1997q4	1997q1	1997q2
Trough	1998q4	1998q2	1998q4	1998q4	1998q4	1998q3	1998q2
Peak	1999q3	1999q4	1999q4	1999q4	1999q2	1999q3	1999q1
Trough	2001q3	2000q3	2001q2	2001q2	2002q1	2001q3	
Peak		2001q1					
Trough		2002q1					2002q1
Peak	2002q2	2002q3	2002q1	2002q2	2003q1	2002q3	
Trough	2003q2	2003q1	2002q4	2003q1	2003q3	2003q1	
Peak	2004q1	2003q3	2004q2	2004q1	2004q3	2004q2	2004q1
Trough	2004q4	2004q3	2005q2	2004q4		2005q1	2005q1
Peak	2006q2	2006q2	2006q2	2006q4		2005q4	

Table 2: Turning points chronologies for the euro area and country-specific acceleration cycles based on GDP

	Euro	Germany	France	Italy	Spain	Belgium	Netherlands
Peak		1990m12	1991m10	1991m8	1991m9	1991m11	
Trough	1992m11	1992m12	1992m11	1992m7	1992m11	1992m11	
Peak	1994m3	1994m9	1994m4	1994m3	1994m6	1995m1	
Trough	1996m2	1995m10	1995m9	1996m3	1996m1	1995m9	1995m3
Peak	1997m4	1997m11	1997m4	1997m4	1997m3	1997m6	1995m11
Trough	1998m10	1998m9	1998m8	1998m11	1999m2	1998m10	1997m1
Peak	1999m9	2000m4	1999m9	1999m8	1999m11	1999m8	2000m1
Trough	2001m9	2001m9	2001m10	2001m7	2001m10	2001m4	2001m8
Peak	2002m4	2002m6	2002m4	2002m4	2002m8	2002m3	2002m4
Trough	2003m4	2003m4	2003m4	2003m2	2003m5	2002m11	2003m4
Peak	2003m10	2003m11	2003m10	2003m8	2004m2	2004m2	2004m1
Trough	2004m11	2004m10	2005m3	2004m11	2004m10	2004m12	2004m12
Peak	2006m4	2006m5	2005m11	2006m1	2006m5	2005m12	2005m12
Trough		2007m3	2006m8				2006m7
Peak			2007m2				

Table 3: Turning points chronologies for the euro area and country-specific acceleration cycles based on IPI

and Table 3 for IPI [5]. We note that a turning point in the euro area is generally shared by a turning point in the countries. As regards GDP, exceptions are the Netherlands, that do not present a deceleration in 2002-03 and are still in an acceleration phase at the end of the sample, and Spain which is decelerating since 2004 Q3. Otherwise, only Germany presents an extra-cycle in 2001-02. Thus, GDP acceleration cycles seem well diffused across the countries. Concerning IPI, the acceleration cycles are also well diffused, as a turning point for the euro area always corresponds to a turning point in each country. Only at the end of the sample, a discordance appears. Indeed, the euro area industry is decelerating since April 2006, but Germany and the Netherlands have switched to an acceleration phase. Moreover, France exhibits an extra cycle in 2006-07. It is noteworthy that because of the well known end-point effects inherent to low-pass filters the last points of the analysis should be taken carefully into account.

In order to assess synchronization among the country-specific cycles, the concordance index allows an estimate of the fraction of time that cycles are in the same phase (decelerating or accelerating)[6]. Let $(S_{it})_t$ denotes the binary variable that represents the phase of the cycle (acceleration: $S_{it} = 0$, deceleration: $S_{it} = 1$) for a given country i. In the bivariate case, for two countries i and j, the concordance index CI can be expressed in this way:

$$CI = \frac{1}{T} \sum_{t=1}^{T} I_t, \tag{6}$$

where

$$I_t = S_{it}S_{jt} + (1 - S_{it})(1 - S_{jt}). \tag{7}$$

At each date t, for all $(S_{it}, S_{jt}) \in \{0, 1\}$, I_t is equal to 1 when $S_{it} = S_{jt}$ and equal to 0 when $S_{it} = (1 - S_{jt})$. This tool is very interesting in empirical studies to assess the synchronization between two cycles. Anyway, we should keep in mind that the concordance index should be misleading because, even if the correlation between S_{it} and S_{jt} is zero, the concordance index

---

[5]For France, we replace the trough in 2001 Q4 by a trough in 2001 Q2, assuming the value in 2001 Q4 is an outlier and by coherence with other countries.

[6]See Artis *et al.* (1997), Artis, Krolzig and Toro (2004), Harding and Pagan (2006) or de Haan *et al.* (2008) for others measures of synchronization.

CI is equal to 0.5 only if the mean of S_{it} and S_{jt} are both equal to 0.5. It is possible to prove that the expectation of the concordance index depends on the unconditional probabilities of S_{it} and S_{jt} (see Harding and Pagan, 2002; Artis, Marcellino and Proietti, 2004). For example, if the unconditional probability is close to 0.9, as it is the case for the business cycle, it can be proven that, even though the correlation coefficient between the countries is zero, the expectation of CI is close to 0.84. Thus, this index has to be carefully considered in empirical studies.

Concordances indices are presented in Table 4. Based on IPI, concordance indices are quite large, except for the Netherlands, suggesting that the industrial activity in euro area countries spends much of the time in the same state of the acceleration cycle. The GDP-based analysis reveals that Italy and Belgium seem to be more synchronized with euro cycle than the other countries, with CIs superior to 0.80. On the opposite, Spain exhibits the lowest CI with the euro area.

	Euro	Germany	France	Italy	Spain	Belgium	Netherlands
Euro	1	0.83	0.86	0.91	0.85	0.81	0.64
Germany	0.73	1	0.74	0.74	0.80	0.72	0.67
France	0.66	0.48	1	0.82	0.74	0.78	0.67
Italy	0.86	0.68	0.70	1	0.77	0.84	0.63
Spain	0.59	0.45	0.52	0.45	1	0.73	0.57
Belgium	0.82	0.68	0.61	0.73	0.64	1	0.62
Netherlands	0.70	0.70	0.50	0.70	0.61	0.70	1
$\hat{\mu}_{GDP}$	0.55	0.45	0.48	0.45	0.59	0.55	0.48
$\hat{\mu}_{IPI}$	0.58	0.42	0.60	0.61	0.54	0.50	0.47

Table 4: Concordance indices for the IPI from Jan. 1996 to Dec. 2006 (upper diagonal) and GDP from 1996 Q1 to 2006 Q4 (lower diagonal)

Harding and Pagan (2006) propose procedures to test the hypothesis that cycles are either unsynchronized or perfectly synchronized, based on the knowledge of the two binary variables $(S_{it})_t$ and $(S_{jt})_t$ describing acceleration cycles in countries i and j, respectively. In this paper, we test the hypothesis that acceleration cycles are strongly non-synchronized [SNS] based on the statistic $\hat{\rho}_S$, namely the estimated correlation coefficient between $(S_{it})_t$ and $(S_{jt})_t$. Harding and Pagan (2006) establish a relationship between the estimated concordance index $\widehat{CI}$ and correlation coefficient $\hat{\rho}_S$, showing that:

$$\widehat{CI} = 1 + 2\hat{\sigma}_S + 2\hat{\mu}_{S_i}\hat{\mu}_{S_j} - \hat{\mu}_{S_i} - \hat{\mu}_{S_j}, \tag{8}$$

where $\hat{\mu}_{S_i} = E(S_{it})$, $\hat{\mu}_{S_j} = E(S_{jt})$ and $\hat{\sigma}_S$ is the covariance between $(S_{it})_t$ and $(S_{jt})_t$ such that:

$$\hat{\sigma}_S = \hat{\rho}_S \sqrt{\hat{\mu}_{S_i}(1 - \hat{\mu}_{S_i})} \sqrt{\hat{\mu}_{S_j}(1 - \hat{\mu}_{S_j})}. \tag{9}$$

For both GDP and IPI, values of $\hat{\mu}_{S_i}$ are presented at the bottom of Table 4. For the euro area as a whole, both values are greater than 0.5 indicating thus that months of decelerating phases are more frequent. For France and Italy, industrial production has experienced more periods of deceleration than periods of acceleration. Only in Germany and the Netherlands the estimated mean is lower than 0.5 for both IPI and GDP, suggesting thus that the empirically estimated unconditional probability of being in an accelerating phase is stronger. It is noteworthy that those values are quite different from those estimated by Harding and Pagan (2006) for the industrial business cycle (although estimation periods are different), pointing out that, for the industrial

activity, recessions are less frequent than deceleration phases.

As suggested in Harding and Pagan (2006), we test the null hypothesis $\rho_S = 0$ starting from the following regression equation:

$$\hat{\sigma}_{S_i}^{-1}\hat{\sigma}_{S_j}^{-1}S_{jt} = a + \rho_S\hat{\sigma}_{S_i}^{-1}\hat{\sigma}_{S_j}^{-1}S_{it} + u_t, \tag{10}$$

where $\hat{\sigma}_{S_i}^2$ and $\hat{\sigma}_{S_j}^2$ are the estimated variances of $(S_{it})_t$ and $(S_{jt})_t$, respectively. In business cycle analysis, both variables $(S_{it})_t$ and $(S_{jt})_t$ involved in the previous regression equation, often present strong autocorrelation due to the duration of cycle phases. For example, for the euro area as a whole, the autocorrelation function for the first lag is equal to 0.84 for IPI and to 0.53 for GDP. This result points out a stronger persistence in IPI acceleration cycle than in GDP acceleration cycle. Thus, testing the null $\rho_S = 0$ requires to take autocorrelation, as well as heteroscedasticity of the errors $(u_t)_t$, into account using standard procedures. In this respect we use a heteroscedastic and autocorrelation consistent (HACC) standard error with Bartlett weights, the number of lags being suggested by Newey-West (1984) [7]. In our application, we consider both GDP and IPI series and we test for each pair of countries the null of SNS, namely $\rho_S = 0$. Results are presented in Table 5 for GDP and Table 6 for IPI, where the uncorrected t-statistics are above the diagonal while those based on HACC standard errors are below the diagonal. Regarding IPI series, there is strong evidence in favour of the rejection of the null hypothesis of SNS, even when taking robust t-ratios into account. Only the Netherlands present robust t-ratios that do not allow to reject the null hypothesis of no association. Concerning GDP, conclusions are less clear-cut, although the null of SNS with the euro acceleration cycle is generally rejected excepted for Spain. Specifically, results for Spain show evidence in favour of the null of no association with any other countries, implying thus an idiosyncratic dynamic for Spain. Robust t-ratios for France suggest also that the null of SNS with all the other countries, except Italy, cannot be rejected.

	Euro	Germany	France	Italy	Spain	Belgium	Netherlands
Euro		3.4*	2.2*	7.2*	1.1	5.3*	3.0*
Germany	3.1*		-0.3	2.5*	-0.5	2.6*	2.9*
France	2.2*	-0.3		2.9*	0.4	1.5	0.0
Italy	8.7*	2.4*	2.5*		-0.5	3.4*	2.9*
Spain	0.9	-0.4	0.3	-0.4		1.8	1.6
Belgium	6.6*	2.7*	1.3	3.8*	1.9		3.0*
Netherlands	2.4*	2.7*	0.0	2.2*	1.3	2.9*	

Table 5: Standard and robust t-statistics for the null hypothesis of strong no synchronisation (SNS) in GDP acceleration cycles for selected countries (uncorrect above the diagonal, HACC below). * significant at the 5% level.

2.3 Comparison with other existing chronologies

To evaluate our dating results, we compare them with other existing information available in the literature or from economic research institutes. In opposition to the business and growth cycles (see Anas *et al.*, 2008, for a review), very few turning point chronologies are available for the acceleration cycle. ECRI publishes a monthly dating of the acceleration cycle for several countries [8]. However, ECRI does not provide a dating for the euro area as a whole, but only for the main

---

[7]We choose the empirical rule of thumb saying that the number of lags is equal to the integer part of $T^{1/3}$.

[8]We use the last available chronology updated in January 2009.

	Euro	Germany	France	Italy	Spain	Belgium	Netherlands
Euro		11.6*	11.8*	15.9*	11.1*	9.2*	3.6*
Germany	8.1*		7.2*	7.4*	9.2*	5.7*	4.2*
France	7.4*	4.8*		9.0*	6.2*	7.9*	4.5*
Italy	13.7*	5.7*	6.5*		7.4*	11.2*	3.3*
Spain	8.2*	5.9*	3.9*	5.2*		6.1*	1.6
Belgium	6.4*	3.6*	5.4*	8.0*	3.9*		2.9*
Netherlands	1.9	2.3*	2.4*	1.9	0.9	1.5	

Table 6: Standard and robust t-statistics for the null hypothesis of strong no synchronisation (SNS) in IPI acceleration cycles for selected countries (uncorrect above the diagonal, HACC below). * significant at the 5% level.

countries of the zone. Therefore, we consider the dating chronologies for Germany, France, Italy and Spain (representing around 80 % of the euro area added value) and we aggregate them by computing a diffusion index weighted by the economic importance of each country in the zone. We use the following diffusion index D_t defined as follows:

$$D_t = \frac{1}{\sum_{i=1}^{4} \omega_i} \sum_{i=1}^{4} \omega_i R_{it}, \tag{11}$$

where ω_i is the economic weight of the country i [9] and R_{it} is a binary variable equal to 1 when the country i decelerates and 0 otherwise. As a decision rule, we use the natural threshold of 0.50 to identify a switch in regimes, namely a turning point of the euro area acceleration cycle. The resulting dating is presented in Table 7.

Harding (2004) also proposes a dating chronology of the euro acceleration cycle based on the Bry-Boschan algorithm by employing the data for Euro area GDP used by Fagan et $al.$ (2005) that ends in 1998. We can also infer a turning point chronology by using the EuroCoin index now published by the Bank of Italy in collaboration with the CEPR (Altissimo et $al.$, 2007). As the EuroCoin index is supposed to track the medium long-term growth rate of the euro area, therefore peaks and troughs of the index delimitate accelerating and decelerating phases. Turning points are estimated with the Bry-Boschan algorithm. From Table 7, it appears that the EuroCoin-based chronology is more closely related to our dating chronology since the deviation from our dating is (in average) of only 1.8 month for EuroCoin-based whereas it is of three and six months for ECRI-based and Harding's chronologies, respectively. Moreover, the standard error of deviations is the lowest for the EuroCoin-based chronology. We also note that the ECRI-based chronology presents a supplementary accelerating phase from November 1988 to May 1989.

3 How to detect in real-time the acceleration cycle?

In this section, we put forward a new probabilistic turning point indicator able to track in real-time each month turning points in the euro area acceleration cycle.

3.1 Choice of the data

Generally, data sets are stemming from three main sources of information: macroeconomic data (hard data), opinion surveys (soft data) and financial data. Hard data are well known for their

---

[9]We choose the normalized weights in the added value at market prices in 2007 (source Eurostat) equal to 35% for Germany, 28.0% for France, 22% for Italy and 15% for Spain.

	Dating	Harding (2004)	ECRI-based	EuroCoin-based
peak	1987 M5	1988 M3 (+10)	1988 M2 (+9)	NA
trough			1988 M11	NA
peak			1989 M5	1989 M5
trough	1993 M1	1993 M3 (+2)	1993 M1 (0)	1993 M3 (+2)
peak	1994 M3	1994 M12 (+8)	1994 M12 (-3)	1994 M7 (+4)
trough	1996 M2	1995 M12 (-2)	1996 M3 (+1)	1995 m10 (-4)
peak	1997 M4	1998 M3 (+11)	1997 M1 (-3)	1997 M11 (+7)
trough	1998 M10	NA	1999 M2 (+4)	1998 M12 (+2)
peak	1999 M9	NA	2000 M5 (+8)	2000 M2 (+5)
trough	2001 M9	NA	2002 M6 (+9)	2001 M11 (+2)
peak	2002 M7	NA	2002 M9 (+2)	2002 M6 (-1)
trough	2003 M4	NA	2003 M8 (+4)	2003 M4 (0)
peak	2004 M1	NA	2004 M4 (+3)	2004 M1 (0)
trough	2004 M11	NA	2005 M2 (+3)	2005 M1 (+2)
peak	2006 M4		2006 M11 (+7)	2006 M6 (+2)
Average		5.8	3.4	1.8
s.e.		5.6	4.1	2.9

Table 7: Turning point chronologies for the euro area acceleration cycle (1987-2007) and leads-lags by comparison with our dating (months in parenthesis). *NA* stands for non-available information.

lack of timeliness: They are indeed published with a strong delay and are often revised from one month to the other. Financial variables have been proved to be leading towards the global economic cycle in many empirical studies and are consequently rather introduced in leading indicators of the cycle (see among others Estrella and Mishkin, 1998, or Anas and Ferrara, 2004). In this paper, as our aim is to develop a coincident indicator of the acceleration cycle, available a few days after the end of the reference month, we focus only on the most frequently watched opinion surveys in central banks and economic institutions.

Several soft data are available on a monthly basis for the euro area and for each specific country. A first alternative would be to consider all the available information and to summarize it into a composite indicator through a dynamic factor model proposed for example by Stock and Watson (2002) or Forni *et al.* (2000). To avoid a too systematic black-box indicator, we prefer to select with caution a few components. We proceed first with this issue: Which is the sector the most closely linked to the acceleration cycle? To answer this question we consider the European Sentiment Index [ESI] computed by the European Commission [EC] and presented in Figure 2, as well as the deceleration phases estimated previously. The ESI is the weighted aggregation of the euro area confidence indicators for five components: industry (40%), services (30%), consumers (20%), retail trade (5%) and building (5%). Each confidence indicator is the arithmetic mean of a few questions from the corresponding EC survey. In order to detect peaks and troughs on each component, as well as on the ESI, we apply the Bry-Boschan algorithm adapted by Harding and Pagan (2002). It turns out that peaks and troughs estimated on the first differences of series are closely linked to the reference acceleration cycle over the period ranging from 1986 to 2007. Dating results are presented in Table 8.

From Table 8, it turns out that both the ESI and its industrial component, namely the ICI (Industrial Confidence Indicator, see Figure 2), are the most closely linked to the reference dating, as regards the total number of cycles and the timing of turning points. The highest concordance index is reached by the ICI (0.75). As expected due to the strong weight of ICI in the computation of ESI, the concordance index of the ESI is also large (0.73). We note that the confidence

	Dating	ΔESI	ΔIndustry	ΔServices	ΔConsumers	ΔRetail	ΔBuilding
peak	1987 M5	1988 M6	1986 M3	na	1988 M11	1988 M9	1988 M7
trough		1990 M9	1987 M1	na	1990 M9	1991 M1	1991 M4
peak		1992 M2	1991 M1	na	1991 M9	1991 M11	1991 M12
trough	1993 M1	1992 M11	1993 M1	na	1992 M10	1992 M9	1993 M2
peak	1994 M3	1994 M4	1994 M4	na	1994 M4	1995 M1	1994 M4
trough	1996 M1	1995 M10	1996 M1	na	1995 M9	1995 M10	1996 M1
peak	1997 M6	1997 M7	1997 M6	1997 M4	1997 M8	1997 M11	1997 M12
trough	1998 M10	1998 M9	1998 M10		1999 M4	1999 M5	
peak	1999 M9	1999 M1	2000 M2			2000 M2	
trough	2001 M7	2001 M10	2001 M7	2001 M7		2002 M2	2002 M8
peak	2002 M7	2002 M3	2002 M5	2002 M2	2001 M12		
trough	2003 M4	2002 M10	2003 M2	2002 M10	2002 M10		
peak	2004 M1	2003 M8	2003 M12	2003 M8	2003 M4		
trough	2004 M11	2004 M5	2004 M11	2005 M3	2005 M5		
peak	2006 M4	2006 M4	2006 M4	2006 M6		2006 M2	2005 M11
Concordance		0.73	0.75	0.53	0.56	0.67	0.71
HACC t-stat		4.45	4.68	1.16	1.48	3.80	3.30

Table 8: Turning points chronologies for the ESI and its components (Jan. 1986 - December 2007), concordance indexes with the dating chronology and robust t-statistics for the null hypothesis of SNS.

indicator in the building sector is also high, but the number of cycles in this series is not in line with the dating chronology. The services sector series is shorter than the other series (starting only in April 1995) and is not strongly marked by a cyclical behavior. The Harding and Pagan (2006) test of SNS is carried out between the reference chronology and the chronologies stemming from each indicator. At the usual level, we accept the fact that services and consumers indicators are strongly non-synchronised with the reference acceleration cycle. As in the previous section, this analysis, based on the ESI components, points out the fact that the euro area acceleration cycle is closely related to the industrial acceleration cycle. Therefore, in the data selection process, we decide to focus only on composite indicators in the industrial sector stemming from various opinion surveys.

Thus we consider various datasets of soft indicators related to the industrial sector for the six main countries of the euro area, namely Germany, France, Italy, Spain, Belgium and Netherlands, and for the euro as a whole. We focus first on euro area aggregated EC composite indicators, that is ESI, ICI and BCI [10] series (see Figure 2), then on ICIs for the six main countries (see Figure 3). Those six series are interesting because they are directly comparable through the EC harmonization program. We observe that peaks and troughs of the differenced series seem to match pretty well with the phases of the acceleration cycle. Then we focus on country-specific industrial composite indicators such as IFO for Germany, INSEE for France, and ISAE for Italy (see Figure 4)[11]. Those series are released the same day, that is the last working day of the reference month. Those national surveys serve as a basis for the construction of the national harmonized ICI released by the EC. Last, we consider also the Purchasing Managers Indexes

---

[10]As the ICI, the Business Climate Indicator [BCI] is a composite index reflecting opinions on the situation in the industrial sector. While ICI is computed using a standard average of some balances of opinions, BCI is computed as the first common factor of a static principal component analysis.

[11]These country-specific indicators are business climate indicators computed by the Institut for Economic Research (IFO – *Institut für Wirtschaftsforschung*) for Germany, the Institute for Studies and Economic Analyses (ISAE – *Istituto di Studi e Analisi Economica*) for Italy and the National Institute for Statistics and Economic Studies (INSEE – *Institut National de la Statistique et des Études Économiques*) for France.

[PMI] in the manufacturing sector, provided by NTC Research. PMIs are often considered by macroeconomic analysts in their economic outlook because they are available for several countries and, according to their provider, they enable an international comparison of economic activity among the countries on the basis that the methodology applied for computation is the same. Indeed, for each country the PMIs are simply the weighted average of five questions asked to a panel of managers. The fact that the weights are identical for all the countries is rather surprising but in spite of their defaults those indicators are carefully watched each month by policy-makers. We decide thus to integrate them in the analysis. For our purpose, the main drawback is the lack of an historical time series, since the manufacturing PMI for the euro area as a whole is only available since June 1997, corresponding to around 10 years of data points. For the four main countries of the zone, the PMIs start in April 1996 for Germany, June 1998 for France, June 1997 for Italy and February 1998 for Spain.

3.2 The econometric framework

We assume now that N series have been selected from the previous step. The issue is how to extract the common cycle of those series. We present the econometric methodology that we used to compute the real-time indicator of the acceleration cycle, based on the class of Hidden Markov-Chain models. Especially, we focus on the Markov-Switching [MS] model popularized by Hamilton (1989) and generalized to the multivariate case by Krolzig (1997) and Kim and Nelson (1998). This kind of model has been used in many empirical studies on business cycle analysis. We refer among others to Layton (1996), Chauvet (1998), Gregoir and Lenglart (2000), Krolzig (2001), Chauvet and Piger (2003, 2008), Ferrara (2003), Anas and Ferrara (2004), Chauvet and Hamilton (2006), Bruno and Otranto (2008) or Anas *et al.* (2008). We propose two econometric models to take the multivariate information into account: a MS-VAR process and a MS factor model.

3.2.1 MS-VAR

We present below the multivariate extension of the Markov-Switching model with $K = 2$ regimes as proposed by Krolzig (1997). This definition can be easily extend to more than two regimes. We define the N-dimensional second order process $(X_t)_{t \in Z} = (X_t^1, \dots, X_t^N)_{t \in Z}$ as a MS(2)-VAR(p) process if it verifies the following equations:

$$X_t - \mu(S_t) = \sum_{i=1}^{p} \Phi_i(S_t)(X_{t-i} - \mu(S_{t-i})) + \varepsilon_t, \tag{12}$$

where $(S_t)_t$ is a random process with values in $\{1, 2\}$, where $(\varepsilon_t)_{t \in Z}$ is a multivariate white noise Gaussian process with variance-covariance matrix $\Sigma(S_t)$ and where $\Phi_1(S_t), \dots, \Phi_p(S_t)$ are $N \times N$ matrices describing the dependence of the model to the regime S_t. The full representation of the model requires the specification of the variable $(S_t)_t$ as a first order Markov chain with two regimes. That is, for all t, S_t depends only on S_{t-1}, i.e.:

$$P(S_t = j | S_{t-1} = i, S_{t-2}, S_{t-3}, \dots) = P(S_t = j | S_{t-1} = i) = p_{ij} \qquad \text{for } i, j = 1, 2. \tag{13}$$

The probabilities p_{ij} $(i, j = 1, 2)$ are the transition probabilities; they measure the probability of staying in the same regime and to switch from a regime to the other one. They provide a measure of the persistence of each regime. Obviously, we get: $p_{i1} + p_{i2} = 1$, for $i = 1, 2$. Estimated durations of regimes, $D(S_t = i)$ for $i = 1, 2$, are given by: $D(S_t = i) = 1/(1 - p_{ii})$. The estimation step enables to get, for each date t, the forecast, filtered and smoothed probabilities of being in

a given regime i, respectively defined by $P(S_t = i | \hat{\theta}, X_{t-1}, \ldots, X_1)$, $P(S_t = i | \hat{\theta}, X_t, \ldots, X_1)$ and $P(S_t = i | \hat{\theta}, X_T, \ldots, X_1)$, where $\hat{\theta}$ is the estimated parameter. Estimation is done by using the EM algorithm proposed by Hamilton (1990).

The choice of the number of regimes K is always an issue when dealing with empirical applications. Some testing procedures have been put forward in the literature to test the number of regimes but cannot be easily implemented (we refer for example to Hansen, 1992, or Hamilton, 1996). In this paper, we assume that $K = 2$ and this choice is discuted in Section 3.4.

3.2.2 Markov-Switching Factor Models

In this model, the information is summarized into an univariate underlying factor, supposed to represent the common evolution of all the series, that switches between two distinct regimes according to a Markov chain. This model was first sketched by Diebold and Rudebusch (1996), while theoretical and empirical aspects are widely discussed in Kim and Nelson (1998). Due to the low number of variables used in this paper, we assume that a single factor is sufficient to account for the variance of the data. Thus, for a single common factor, we define the model as follows, for $n = 1, \ldots, N$:

$$X_t^n = \gamma_n F_t + u_t^n, \tag{14}$$

with

$$\phi(B) F_t = \mu(S_t) + \varepsilon_t, \tag{15}$$

where γ_n are referred to as the loadings, $(u_t^n)_t$ is supposed to follow a Gaussian stationary AR(1) process with finite variance σ_n^2, $(\varepsilon_t)_t$ is a Gaussian white noise process with unit variance, $(S_t)_t$ is a two-states Markov chain defined by equation (13), and $\phi(B) = I - \phi_1 B - \ldots - \phi_p B^p$. We assume that $(F_t)_t$ and the idiosyncratic noises $(u_t^n)_{n=1,\ldots,N}$ are non-correlated and that the idiosyncratic noises $(u_t^n)_{n=1,\ldots,N}$ are not cross-correlated.

Parameter estimation of this model can be carried out either simultaneously, as proposed by Kim and Nelson (1998), or in two steps, by estimating first the common factor $(\hat{F}_t)_t$ and then by fitting a MS(K)-AR(p) process on the estimated factor. As our aim is to propose an operational tool to be computed on a monthly basis, we prefer to tend towards the simplest estimation method, namely the two-step procedure, assuming that simplicity goes along with robustness. Indeed, preliminary results with the simultaneous estimation method have shown non-convergence issues in the estimation algorithm. The common factor estimation has been carried out according to two distinct methods. We estimate first a static common factor model ($\phi(B) = I$ in equation (15)), referred to as Static Factor Markov-Switching [SFMS]. Loadings are thus estimated by using the principal component analysis. Then we introduce dynamics into the factor, referred to as Dynamic Factor Markov-Switching [DFMS], by assuming that the unobserved factor in equation (15) is driven by an AR(2) process. Dynamic factor estimation is carried out by maximum likelihood without any identification restriction, through a Kalman filter[12]. Both estimations methods are compared in the application section.

3.3 Indicator construction and quality criteria

Our aim is to construct the *best* acceleration cycle turning point indicator in the sense that it allows the more precise reproduction of the phases of the acceleration cycle, as described by the reference dating presented in Table 1. The turning point indicator is based on the filtered

---

[12]Parameter estimation is carried using the RATS software.

probabilities of being in a given regime. At each date t, the indicator I_t is computed by taking the difference between the probability of being in the high regime (acceleration) and the probability of being in the low regime (deceleration). When the indicator is close to 1, it means that the economy is accelerating and when the indicator is close to -1, we infer that the economy is decelerating. To help the understanding of the indicator we propose a decision rule based on a threshold $\beta \in [0,1]$. We will say that the economy belongs to an accelerating phase if $I_t \in]\beta, 1]$ and to a decelerating phase if $I_t \in [-1, -\beta[$. The threshold β is a free parameter estimated empirically and is generally set to 0.33 or 0.50.

To assess the quality of the indicator $(I_t)_{t=1,\ldots,T}$, we propose several criteria. Let $(R_t)_{t=1,\ldots,T}$ be the binary variable such as $R_t = 1$ if the economy is decelerating at date t and $R_t = 0$ otherwise. This variable is computed according to the reference dating. Each criterion depends on the threshold β in use in the decision rule.

The first considered criterion is the classical Quadratic Probabilistic Score defined by:

$$QPS(\beta) = \frac{1}{T} \sum_{t=1}^{T} (\mathbf{1}_{(I_t < -\beta)} - R_t)^2, \tag{16}$$

where $\mathbf{1}_{(A)} = 1$ if A is true, and zero otherwise. This criterion is used in many empirical studies to assess the concordance degree between the indicator and a reference dating. However, this criterion presents several drawbacks. Especially, two non-correlated variables may present a high value of QPS if their persistence is strong (Harding and Pagan, 2006). This is typically the case when dealing with the classical business cycle in industrial countries for which probabilities of staying in the same regime are greater than 0.9.

We now put forward a more symmetric criterion that takes also into account periods where the indicator lies in the intermediate phase. We attribute the null value when the indicator is in the same phase as the reference dating, the value 2 when the indicator is in the opposite phase and the value 1 when the indicator belongs to the intermediate phase, that is between $-\beta$ and β. This cyclical goodness of fit (CGoF) criterion, that has to be minimized, is defined by:

$$CGoF(\beta) = \frac{1}{T} \sum_{t=1}^{T} u_t(\beta), \tag{17}$$

where

$$u_t(\beta) = \begin{cases} 1 - (1_{(I_t > \beta)} - 1_{(I_t < -\beta)}), & \text{if } R_t = 0 \\ 1 + (1_{(I_t > \beta)} - 1_{(I_t < -\beta)}), & \text{if } R_t = 1 \end{cases} \tag{18}$$

The third criterion that we use in this empirical part is the readability criterion. We start from the idea that the intermediate regime corresponds to a form of uncertainty in which the signal is very difficult to interpret. Therefore, a readable indicator is an indicator that does not stay during a long time in the intermediate zone. We define the readability criterion by:

$$Readability(\beta) = \frac{1}{T} \sum_{t=1}^{T} 1_{(-\beta \leq I_t \leq \beta)}. \tag{19}$$

This criterion estimates the number of times that the indicator lies in the intermediate phase. Note that these three criteria should be minimized.

3.4 Empirical results

In this section, we consider the various opinion survey series over the sample January 1992 to September 2007. If we note $(Y_t)_t$ one of the original opinion survey series, we have pointed out previously that peaks and troughs of the series in first differences, that is ΔY_t, match with peaks and troughs of the acceleration cycle. Therefore, in order to detect those peaks and troughs, we have to identify the switches in acceleration regimes, namely the switches in the regimes of the twice differenced series $\Delta^k \Delta Y_t$, where the operator Δ^k is defined such as $\Delta^k = I - B^k$, with B the lag operator. This twice-differenced series $\Delta^k \Delta Y_t$ appears very noisy and therefore the signal extraction step becomes very tricky. The choice of the integer k in the operator $\Delta^k \Delta$ is a way to reduce the noise without introducing too strong distortions in the cycle. However, this choice is totally empirical. To assess the value of k, we first work with the ESI, BCI and ICI for aggregate euro area. After several tries on each series, it turns out that $k = 6$ provides with the best trade-off between noise and lag in terms of replication of the cycle according to the quality criteria. Thus we decide to keep this lag $k = 6$ in the remaining analysis, that is all the models are applied to the series $\Delta^6 \Delta Y_t$.

Regarding Markov-Switching models specification, several choices have to be clarified. The choice of the number of regimes is a not an obvious issue. When dealing with classical business cycles, most of the papers prefer to keep the original two-regime specification of Hamilton (1989) while some authors argue in favour of the presence of a third regime enabling a more precise description of cycle dynamics (e.g. Sichel, 1994, or Ferrara, 2003). When dealing with the acceleration cycle, it turns out that two regimes are sufficient to reproduce dynamics. Indeed, from an empirical point of view, we have observed that this third regime is not persistent and is rather related to strong shocks affecting the series than to an intermediate regime of constant growth. Thus the three-regime specification does not enable to improve the replication of the acceleration cycle. This fact relates to the characteristics of the acceleration cycle that is defined as sequence of two types of phases: accelerating and decelerating ones. Indeed, it turns out that the intermediate third regime, that corresponds to extended periods for which the growth rate is constant, is very rare in practice. Another usual specification in business cycle analysis allows an idiosynchratic variance in each regime, suggesting that uncertainty is stronger during recession periods. In our framework, parameter estimation has showed that both variances are not significantly different. Therefore we impose an identical variance during accelerating and decelerating phases in the models. Note also that the autoregressive order p of the MS(2)-VAR(p) model is set equal to zero. Increasing this order p deteriorates strongly the cyclical replication ability of the models. Last, due to the low number of variables involved in multivariate DFMS and SFMS models, it is assumed that a single factor is sufficient to summarize the information conveyed by opinion surveys. Parameter estimates of all the models, as well as estimated phase durations, are presented in Table 9.

First, we focus on the opinion surveys in the industry released by the EC for the euro area as a whole (ESI, BCI and ICI, see Figure 2). We apply an univariate MS model (equation (12) with $N = 1$) to those three series over the sample Jul. 1992 - Sep. 2007. Parameter estimates of those three models are proportionally comparable between them. Estimated durations of decelerating phases correspond to the reference average duration evaluated in the first part of this paper (16 months), especially for the ICI. On the other hand, estimated durations of accelerating phases are shorter than expected (12 months on the average). This latter stylized fact is true for all the approaches, with various degrees. Turning point indicators stemming from these three approaches (MS-VAR, SFMS and DFMS) are presented in Figure 5 and values of the quality

	$\mu(S_t = 1)$	$\mu(S_t = 2)$	σ_ε	p_{11}	p_{22}	$D(S_t = 1)$	$D(S_t = 2)$
Confidence Indexes							
ESI	-1.01	1.80	1.57	0.93	0.88	14	8
BCI	-0.12	0.21	0.17	0.93	0.87	14	8
ICI	-0.89	1.90	1.32	0.94	0.86	16	7
Six main ICIs							
MSVAR				0.94	0.86	16	7
Germany	-0.91	2.10	1.93				
France	-1.19	2.58	3.02				
Italy	-0.90	1.93	2.89				
Spain	-0.71	1.56	2.81				
Netherlands	-0.34	0.78	2.01				
Belgium	-1.00	2.30	2.94				
SFMS	-0.47	1.09	0.72	0.94	0.87	18	7
DFMS	-0.46	1.06	0.72	0.95	0.89	21	9
Three national surveys							
MSVAR				0.91	0.86	11	7
IFO	-0.59	0.88	1.50				
INSEE	-1.37	2.00	2.04				
ISAE	-0.88	1.30	2.33				
SFMS	-1.60	2.69	2.05	0.91	0.85	11	7
DFMS	-0.50	0.80	0.60	0.91	0.86	11	7
PMIs							
PMI Euro	-0.41	2.10	1.1	0.95	0.74	22	4
Four main PMIs				0.96	0.74	25	4
Germany	-0.32	2.31	1.59				
France	-0.46	2.97	1.82				
Italy	-0.26	1.56	1.49				
Spain	-0.38	2.35	1.31				

Table 9: Parameter estimates of the various multivariate MS models over the period Jan. 1992 - Sep. 2007 (except for PMIs since 1998 only). Durations D of each regime are expressed in months.

criteria are contained in Table 10. All the indicators replicate the acceleration cycle, but the ICI presents better results in terms of quality criteria. Especially, QPS and CGoF are lower than those of ESI and BCI with $\beta = 0.5$. We also note that the QPS of the ICI is the lowest among all approaches with $\beta = 0.5$.

In a second step, we consider the ICI for the six main euro countries, namely Germany, France, Italy, Spain, Belgium and Netherlands (see Figure 3). We fit multivariate MS-VAR, SFMS and DFMS models to this six-dimensional vector. Parameter estimates of the MS-VAR model correspond to those stemming from the univariate MS model applied to ICI. Including dynamics in the DFMS model leads to slightly over-estimate durations. The resulting turning point indicators stemming from the three models are presented in Figure 6 along with the reference dating chronology. We observe that, by including dynamics, the DFMS model is not significantly different from the SFMS model. Indeed, the estimated parameters of the AR(2) process are $\hat{\phi}_1 = -0.12$ and $\hat{\phi}_2 = 0.04$ [13]. Parameter estimate $\hat{\phi}_2$ is not significant, but $\hat{\phi}_1$, even low, can be considered as non-null with a strong type I risk. When looking at the quality criteria in Table 10, we note that results from the SFMS and DFMS models are quite similar (goodness of fit criteria being slightly lower for SFMS). A threshold of $\beta = 0.33$ enables to improve the readability of the signal (the

---

[13]To save space we do not display all the parameters of models. They are available upon request from the authors.

	$\beta = 0.50$			$\beta = 0.33$		
	QPS	CGoF	Readibility	QPS	CGoF	Readibility
Confidence Indexes						
ESI	0.213	0.486	0.224	0.229	0.503	0.153
BCI	0.197	0.410	0.147	0.186	0.361	0.087
ICI	0.164	0.377	0.147	0.175	0.377	0.082
Six main ICIs						
MSVAR	0.180	0.382	0.131	0.175	0.372	0.071
SFMS	0.175	0.372	0.120	0.169	0.344	0.071
DFMS	0.175	0.388	0.120	0.191	0.377	0.060
Three national surveys						
MSVAR	0.208	0.404	0.186	0.191	0.399	0.093
SFMS	0.202	0.426	0.153	0.186	0.366	0.093
DFMS	0.202	0.399	0.153	0.180	0.382	0.077
PMIs						
PMI euro	0.239	0.504	0.060	0.239	0.496	0.034
Four main PMIs	0.257	0.543	0.048	0.257	0.543	0.048

Table 10: Quality criteria for turning point indicators with $\beta = 0.50$ and $\beta = 0.33$

value of the criteria has been divided by two). When comparing with the results obtained for the euro area ICI, we note that the ICI-based turning point indicator provides competitive results.

We focus now on the most frequently watched national opinion surveys, namely those provided by IFO, INSEE and ISAE (see Figure 4). Using those three series, we estimate multivariate MS-VAR, SFMS and DFMS models over the sample Jul. 1992 - Sep. 2007. The resulting probabilistic indicators are presented in Figure 7. All three models lead to equal estimated durations that tend to under-estimate reference durations. Quality criteria are presented in Table 10. From those results, it seems that the signal emmitted by the MSVAR is less readable than the two others with $\beta = 0.5$, otherwise it is difficult to discriminate between models. However, it appears that the previous approach with the six ICIs outperform the approach including only the three surveys, all the criteria having higher values with this latter approach.

Last we focus on the PMIs. As for the other opinion survey sources, we apply the same procedure, that is we fit a MS model to the euro area PMI over the sample Jan. 1998 - Sep. 2007 and a MS-VAR model to the four main countries of the zone (Germany, France, Italy and Spain) over the sample Jan. 1999 - Sep. 2007. Results are presented in Figure 8. It turns out that the models do not enable to describe correctly the euro area acceleration cycle as defined by the benchmark dating. Indeed, duration of decelerating phases is strongly over-estimated while the inverse prevails for accelerating phases. This is certainly due to the fact that not enough cycles are available for the model. Consequently, in the lack of back-calculated data, we do not integrate those variables in our models for the monthly assessment of acceleration cycle turning points.

Finally, we propose a real-time exercise with very recent data ranging from January 2006 to December 2008. Over this sample, we have identified a peak in April 2006 in the dating exercise in the first part of the paper. In this experience, we compute first a turning point indicator for data over the sample January 1992 - December 2005, then, in a recursive scheme, we add each month a new data point, we re-estimate the model and we compute a new probabilistic indicator. Results are presented in Figure 9 for the SFMS model and in Figure 10 for the DFMS

model. First, we note that the DFMS model provides a timely signal of a peak in April 2006 when the indicator crosses the threshold $\beta = -0.5$. A persistent signal is emitted by the SFMS model only from June 2006 and is thus a bit lagged. We also note that both indicators are rather persistent. Indeed, with a threshold of $\beta = -0.5$, SFMS presents only one false signal in March 2008 and DFMS presents two false signals in July 2006 and in February 2007. If we choose a threshold $\beta = -0.33$, there is only one signal in July 2006 for DFMS. Last note that revisions in the indicators are very low.

To sum up the empirical results, the approaches including the information related to the ICIs, for both the aggregate euro area and the six main countries, provide the lowest quality criteria. Among the three types of multivariate models considered (MSVAR, SFMS and DFMS), it seems difficult to strongly argue in favour of one of them, according to the quality criteria. However, the DFMS model seems to over-estimate phase durations. For parcimony reasons, the SFMS model would be more convenient for a real-time use in order to detect turning points in the acceleration cycle. Note also that PMIs do not appear appropriate for this kind of exercise.

4 Conclusion

The follow-up of accelerations and decelerations of the euro area economy is of great interest for short-term analysts. In this paper we come up with two main results that are useful for studying the euro area acceleration cycle. First we have constructed a reference turning point chronology, on a monthly basis, for the euro area acceleration cycle from 1987 to 2006 based on estimated turning point dates of both GDP and IPI. Second, we have put forward a monthly real-time turning point indicator based on information conveyed by opinion surveys carefully watched by central banks. We empirically prove that this probabilistic indicator, computed from multivariate Markov-Switching models, is able to track each month the acceleration cycle of the euro area.

In this paper, we also point out that accelerations and decelerations of the economy are mainly generated by the industrial sector. In this respect, further empirical research could be to add progressively quantitative indicators related to the industrial activity to assess the gain in reliability at the cost of a more delayed indicator. A sectoral approach could be also fruitful. From a methodological point of view, a focus should be made on improving parameter estimation in dynamic factor models for which the factor switches according to a Markov chain as proposed by Kim and Nelson (1998). Especially, effort should be concentrated on the computational aspects of such model for a regular use by practitioners.

References

[1] Altissimo, F., Cristadoro, R., Forni, M., Lippi, M., and Veronese, G. (2007), New Eurocoin: Tracking economic growth in real time, Temi di Discussione 631, Banca d'Italia.

[2] Anas, J. and Ferrara, L. (2004), Turning points detection: The ABCD approach and two probabilistic indicators, *Journal of Business Cycle Measurement and Analysis*, 1, 1-36.

[3] Anas, J., Billio, M., Ferrara, L. and M. LoDuca (2007), A turning point chronology for the Euro-zone, in *Growth and Cycle in the Euro zone*, G.L. Mazzi and G. Savio (eds.), 261-274, Palgrave MacMillan, New York.

[4] Anas, J., Billio, M., Ferrara, L. and Mazzi, G.-L. (2008), A system for dating and detecting cycles in the Euro area, *The Manchester School*, 76, 549-577.

[5] Artis, M., Marcellino, M. and Proietti, T. (2004), Dating business cycles: A methodological contribution with an application to the Euro area, *Oxford Bulletin of Economics and Statistics*, 66, 537-565.

[6] Artis, M., Krolzig, H-M. and Toro, J. (2004), The European business cycle, *Oxford Economic Papers*, 56, 1-44.

[7] Banerji, A. (1999), The three Ps: Simple tools for monitoring economic cycles, *Business Economics*, 34, 72-76.

[8] Bengoechea, P., Camacho M. and Perez-Quiros G. (2006), A useful tool to identify recessions in the Euro-area, *International Journal of Forecasting*, 22, 735-749.

[9] Bruno, G., Otranto, E. (2008), Models to date the business cycle: The Italian case, *Economic Modelling*, 25, 899-911.

[10] Bry, G. and Boschan, C. (1971), *Cyclical Analysis of Time series: Selected Procedures and Computer Programs*, NBER, Columbia University Press.

[11] Burns, A.F., and Mitchell, W.C. (1946), *Measuring Business Cycles*, NBER, Columbia University Press.

[12] Camacho, M., Perez-Quiros, G. and Saiz, L. (2008), Do European business cycles look like one?, *Journal of Economic Dynamics and Control*, 32, 2165-2190.

[13] CEPR (2003), Euro Area Business Dating Committee, Press Release, September 22, 2003.

[14] CEPR (2009), Euro Area Business Dating Committee, Press Release, March 31, 2009.

[15] Chauvet, M. (1998), An econometric characterization of business cycle dynamics with factor structure and regime switching, *International Economic Review*, 39, 969-996.

[16] Chauvet, M. and Hamilton, J. (2006), Dating business cycle turning points in real time, in *Nonlinear Time Series Analysis of Business Cycles*, Milas C., Rothman P., Van Dijk D. (eds.), Elsevier Science, Amsterdam.

[17] Chauvet, M. and Piger, J. (2003), Identifying business cycle turning points in real time, *Federal Reserve Bank of St. Louis Review*, 85, 47-61.

[18] Chauvet, M. and Piger, J. (2008), A comparison of the real-time performance of business cycle dating methods, *Journal of Business and Economic Statistics*, 26, 42-49.

[19] Clements, M.P. and Krolzig, H.M. (2003), Business cycle asymmetries characterization and testing based on Markov-switching autoregressions, *Journal of Business and Economic Statistics*, 21, 196-211.

[20] Demers, F. and MacDonald, R. (2007), The Canadian business cycle: A comparison of models, Working Paper No. 2007-38, Bank of Canada.

[21] Diebold, F.X. and Rudebusch, G.D. (1996), Measuring business cycles: A modern perspective, *Review of Economics and Statistics*, 78, 67-77.

[22] Engel, J., Haugh, D. and Pagan, A. (2005), Some methods for assessing the need for non-linear models in business cycle analysis, *International Journal of Forecasting*, 21, 651-662.

[23] Estrella A., Mishkin F. (1998), Predicting U.S. recessions: Financial variables as leading indicators, *The Review of Economics and Statistics*, 80, 45-61.

[24] Fagan, G., Henry, J. and Mestre, R. (2005), An area-wide model for the euro area, *Economic Modelling*, 22, 39-59.

[25] Ferrara, L. (2003), A three-regime real-time indicator for the US economy, *Economics Letters*, 81, 373-378.

[26] Forni, M., Hallin, M., Lippi, M. and Reichlin, L., (2000), The generalized dynamic-factor model: Identification and estimation, *Review of Economics and Statistics*, 82, 540-554.

[27] Gomez, V. (2001), The use of Butterworth filters for trend and cycle estimation in economic time series, *Journal of Business and Economic Statistics*, 19, 365-373.

[28] Gregoir, S. and Lenglart, F. (2000), Measuring the probability of a business cycle turning point by using a multivariate qualitative hidden Markov model, *Journal of Forecasting*, 19, 81-102.

[29] de Haan, J., Inklaar, R. and Jong-A-Pin, R. (2008), Will business cycles in the euro area converge? A critical survey of empirical research, *Journal of Economic Surveys*, 22, 234-273.

[30] Hamilton, J.D. (1989), A new approach to the economic analysis of nonstationary time series and the business cycle, *Econometrica*, 57, 357-384.

[31] Hamilton, J.D. (1990), Analysis of time series subject to changes in regime, *Journal of Econometrics*, 45, 39-70.

[32] Hamilton, J.D., (1996), Specification testing in Markov-switching time series models, *Journal of Econometrics*, 70, 127-157.

[33] Hansen, B.E., 1992, The likelihood ratio test under non-standard conditions: testing the Markov trend model of GNP, *Journal of Applied Econometrics*, 7, S61-S82 (supplement).

[34] Harding, D. (2004), Non-parametric turning point detection, dating rules and the construction of the Euro-zone chronology, in *Monographs of Official Statistics: Statistical Methods and Business Cycle Analysis of the Euro zone*, G.L. Mazzi and G. Savio (eds.), Eurostat, 122-146.

[35] Harding, D., Pagan, A. (2002), Dissecting the cycle: A methodological investigation, *Journal of Monetary Economics*, 49, 365-381.

[36] Harding, D., Pagan, A. (2006), Synchronization of cycles, *Journal of Econometrics*, 132, 59-79.

[37] Kim, C-J., Nelson, C.R. (1998), Business cycle turning points, a new coincident index, and tests of duration dependence based on a dynamic factor model with regime switching, *Review of Economics and Statistics*, 80, 188-201.

[38] Krolzig, H.M. (1997), *Markov-Switching Vector Autoregressions. Modelling, Statistical Inference and Applications to Business Cycle Analysis*, Springer, Berlin.

[39] Krolzig, H.M. (2001), Markov-switching procedures for dating the Euro-zone business cycle, *Quarterly Journal of Economic Research*, 3, 339-351.

[40] Layton, A.P. (1996), Dating and predicting phase changes in the U.S. business cycle, *International Journal of Forecasting*, 12, 417-428.

[41] Layton, A.P., Smith, D.R. (2007), Business cycle dynamics with duration dependence and leading indicators, *Journal of Macroeconomics*, 29, 855-875.

[42] Mazzi, G.-L., and Savio, G. (2007), *Growth and Cycle in the Eurozone*, Palgrave-MacMillan, New York.

[43] Mintz, I. (1969), Dating postwar business cycles: Methods and their application to Western Germany, 1950-67, Occasional Paper No. 107, NBER.

[44] Mönch, E. and Uhlig, H. (2005), Towards a monthly business cycle chronology for the Euro area, SFB Discussion Paper No 649, April 2005.

[45] Newey, W.K., West, K. (1994), Automatic lag selection in covariance matrix estimators, *Review of Economic Studies*, 61, 4, 631-653.

[46] Sensier, M. and van Dijk, D. (2004), Testing for changes in volatility of US macroeconomic time series, *Review of Economics and Statistics*, 86, 833-839.

[47] Sichel, D.E. (1994), Inventories and the three phases of the business cycle, *Journal of Business and Economic Statistics*, 12, 269-277.

[48] Stock, J. and Watson, M. (2002), Forecasting using principal components from a large number of predictors, *Journal of the American Statistical Association*, 97, 1167-1179.

[49] Summers, P. (2005), What caused the great moderation? Some cross-country evidence, *Economic Review*, Federal Reserve Bank of Kansas City, Third Quarter 2005.

[50] Zarnowitz, V., Ozyldirim, A. (2006), Time series decomposition and measurement of business cycles, trends and growth cycles, *Journal of Monetary Economics*, 53, 1717-1739.
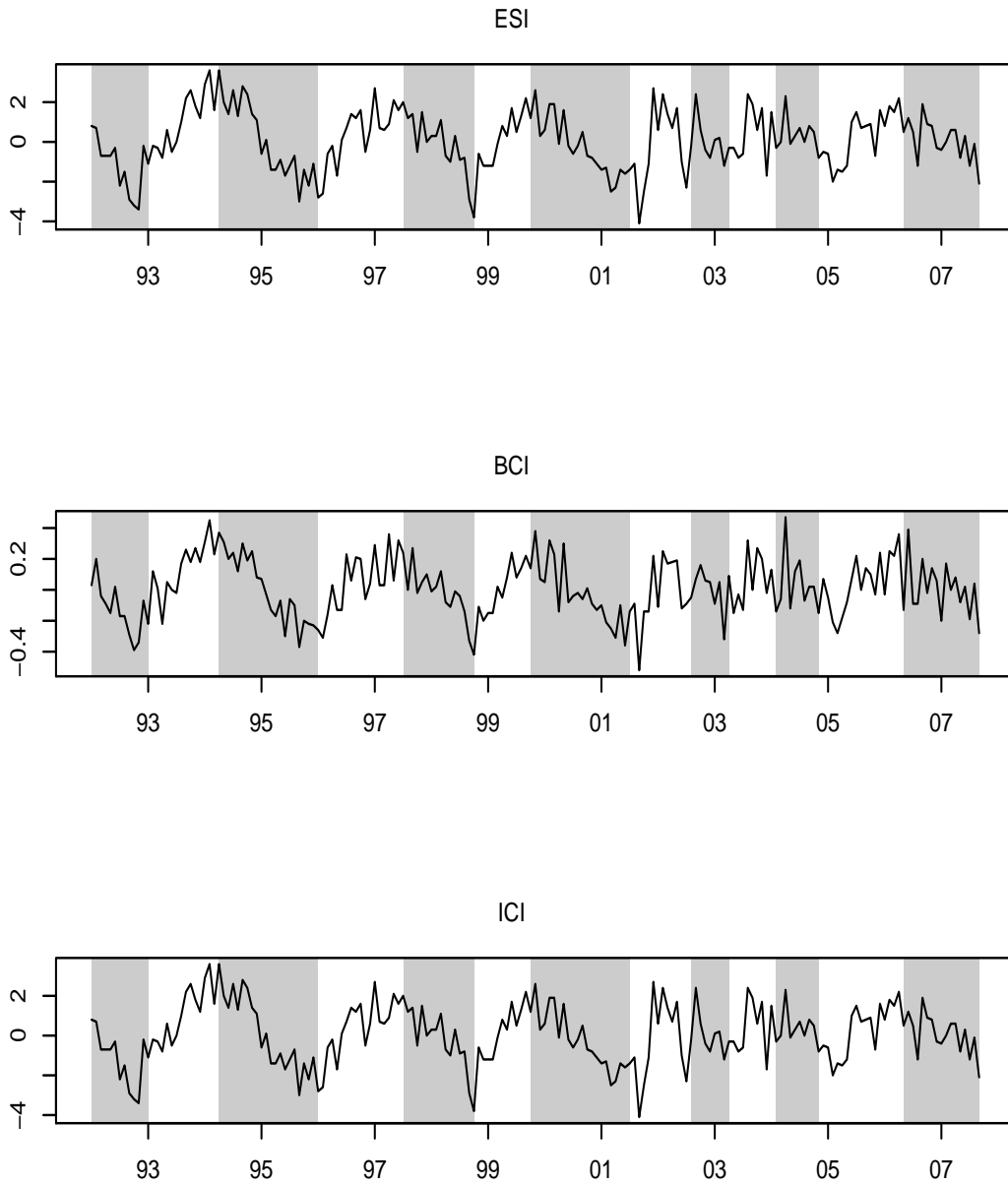
Figure 2: ESI, BCI and ICI (in fist differences) and phases of deceleration in the euro area (shaded areas) over the period January 1992 - September 2007.
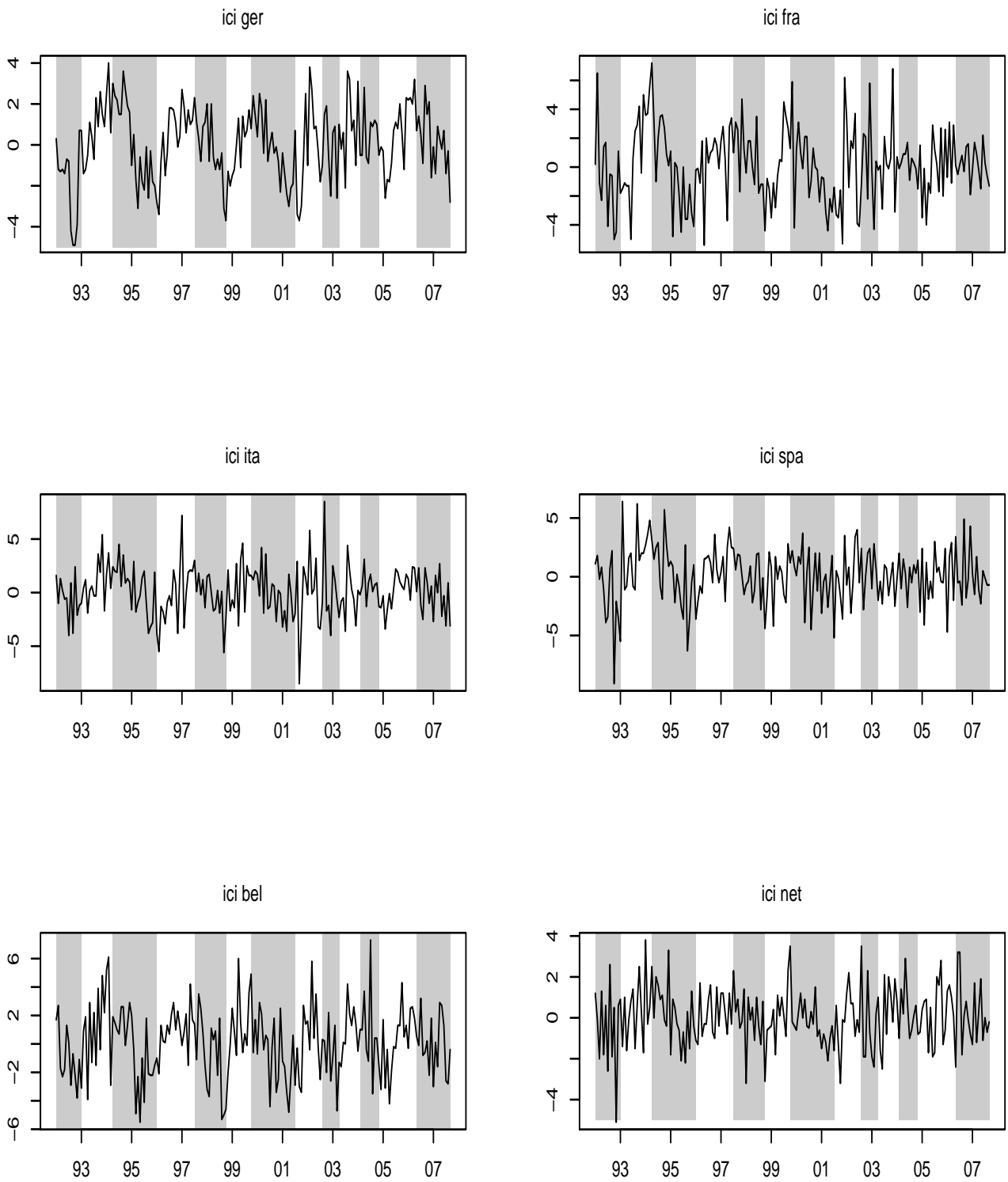
Figure 3: ICIs for the 6 main Euro area countries (in first differences) and phases of deceleration in the euro area (shaded areas) over the period January 1992 - September 2007.
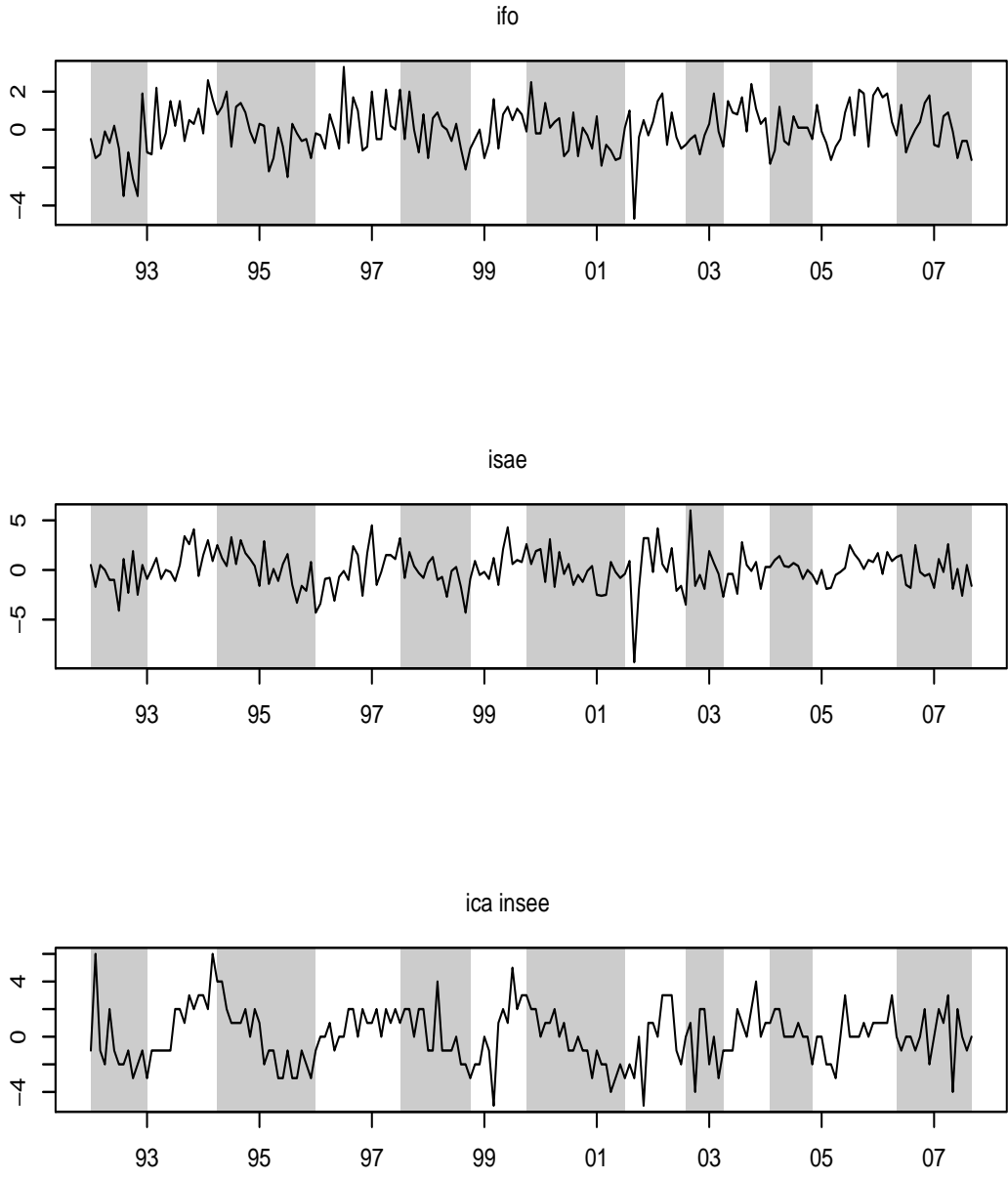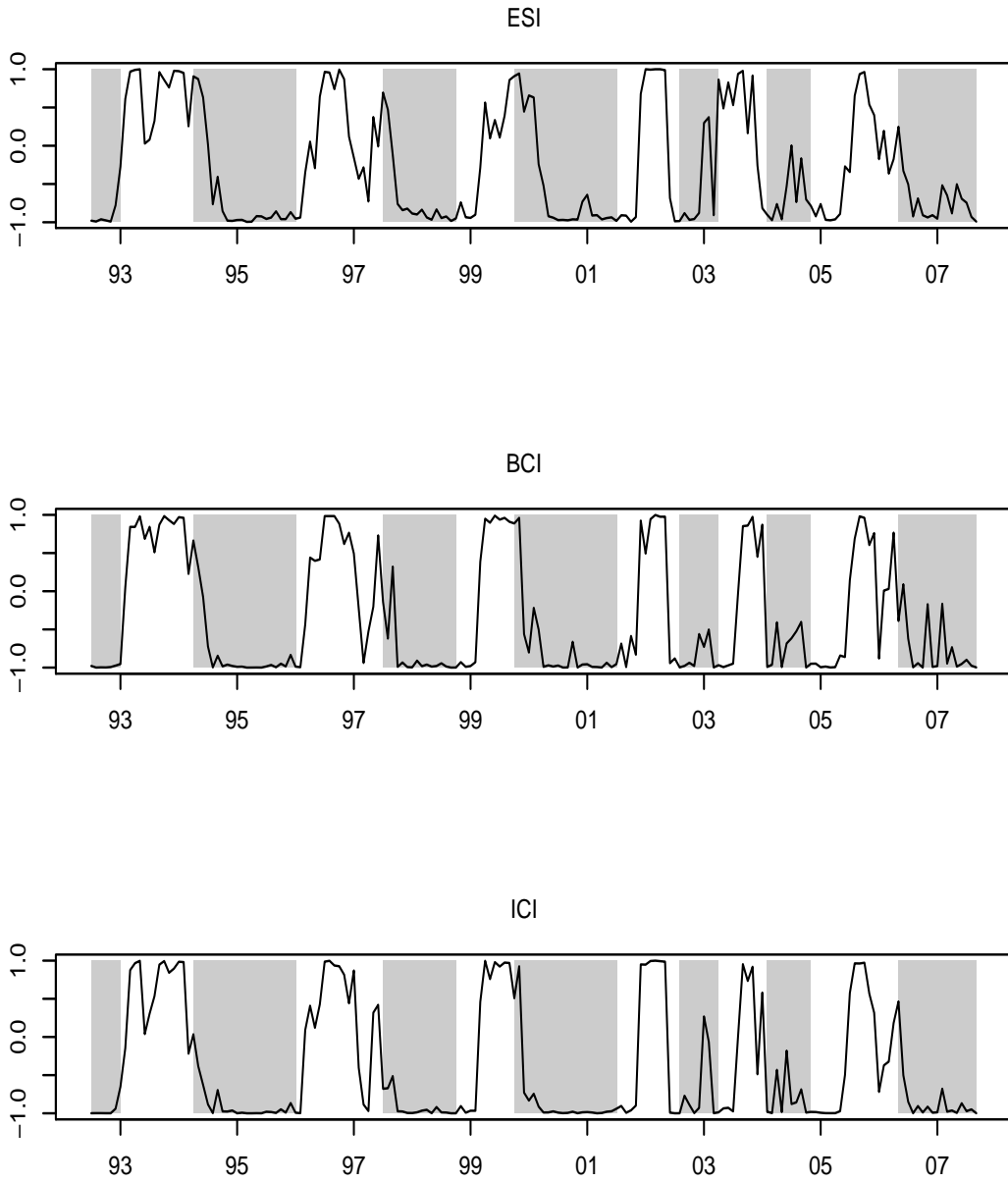
Figure 4: Composite Confidence Indicators from IFO, ISAE and INSEE (in first differences) and phases of deceleration in the euro area (shaded areas) over the period January 1992 - September 2007.

Figure 5: Probabilistic indicators stemming from ESI (top), BCI (middle) and ICI (bottom)(Jul. 1992 - Sep. 2007)

Figure 6: Probabilistic indicators stemming from MS-VAR model (top) SFMS model (middle) and DFMS model (bottom) applied to the six country-specific $\Delta\Delta^6 ICI$ (Jul. 1992 - Sep. 2007)

Figure 7: Probabilistic indicators stemming from MS-VAR model (top) SFMS model (middle) and DFMS model (bottom) applied to the three country-specific confidence index (IFO, Insee and Isae) filtered by $\Delta\Delta^6$ (Jul. 1992 - Sep. 2007)
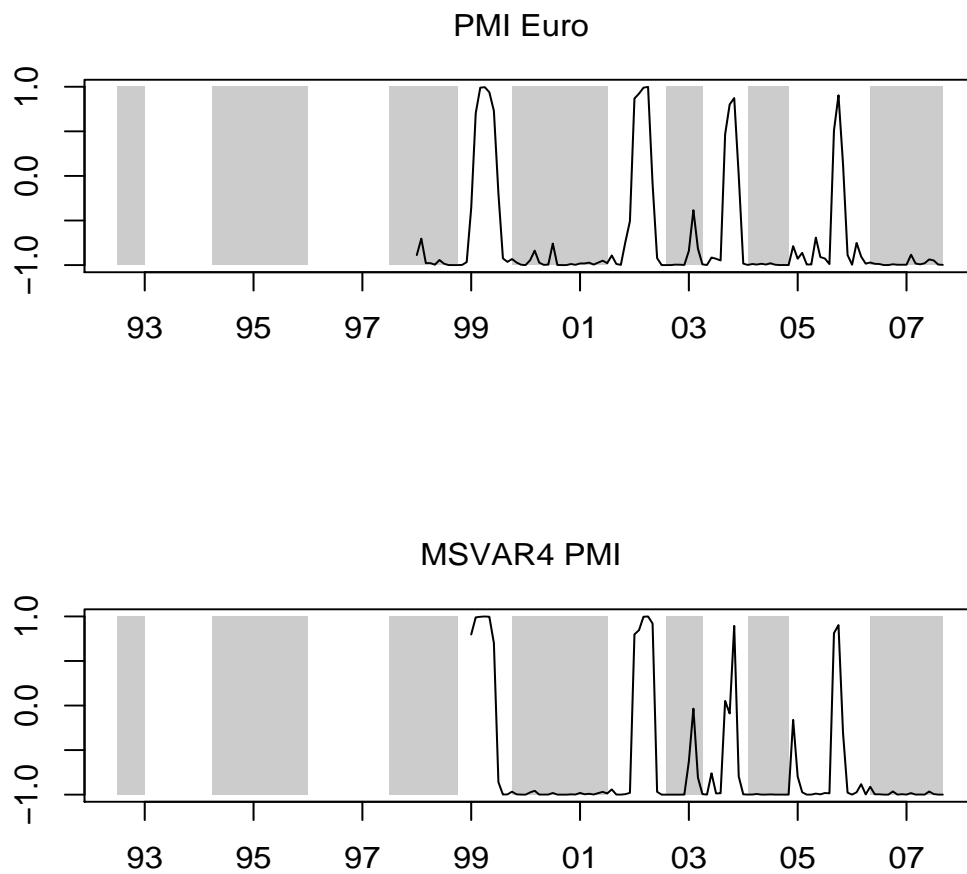
Figure 8: Probabilistic indicators stemming from a MS model applied to PMI euro (top, Jan. 1998 - Sep. 2007) and from a MS-VAR model applied to the 4 main PMIs (bottom, Jul. 1999 - Sep. 2007)
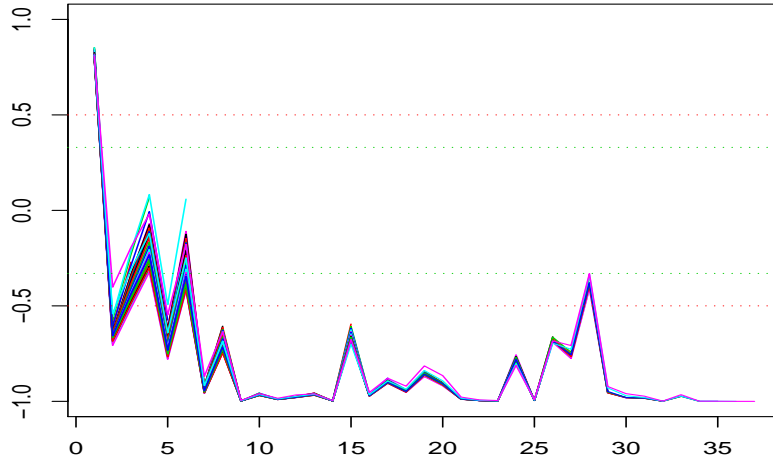
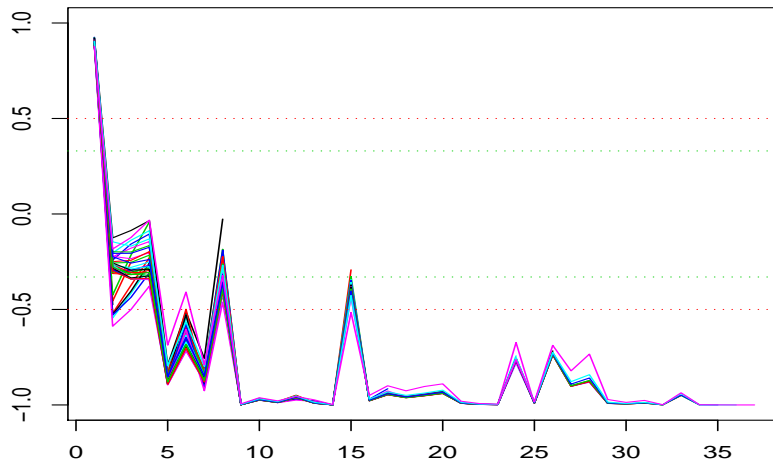Figure 9: Real-time indicator obtained with the SFMS model (Jan. 2006 - Dec. 2008)

Figure 10: Real-time indicator obtained with the DFMS model (Jan. 2006 - Dec. 2008)