14 Cyclical Composite Indicators Detecting Turning Points

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14.1 Introduction

The problem of detecting turning points in the business cycles in a timely manner is an important issue with the grave impact for the policy makers. Quick and reliable recognition of possible slowdown or recession allows for a quick response in terms of fiscal and monetary policy. However, there is always a trade-off between speed and accuracy. Therefore, in constructing the indicators, we focused on reliability rather than flagging every decrease in the economic growth. Out of the three types of indicators used in the turning point detection: leading – used to predict, coincident – used to detect and lagging – used to confirm, we have chosen the coincident ones. This chapter describes three coincident indicators, proposed in a few versions, which can be used in detection of the turning points. They were introduced already in the literature, but we believe that a more exhausting description could be beneficial. Also, the indicators were tested "in field" in the last years and developed further in order to incorporate recent findings. In order to make the indicators and turning points easier to be understood we first introduce the concept of three types of fluctuations, which are usually discussed in the literature: classical business cycle, growth cycle and acceleration (also referred to as the growth rate) cycle, showing their interweaving nature in the $\alpha AB\beta CD$ approach, which was initially proposed by Anas and Ferrara (2004a).

Each characterization of cyclical movements has obviously advantages and drawbacks, and relates to specific aspects of economic cycles. We also show the chronology of the past business cycles to illustrate how the cycles looked like and in order to give real-life examples. As practice shows, real series quite often follow a very intriguing pattern stemming out from the economic conditions creating the cycles of various lengths. They are described in detail in the Section 14.2. The dating exercise is however not as easy as it seems to be, as it has to be based on sufficiently long time-series covering several cycles. Unfortunately this requirement is difficult to fulfill because statistics can be affected by 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. Therefore, the analysis of turning point usually requires a complex and thorough approach.

The next parts of the chapter are arranged in the following way: Section 14.2 explains and illustrates the $\alpha AB\beta CD$ approach, giving theoretical background to the subsequent analysis; Section 14.3 shows methodology for dating chronology and gives examples for the euro area; Section 14.4 as the most bulky part, introduces the indicators, first in the univariate approach and then in the multivariate one. The indicators are described in details, including methodology, component variables and models used to develop them. At the end a set of indicators for the euro area is shown as an example. Section 14.5 concludes, an annex is provided in section 14.6.

14.2 The extended αABβCD approach of economic cycles

In this section we describe the empirical approach developed by Eurostat to monitor economic cycles turning points, referred to as the extended αABβCD approach. This approach is based on the classification of economic cycles into business, growth and acceleration cycles. Each type of cycle possesses its own turning points and there exists a sequence of turning points. Here, we recall the definition of those cycles and define the various turning points.

14.2.1 The $ABCD$ approach for business and growth cycles

In the literature on business cycle analysis, the studies generally refer to the business or growth cycles. Basically, the business cycle refers the (log-)level of the series, as defined by Burns and Mitchell (1946). Turning points of the business cycle delimit 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. Both business and growth cycles have been widely studied in the literature (Artis et al. (2004), Artis et al. (2004), Anas and Ferrara (2004a), Zarnowitz and Ozyildirim (2006), Anas et al. (2007a), Anas et al. (2007b)).

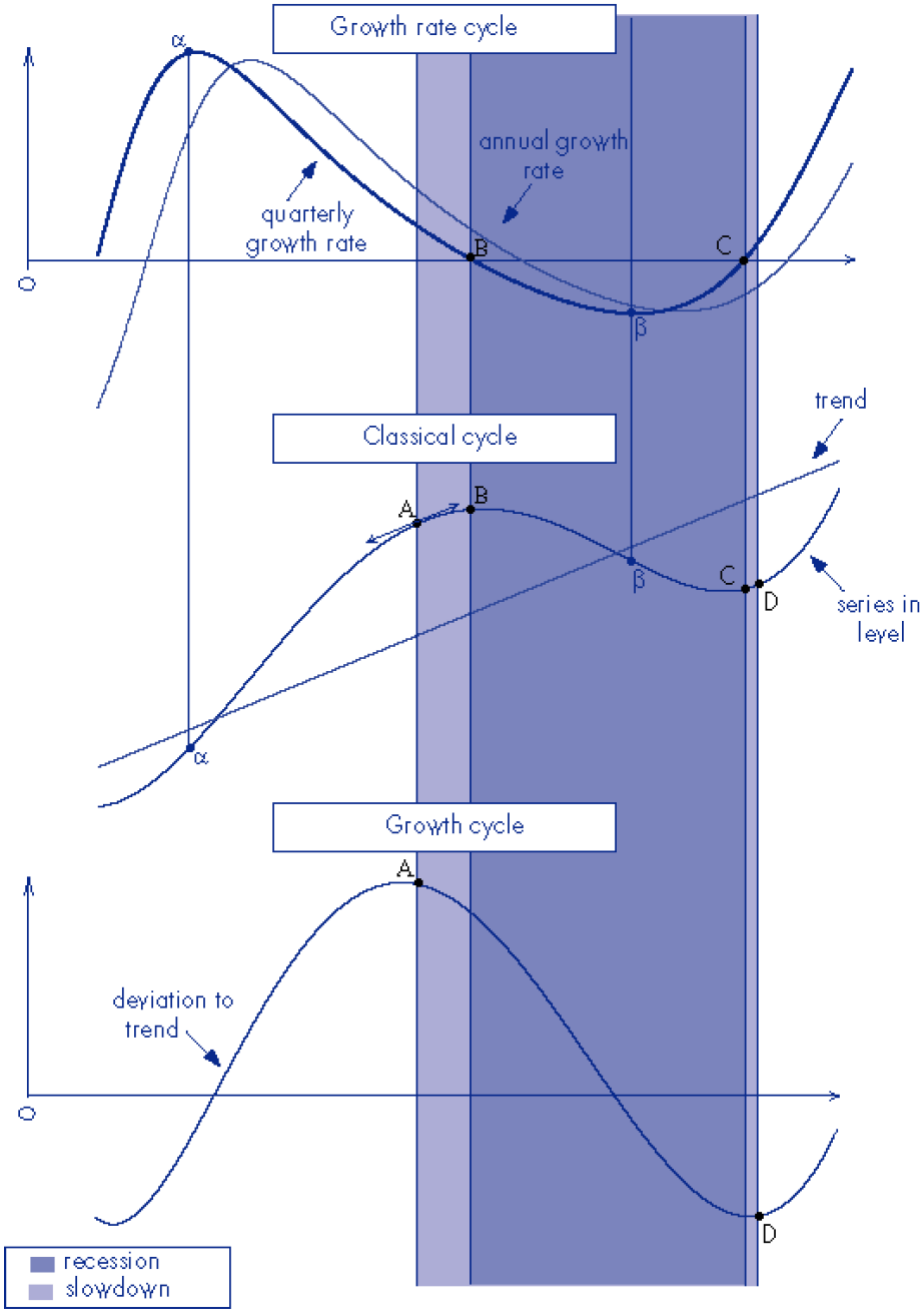
We recall here briefly the ABCD approach proposed by Anas and Ferrara (2004a) and in use at Eurostat. Specific turning points are associated with business and growth cycles. Points B and C will be the extreme points of the classical cycle, while points A and D will be those of the growth cycle (see Figure 14.1). The ABCD approach is based on the four following principles:

- The turning point 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 materialize in a peak in the growth cycle (point A) and, if it is getting worse, the growth rate will become negative (point B) implying thus a recession. For an upward movement, the sequence will be a trough in the business cycle (point C) and a recovery of the growth rate above the trend growth rate (point D).
- 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). This is for example what happened between 1999 and 2003 for the euro area. the temporal sequencing of those points (A and B for peaks and C and D for troughs) the $ABCD$ strategy for turning points analysis.
- It is worth noticing that the $ABCD$ approach is an empirical one. The empirical analysis we propose does not rely on any theoretical approach of the nature and the causes of the cycles. Therefore, it cannot be seen as a proposal for an unified theory that applies to both business and growth cycles alike. This is rather a data-driven approach that enables to provide successive real-time signals to decision makers in terms of turning points. There are different patterns for cyclical evolutions. 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 thus 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.
- For both dating and real-time detection exercises, business and growth cycles are treated separately, although the ABCD chronology has to be respected.

14.2.2 Extension of the $ABCD$ approach to the acceleration cycle

Beyond the business and growth cycles discussed above, the empirical literature focuses also on the acceleration cycle, sometimes referred to as the growth rate cycle. 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

Figure 14.1: $\alpha AB\beta CD$ approach: A theoretical example (source: Anas and Ferrara (2004a)). Turning points of the business cycle (middle) are B and C, those of the growth cycle (bottom) are A and D and those of the acceleration cycle (top) are α and β.



a cycle is very interesting for the short-term economic analysis of the euro area, not often affected by recessions, because of its high frequency. Indeed, this high frequency enables to provide with a cyclical diagnosis on a frequent basis. However, its more pronounced volatility implies a more complex real-time detection and it is often uneasy to have a clear economic interpretation for the phases of the acceleration cycle.

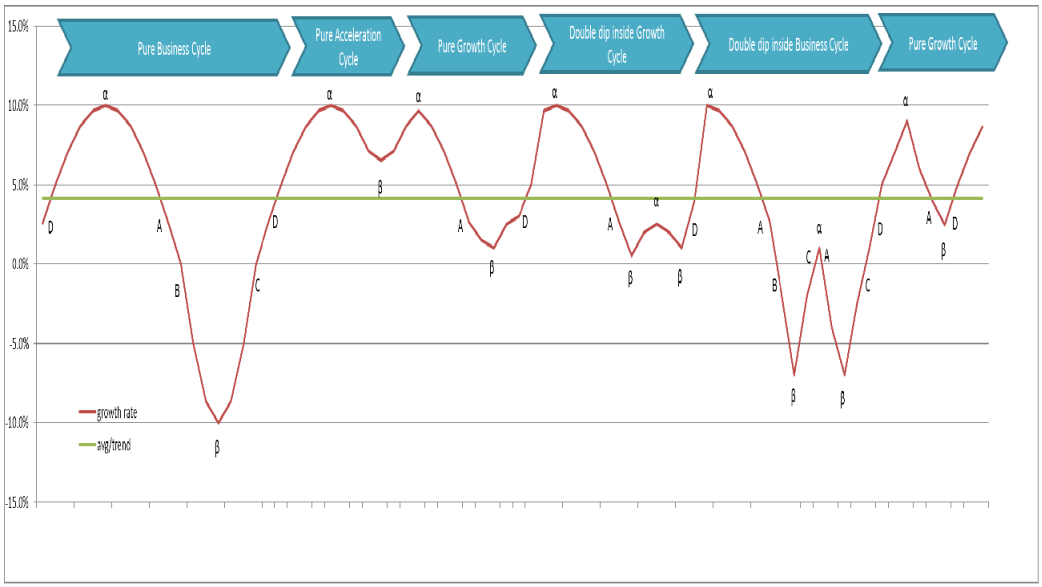
The acceleration cycle can be easily integrated into the framework of the ABCD approach. Let denote respectively α and β the peaks and troughs of the acceleration cycle that can be seen on Figure 14.1 (top graph). It is clear that a peak A in the growth cycle is necessarily preceded by a peak in the acceleration cycle α. Obviously, the activity decelerates before its growth rate falls below its tendencial growth rate. However, the

reverse is not true, that is a peak α does not necessarily imply a peak A: the growth rate can increase again without having reached its tendencial value. Following the same principle, concerning the exit of the cycle, a trough β occurs before a trough D, but here again the occurrence of β does not imply necessarily D. This sequence of turning points $\alpha AB\beta CD$, that we define in this chapter as the *extended ABCD approach*, constitutes an useful tool to assess the conjunctural economic fluctuations, both for dating and detecting exercises. For example, during a recession phase, the first optimistic signal will be given at the trough β, where the growth rate of the activity will begin an ascending phase. The exit of the recession will occur lately at point C where the growth rate will become positive.

14.2.3 Examples

In order to illustrate how the cycles can look, the following graph shows the theoretical cases, which could be encountered in empirical analysis. The examples are of course exaggerated and are not likely to exist in the real economy. There are two graphs - the first one, Figure 14.2, showing the growth rate and the second one, Figure 14.3, showing the corresponding GDP value.

Figure 14.2: Growth rate: Illustrative example



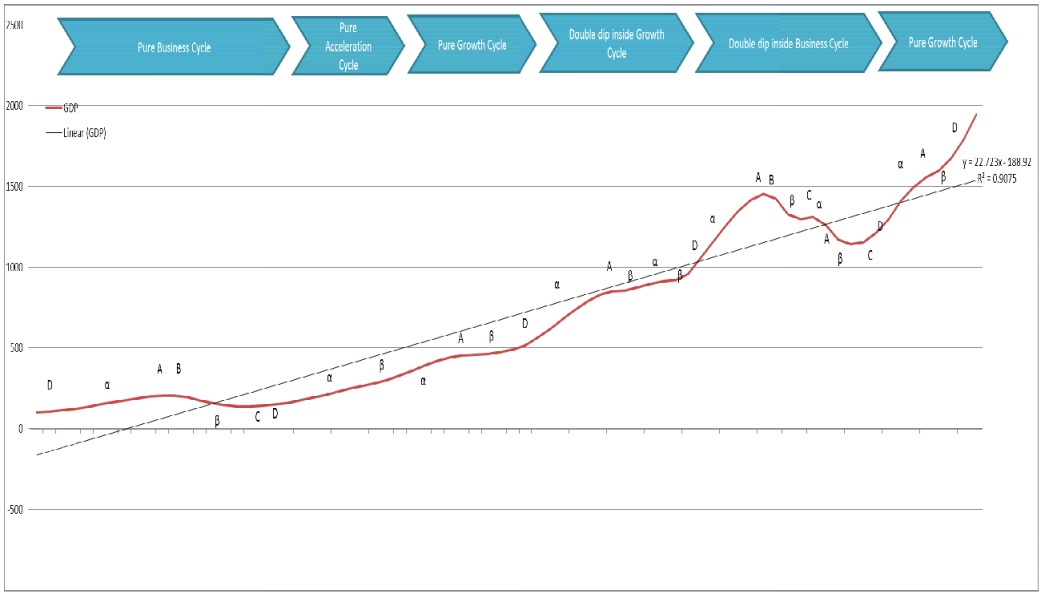
The timelines of above graphs are synchronized to show how the turning points and the $\alpha AB\beta CD$ sequences are exactly the same in both.

The real sequences are unfortunately less straightforward and turning points are not that obvious to spot.

14.3 Dating chronologies

Based on the previous $\alpha AB\beta CD$ approach, the first step towards the construction of a composite cyclical indicator for turning points is the construction of a reference chronology of cyclical turning points. In this section, we point out the need for such dating chronology, we briefly describe the tools available for its construction then we provide the euro area chronologies as an example.

Figure 14.3: GDP: Illustrative example



14.3.1 Why is it important?

The need for a cyclical turning point chronology is now widely recognized by experts and practitioners of economic analysis. As an example of application, it may help to compare the cycles between nations or to point out links between the cycles of various economic aggregates. However, it turns out that the most important use of the turning point chronology consists in establishing a reference cycle dating for a given country or economic area. Indeed, this reference cycle is often used in empirical studies either to classify economic series according to their properties (leading, coincident or lagging) or to validate real-time detection and forecasting methods. It is obvious that dating is an ex post exercise. In this respect, accuracy is a more important criterion than timeliness. Because of the lack of timeliness, dating may not be useful for economic decision-making. As a matter of fact, governments and central banks are very sensitive to indicators showing signs of deterioration in growth to allow them to adjust their policies sufficiently in advance, avoiding further deterioration or a recession. In this respect, timing is important and the earlier the signal, the better. This issue is linked to the *real-time detection* concept. However, to validate their methods of real-time detection, researchers need a reference turning point chronology for the cycle they 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),CEPR (2009)) or Eurostat (Mazzi and Savio (2007), or Anas et al. (2008)), have proposed a reference dating for the business cycle. Eurostat proposes also a turning point chronology for the growth cycle integrated with 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 et al. (2004), Artis et al. (2004), Anas and Ferrara (2004a), **?**, Anas et al. (2007a). A review of the various turning point chronologies can be found in the paper of Anas et al. (2008). A historical turning point chronology of the euro area acceleration cycle has been proposed in Harding (2004), but his analysis ends in 1998, and more recently in Darné and Ferrara (2011).

[1] www.oecd.org

14.3.2 Methodology

According to the results of Anas and Ferrara (2004b) and Anas et al. (2007a) in the framework of turning points dating chronology, we are in favor of non-parametric procedures instead of parametric ones used for example in Schirwitz (2009) for the German case. Indeed, as regards the dating exercise, which is an *ex post* exercise, it turns out that parametric models tend to be less robust to the sample size. That is when new data arrives, there is a non-null probability to observe changes in estimated parameters, leading thus to changes in the estimated probability of being in a given phase of the cycle. Obviously, revising the chronology through time is something that has to be avoided. Non-parametric methods do not present such drawbacks. In addition, non-parametric approaches can be easily adapted to different series and countries. But it is noteworthy that parametric models (presented in Ferrara and Mazzi (2016), this volume) are more adapted to the real-time detection of turning points in the economic cycles. Generally, a basic version of the non-parametric dating algorithm proposed by Bry and Boschan (1971) (BB hereafter) and modified by Harding and Pagan (2002) is implemented. 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. (2007a) or Demers and MacDonald (2007), Anas et al. (2008), or Darné and Ferrara (2011)). This methodology is often applied to the broadest measure of economic activity, that is GDP, but can be implemented on monthly proxy variables such as industrial production or any synthetic indicator reflecting aggregate activity. From this aggregated dating, some stylized facts of the cycle (duration, amplitude, excess etc.) are also measured to validate this turning point chronology.

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

$$\{(\Delta_k Y_t, \ldots, \Delta_1 Y_t) > 0, (\Delta_1 Y_{t+1}, \ldots, \Delta_k Y_{t+k}) < 0\} \tag{14.1}$$

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

$$\{(\Delta_k Y_t, \ldots, \Delta_1 Y_t) < 0, (\Delta_1 Y_{t+1}, \ldots, \Delta_k Y_{t+k}) > 0\}, \tag{14.2}$$

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.

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 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 area.

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 of the series at date of peak and Y_{t_T} is the growth rate at 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:

$$S_j = 0.5 \times D_j \times A_j. \tag{14.3}$$

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:

$$C_j = \left| \sum_{i}^{D_j} (Y_i - Y_0) \right| - 0.5 \times A_j, \tag{14.4}$$

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 the approximation 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:

$$E_j = (C_j - S_j)/D_j. \tag{14.5}$$

This excess index E_j proposed by Harding and Pagan (2002) 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.

Assume now that we get at disposal n dating chronologies. Typically, this can be the case for an indirect dating of a monetary union (e.g. euro area) or a trade area (e.g. Asean, European Union etc.). Alternatively, for a single country we can have a decomposition into n sectors. The issue is how to assess the synchronization or the diffusion of cycles among the n components.

A first tool is the following diffusion index D_t defined as follows:

$$D_t = \frac{1}{\sum_{i=1}^{n} \omega_i} \sum_{i=1}^{n} \omega_i R_{it}, \tag{14.6}$$

where ω_i is the weight of the ith component and R_{it} is a binary variable equal to 1 when the component i is in the low phase of the cycle 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 in the aggregate.

Second, 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).[2] Let $(S_{it})_t$ denote the binary variable that represents the phase of the cycle (low phase : $S_{it} = 0$, high phase : $S_{it} = 1$)

[2] See Artis et al. (2004), Artis et al. (2004), Harding and Pagan (2002) or Montoya, L. and de Haan, J. (2008) for others measures of synchronization.

for a given component i. In the bivariate case, for two components i and j, the concordance index CI can be expressed in this way:

$$CI = \frac{1}{T}\sum_{t=1}^{T} I_t, \tag{14.7}$$

where

$$I_t = S_{it}S_{jt} + (1 - S_{it})(1 - S_{jt}). \tag{14.8}$$

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 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 et al. (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.

Harding and Pagan (2006) propose procedures to test the hypothesis that cycles are either un-synchronized 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 chapter, we test the hypothesis that acceleration cycles are either strongly non-synchronized [SNS] or strongly perfectly positively synchronized [SPPS] 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:

$$\widehat{CI} = 1 + 2\hat{\sigma}_S + 2\hat{\mu}_{S_i}\hat{\mu}_{S_j} - \hat{\mu}_{S_i} - \hat{\mu}_{S_j}, \tag{14.9}$$

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:

$$\hat{\sigma}_S = \hat{\rho}_S\sqrt{\hat{\mu}_{S_i}(1 - \hat{\mu}_{S_i})}\sqrt{\hat{\mu}_{S_j}(1 - \hat{\mu}_{S_j})}. \tag{14.10}$$

First, as suggested in Harding and Pagan (2006), the null SNS hypothesis $\rho_S = 0$ can be tested starting from the following regression equation:

$$\hat{\sigma}_{S_i}^{-1}\hat{\sigma}_{S_j}^{-1}S_{jt} = a + \rho_S\hat{\sigma}_{S_i}^{-1}\hat{\sigma}_{S_j}^{-1}S_{it} + u_t, \tag{14.11}$$

where $\hat{\sigma}^2_{S_i}$ and $\hat{\sigma}^2_{S_j}$ 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 auto-correlation due to the duration of cycle phases. For example, for the euro area as a whole, the auto-correlation function for the first lag is equal to 0.84 for IPI and to 0.53 for GDP. Thus, testing the null $\rho_S = 0$ requires to take auto-correlation, as well as heteroscedasticity of the errors $(u_t)_t$, into account using standard procedures. In this respect we use a heteroscedastic and auto-correlation consistent (HACC) standard error with Bartlett weights, the number of lags being suggested by Newey and West (1984).

In addition to the previous bivariate tests, the multivariate test of Harding and Pagan (2006) enables to test the null hypothesis of strong multivariate non-synchronization (SMNS) among n countries. We recall briefly

the test procedure and we refer to the original paper for further details. This GMM-based procedure starts from the following $n(n+1)/2$ moment conditions:

$$E(h_t(\theta, S_t)) = 0, \tag{14.12}$$

where

$$h_t = \begin{bmatrix} S_{1t} - \mu_{S_1} \\ \vdots \\ S_{nt} - \mu_{S_n} \\ \frac{(S_{1t}-\mu_{S_1})(S_{2t}-\mu_{S_2})}{\sqrt{\mu_{S_1}(1-\mu_{S_1})\mu_{S_2}(1-\mu_{S_2})}} - \rho_S^{12} \\ \vdots \\ \frac{(S_{(n-1)t}-\mu_{S_{(n-1)}})(S_{nt}-\mu_{S_n})}{\sqrt{\mu_{S_{(n-1)}}(1-\mu_{S_{(n-1)}})\mu_{S_n}(1-\mu_{S_n})}} - \rho_S^{(n-1)n} \end{bmatrix},$$

and where $\theta' = (\mu_1, \ldots, \mu_n, \rho_S^{12}, \ldots, \rho_S^{(n-1)n})$. For the SMNS case, the restricted parameter vector of dimension $n(n+1)/2$ is such that $\theta_0' = (\mu_1, \ldots, \mu_n, 0, \ldots, 0)$. Under the null of SMNS, the statistic

$$W_{SMNS} = \sqrt{T} g(\theta_0, \{S\}_{t=1}^T)' \hat{V}^{-1} \sqrt{T} g(\theta_0, \{S\}_{t=1}^T) \tag{14.13}$$

where $g(\theta_0, \{S\}_{t=1}^T) = \frac{1}{T}\sum_{t=1}^T h_t(\theta_0, S_t)$ and where $\hat{V}$ is the robust HACC estimator of the variance-covariance matrix of $\sqrt{T} g(\theta_0, \{S\}_{t=1}^T)$, has an asymptotic $\chi^2_{(n(n-1)/2)}$ distribution.

An application of those concepts can be found in Darné and Ferrara (2011), as regards the euro area acceleration cycle.

14.3.3 Comparing chronologies

In this subsection, we show how chronologies can vary when alternative dating algorithms are applied or when we refer to different variables. As a first example the chronology from Bruno and Otranto (2008) is proposed. The historical results obtained with the different methods are compared with the dating provided by ISAE.

In order to show how the chronologies might look like depending on the method used, the table below summarizes six different methods used to achieve the same goal - namely the chronology for the Italian economy. Table 14.1 shows the Italian chronology based on six different dating methods.

The names of the different methods are as follows:

ISAE: official dating provided by ISAE;

INDNP: Indirect non-parametric detection;

INDMIX: Indirect mixed detection;

DIRNP: Direct non-parametric detection;

DIRMIX: Direct mixed detection;

DIRP: Direct fully parametric detection.

The results obtained show a tendency of the direct methods to find out more cycles than those detected by ISAE (three more for DIRNP and DIRMIX, two more for DIRP), while the indirect methods are more reliable with respect to this point, having detected only one extra-cycle each.

Table 14.1: Italian chronology based on six different dating methods

Turning points	ISAE	INDNP	INDMIX	DIRNP	DIRMIX	DIRP
Peak	I 74	XII 73	II 74	II 74	I 74	I 74
Trough	V 75	VIII 75	V 75	VIII 75	VIII 75	V 75
Peak	II 77	XII 76	XII 76	I 77	XII 76	XI 76
Trough	XII 77	I 78	I 78	XII 77	XII 77	IX 77
Peak	III 80	I 80	II 80	I 80	III 80	XI 79
Trough				VI 81		
Peak				II 82		
Trough	III 83	III 83	II 83	II 83	V 83	V 83
Peak			VIII 85		VIII 84	VIII 85
Trough			I 86		I 85	I 86
Peak		VIII 89		IV 90	XI 89	II 90
Trough		VI 90		XII 90	III 91	
Peak	III 92	II 92	XII 91	I 92	II 92	
Trough	VII 93	VII 93	VII 93	VIII 93	VIII 93	VIII 93
Peak	XI 95	X 95	VIII 95	XII 95	VIII 95	XII 95
Trough	XI 96	VIII 96	IX 96	VI 96	XII 96	XII 96
Peak				VII 98	XII 97	XII 97
Trough				I 99	XII 98	IV 99
Peak	XII 00	X 00	X 00	XI 00	XII 00	XI 00
Trough		XII 01	XII 01	III 02		

The second example is based on Darné and Ferrara (2009) and shows chronologies for acceleration cycles for the six major European economies. Table 14.2 shows cycles based on GDP, table **??** the ones based on IPI.

Table 14.2: Acceleration cycles based on GDP

Turning point	Euro	Germany	France	Italy	Spain	Belgium	Netherlands
Trough	1996 Q1	1996 Q1	1996 Q1	1996 Q2		1996 Q1	1996 Q1
Peak	1997 Q2	1997 Q2	1998 Q2	1997 Q2	1997 Q4	1997 Q1	1997 Q2
Trough	1998 Q4	1998 Q2	1998 Q4	1998 Q4	1998 Q4	1998 Q3	1998 Q2
Peak	1999 Q3	1999 Q4	1999 Q4	1999 Q4	1999 Q2	1999 Q3	1999 Q1
Trough	2001 Q3	2000 Q3	2001 Q2	2001 Q2	2002 Q1	2001 Q3	
Peak		2001 Q1					
Trough		2002 Q1					2002 Q1
Peak	2002 Q2	2002 Q3	2002 Q1	2002 Q2	2003 Q1	2002 Q3	
Trough	2003 Q2	2003 Q1	2002 Q4	2003 Q1	2003 Q3	2003 Q1	
Peak	2004 Q1	2003 Q3	2004 Q2	2004 Q1	2004 Q3	2004 Q2	2004 Q1
Trough	2004 Q4	2004 Q3	2005 Q2	2004 Q4		2005 Q1	2005 Q1
Peak	2006 Q2	2006 Q2	2006 Q2	2006 Q4		2005 Q4	

14.3.4 Euro area chronologies

Since 2007, Eurostat started to elaborate and update on quarterly basis euro area chronologies for the growth and the business cycles according to the ABCD approach. Starting from 2011, also the acceleration chronology was added. Together with the euro area, chronologies for 11 economies have been regularly compiled and updated: Germany, France, Italy, Belgium, the Netherlands, Spain, Portugal, Austria, Finland, Greece and Ireland. The compilation of the chronologies for the remaining countries is still ongoing. The euro area

Table 14.3: Acceleration cycles based on IPI

Turning point	Euro	Germany	France	Italy	Spain	Belgium	Netherlands
Peak		XII 1992	X 1991	VIII 1991	IX 1991	XI 1991	
Trough	XI 1992	XII 1992	XI 1992	VII 1992	XI 1992	XI 1992	
Peak	III 1994	IX 1994	IV 1994	III 1994	VI 1994	I 1995	
Trough	II 1996	X 1995	IX 1995	III 1996	I 1996	IX 1995	III 1995
Peak	IV 1997	XI 1997	IV 1997	IV 1997	III 1997	VI 1997	XI 1995
Trough	X 1998	IX 1998	VIII 1998	XI 1998	II 1999	X 1998	I 1997
Peak	IX 1999	IV 2000	IX 1999	VIII 1999	XI 1999	VIII 1999	I 2000
Trough	IX 2001	IX 2001	X 2001	VII 2001	X 2001	IV 2001	VIII 2001
Peak	IV 2002	VI 2002	IV 2002	IV 2002	VIII 2002	III 2002	IV 2002
Trough	IV 2003	IV 2003	IV 2003	II 2003	V 2003	XI 2002	IV 2003
Peak	X 2003	XI 2003	X 2003	VIII 2003	II 2004	II 2004	I 2004
Trough	XI 2004	X 2004	III 2005	XI 2004	X 2004	XII 2004	XII 2004
Peak	IV 2006	V 2006	XI 2005	I 2006	V 2006	XII 2005	XII 2005
Trough		III 2007	VIII 2006				VII 2006
Peak			II 2007				

final chronology is obtained by comparing the direct dating based on euro area aggregates with an indirect one obtained by a weighted average of national chronologies. A particular effort in compiling the euro area chronologies is made in order to minimise the discrepancies between the direct and indirect dating. The dating methodology used is the one described in 3.2. Table 14.4 shows the real turning points identified for the euro area acceleration, growth and business cycles, starting in 1973.

Table 14.4: Chronology for the Euro Area - $\alpha AB\beta CD$ sequences

Period	α	A	B	β	C	D	Cycle type
1973-74	1973 Q1	1974 Q1	1974 Q2	1974 Q3	1975 Q1	1975 Q3	Pure Business Cycle
1975-77	1975 Q4	1977 Q1		1977 Q2		1978 Q2	Pure Growth Cycle
1978-81	1978 Q4	1979 Q4	1980 Q1	1980 Q2	1980 Q4	1981 Q1	Pure Business Cycle
1981-82	1981 Q1	1981 Q4	1981 Q4	1982 Q2	1982 Q4	1982 Q4	Pure Business Cycle
1983-84	1983 Q4			1984 Q2			Pure Acceleration Cycle
1985-87	1985 Q4	1986 Q1		1986 Q4		1987 Q2	Pure Growth Cycle
1987-89	1987 Q4			1989 Q2			Pure Acceleration Cycle
1991-93	1991 Q1	1992 Q1	1992 Q1	1992 Q3	1993 Q3	1993 Q3	Pure Business Cycle
1995-96	1995 Q1	1995 Q1		1996 Q1		1996 Q4	Pure Growth Cycle
1997-98	1997 Q2	1998 Q1		1998 Q4		1999 Q1	Pure Growth Cycle
2000-01	2000 Q1	2000 Q3		2001 Q3			Double dip inside Growth Cycle
2002-03	2002 Q2			2003 Q1		2003 Q3	Double dip inside Growth Cycle
2003-05	2003 Q4			2005 Q1			Pure Acceleration Cycle
2006-09	2006 Q2	2008 Q1	2008 Q1	2009 Q1	2009 Q2	2009 Q3	Pure Business Cycle
2010-13	2010 Q2	2011 Q3*	2011 Q3*	2012 Q4*	2013 Q1*	2013 Q1*	Pure Business Cycle

* provisional dating

We already mentioned the importance of keeping past turning points constant across different releases of the chronologies. Nevertheless, since in the latest years, variables unavoidably subject to revision, the chronologies related to the recent time periods are labelled as provisional. As a general rule we consider that statistical variables can be revised over a maximum 3-4 years so that during this periods we accept that the turning points can change across different releases. By contrast, past turning points are frozen and, only in some exceptional cases, we accept to revise them.

14.4 Construction of turning point indicators

In this section, we review the various steps towards the construction of turning point indicators for each type of economic cycle. We focus our attention on variable selection and model selection aspects, as well as on the criteria for evaluating the indicators. The section ends with an illustration of this approach based on the euro area coincident indicators, currently compiled by Eurostat.

14.4.1 Data selection

Generally, datasets used for the development of cyclical indicators are stemming from three main sources of information: macroeconomic data (hard data), opinion surveys (soft data) and financial data. Hard data is strongly correlated with business cycles but is well known for its lack of timeliness: it is indeed published with a strong delay and is often revised from one month to the other. This constitutes a major drawback for practitioners involved in real-time analysis. 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 Stock and Watson (2002)). Especially, term spread, namely the difference between long-term and short term interest rates, has proved to be a leading index of recessions (see for example, Estrella et al. (2003), Kauppi and Saikkonen (2008), or Rudebusch and Williams (2009)). Also stock prices (Farmer, 2011) or oil prices (Hamilton (2003)) are leading variables that can be integrated in models to anticipate turning points. Bellégo and Ferrara (2012) have also shown that aggregating financial information from several variables through a factor-probit model can be a fruitful strategy when one aims at anticipating cyclical turning points. Opinion surveys are the most frequently watched variables in economic institutions. They convey useful information as regards the current state of the economic cycle. They also possess the great advantage of not being revised after their release and are timely available, usually before the end of the reference month.

Choosing among a large set of economic variables is not an easy task. Generally two approaches are taken. The first one consists in reducing the dimension of the problem by estimating a dynamic factor model as the ones proposed by Stock and Watson (2002) or Forni et al. (2005). The estimated factors are a linear combination of original variables and take into account the cross-correlation among those variables. Estimated factor can in turn be used as coincident or leading indicators of economic cycles. The second approach relies on a small set of variables (carefully selected for their ability to track economic cycles) from a larger dataset. The selection process can be done by optimizing a given criterion, such as the Quadratic Probabilistic Score (QPS, see Diebold and Rudebusch (1989)) for example, or by using a selection algorithm such as the LASSO one. In this chapter, we privilege this second approach based on a narrow set of variables keeping in mind that it is easier to explain changes in the values of the indicator in real-time, by comparison with information extracted from a large dataset.

14.4.2 Model selection

Starting from a n-vector of variables $(x_t^1, \ldots, x_t^n)$, the objective is to compute an indicator lying between 0 and 1 such that the economy belongs to the low phase of the cycle when the indicator is close to one and belongs to the high phase of the cycle when the indicator is close to zero. In this respect, non-linear models that provide a probability of being in a given regime at any given date t are of great interest. A review of such models is proposed by Ferrara and Mazzi (2016). Among those non-linear models, it turns out that multivariate Markov-Switching models are of great interest and have proved their ability to reproduce business cycles; we refer among others to Hamilton (1989), Krolzig (1997), Chauvet (1998), Kim and Nelson (1998), Ferrara (2003), Anas and Ferrara (2004b), Chauvet and Hamilton (2006), Bengoechea et al. (2006), Anas et al. (2008), Camacho and Perez-Quiros (2010), Darné and Ferrara (2011).

Multivariate models

Markov-Switching models were first introduced in the business cycle literature by Hamilton (1989) to deal with non-linear time-series. In particular, Markov-Switching models were originally proposed to model discrete shifts in the mean growth rate of a non-stationary time-series, that is, episodes across time in which the dynamic behavior of a series undergoes abrupt changes. The first application of this class of models was to the U.S. business cycle.

Following the literature on VAR models, Hamilton (1989) used an auto-regressive process to approximate an observable non-stationary, in the sense stated above, time-series, namely the U.S. real GNP. Hamilton's seminal idea was to assume the parameters of the auto-regressive model to be time-varying and evolving according to a latent Markov-chain process. Conditional on the unobservable variable, the auto-regressive model is assumed to be time-invariant. In this respect, Markov-Switching models are an extension of traditional VAR models.

As for the latent state-variable, it is only natural to assume that regime changes are not directly observed by the researcher; instead, he or she must draw inference on their occurrence based on the realizations of the observable time-series. The estimated probability of occurrence of a shift in the regime of the latent variable is used, within our investigation on economic cycles, to assess the prevailing economic regime (being, say, either contraction or expansion) at any given point in time.

Formally, the most general specification of the Markov-Switching model we consider is one in which all the parameters of the auto-regressive model are conditional on the state of the latent Markov-chain (s_t):

$$y_t = \alpha(s_t) + \sum_{j=1}^{p} \beta_j(s_t) y_{t-j} + \epsilon_t, \tag{14.1}$$

where $\epsilon_t \; N(0, \sigma^2(s_t)), t = 1, \ldots, T$. In Hamilton's original model the observable endogenous variable y_t is the quarterly percentage change in U.S. real GNP, so that the observable variable is piecewise stationary[3].

The definition of the data generating process requires, in addition to the model for the observable time-series, the specification of the process followed by the latent variable. As stated above, a first-order ergodic discrete-state Markov-chain is the stochastic process that governs the realization of the unobservable state-variable. Under the assumption of time-invariant transition probabilities, the Markov-chain process above is defined by the transition probabilities in (14.2):

$$Pr(s_t = j | s_{t-1} = i, s_{t-2}, s_{t-3}, \ldots) = Pr(s_t = j | s_{t-1} = i) = p_{i,j}, \tag{14.2}$$

for $i, j = 1, \ldots, M$. Transition probabilities measure the probability of either staying in the same regime or switching to another regime in moving from time $t-1$ to time t. The definition of a first-order Markov-chain implies that the probability of observing regime j at time t depends only on the regime prevailing at the previous time.

Hamilton (1990) also proposed a non-linear iterative algorithm named Expectations Maximization (EM) that allows estimating the population parameters (auto-regressive coefficients and transition probabilities) by Maximum-Likelihood.

The filtering and smoothing algorithms that are embedded in the EM technique allow, as a by-product of the estimation process, to draw inference on the probability of the prevailing regime of the latent variable.

[3] It is worth noting that in model (14.1) the intercept is state-dependent, whereas Hamilton (1989) considered a mean-adjusted form. Contrary to linear VAR model, these two specifications are not equivalent for the class of Markov-Switching VAR models. We refer to Krolzig (1997) for a proof.

The two algorithms above are actually named after the estimate they provide of the smoothed and filtered probabilities, respectively, of the unobserved states of the Markov-chain. Smoothed probabilities are defined as the estimated probabilities of observing a state of the latent Markov-chain at time t given the whole sample information of the observed time-series. Filtered probabilities differ from them since they are conditional only on the observed variable available at time t. For a thorough description of the EM estimation method we refer to Hamilton (1990) and Krolzig (1997).

Despite several extensions of Hamilton's original model proposed in the literature, in our application to the estimation of probabilistic coincident indicators of the Euro area's economic cycles we prefer to focus on parsimonious Markov-Switching models. As a matter of fact, we empirically found more convenient to assume that only some parameters are dependent on the state-variable whereas the remaining ones are regime invariant. More in detail, we used model specifications in which the intercept term and the variance of the error term depend on the same latent state-variable. Furthermore, the order of the auto-regressive polynomial is set at zero. Therefore, although in a trivial way, the auto-regressive coefficients are time-invariant and not subject to changes in regime.

Following a notation firstly introduced by Krolzig (1997), the models we used in our empirical research can be denoted as MSIH(K)-VAR(0), where MS obviously stands for Markov-Switching; the letters I and H indicate, respectively, that the intercept and variance of the errors are time-dependent as they are governed by a common latent discrete Markov-chain. The number of regimes of this latent variable is K. Finally, VAR(0) indicates that the order of the lag polynomial is zero. Obviously, a particular case of this representation, when the vector of variables X is unidimensional, is the MS model of the form MSIH(K)-AR(0).

As for the estimation of the model parameters, we applied the EM method referred to above as it was coded in the MSVAR algorithm by Krolzig.

Constructing composite indicators for turning point detection

In the context of euro area's economic cycles, we aim at constructing composite probabilistic indicators to detect in real-time the occurrence of a shift in economic regime of the business, growth and acceleration cycles. As it is our purpose to provide real-time signals, the relevant measure of the prevailing regime is the filtered probabilities. We thereby use Markov-Switching models to estimate filtered probabilities from several economic variables and then aggregate them into probabilistic composite indicators.

The construction of composite probabilistic indicators heavily relies on the interpretation of the Markov-Switching models in terms of economic cycle. This is achieved by assigning an economic meaning to the latent state-variable: its regimes can be thought of representing the different phases of the economic cycle. For example, in the case of a two-state Markov-chain, it is straightforward to interpret one regime (say, the one with a positive intercept) as expansionary and the other one (say, the one with a negative intercept) as recessionary. From the association between states of the latent variable and economic regimes follows immediately that filtered probabilities can be interpreted as a measure of the probability of observing a given phase of the cycle at every point in time. This interpretation of the filtered probabilities in terms of economic cycle paves the way to the construction of the composite indicators, which is the goal of our investigation.

As we aim at constructing composite coincident indicators of the Euro area's business, growth and acceleration cycles, we have to define what regimes of the latent Markov-chain are associated with recession, slowdown and deceleration periods, respectively. Such an issue could in principle be settled a priori if the researcher has strong believes, perhaps based on an economic theory, about what regimes of the latent state-variable are actually representing specific phases of the economic cycle. In our empirical analysis we rather preferred to follow a more flexible approach and relate states of the latent variable to economic regimes by looking ex-post at the signs and magnitudes of the state-dependent intercept.

In the following section, for each of the component variables of the coincident indicators we built, we will provide a description of the interpretation we gave to the states of the latent Markov-chain.

The final point we make concerns to two issues that so far have remained in the background, that is, how to select the component variables and how to aggregate them. As far as the variable selection is concerned, we focus on variables included in the PEEIs (Principal European Economic Indicators). They span from hard economic variables (e.g. industrial production and unemployment rate) to soft variables (e.g. business surveys). As we will show in a later section, the first class of variables plays a major role in obtaining a coincident indicator of the business cycle, whereas soft variables are mainly used for the acceleration cycle. The growth cycle coincident indicator is obtained by using both hard and soft data.

As for the aggregation method, we used two different approaches that are tied to two different specifications of the Markov-Switching models. In the first one, a single equation Markov-Switching model is separately fitted to each component variable and the filtered probabilities that are obtained as a by-product are aggregated and the composite coincident indicator is finally constructed as a weighted average:

$$\text{Indicator}_t = \sum_{k=1}^{N} w_k Pr(\text{Downturn}_t^k), \tag{14.3}$$

where $Pr(\text{Downturn}_t^k)$ is the probability that the $k-th$ component variable is either in a recession, slow-down or deceleration of the respective cycle at time t. w_k is the weight given to the $k-th$ component; the weight attached to the downturn probabilities of each component variable reflects the accuracy in locating the phases of the economic cycle under study. The dating chronologies presented in a previous section are used as benchmark for this assessment. In other words, following this approach, the coincident indicators for the business, growth and acceleration cycles are independently compiled by using the most appropriate set of variables and weighting scheme. The main drawbacks of this approach are the role that subjective appreciation can play in the definition of the weighting scheme and the fact that there is no guarantee that the three indicators correctly follow the αABβCD sequence.

The second approach entails the estimation of a multivariate Markov-Switching model, instead of the several single equation models above. It immediately follows that the aggregation procedure in the second case is embedded in the estimation of the multivariate model. In this respect, the researcher loses control of the aggregation step. If, on the one hand, this avoids his or her discretion in defining the weighting scheme, on the other hand does impede to build in further knowledge into the composite indicator, such as for example the accuracy of each component in locating downturn phases of the economic cycle.This approach can obviously allow for the independent estimation of the coincident indicators for the business, growth and acceleration cycles, based on multivariate models. Nevertheless, the biggest advantage of following this approach is represented by the possibility of jointly estimating coincident indicators for the growth and business cycles in a multivariate context. To achieve this objective, variables able to explain both cycles have to be selected and, within the MS-VAR model, the number of regimes has to be increased in order to describe all economic phases. The jointly construction of the business and growth cycle indicators will avoid any risk inconsistency with the ABCD sequence. Unfortunately, the multivariate modelling strategy cannot be extended also to the acceleration cycle due to the asymmetry characterising the sequence of peaks with respect to the sequence of troughs within the αABβCD approach.

14.4.3 Assessment of turning point indicators

To assess the quality of the model concerning business cycle replication (in-sample evaluation) or concerning the forecast evaluation (out-of-sample evaluation) several criteria have been proposed. Probability forecasts are often evaluated using the quadratic probabilistic score of Brier (1950) defined by :

$$QPS = \frac{1}{T}\sum_{t=1}^{T}\left(\hat{P}_t - r_t\right)^2, \tag{14.4}$$

where $\hat{P}_t$ is the estimated probability of being in a given regime (e.g. recession) and r_t is the reference one-zero variable. The QPS is bounded between 0 and 1, values close to zero implying a good quality in terms of business cycle replication, and conversely.

Another statistic computed as goodness-of-fit measure to the reference chronology is the Concordance Index, which is defined as follows:

$$CI = \frac{1}{T}\left[\sum_{t=1}^{T} I_t \times r_t + \sum_{t=1}^{T}(1 - I_t) \times (1 - r_t)\right], \tag{14.5}$$

where r_t is the reference binary variable already used in the QPS and where I_t is a binary random variable that takes value 1 if $\hat{P}_t > \kappa$ and 0 otherwise, where κ is a given threshold between 0 and 1. Following the approach proposed by Hamilton (1989), the natural critical value of $\kappa = 0.5$ is often chosen. However, the choice of κ can be discussed and selected by ad-hoc methods according to a specific criterion. Obviously, there is a trade-off between the timeliness and the reliability of the signal. Other threshold values κ different from 0.5 may be used to provide a better goodness of fit to the reference turning point chronology. This point is rarely considered in research papers but has major practical implications as regards the economic interpretation of the signal. A good practice would be to assess the sensitivity of the signal to the values of κ as for example in Darné and Ferrara (2011).

Another often used measure is the log-probability score (LPS) defined by:

$$LPS = \frac{1}{T}\sum_{t=1}^{T}\left[r_t \log(\hat{P}_t) + (1 - r_t)\log(1 - \hat{P}_t)\right]. \tag{14.6}$$

The LPS is non-negative and penalizes large mistakes more heavily than the QPS. The Kuipers Score is also sometimes used and is defined by:

$$KS = H - F, \tag{14.7}$$

where H is the hit rate, that is the proportion of total number of regimes 1 that were correctly reproduced, and where F is the false signal rate, that is the proportion of the total number of regimes 0 that were incorrectly estimated as being regime 1. Those rates can be estimated respectively by :

$$H = \frac{\sum_{t=1}^{T} r_t I_t}{\sum_{t=1}^{T} r_t} \tag{14.8}$$

and

$$F = \frac{\sum_{t=1}^{T}(1 - r_t) I_t}{\sum_{t=1}^{T}(1 - r_t)}, \tag{14.9}$$

where I_t is defined above. We refer also to Chauvet and Hamilton (2006) for the concept of hitting probabilities.

14.4.4 A set of euro area coincident indicators: An empirical illustration

Since 2007, Eurostat started the compilation of a set of euro area coincident indicators for a real-time monitoring of the euro area cyclical situation. Those indicators are regularly compiled on a monthly basis and they refer to acceleration, business and growth cycle. The three indicators are labelled Acceleration Cycle Coincident Indicator (ACCI), Business Cycle Coincident Indicator (BCCI) and Growth Cycle Coincident Indicator (GCCI). Since 2011, Eurostat also started to compile a pair of coincident indicators for growth cycle and business cycle based on a multivariate Markov-Switching model labelled respectively MS-VAR GCCI and MS-VAR BCCI. They aimed to overcome the risk of inconsistencies between the BCCI and the GCCI due to the different lags in detecting turning points.This subsection describes those indicators and shows their behaviour based on the latest releases.

ACCI

The coincident indicator of the acceleration cycle (ACCI) returns the probability of a deceleration of the euro area growth rate cycle. As stated above, this is not really a composite indicator as it is based upon only one variable, namely the economic sentiment indicator (ESI). More specifically, the ACCI is obtained by fitting a MSI(3)-AR(0) model to the ESI differenced twice, first over 6 months and then over 1 month. The double differentiation of the endogenous variable is consistent with the definition of acceleration as change in the pace of growth.

As for the interpretation of the above model in terms of the growth rate cycle, the first regime, which is the only regime for which the state-dependent intercept takes on a negative value, is assumed to identify the deceleration phases of the growth rate cycle. Deceleration probabilities are accordingly set equal to the filtered probabilities of this regime.

The latest release of the ACCI estimated in June 2015 is graphically illustrated in Figure 14.4 below.

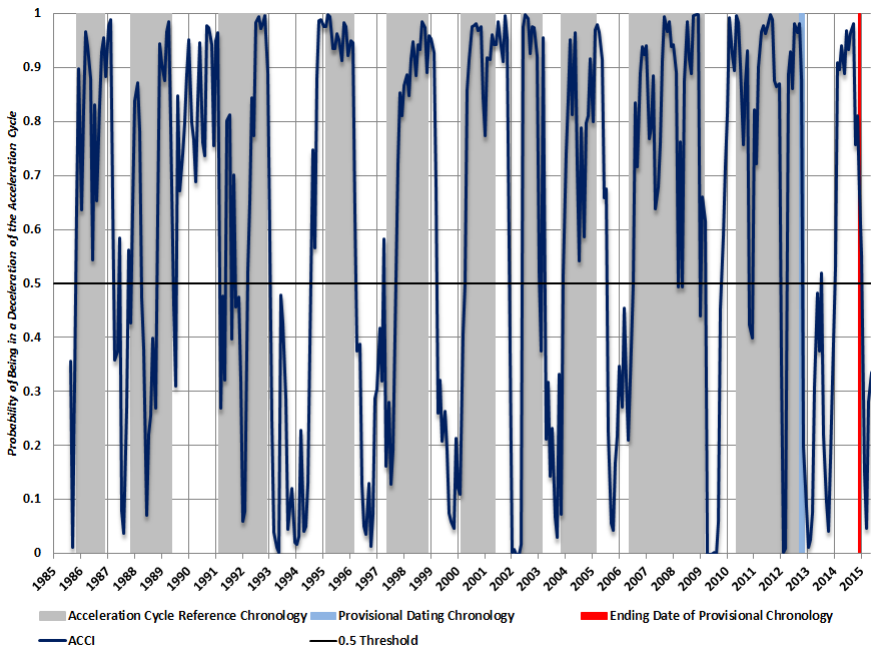
Over the period stretching from August 1985 to December 2014, the ACCI does not miss any of the ten decelerations of the euro area acceleration cycle (type-I error). However, it signals a deceleration between mid-1989 and early 1991 that was not identified in the reference dating chronology (type-II error). Further, between January 2014 and January 2015 the ACCI has been signaling a deceleration not identified in the reference chronology; however, as the reference chronology over the last two years is still provisional, evidence for a false deceleration is not yet conclusive. Overall, the ACCI is quite accurate in signaling the decelerations of the growth rate cycle. Four out of the ten peaks are detected with an average delay of 0.9 months, whereas other four peaks are signaled 1.7 months in advance, on average. The remaining two peaks are exactly located as in the reference chronology.

The accuracy of the ACCI is summarized by the QPS and Concordance Index statistics reported in Table 14.1.

Table 14.1: ACCI's Accuracy Statistics

QPS	Concordance Index
0.22	0.71

Figure 14.4: ACCI from August 1985 to May 2015 (blue line) and decelerations of the growth rate cycle (grey shaded areas).



GCCI

The Growth Cycle Coincident Indicator (GCCI) is a measure of the probability of slowdown of the euro's area growth cycle. The GCCI is obtained as an equally weighted average of the slowdown probabilities estimated from five component variables. The first two components pertain to the real economy, namely, the industrial production index and the imports of intermediate goods from outside the euro area. The remaining three components are all surveys, namely, the employment expectations in the industry for the months ahead, the construction confidence indicator and the consumer confidence indicator.

All the five GCCI's components are seasonally adjusted. The first two components, namely the ones related to the real economy, are differenced twice; only one differentiation is taken for each of the three soft variables. As shown in the Table below, a MSIH(4)-AR(0) model is fitted to the IPI and Imports variables. The slowdown phases are obtained by summing the filtered probabilities of the first two regimes, as these two regimes are characterized by negative values of the state-dependent intercept. A MSI(2)-AR(0) model is fitted to the survey variables, such that the slowdown periods are associated to the first regime, that is, to the state for which the intercept takes on a negative value.

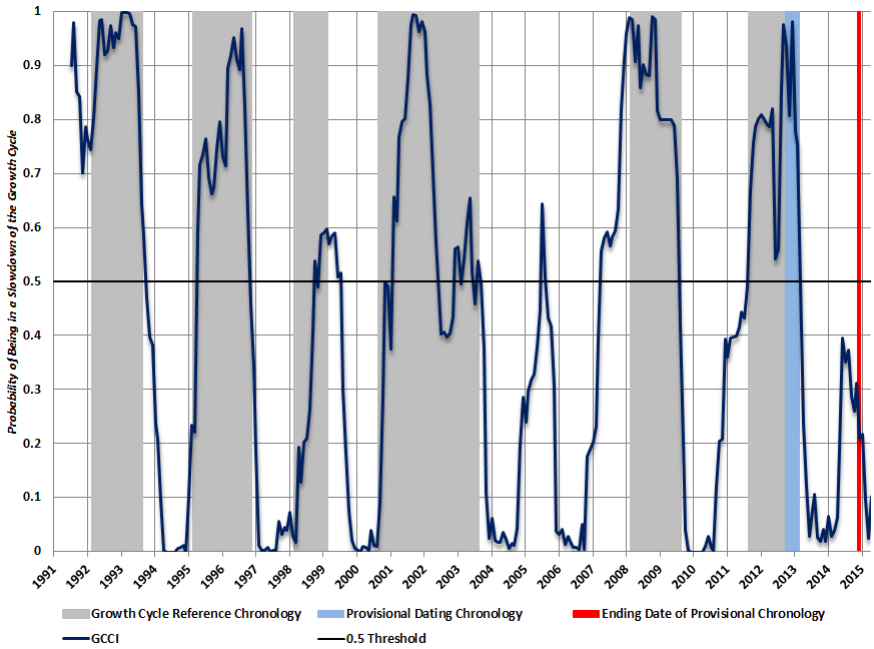
Table 14.2: GCCI's Components

Variable	Seasonal Adjustment	Source	Sample	Differentiation	MS Model	Recession Regime(s)	Weight
Industrial Production Index	SA	Eurostat	1991-2015	12- and 6-month	MSIH(4)-AR(0)	R1+R2	0.20
Imports of Intermediate Goods	SA	Eurostat	1991-2015	12- and 6-month	MSIH(5)-AR(0)	R1+R2	0.20
Employment Expectations	SA	DG-EcFIN	1985-2015	6-month	MSI(2)-AR(0)	R1	0.20
Construction Confidence Indicator	SA	DG-EcFIN	1985-2015	6-month	MSI(2)-AR(0)	R1	0.20
Consumer Confidence Indicator	SA	DG-EcFIN	1985-2015	6-month	MSI(2)-AR(0)	R1	0.20

The GCCI is compared to the reference dating chronology of the growth cycle over the period July 1991 - December 2014 to assess the accuracy of the former in locating the slowdowns experienced in the euro area. The GCCI signals all the six slowdowns identified in the reference chronology (no type-I error). However, the slowdown caused by the Asian crisis between 1998 and 1999 is detected by the GCCI with some delay (7 months) and not as strongly as the other five slowdowns (the GCCI does not exceed 0.6 during this period).

No false slowdowns (type-II error) are signaled by the GCCI; however, the start of the 2008-2009 slowdown is detected 11 months in advance compared to the reference chronology. This is an exception, as three out of the five peaks in the reference chronology are signaled with an average delay of 2.6 months. Recently, the GCCI had been increasing in the second half of 2014, though it remained below the 0.5 threshold. This increase was entirely due to the slowdown probabilities derived from the IPI and Imports components.

Figure 14.5: GCCI from July 1991 to April 2015 (blue line) and slowdowns of the growth cycle (grey shaded areas).



Accuracy statistics (QPS and Concordance Index) for the GCCI are reported in Table 14.3.

Table 14.3: GCCI's Accuracy Statistics

QPS	Concordance Index
0.13	0.84

BCCI

The probability of a recession of the euro area business cycle is provided by the BCCI. Three variables are included in the BCCI: Industrial Production Index, unemployment rate and new passenger car registrations. All the three components of the BCCI are variables pertaining to the real economy and seasonally adjusted.

Following Hamilton (1989), the endogenous observable variables are differenced to achieve stationarity. The order of differentiation and the MS model for each variable is chosen empirically case by case, with the aim of reaching the highest accuracy in locating the recessions of the business cycle. For all the component variables, the regime of the latent variable that is assumed to identify recession phases of the business cycle is the first one, that is, the regime for which the state-dependent intercept is the lowest. This is a negative value for all the three models. However, for the IPI and unemployment rate models, also the second regime is characterized by statistically significant negative intercepts, though this regime is not assumed to identify recession periods.

Finally, the composite probabilistic indicator of the business cycle is obtained as a weighted average of the recession probabilities obtained from the three components. The weight given to each variable is proportional

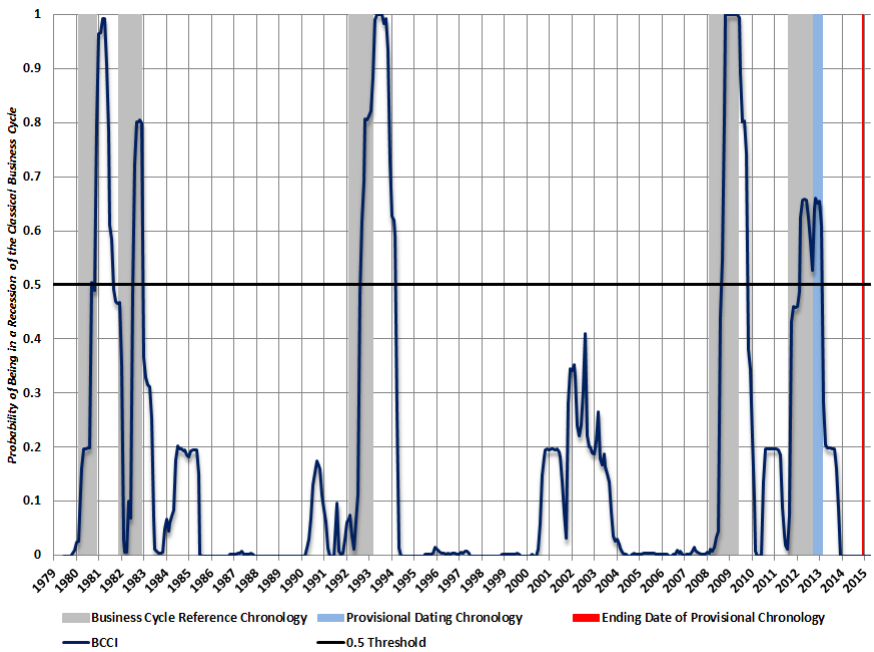
to the number of phases of the business cycle correctly located and inversely related to the number of phases of the business cycle that are missed or falsely detected.

Table 14.4: BCCI's Components

Variable	Seasonal Adjustment	Source	Sample	Differentiation	MS Model	Recession Regime(s)	Weight
Industrial Production Index	SA	Eurostat	1971-2015	12-month	MSIH(4)-AR(0)	R1	0.34
Unemployment Rate	SA	Eurostat	1976-2015	3-month	MSI(3)-AR(0)	R1	0.46
New Passenger Car Registrations	SA	ACEA	1979-2015	12-month and MA3	MSI(3)-AR(0)	R1	0.20

When comparing the BCCI with the reference dating chronology of the business cycle it turns out that the BCCI locates all the five recessions suffered by the euro area between 1979 and 2014. The main backdrop of the BCCI is its lag in detecting peaks and troughs, 7.0 and 5.6 months on average, respectively.

Figure 14.6: BCCI from June 1979 to April 2015 (blue line) and recessions of the business cycle (grey shaded areas).



QPS and Concordance Index statistics related to the BCCI are reported in Table 14.5.

Table 14.5: BCCI's Accuracy Statistics

QPS	Concordance Index
0.12	0.85

MS-VAR GCCI and MS-VAR BCCI

It should be noted that the BCCI and GCCI are obtained separately one from another as single-equation Markov-Switching models are estimated independently and the recession/slowdown probabilities estimated from them are then aggregated. The downside is that turning points signaled by these two probabilistic indicators need not to comply with the ABCD approach. Indeed, in the overlapping period 1991-2014 of these two probabilistic indicators, the trough (C) of two out of the three recessions are detected after the

corresponding trough (D) of the growth cycle: March 1994 (C) vs. September 1993 (D) and October 2009 (C) vs. July 2009 (D).

To overcome this drawback we devised the estimation of coincident indicators of the business and growth cycles that were consistent by construction with the ABCD approach. We built this pair of coincident indicators through a multivariate Markov-Switching model. We empirically specified a MSIH(4)-VAR(0) and fitted it to four variables over the period February 1985 - April 2015: the industrial production index, the unemployment rate, new passenger car registrations and the employment expectations in the industry.

The filtered probabilities obtained as a by-product of the estimation of the Markov-Switching model above are used to jointly construct both a coincident indicator of the business cycle (MS-VAR BCCI) and a coincident indicator of the growth cycle (MS-VAR GCCI).

The first regime of the latent Markov-chain is assumed to correspond to periods of recession, thereby the MS-VAR BCCI is set equal to the filtered probabilities estimated for this regime. The co-joint coincident indicator of the growth cycle (MS-VAR GCCI) is obtained by summing the filtered probabilities of the first two regimes.

The endogenous variables of the model, as well as their order of differentiation considered in the model specification, are summarized in Table 14.6.

Table 14.6: Components of the MS-VAR GCCI and MS-VAR

Variable	Seasonal Adjustment	Source	Differentiation Order
Industrial Production Index	SA	Eurostat	12-month
Unemployment Rate	SA	Eurostat	1-month
New Passenger Car Registrations	SA	ACEA	3-month
Employment Expectations	SA	DG-EcFIN	1-month

It is worth noticing that, contrary to the BCCI and GCCI, no explicit weights are required for the MS-VAR BCCI and MS-VAR GCCI. As we stated above, the aggregation procedure is implicit in the multivariate specification.

The latest release of both the MS-VAR GCCI and MS-VAR BCCI is shown in Figure 14.7, where they are compared to the reference dating chronology of the growth and classical business cycles, respectively.

All the seven slowdowns observed in the euro area since 1985 are correctly signaled by the MS-VAR GCCI. The average delay in detecting six out of the seven peaks of the growth cycle is 2.0 months. However, the MS-VAR GCCI falsely detects a slowdown between mid-2005 and mid-2006, which is not identified in the reference chronology. Moreover, the last slowdown stretches up to January 2015, that is almost two years after the last trough in the reference chronology (2013Q1). This constrasts with the GCCI whose last slowdown signal ended in February 2013.

The MS-VAR BCCI does not miss any of the three recessions suffered since 1985 nor it falsely signals any recession. The three peaks of the classical business cycle are detected with an average delay of 2.3 months, compared to the 7.0 months for the BCCI.

As summarized in Table 14.7, QPS and Concordance Index suggest that the MS-VAR BCCI is quite more accurate than the BCCI in locating the recessions in the euro area. However, the same statistics are pointing at a slightly greater accuracy of the GCCI compared to the MS-VAR GCCI in signaling slowdown of the growth cycle.

Finally, as pointed out above, turning points signals derived from the MS-VAR GCCI and MS-VAR BCCI are consistent with the ABCD approach.

Figure 14.7: MS-VAR BCCI (upper panel) and MS-VAR GCCI (lower panel) from August 1985 to April 2015, slowdowns of the growth cycles and recessions of the business cycle (both in grey shaded areas).

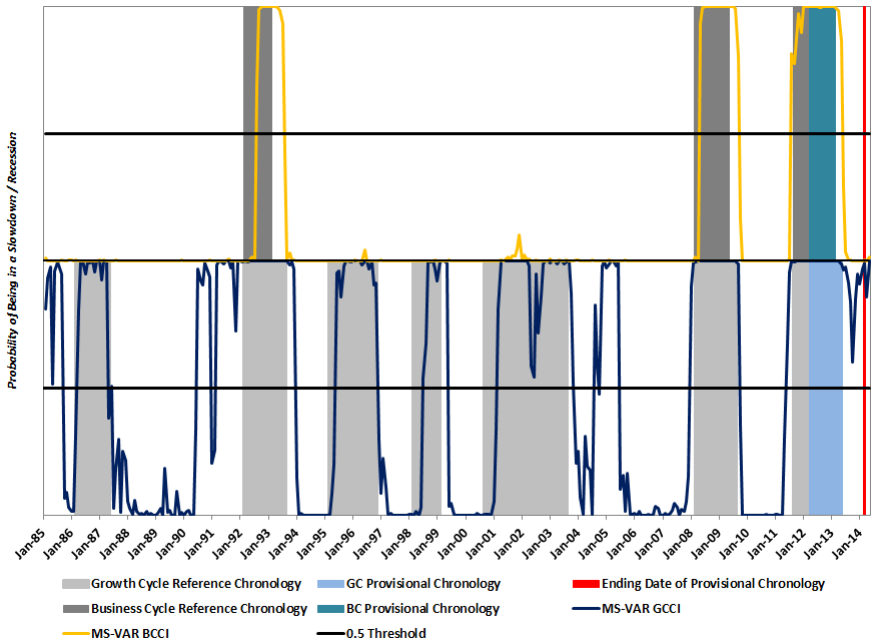


Table 14.7: MS-VAR GCCI's Accuracy Statistics

Indicator	QPS	Concordance Index
MS-VAR GCCI	0.22	0.74
MS-VAR BCCI	0.05	0.94

Member states extension

After the 2008-2009 global economic and financial crisis, we observed a decreasing tendency of the degree of synchronisation among euro area member countries, so that, by looking only at the euro area cyclical situation, the picture was less informative than before. For this reason, it was decided to extend the cyclical monitoring also at the euro area largest economies. Due to the positive results obtained with the multivariate models, we decided to adopt it also at country level while we decided not to produce an ACCI by country. The countries considered in a first phase were Germany, France, Italy, Spain, Belgium, the Netherlands and Portugal, while the construction of coincident indicators for the remaining euro area member countries is still ongoing. We adopt the same variable and model selection strategy as for the euro area but, in order to achieve better results we did some specific fine-tuning, keeping into account some countries' specificities. The model specification, as well as the selected variables, are shown in table 14.12.

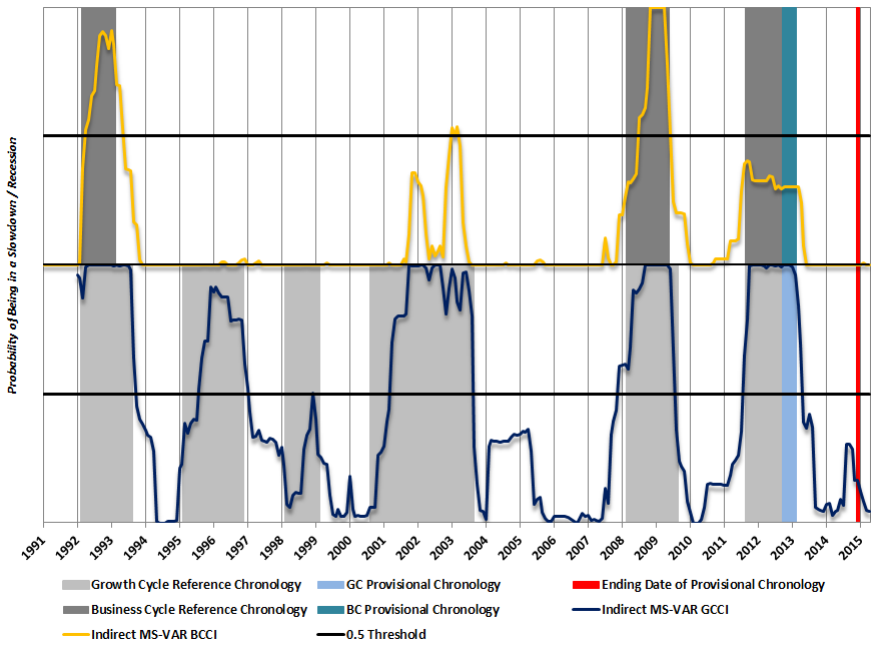
It is worth noticing as in the model specification there are few exceptions with respect to the general specification adopted for the euro area which was used as the reference also at country level. The first one is the presence of five regimes in the models for Italy and Portugal, instead of the four usually adopted. This is probably due to the presence of stagnation phases for the Portuguese and Italian economies, which were not properly captured by the four regimes so that a specific one was requested. The second kind of exception is constituted by the fact that models for Portugal and Belgium do not include any heteroskedastic component which is determined by the fact that expansionary and recessionary phases for those countries were not as much asymmetric as for the other ones. Portugal is the country for which the model adopted is more distant from the other ones since it presents at the same time both the exceptions mentioned above.

Table 14.8: Model summary for the major MS

Country	Model	Recessions	Slowdown	Variables					
				IPI	UR	BUIL	IND	CONS	RETA
Belgium	MSI(4)-VAR(0)	R1	R1+R2	6	3	6	3	-	3
France	MSIH(4)-VAR(0)	R1	R1+R2	6	1	3	-	1	12
Germany	MSIH(4)-VAR(0)	R1	R1+R2	3	3	3	-	6	12
Italy	MSIH(5)-VAR(0)	R1	R1+R2	3	3	-	12	12	3
Netherlands	MSIH(4)-VAR(0)	R1	R1+R2	12	-	6	3	1	1
Portugal	MSI(5)-VAR(0)	R1+R2	R1+R2+R3	6	-	3	3	12	1
Spain	MSIH(4)-VAR(0)	R1	R1+R2	12	12	3	6	12	-

Starting from the indicators developed for the member states, we also derived an euro area pair of coincident indicators indirectly computed as a weighted average of the growth cycle and business cycle filtered probabilities returned by each country model where the weights are based on GDP share. Even if the indirect indicators are based on seven countries, since their GDP accounts for more than 80% of the euro area one, we can assume that the indicators actually computed are a very good proxy of the ones calculated based on all euro area countries. Figure 14.8 shows the behaviour of the indirect indicators for the growth cycle and the business cycle.

Figure 14.8: Indirect MS-VAR BCCI (upper panel) and Indirect MS-VAR GCCI (lower panel) from January 1992 to April 2015, slowdowns of the growth cycles and recessions of the business cycle (both in grey shaded areas)



Based on the regular monthly production (complemented by an historical simulation exercise) of the euro area direct and indirect indicators as well as of the member countries ones, we have been able to identify several useful elements to evaluate the performance and the quality of them. In particular, we have concentrated our attention on the presence/absence of false signals and of missed cycles, as well as on the detection lag of peaks and troughs and on the degree of concordance between the indicators and the historical chronologies as measured by the Concordance Index and the Brier's Score. Tables 14.13 and 14.14 synthesize those elements for the MS-VAR GCCI and the MS-VAR BCCI respectively.

By looking at tables 14.13 and 14.14, we observe generally a good degree of concordance between the indi-

Table 14.9: Growth cycle outcome summary

Country	Slowdown missed	False slowdown	Average delay in locating slowdowns start (in months)	Accuracy in signalling slowdown	
				Brier's Score (QPS)	Concordance Index
Belgium	0	1 (2005)	0.7	0.22	0.76
France	0	0	2.8	0.18	0.82
Germany	1 (1998)	0	2.3	0.26	0.73
Italy	0	0	4.2	0.24	0.76
Netherlands	1 (1995-1996)	0	1.4	0.16	0.82
Portugal	0	3	0.8	0.18	0.80
Spain	1 (1997-1998)	0	3.5	0.24	0.76
EA direct	0	1 (2004-2005)	2.0	0.22	0.74
EA indirect	1 (1998)	0	3.0	0.10	0.87

Table 14.10: Business cycle outcome summary

Country	Recessions missed	False recessions	Average delay in locating peaks (in months)	Accuracy in signalling slowdown	
				Brier's Score (QPS)	Concordance Index
Belgium	1	0	7.3	0.13	0.87
France	0	0	2.5	0.02	0.98
Germany	0	1 (2001-2002)	2.7	0.08	0.92
Italy	1 (2001)	0	1.8	0.16	0.84
Netherlands	0	0	3.5	0.17	0.83
Portugal	0	0	4.3	0.12	0.88
Spain	0	0	2.3	0.05	0.94
EA direct	0	0	2.3	0.05	0.94
EA indirect	1 (2011-2013)	0	2.5	0.06	0.90

cators and the chronologies even if, especially for the euro area, some discrepancies emerged, especially in the latest period, let's say after 2011. At the euro area level both direct and indirect indicators perform similarly, at least until 2011. Indirect BCCI missed the last euro area recession while the direct one correctly detected it. For the GCCI, one missed cycle appears for the indirect indicator while one false signal appears for the direct one. When looking at the member countries indicators, we notice that both MS-VAR GCCI and MS-VAR BCCI for France are performing very well, with the only exception of a false signal recorded by the MS-VAR GCCI. Also for Germany and the Netherlands, the MS-VAR BCCI performs very well while there is room for improvement for the MS-VAR GCCI. Some improvements are required for the MS-VAR GCCI of Portugal to reduce the number of false signals and for Italy and Spain to increase timeliness. Concerning the MS-VAR BCCI, improvements are required for Belgium in order to reduce the number of missed cycles and, again for Belgium and Portugal, for increasing the timeliness.

The latest turning points based on the MS-VAR GCCI and MS-VAR BCCI for euro area and member countries as well as the ACCI, only ofr the euro area, are reported in Table 14.15.

Table 14.11: Growth, Business and Acceleration Cycle datings

		Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
Euro-Area	Growth cycle Provisional dating			2008Q1	2009Q3			2011Q3	2013Q2		
	Direct MS-VAR GCCI			12/2007	09/2009			05/2011			01/2015
	Indirect MS-VAR GCCI			11/2007	07/2009			07/2011	04/2013		
	Business cycle Provisional dating			2008Q1	2009Q2			2011Q3	2013Q1		
	Direct MS-VAR BCCI			04/2008	09/2009			07/2011	05/2013		
	Indirect MS-VAR BCCI			06/2008	06/2009						
	Acceleration cycle Provisional dating			2006Q2	2009Q1	20110Q2			2012Q4		
	Direct MS-VAR ACCI			06/2006	03/2009	12/2010	12/2011	03/2012	10/2012	12/2013	01/2015
Germany	Growth cycle			05/2008	07/2009			09/2011	03/2013		
	Business cycle			10/2008	06/2009						
France	Growth cycle			08/2007	07/2009			07/2011	08/2013		
	Business cycle			06/2008	05/2009						
Italy	Growth cycle			11/2007	06/2009			06/2011	05/2013		
	Business cycle			11/2007	04/2009			07/2011	04/2013		
Spain	Growth cycle			08/2007	11/2009			06/2010	08/2013		
	Business cycle			01/2008	11/2009			06/2011	04/2013		
Netherlands	Growth cycle			05/2008	12/2009			02/2011	02/2013		
	Business cycle			9/2008	12/2009			02/2011	10/2011		
Belgium	Growth cycle			08/2007	09//2009			04/2011			
	Business cycle			07/2008	04/2009			05/2012	06/2012		
Portugal	Growth cycle	12/2005	07/2006	06/2007	05/2009			06/2010	07/2013		
	Business cycle			05/2008	05/2009			09/2010	03/2012		

The table confirms the prevailing idiosyncratic behaviour of the euro area member countries, especially since 2011, accompanied by a low degree of synchronisation and diffusion of turning points. In particular, France and Germany did not enter in recession during the 2011-2013 period, while the Netherlands was only marginally affected by it. The remaining countries experienced a recession in 2011-2013 including the euro area (following the direct MS-VAR BCCI). All the euro area and its member countries experienced a slowdown phase started in 2011. Those elements show how the lack of synchronisation and diffusion is greater for the business cycle than for the growth cycle.

14.5 Conclusions

The construction and the maintenance of turning points composite indicators is a very complex task going through different steps. In this chapter we have describes in details such steps, providing either methodological or an empirical justification aiming to provide guidance for the compilation of turning points composite indicators. In particular, we have stressed how, in this specific case, it is not compulsory focusing on one reference cycle but, by referring to the ABCD sequence or to the αABβCD one, it is possible to simultaneously monitoring alternative cycles. Furthermore, we have stressed the importance of regularly maintaining turning points chronologies in order to dispose of a benchmarking reference for the composite indicators which allows for a continuous real-time monitoring of their performance. In the chapter we have also shown as composite indicators can be compiled by using various specifications within the family of the Markov-Switching models.

The outcomes of the indicators is very sensitive to the model specification so that it is essential to carefully chose the most appropriate one in relation to the objectives and the needs that they have to achieve and serve. In this respect, despite its computaional complexity, the multivariate Markov-Switching models have proven to be a powerful instrument for constructing composite indicators which always respects the ABCD sequence. Nevertheless, under the condition that the coincident indicators for growth and business cycles, based on univariate modelling of component variables have the same degree of timeliness, this approach can become again very appealing.

14.6 Annex

14.6.1 Introduction

The compilation of cyclical composite indicators for the detection or forecasting of turning points, as described in this chapter 14, can be a quite complex process. During this process, several important decisions have to be taken which will affect substantially the overall quality of the process and the validity of its results. For this reason, in this annex I am proposing an operational scheme for the construction and, validation and maintenance of cyclical turning points indicators. Similar step by step approaches have already been presented in Mazzi and Montana (2009) and inMazzi et al. (2017) , focusing respectively on the univariate BCCI and GCCI and on the multivariate MSVAR-BCCI and MSVAR-GCCI.

There are some innovative features which characterise the approach proposed in this annex with respect to the other already mentioned schemes. The first one is that here I am merging the schemes for the univariate indicators and for the multivariate ones into a single sequential process. The second is that here, together with a detailed description for each step, I am also proposing some suggestions and recommendations for the compilers. Finally, I have added a couple of steps providing guidance on how to ensure a regular monitoring of the indicators' performance and about the revision policy to be followed.

This annex is structured as follows: Section 14.6.2 describes the preliminary steps to be followed for the construction of turning points indicators; section 14.6.3 is devoted to the presentation of steps related to the modelling strategy and model selection aspects, while section 14.6.4 will describe the validation steps leading to the identification of the best indicator(s). Section 14.6.4 also proposes steps related to the implementation of a regular monitoring and revision strategy for the turning points indicators developed in previous steps, and discusses some dissemination issues. Section 14.6.5 will contain some concluding remarks.

14.6.2 Preliminary steps to the construction of turning points indicators

In this section we are presenting the first 3 steps for the construction of turning points indicators. In such steps, and especially in the first two, crucial decisions are required which will influence and conditioning the decisions to be taken in the subsequent steps.

Step 1 - Identification of the cycle to be monitored

(A) Description

Prior to any other action, business cycle analysts have to identify the cycle(s) to focus on. This decision is typically influenced by some factors stemming from the user's needs, policy-makers request, characteristics of the national economy, data availability and so on. Traditionally analysts have focused their attention on three main definitions of cycles:

1. Classical Business cycle (Burns and Mitchell definition; 1946), which is very relevant for detecting recessions but not very informative during usually quite long expansion phases.
2. Growth cycle (Output gap), which is very relevant to understand the position with respect to the potential output (trend) and more informative also during the expansion phases of business cycle. It leads to the peaks and troughs of the business cycle but it doesn't detect the start and the end of recessions. The output gap is also considered very relevant, especially by central banks, to anticipate inflation rate based on the modern Phillips curve relating inflation and output gap. The main weak point of the growth cycle is represented by the fact that the choice of alternative de-trending techniques can be substantially

affect the shape and the location of turning points. Furthermore, de-trending filters can produce very unstable growth cycle estimates at the end of the series.

3. Growth rate cycle (Acceleration cycle), which is characterised by the highest number of fluctuations and a high degree of volatility. It leads to the growth cycle peaks and business cycle troughs corresponding to the inflexion points of the classical business cycle. They determine the acceleration and deceleration phases of the economy.

In addition, it is also possible jointly monitoring more cycles as proposed by Anas and Ferrara (2004a,b). In this paper they propose to jointly follow the growth and business cycles within an integrated framework. This framework is defined by the 4 turning points associated to the two cycles and by the logical sequence of peaks and troughs. Such logical sequence of turning points assumes that peaks of the growth cycle anticipate those in business cycle and troughs in business cycle anticipate them in the growth cycle. Consequently, the framework has been defined by the sequence ABCD where A and D are respectively peak and trough of the growth cycle and B and C the peak and trough of business cycle.

In the same papers, the authors also include an extended version of this framework incorporating the acceleration cycle. In this case, the logical sequence of turning points becomes αABβCD where α and β are respectively the peak and the trough of the acceleration cycle.

Based on the Eurostat experience I consider that the monitoring of the cyclical economic situation is ensured by the simultaneous follow-up of the growth and the business cycles within the ABCD framework. The extension of the framework to include the acceleration cycle should provide more insight on the accelerating or decelerating behaviour of the economy, which can be very relevant especially in periods of slow or moderate growth. On the other hand, the risks associated to the high volatility of the acceleration cycle have to be carefully evaluated. Obviously, this approach can be quite resource consuming and in a first phase a country can decide to follow an easier strategy focusing on just a cycle.

(B) Recommendations

Key recommendations are the following:

1. Privilege as much as possible the adoption of the simultaneous monitoring of business and growth cycle within the ABCD framework with possible extensions to the $\alpha AB\beta CD$ one.
2. In case where resource constraints or problems in data availability do not allow for implement the recommendation 1, a single indicator should be developed instead. In this case, also based on the Eurostat experience, the suggestion is to concentrate on the growth cycle since it is more informative especially for developing and emerging economies.

Step 2 - Constructing a historical dating chronology

(A) Description

A historical dating chronology for each of the cycle selected in the previous step is an essential tool to benchmark the turning points indicators to be developed in the following steps. Without a historical chronology, the validation of turning points indicators could not be performed from a statistical point of view lowering considerably their relevance and compromising the methodological soundness of the whole constructing process.

For the reasons mentioned above, it is crucial at this stage to search for the existence of official historical dating chronologies, if any, or for other reference chronologies regularly updated and maintained, based on sound methodologies. If such chronologies do not exist or do not cover, totally or partially, the cycle's definitions to be monitored, before computing turning points indicators, they have to be constructed possibly adopting a simple dating rule. Statistical dating chronologies should cover a time horizon as long as possible, also depending

on data availability. They should be constructed with the aim of keeping past turning points, after a certain number of years, fixed, even we have to be aware of the difficulty of such objective, especially in presence of big revision in official statistics.

(B) Recommendations

Main recommendations for this step can be synthesised as follows:

1. Use the quarterly GDP plus one or two more monthly key variables such as industrial production, and unemployment rate as reference variables from the historical dating chronologies.
2. Use a simple non-parametric dating rule such as the Hardin and Pagan (2002) to identify past turning points;
3. Even if in step 1 it has been decided to focus on just one cycle, compute the historical dating chronologies for all 3 cyclical definitions. This will be not very complex and the benefits very relevant for future analysis;
4. When constructing the chronologies for various cycles, ensure that the ABCD sequence or its extended version αABβCD are fulfilled.

Step 3 - Construction of a dataset to be used for the construction of cyclical turning points indicators

(A) Description

A middle-sized dataset has to be developed at this stage. It will constitute the main statistical base for the following steps where data and model selection tasks will be performed. To allow the jointly monitoring of the business growth and acceleration cycles, the dataset should mainly contain the key macro-economic indicators, available possibly at monthly frequency, as well as opinion surveys data and, eventually, other soft and hard indicators which could be useful for detecting and forecasting turning points. If only growth and acceleration cycles will be targeted, then the data set should mainly contain soft data and only a few numbers of key macro-economic indicators. By contrast, if the business cycle is targeted, then there is no need to have opinion surveys data in the dataset which should contain only macro-economic indicators and, if needed, other relevant soft data such as financial variables.

The data set should contain the original values of the indicators as well as their most appropriate data transformation to highlighting cyclical movements. The dataset should contain in priority seasonally adjusted data but also non seasonal adjusted ones should be included mainly for advance research projects. Ideally the dataset should contain the vintages of the selected indicators recorded over a sufficiently long time horizon covering possibly two cycles at least.

(B) Recommendations

Main recommendations for this step can be synthesised as follows:

1. The dataset containing the selected indicators should be regularly updated and maintained, subject to a continuous quality monitoring and be regularly backed up in order to create historical vintages if not previously available.
2. The size, composition and structure of the dataset should target the cycles to be monitored as in step 1.

14.6.3 Steps towards the construction of turning points indicators

In this section, I am presenting the various aspects of the modelling strategies to be followed for constructing univariate cyclical turning point indicators as well as multivariate ones.

Step 4 - Variable selection

(A) Description

Starting from the middle-sized dataset developed in step 3, a variable selection process is necessary at this stage in order to identify small number of variables to be considered as candidate component of the cyclical turning points indicators to be constructed. Such selection will be mainly based on the ability shown by each variable in the dataset of timely and precisely detecting turning points within a simulation exercise against the non-parametric historical dating chronologies constructed in step 2. The best possible scenario for this exercise is represented by a real-time simulation by using as much as possible past vintages of the variables to be tested.

The ability of the variables to timely and precisely detect turning pints will be assessed by using simple statistical tools such as graphical investigation or the use of very simple time-series models to be fitted to each variable. Obviously, the specific characteristics of each series should be considered when deciding which kind of turning points they are supposed to be able to detect. For example, as already mentioned in the previous step, it will be inappropriate and even misleading to test the ability of detecting business cycle turning points by opinion surveys data which, by definition, measure only growth cycle and likely acceleration cycle.

(B) Recommendations

Main recommendations for this step can be synthesised as follows:

1. Since large scale based indicators do no necessarily perform better than small scale ones, and also considering that they can be more complex to maintain and monitor, the main suggestion is to identify a relatively small number of candidate variables to be used in the following steps.
2. Use all statistical knowledge about the series in the dataset, such as their characteristics, peculiarities etc., as priors in the variable selection exercise.

Step 5 - The modelling strategy

(A) Description

The modelling strategy for the construction of cyclical turning points indicators has to be modelled on the choices made in step1. If in step1 it has been decided to focus on just one cycle, either the business or the growth one (the acceleration could be much more rare as a choice), the chosen variables should be modelled by means of univariate model and the results should be aggregated by using a simple aggregation scheme.

In the case where the growth and the business cycle have been chosen to be monitored in step 1 then it is possible to evaluate competing alternatives. The first one is similar to the one proposed for constructing an indicator for a single cycle and it will consist of estimating independent indicators for each cycle by using univariate models fitted to each component and a simple aggregation scheme at the end. The alternative is a jointly multivariate modelling of the growth and business cycle which will avoid the aggregation step and the identification of the weighting scheme. If also the acceleration cycle was included step 1, for this cycle it is

necessary to proceed always with an independent modelling since, for purely mathematical reasons, it is not possible to simultaneously model growth business and growth cycle. So in this case there will be multivariate model for growth and business cycle and a univariate model for acceleration cycle.

Finally, it has to be noted that several non-linear techniques, as discussed in chapter 13, could be used for constructing turning points indicators. Nevertheless, based on the interaction evidence, and also on personal experience (see Billio, Ferrara et al 2013) I assume in the following of this annex, consistently to that done in chapter 14, that the Markov switching models are adopted by default.

(B) Recommendations

Main recommendations for this step can be synthesised as follows:

1. Provide a clear statement on the chosen modelling strategy and on its justifications.
2. Within the class of best performing models, privilege simple, easily replicable and economically interpretable ones.

Step 6 - Model specification: univariate case

(A) Description

In order to simplify the presentation, I am assuming here that all 3 cycles should be monitored by means of turning points indicators independently constructed based on univariate modelling of the component series. Obviously, this description also applies to the cases where only two or one cycle has to be monitored. For each cycle to be monitored the candidate series will be modelled by means of a univariate MS model:

$$MSIH(k) = AR(l)$$

Where H indicates the presence of the heteroscedastic components, K the number of regimes and L the number of lags of the autoregressive part. Each model should target one of the selected cycles: acceleration, business or growth cycle following the characteristics of the variable involved. Consequently, the number of regimes and the presence of heteroscedasticity should vary accordingly.

(B) Recommendations

Main recommendations for this step can be synthesised as follows:

1. Privilege univariate models with a number of regimes not exceeding 3, keeping in mind that, especially for the growth and the acceleration cycles, two regimes should usually be enough.
2. Models without autoregressive structure ($l = 0$) should be privileged.

Step 7 - Model selection: univariate case

(A) Description

From step 6, N univariate best fitting models are identified for each reference cycle. Each of them will return a probability of being in recession, slowdown or deceleration phase according to the reference cycle. For each reference cycle a number of turning points indicators will be then derived as a weighted average of the recessions/slowdown/deceleration probability returned by K components series where $k < n$.

In practical terms the outcome of this step will constitute of $M1$ indicators for the acceleration cycle, labelled ACCI ($M1$), $M2$ indicators for the growth cycle labelled GCCI ($m2$) and $M3$ indicators for the business cycle labelled as BCCI ($M3$). Formally this step will lead to the compilation of the following turning points indicators:

Main recommendations for this step can be synthesised as follows:

1. $M1$ acceleration cycle composite indicators ACCI of the form:

$$ACCI(j_1, t) = \sum_{i=1}^{k_1} h(i) p^{ac(i,t)} \qquad j_1 = 1 \ldots m_1, t = 1 \ldots T, \tag{14.1}$$

   K_1 is the number of variables included in the j_1 indicators, $h(i)$ are standardised weights so that $\sum_{i=1}^{k_1} h(i) = 1$ and $p^{ac(i,t)}$ are the deceleration probabilities returned by each component variable at time t. If $ACCI(j_1, t) > 0.5$ the economy is in a deceleration phase.

2. $M2$ growth cycle composite indicators GCCI of the form:

$$GCCI(j_2, t) = \sum_{i=1}^{k_2} w(i) p^{gc(i,t)} \qquad j_2 = 1 \ldots m_2, t = 1 \ldots T, \tag{14.2}$$

   $W(i)$ are standardised weights withe same properties as $h(i)$, k_2 is the number of variables included in the j_2 indicator and $p^{gc(i,t)}$ is the slowdown probability returned by each k_2 component series at time T. When $GCCI(j_2, t) > 0.5$ the economy is in a slowdown phase meaning that it is growing below the trend.

3. $M3$ business cycle composite indicators BCCI of the form:

$$BCCI(j_3, t) = \sum_{i=1}^{k_3} v(i) p^{bc(i,t)} \qquad j_3 = 1 \ldots m_3, t = 1 \ldots T, \tag{14.3}$$

   $v(i)$ is a set of standardised weights with the same properties of $h(i)$ and $W(i)$, k_3 is the number of variables included in the j_3 indicator and $p^{bc(i,t)}$ is the recession probability returned by each k_3 components at time t. If $BCCI(j_3, t) > 0.5$ the economy is in a recessionary phase.

In all cases 0.5 is usually the adopted threshold associated to the so called natural rule of Hamilton (1989). Since the growth cycle and the business cycle indicators, GCCI and BCCI, are independently compiled, there is no guaranty that when $BCCI > 0.5$, implies $GCCI > 0.5$, consequently the ABCD sequence is not automatically fulfilled.

(B) Recommendations

Main recommendations for this step can be synthesised as follows:

1. Since the 0.5 threshold has demonstrated in several empirical studies to be a good compromise between the flexibility and timeliness in detecting turning points on one hand and the risk aversion which could characterise such indicators, it should be adopted for all turning points indicators.

2. Keep the number of components for each indicator as much as possible limited, possibly not exceeding 5. This limitation will contribute to avoid that the procedures for constructing turning points become too heavy and difficult to be managed, maintained and interpreted.

3. Check the compliance of the BCCI(s) and the GCCI(s) indicators with the ABCD sequence and privilege those indicators which fulfil the sequence.

4. In case of inconsistency with the ABCD sequence, consider the possibility to move to a multivariate strategy as described in steps 8 and 9.

Step 8 - Model specification: multivariate case

(A) Description

Selected variables in step 4 are here used to identify and estimate a number of vector autoregressive Markov-Switching models (MS-VAR):

$$MSIH(K) - VAR(L), \tag{14.4}$$

where H indicates the presence of heteroskedasticity, (K) is the number of regimes and (L) the number of lags of the autoregressive part. This multivariate model aims to simultaneously produce turning points indicators for the business and growth cycle respectively. Dealing simultaneously with growth cycle and business cycle implies a number of regimes not smaller than 3 so $k => 3$, while the heteroskedastic part H can or cannot be present depending on the degree of asymmetry of fluctuations. Based on the Eurostat experience, the most commonly found number of regimes for these indicators is 4. Concerning the heteroskedasticity, its presence has been significantly detected in most multivariate models.

(B) Recommendations

1. Keep the number of regimes as much as possible small and easy to be justified and interpreted. The number of regimes exceeding 5 should be avoided either for the related computational complexity or for the difficult interpretation in economic terms.
2. Privilege models with $L = 0$ meaning not ar structure, unless there is an empirical significant evidence indicating that models with $l > 0$ outperform these with $l = 0$.
3. In case where $l > 0$, the number of lags should be kept as small as possible and not exceeding 3.

Step 9 - Model selection: multivariate case

(A) Description

From step 8, N best fitting models are identified, each of them producing a pair of coincident indicators for the growth cycle and the business cycle respectively, labelled as MS-VAR GCCI (multivariate growth cycle coincident indicator) and MS-VAR BCCI (multivariate business cycle coincident indicator):

$$MS - VAR\,GCCI(j) \text{ and } MS - VAR\,BCCI(j);\ j = 1 \ldots n. \tag{14.5}$$

Each composite indicator is defined between 0 and 1, and can be viewed as a composite probability of being in a recessionary phase for the MS-VAR BCCI (j) and in a slowdown phase for the MS-VAR GCCI (j). The recession/slowdown regions are defined on the basis of a threshold, usually set up to 0.5. Obviously higher values for the threshold as well as smaller ones can be used. In the first case, the indicators should detect less fluctuation, missing some cycles, while in the second one they will detect more fluctuations than really occurring cycles (see chapter 14 for more details). By adopting the 0.5 threshold we can have then the following cases:

- MS-VAR BCCI (j) > 0.5 = recession
- MS-VAR GCCI (j) > 0.5 = slowdown
- MS-VAR BCCI (j) < 0.5 =recovery

- MS-VAR GCCI (j) < 0.5 = expansion

One of the most interesting features of this multivariate class of models is that by construction,

$$MS - VAR\,BCCI(j) > 0.5 \text{ and } MS - VAR\,GCCI(j) > 0.5, \tag{14.6}$$

so that the ABCD sequence is always fulfilled.

(B) Recommendations

1. Since the 0.5 threshold has demonstrated in several empirical studies to be a good compromise between the flexibility and timeliness in detecting turning points on one hand and the risk aversion which could characterise such indicators, it should be adopted for all turning points indicators.
2. Keep the number of components series as small as possible and possibly not exceeding 5. In addition to the advantages mentioned in recommendation 2 of step 8, in the multivariate case, this will contribute to reduce the risks of lack of convergences of the estimation algorithms.

14.6.4 Model validation and the identification of the best indicator(s)

In this section I am describing the validation process of the indicators developed in step 7 (univariate indicators) and in step 9 (multivariate indicators). Later, the main criteria allowing for the identification of the most performing indicators for each group will be presented.

Step 10 - Dynamic comparison of the turning points indicators

(A) Description

Within a dynamic simulation exercise, the $M(i)\,i = 1, 2, 3$ univariate indicators developed in section 7 for the acceleration, growth and business cycle, as well as the N pair of multivariate composite indicators for the growth and the business cycle are compared with the non-parametric historical turning point dating developed in step 2. The time span for this comparative exercise should be long enough and contain a certain number of cycles in order to allow for the identification of strong and weak points of each indicator in detecting turning points. Obviously, the best possible way to conduct this exercise is in real-time, by using historical vintages instead of final vintages.

(B) Recommendations

1. Select a time span possibly not shorter than 15-20 years including at least 2-3 recessionary events and a higher number of other cyclical movements.
2. Privilege the use of historical vintages whenever available even for a subset of the selected time span.

Step 11 - Identification of the best performing indicators

(A) Description

The identification of the best performing ACCI, BCCI and GCCI as developed in step 7, as well as of the best pair of MS VAR-BCCI and MS VAR-GCCI, as developed in step 9, is based on the outcome of step 10, using the following statistical criteria:

- Average lead/lag in identifying peaks;
- Average lead/lag in identifying troughs;
- number of false cycles detected;
- number of missing cycles;
- Concordance Index;
- Brier's Score (QPS).

In an ideal situation, in case of coincident indicators the average lag in detecting turning points should be 0 or very small, while in the case of leading indicators the average lead in anticipating turning points should be positive. Furthermore, we should also expect that both the number of false signals as well as the number of missing cycles should be 0. Nevertheless, such an ideal situation is not achievable since the number of false signals and the number of missing cycles have to be viewed as the type2 and type1 errors of the estimation process. In statistical inference, we have learned that it is impossible to minimise simultaneously both errors and that a choice had to be made.

Finally, still in an ideal case a concordance index equal to 100 or very close and a QPS near 0 can be expected.

(B) Recommendations

1. Since the risk associated to the announcement of a non-existing cycle is considered higher than the one associated to missing a cycle, I recommend privileging the indicators minimising type 2 error.
2. Indicators characterised by high delays in the identification of turning points, especially peaks, should be discarded because they will not be useful in practice.
3. Indicators showing a constant behaviour over the simulation period should be preferred to these with a highly variable performance.

(5) - Regular monitoring of the turning points indicators

In this section we provide guidance on the regular assessment of the indicators' performance as well as on the strategy to be adopted to revise indicators on regular bases.

Step 12 - Regular assessment of the indicators' performance

(A) Description

The same criteria used to select the best performing indicator(s) in the previous step, can be used here to regularly assess the performance of the selected indicator(s), in particular to discover if it is subject to any kind of deterioration during the time. In chapter 14, summary tables have been proposed to compare the behaviour of indicators across countries. In these tables, one for each cycle, together with the indicator model specification, all 6 statistical criteria presented in step 11 are displayed. This is a very useful and powerful tool to evaluate on a regular base the performance of the chosen indicator(s) and to highlight possible risks of deterioration.

(B) Recommendations

1. Implement for each cycle (acceleration, growth and business cycle) and for each indicator a table following the scheme presented in chapter14 and regularly update it.

2. Update the table at least twice a year but ideally every quarter.

Step 13 - Revisions

(A) Description

When constructing composite indicators for detecting or anticipating turning points, it is essential to ensure a stability of the signals over the time. This implies a high stability of subsequent vintages of the indicators. In practical terms, there are several factors which can affect such stability. The first one is related to the regular revision process which characterises most macroeconomic variables. Unfortunately, this process is not on the hands of the compilers of turning points indicators but of data producers. Nevertheless, routine revision process is quite smooth and rarely produces changes able to affect the signals returned by composite indicators. Such uncommon events are generally associated to the occurrence of big shocks such as at the beginning of the global financial and economic crisis where data have been subject to huge revisions.

Other elements that can impact the stability of the signals returned by composite turning points indicators is constituted by the decisions taken by the compilers concerning the re-estimations and re-specification strategies for the indicators. Re-estimating and re-specifying too often the models is obviously improving the precision of the latest estimates but the counterpart is a high degree of instability over the times which can confuse policy-makers and analysts. On the other hand, never re-estimating and re-specifying the models, is progressively lowering their ability to timely and reliably detect turning points. An intermediate solution able to find a balance in the trade-off between timeliness and reliability from one hand and the stability on the other hand is necessary. The Eurostat experience demonstrated that a conservative approach privileging the stability of the indicators over the time is preferable.

(B) Recommendations

1. Establish a regular contact with data producers in order to better understand the regular revision process characterising the macroeconomic variables included in composite indicators for turning point detection.
2. Re-estimate the model parameters on yearly basis unless relevant anomalies in the data (e.g. very significant outliers, level shift, unexpected revisions, etc.) occur during the year. In such case, the need for an exceptional re-estimation of the models has to be evaluated.
3. Re-specify and re-identify the models usually every 5 years or whenever major revisions (e.g. changes in methodology definition and classification of macroeconomic indicators) occur. In such cases, the need for the re-specification and the re-identification of the models has to be evaluated.

(6) Dissemination of composite indicators for turning point detection

Step 14 - Dissemination issues

(A) Description

The most logical way to disseminate turning point indicators is the traditional one based on the presentation of their behaviour using tables and graphs to which regular press releases could be also associated. Nevertheless, the interpretation of the turning points indicators is not so evident especially for non-expert users. This interpretation can become even more complex when multiple indicators are released for example for the simultaneous detection of turning points indicators for the growth and business cycle within the ABCD approach. In order to simplify the reading of the indicators and to provide a synthetic message it is then advisable to complement the usual dissemination way with graphical or visual dissemination tool explicitly designed for

business cycle analysis. All turning points indicators have also to be properly documented within a standard metadata framework agreed at the international level.

(B) Recommendations

1. Complement the standard dissemination of composite indicators for turning point detection with advanced graphical and visualisation tools able to simplify their interpretation and to give a clear picture of the business cycle situation.
2. Provide a standard metadata file for each turning point indicators in line with the international standards and complement it, if needed, by more technical documentations and papers.

14.6.5 Conclusions

In this annex, I have generalised and completed the step-by-step approaches already presented in Mazzi and Montana (2009) and Mazzi et al. (2017). The step-by-step approach proposed here tries to cover all phases in the construction of composite indicators for turning point detection, starting from the decision on what to compile to the compilation process until the dissemination of the indicators. The recommendations provided at each step are generally based on methodological considerations also supported by the experience that Eurostat has made in the compilation of such indicators since 2007.

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