A multivariate system for turning point detection in the euro area

MONICA BILLIO, LAURENT FERRARA,
GIAN LUIGI MAZZI, FILIPPO MOAURO

2016 edition

STATISTICAL
WORKING PAPERS

eurostat

A multivariate system for turning point detection in the euro area

2016 edition

Europe Direct is a service to help you find answers
to your questions about the European Union.

Freephone number (*)**:**

00 800 6 7 8 9 10 11

(*) The information given is free, as are most calls (though some operators, phone boxes or hotels may charge you).

More information on the European Union is available on the Internet (http://europa.eu).

Luxembourg: Publications Office of the European Union, 2016

ISBN 978-92-79-57965-3
ISSN 2315-0807
doi: 10.2785/73495
Cat. No: KS-TC-16-007-EN-N

Content

Abstract

In the paper we introduce a system for statistical detection of turning points in the euro area based on the class of multivariate Markov-switching models. Component series considered in the application are monthly short term statistics released by Eurostat, business and consumer surveys released by DG-ECFIN and new cars registrations released by ACEA. The main advantage of the proposed approach is that it jointly derives a couple of coincident indicators for both the classical business cycle and the growth cycle; further, it assures the sequence of turning points to be coherent with the ABCD approach, an occurrence which is not guaranteed by applying the univariate approach for the pair of coincident indicators. The application considers an extensive combination of multivariate setups, comparing the results with those related to the univariate approach. Selection of the most appropriate multivariate system is carried out by adopting a set of statistical benchmarking criteria with respect to a reference dating chronology.

Keywords: univariate and multivariate Markov-switching models, business cycle, growth cycle, dating and detecting turning points.

Acknowledgements:

Paper first presented at the 6th Centre for Growth and Business Cycle Research Conference in Manchester (July 2011). The authors are grateful to the conference participants for their feedback and comments. The paper has benefitted from the outcomes of the multi-annual PEEIs project financed by Eurostat.

Authors:

Monica Billio ([1]), Laurent Ferrara ([2]), Gian Luigi Mazzi ([3]), Filippo Moauro ([4])

([1]) Monica Billio, University of Venice, Italy. Email: billio@unive.it.

([2]) Laurent Ferrara, Bank of France, Paris, France. Email: Laurent.Ferrara@banque-france.fr.

([3]) Gian Luigi Mazzi, Eurostat, Luxembourg; email: gianluigi.mazzi@ec.europa.eu.

([4]) Filippo Moauro, Istat, Rome, email: moauro@istat.it.

1. Introduction

Main aims of business cycle analysis are to detect, in real-time, and anticipate, as far as possible, economic fluctuations with particular attention paid to turning points. The achievements of such goals strongly depend on the availability of a reliable historical analysis of main cyclical events. The accurate dating of past turning points as well as a detailed description of cyclical movements like length, deepness and symmetry are essential elements of this historical analysis.

The dating and detection processes are not an easy task for several reasons. First we need to refer to a specific definition, i.e. classical business cycle, growth cycle or acceleration cycle, since distinct definitions tackle different features. Each characterisation has obviously advantages and drawbacks, and relates to specific aspects of economic fluctuations. Second, the dating exercise has to be based on sufficiently long time-series covering several cycles. Unfortunately this requirement is difficult to fulfil because statistics can be affected by 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 standpoint.

Since several years Eurostat is strongly involved in the development of composite indicators of the growth cycle (hereafter referred to as GCCI) and of the business cycle (hereafter referred to as BCCI) adopting the class of univariate Markov-switching models. This means that each indicator is derived independently from each other concerning the involved set of time-series, their relative contribution at the composite indicators, and the order of the univariate Markov-switching model fitted to each component series. Finally, the filtered probabilities obtained as a by-product of the estimation algorithm for each time-series are aggregated together, in order to provide respectively the GCCI and the BCCI.

Both the GCCI and BCCI have been regularly used in the assessment of the euro area business cycle situation since 2006 according to the methodology developed in Anas et al. (2008). Both indicators have proven to be reliable and accurate and represented a significant tool for business cycle analysis in recent years. The indirect approach assures high flexibility in model estimation and the use of different set of time-series according to the specific needs of the BCCI and GCCI. By contrast, the sequence of turning points of the classical business cycle, detected together with those of the growth cycle didn't fully satisfy the ABCD approach proposed by Anas and Ferrara (2004), an occurrence which has been experienced especially during the recent deep recession.

The aim of this paper is to verify whether a multivariate specification belonging to the class of Markov-switching models could be used to jointly derive a pair of coincident indicators of the classical business cycle and of the growth cycle for the euro area. It presents the results of an extensive application with a large combination of multivariate setups and comparative analysis also with respect to the univariate approach. The selection of the most appropriate multivariate system is carried out by adopting a set of statistical benchmarking criteria with respect to a reference dating chronology.

The outline of the paper is the following: section 2 shortly introduces the univariate approach currently followed by Eurostat to derive the BCCI and the GCCI for the euro area, whereas section 3 provides evidence of most recent results for both indicators; section 4 is devoted to the design of the experiment for the multivariate approach, with details on the dataset used, model specification and selection criteria of final estimates. Section 5 deals with the empirical application of the Multivariate approach and section 6 with a summary view of turning points detected through the univariate and multivariate approach. Finally, section 7 shortly concludes.

2. The univariate approach to the euro area BCCI and GCCI

The BCCI

The BCCI implemented by Eurostat through the univariate approach, shortly mentioned in the introduction, measures each month the probability of being in the low phase of the business cycle (recession) of the euro area. Each month it assesses the occurrence or not of turning points B and C in the ABCD approach according to the methodology developed in Anas et al. (2008).

The indicator summarises the information coming from 3 component series:

1. Industrial production index (IPI hereafter), total except construction, source Eurostat, available from January 1990 as index of volume 2000=100; the series is completed by a provisional back-calculation of the index until January 1977;
2. Unemployment rate in percentage (UR hereafter), source Eurostat since January 1993 further completed by provisional back-calculated values until January 1975;
3. New car registrations in volume (NPCR hereafter), source ACEA since January 1978.

All the series are adjusted for seasonal variations and the IPI also for calendar effects and further subject to a proper differentiation to get a stationary indicator.

Starting date of the BCCI is June 1979. For each of the 3 components a monthly latent variable is associated taking a value of 1 if the time series belongs to the low phase of the business cycle and 0 otherwise. A MS model-based approach is adopted to measure the state of the economy at each time period and the corresponding transition probabilities of moving from one state to the other. For all the components, model estimation is carried out with a 3-regime MS model with the same variance in each regime.

The final value for the BCCI at time t is obtained aggregating the estimated probabilities of being in a low phase of the business cycle returned by the 3 MS models associated to the component series. These measures are referred as filtered probabilities, i.e. conditional to the information set available up to time t. A weighted average is used as aggregation criterion among the 3 component series, with values 0.34, 0.46 and 0.20 respectively for IPI, UR and NPCR. The selected weights reflect the relative reliability of each component series in correctly detecting turning points.

The GCCI

The GCCI implemented by Eurostat measures each month the probability of being in the low phase of the growth cycle (slowdown) of the euro area. Each month it assesses the occurrence or not of turning points A and D in the ABCD approach according to the methodology developed in Anas et al. (2008).

The indicator summarises the information coming from 5 component series:

1. Employment expectations for the months ahead in the industry survey (INDEA7 hereafter), source DG-ECFIN, available from January 1985 as balance of opinions;
2. Construction confidence indicator (BUIEA99 hereafter), source DG-ECFIN, available from January 1985 as balance of opinions;
3. Financial situation over the last 12 months in the consumer survey (CONSEA1 hereafter), source DG-ECFIN, available from January 1985 as balance of opinions;
4. IPI;

5. Imports of intermediate goods from outside euro area, source Eurostat, available from January 1989 as index of volume 2000=100;

All the series are adjusted for seasonal variations while the IPI and Imports of intermediate goods are also corrected for calendar effects. All series are then subject to a proper differentiation to get a stationary indicator.

Starting date of the GCCI is July 1991. For each of the 5 components a monthly latent variable is associated taking a value of 1 if the time series belongs to the low phase of the growth cycle and 0 otherwise. A Markov-switching (MS) model-based approach is adopted to measure the state of the economy at each time period and the corresponding transition probabilities of moving from one state to the other. For all the components, model estimation is carried out with a 2-regime MS model with the same variance in each regime.

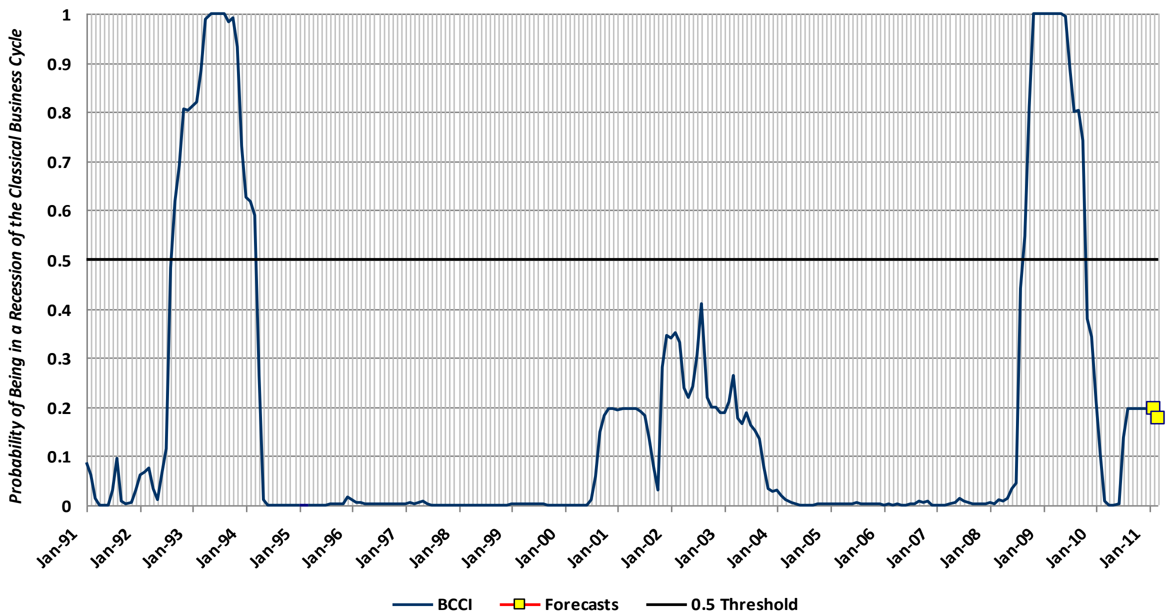
The final value for the GCCI at time t is obtained aggregating the estimated probabilities of being in a low phase of the growth cycle returned by the MS models associated to the 5 component series. These measures are referred as filtered probabilities, i.e. conditional to the information set available up to time t. The equal weighted average is used as aggregation criterion among the 5 component series.

3. Empirical evidence of univariate methods

Figures 1 and 2 present respectively, the BCCI in the period from January 1991 to March 2011 and the GCCI in the period from July 1991 to March 2011. Both figures refer to the cyclical assessment of the euro area estimated in December 2010. Note that the last two months are based on forecasting probabilities, yellow-boxed-red line in the figures, which also show the 0.5 probability threshold.

According to these estimates, November 2009 is the first month of the recent recovery for the BCCI, with latest peak and trough of the euro area business cycle located in August 2008 and October 2009 respectively. Concerning the GCCI, August 2009 is the first month since April 2007 in which the GCCI signals a recovery in the euro area economy, with latest peak and trough of the euro area growth cycle located in March 2007 and July 2009 respectively.

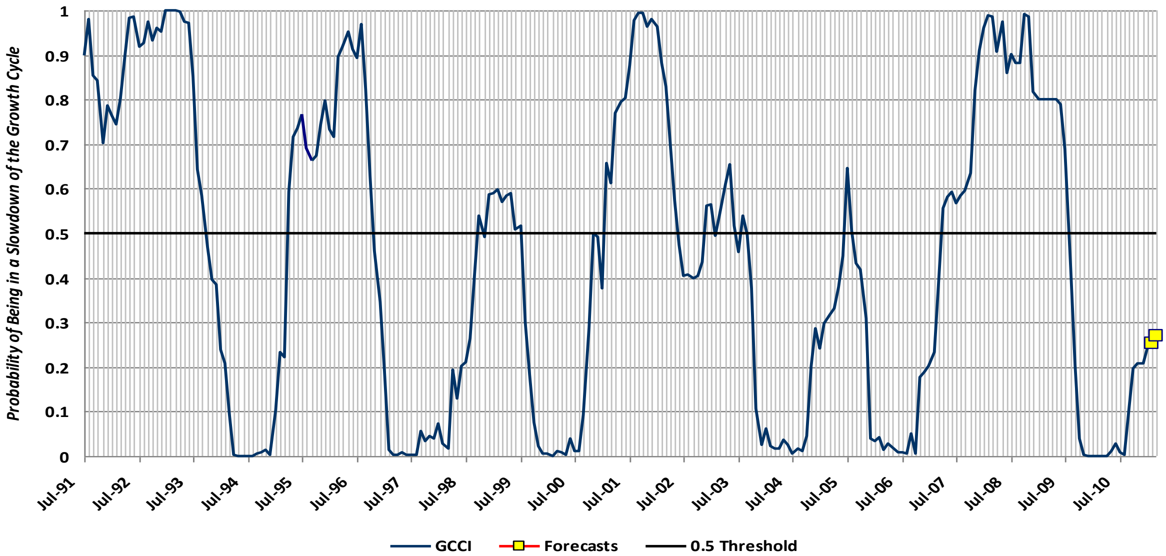
Figure 1: **The BCCI in the period from January 1991 to March 2011**



Source: Authors' calculations

Note that this behaviour is not in line with the ABCD approach for which a trough of the growth cycle should be preceded by one of the business cycle. Several explanations are possible: from an economic standpoint the euro area economy might have entered in a double-dip phase, i.e. a growth cycle fluctuation without a business cycle fluctuation, an event occurred only in the period 1980-82. Alternatively, this inconsistency can be due to the lagging behaviour of the BCCI with respect to the GCCI. Finally, another, more statistical explanation, could be that, since the set of data used for both indicators is not uniform and they are computed independently from each other, the fulfilment of the ABCD sequence is not ensured.

Figure 2: **The GCCI in the period from July 1991 to March 2011**



Source: Authors' calculations

4. Design of experiment for the multivariate approach

The multivariate approach presented here allows a direct and joint derivation of a pair of turning point indicators for the business cycle and the growth cycle respectively. It consists in a multivariate Markov-switching model fitted to a common set of time-series. Then, the filtered probabilities stemming from the estimation procedure are used to compute both the indicators simultaneously by summing up the filtered probabilities belonging to the distinct regimes. The final result is a pair of non-overlapping recession/slowdown probabilities for both the classical business cycle and the growth cycle.

The selection of the final multivariate Markov-switching setup depends on several aspects: first the set of time series to be included as endogenous variables in the model; second, the order of differentiation to apply to each series; third, the combination of series to consider in the model; forth, the specification of the Markov-switching model. As selection criteria among the set of the huge amount of all possible model specifications, we adopt a set of statistics to determine the best solution through an automatic screening procedure.

Data

Only six out of the seven time-series currently used in the construction of the BCCI and GCCI of previous sections, i.e. IPI, UR, NPCR, INDEA7, BUIEA99 and CONSEA1 are retained in the multivariate exercise. The series of imports of intermediate goods (component of the GCCI) is excluded. This is due to its lack of timeliness, since the release of month t refers to month t – 3 in contrast to the rest of the series, whose delay is only of one or two months with respect to the reference month.

Differentiation

As in the univariate approach these set of series are not considered in their levels but are subject to transformation. Depending on whether the time-series is one belonging to the real economy (IPI, UR and NPCR) or to a survey (INDEA7, BUIEA99, CONSEA1), the growth rate or difference over 1, 3, 6, 9 and 12 months are taken, respectively. A particular case is represented by the Unemployment Rate, in fact, in that case, due to the nature of the time-series such that an increase (decrease) in the rate of unemployment should increase (decrease) the probability of being in recession, the inverted difference over 1, 3, 6, 9 and 12 months are taken instead of the growth rate as for the other two time-series representing the real-economy.

Combination of time-series

Furthermore, to get a deeper understanding of the contribution given by each time-series, the six selected time-series are not bundled together once and for all in each Markov-switching model; but, they are taken two-by-two, three-by-three, four-by-four, five-by-five and, finally, the six ones altogether. However, as the IPI component is present in both the BCCI and GCCI, this time-series is included in each n-uple above. As an example, consider the case in which the six time-series are taken three-by-three: the total number of unordered distinct triples that can be obtained by taking six time-series three-by-three is given by the combinations without repetitions of six elements taken three-by-three; however, as we keep fixed one element, namely the IPI time-series, the cases in the example shrink to the combinations without repetitions of five elements taken two-by-two.

Markov-switching specification

Finally, six Markov-switching models are fitted to each of the cases listed above. In the light of the results of our own previous researches as well as of the economic literature on the business cycle, we restrict the specifications considered to multivariate Markov-switching (MS) models with an autoregressive polynomial of order 0 (nevertheless some dynamic is induced through the latent variable), whose intercept term (denoted with the capital letter I) is function of the latent state-variable and that could allow or not for state-dependent heteroskedasticity (Markov-switching models that allow for state-dependent heteroskedasticity are labelled with H).

Note that, in the literature as well as in our own experience, it has been proved that Markov-switching models with autoregressive polynomial with an order higher than 0 are less able to detect turning points than models without autoregressive component. As for the latent state-variable (K), this is a Markov chain of the first order whose discrete domain is limited to 3, 4 and 5 regimes; actually, on one hand, a 2-regime state variable has resulted adequate when dealing with the growth cycle rather than with the classical business cycle and, even if it were not the case, there is no room to jointly derive a pair of coincident indicators, one for each cycle, from a 2-regime state variable. On the other hand, a higher number of states, that is more than 5 regimes, is redundant, adding nothing in terms of economic interpretation.

All in all, in the class of Markov-switching models, we focus only on the following six multivariate specifications:

i. MSI(3)–VAR(0)

ii. MSIH(3)–VAR(0)

iii. MSI(4)–VAR(0)

iv. MSIH(4)–VAR(0)

v. MSI(5)–VAR(0)

vi. MSIH(5)–VAR(0)

Total number of model estimates

To summarise, having fixed the number of time-series to group together as endogenous variables (Nr. Components), by combining the five data transformations and the six model specifications considered, the whole number of cases that results can be computed applying formula (1):

$$\binom{Nr.Time-series-1}{Nr.Components-1} \times Nr.Tranformations^{Nr.Components} \times Nr.Models, \tag{1}$$

where *Nr. Time-series* is equal to 6, that is, to all the time-series considered in this report. By subtracting one to both the Nr. Time-series and Nr. Components, we take into account the fact that, as previously stated, the IPI is included in every n-tuple. In total the number of Markov-switching models to fit to the respective set of endogenous time-series is equal to 233,250. Estimation is carried out through the Expectation Maximization (EM) algorithm.

Definition of recession probabilities

First, we examine the case of a 3-regime Markov-switching model; in this case, in order to obtain two distinct coincident indicators the researcher has no choice: remembering that the regimes of the latent variable are sorted in ascending order according to the sign of the respective intercept term, filtered probabilities of the first regime are assumed to be the probabilities of being in a recession of the classical business cycle. It follows that, probabilities of being in a recession of the growth cycle (hereafter referred to as slowdown) are defined as the sum of the filtered probabilities of regimes 1 and 2, where the second regime is usually characterised by a negative sign in the intercept.

When the number of states of the latent variable is greater than 3, the issue is not so straightforward. Indeed, when the cardinality of the hidden Markov chain is equal to 4 the following pairs of possibilities are considered:

business cycle recession probabilities	=	regime 1 filtered probabilities	
growth cycle recession probabilities	=	regime 1 filtered probabilities + regime 2 filtered probabilities	(2)

business cycle recession probabilities	=	regime 1 filtered probabilities + regime 2 filtered probabilities	
growth cycle recession probabilities	=	regime 1 filtered probabilities + regime 2 filtered probabilities + regime 3 filtered probabilities	(3)

In the same fashion, besides the possibilities above listed, in the case of a latent variable with cardinality 5, which is the highest number here considered, there is one more alternative:

business cycle recession probabilities	=	regime 1 filtered probabilities + regime 2 filtered probabilities + regime 3 filtered probabilities	
growth cycle recession probabilities	=	regime 1 filtered probabilities + regime 2 filtered probabilities + regime 3 filtered probabilities + regime 4 filtered probabilities	(4)

Although a-priori we expect that the last pair of coincident indicators is not very probable, we do not exclude this case in the experiment.

In a further step, these recession probabilities are used to obtain a set of binary signals of whether the euro area economy is experiencing or not a recession of the classical business cycle. To verify this hypothesis, we assume the ‘0.5 natural’ decision rule advocated by Hamilton: if recession probabilities are above the 0.5 threshold a recession signal (1) is emitted, whereas a no recession signal (0) is returned otherwise.

Finally, these signals are used to derive a historical sequence or turning points of both the classical business and growth cycle to be compared with the respective reference dating chronology. No further censoring rule is applied.

Selection criteria

To conclude this section, we present the criteria which will be used to select among the huge number of alternatives listed above. As in previous works on this topic, we consider the QPS by Score of Brier (1950) and the Concordance Index by Harding and Pagan (2002).

Moreover, in order to avoid the occurrence of lagging coincident indicators with respect to the reference chronologies, we explicitly take into account two more statistics: the first one (hereafter referred to as Lags) counts the number of months by which the turning points sequence stemming from a given Markov-switching model estimated here lags behind the reference dating chronology. According to its definition, this statistic assesses by how many months the peaks located by the coincident indicator are delayed with respect to the ones pinpointed by the reference dating chronology.

Nevertheless, if we are considering only this statistic we could incur in the error of selecting a model that is not lagging the reference dating but that returns a high number of false recession signals. Consider then the paradoxical situation of a model that conveys a recession signal throughout the whole sample: in this case, the count of the lags is zero, but the model is clearly unable to deal with economic cycles. To avoid such a misleading situation, a second statistic is introduced (hereafter referred to as Excess): it counts the number of months for which a Markov-switching model does emit a recession signal, while the reference chronology does not. According to its definition this statistic takes into account by how many months the troughs obtained from a coincident indicator lag behind the trough dates of the reference dating chronology. However, it should be stressed that this statistic increases as a false recession signal is emitted by the coincident indicator and therefore it is unable to separate out this feature from the lags of the troughs.

Before moving to next section devoted to implementation and results, it is worth noting that throughout this work, two classes of reference dating chronologies are adopted and used as benchmark to compute the statistics described above. As in our previous works, we consider the (final) dating chronologies of the classical business and growth cycle proposed in Anas et al. (2007); in such a way we can build a link between the present paper and previous works.

These dating chronologies are final in the sense that they are not subject to revisions in the future. However, these dating chronologies are limited to the time horizon between 1971 and 2002, therefore they are not useful to assess the ability of multivariate Markov-switching models in picking out turning points of the last recession for both the classical business and growth cycles. In order to overcome this problem, each (final) dating chronology is merged with a provisional dating chronology that tracks down the turning points of either the classical business or growth cycles, respectively.

As for the provisional dating chronology of the growth cycle, in the period not covered by the (final) dating chronology, it locates a trough (D) in August 2003 and a peak (A) in February 2008. Concerning the provisional dating chronology of the classical business cycle, it pinpoints a peak (B) in February 2008.

It should be stressed that, the hedge effect by which the non-parametric procedure used in the historical dating process is affected, could explain the fact that the following troughs of either the classical business cycle (C) or growth cycles (D) have not been detected yet.

5. Implementation of the multivariate approach and results

In detail, the automatic screening procedure is the following: for each case we compute the QPS, Concordance Index, Lag and Excess statistics both with respect to the classical business cycle and growth cycle final dating chronologies. The resulting figures are compared with the same statistics estimated for the two benchmarks given respectively by the univariate BCCI and GCCI of sections 2 and 3.

Finally, we select the cases for which either the Lag and/or Excess statistics are less or equal to the ones estimated for the BCCI and GCCI. Of course the analysis is carried out also with respect to the QPS and Concordance Index. All the comparisons are referred to the final dating chronology, as well as to the one obtained merging the final and the provisional dating chronologies.

It must be stressed that, as previously noted, the three surveys time-series are available since January 1985, while on the contrary the IPI, Unemployment Rate and New Passenger Car Registrations time-series have been historically reconstructed back to January 1971. It follows that, as we use a multivariate Markov-switching model, we are constrained by the time-series with the least number of observations. This means that we are forced to neglect all the observations of IPI, Unemployment Rate and New Passenger Car Registrations before 1985 and therefore all the models are estimated taking the common sample to all the six time-series, which starts in January 1985. For ease of comparison, this limitation is voluntarily applied also to the multivariate models that do not include any surveys.

However, by constraining the estimation sample to start in 1985, we endanger the significance of the four statistics computed for the coincident indicator of the classical business cycle. This is because, the (final) reference dating chronology adopted for the classical business cycle locates only one recession between 1985 and 2002, namely the one occurred in 1992–1993. Note that the growth cycle contains five recessions in the same time frame.

In order to partly overcome this significance issue, a second benchmark is introduced for coincident indicator of the classical business cycle, namely the aforementioned provisional reference chronology. For ease of comparison, also for the coincident indicator of the growth cycle a provisional dating chronology is used as benchmark to compute the four considered statistics.

Table 1: Selected coincident indicators of both the classical business cycle and growth cycle

Model	MS-VAR BCCI					MS-VAR GCCI				
	Recession Proba-bilities	QPS	CI	Lag	Excess	Recession Proba-bilities	QPS	CI	Lag	Excess
September 2009 Indicators	–	0.077	0.919	7	10	–	0.146	0.797	24	4
IPI(3),UR(1),BUIEA99(1) MSIH(4)-VAR(0)	R1	0.060	0.939	5	8	R1+R2	0.133	0.826	16	8
IPI(3),UR(1),INDEA7(1),BUIEA99(1) MSIH(5)-VAR(0)	R1	0.059	0.938	5	8	R1+R2	0.166	0.804	24	3
IPI(6),UR(1),NPCR(3),INDEA7(1) MSIH(4)-VAR(0)	R1	0.044	0.952	6	4	R1+R2	0.166	0.797	24	4
IPI(6),UR(3),NPCR(12),INDEA7(3)BUIEA99(3) MSI(5)-VAR(0)	R1+R2	0.059	0.941	4	8	R1+R2+R3	0.183	0.790	26	3
IPI(3),UR(1),NPCR(1),INDEA7(1)BUIEA99(1) MSIH(5)-VAR(0)	R1	0.060	0.939	5	8	R1+R2	0.112	0.884	11	5
IPI(6),UR(1),NPCR(1),INDEA7(1)BUIEA99(1) MSIH(5)-VAR(0)	R1	0.041	0.957	5	4	R1+R2	0.144	0.833	17	6

Note: Reported statistics are computed with respect of the final dating chronologies of the classical business cycle and growth cycle, respectively.
Source: Authors' calculations

Therefore, two sets of statistics are provided: the first set contains the statistics computed when the final dating chronologies are used as benchmark (Table 1); while the second one includes the same statistics compiled when the dating chronologies adopted as benchmark are generated by merging the final and the provisional dating chronologies (Table 2).

Each table gives a picture of most significant coincident indicators derived by using 3, 4 and 5 time-series as endogenous variables of the multivariate Markov-switching models. In both tables the first column provides the model specification; columns from 2 to 6 deal with the coincident indicator of the classical business cycle (hereafter referred to as $_{\text{MS-VAR}}$BCCI), while columns from 7 to 11 deal with the coincident indicator of the growth cycle (hereafter referred to as $_{\text{MS-VAR}}$GCCI). In each group of columns, the first column explains which regimes of the latent variable are used to obtain the recession probabilities, the second reports the QPS, the third lists the Concordance Index, the fourth and fifth columns show the Lag and Excess statistics, respectively. The first row of each table reports the statistics computed for the univariate coincident indicators (BCCI and GCCI) computed in September 2009.

Table 2: **Selected coincident indicators of both the classical business cycle and growth cycle**

Model	$_{\text{MS-VAR}}$BCCI					$_{\text{MS-VAR}}$GCCI				
	Recession Proba-bilities	QPS	CI	Lag	Excess	Recession Proba-bilities	QPS	CI	La g	Excess
September 2009 Indicators	–	0.077	0.919	13	10	–	0.146	0.797	36	8
$_{\text{IPI(3),UR(1),BUIEA99(1)}}$MSIH(4)-VAR(0)	R1	0.051	0.949	7	8	R1+R2	0.114	0.853	21	16
$_{\text{IPI(3),UR(1),INDEA7(1),BUIEA99(1)}}$MSIH(5)-VAR(0)	R1	0.050	0.949	7	8	R1+R2	0.141	0.825	33	7
$_{\text{IPI(6),UR(1),NPCR(3),INDEA7(1)}}$MSIH(4)-VAR(0)	R1	0.046	0.952	10	17	R1+R2	0.141	0.827	29	17
$_{\text{IPI(6),UR(3),NPCR(12),INDEA7(3)BUIEA99(3)}}$MSI(5)-VAR(0)	R1+R2	0.051	0.947	7	8	R1+R2+R 3	0.164	0.806	32	23
$_{\text{IPI(3),UR(1),NPCR(1),INDEA7(1)BUIEA99(1)}}$MSIH(5) -VAR(0)	R1	0.050	0.949	7	8	R1+R2	0.182	0.795	32	28
$_{\text{IPI(6),UR(1),NPCR(1),INDEA7(1)BUIEA99(1)}}$MSIH(5) -VAR(0)	R1	0.041	0.958	8	4	R1+R2	0.161	0.813	22	27

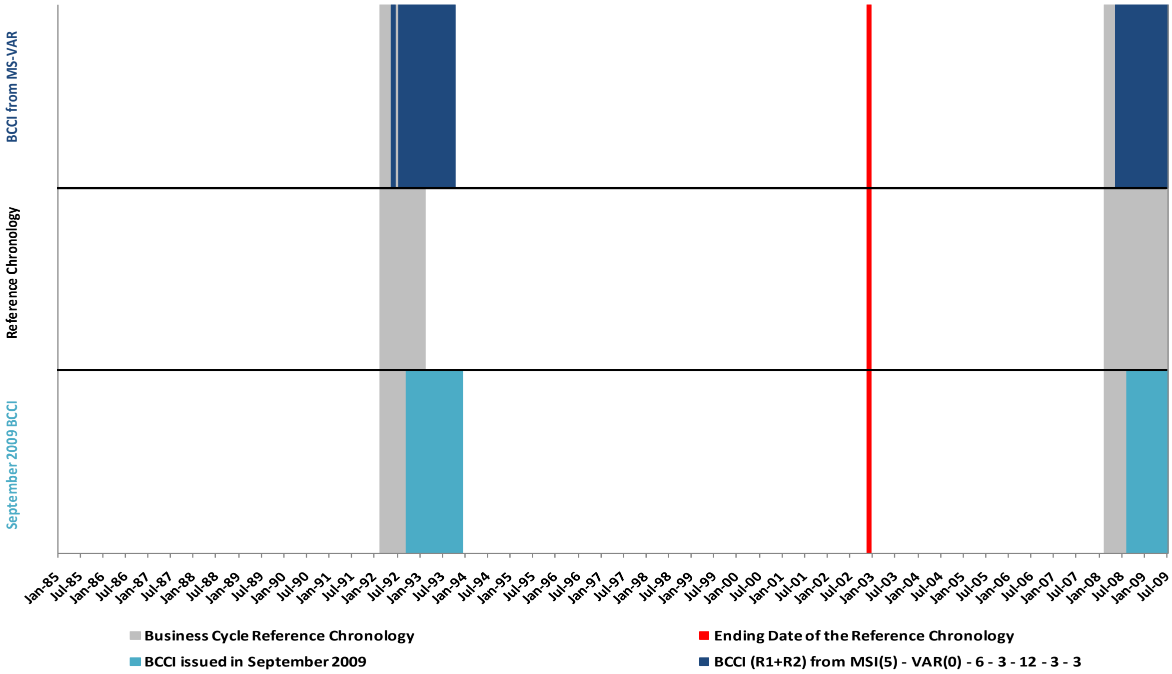
Note: Reported statistics are computed with respect of the merged (= final merged with provisional) dating chronologies of the classical business cycle and growth cycle, respectively.
Source: Authors' calculations

Note that the model specification of the first column follows a shorthand notation. As an example, consider the first $_{\text{MS-VAR}}$BCCI contained in Table 1 above: we denote with $_{\text{IPI(3),UR(1),BUIEA99(1)}}$MSIH(4)–VAR(0)$^{\text{BCCI:R1}}$ the coincident indicator of the classical business cycle obtained by the regimes 1 filtered probabilities stemming from the MSIH(4)–VAR(0) model fitted to the 3-month growth rate of the IPI, the inverted difference over 1 month of the UR and the difference over 1 month of the BUIEA99. The coincident indicator of the growth cycle is labelled as $_{\text{IPI(3),UR(1),BUIEA99(1)}}$MSIH(4)–VAR(0)$^{\text{GCCI:R1+R2}}$, where the only difference with respect to the coincident indicator of the classical business cycle is in the superscript GCCI:R1+R2, which denotes that the coincident indicator of the growth cycle is obtained by adding regime 1 and regime 2 filtered probabilities.

Concerning the classical business cycle as it is expressed by the final dating chronology, all the coincident indicators but one return a sum of the Lag and Excess statistics lower than the corresponding sums for the BCCI computed in September 2009. All the 6 coincident indicators reported in the tables above, have QPS and Concordance Index lower and higher, respectively, than the corresponding statistics related to the September 2009 BCCI. Furthermore, they dominate the September 2009 BCCI both in terms of the Lag and Excess statistics. As a result these figures provide evidence in favour of the goodness of multivariate Markov-switching modelling to deal with the classical business cycle.

Looking at the growth cycle, as it is expressed in the final dating chronology, the picture is somewhat less satisfactory. In fact, 1 coincident indicator among the 6 cases of table 1 return a Lag statistic higher than the one related to the GCCI issued in September 2009, whereas 2 cases are characterised by an Excess statistic higher than the one of the September 2009 GCCI. Further in 1 case the sum of Lag and Excess statistics is higher than the September 2009 GCCI.

Figure 3: **Classical business cycle: recession phases derived from the IPI(6),UR(3),NPCR(12),INDEA7(3),BUIEA99(3)MSI(5)–VAR(0)BCCI:R1+R2 coincident indicator (upper panel) and from the BCCI actually computed in September 2009 (lower panel)**



Note: Recession phases of the classical business cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009
Source: Authors' calculations

Results for ${}_{IPI(6),UR(3),NPCR(12),INDEA7(3),BUIEA99(3)}MSI(5)–AR(0)$

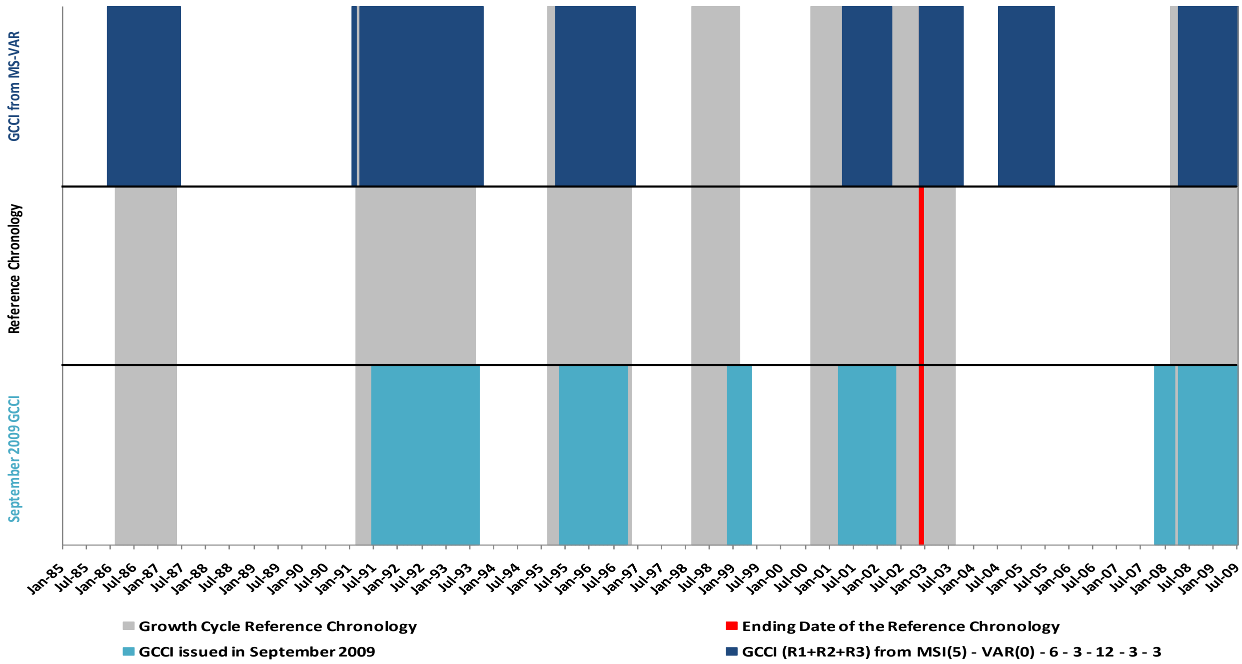
According to figures reported in Table 1, the ${}_{IPI(6),UR(3),NPCR(12),INDEA7(3),BUIEA99(3)}MSI(5)–AR(0)^{BCCI:R1+R2}$ coincident indicator returns a Lag statistic equal to 4, which represents a significant improvement with respect to 7 recorded by the September 2009 BCCI. Figure 3 represents the recessionary phases of the classical business cycle derived by applying the *0.5 'natural rule'* both to the ${}_{IPI(6),UR(3),NPCR(12),INDEA7(3),BUIEA99(3)}MSI(5)–VAR(0)^{BCCI:R1+R2}$ coincident indicator (upper panel) and to the BCCI actually computed in September 2009 (lower panel).

It is worth noting that the statistics we are commenting are computed adopting as benchmark the final dating chronology. Nonetheless, in Figure 3 we depict also the provisional dating chronology and defer to a later moment the presentation and discussion of the respective statistics.

Besides minimising the Lag statistic, the ${}_{IPI(6),UR(3),NPCR(12),INDEA7(3),BUIEA99(3)}MSI(5)–VAR(0)^{BCCI:R1+R2}$ coincident indicator, when compared to the BCCI released in September 2009, also improves all the three remaining statistics. In particular, the Excess statistic related to the former coincident indicator is equal to 8, whereas it is 10 for the latter one. Nevertheless, despite this improvement, the ${}_{IPI(6),UR(3),NPCR(12),INDEA7(3),BUIEA99(3)}MSI(5)–VAR(0)^{BCCI:R1+R2}$ coincident indicator still appears to be lagged with respect to the reference dating chronology. Once more, this statement is conditional to the fact that only one recession lies in the time horizon embraced by the analysis.

When we extend the reference dating chronology by incorporating the provisional dating, we can appreciate that both the ${}_{IPI(6),UR(3),NPCR(12),INDEA7(3),BUIEA99(3)}MSI(5)–VAR(0)^{BCCI:R1+R2}$ coincident indicator and the September 2009 BCCI identify the last recession of the classical business cycle. However, the latter coincident indicator detects with a delay of 6 months the date of the last peak, whereas the former is only 4-month lagged with respect to the reference dating chronology.

Figure 4: **Growth cycle: recession phases derived from the IPI(6),UR(3),NPCR(12),INDEA7(3),BUIEA99(3)MSI(5)–VAR(0)GCCI:R1+R2+R3 coincident indicator (upper panel) and from the GCCI actually computed in September 2009 (lower panel).**



Note: Recession phases of the growth cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009.
Source: Authors' calculations

Figure 4 repeats the same exercise as above for the case of the growth cycle. The upper panel depicts the recessionary phases of the growth cycle derived by applying the *0.5 'natural rule'* to the ${}_{IPI(6),UR(3),NPCR(12),INDEA7(3),BUIEA99(3)}MSI(5)\text{–}VAR(0)^{GCCI:R1+R2+R3}$ coincident indicator. The same decision rule is applied to the September 2009 GCCI and the resulting recessionary phases are represented in the lower panel of Figure 4.

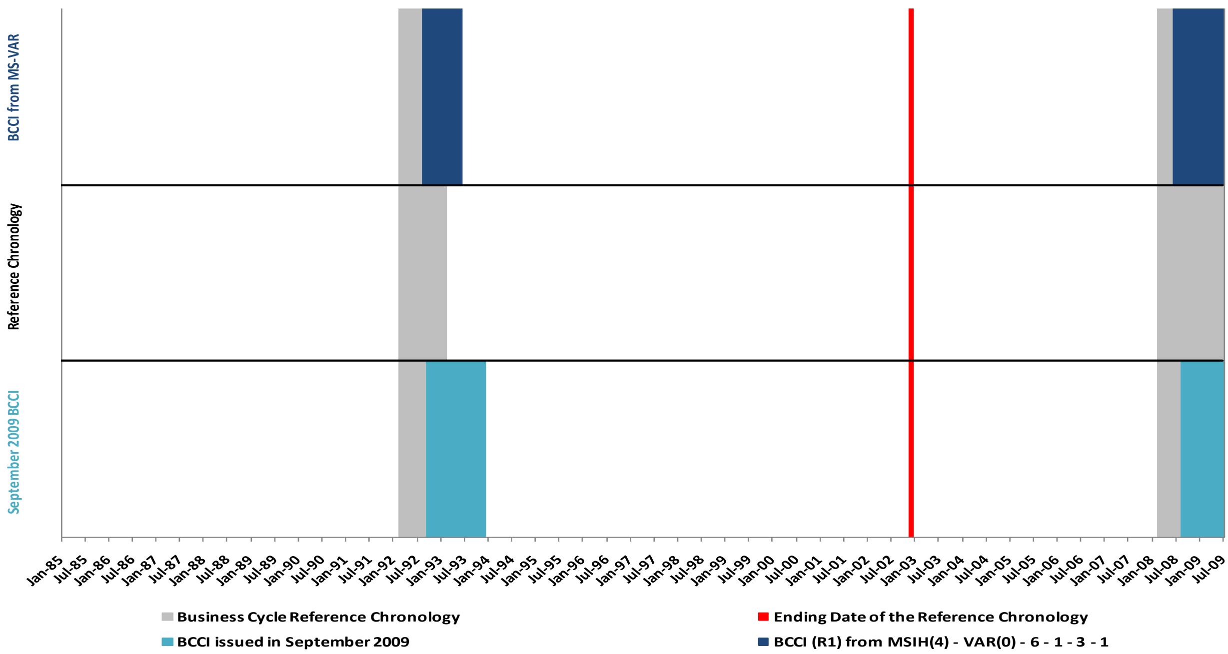
In this case, only one out of the four statistics is improved with respect to the GCCI computed in September 2009. In particular, the Lag statistic associated to the ${}_{IPI(6),UR(3),NPCR(12),INDEA7(3),BUIEA99(3)}MSI(5)\text{–}VAR(0)^{GCCI:R1+R2+R3}$ coincident indicator is equal to 26, while it is 24 for the September 2009 GCCI. Graphical inspection of **Error! Reference source not found.**4 allows us to explain these figures: ather than being a deterioration in the timely detection of the peaks of the growth cycle, it is the fact that the ${}_{IPI(6),UR(3),NPCR(12),INDEA7(3),BUIEA99(3)}MSI(5)\text{–}VAR(0)^{GCCI:R1+R2+R3}$ coincident indicator completely misses the slowdown between 1998 and 1999 which is the cause behind the poor performance in terms of the Lag statistic.

Furthermore, when we merge the final dating chronology with the provisional one, we see how the multivariate coincident indicator locates a false recession between August 2004 and September 2005. This increases the Excess statistic to 19, see table 2, compared to 8 of the September 2009 GCCI in the same period.

Results for ${}_{IPI(6),UR(1),NPCR(3),INDEA7(1)}$MSIH(4)–VAR(0)

We then present the ${}_{IPI(6),UR(1),NPCR(3),INDEA7(1)}$MSIH(4)–VAR(0)$^{BCCI:R1}$ coincident indicator, as it minimises the Excess statistic to 4 months. As no false recession signals are emitted neither from the September 2009 BCCI, this improvement can be explained with the increased timeliness in locating the only trough of the classical business cycle within the time frame considered. This feature clearly emerges by comparing the upper and lower panels of Figure 5.

Figure 5: Classical business cycle: recession phases derived from the IPI(6),UR(1),NPCR(3),INDEA7(1)MSIH(4)–VAR(0)BCCI:R1 coincident indicator (upper panel) and from the BCCI actually computed in September 2009 (lower panel).



Note: Recession phases of the classical business cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009.
Source: Authors' calculations

While minimising the Excess statistic, the ${}_{IPI(6),UR(1),NPCR(3),INDEA7(1)}$MSIH(4)–VAR(0)$^{BCCI:R1}$ coincident indicator also improves, although of only 1 month, the timeliness in detecting the only peak of the final dating chronology. Indeed, the Lag statistic related to the ${}_{MS\text{-}VAR}$BCCI is equal to 6, whereas it is 7 for the September 2009 BCCI.

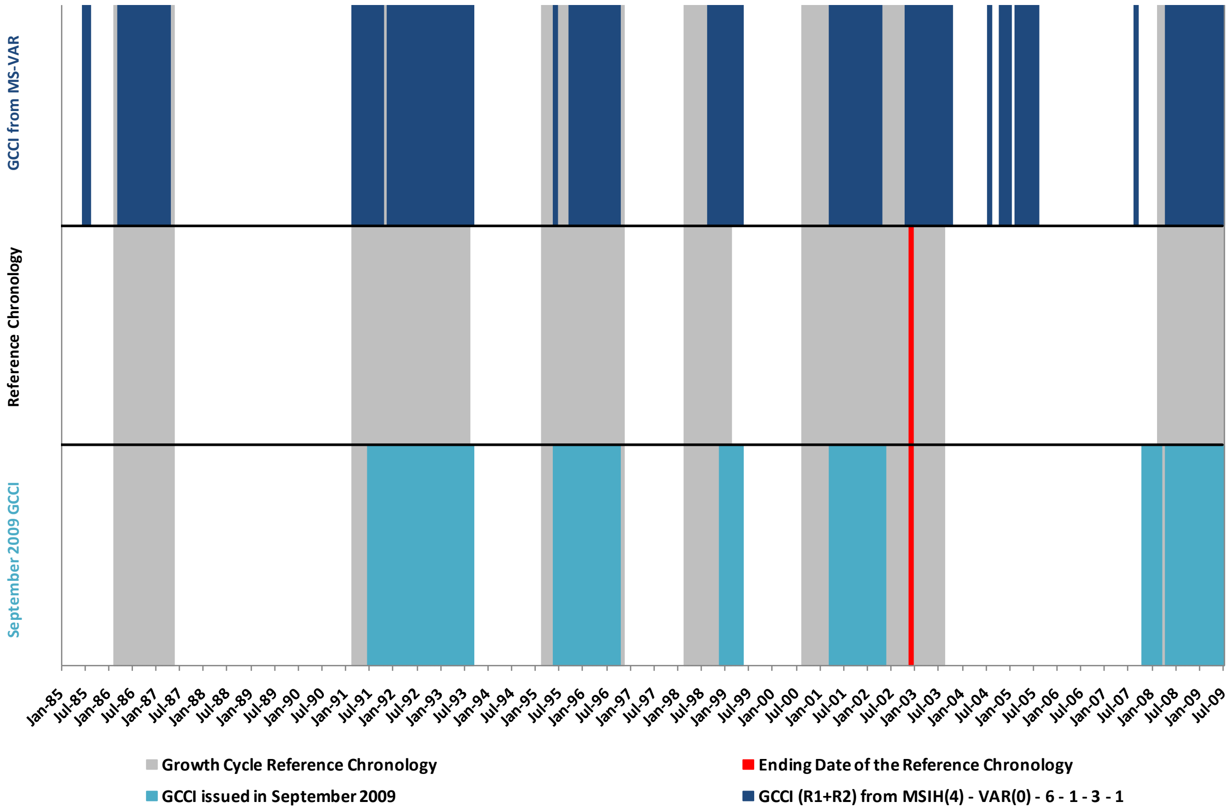
When we take into consideration the longer reference dating chronology with the provisional one, table 2, the Lag statistic belonging to the ${}_{IPI(6),UR(1),NPCR(3),INDEA7(1)}$MSIH(4)–VAR(0)$^{BCCI:R1}$ model rises to 10, as this latter model detects with four months of delay the last peak of the classical business cycle. Nevertheless, as far as the detection of the peaks of the classical business cycle is concerned, the ${}_{MS\text{-}VAR}$BCCI still has a greater timeliness than the September 2009 BCCI, whose Lag statistic is equal to 13.

Concerning the growth cycle, the ${}_{IPI(6),UR(1),NPCR(3),INDEA7(1)}$MSIH(4)–VAR(0)$^{GCCI:R1+R2}$ coincident indicator returns the same values as the September 2009 GCCI for both the Lag and Excess statistics, namely 24 and 4, respectively. Nevertheless, by graphical inspection of Figure 6, it appears that the two coincident indicators are not matching.

The coincidence of statistics does not hold anymore when the provisional dating chronology is included in the analysis: on one hand, the Lag statistic of the ${}_{IPI(6),UR(1),NPCR(3),INDEA7(1)}$MSIH(4)–VAR(0)$^{GCCI:R1+R2}$ coincident indicator increases from 24 to 29, while it rises to 36 for the September

2009 GCCI; on the other hand, the Excess statistic increases from 4 to 17 and to 8 for the ${}_{\text{IPI(6),UR(1),NPCR(3),INDEA7(1)}}\text{MSIH(4)–VAR(0)}^{\text{GCCI:R1+R2}}$ coincident indicator and September 2009 GCCI, respectively. This is due to the fact that, as it appears from Figure 6, the former coincident indicator identifies a false recession between November 2004 and August 2005.

Figure 6: **Growth cycle: recession phases derived from the IPI(6),UR(1),NPCR(3),INDEA7(1)MSIH(4)–VAR(0)GCCI:R1+R2 coincident indicator (upper panel) and from the GCCI actually computed in September 2009 (lower panel).**

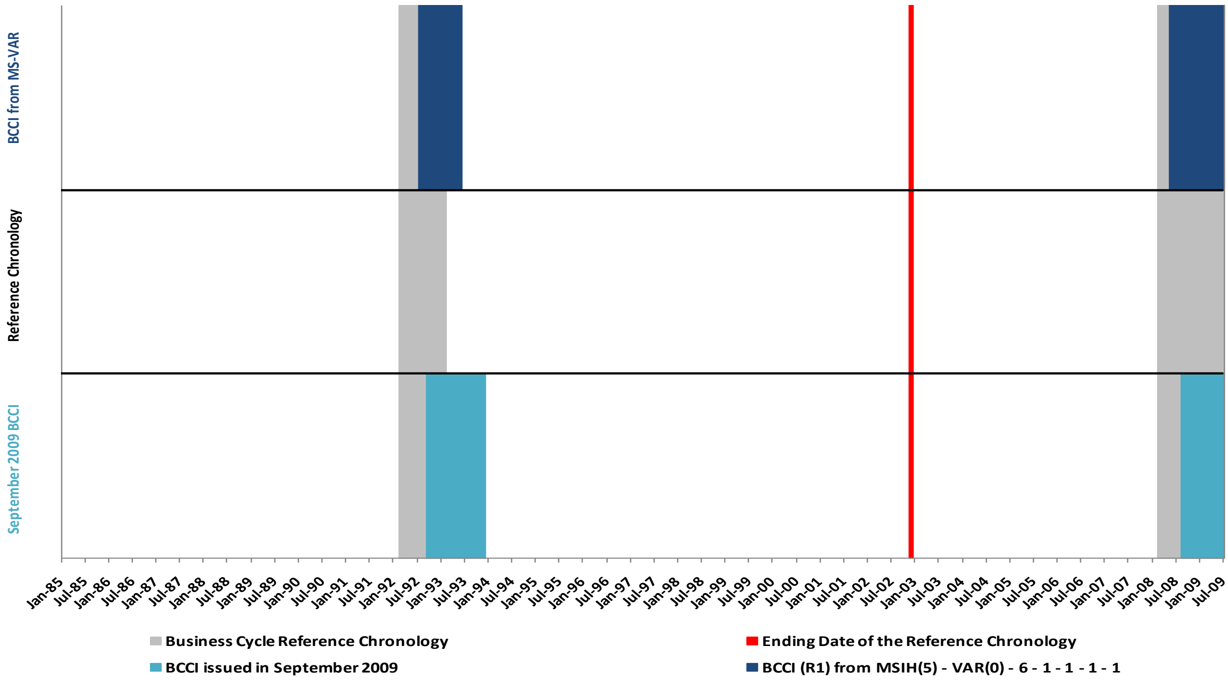


Note: Recession phases of the growth cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009.
Source: Authors' calculations

Results for ${}_{\text{IPI(6),UR(1),NPCR(1),INDEA7(1),CONSEA1(1)}}\text{MSIH(5)–VAR(0)}$

The ${}_{\text{IPI(6),UR(1),NPCR(1),INDEA7(1),CONSEA1(1)}}\text{MSIH(5)–VAR(0)}^{\text{BCCI:R1}}$ coincident indicator returns the highest Concordance Index, the lowest QPS, and the lowest sum of Lag and Excess in both the dating chronologies of table 1 and 2. Further, Figure 7 shows how the ${}_{\text{IPI(6),UR(1),NPCR(1),INDEA7(1),CONSEA1(1)}}\text{MSIH(5)–VAR(0)}^{\text{BCCI:R1}}$ coincident indicator is more timely than the September 2009 BCCI in detecting the peaks of both the 1992–1993 recession and also of the last recession; it also reduces the delay in locating the sole trough of the classical business cycle.

Figure 7: **Classical business cycle: recession phases derived from the IPI(6),UR(1),NPCR(1),INDEA7(1),CONSEA1(1)MSIH(5)–VAR(0)BCCI:R1 coincident indicator (upper panel) and from the BCCI actually computed in September 2009 (lower panel).**



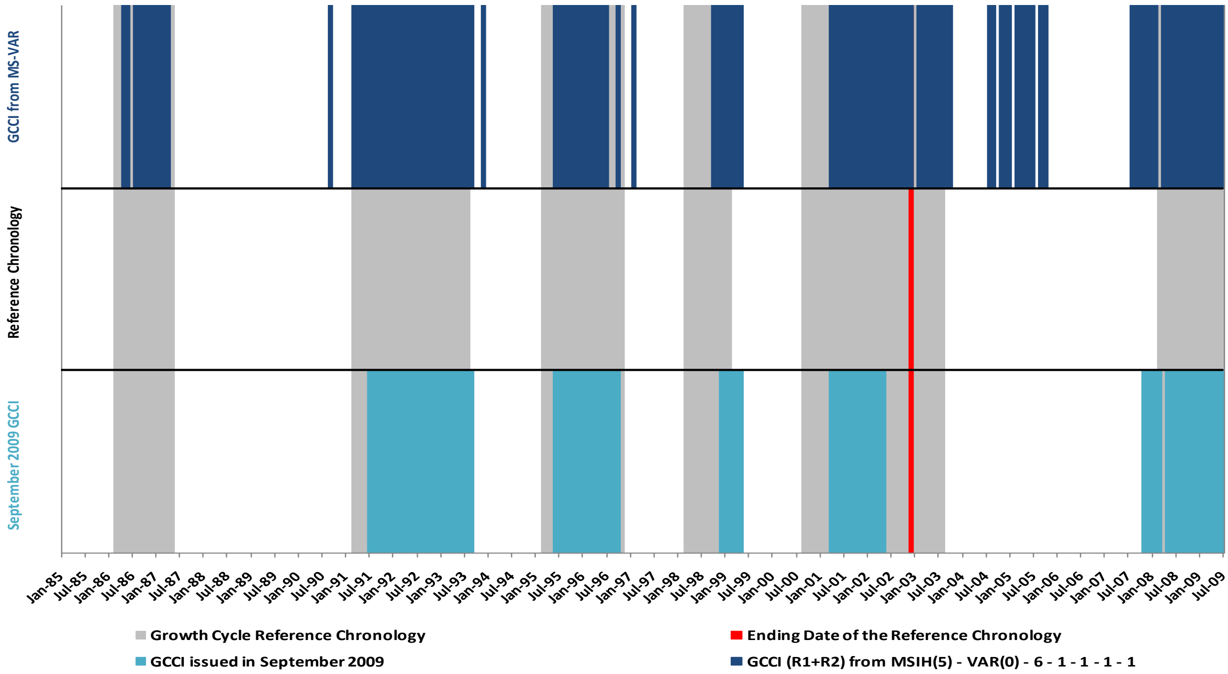
Note: Recession phases of the classical business cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009.
Source: Authors' calculations

The behaviour of the growth cycle is analysed in Figure 8. It turns out that the ${}_{IPI(6),UR(1),NPCR(1),INDEA7(1),CONSEA1(1)}MSIH(5)\text{–}VAR(0)^{GCCI:R1+R2}$ is more timely than the September 2009 GCCI as far as the detection of the peaks of the growth cycle is concerned. In fact, the Lag statistic associated to the former coincident indicator is 17 while it is 24 for the latter one. On the contrary, the Excess statistic returned by the ${}_{MS\text{-}VAR}GCCI$ is slightly higher than the one of the September 2009 GCCI, namely 6 versus 4.

These features are magnified when the provisional dating chronology is merged to the final one. As for the Lag statistic, it increases to 22 for the ${}_{IPI(6),UR(1),NPCR(1),INDEA7(1),CONSEA1(1)}MSIH(5)\text{–}VAR(0)^{GCCI:R1+R2}$ coincident indicator and to 36 for the September 2009 GCCI.

Concerning the Excess statistic, the effect is even more pronounced, indeed, the figure referred to the ${}_{MS\text{-}VAR}GCCI$ skyrockets to 27, while the value related to the September 2009 GCCI rises to 8. In the same fashion as for the previous coincident indicators derived in the multivariate modelling framework, this last effect is due to the fact that the ${}_{IPI(6),UR(1),NPCR(1),INDEA7(1),CONSEA1(1)}MSIH(5)\text{–}VAR(0)^{GCCI:R1+R2}$ coincident indicator identifies a recession between 2004 and 2005, which is not located in the provisional reference chronology.

Figure 8: Growth cycle: recession phases derived from the IPI(6),UR(1),NPCR(1),INDEA7(1),CONSEA1(1)MSIH(5)–VAR(0)GCCI:R1+R2 coincident indicator (upper panel) and from the GCCI actually computed in September 2009 (lower panel).



Note: Recession phases of the growth cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009.
Source: Authors' calculations

Results for $_{IPI(3),UR(1),INDEA7(1),BUIEA99(1)}$MSIH(5)–VAR(0)

As for the Excess statistic, its lowest value among all the cases considered is returned by the $_{IPI(3),UR(1),INDEA7(1),BUIEA99(1)}$MSIH(5)–VAR(0)$^{GCCI:R1+R2}$ coincident indicator.

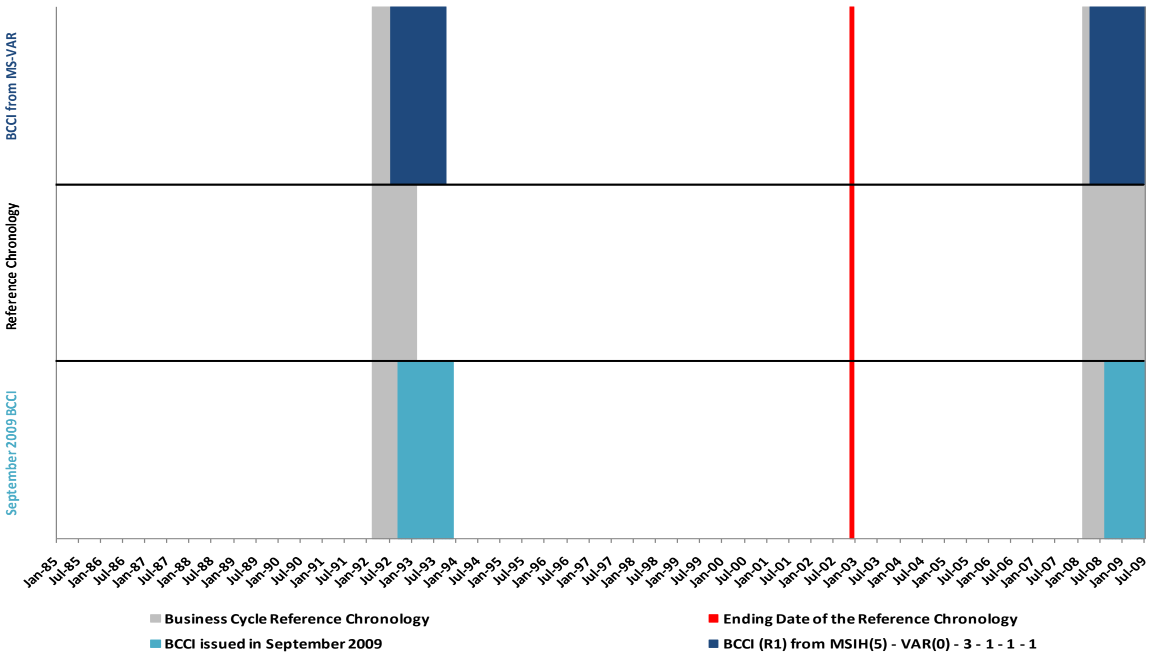
However, for ease of comparison with the above discussion, we first deal with the classical business cycle. Like in the previous analysis, in the upper panel of Figure 9 we present the recession phases derived from the coincident indicator stemming from the multivariate Markov-switching model here studied; in the same fashion, recession phases from the BCCI computed in September 2009 are depicted in the lower panel.

Lag statistic for the $_{IPI(3),UR(1),INDEA7(1),BUIEA99(1)}$MSIH(5)–VAR(0)$^{BCCI:R1}$ coincident indicator is equal to 5 (table 1) and 7 (table 2), when confronted with the final and merged dating chronologies, respectively. They are 7 and 13 for the September 2009 BCCI. This is the result of the greater timeliness of the $_{MS\text{-}VAR}$BCCI in detecting the recession of the final dating chronology as well as the last recession of the classical business cycle included in the provisional dating chronology.

Also the Excess statistic related to the $_{IPI(3),UR(1),INDEA7(1),BUIEA99(1)}$MSIH(5)–VAR(0)$^{BCCI:R1}$ coincident indicator is lower than the one associated to the September 2009 BCCI, namely 8 versus 10 for both reference dating chronologies of tables 1 and 2.

As both the Lag and Excess statistics of the $_{IPI(3),UR(1),INDEA7(1),BUIEA99(1)}$MSIH(5)–VAR(0)$^{BCCI:R1}$ coincident indicator are lower than the ones of the September 2009 BCCI, it is not surprising that the same relation is true for both the QPS and Concordance Index statistics.

Figure 9: **Classical business cycle: recession phases derived from the IPI(3),UR(1),INDEA7(1),BUIEA99(1)MSIH(5)–VAR(0) coincident indicator (upper panel) and from the BCCI actually computed in September 2009 (lower panel).**

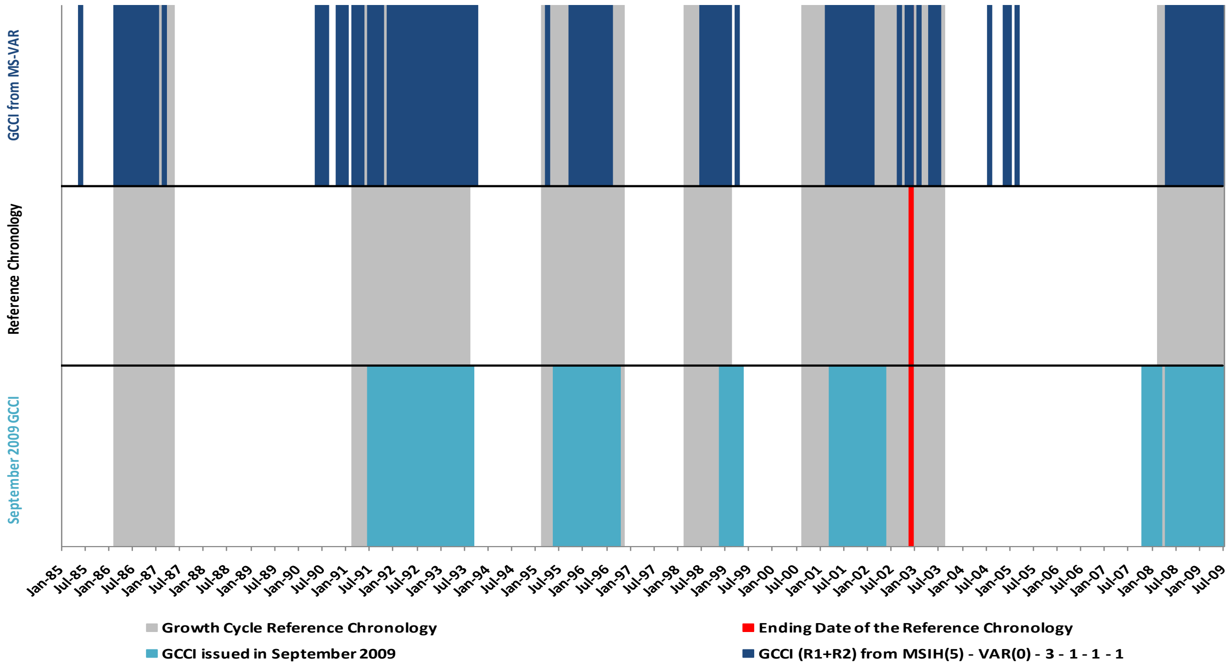


Note: Recession phases of the classical business cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009.
Source: Authors' calculations

Figure 10 finally deals with the growth cycle. In order to better grasp the insight given by Figure 10 we also provide the values of Lag and Excess statistics. Consider first the final dating chronology, when compared to the September 2009 GCCI, the ${}_{IPI(3),UR(1),INDEA7(1),BUIEA99(1)}$MSIH(5)–VAR(0)$^{GCCI:R1+R2}$ coincident indicator returns values for both the Lag and Excess statistics that are at least equal to ones provided by the September 2009 GCCI, namely 24 and 3 versus 24 and 4 (table 1). When the final dating chronology is extended with the provisional one, the gap in terms of the Lag statistic between the ${}_{MS\text{-}VAR}$GCCI and the September 2009 GCCI widens; indeed the Lag and Excess statistics are 33 and 7 versus 36 and 8, respectively.

Despite the fact that the observed improvement is not very noticeable, it must be stressed that, contrary to the cases previously listed, it is the only multivariate model which outperforms for all four statistics considered the BCCI and GCCI computed in September 2009.

Figure 10: Growth cycle: recession phases derived from the IPI(3),UR(1),INDEA7(1),BUIEA99(1)MSIH(5)–VAR(0)GCCI:R1+R2 coincident indicator (upper panel) and from the GCCI actually computed in September 2009 (lower panel).



Note: Recession phases of the growth cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009.
Source: Authors' calculations

As far as the growth cycle is concerned, this achievement is explained by the fact that, contrary to all the Markov-switching models previously examined, the $_{\text{IPI(3),UR(1),INDEA7(1),BUIEA99(1)}}$MSIH(5)–VAR(0) one emits only a few of short-lived (at most of 2-month duration) recession signals in the period 2004–2005. Due to their short-lived duration, these recession signals can be ruled out by applying a simple censoring rule.

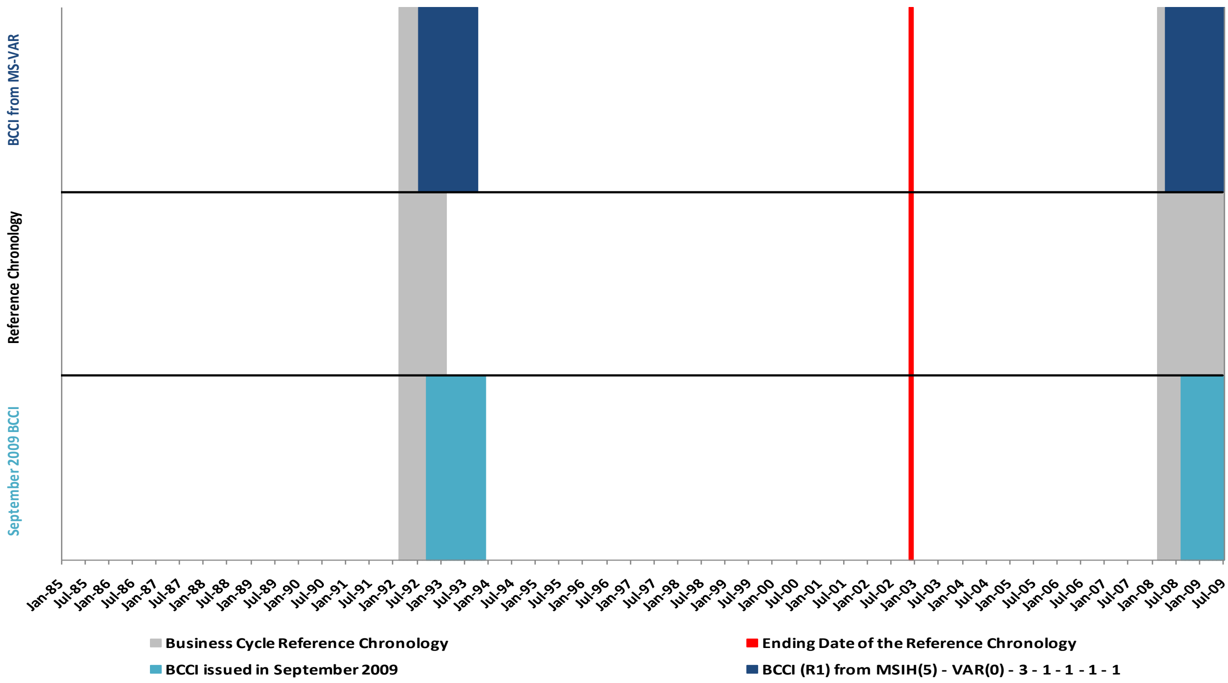
Results for $_{\text{IPI(3),UR(1),NPCR(1),INDEA7(1),BUIEA99(1)}}$MSIH(5)–VAR(0)

If we relax the constraint on the Excess statistic and accept values higher than the one returned by the September 2009 GCCI, the coincident indicator that minimises the Lag statistic with respect to the merged dating chronology is the $_{\text{IPI(3),UR(1),NPCR(1),INDEA7(1),BUIEA99(1)}}$MSIH(5)–VAR(0)$^{\text{GCCI:R1+R2}}$.

Once again, the discussion begins dealing with the case of the classical business cycle. Figure 11 below provides a graphical tool that helps to figure out the statistics related to the $_{\text{IPI(3),UR(1),NPCR(1),INDEA7(1),BUIEA99(1)}}$MSIH(5)–VAR(0)$^{\text{BCCI:R1}}$ coincident indicator.

As far as only the final dating chronology is concerned, both the Lag and Excess statistics computed for this $_{\text{MS-VAR}}$BCCI are lower than the ones returned by the September 2009 BCCI, namely 5 versus 7 and 8 versus 10, respectively. The same relation holds when the provisional dating chronology is merged with the final one: the Lag and Excess statistics are 7 versus 13 and 8 versus 10, respectively. More in detail, although they are both delayed, the $_{\text{MS-VAR}}$BCCI is leading by two months the former one in detecting the peak of February 1992 and by four months the last peak in February 2008.

Figure 11: **Classical business cycle: recession phases derived from the IPI(3),UR(1),NPCR(1),INDEA7(1),BUIEA99(1)MSIH(5)–VAR(0)BCCI:R1 coincident indicator (upper panel) and from the BCCI actually computed in September 2009 (lower panel).**

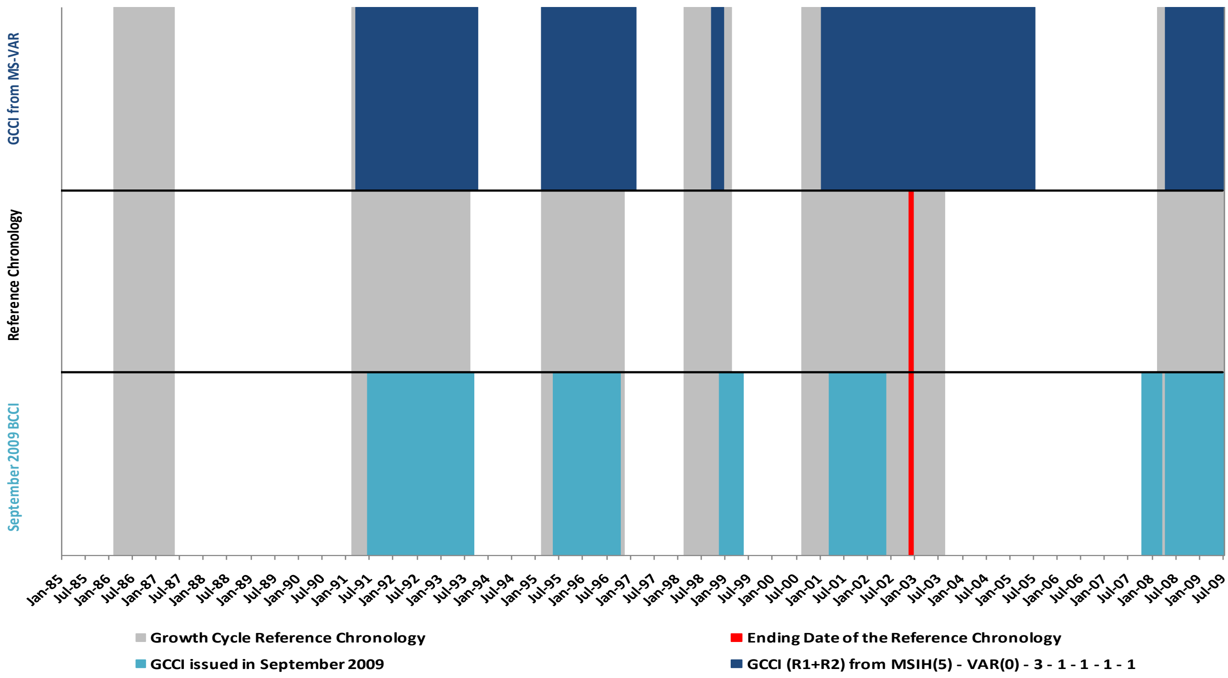


Note: Recession phases of the classical business cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009.
Source: Authors' calculations

Figure 12 shows how the $_{IPI(3),UR(1),NPCR(1),INDEA7(1),BUIEA99(1)}$MSIH(5)–VAR(0)$^{GCCI:R1+R2}$ coincident indicator is characterised by the lowest value for the Lag statistic among all the coincident indicators considered here: the most relevant improvements are obtained in locating the peaks of the recessions between 1991 and 1993 and between 1995 and 1996.

However, also this $_{MS\text{-}VAR}$GCCI identifies a long lasting recession between February 2001 and July 2005; as the corresponding recession included in the reference dating chronology ends in August 2003, the exceeding period contributes to increase the Excess statistic up to 28, while it is only 8 for the September 2009 GCCI.

Figure 12: Growth cycle: recession phases derived from the IPI(3),UR(1),NPCR(1),INDEA7(1),BUIEA99(1)MSIH(5)–VAR(0)GCCI:R1+R2 coincident indicator (upper panel) and from the GCCI actually computed in September 2009 (lower panel).



Note: Recession phases of the growth cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009.
Source: Authors' calculations

Results for $_{\text{IPI(3),UR(1),BUIEA99(1)}}$MSIH(4)–VAR(0)

Finally, the last coincident indicator considered here is the $_{\text{IPI(3),UR(1),BUIEA99(1)}}$MSIH(4)–VAR(0)$^{\text{GCCI:R1+R2}}$, which returns the lowest value for the sum of Lag and Excess statistics and the QPS and a good performance for the Concordance Index. All these statistics are computed with respect to a benchmark that is obtained by extending the final dating chronology of the growth cycle with the provisional one.

Upper panel of Figure 13 below illustrates the comparison between the $_{\text{IPI(3),UR(1),BUIEA99(1)}}$MSIH(4)–VAR(0)$^{\text{BCCI:R1}}$ coincident indicator and the classical business cycle dating chronology. The $_{\text{MS-VAR}}$BCCI at hand improves all the four statistics considered when confronted with the September 2009 BCCI. In particular, the Lag statistic associated to the former coincident indicator is 5 (table 1) and 7 (table 2), depending on whether it is computed with respect to the final or merged dating chronologies, respectively; over the same periods, the latter coincident indicator returns values of the Lag statistic equal to 7 and 13, respectively.

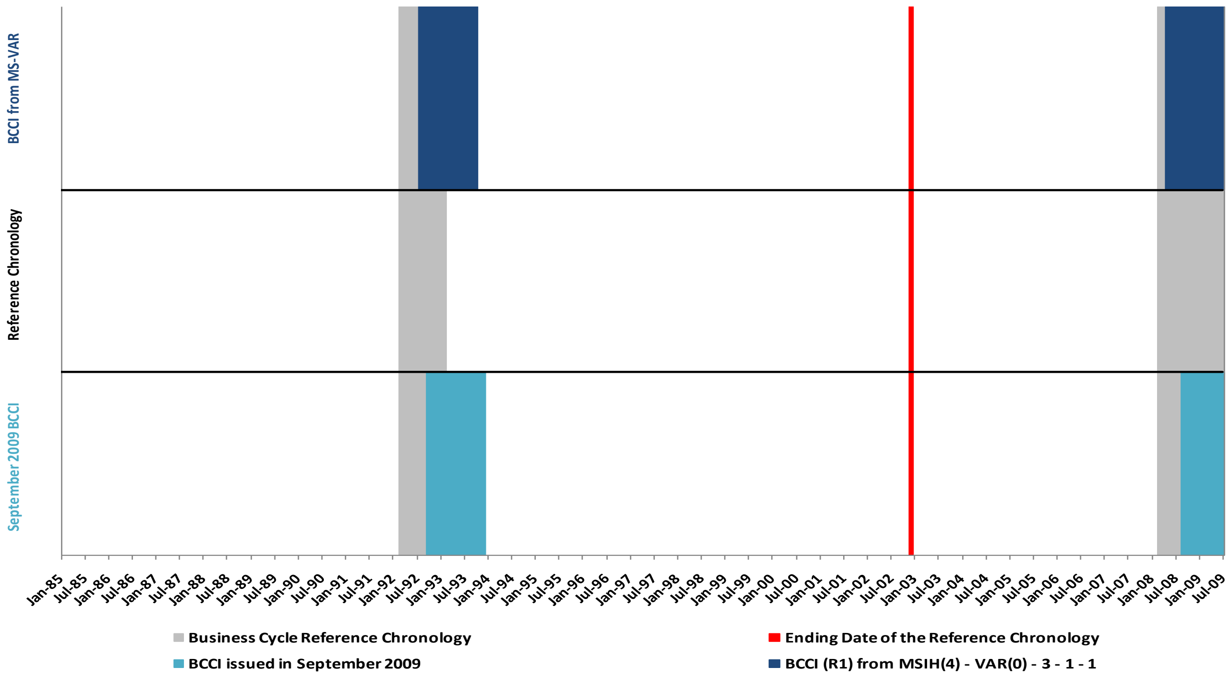
As for the Excess statistic, the figure associated to the $_{\text{MS-VAR}}$BCCI is 8 for both reference dating chronologies of table 1 and it is 10 for the September 2009 BCCI.

As far as the analysis of the growth cycle is concerned, the $_{\text{IPI(3),UR(1),BUIEA99(1)}}$MSIH(4)–VAR(0)$^{\text{GCCI:R1+R2}}$ coincident indicator considerably reduces the Lag statistic to 21, while it is 36 for the September 2009 GCCI, when both of them are obtained with respect to the final dating chronology extended by the provisional one. This appears from Figure 14, where it is shown that the former coincident indicator locates with a greater timeliness than the latter all the recessions of the reference dating chronology.

However, also in this case, a few short-lived (of at most 2-month duration) recession signals are emitted between October 2004 and March 2005.

Contrary to the ${}_{IPI(3),UR(1),NPCR(1),INDEA7(1),BUIEA99(1)}MSIH(5)\text{–}VAR(0)^{GCCI:R1+R2}$ coincident indicator, the ${}_{IPI(3),UR(1),BUIEA99(1)}MSIH(4)\text{–}VAR(0)^{GCCI:R1+R2}$ one does not simultaneously dominates the September 2009 GCCI in terms of all the four statistics considered. In fact, the Excess statistic associated to the latter ${}_{MS\text{-}VAR}GCCI$ is greater than the figure for the September 2009 GCCI.

Figure 13: **Classical business cycle: recession phases derived from the IPI(3),UR(1),BUIEA99(1)MSIH(4)–VAR(0)BCCI:R1 coincident indicator (upper panel) and from the BCCI actually computed in September 2009 (lower panel)**



Note: Recession phases of the classical business cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009.
Source: Authors' calculations

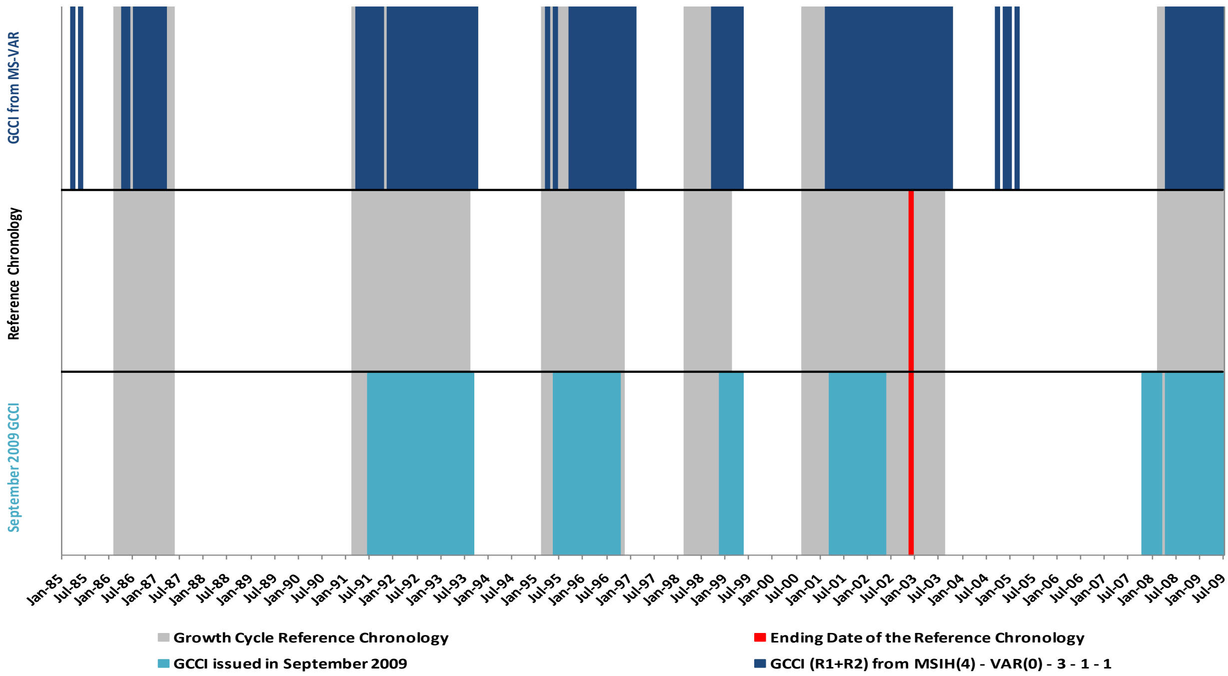
Nevertheless, the same statistics could lead to different conclusions when we leave the comparison with the GCCI issued in September 2009, which limits between July 1991 and July 2009 the period over which the statistics are computed, and extend as far back in time as possible the period taken into account. In fact, when the same four statistics are computed over the period 1985–2009, a rather distinct picture emerges. Although the gap in terms of the Lag statistic between the two ${}_{MS\text{-}VAR}GCCIs$ reduces from 32 minus 21 to 37 minus 27, this loss is more than compensated by the gain in the Excess statistic: the figure generated from the ${}_{IPI(3),UR(1),BUIEA99(1)}MSIH(4)\text{–}VAR(0)^{GCCI:R1+R2}$ coincident indicator increases only by two months (from 14 to 16), while it rises from 7 to 14 for the ${}_{IPI(3),UR(1),NPCR(1),INDEA7(1),BUIEA99(1)}MSIH(5)\text{–}VAR(0)^{GCCI:R1+R2}$ coincident indicator.

It turns out that the ${}_{IPI(3),UR(1),BUIEA99(1)}MSIH(4)\text{–}VAR(0)^{GCCI:R1+R2}$ coincident indicator is better able than the ${}_{IPI(3),UR(1),NPCR(1),INDEA7(1),BUIEA99(1)}MSIH(5)\text{–}VAR(0)^{GCCI:R1+R2}$ one to adhere to the growth cycle. This statement is corroborated by the fact that, among all the coincident indicators considered, the latter one returns the lowest values for the sum of Lag and Excess statistics as well as lowest values for the QPS and highest values for the Concordance Index.

As for the classical business cycle, the ${}_{IPI(3),UR(1),BUIEA99(1)}MSIH(4)\text{–}VAR(0)^{BCCI:R1}$ and ${}_{IPI(3),UR(1),NPCR(1),INDEA7(1),BUIEA99(1)}MSIH(5)\text{–}VAR(0)^{BCCI:R1}$ coincident indicators are almost indistinguishable.

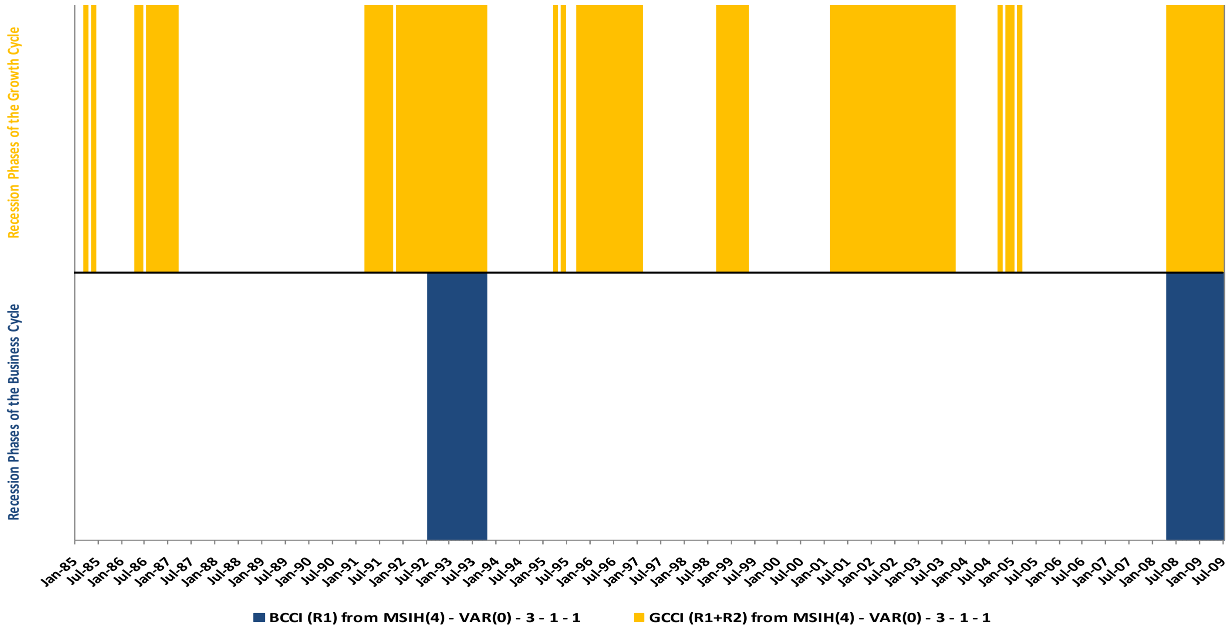
Finally, Figure 15 shows that the $_{IPI(3),UR(1),BUIEA99(1)}$MSIH(4)–VAR(0) model produces two coincident indicators, one of the classical business cycle and one of the growth cycle, that are consistent with the ABCD approach. In fact, as it immediately appears by graphical inspection of Figure 15 below, on one hand, the peaks of the classical business cycle are preceded by (or at least are coincident with) the peaks of the growth cycle and, on the other hand, the troughs of both cycles are coincident. However, it should be noted that this statement is based only on two recessions of the classical business cycle, of which only one of them is complete.

Figure 14: **Growth cycle: recession phases derived from the IPI(3),UR(1),BUIEA99(1)MSIH(4)–VAR(0)GCCI:R1+R2 coincident indicator (upper panel) and from the GCCI actually computed in September 2009 (lower panel)**



Note: Recession phases of the growth cycle reference dating chronology are depicted in background and in the mid panel as grey shaded areas: final dating chronology between January 1985 and December 2002, provisional dating chronology from January 2003 to July 2009.
Source: Authors' calculations

Figure 15: **Recession phases of the classical business cycle derived from the IPI(3),UR(1),BUIEA99(1)MSIH(4)–VAR(0)BCCI:R1 coincident indicator (upper panel) and recession phases of the growth cycle derived from the IPI(3),UR(1),BUIEA99(1)MSIH(4)–VAR(0)GCCI:R1**



Source: Authors' calculations

6. Summary of turning points from the last cyclical assessment

In this section we give a summary view of the turning points of the last recession of both the growth and classical business cycles that were identified through the coincident indicators discussed so far. Two further alternative indicators are considered for the business cycle. These turning points are compared to the peaks and troughs dates in the provisional dating chronology.

The upper panel of Table 3 and Figure 16 deal with the growth cycle. As far as this cycle is concerned, two coincident indicators are estimated on a monthly basis:

i. the usual Growth Cycle Coincident Indicator (GCCI) and

ii. a coincident indicator (Multivariate MS) that is obtained as a by-product of fitting the multivariate Markov-Switching MSIH(4)–AR(0) model to a selected differentiation of IPI (of order 6), UR (of order 1), NPCR (of order 3) and Employment Expectations for the Months ahead INDEA7 (of order 1). In terms of previous section notation we refer to the ${}_{IPI(6),UR(1),NPCR(3),INDEA7(1)}MSIH(4)–VAR(0)^{GCCI}$ indicator, which has provided a more reliable performance over the last cyclical assessments.

The classical business cycle is tackled in the lower panel of Table 3 and Figure 16. In this case, four coincident indicators are provided:

i. the usual Business Cycle Coincident Indicator (BCCI);

ii. the coincident indicator from the multivariate Markov-Switching model previous described when dealing with the growth cycle;

iii. a coincident indicator ${}_{MS}BCCI^{WS1}$ that is obtained by fitting two properly identified Markov-switching models to the IPI and Unemployment Rate and by then aggregating the resulting recession probabilities according to a specific weighting scheme (*WS1*);

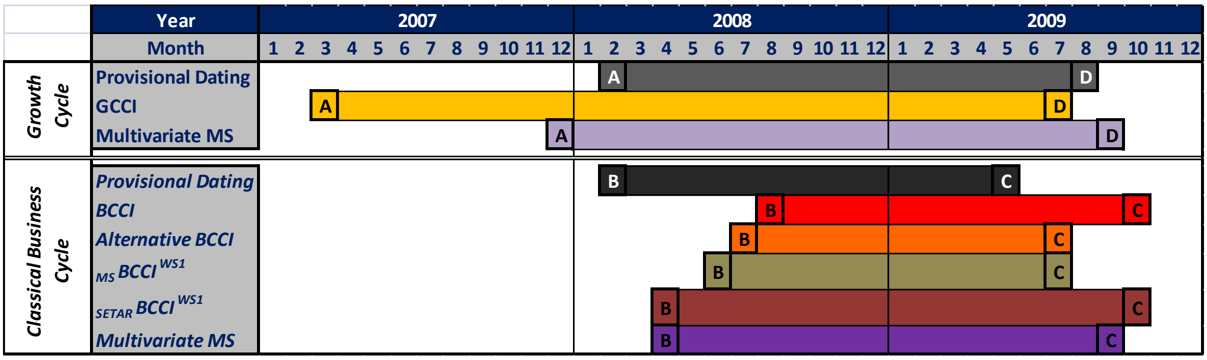
iv. a coincident indicator ${}_{SETAR}BCCI^{WS1}$ that is obtained by, first fitting two properly identified SETAR models to the IPI and Unemployment Rate and then, by aggregating the resulting recession signals according to the same weighting scheme used above.

Table 3: The Summary of turning points of the last phase of both the growth cycle and classical business cycle obtained from the usual BCCI and GCCI as well as some alternative coincident indicators

Economic Cycle	Coincident Indicator	Peak	Trough
Provisional Dating of the Growth Cycle		February 2008	August 2009
Growth Cycle	GCCI	March 2007	July 2009
	Multivariate MS	December 2007	September 2009
Provisional Dating of the Business Cycle		February 2008	May 2009
Classical Business Cycle	BCCI	August 2008	October 2009
	Multivariate MS	April 2008	September 2009
	${}_{MS}BCCI^{WS1}$	June 2008	July 2009
	${}_{SETAR}BCCI^{WS1}$	April 2008	October 2009

Source: Authors' calculations

Figure 16: **Summary of turning points of the last phase of both the growth cycle and classical business cycle obtained from the usual BCCI and GCCI as well as some alternative coincident indicators**



Source: Authors' calculations

7. Conclusions

The study carried out proved that multivariate Markov-switching modelling is a fruitful approach when dealing either with the classical business cycle or the growth cycle.

We used multivariate Markov-switching models to jointly derive coincident indicators of both the classical business cycle and of the growth cycle. On one hand, most of the MS-VAR^{BCCI} were better able than the BCCI to timely detect turning points of the classical business cycle. On the other hand, only one MS-VAR^{GCCI} returned a greater timeliness than the GCCI in locating the troughs of the growth cycle. The poor performance of all the MS-VAR^{GCCIs} presented here is due to the fact that they identify a false recession of the growth cycle between 2004 and 2005. The detection of this false slowdown appears to be independent from the number of regimes of the latent variable, from the state-dependent heteroskedasticity, from the time-series included and from their respective transformation. It could be explained only with the presence of the IPI, which is introduced as endogenous variable in all the cases considered. Moreover, this opposing behaviour between MS-VAR^{BCCIs} and MS-VAR^{GCCIs} can partly be explained by the fact that only two recessions of the classical business cycle are located by the reference dating chronology, whereas the growth cycle counts five slowdowns between 1991 and 2009.

Among the selected list of 6 cases discussed in this paper the ${}_{IPI(6),UR(1),NPCR(3),INDEA7(1)}$MSIH(4)–VAR(0) model has provided a pair of coincident indicators, one of the classical business cycle and one of the growth cycle, better dealing with both economic cycles. They represent an overall improvement with respect to the current univariate BCCI and GCCI, even if both of them are still slightly delayed when compared to the respective reference dating chronology.

References

1. Anas, J. and Ferrara, L., 'Turning points detection: the ABCD approach and two probabilistic indicators', *Journal of Business Cycle Measurement and Analysis*, No. 1, Vol. 2, 2004, pp. 1-36.
2. Anas, J., M. Billio, L. Ferrara and M. Lo Duca (2007), 'A turning point chronology for the Euro-zone classical and growth cycle, in Growth and Cycle in the Eurozone', Eds G.L. Mazzi and G. Savio, Palgrave Macmillan, pp. 261–274.
3. Anas, J., Billio, M., Ferrara, L. and Mazzi, G.L., 'A System for Dating and Detecting Turning Points', *Manchester Bulletin*, Vol. 76, No 5, 2008, pp. 549-577.
4. Brier, G. W. (1950). 'Verification of forecasts expressed in terms of probabilities'. *Monthly Weather Review*, Vol. 78, 1–3.
5. Harding, D. and Pagan A. (2002), 'Dissecting the Cycle: A Methodological Investigation', *Journal of Monetary Economics*, 49/2, pp. 365–381.

HOW TO OBTAIN EU PUBLICATIONS

Free publications:

- one copy:
  via EU Bookshop (http://bookshop.europa.eu);
- more than one copy or posters/maps:
  from the European Union's representations (http://ec.europa.eu/represent_en.htm);
  from the delegations in non-EU countries (http://eeas.europa.eu/delegations/index_en.htm);
  by contacting the Europe Direct service (http://europa.eu/europedirect/index_en.htm) or
  calling 00 800 6 7 8 9 10 11 (freephone number from anywhere in the EU) (*).

  (*) The information given is free, as are most calls (though some operators, phone boxes or hotels may charge you).

Priced publications:

- via EU Bookshop (http://bookshop.europa.eu).

KS-TC-16-007-EN-N

A multivariate system for turning point detection in the euro area

MONICA BILLIO, LAURENT FERRARA,
GIAN LUIGI MAZZI, FILIPPO MOAURO

This paper introduces a multivariate Markov-Switching model allowing for a simultaneous construction of coincident indicators for turning points detection for both business and growth cycles. The best performing multivariate model is then chosen within a wide simulation exercise.

For more information

http://ec.europa.eu/eurostat/

Publications Office

ISBN 978-92-79-57965-3