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Business Cycle Analysis with Multivariate Markov Switching Models[1]

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Abstract
The class of Markov switching models can be extended in two main directions in a multivariate framework. In the first approach, the switching dynamics are introduced by way of a common latent factor. In the second approach a VAR model with parameters depending on one common Markov chain is considered (MSVAR). We will extend the MSVAR approach allowing for the presence of specific Markov chains in each equation of the VAR (MMSVAR). In the MMSVAR approach we also explore the introduction of correlated Markov chains which allow us to evaluate the relationships among phases in different economies or sectors and introduce causality relationships, which allow a more parsimonious representation. We apply our model to study the relationship between cyclical phases of the industrial production in the US and Euro zone. Moreover, we construct a MMS model to explore the cyclical relationship between the Euro zone industrial production and the industrial component of the European Sentiment Index.

Keywords
Economic cycles, Multivariate models, Markov switching models, Common latent factors, Causality, Euro-zone

JEL Codes
C50, C32, E32

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1. Introduction

Since the early work by Burns and Mitchell (1946), many attempts have been made to measure and forecast business cycles. Recently, approaches based on time series econometrics, have emerged. The most representative works are the Stock-Watson model (Stock and Watson 1989, 1991, 1993) which focuses on comovements among macroeconomic variables, and the univariate regime switching model developed by Hamilton (1989, 1990) which is based on the intuition that turning points and changes in regime are related. Moreover, Diebold and Rudebusch (1996) and Kim and Nelson (1998, 1999) synthesised the two approaches allowing for both comovements among macroeconomic variables and switching regimes.

The main advantage of Markov-switching processes, often advocated in the literature, is their ability to take into account the asymmetry of a time series and features such as non linearity and the persistence of extreme observations: these features are crucial in business cycle analysis.

There is a large literature that uses switching regime models in order to recognise business cycle phases. The starting point of this literature is that there is a relationship between the concepts of changes in cyclical phases and change in regime. Moreover, this relationship has been confirmed by empirical studies (Clements and Krolzig 1998 and 2000, Krolzig 1997a, 1997b, 2000 and 2001, Krolzig and Sensier 1999, Krolzig, Marcellino and Mizon 2000, Krolzig and Toro 2000 and 2001, Diebold and Rudebusch 1996 and 1999, Kim and Nelson 1998 and 1999, Chauvet 1998, Kauffmann 2000, Layton 1996, Anas and Ferrara 2002, Harding and Pagan 2001a, Ferrara 2003). Therefore, contractions and expansions are modeled as switching regimes of the stochastic process generating the growth rate of some economic variables.

In any case some words of caution have to be spent on the Markov switching approach to the business cycle. When using parametric models, such as MS-VAR processes, no a priori definition of business cycle is imposed: by means of the Markov switching model approach, different regimes are identified, indeed these regimes differ in terms of average growth rates and/or growth volatilities. In many cases the MS approach properly detects the classical cycle phases, but not necessarily this happens. The model only indicates some differentiation of the growth rate of the economy. The regime of low growth could also have positive mean: the correct detection of the cycle depends on the features of the analysed series. The MS-VAR approach lets the data describe the features of the different phases of the economy. Actually, this approach simply represents the idea that economies are characterised by different phases.

Even if there is no perfect correspondence between cyclical phases and detected regimes this approach could be useful, especially in the case when detected regimes show an high level of persistence. In this respect, we think that Markov-Switching models could provide information useful to improve the perception of the current state of the economy. Moreover, useful information is provided by the transition matrix which describes how phases evolve: by modelling different economies or sectors with specific Markov chains (MMS VAR) we can get transition matrices providing useful information on how their phases are related.

This work deals with the multivariate extensions of Markov-Switching models and their reliability in Business cycle analysis. We extend basic MS VAR models (Krolzig 1997) allowing for a specific Markov chain in each equation of the VAR (Multiple Markov Switching VAR models, MMS VAR). Moreover in the MMS VAR approach we explore the introduction of correlated Markov chains which can produce useful information on the relationship between phases in different countries, and causality relationships, which can allow more parsimonious representations.

2. Multivariate extensions of Markov switching models: a review

The class of Markov switching models can be extended in several directions in a multivariate framework. Concerning the description of business cycle phases and the detection of turning points, two main approaches have been proposed. The first one consists in jointly considering dynamic factor models and regime switching as proposed by Diebold and Rudebusch (1996). In this case, there are two levels of latent variables (the common factor and the Markov chain) and serious estimation difficulties arise.

In the second approach, no common factors are used. The analysis of business cycle phases and the detection of turning points is provided by a multivariate version of the basic Markov switching AR model of Hamilton (1989). The class of Markov Switching VAR models (MS VAR) has been proposed by Krolzig (1997).

2.1 Dynamic factor models

Diebold and Rudebusch (1996) proposed to model simultaneously the two main stylised facts of the business cycle: (i) co-movements among economic variables through the cycle, and (ii) non linearity in the evolution of the business cycle. In fact, they tried to conciliate the recent works on two separate areas of the business cycle research, namely common factor extraction and non-linear modelling trough Markov-Switching models.

However, the introduction of a latent factor in the switching regime model makes the estimation and the inference more difficult: this happens because the Hamilton's filter is no longer useful. Then, the use of a dynamic factor model with regime switching requires more sophisticated estimation techniques. From a methodological point of view, in the literature some solutions have been proposed.

First of all, the use of approximations. Following Harrison and Stevens (1976), in order to avoid that the number of states increases exponentially at each iteration, an average is performed, then the Hamilton's filter can be adapted[1].

Secondly, simulation based approximations can be useful to obtain a filtering algorithm. In a classic framework, an importance sampling technique (see Billio and Monfort, 1998) or a Markov Chain Monte Carlo approach can allow to obtain the maximum likelihood estimator[2]. Otherwise, in a Bayesian framework a Markov chain Monte Carlo approach based on the data augmentation principle and the use of a multi-move sampler[3] can yield samples out of the joint posterior distribution of the unobservable common factor, the latent state variable and all model parameters, allows to obtain the parameter estimates and the latent factors dynamics[4]. .

2.2 Markov switching VAR

This approach does not necessitate the previous identification of a common factor and consists in directly considering the series in a multivariate model. Following Krolzig (1997), it is possible to consider a VAR model with parameters depending on a common Markov chain. This common latent variable is assumed to represent the phases of the common cycle and is used to detect turning points.

The assumption of a single Markov chain is consistent with the existence of a common and coincident cycle in the analyzed set of economies. Using a single Markov chain is undoubtedly a way of producing a description of the common cycle phases and aggregating turning points: in some way the model finds the turning point that best fits the group of turning points that we can usually observe in a set of different economies when there is a

[1] See Kim (1994), Kim and Nelson (1998 and 1999), Chauvet (1998) for the definition and application of the Kim's approximated filter.

[2] See the Simulated Likelihood Ratio Method in Billio, Monfort and Robert (1998), or the Simulated EM algorithm in Shephard (1993).

[3] See Carter and Kohn (1994), Frühwirth-Schnatter (1994), Shephard (1994), and de Jong and Shephard (1995).

[4] For some applications see Kim and Nelson (1999), Luginbuhl and de Vos (1999) and Kaufmann (2000).

change of phase. In any case, using this class of models, it is not possible to evaluate the relationship among phases in different sectors or economies.

In the next section, we deal with simple MS VAR models with a single Markov chain representing the common cycle (Artis, Krolzig and Toro 2002) and models with multiple Markov chains (MMS VAR) which represent country or sector specific factors. Considering specific Markov chains and their relationships provide useful additional information that can be used in business cycle analysis. When dealing with multiple Markov chains, we consider different specifications of the transition matrix, involving different hypotheses on the relationship among the specific chains.

3. Multiple Markov switching VAR (MMS VAR) models

The MS-VAR with a single Markov chain introduced by Krolzig (1997) is the simplest multivariate Markov switching model that can be used in business cycle analysis. To give an idea of this approach, we propose the following specification:

$$(y_t - \mu(S_t)) = \sum_{j=1}^{p} \phi_j (S_t)(y_{t-j} - \mu(S_{t-j})) + \varepsilon_t$$

where $\varepsilon_t \sim N(0, \sigma^2(S_t))$, y_t is a n-dimensional vector which contains the endogenous variables and ε_t contains the idiosyncratic disturbances of each endogenous variable. The common latent variable $S_t=1,..,M$ follows a Markov chain with constant transition probabilities and is assumed to represent the phases of the common cycle. Usually, in business cycle analysis, only the mean and sometimes the covariance matrix is supposed to depend on the common latent variable, while the other parameters are considered to be constant.

Following Krolzig (1997), it is also possible to use an alternative specification where the intercept term depends on the Markov chain in order to allow a different dynamic of the variable y_t:

$$y_t = \upsilon(S_t) + \sum_{j=1}^{p} \alpha_j (S_t) y_{t-j} + \varepsilon_t$$

The problems arising when dealing with this kind of model, concern the necessity to estimate a large set of parameters. In fact, the number of parameters grows exponentially with the number of regimes. In particular, we have to consider:

- the mean of each series in each regime: ***Mn*** parameters.
- the covariance matrix in each regime: ***M[n(n+1)/2].***
- ***M x (M-1)*** elements of the transition matrix of the Markov chain.

For example, if $n = 2$ and $M = 3$ the total number of parameters to estimate is *21*. This is already a large number of parameters, but it is small in comparison with the models that are useful for practical applications.

The assumption of a single Markov chain is consistent with the existence of a single common and coincident cycle in the analyzed set of economies. However, even if we can hypothesise a common business cycle, empirical analyses suggest that this cycle could not be synchronised.

Using a single Markov chain is undoubtedly a way to aggregate turning points and produce a description of the common cycle phases: in some way, the model finds the turning point that best fits the group of turning points that we can usually observe in a set of different series when there is a change of phase.

To improve our comprehension of the connections among the phases of different economies or sectors and then to produce a better description of how phases evolve, it is necessary to consider that turning points are not always coincident. This happens when different series aredriven by different unobserved factors: for this reason, we are going to consider models which explicitly use multiple Markov chains.

3.1 Multiple Markov chains

Even if a single business cycle in a group of economies (e.g. the European Monetary Union) exists, there could be no synchronization among the phases of the different economies or among those of different sectors of a single economy. In order to take into account this possibility, it is necessary to relax the hypothesis that a single Markov chain drives the shifts in different economies or sectors. In the general case, we can assume that the change in the regime of each series is driven by a specific Markov chain. Then, it is possible to provide indications on how to aggregate the turning points and to produce a single chronology.

We then consider a VAR model in which each equation has the following form, with switches in the intercept term[5] and in the variance:

[5] As for the previous model, we can consider a switching variance.

$$y_{it} = \upsilon(S_{it}) + \sum_{j=1}^{p} \alpha_j y_{it-j} + \varepsilon_{it}\,, \qquad \text{where } \varepsilon_{it} \sim N(0,\sigma^2(S_t)) \text{ and } i=1, \ldots, n.$$

The regime shift of each of the *n* endogenous variables is driven by a specific Markov chain with *M* regimes. For estimation purposes, the *n* specific chains are combined in a single Markov chain with M^n regimes. The regimes of the joint Markov chain are all the possible combinations of the regimes of the specific chains: it is crucial to study the transition matrix of the joint process because it contains information on the relationship among the phases of the different series. Hence, the advantage of this approach is that the relationship among the phases in different countries is explicitly taken into account and described.

Clearly, the number of parameters that have to be estimated rises enormously and this produces serious difficulties in the estimation of the model. We have to estimate the following set of parameters:

- the mean and the variance of the series in each specific regime: 2***Mn.***
- the correlation between series in each regime: ***Mn(n-1)n/2.***
- ***Mn(Mn-1)*** elements of the transition matrix of the common Markov chain.

For example, if *n = 2* and *M = 3* and we impose no constraints on the transition matrix of the joint process, we will have a *9 x 9* transition matrix with *72* transition probabilities that have to be estimated. In this case the total number of parameters we have to estimate is *93*.

The likelihood function could be characterised by many local maxima, and there are strong convergence problems (for details see Breunig and Pagan 2002 and Boldin 1996). Moreover, in business cycle analysis, short time series have often to be treated and the accuracy of the estimates could be even more compromised.

By considering simple constraints based economic considerations or imposing a dependence structure based on *a priori* ideas, it is possible to reduce the number of parameters which are necessary to define the transition matrix. As we will see in section 4, most of the 72 transition probabilities are not different from zero and this will help us in estimating the model. It is also possible to formally test whether the constraints are consistent with the data and thus understand whether we are working in the right direction.

3.2 Modelling the transition matrix

The aim is to describe the connections between the phases of cycles in different countries or in different sectors of the economy. Markov switching models with specific chains allow us to describe these connections by making some assumptions on the transition matrix that drives the joint Markov process of all the specific factors.

In the literature there are four possibilities (following Hamilton and Lin, 1996, and Susmel, 1998):

- Common regimes (existence of a unique Markov chain);
- Independent Markov chains;
- Related regimes;
- General specification.

These allow the description of interesting phenomena but do not give the complete range of possibilities. In the following we propose also this strategies:

- To model the transition matrix;
- To consider dependent and correlated Markov chains (Billio, 2002).

3.2.1 Independent and related Markov chains

If we assume that there is no relationship among phases in different economies or sectors we can use independent Markov chains. In this case the transition matrix of the joint Markov process is given by the Kronecker product of the transition matrix of each specific chain. Suppose for example that we have two Markov chains, s_t and z_t. (n=2) with three regimes (M=3). Then we have the following result:

$$P = P_s \otimes P_z$$

where P is the *9 x 9* matrix of the joint process and P_i is the *3 x 3* transition matrix of the country or sector specific Markov chain. The advantage of this approach is the limited number of parameters to estimate: in order to get the transition matrix of the joint process we only have to estimate the transition probabilities of the Markov chain of each series. Considering the other parameters of the model, the total number of parameters to estimate is 33.

The hypothesis of independent cycles could be not consistent with the cycle in Europe and often it is not consistent when considering different sectors of an economy. This specification could in any case be useful if we need to formally test whether or not the specific cycles are related. For example could be useful before extracting a common factor from a group of series of different sectors. In fact, it is possible to formally test the null of related Markov chains against the alternative of independent Markov chains with a simple Likelihood Ratio test. In this way it is possible to implement a selection strategy to choose the variables to include in the multivariate model: those showing no connections can be discarded.

It must be underlined that the only difference between this approach and the univariate MS model is that a regime dependent correlation is estimated. We can get the same transition matrix of the joint process considering only the transition matrices we get from the univariate analysis, but in this case it is not possible to formally test the hypothesis of independence against the one of related chains.

Concerning the related regime case, the forces that govern both cycles are the same, but are not in phase. Two sub-cases can be considered: the first cycle shifts before so $z_t=s_{t-1}$ and causality is reversed, namely $s_t=z_{t-1}$. This type of relation strongly simplify the transition matrix since the number of parameter is simply 2 and it is useful to describe lead or lag relationships among the economies.

3.2.2 Modelling the general transition matrix

In the general specification no *a priori* structure on the transition matrix is imposed. In the case of two series and specific Markov chains with three regimes each one, the joint process is characterised by the following *9 x 9* transition matrix:

EE-EE	EE-SE	EE-RE	EE-ES	EE-SS	EE-RS	EE-ER	EE-SR	EE-RR
SE-EE	SE-SE	SE-RE	SE-ES	SE-SS	SE-RS	SE-ER	SE-SR	SE-RR
RE-EE	RE-SE	RE-RE	RE-ES	RE-SS	RE-RS	RE-ER	RE-SR	RE-RR
ES-EE	ES-SE	ES-RE	ES-ES	ES-SS	ES-RS	ES-ER	ES-SR	ES-RR
SS-EE	SS-SE	SS-RE	SS-ES	SS-SS	SS-RS	SS-ER	SS-SR	SS-RR
RS-EE	RS-SE	RS-RE	RS-ES	RS-SS	RS-RS	RS-ER	RS-SR	RS-RR
ER-EE	ER-SE	ER-RE	ER-ES	ER-SS	ER-RS	ER-ER	ER-SR	ER-RR
SR-EE	SR-SE	SR-RE	SR-ES	SR-SS	SR-RS	SR-ER	SR-SR	SR-RR
RR-EE	RR-SE	RR-RE	RR-ES	RR-SS	RR-RS	RR-ER	RR-SR	RR-RR

For each series, the regime *E* means fast expansion (above the trend growth rate), *S* slow expansion (below the trend growth rate) and *R* recession. The elements of the matrix are the probabilities of a transition from a regime of the joint process to another. The regimes of the joint process are all the possible combinations of the three regimes (*R*, *S* ,*E*) of each series.

In order to reduce the number of parameters that must be estimated it is possible to impose some constraints based on simple economic considerations. For example, it is reasonable to impose that it is not possible that an expansion is followed by a recession and *vice versa*. In this way, we impose that the expected relationship between turning points of different cycles (classical and growth) described by the ABCD approach (see Anas and Ferrara, 2002b, and

Anas, Billio, Ferrara and Lo Duca, 2003) is respected. Firstly, we will have the growth cycle peak then the business cycle peak and the latter will be followed by the business cycle trough and finally by the growth cycle trough. If we proceed in this way, the transition matrix is naturally reduced and only 40 elements have to be estimated: the total number of parameters then decreases to 61. The number of parameters to estimate is reduced, but it is still large and strong convergence problems remain.

Even if there is the possibility to impose further constraints (for example: constant correlation, constant variance, other transition probabilities set to zero), it is difficult to have less than 40 parameters. Then, from a practical point of view, we are limited to the analysis of 2 series with 3 regimes or 3 series with 2 regimes. For this reason this method could be used when dealing with two sectors of the economy of an area or with groups of countries.

3.2.3 Markov switching VAR and Granger causality

In general, in a VAR context, the identification of causality relations allows more parsimonious representations. In the literature there are very few attempts to address this issue in Markov switching VAR models: one exception is Warne (2000), who analyses how the Granger causality concept allows improving the regime inference.

In this context, we propose to describe causality relationships by working with Markov chains (see also Mosconi and Seri 2001 for binary data model). This is certainly useful in order to describe the relationships between leading and lagging countries, or to describe the relation between business surveys and macroeconomic variables. Using this approach it is possible to reduce the number of parameters required to define the transition matrix. Moreover, in a multi-country/multi sector framework, this type of model allows us to explain the interactions among macro-areas.

The independent and common cases present in the previous sections are not of interest if we would like to understand the causality between two cycles. Concerning the identification of the transition matrix, with 3 states, the independent case requires 6 parameters, while the general specification requires 72 parameters. Using the causality approach it is possible to describe several correlated cases with a number of parameters comprising between 6 and 72.

In particular, if s_t and z_t are two Markov chains and S_t is the resulting joint process, in the general specification we can decompose the transition probabilities of S_t as follows:

$$\begin{aligned} P(S_t \mid S_{t-1}) &= P(s_t, z_t \mid s_{t-1}, z_{t-1}) \\ &= P(s_t \mid z_t, s_{t-1}, z_{t-1})\, P(z_t \mid s_{t-1}, z_{t-1}) \end{aligned}$$

We can now define the Granger non causality for a Markov chain. Let $\underline{s_{t-1}} = s_{t-1}, s_{t-2}, \ldots, s_0$.

<u>*Strong one step ahead non causality (Granger non causality)*</u>: $\underline{s_{t-1}}$ does not strongly cause z_t one step ahead, given $\underline{z_{t-1}}$ if:

$$P(z_t \mid \underline{s_{t-1}}, \underline{z_{t-1}}) = P(z_t \mid \underline{z_{t-1}})$$

This means that we can assume than $\underline{s_{t-1}}$ does not strongly cause z_t one step ahead if $\underline{s_{t-1}}$ contains no information on z_t.

Similarly, $\underline{z_{t-1}}$ does not strongly cause s_t one step ahead, given $\underline{s_{t-1}}$ if:

$$P(s_t \mid \underline{s_{t-1}}, \underline{z_{t-1}}) = P(s_t \mid \underline{s_{t-1}})$$

■

As one can see the non causality definition involves the marginal distributions conditional to the past: then, to study the causality it is necessary to consider the transition probabilities of the Markov process. Let we see how we can construct a transition matrix starting from the non causality definition.

Let us consider specific chains (s_t and z_t) with two states: the independent case asks for 4 parameters while the most general model (see the above general specification) representing $P(S_t \mid S_{t-1})$ involves 16 parameters to define the transition matrix. More precisely, since the sum of each row is equal to one, just 12 parameters are enough to describe the conditional distribution completely.

Let us see how we can obtain a suitable representation with a number of parameters comprised between 4 and 12.

The following vector represents the four possibilities of the joint Markov chain S_t:

$$X_t = (1,\, s_{t-1},\, z_{t-1},\, s_{t-1} z_{t-1})'$$
$$= (1,\, s_{t-1})' \otimes (1,\, z_{t-1})'$$

It is simply to verify that we can represent the joint probability of s_t, z_t as follows:

$$P(s_t, z_t \mid s_{t-1}, z_{t-1}) = P(s_t \mid z_t, s_{t-1}, z_{t-1})\, P(z_t \mid s_{t-1}, z_{t-1})$$
$$= \frac{exp(\alpha_1 Y_t)}{1 + exp(\alpha_1 Y_t)} \frac{exp(\alpha_2 X_t)}{1 + exp(\alpha_2 X_t)}$$

where

$$Y_t = (1,\, s_t)' \otimes (1,\, s_{t-1})' \otimes (1,\, z_{t-1})'$$

$$=(1,\ s_{t-1},\ z_{t-1},\ s_{t-1} z_{t-1},\ s_t,\ s_t z_{t-1},\ s_t s_{t-1},\ s_t s_{t-1} z_{t-1}\ )'$$

and X_t has already been defined.

Now, Y_t and X_t involve respectively 8 and 4 parameters, then we simply have an alternative parameterization of the transition matrix. Such parameterization is very useful since it allows us to simply impose the non causality restrictions by easily restricting the transition matrix to be described by a number of parameters comprised between 4 and 12.

In particular, if $\underline{s_{t-1}}$ does not strongly cause z_t one step ahead, given $\underline{z_{t-1}}$, the X_t vector reduces to $X_t=(1, z_{t-1})'$ and the number of parameters reduces to 10.

In this setting we can investigate if z_t causes s_t in the Granger sense or the contrary without imposing common states, which is very useful for understanding which series can be useful in predicting the business cycle. Moreover, this type of decomposition allows us to describe all the previous specifications besides other even more interesting cases.

4. Applications

We apply the MMS model using different specifications of the transition matrix in order to study the relationships between industrial cyclical phases in the U.S. and Euro zone. Moreover, we construct a MMS model in order to explore the cyclical relationships between the Euro zone industrial production and the industrial component of the European Sentiment Index (ESI).

4.1 Data set

<u>IPI Euro zone</u>

In order to get the aggregate Industrial Production index at the Euro zone level, a back recalculation has been performed. The Industrial production indices at country level are taken from the GRETA database. They represent the total production adjusted by working days (WDA). With 9 countries starting in 1970, an Euro9 aggregate is calculated by weighting adequately the 9 indices. Then, a Euro10 aggregate is calculated from 1975 when Ireland become available and a regression is performed to estimate a new Euro10 starting from 1970. Similarly, a Euro11 starting in 1970 is obtained by a regression of Euro11 (available since 1977 by adding Greece) over Euro10. Finally, the Euro12 starting from 1970 is calculated by a regression of the available Euro12 in New-Chronos since 1985 over Euro11. The final data set covers the period from January 1970 to December 2002.

Data have then been pre-treated by using the TRAMO-SEATS method in Demetra[6].

IPI U.S.A.

The manufacturing index for major industry groups has been considered. The index is published monthly by the Federal Reserve and is already adjusted for seasonal effects. The data set covers the period from January 1919 to August 2003.

ESI

The Economic Sentiment Index (ESI) is released monthly and is a combination of opinion surveys data computed by the European Commission since 1970. The index has been changed in its composition and weighting scheme in 1999 for statistical reasons without a clear economic justification. Today, the ESI is composed of the confidence indices in the sectors of industry, construction, retail and households. Its economic interpretation is not straightforward and the challenge is to evaluate how it relates to the European economic cycle (see Batchelor 2002, Doz and Lenglart 2001, Vanhaelen, Dresse and DeMulder 2000). The data set covers the period from July 1985 to July 2003.

4.2 A MMS model for the Euro zone and the U.S. industrial productions

The MMS model introduced in section 3 aims at describe the growth rate over three months of the industrial production in Europe and in the U.S.A. to detect cyclical phases and analyse the relationships between the two macro areas.

Our aim is to simultaneously take into account fluctuations of the business and growth cycles using a single model (see for instance Anas and Ferrara, 2002b, and Anas, Billio, Ferrara and Lo Duca, 2003 for more detailed connections between the two cycles). According to this idea, for both Euro zone and the U.S.A. a specific Markov chain with three regimes is used. The three regimes have the following economic interpretation:

- Low growth regime, Recession (labeled ***R***): the regime is usually characterized by a negative average growth rate and it is associated to the classical recessions.

[6] No trading day adjustment is used since data are already WDA. Sometimes, the airline model was imposed to avoid a non parsimonious model or to avoid too many outliers. Similarly, the critical limit for outliers was sometimes fixed to 3.0 to avoid too many outliers. Generally, we avoided the presence of level shift outliers except obviously in the case of the German series. The only outlier found in the Euro12 series was an additive outlier in June 1984.

– Intermediate growth regime, Slow Expansion (labeled ***S***): we assume that the growth rate of the economy is below its trend growth rate (low phase of the growth cycle without recession).
– High growth regime, Fast Expansion (labeled ***E***): we assume that the growth rate of the economy is above its trend growth rate (high phase of the growth cycle).

There is no theoretical reason which guarantees that it is possible to use this interpretation of the regimes, but in empirical applications the relationships between the three regimes and the phases of growth and business cycle is quite strong. Moreover, the use of a three regime models avoids the recession regime (*R*) to have a positive mean. Even if, as mentioned, detected regimes and phases of the cycle could be not perfectly related, we think that using a three regime model with this interpretation improves our ability to understand the meaning of a regime. Furthermore, we noticed that if recessions are well dated with a two regime model, the introduction of a third regime has not a significant impact on the dates of the recessions: it usually splits in two regimes (fast growth and low growth) the single expansion regime found using a two regime model (see also Krolzig, 2003 and Artis, Krolzig and Toro, 2002). However, it is noteworthy to underline that this interpretation of the three regimes implicitly assumes a constant long-term growth rate over the whole sample period. That is, the estimated growth cycle is the deviation from a linear trend, instead of being computed through a specific filter. Nonetheless, we can consider this specification as a local approximation.

Once the parameters of the model have been estimated, in order to detect phases we simply assign the observation at time t to the regime with the highest smoothed probability. Concerning turning points detection, a trough is the last observation of the low growth regime and a peak is the last observation of the high growth regime.

In the case of our three regime model, we will proceed in the following way in order to date business and growth cycle phases:

- Concerning the business cycle, we obtain the smoothed probabilities of an expansion (labeled ***EX***) by summing the smoothed probabilities of the second regime (*S*) and the third regime (*E*). The recession regime of the business cycle (labeled ***RE***) is the regime *R* of the starting model. In this way, we have again two regimes which are supposed to represent the business cycle phases.
- Concerning the growth cycles, we obtain the smoothed probabilities of the under trend phase (labeled ***L***) by summing the smoothed probabilities of the first regime (*R*) and the second regime (*S*). The high regime of the growth cycle (labeled ***H***) is the regime

E of the starting model. In this way we have again two regimes which are supposed to represent the growth cycle phases.

Starting from the general model with regime dependent mean and covariance matrix (no autoregression terms are considered) and 72 unrestricted conditional probabilities, we reduce the number of parameters by imposing some restrictions. In particular we set to zero all the transition probabilities that results very close to zero in the first estimation of the model. In the final specification only the mean and the variances are regime dependent while the transition matrix is reduced to only 17 unrestricted elements and the correlation is constant across regimes (see tables 1 and 2 for the estimated parameters and the standard errors). In table 3 the test on the validity of the joint restrictions is reported.

From table 1, it is possible to note that in the positive regimes (*E* and *S*) the mean growth rate over three months of the U.S. is greater than that of the Euro zone. In particular, in the regime E the average growth rate for the U.S. is 2% while for the Euro zone is 1.3%, while in the regime S is 0.48% for the U.S. and 0.23% for the Euro Zone. In the negative regime (*R*) the growth rate for the U.S. is -1.44% against -1.3% for the Euro zone which means that recessions in the U.S. are on average more severe. Concerning the volatility of the growth rate, it is possible to note that in Europe the volatility is greater than in the U.S. The most volatile regime is *R*, while the lowest is the intermediate regime *S* for both the areas.

In figures 1 and 2 the detected low phases of the business and the growth cycle are reported for both the areas. In particular, concerning figure 1 it is important to underline the correspondence between regime *R* for the Euro zone and for the U.S. and the well known episodes of recession. The first oil shock, the double dip at the beginning of the eighties, the recession in the U.S. at the beginning of the nineties, the Euro zone recession in 1992 and the possible 2001 recession are all well detected. Moreover, very low uncertainty is associated to the regime classification and by a visual inspection it is possible to note that the U.S. leads Europe in entering in recession. Concerning figure 2, it is possible to note that the slowdown periods emerging from the graph are strictly connected to the growth cycle low phases. For example, by comparing the reference chronology of the growth cycle published by the ECRI for the U.S.[7] with the periods observed in the figure, it is possible to note that the slowdown of 1973-1975, the persistent low growth across the end of the seventies and at the beginning of the eighties, the slowdown of 1984-1987 and especially the slowdown starting in April

[7] For the Euro zone there does not exist a reference chronology for both the growth and business cycles.

2000 are well detected and turning points do not differ significantly. Moreover, it is possible to note that most of the times, the shifts to the low phase of the growth cycle in the U.S. lead those of the Euro zone.

Both for the business and the growth cycles the low phases detected with the MMS approach are not erratic but display a very high persistence, hence regimes should be considered informative by policy makers.

The most interesting feature of the MMS model is that it allows us to estimate the transition matrix of the Markov chain determining the joint evolution of the phases in the Euro zone and in the U.S: this could produce useful information on the relationship between the cycle of the two areas. The final transition matrix is reported in table 4. It is noteworthy that we can accept the equality of zero of most of the transition probabilities. In many rows there are only two or three elements different from zero and this means that there is little uncertainty about the following regime. Let us consider for example the row *SR*, which reports the probabilities to go to another regime starting from the intermediate regime (*S*) for the Euro zone and from the recession regime (*R*) for the U.S. In this row only two probabilities are different form zero: that one of staying in *SR* and that one of getting to *RR*. We can thus conclude that the U.S. leads the Euro zone to a recession. Since the expected duration of *SR* is 2.98 months (see table 5), we can conclude that when we are in the *SR* regime, Europe will move to the regime *R* in 3 months, which is the average lead of the U.S.

The analysis of the remaining elements of the 9x9 matrix is quite tedious. To simplify, we will analyse a reduced version of the matrix. Starting from the full transition matrix of the 9 regime Markov chain, it is easy to get the 4 by 4 transition matrix referring to the business cycle. The same simplification can be performed if we want to analyse the growth cycle (see tables 6 and 7).

<u>Analysis of the business cycle:</u>

Table 6 gives the transition matrix for the business cycle. We consider the following two regimes for each chain: regime *EX* corresponds to the sum of regime *E* and regime *S* of the starting model, meaning that the economy is expanding, while the regime *RE* is simply the recession regime *R*.

Let us start considering the exit of *EX-EX* regime: this regime is very persistent and its expected duration is 30.5 months; it is striking that the only possible exit from *EX-EX* is *EX-RE*, which means that the U.S. shifted to the recession regime. Moreover we observe that once we get *EX-RE*, there is a 84% probability to enter *RE-RE*, which indicates that both the

U.S. and the Euro zone are in the recession phase and only 16% probability to get back to *EX-EX*. Since the expected duration of the *EX-RE* regime is 4 months, we can conclude that if the U.S. enters in the recession phase, there is an high probability that the Euro zone will follow in 4 months. The transition matrix is clearly indicating a lead of the U.S. in entering recessions.

Finally, we observe that, from *RE-RE* there is a 86% probability of a shift to the *EX-EX* regime which means synchronization in exiting the recession and 14% probability to get to *RE-EX* which means that the U.S. switches in advance. It is striking that, once in *RE-EX*, the only possible exit is *EX-EX* which means that the U.S. drives the recovery. The average lead in this case is 8.5 months.

We can conclude that, both in entering and exiting business cycle recessions, the U.S. leads the Euro zone or the shift are synchronised.

<u>Analysis of the growth cycle</u>

Table 7 gives the transition matrix for the growth cycle. Differently from the business cycle transition matrix, there is no clear evidence of a lead of the U.S. Starting from the above the trend phase for both areas (regime *HH*), there is the same probability to get *HL* and *LH* and no synchronised shift to the below trend phase (*LL*) is possible. From the regimes *HL* and *LH* it is possible to get *LL* but also to *HH*, so no clear lead is showed by any area in entering the low phase of the growth cycle. Consider now the *LL* regime: it may happen a synchronised exit to *HH*, but in the most of the cases, with a 89% probability, the exit is *LH* which means that the U.S. exit in advance. Once in *LH*, it is possible to move to *SS* again but the exit could also be *HH*: we can thus conclude that the U.S. lead the Euro zone in exiting the low phase of the growth cycle or the exit is synchronised. In any case, the Euro zone never leads the U.S. in exiting the low phase.

The more complex dynamic described by the transition matrix of the growth cycle could be due to the fact that the low phase of the growth cycle is more connected to the area specific shocks than a recession. Recessions in fact are more synchronised and in most of the cases seem to be the results of global shocks.

In conclusion, the transition probabilities have to be studied with caution. Some of them may be influenced by the presence of specific cycles especially those concerning the growth cycle. On the contrary, when the U.S shift in a business cycle recession we expect the Euro zone to follow within a few months. This “catching up” effect can be seen if we consider the evolution of the conditional mean of each area to the steady state mean (unconditional mean) given a starting regime. The conditional mean at time *t* is the average of the means in different regimes weighted by the probability of the corresponding regime at time *t*. Starting with a specified regime (among the nine) for both the Euro zone and the U.S. at time $t=1$ we multiply i times the 9×9 transition matrix to compute the conditional probability of each regime and the conditional mean at time $t+i$. *A*fter a few iterations the conditional probabilities and the conditional means converge to their steady state (unconditional) values. Table 8 shows the evolution of the conditional means of both areas starting from different regimes. It is possible to note that there is a strong inter-relationship between the two areas, in particular given a starting state for Europe, the evolution of the conditional mean of this area is quite different depending on which is the starting state for the U.S. Let us consider now the evolution of the conditional mean starting from regime *ER* and *SR*: it is evident the catching up process. If we start from *ER*, the U.S. recover to the steady state while the Euro zone before reaching the steady state experiences a period of low growth. The same happens starting from the *SR* regime, since it is evident that a deterioration of the economic condition in the Euro zone is expected. The opposite does not happen when the business condition in Europe is bad: starting from the *RE* and *RS* regimes, the U.S. are not strongly affected by the European conditions, in fact they reach directly their steady state growth without showing a catching up process. On the contrary, in the case of the regime *RE*, the Euro zone seems to exit from the bad condition very quickly.

4.2 A causality analysis of the Euro zone and the U.S. industrial productions

To get a more detailed description of the relationship between growth cycles phases in the U.S. and in the Euro zone, we consider the industrial production indexes without the trend. The trend has been extracted with the two stages Hodrick Prescott filter calibrated to maintain all the fluctuations between 1.5 and 8 years (see Artis, Marcellino and Proietti, 2002). The series without the trend are reported in figure 3: peaks and troughs of the series correspond to peaks and troughs of the growth cycle.

In order to get a representation of the growth cycle phases in terms of Markov chains we implement an MMS VAR(1) model. This produces a little delay in detecting turning points but in any case the phases are well described. Starting from the general model with regime dependent mean and variances and 12 unrestricted conditional probabilities, we reduce the number of parameters by imposing some restrictions. In the final specification only the intercepts and the correlation are regime dependent, while the transition matrix is reduced to only 6 unrestricted elements and the correlation is constant across regimes (see tables 9 and 10 for the estimated parameters and the standard errors). In table 11 the test for the validity of the joint restrictions is reported. Looking at table 9 it is possible to note that the intercept terms associated to the low regime are negative for both series.

Figure 4 reports the smoothed probability of being in the low phases of the growth cycle. If one compares figure 4 with figure 2 reporting the classification of the growth cycle derived from the MMS model with 9 regimes, it is possible to note that phases are very similar, moreover in figure 4 regimes are less erratic: as mentioned, this is because the 9 regime model involves an approximation assuming a constant trend growth rate.

Concerning the transition matrix, which is reported in table 12, we can evidence some important information. Let us start by considering the exit from the *HH* regime: there are two possible exits, *LL* (18% probability) and *HL* (82% probability). If we move to *LL* it means that both areas switch to the low phase but if we go to *HL* it means that only the U.S. shift to the low regime. Moreover, we observe that once we get to *FS* we can only exit it by entering in *LL*. The transition matrix indicates that in most of the cases there is a lead of the U.S. in entering the below trend phase or at least the shift is synchronized. The same happens in exiting the *LL* regime: we have a 21% probability to get *HH* and a 79% probability to get *LH*. In the latter case, the only possible exit is *LL*, hence the U.S. are leading again the Euro zone or at least the exits from the below trend phase are synchronised.

Finally, given the evidence that the U.S. lead the change in phase, we tested the null that shifts in the U.S. do not cause shifts in the Euro zone (USA NC EU) and that shifts in the Euro zone do not cause shift in the U.S. (EU NC USA). Results of the test are reported in table 13. As it was expected the null "USA NC EU" is rejected. However, also the null "EU NC USA" is rejected.

4.3 A MMS model for the Euro zone industrial production and the industrial survey of the ESI

In figure 5, the standardised industrial component of the ESI in levels (SIND) and the standardised Euro zone IPI without the trend component (SIPI) are reported[8]. Concerning peaks and troughs of the SIPI without the trend, they have a clear meaning since they indicate us that the growth rate is equal to the trend growth rate hence peaks and troughs of the SIPI

[8] The trend has been extracted with the two stages Hodrick Prescott filter calibrated to maintain all the fluctuations between 1.5 and 8 years (see Artis, Marcellino and Proietti, 2002).

are the turning points of the growth cycle of the industrial production. By a visual inspection of figure 5, it is possible to note that starting from the beginning of the nineties until today, the turning points of the SIPI and those of the SIND are strictly connected. Moreover turning points of the survey seems to lead those of the growth cycle of the industrial production.

To get a representation of the above mentioned cyclical phases in terms of Markov chains, we implement an MMS VAR(1) model. This produce a little delay in detecting turning points but in any case the phases are well described. Starting from the general model with regime dependent means and covariance matrix and 12 unrestricted conditional probabilities, we reduce the number of parameters by imposing some restrictions. In the final specification only the intercepts are regime dependent while the transition matrix is reduced to only 6 unrestricted elements and the correlation is constant across regimes (see tables 14 and 15 for the estimated parameters and the standard errors). In table 16 the test for the validity of the joint restrictions is reported.

Figure 6 reports the smoothed probabilities of being in the low phase of the growth cycle. It is possible to note that there is a clear relationship between change of phase detected by the model and the turning points exhibited by the series in figure 5. Moreover, a lead of the survey is again visible.

Analysing the transition matrix reported in table 17, we can illustrate some important information. Let us start by considering the exit from the *HH* regime. The two possible exits are *LL* (60% probability) and *HL* (40% probability). If we go to *LL* it means that both areas switch to the low phase, but if we go to *HL* it means that only the survey shift to the low regime. Moreover, we observe that once we move to *HL* we can only exit by entering in *LL*. The transition matrix indicates that in some cases there is a lead of the survey in entering the below trend phase or at least the shifts are synchronized. The same happens in exiting the *LL* regime: we have a 43% probability to get *HH* and a 57% probability to get *LH*. In the latter case the only possible exit is *LL*, hence the survey leads again the industrial production or at least the two exits from the below trend phase are synchronised.

Finally, we tested the null that shifts in the survey do not cause shifts in the Euro zone IPI growth cycle phase (IND NC IPI) and that shifts in the SIPI do not cause shift in the SIND. (IPI NC IND). Results of the test are reported in table 18. As it was expected the null “IND NC IPI” is rejected but also the null “IPI NC IND” is rejected.

5 Conclusions

In this paper we extend the classical MS VAR approach to the business cycle proposed by Krolzig (1997) introducing multiple Markov chain producing specific shifts in the parameters of each equation of the VAR (MMS VAR). Differently from the MS VAR approach, which allows us to describe the common cycle and the evolution of its phases, the MMS VAR approach allows us to describe the relationship among cyclical phases of different countries or different sectors. Moreover we introduce a re-parameterization of the model which allows us to introduce causality relationships and test for them.

The MMS VAR models and their different specifications are used to analyse the relationship between the industrial cycle in the Euro zone and in the U.S. and the relationship between the cyclical phases of the industrial production in the Euro zone and the phases exhibited by the industrial component of the ESI.

Concerning the relationship between the Euro zone and the U.S. industrial productions, the estimated transition matrix of the MMS model shows that the U.S. most of the time leads the Euro zone in both the business and the growth cycle. Moreover, we conduct a study of the evolution of the conditional mean to its steady state value and we show that there is a strong inter-relationship between the two macro areas. In particular, the evolution of the business condition in the Euro zone is strongly affected by the current condition in the U.S. In order to evaluate the causality relationship between the growth cycles phases in the two macro areas, we estimate a MMS model for the Euro zone and the U.S. industrial productions without the trend components. The lead of the U.S. is graphically confirmed but the null of non causality is rejected in both directions.

Finally, we consider a MMS model to study the relationship between the growth cycle phases of the industrial production in the Euro zone and the phases of the industrial component of the ESI index. The estimated transition matrix shows that change in phases of the industrial survey and those of the industrial sector are at least synchronised and sometimes those of the survey are in advance (in particular in the last part of the sample). However, the null of non causality is again rejected in both directions.

References

Anas J., Billio M., Ferrara L. and Lo Duca M. (2003), A turning point chronology for the Euro-zone classical and growth cycle, to be presented Colloquium on "*Modern Tools for Business Cycle Analysis*", Luxembourg, October 2003.

Anas, J. and Ferrara, L. (2002a), "Un indicateur d'entrée et sortie de récession :application aux Etats-Unis", Document de travail No. 58, Centre d'Observation Economique, Paris (www.coe.ccip.fr).

Anas, J. and Ferrara, L. (2002b), "Detecting cyclical turning points: the ABCD approach and two probabilistic indicators ", paper presented at the *26th Ciret Conference* in Taiwan, October 2002 (www.coe.ccip.fr).

Anas, J. and Ferrara, L. (2002c), "A comparative assessment of parametric and non-parametric turning points methods: the case of the Euro-zone economy", paper presented at the Colloquium on "*Modern Tools for Business Cycle Analysis*", Luxembourg, November 2002 (www.coe.ccip.fr).

Artis M. J., Krolzig H. and Toro J. (2002), The European business cycle, *Working paper ECO*, n° 99-24, European University Institute, Florence.

Artis M. J., Marcellino M., Proietti T., (2002), Dating the Euro area Business Cycle, *Working paper*, European University Institute, Florence.

Batchelor R. A., (2002) Confidence indexes and the probability of recession: a Markov switching model, *Indian Economic Review,* 36 (1) , 107-124.

Billio M. (2002), Correlated Markov chains, *manuscript* GRETA, Venice.

Billio M. and A. Monfort (1998), Switching state space models: likelihood, filtering and smoothing, *Journal of Statistical Planning and Inference* 68/1, 65-103.

Billio M., A. Monfort and C.P. Robert (1998), The simulated likelihood ratio (SLR) method, *Document de Travail du CREST* 9828, Paris.

Breunig R. and Pagan A. (2002), Specification Testing of Markov Switching Models, paper presented at the 13th $(EC)^2$ Conference "*Model selection and evaluation*", Bologna, Italy, November 2002.

Boldin M. D. (1996), A check on the robustness of Hamilton's Markov Switching model approach to the economic analysis of the business cycle, *Studies in Nonlinear Dynamics and Econometrics* 1, 35-46.

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

Carter C. K. and P. Kohn (1994), On Gibbs sampling for state space models, *Biometrika 84*, 541–53.

Chauvet M. (1998), An Econometric Characterisation of Business Cycle Dynamics with Factor Structure and Regime Switching, *International Economic Review* 39, 969-996.

Chauvet M. (1999), Stock Market Fluctuations and the Business Cycle, *working paper* Department of Economics, University of California, Riverside (research.moore.sc.edu/workshop/papers/Chauvejr.rtf).

Chen S.W. and J.L. Lin (2000), Identifying turning points and business cycles in Taiwan: A multivariate dynamic Markov-switching factor model approach, *Academia Economic Papers*, 28, 289–321.

Chin D. and Geweke J. (2000), Predicting turning points, *Working Paper*, Federeal Reserve Bank of Minneapolis.

Clements M.P., Krolzig H.M., (2000), Modelling Business Cycle Features using Switching Regime Models, *Discussion Paper*, Institute of Economics and Statistics Oxford.

Clements M.P., Krolzig H.M., (2003), Business cycle asymmetries: characterization and testing based on Markov-Switching autoregressions, *Journal of Business and Economic Statistics*, 21/1, 196-211.

Davig T., (2002), Markov switching durations: an assessment of U.S. business cycles, *Working Paper.*

Diebold F. X. and Rudebusch G. D. (1996), Measuring business cycles: a modern perspective, *Review of Economics and Statistics* 78/1, 67-77.

Doz C. and Lenglart F., (2001), Dynamic Factor analysis: estimation and test with an application to the European business surveys, paper presented at the CEPR/ Banca d'Italia Conference in Rome, September 2001.

Frühwirth-Schnatter S. (1994), Data augmentation and dynamic linear models. *Journal of Time Series Analysis 15*, 183–202.

Guegan D., (2003), Business and Financial Cycles: How to measure them and to measure their Interdependency? Note de recherché IDHE-MORA no. 07-2003, paper presented at the Forecasting Financial Markets conference, Paris, June 2003.

Guerrero G. (2002), Markov-Switching Models of Business Cycle: Can the Econometric Model detect the growth regime? *Working paper* EUREQua, Maison des Sciences Economiques (www.ecomod.net/conferences/ecomod2002/ papers/guerrero.pdf).

Hamilton J. D. (1989), A new approach to the economic analysis of non stationary time series and the business cycle, *Econometrica* 57/2, 357-384.

Hamilton J.D. and G. Lin (1996), Stock market volatility and the business cycle, *Journal of Applied Econometrics* 11, 573-593.

Harrison P.J. and Stevens, C.F. (1976), Bayesian forecasting, *Journal of the Royal Statistical Society* B 38, 205-247.

Kaufmann S. (2000), Measuring business cycles with a dynamic Markov switching factor model: an assessment using Bayesian simulation methods, *The Econometrics Journa*l 3/1, 39-65.

Kholodilin K. (2001), Latent Leading and Coincident Factors Model with Markov-Switching Dynamics, *Economics Bulletin* 3, 1-13.

Kim C.J. (1994), Dynamic linear models with Markov-switching, *Journal of Econometrics* 60, 1-22.

Kim C. J., Morley J. and Piger J. (2002), A Markov-Switching Model of Business Cycle Dynamics with a Post-Recession "Bounce-Back" Effect, wc.wustl.edu/workingpapers/Kim_Morley_Piger.pdf.

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

Kim, C.J. and C. R. Nelson (1999), *State-Space Models with Regime Switching*. Cambridge, MIT Press.

Kim C.J., Piger J., Startz R., (2003), Estimation of Markov regime switching regression models with endogenous switching, *working paper* 2003-015A, Federal Reserve Bank of St.Luis.

Krolzig H.M. (1997), Markov-switching vector autoregressions. Modelling, statistical inference and applications to business cycle analysis*, Springer*, Berlin.

Krolzig H.M. and Toro J. (2001), Classical and Modern Business Cycle Measurement: The European Case. *Working paper* Institute of Economics and Statistics Oxford (www.econ.ox.ac.uk/research/hendry/ paper/HMKJTeurosty.pdf).

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

Krolzig, H.-M. (2003), Constructing turning point chronologies with Markov-switching vector autoregressive models: the euro-zone business cycle, in: Eurostat (ed.), Proceedings on "*Modern Tools for Business Cycle Analysis*", Monography in Official Statistics.

Layton A.P. and Smith D. (2000), A further note to the three phases of the US business cycle, *Journal of Applied Economics*, 2000, 32, 1133-1143.

Layton A.P. and Katsuura M. (2001a), A new business cycle turning point signalling system using the Markov Switching model, *Applied Economics* 33, 59-70.

Layton A.P. and M. Katsuura (2001b), Comparison of Regime Switching, Probit and Logit Models in Dating and Forecasting US Business Cycles, *International Journal of Forecasting* 17, 403-17.

Luginbuhl R. and de Vos A. (1999), Bayesian Analysis of an Unobserved-Component Time Series Model of GDP with Markov-Switching and Time-Varying Growths, *Journal of Business and Economic Statistics* 17/4, 456-65.

Mosconi R., Seri R. (2001), Non-Causality in Bivariate Binary Time Series, http://www.crest.fr/pageperso/lfa/seri/SeriFr.HTM.

Shephard N. (1993), Fitting non-linear time series models, with applications to stochastic variance models, *Journal of Applied Econometrics* 8, 135-152.

Shephard N. (1994), Partial non-Gaussian state space, *Biometrika* 81, 115–31.

Smith P.A. and Summers P.M, (2002), How well do Markov switching models describe actual business cycles? The case of synchronisation, *Working Paper* University of Melbourne..

Susmel R. (1998), Switching volatilities in international equity markets, *manuscript* Department of Finance, University of Houston.

Stock J.H. and Watson M. W. (1989), New indexes of coincident and leading indicators, in: *Macroeconomics Annual*, vol. 4, MIT Press.

Vanhaelen, J.-J., Dresse, L. and DeMulder, J. (2000), The Belgian industrial confidence indicator: leading indicator of economic activity in the Euro area, Economic Surveys and Data Analysis, Proceedings of the 25th CIRET Conference in Paris, October 2000, OECD Publications, Paris.

Warne A. (2000), Causality and Regime Inference in a Markov Switching VAR, Sveriges Riksbank.

Table 1: Estimated parameters and standard errors of the MMS model for the Euro zone and the U.S. Industrial Productions. The growth rate over three months has been considered.

Parameter	Estimate	Standard error
$\mu_{E,EU}$	0.0133	0.0004
$\mu_{S,EU}$	0.0023	0.0003
$\mu_{R,EU}$	-0.0130	0.0011
$\mu_{E,USA}$	0.0200	0.0009
$\mu_{S,USA}$	0.0048	0.0009
$\mu_{R,USA}$	-0.0144	0.0029
$\sigma_{E,EU}$	0.0053	0.0003
$\sigma_{S,EU}$	0.0032	0.0002
$\sigma_{R,EU}$	0.0088	0.0007
$\sigma_{E,USA}$	0.0090	0.0005
$\sigma_{S,USA}$	0.0063	0.0009
$\sigma_{R,USA}$	0.0236	0.0019
ρ	0.2441	0.0929

Table 2: Estimated transition probabilities.

Transition probability	Estimate	Standard error
EE to SE	0.0540	0.0237
SE to SE	0.6018	0.0982
SS to SE	0.1685	0.0566
SE to RE	0.0205	0.0204
RE to RE	0.7822	0.1953
EE to ES	0.0471	0.0208
ES to ES	0.8813	0.0514
SE to SS	0.1977	0.0461
SS to SS	0.7503	0.0639
RS to RS	0.9199	0.0771
RR to RS	0.0209	0.0208
ES to ER	0.0824	0.0455
ER to ER	0.6401	0.1828
SS to SR	0.0543	0.0317
ER to SR	0.2457	0.1464
SR to RR	0.3351	0.1169
RR to RR	0.8563	0.0507

Table 3: Joint test for the restrictions imposed to the general model.

L_unr	L_res	$\chi^2(63)$	P-value
3042.62	3016.66	51.92	0.84

Table 4: Final specification of the transition matrix.

	EE	*SE*	*RE*	*ES*	*SS*	*RS*	*ER*	*SR*	*RR*
EE	**0.90**	**0.05**	0.00	**0.05**	0.00	0.00	0.00	0.00	0.00
SE	**0.18**	**0.60**	**0.02**	0.00	**0.20**	0.00	0.00	0.00	0.00
RE	0.00	**0.22**	**0.78**	0.00	0.00	0.00	0.00	0.00	0.00
ES	0.00	**0.04**	0.00	**0.88**	0.00	0.00	**0.08**	0.00	0.00
SS	**0.03**	**0.17**	0.00	0.00	**0.75**	0.00	0.00	**0.05**	0.00
RS	0.00	0.00	0.00	0.00	**0.08**	**0.92**	0.00	0.00	0.00
ER	0.00	0.00	0.00	**0.11**	0.00	0.00	**0.64**	**0.25**	0.00
SR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.66**	**0.34**
RR	0.00	0.00	0.00	0.00	**0.12**	**0.02**	0.00	0.00	**0.86**

Table 5: Unconditional probabilities and expected duration of each regime.

	Unconditional Probabilities	**Expected Duration**
EE	0.29	9.89
SE	0.13	2.51
RE	0.01	4.59
ES	0.15	8.43
SS	0.18	4.00
RS	0.03	12.49
ER	0.03	2.78
SR	0.05	2.98
RR	0.12	6.96

Table 6: Transition matrix for the business cycle phases; unconditional probabilities and expected duration of each regime.

	EX-EX	*RE-EX*	*EX-RE*	*RE-RE*	*Unc Prob*	*Exp Dur*
EX-EX	0.97	0.00	0.03	0.00	0.74	30.47
RE-EX	0.12	0.88	0.00	0.00	0.05	8.43
EX-RE	0.04	0.00	0.75	0.21	0.09	4.00
RE-RE	0.12	0.02	0.00	0.86	0.12	7.14

Table 7: Transition matrix for the growth cycle phases; unconditional probabilities and expected duration of each regime.

	HH	*LH*	*HL*	*LL*	*Unc Prob*	*Exp Dur*
HH	0.90	0.05	0.05	0.00	0.29	9.89
LH	0.16	0.65	0.00	0.18	0.15	2.90
HL	0.00	0.03	0.92	0.05	0.18	13.28
LL	0.01	0.08	0.00	0.91	0.39	11.17

Figure 1: Smoothed probabilities of a business cycle recession in the Euro zone (EU) and in the U.S. (USA).

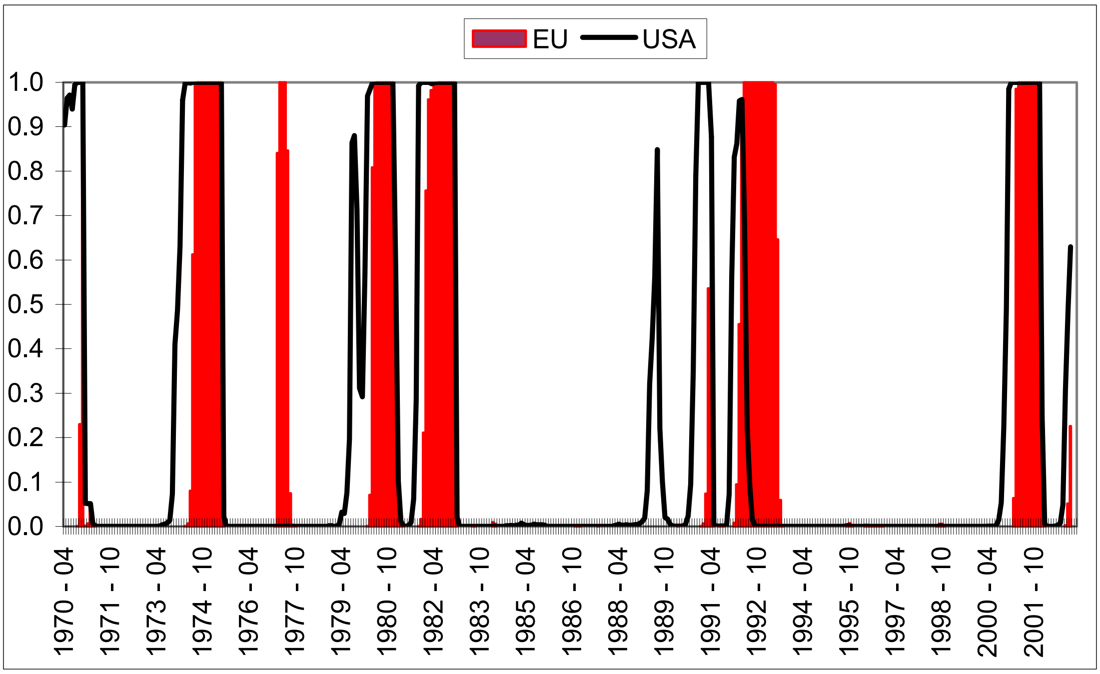


Figure 2: Smoothed probabilities of the low phase of the growth cycle in the Euro zone (EU) and in the U.S. (USA).

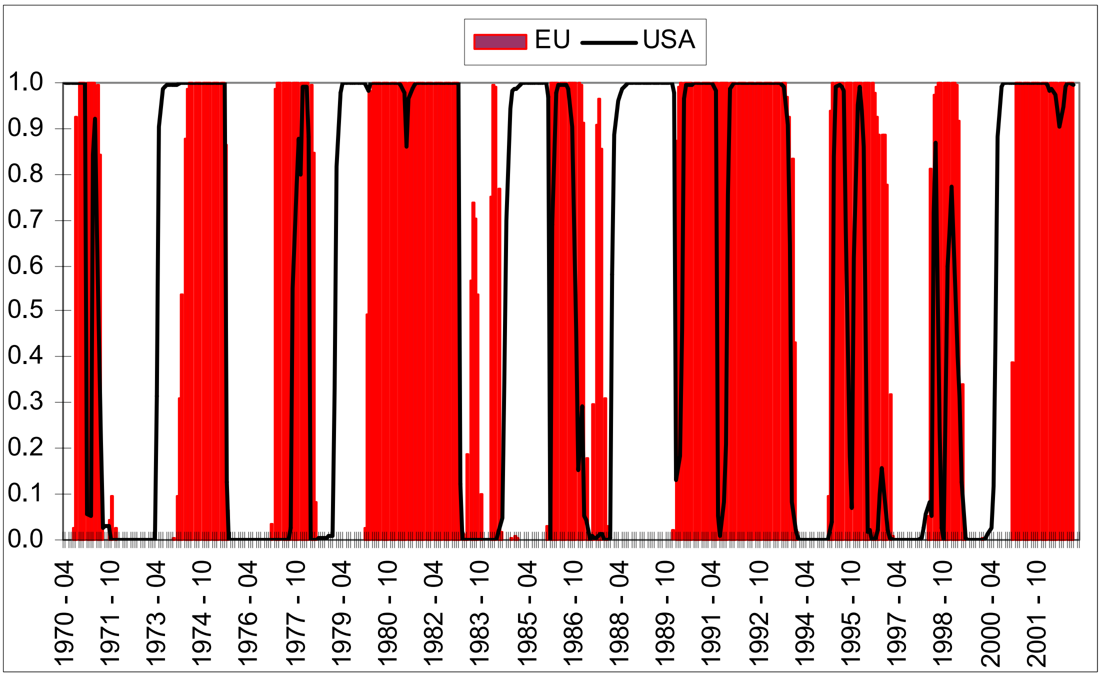


Table 8: Impulse response analysis. Evolution of the conditional mean in the Euro zone (EU) and in the U.S.A. (USA) given a starting regime.

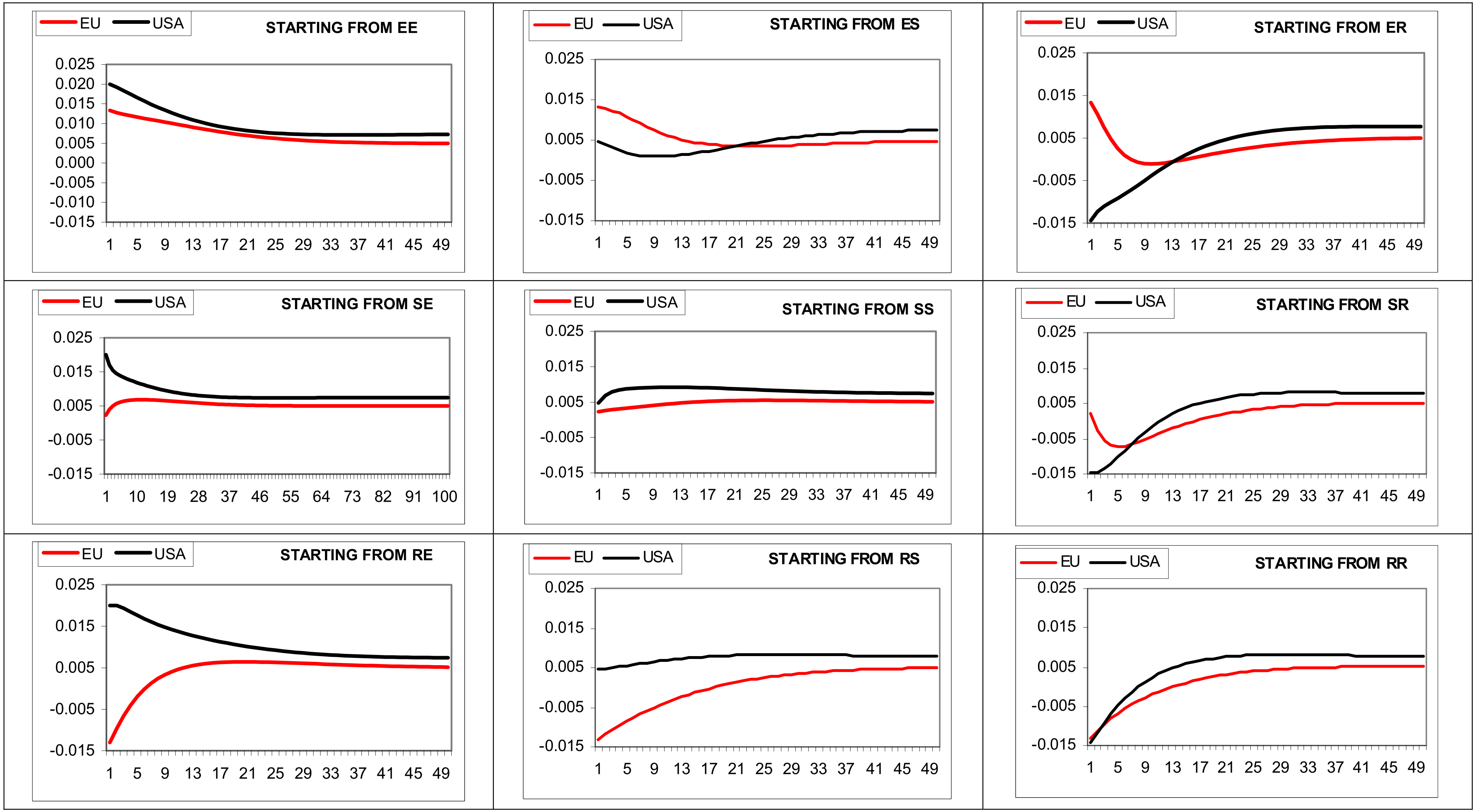


Figure 3: Standardised Industrial Production Indexes without the trend component for Euro zone (SDEU) and the U.S. (SDUSA).

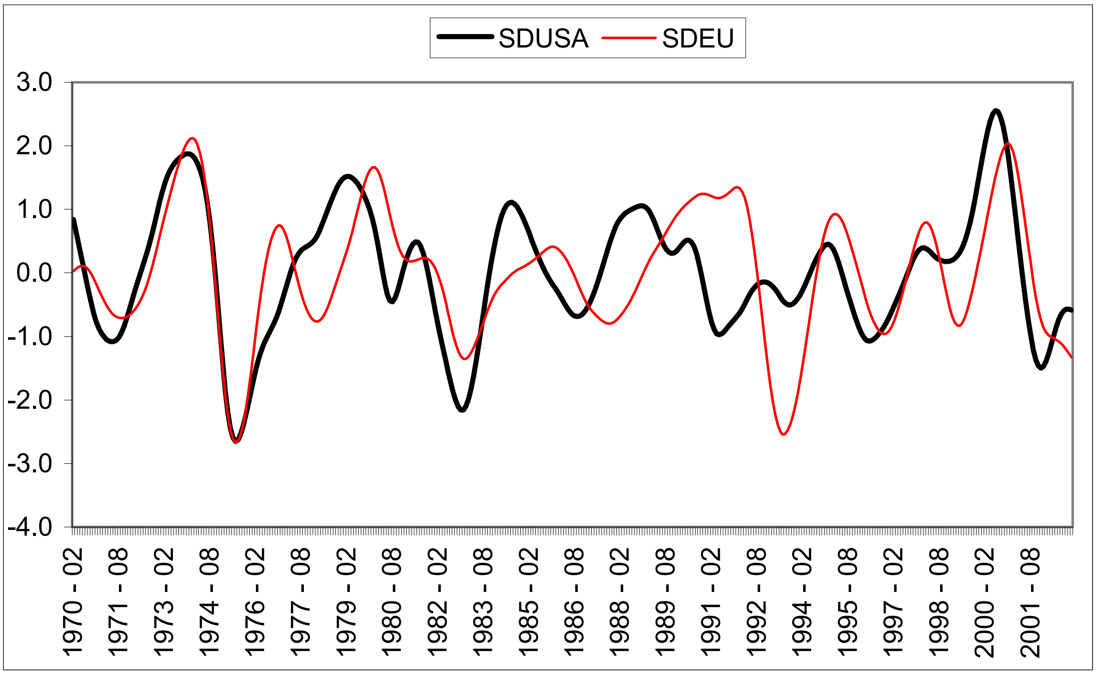


Table 9: Estimated parameters and standard errors of the MMS model with 4 regimes for the Euro zone and the U.S. standardised Industrial Production Indexes without the trend component.

Parameter	Estimate	Standard error
$\upsilon_{F,EU}$	0.0745	0.0064
$\upsilon_{S,EU}$	-0.0807	0.0068
$\upsilon_{F,USA}$	0.0625	0.0064
$\upsilon_{S,USA}$	-0.0778	0.0064
σ_{EU}	0.0085	0.0061
σ_{USA}	0.0185	0.0027
Φ_{EU}	0.9969	0.0046
Φ_{USA}	0.9844	0.0045
$\rho_{E,E}$	0.9203	0.0172
$\rho_{S,E}$	0.7338	0.0415
$\rho_{E,S}$	0.9196	0.0147
$\rho_{S,S}$	0.9124	0.0190

Table 10: Estimated transition probabilities and standard errors.

Transition probability	Estimate	Standard error
LH to LH	0.9282	0.0248
LL to LH	0.1104	0.0355
HH to HL	0.0861	0.0296
HH to LL	0.0233	0.0164
HL to LL	0.0861	0.0277
LL to LL	0.8636	0.0397

Table 11: Test for the validity of the joint restrictions imposed to the general model.

L_unr	L_res	$\chi^2(6)$	p-value
1224.84	1224.84	0.00	0.00

Table 12: Final specification of the transition matrix and expected duration of each regime.

	HH	**LH**	**HL**	**LL**	***Exp Dur***
HH	**0.89**	0.00	**0.09**	**0.02**	9.14
LH	**0.07**	**0.93**	0.00	0.00	13.92
HL	0.00	0.00	**0.91**	**0.09**	11.62
LL	**0.03**	**0.11**	0.00	**0.86**	7.33

Table 13: Non causality tests.

Null	L unr	L null	$\chi^2(2)$	p-value
USA NC EU	1227.04	1155.24	143.60	0.00
EU NC USA	1227.04	1173.18	107.72	0.00

Figure 4: Smoothed probabilities of the low phase of the growth cycle in the Euro zone (SDEU) and in the U.S. (SDUSA).

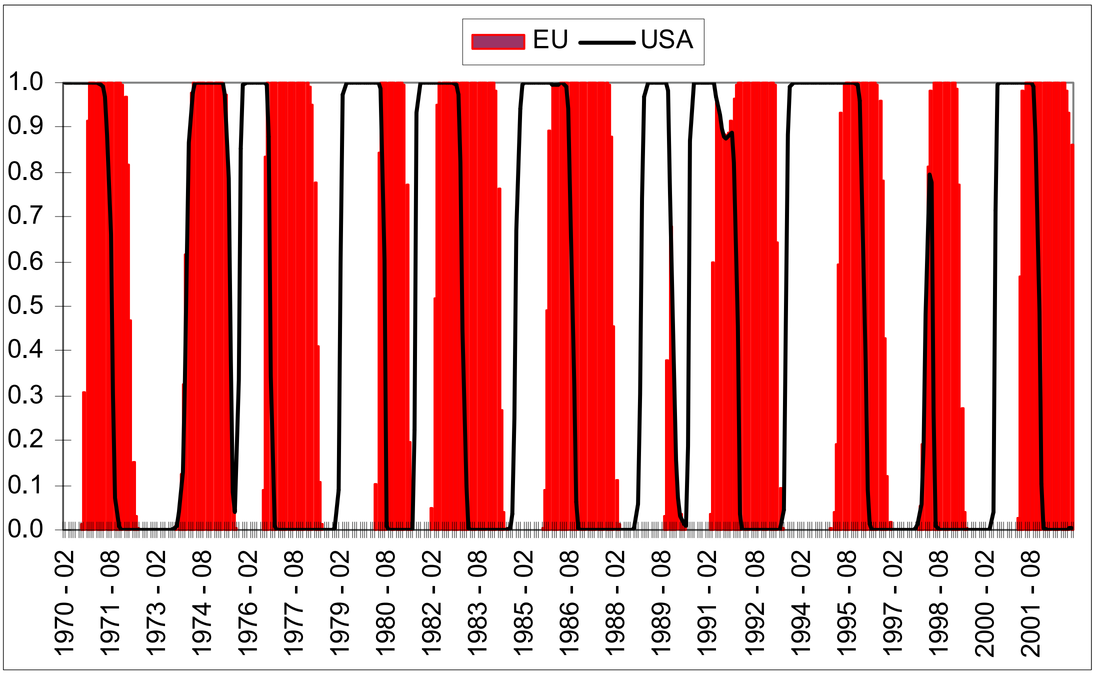


Figure 5: Standardised Industrial Production Index without the trend component for the Euro zone (SIPI) and standardised level of the industrial survey (SIND).

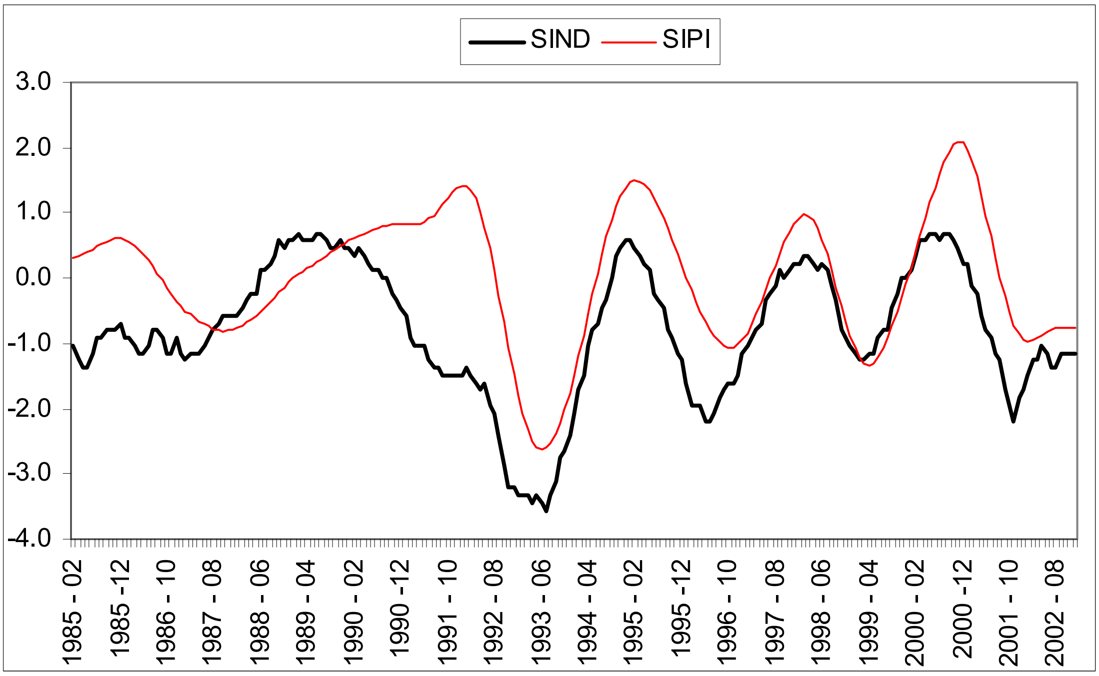


Table 14: Estimated parameters and standard errors of the MMS model with 4 regimes of Euro zone standardised Industrial Production Indexes without the trend component and standardised industrial survey.

Parameter	Estimate	Standard error
$\upsilon_{F,IPI}$	0.0819	0.0091
$\upsilon_{S,IPI}$	-0.1574	0.0125
$\upsilon_{F,IND}$	0.0436	0.0163
$\upsilon_{S,IND}$	-0.1336	0.0214
σ_{IPI}	0.0147	0.0051
σ_{IND}	0.0429	0.0061
Φ_{IPI}	0.9883	0.0081
Φ_{IND}	0.9556	0.0112
ρ	0.5761	0.0600

Table 15: Estimated transition probabilities and standard errors.

Transition probability	Estimate	Standard error
LH to LH	0.5735	0.2394
LL to LH	0.0411	0.0418
HH to HL	0.0215	0.0162
HH to LL	0.0245	0.0165
HL to LL	0.0912	0.0633
LL to LL	0.9287	0.0312

Table 16: Test for the validity of the joint restrictions imposed to the general model.

L_unr	L_res	$\chi^2(9)$	p-value
514.17	512.66	3.02	0.96

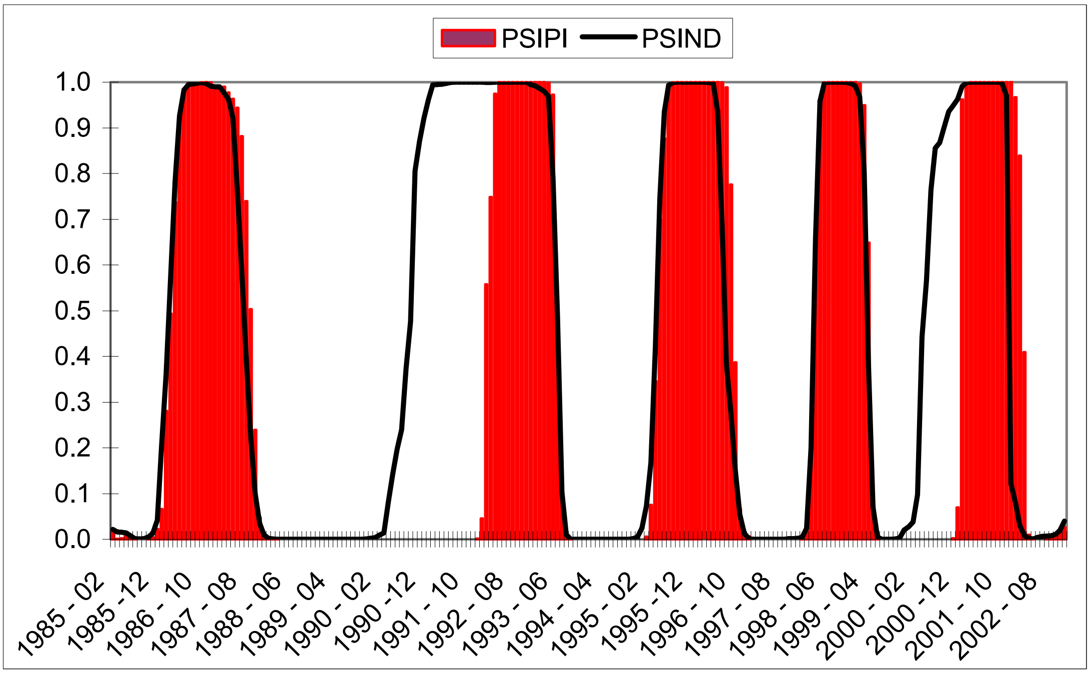
Table 17: Final specification of the transition matrix and expected duration of each regime.

	HH	**LH**	**HL**	**LL**	***Exp Dur***
HH	**0.95**	0.00	**0.02**	**0.03**	21.73
LH	**0.43**	**0.57**	0.00	0.00	2.34
HL	0.00	0.00	**0.91**	**0.09**	10.97
LL	**0.03**	**0.04**	0.00	**0.93**	14.03

Table 18: Non causality tests.

TEST	F unr	F null	$\chi^2(2)$	p-value
IND NC IPI	512.82	508.96	7.72	0.02
IPI NC IND	512.69	508.42	8.53	0.01

Figure 6: Smoothed probabilities of the low phase of the growth cycle in the Euro zone (PSIPI) and smoothed probabilities of the low phase of the standardised industrial survey (PSIND).



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First Draft: data

Abstract
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