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The European Business Cycle

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Abstract

This paper deals with the existence of a common European growth cycle and its identification. Based on the analysis of some descriptive statistics in the time and frequency domain there is clear evidence of comovement in output growth among European countries. Univariate Markov switching autoregressions (MS-AR) are used for individual countries in order to detect changes in the mean growth rate of industrial production. The smoothed probabilities obtained from these models give support to the previous descriptive statistics regarding the possibility of inferring a common European cycle from modelling jointly the industrial production indices of the nine countries under study. An MS-VAR model is used to identify the common cycle in Europe and the results confirm the existence of such a cycle. The European business cycle is dated on the basis of the regime probabilities, and the contribution of the European business cycle to the individual country cycles is investigated.An appendix includes a similar analysis for GDP.

JEL Classification: E32, F43, F47, C32.

Keywords: International business cycles; European Union; Markov switching; Structural breaks; Time series analysis.

1 Introduction

The constitution of the European Monetary Union has raised several interesting issues. Among them, one of paramount relevance concerns the existence of a common cycle among the member countries. A lack of business cycle synchronization could complicate the operation of monetary policy in the union and constitutes a negative indicator in the optimal currency area literature for the formation of a monetary union. On the other hand it has been argued recently that the formation of a monetary union in itself creates a tendency for business cycle symmetry to emerge. If this condition holds for the European monetary Union and the quasi-union of the Exchange Rate Mechanism of the European Monetary System,then we might expect already to be able to find an emergent ”European cycle” which will become more dominant in future years. This paper addresses the issues of identification and dating of an European business cycle using Markov-switching vector autoregressions.

A strand of literature has recently focussed on the asymmetry of shocks in the European Union in order to evaluate the European Union as an optimal currency area. An important part of this literature uses structural vector autoregressions (SVARs)[1]. The moving average representation of this vector autoregression is obtained and its structural form is recovered by imposing convenient restrictions. The moving average representation of the SVAR can track the response of a variable to structural shocks (the original Gaussian innovations are orthogonalized through appropriate restrictions). Furthermore a variance-decomposition analysis can shed light on the proportion of the variance of certain variables explained by different innovations at different time horizons. For European data, Bayoumi and Eichengreen (1993) use the type of restrictions introduced by Blanchard and Quah (1989) in order to asses the relative importance of supply and demand shocks in different European countries. The results are compared with what could be considered an optimal currency area, the US. They conclude that disturbances within the EU as a whole are less correlated than those within the US, suggesting a potential relative cost of moving to a monetary union. Many other authors have extended the shock-accounting exercise using SVARs in various directions with contradictory results.

[1] Cochrane (1997) offers a critical review of SVAR methodology.

Another strand of the literature makes use of possibly existing cointegrating relations among the variables . Departing from a cointegrated vector autoregression, the Granger representation permits the level of the series to be expressed in terms of the common stochastic trends which drive the system. These common trends are identified as some type of economic shock and their relative importance in determining the variables is assessed. This methodology is related to work by King, Plosser, Stock and Watson (1991). An interesting application for the European case can be found in Hoffmann (1998).

A third strand of the literature has moved to a more disaggregated level. Studying the behavior of output at an industry level, this part of the literature analyzes the relative importance of industry-level factors, nation-level factors and the common factor in explaining the variance of output[2]. Bayoumi and Prasad (1997) use an error component model in order to analyze the role of the exchange rate as an adjusting mechanism and its dependence upon the industry structure across countries. Exchange rates are found to provide an effective adjustment mechanism if disturbances are industry-specific and industries are highly concentrated within regions. On the other hand exchange rates could not work as a mitigating device if industries were diversified across regions and shocks were country-specific. Bayoumi and Prasad (1997) conclude that region-specific disturbances dominate in the US. Whereas in the European Union, country-specific disturbances are prevalent in the traded-good sector, though over all sectors the relative importance of country-specific disturbances has declined in the 1980s. Norrbin and Schlaenhauf (1996) extend this analysis to a dynamic setup[3]and analyze behavior across countries and industries in terms of industry-specific factors, nation-specific factors and the common factor. The set of countries consists of nine industrial economies and the sample extends from 1956:1 to 1992:4. Their analysis suggests that, in this

[2]Stockman (1996) and Costello (1993) are among the earliest contributions in the business cycle literature using this technique. Stockman (1996) investigates the existence of a world business cycle, and Costello (1993) contains an application explaining the relationship between output growth and productivity.

[3]Interestingly enough, Norrbin and Schlaenhauf (1996) use the Kalman filter for parameter estimation though they do not implement the smoother in order to obtain the common component. This common component would be close to the idea of the coincident indicator of Stock and Watson (1991) for the US and would represent a measure of the business cycle.

period, the nation-specific factor is the most relevant in explaining the variation of output.

It would be quite difficult to summarize all the results of the literature reviewed above. However, whether the factors that move output growth in the European countries are supply or demand driven or whether they are industry specific or nation specific, there seems to be a great commonality across countries, and it seems clear that this commonality could be referred to as the European Business Cycle. It seems to us that trying to extract the European business cycle represents a conclusion to the shock-accounting literature in Europe. If there is sufficient comovement among some country-specific indices of economic activity, then there is room for a common monetary and fiscal policy.[4]

Looking for an indicator of the business cycle in Europe should not be very different from following the same exercise at the one-country level. In a recent paper, Diebold and Rudebusch (1996) summarize the most important contributions to business cycle research in the last twenty years. This could serve both as a summary of most recent efforts by business cycle scholars, but it can be also seen as an optimal "methodology" to extract from a group of economic time series a common component that characterizes the concept of a business cycle. In this respect our paper is very close to this "methodology". Although some early attempts have tried to identify a common coincident composite indicator for a group of countries, to our knowledge, this is the first attempt to extract the common European cycle offering a joint statistical model for a relevant group of European economies.[5]

The paper proceeds as follows: Section one analyzes some time domain and frequency domain statistics which will shed some light on the co-

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[4] We will deal with indices of industrial production (IIP) in the main body of the paper. A complementary analysis is presented in the appendix for gross domestic product (GDP). A more detailed analysis should take into account different disaggregated sectors. An idea implicit in this paper is that the comovement in individual countries can be well summarized by the behaviour of the national aggregate, though strictly this is a question that might deserve separate investigation.

[5] Lumsdaine and Prasad (1997) use time-varying weights in order to identify a common component, where the weights are given by the conditional variance found by appying univariate GARCH model to the index of industrial production series.

movements among the industrial production indices in Europe. The analysis is broken into two sample periods (before and after the introduction of the Exchange Rate Mechanism(ERM)), the USA and Germany are used as benchmark countries[6]. Both types of statistics show some evidence of a higher commonality among European countries in the second subsample. Section two gives a statistical characterization of the growth cycles in output employing univariate Markov-switching models. The results suggest the existence of a common cycle driving output for the individual European economies. Section three then studies the cointegration properties of the system of variables and presents the results from a Markov-switching vector autoregression (MS-VAR) exhibiting a common cycle consisting of three phases of the business cycle. Section four concludes.

2 The European affiliation

This section builds on Artis and Zhang (1997) and extends their previous analysis in several directions[7].We analyze the rate of growth of seasonally adjusted industrial production indices of nine European countries obtained from the OECD database. Our main interest is in the growth cycle definition of the business cycle, or fluctuations around a trend and whether there has been an increased synchronization of the business cycle in the European countries, moving away from the USA business cycle. In order to investigate this hypothesis Germany and USA are taken as benchmarks and comovements of the rate of growth are analyzed with respect to these countries. The series are first corrected for outliers using the approach of Tsay (1984) and Chen and Liu (1993) [8] and then smoothed in order to reduce the importance of short run erratic fluctuations. Three different smoothing techniques are used: a centered seven-

[6] The significance of the breakpoint is that the introduction of the ERM makes a venture, among the countries involved, into a quasi-fixed exchange rate regime.

[7] First, comovements in the rate of growth of industrial production index between countries in the pre and post ERM period are analyzed instead of the cyclical component as in Artis and Zhang (1997). Second, our analysis considers not only time domain statistics but frequency domain statistics as well.

[8] The program Tramo (Time series regression with ARIMA noise missing observations and Outlier) by Gomez and Maravall (1992) was used to implement this procedure.

term moving average, the Hodrick and Prescott filter (dampening parameter $\lambda = 50000$) and an unobserved component model based on the decomposition of the series into an irregular component and a trend component[9]. Results from all of three are presented to show their robustness to the smoothing technique used. Two different sample periods are analyzed, one corresponding to 1965:5 – 1979:3 or the pre-ERM period, and a second period that goes from 1979:4 to 1997:6, or post-ERM period. In order to analyze the degree of synchronization of the business cycle we first obtain cross-correlations at displacement zero for the two different sample periods. This analysis is further extended to the frequency domain, where the squared coherence is studied at the relevant business cycle frequencies.

2.1 Time domain statistics

Table 1 Cross correlation at displacement zero for the sample period 1965:5-1979:3.

	Germany			USA		
	U.C.	HP-filter	7-MA	U.C.	HP-filter	7-MA
France	0.492	0.800	0.648	0.414	0.668	0.613
Italy	0.300	0.472	0.354	0.393	0.749	0.524
NL	0.713	0.800	0.710	0.348	0.185	0.396
Austria	0.475	0.850	0.544	0.279	0.385	0.347
Belgium	0.593	0.823	0.633	0.437	0.565	0.529
Spain	0.422	0.547	0.387	0.389	0.576	0.450
Portugal	0.289	0.516	0.233	0.157	0.658	0.244
UK	0.403	0.690	0.566	0.329	0.794	0.581

Looking at the cross correlations it seems that irrespective of the smoothing technique employed, in all countries under study there has been a greater degree of synchronization with the German cycle and a lower degree of synchronization with the USA in the ERM period, if compared with the pre-ERM period. An important exception is the UK, for which the correlation in the

[9] The appendix includes a discussion of these smoothing techniques.

Table 2 Cross correlation at displacement zero for the sample period 1979:4-1997:6.

	Germany			USA		
	U.C.	HP-filter	7-MA	U.C.	HP-filter	7-MA
France	0.577	0.804	0.629	0.173	0.367	0.293
Italy	0.250	0.557	0.403	0.245	0.365	0.236
NL	0.362	0.778	0.340	0.175	0.491	0.254
Austria	0.543	0.924	0.571	0.075	0.181	0.115
Belgium	0.486	0.754	0.468	0.077	0.331	0.156
Spain	0.499	0.602	0.325	0.197	0.392	0.145
Portugal	0.260	0.670	0.257	-0.127	-0.314	-0.135
UK	0.321	0.122	0.266	0.242	0.622	0.368

ERM period decreases both with respect to the German and to the US business cycle.

2.2 Frequency domain statistics

In this section we look at frequency domain statistics that might offer information about the comovement of industrial production in some countries in Europe. We will mainly analyze the coherence of pairs of two series at the relevant business cycle frequencies. This statistical analysis comes with two main caveats. First, looking at a specific frequency assumes regularity in the duration of the business cycle something we do not assume in our later statistical analysis[10]. Secondly, analyzing the coherence for two countries does not consider the possible influence of a third country in accounting for part of its behavior at the corresponding frequencies.

A time series is generally characterized by its correlation function, and the analysis is thus done in the time domain. In the frequency domain the properties of the series are characterized by the spectral density function. The spectral density function is obtained applying a Fourier transform to the autocovariance function. Though both functions contain the same information, the fre-

[10] The best model obtained in section 4 is a Markov-switching model with three regimes: recession , growth and high growth, each of them with a particular duration.

quency domain analysis can be helpful for studying particular features, such as the part of the variance that is explained by the behavior of the time series at certain frequencies.

Starting from a covariance-stationary process $\{y_t\}_{t=-\infty}^{t=\infty}$ with $\mathsf{E}[y_t] = \mu$, we define the j^{th} autocovariance as:

$$\gamma_j = \mathsf{E}\left[(y_t - \mu)(y_{t-j} - \mu)\right].$$

Its autocovariance-generating function can be defined as:

$$g_y(z) = \sum_{j=-\infty}^{j=\infty} \gamma_j z^j$$

and the population spectrum will be defined by :

$$f(w) = \sum_{j=-\infty}^{j=\infty} \gamma_j e^{-iwj}$$

where w denotes the frequency.

For a covariance-stationary vector process we can alternatively define:

$$\gamma_{jm}(h) = \mathsf{E}\left[(y_{jt} - \mu_j)(y_{m,t-h} - \mu_m)\right]$$

where $\mu_j = \mathsf{E}[y_{jt}]$ and the spectral density function for the vector process is then defined as:

$$g_y(z) = \sum_{j=-\infty}^{j=\infty} \Gamma_j z^j.$$

For the vector process we could obtain the cross-covariance between two pairs of series associated with a frequency of interest.

If we use sample statistics instead of the population values, we will hence talk of the periodogram instead of the spectrum, and of the cross periodogram instead of the cross spectrum.

The periodogram of an individual series in terms of the original observations can be defined as:

$$I_n(w_k) = \frac{2}{T}\left[\left(\sum_{t=1}^{T} x_t \cos w_k t\right)^2 + \left(\sum_{t=1}^{T} x_t \sin w_k t\right)^2\right] \quad k = 1, \ldots, m$$

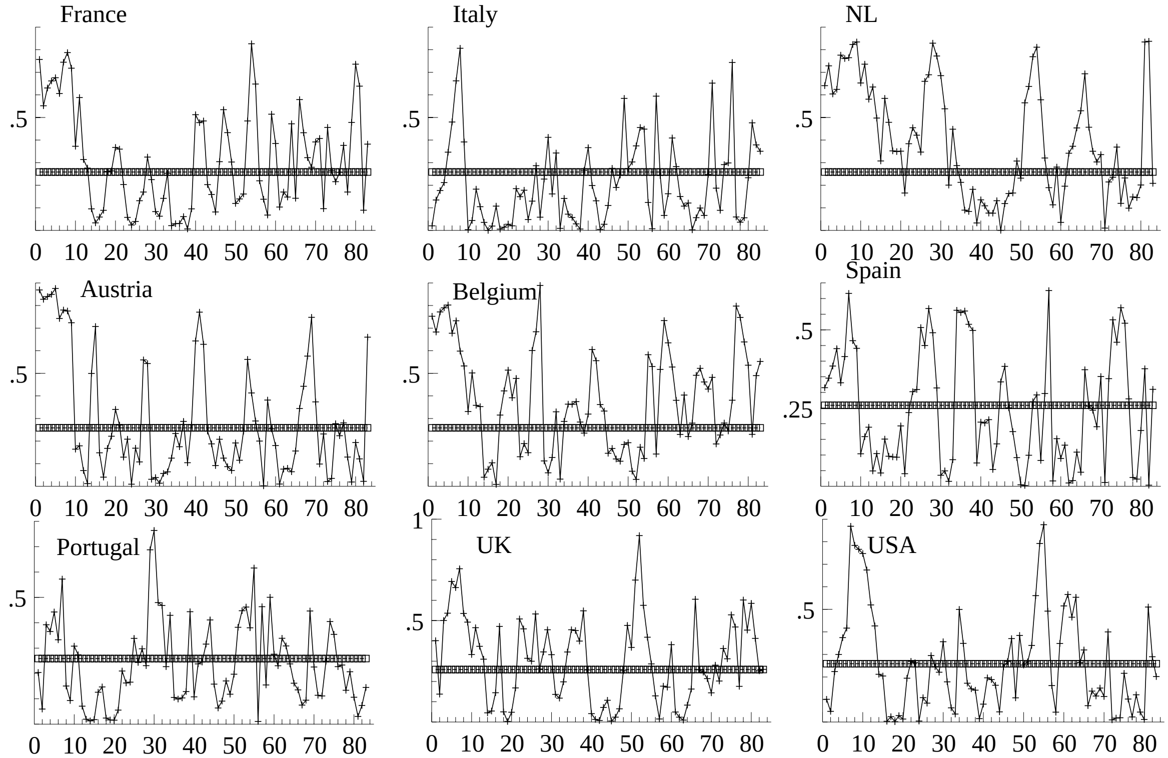

Figure 1 Squared coherence of Germany with respect to European countries and USA from 1965:5-1979:3.

where $m = \frac{T-1}{2}$ for t odd, or:

$$I_n\left(w_k\right) = \frac{T}{2}\left(a_k^2 + b_k^2\right) \quad k = 1, \ldots, m.$$

with:

$$a_k = 2\frac{\sum_{t=1}^{T} x_t \cos w_k t}{T} \quad k = 1, \ldots, m$$

$$b_k = 2\frac{\sum_{t=1}^{T} x_t \sin w_k t}{T} \quad k = 1, \ldots, m$$

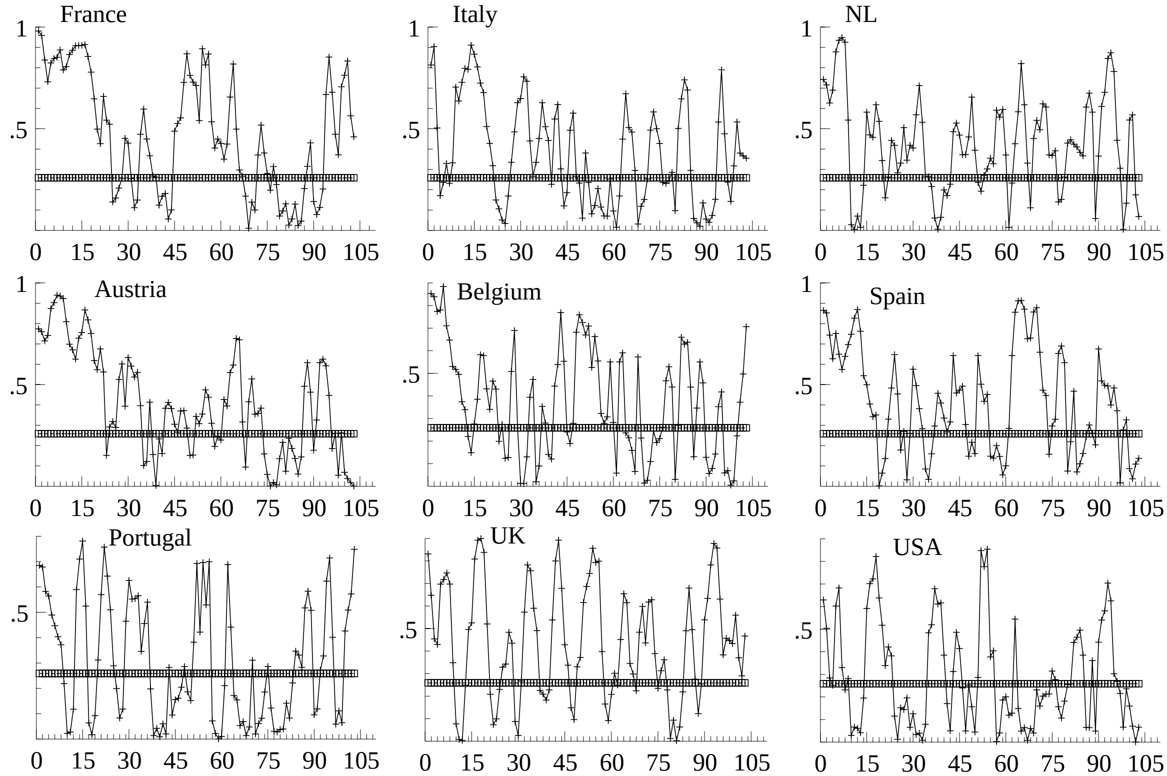

Figure 2 Squared coherence of Germany with respect to European countries and USA from 1979:4-1997:6.

Let us further define the cross periodogram as:

$$I_{12n}\left(w_k\right)\begin{cases} \frac{n}{2}\left[a_{1k}a_{2k}+b_{1k}b_{2k}-i(a_{1k}b_{2k}-b_{1k}a_{2k})\right] & w_k\neq 0 \\ 2na_{1k}a_{2k} & w_k=0 \end{cases}$$

with

$$\lim_{n\to\infty}E\{I_{12n}\left(w_k\right)\}=4\pi f_{12}\left(w_k\right).$$

If we similarly define for the periodogram,

$$f_{ij}\left(w_k\right)=\frac{1}{4\pi}I_{ijn}\left(w_k\right)\quad for\ i=j$$

The squared coherence can be defined as:

$$K^2\left(w_k\right)=\frac{\left|f_{12}\left(w_k\right)\right|}{f_{11}\left(w_k\right)f_{22}\left(w_k\right)}.$$

The squared coherence between a pair of times series captures the correlation between them at the frequencies of interest. The business cycle can be correspondingly defined as “high coherence between two economic time series at the relevant business cycle frequencies”. The squared coherence can be written in terms of the smooth estimators of the periodogram, as:

$$K^2\left(w_k\right)=\frac{\left|\overline{f_{12}}\left(w_k\right)\right|}{\overline{\overline{f_{11}\left(w_k\right)f_{22}\left(w_k\right)}}}.$$

Furthermore, it can be shown, see Fuller (1976), that for $K^2\left(w_k\right) \neq 0, K^2\left(w_k\right)$ is approximately normally distributed, and the test for the hypothesis $K^2\left(w_k\right)=0$ can be done using the statistic:

$$\frac{4dK^2\left(w_k\right)}{2\left[1-K^2\left(w_k\right)\right]}\sim F^2_{4d},$$

where d is the window width.

Figure 1 contains the squared coherence between Germany and the rest of the countries under analysis for the period 1965:5 to 1979:3 for the relevant frequencies(from 0 to π),whilst figure 2 contains the same analysis for the period 1979:4–1997:6. Note that for a process of frequency w the corresponding period is $\frac{2\pi}{w}$. The frequencies in our case are defined as,

$$w_j=\frac{2\pi}{T} \qquad j=1...\frac{T-1}{2}$$

So each frequency has a corresponding period of $\frac{2\pi}{w_j}=\frac{T}{j}$ where T is the number of observations. We are interested in the value of the squared coherence around the business cycle frequencies which correspond to periods between 6-8 years. That is, we are interested in the squared coherence for $6<\frac{T}{j}<8$ or in terms of the ordinates j, we are interested in the squared coherence at values of $6<j<8$ and $6<j<8$ for the second period. A straight line at 0.25871 is drawn reflecting those values that are significant.

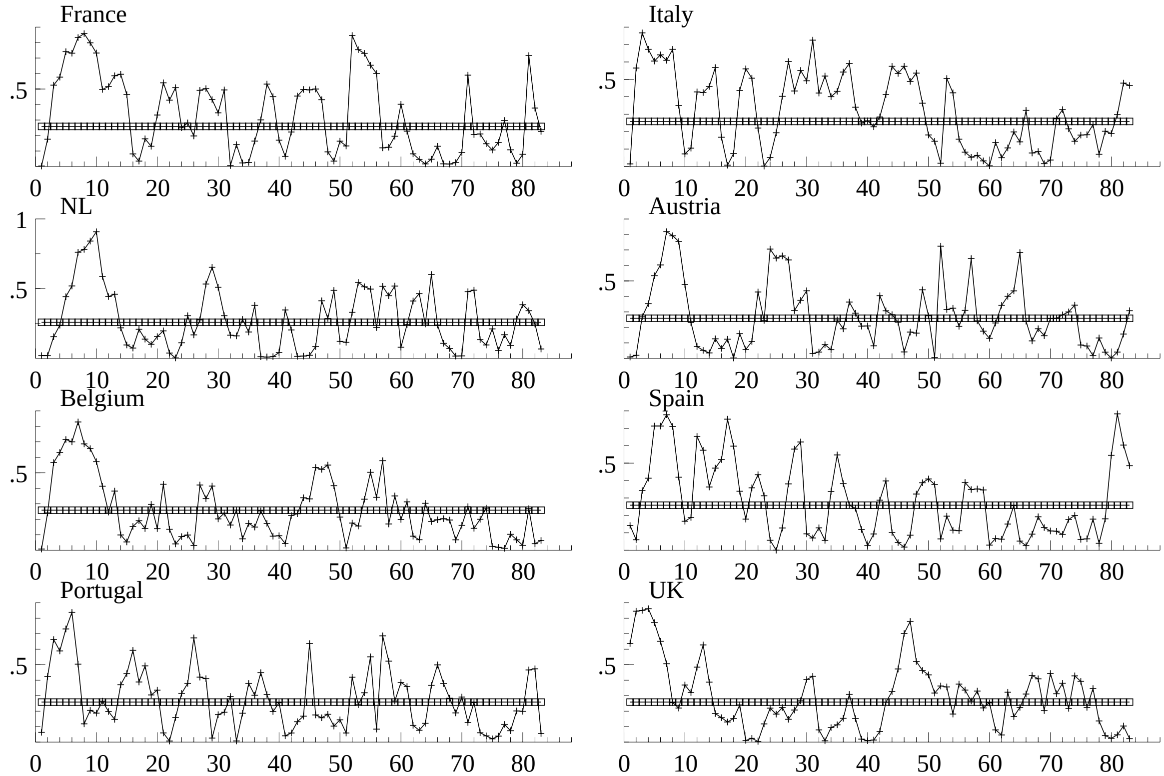

Figure 3 Squared coherence for USA-European countries from 1965:5-1979:3.

Any values under the straight line can be judged to be insignificant at a 95 % level. Figures 3 and 4 contain a corresponding analysis taking the USA as the benchmark.

Comparing the four figures it appears that there has been a decrease in the correlation between the USA´s IIP and that of most European countries at the relevant business cycle frequency, whereas on the contrary, the correlation between Germany´s IIP and that of other European countries had increased at the relevant business cycle frequency. Most striking are the cases of Spain and Portugal.

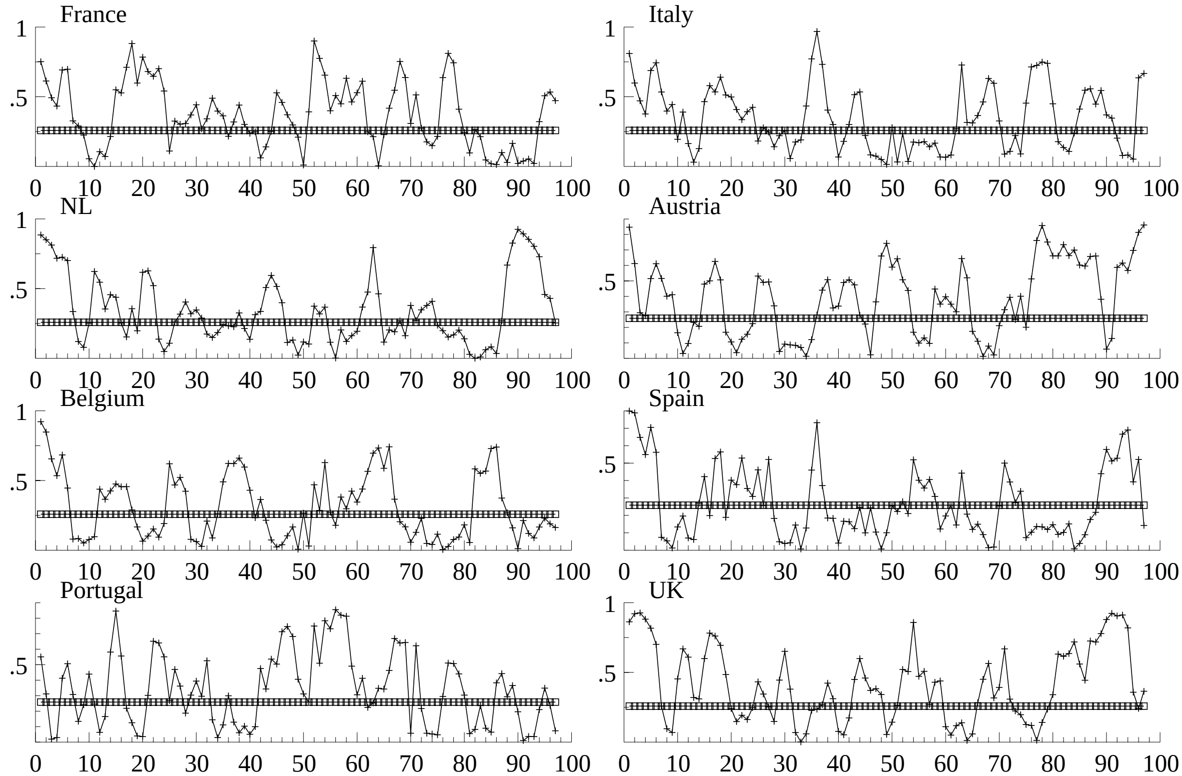

Figure 4 Squared coherence for USA-European countries from 1979:4-1997:6.

3 Univariate Analysis

Recent theoretical and empirical business cycle research has revived interest in the co-movement of macroeconomic time series and the regime-switching nature of macroeconomic activity. For the statistical measurement of macroeconomic fluctuations, the Markov-switching autoregressive time series model has become increasingly popular since Hamilton's (1989) application of this technique to measuring the US business cycle. There have been a number of subsequent extensions and refinements. Contractions and expansions are modelled as switching regimes of the stochastic process generating the growth rate of real GNP Δy_t:

$$\Delta y_t - \mu(s_t) = \alpha_1 \left(\Delta y_{t-1} - \mu(s_{t-1})\right) + \ldots + \alpha_4 \left(\Delta y_{t-4} - \mu(s_{t-4})\right) + u_t. \quad (1)$$

The regimes are associated with different conditional distributions of the growth rate of real GNP, where the mean μ_1 is positive in the first regime ('expansion') and negative in the second regime ('contraction'), $\mu_2 < 0$. The variance of the disturbance term, $u_t \sim \mathsf{NID}(0, \sigma^2)$, is assumed to be the same in both regimes.

The general idea behind this class of regime-switching models is that the parameters of a VAR depend upon a stochastic, unobservable regime variable $s_t \in \{1, \ldots, M\}$. The stochastic process generating the unobservable regimes is an ergodic Markov chain defined by the transition probabilities:

$$p_{ij} = \Pr(s_{t+1} = j | s_t = i), \quad \sum_{j=1}^{M} p_{ij} = 1 \quad \forall i, j \in \{1, \ldots, M\}. \tag{2}$$

By inferring the probabilities of the unobserved regimes conditional on an available information set, it is then possible to reconstruct the regimes. [11]

The data correspond to monthly industrial production indices for the nine economies from 1970:1 to 1996:12, and were drawn from the OECD database. The original series together with a seventh order moving average of the original series are plotted in Figure 5. From the graph a break can be inferred in the trend growth rate in the second half of the 70s, especially for the case of France, Netherlands, Spain, Portugal and Austria. This will become an important issue both at the time of specifying the cointegrating properties of the series as well as in identifying the number of regimes when we move to the multivariate analysis in section 4.1.

The presence of unit roots in the data can be checked with the augmented Dickey and Fuller (1981), ADF, test. The null hypothesis is $H_0 : \psi_1 = 0$ in the regression:

$$\Delta y_t = \beta + \sum_{i=1}^{p-1} \psi_i \Delta y_{t-i} + \varepsilon_t$$

The null of a unit root cannot be rejected at a 10 % level. If we take the differenced time series, the ADF test rejects the null of an integrated process at

[11] Maximum likelihood (ML) estimation of the model is based on a version of the Expectation-Maximization (EM) algorithm discussed in Hamilton (1990) and Krolzig (1997b). All the computations reported in this paper were carried out in Ox 1.20a, see Doornik (1996).

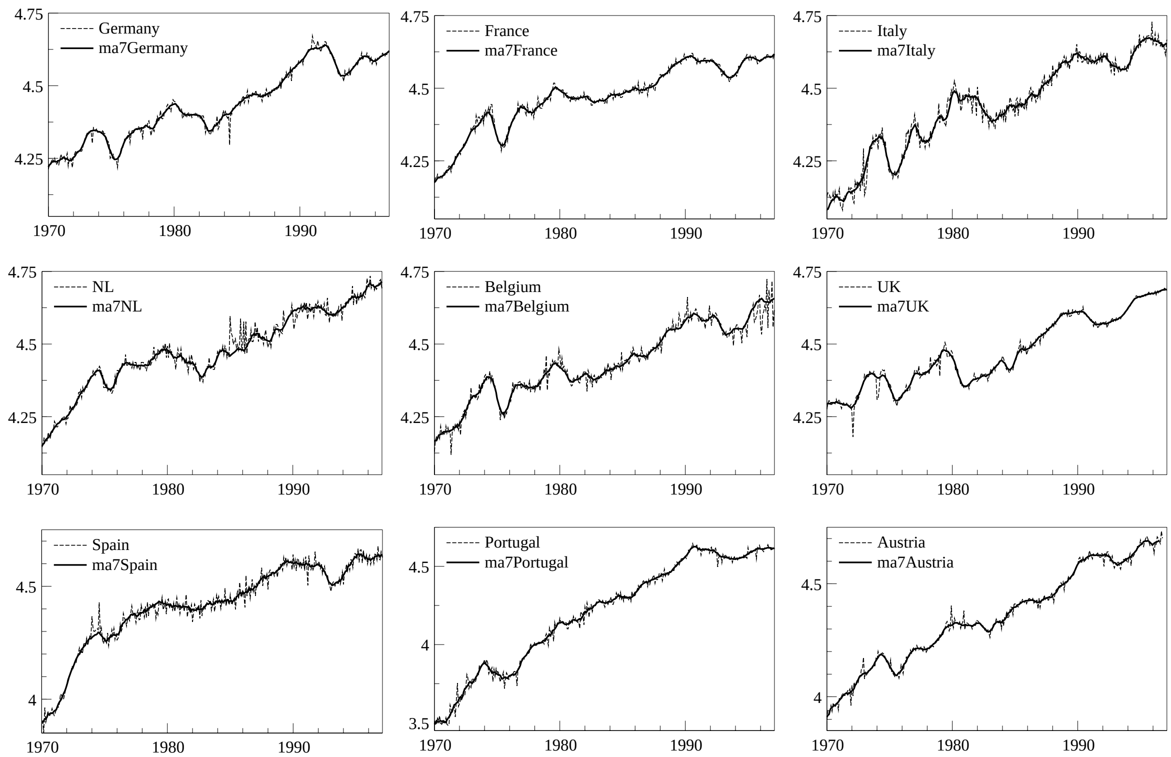

Figure 5   Industrial Production Index.

the 5 % level and hence y_t was found to have a stochastic trend. As discussed earlier, the series have been corrected for outliers using Tramo and smoothed by taking seven-month moving averages. The effect of this procedure is shown in Figure 5. First differences are then taken to achieve stationarity.

An issue of paramount difficulty at the time of specifying the MS-AR is the choice of the number of regimes. Due to the existence of a nuisance parameter under the null hypothesis, the likelihood ratio test statistic for testing the number of regimes does not posses an asymptotic χ^2 distribution. One solution to this problem is to use the procedures proposed by Hansen (1992), (1996) and Garcia (1993). However they are computationally very expensive. An alternative specification strategy had been proposed by Krolzig (1996),which is based on the ARMA(p^*, q^*) representation of the MSM(M)-AR(p) or MSI(M)-AR(p) process. This strategy can be summarized as follows: (i) the univariate ARMA analysis is carried out and the best model is chosen on the basis of some likelihood criterion (AIC or Schwarz); (ii) the ARMA model can be seen as coming from the corresponding MS-AR; (iii) this MS-AR can be seen as the point of departure in a general-to-specific modelling strategy.

Maximum likelihood estimation of the corresponding MS-VAR model can then be carried out using the EM algorithm. The time paths of the smoothed, filtered and predicted probabilities are presented in Figure 6 . The filtered probability can be understood as an optimal inference on the state variable(whether we are in boom or recession) at time t using only the information up to time t, *i.e.* $\Pr(s_t = m \mid Y_t)$, where m stands for a given regime. The smoothed probability stands for the optimal inference on the regime at time t using the full sample information, $\Pr(s_t = 1 \mid Y_T)$. Lastly, the predicted probability stands for the optimal inference on the regime at time t using all available information at time $t-1$, $\Pr(s_t = 1 \mid Y_{t-1})$

Important issues that arise in our analysis are: (i) the convergence process of Spain, Portugal and Austria and (ii) the secular decline of the mean growth rates of most OECD countries in the post-Bretton Woods era (see also Krolzig (1997a) and Lumsdaine and Prasad (1997)). A two-regime model representing contractions and expansions is unable to reflect these two stylized facts of the postwar economic history of Western Europe. Therefore we extend the Markov-switching process for a third regime. For Germany, two regimes were sufficient on the basis of likelihood criteria. One might also expect that recessions would affect the volatility of the series. We take account of this fact by allowing the variances of the Gaussian innovations to vary over the cycle. For France, Austria and Portugal this effect was significant.

The estimation results are given in table 3 which also reports measures of the persistence of recession: the expected number of months a recession prevails (duration) and the unconditional (ergodic) probability of recessions. The associated regime probabilities using first differences are depicted in Figure 6 for the case of a three-regime process. The univariate MS-AR models are not fully able to capture the different regimes. Whereas for Germany and the UK they seem to capture relatively well the different recessionary periods , in the case of France, the MS-AR misses the recession that took place in the early

Table 3 Univariate MS-AR Models of the Business Cycle.

	Germany	UK	France	Italy	NL	Belgium	Austria	Spain	Portugal
Regime-dependent intercepts (10^{-2})									
ν_1	-0.191	-0.115	-0.398	-0.699	-0.419	-0.563	-0.353	-0.091	-0.281
ν_2	0.131	0.069	0.014	0.073	0.114	0.066	0.086	0.511	0.222
ν_3		0.083	0.004	0.691	0.641	0.429	0.503	1.349	0.881
Autoregressive parameters									
α_1	0.655	0.820	0.525	0.333	0.122	0.448	0.350	0.061	0.208
α_2								0.109	
Regime-dependent variances (10^{-6})									
σ_1^2	5.899	4.503	4.422	16.324	6.472	6.618	7.562	18.732	17.565
σ_2^2			1.343				4.030		12.124
σ_3^2			4.208				8.968		30.372
Persistence of Recessions (Regime 1)									
Erg. Prob	0.206	0.004	0.079	0.087	0.175	0.078	0.119	0.513	0.161
Duration	16.751	13.185	10.071	11.362	6.007	6.275	7.524	28.217	23.152
Log Lik.	1473.60	1559.60	1497.60	1282.05	1393.77	1421.71	1403.85	1271.23	1279.48
LR Test	16.12	25.50	38.36	52.89	86.07	28.57	72.04	72.99	90.46

eighties. The case of Spain probably delivers the worst fit, with difficulties distinguishing clearly the recessionary periods. It is worthwhile stressing that Hamilton's type of models capture only partially some of the stylized facts of business cycle fluctuations. This type of model captures the non- linearity or asymmetry stressed in some part of the literature but the univariate models obviously cannot capture the idea of comovement among time economic series. Hence including some further variables would not only complement the definition of the business cycle,but would improve the inferences of the Markov process if a business cycle exists.

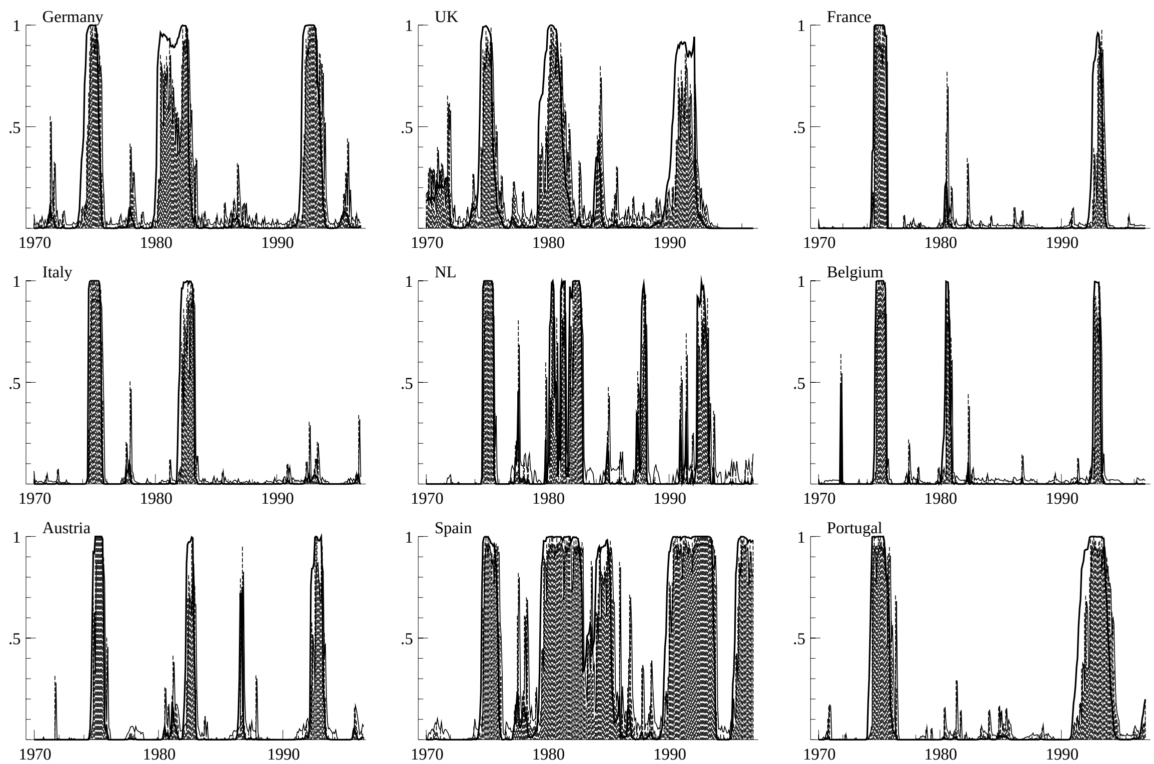

Figure 6   Probabilities of a Recession.

The contemporaneity of the regime shifts in the growth process of the nine European countries suggests a system approach to the investigation of the common cycle of these countries which constitutes the European business cycle. A rough measure of this contemporaneity is presented in Table 4, where the cross correlations of the smoothed probabilities of being in a recession are presented. Further information can be obtained from the cross correlations at different leads an lags of the same smoothed probabilities. This information is presented in table 4, where lagged cross correlations are to be read from from right to left(the reference country is the one placed in the left column) and lead cross correlations can be read from top to bottom(the reference country is the one placed in the top row).

Table 4 Cross correlation at displacement zero of the smoothed probability of being in a recession for the sample period 1970:1-1996:7.

	Germany	France	Italy	NL	Austria	Belgium	Spain	Portugal	UK
Germany	1.00								
France	0.54	1.00							
Italy	0.46	0.49	1.00						
NL	0.73	0.53	0.55	1.00					
Austria	0.61	0.73	0.64	0.70	1.00				
Belgium	0.55	0.82	0.40	0.59	0.65	1.00			
Spain	0.53	0.34	0.28	0.45	0.39	0.35	1.00		
Portugal	0.54	0.72	0.29	0.34	0.56	0.53	0.40	1.00	
UK	0.34	0.29	0.21	0.25	0.12	0.39	0.55	0.34	1.00

4 An MS-VAR Model of the European Business Cycle

In this section the Hamilton model is generalized to a Markov-switching vector autoregressive (MS-VAR) model characterizing international business cycles as common regime shifts in the stochastic process of economic growth of interdependent countries. By generating dynamic factor structures, this research strategy provides also a synthesis of the dynamic factor and the non-linear approach for the modelling of macroeconomic fluctuations.

Despite the importance of the transmission of shocks across countries, the identification common cycles and the recent appreciation of empirical busi-

Table 5 Cross correlation at lead 6 of the smoothed probability of being in a recession for the sample period 1970:1-1996:7.

	Germany	France	Italy	NL	Austria	Belgium	Spain	Portugal	UK
Germany	0.72	0.22	0.09	0.42	0.20	0.26	0.45	0.39	0.45
France	0.56	0.51	0.27	0.30	0.44	0.36	0.20	0.67	0.26
Italy	0.61	0.22	0.55	0.40	0.32	0.13	0.22	0.23	0.12
NL	0.62	0.18	0.22	0.36	0.19	0.20	0.37	0.31	0.39
Austria	0.61	0.34	0.39	0.39	0.37	0.22	0.30	0.53	0.24
Belgium	0.52	0.39	0.23	0.30	0.34	0.25	0.23	0.51	0.36
Spain	0.47	0.23	0.18	0.32	0.21	0.27	0.74	0.29	0.59
Portugal	0.48	0.54	0.19	0.26	0.42	0.40	0.36	0.82	0.43
UK	0.13	0.08	0.04	0.01	-0.07	0.11	0.32	0.13	0.71

ness cycle research, there has been little attempt to investigate cross-country effects with modern non-linear time series models. However, these studies consider business cycle phenomena for individual countries. First attempts at the analysis of international business cycles with Markov-switching models have been undertaken by Phillips (1991), Filardo and Gordon (1994) and Krolzig (1997a). Phillips's study of two-country two-regime models was the very first multivariate Markov-switching analysis of all. Filardo and Gordon (1994) have extended his analysis to a trivariate two-regime model by using leading indicators for the prediction of turning points. In this paper we follow the approach proposed in Krolzig (1997a), stressing the importance of a data-driven model specification which enables us to derive new and economically meaningful results.

4.1 Cointegration Analysis

Our point of departure is a Markov switching vector equilibrium correction model which is a Markov switching p^{th} order vector autoregression with cointegration rank r and M regimes, MSCI$(M,r)-$VAR(p), where both the drift term and the equilibrium mean of the cointegrating vector are allowed to change[12].The analysis of this type of model can be based on the VARMA representation for MS-VAR models. On the basis of this representation, a two stage maximum likelihood procedure can then be applied: the first stage involves approximating the VARMA with a finite-order VAR model and applying Johansen's maximum likelihood procedure, see Johansen (1995). On the second stage, conditional on the estimated cointegrated matrix, the remaining parameters of the vector error correction representation of the MSCI-VAR process are estimated using the EM algorithm.

We consider processes where $y_t \sim I(1)$ is integrated of order one, such that Δy_t is stationary. y_t is called cointegrated if there is some vector β such that $\beta' y_t$. is stationary. For a $k \times 1$ vector of variables we can find at most $k-1$ cointegrating relationships. If we depart from a p^{th} order VAR process with a Markov switching intercept and with $y_t \sim I(1)$,

$$y_t = \sum_{i=1}^{p} A_i y_{t-i} + u_t + v(s_t)$$

Then y_t admits a vector error correction representation,

$$\Delta y_t = \sum_{i=1}^{p-1} \Gamma_i y_{t-i} + \Pi y_{t-p} + u_t + v(s_t)$$

where $\Gamma_i = -I - \sum_{j=1}^{i} A_j$ for $i = 1, \ldots, p-1$ and $\Pi = \mathsf{I}_k - \sum_{i=1}^{p} \Gamma_i$. The rank of Π is called the cointegrating rank . If Π has rank $r < p$, it then allows the following representation $\Pi = \alpha\beta'$ where α and β are $k \times r$ full rank matrices.

Table 6 shows the cointegrating results for a VAR(10), that could be seen as an approximation of the underlying MS-VAR process. Though the trace test seems to suggest four or five significant cointegrating relationships depending upon the level of significance chosen, graphical inspection of the recursively calculated eigenvalues suggests that these long run relations broke down at some point within the sample of our analysis (see figure 7).

Some economic insight might help to interpret these results. An important economic feature of our period of investigation has been the convergence

[12]Krolzig (1996) discusses how the cointegration properties of the MS-VECM can be analyzed with a vector autoregression (VAR) of finite order.

Table 6 Johansen Cointegration Likelihood Ratio Test.

	Maximal Eigenvalue Test			Trace Test		
H_0 :rank= r	-Tlog(1-μ)	$T-nm$	95%	-$T\sum$ log(.)	T-nm	95%
$p=0$	62.9*	47.4	61.3	286.8**	216.3	222.2
$p\leq 1$	45.9	34.6	55.5	223.9**	168.9	182.8
$p\leq 2$	45.6	34.4	49.4	178.0**	134.2	146.8
$p\leq 3$	37.6	28.4	44.0	132.4**	99.9	114.9
$p\leq 4$	34.9	26.3	37.5	94.8*	71.5	87.3
$p\leq 5$	22.1	16.7	31.5	59.9	45.1	63.0
$p\leq 6$	17.8	13.4	25.5	37.7	28.5	42.4
$p\leq 7$	11.3	8.5	19.0	20.0	15.1	25.3
$p\leq 8$	8.7	6.5	12.3	8.7	6.5	12.3

** Significant at 1% level, * Significant at 5% level.

of the European economies . Convergence could be understood in two different ways: relative convergence [13] and convergence in the phase/coherence of the cycle. Convergence in the phase/cycle of the cycle could be inferred from the descriptive statistical analysis conducted in section 2.1. In section 2.2 we introduced some frequency domain statistics aiming at making some inference on the co-movements of the times series at the relevant business cycle frequencies and pinpoint some convergence. We are aware that the analysis has two main limitations. First, coherence does not offer enough information about the existence of a common cycle if we compare two series of industrial production. This is because a country could go into a boom when the other is in a recession, and still the coherence will record a high value. Coherence shows the correlation but not its sign. Secondly, a phase analysis should complement the coherence analysis. One time series can lag another for n periods and still have a high coherence at relevant frequencies. It is easy to see that if we took a covariance stationary series x_t and operated on it with the lag operator producing another covariance stationary series , say y_t,then x_t and y_t will have a coherence of 1 at every frequency despite the lag in the phase. Hence a more adequate definition of the business cycle should include this phase property.

[13] This should not be confused with the concepts of β and σ convergence introduced by Barro and Sala-i Martin (1992).

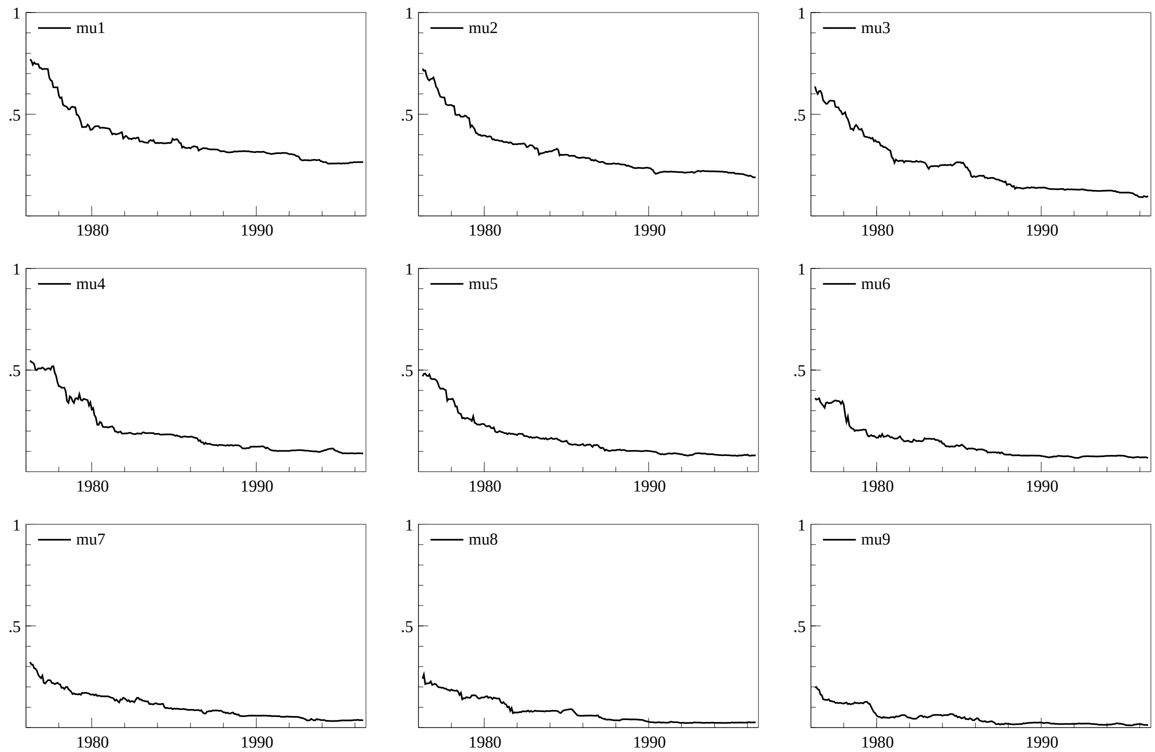

Figure 7   Eigenvalues from a Recursive Cointegration Analyis.

Relative convergence is a more subtle issue, though some intuition about this type of convergence can be gained by looking at the change in the mean growth of industrial production and the graphical representation of the series. Relative convergence could be better understood if we look at the following cointegrating VAR:

$$\Delta x_t = \tau + \alpha\beta' x_{t-1} + u_t$$

We can separate the intercept term into the growth change and the equilibrium mean, such that τ can be written as,

$$\tau = \gamma - \alpha\mu$$

with,

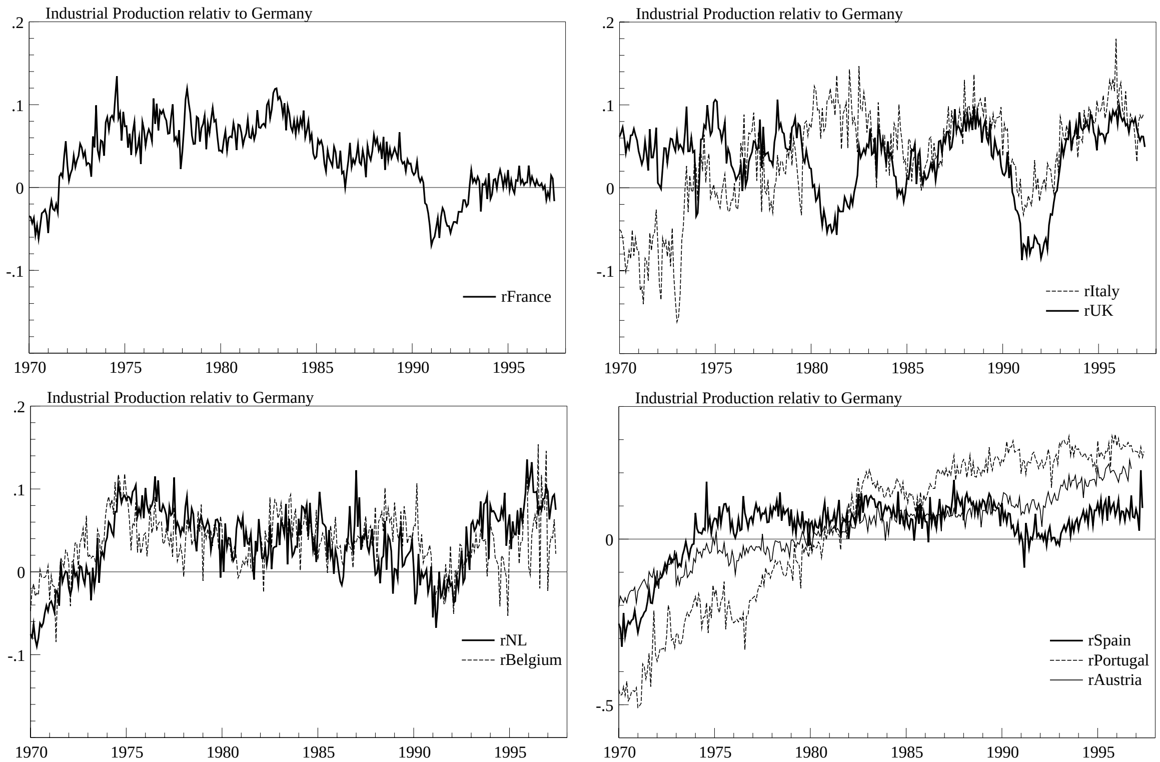

Figure 8   Cointegration Results.

$$\gamma = \beta_{\perp} \left(\alpha'_{\perp} \beta_{\perp} \right)^{-1} \alpha'_{\perp} \tau.$$

We can thus rewrite the equation as,

$$\Delta x_t - \gamma = \alpha \beta' x_{t-1} - \alpha \mu + u_t$$

For given initial conditions , it can be seen that,

$$E\left[\beta' x_t\right] = \left(\alpha' \beta\right)^{-1} \alpha' \tau = \mu$$

And hence in general, considering the drift and the equilibrium mean, the equation can be written as:

$$\Delta x_t - \gamma = \alpha \left(\beta' x_{t-1} - \mu \right) + u_t$$

We could present two types of convergence, type I and type II convergence. Type I convergence will relate to the fact that the relative gap in output between two countries has been reduced. Type II convergence refers to the situation in which the relative output gap between two countries has remained stable(the equilibrium has not changed), though there has been a shift in the drift term, a change in the rate of growth .

We refer to type I convergence in the case of a shift in the equilibrium mean. Thus, if a cointegrating relationship existed between the output of two countries at some time t and at some later period $t > 0$, there has been a shift in the equilibrium mean that has reduced it,so that at some time $t > 0$, $\mu^* = \mu + \Delta\mu$, then we would have an instance of Type I convergence.

Whereas if for some time $t < 0$,there existed a cointegrating relationship between a pair of countries which were growing at the same rate of growth, and for some $t > 0$, a shift in the drift term take place as $\gamma^* = \gamma + \Delta\gamma$, that breaks the previous long-run relationship,then we would have an instance of type two convergence. Type I and type II convergence are very much related to the concept of co-breaking:see Hendry (1995).

Type I convergence implies type II convergence, but the reverse is not true. We are likely to have seen these two types on convergence in Europe in the last 20 years. In the early eighties some countries in Europe experienced rates of growth much higher than those of their European counterparts, showing type I convergence. On the other hand , the equilibrium mean or relative output had changed between some countries. This is clearly seen in Figure 5.

Furthermore the equilibrium mean of any interpretable cointegrating relationship seems to have changed as well, as can be seen from figure 8. The relative industrial production of any country with respect to any other (say, we take Germany as the benchmark) can be considered as an economically interpretable cointegrating relationship[14]. Long-run convergence implies a breakdown in any meaningful cointegrating relationship. Figure 8 shows how the

[14]Cointegration relationships involving a higher number of countries could be seen as being valid although not easily interpretable from an economic point of view.

equilibrium means of these relationships moved in time. Only after 1980 and for a reduced set of countries do these bivariate relationships seem to be stationary. If we look at them from the perspective of the common stochastic trends of the system, the previous argument amounts to saying that the relative weight of the stochastic trends in determining the level of the series has changed. Obviously, the final rejection of cointegration was based on the recursive eigenvalues and the above arguments are intended to shed some light on why the breakdown in the relationships took place.

4.2 The MS-VAR

For the reasons discussed earlier we consider a three-regime Markov-switching vector autoregression with regime-dependent covariances:

$$\Delta y_t = \nu(s_t) + A_1 \Delta y_{t-1} + A_7 \Delta y_{t-7} + u_t, \quad u_t | s_t \sim \mathsf{NID}(\mathbf{0}, \Sigma(s_t)), \quad (3)$$

where Δy_t is the vector of growth rates (first differences smoothed by taking seven-month moving averages and controlled for outliers). Three vectors ν_1, ν_2, ν_3 of regime-conditional mean growth rates of Δy_t are distinguished. The ML estimates of this model are given in Table 7. Major differences in the mean growth rate across regimes and a contemporaneous correlation structure in the data are evident. We found that this model is congruent. The contribution of the European business cycle to the process of economic growth in the nine European countries is depicted in Figure 10. The presence of the third regime in this growth model of the European business cycle reflects the catching-up process of some of the countries.

The different persistence of the regimes can be observed by analyzing the transition probabilities. Note from the transition matrix given in table 7, that the ”high growth regime” can only be reached through the ”growth regime” and not directly from a recessionary period. The transition matrix allows us to observe the asymmetry of the business cycle in terms of the duration of recessions and the two types of growth period. Whereas recessions have a duration of approximately 22 months, the ”growth” state has a duration almost double this(42.7 months) and the ”high growth” state tends to last 32.2 months.

Table 7 Estimation Results: The MS-VAR Model of the European Business Cycle.

	Germany	UK	France	Italy	NL	Belgium	Austria	Spain	Portugal
Regime-dependent intercepts 10^{-2}									
Regime 1	-0.033	-0.073	-0.088	-0.025	-0.178	-0.073	-0.006	-0.011	0.048
Regime 2	0.017	0.088	0.051	0.086	0.213	0.069	0.193	0.142	0.271
Regime 3	-0.017	0.047	0.300	0.076	0.405	0.064	0.258	0.860	0.688
Autoregressive parameters at lag 1									
Germany	0.657	-0.011	0.132	0.042	0.139	0.102	0.308	0.277	0.229
UK	0.059	0.782	0.063	-0.119	-0.194	0.056	-0.086	-0.034	-0.165
France	0.106	0.027	0.489	0.409	0.036	0.211	0.052	0.051	-0.022
Italy	0.036	0.012	0.056	0.452	-0.045	-0.016	-0.027	0.052	-0.045
NL	0.029	-0.051	-0.011	-0.028	0.346	0.025	0.030	-0.197	-0.196
Belgium	-0.009	0.060	0.089	-0.040	0.129	0.465	-0.005	0.189	-0.050
Austria	0.109	-0.068	-0.001	-0.038	-0.037	0.022	0.371	-0.037	0.122
Spain	0.037	0.039	-0.007	0.022	0.077	-0.006	0.000	0.151	-0.051
Portugal	-0.001	0.047	0.003	0.041	-0.049	0.039	0.025	0.004	0.389
	log-likelihood		12801.48		(vs. linear 12616.00)				
	AIC	-78.19	(-77.74)	HQ	-76.64	(-76.72)	SC	-74.30	(-75.19)

	p_{1i}	p_{2i}	p_{3i}	Duration	Ergodic Prob.	Observations
Regime 1	0.955	0.018	0	22.2	0.249	70.3
Regime 2	0.045	0.977	0.031	42.7	0.633	184.6
Regime 3	0	0.006	0.969	32.2	0.118	65.1

In the case of Germany and UK,the values for the regime-dependent intercept are not in the ascending order(that is recession,growth,high growth as we interpret them)that characterizes the other countries. [15] This could be interpreted as implying that the third regime stands for high growth in the south and hence asymmetries in the European cycle. The asymmetry applies to the period when the third regime is observed and hence, the asymmetry has been reduced in the second regime, which is the one that we have observed recently. Figure 10 catches the contribution to the mean of the Markov chain, and can clarify this interpretation of the results. For all countries except UK and Germany the contribution to the mean is higher for the period where the third regime is observed relative to the contribution to the mean for the period where the second regime is observed. The third regime really picks up this catching up process in the early 70s.

4.3 Dating the European business Cycle

The classification of the regimes and the dating of the business cycle amounts to assigning every observation y_t to a given regime $m = 1, 2, 3$. The rule that is applied here is to assign the observation at time t, according to the highest smoothed probability,i.e.:

$$m^* = \arg\max_m \Pr(s_t = m \mid Y_T)$$

At every point in time, a smoothed probability of being in an given regime is calculated (the inference is made using the whole set of data points), and we will assign that observation to a given regime according to the highest smoothed probability. For the simplest case of two regimes, the rule reduces to assigning the observation to the first regime if $\Pr(s_t = 1 \mid Y_T) > 0.5$ and assigning it to the second regime if $\Pr(s_t = 1 \mid Y_T) < 0.5.$

The latter procedure allows a corresponding dating of the European Business Cycle which is given in table 8. The peak date denotes the period t just before the beginning of a recession, i.e. $\Pr(s_t = 1 \mid Y_T) < 0.5$ and $\Pr(s_{t+1} = 1 \mid Y_T) > 0.5.$; the trough is the last period of the recession.

[15] Note that they are not means but intercepts but the descending order of the intercept should coincide with that of the mean.

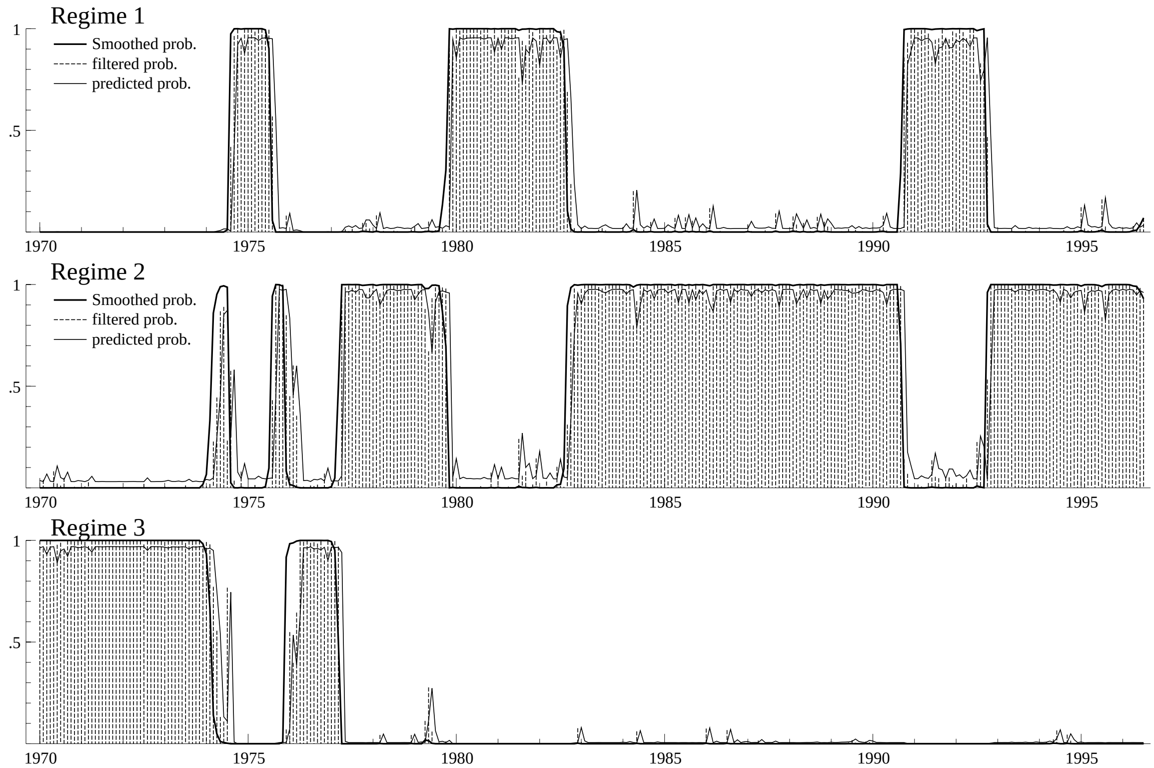

Figure 9 The European Business Cycle.

The results are compared to the dating based on the GDP model discussed in appendix A. Note that the regime classification is independent of the weight of any country. Scaling one of the countries would result in the same regime classification. It is important to stress this fact because our model is not addressing the issue of which countries drive the European cycle but whether that cycle can be extracted and dated.

4.4 Contribution of the European business cycle to the country-specific cycles

The contribution of the European business cycle to the individual countries can be measured by decomposing the time series vector into a Gaussian component and a non-Gaussian component reflecting the effects of the Markov

Table 8 Dating of the European Business Cycle.

MSVAR for IIP Growth[1]			MSVAR for GDP Growth[2]		
Peak	Trough	Duration[3]	Peak	Trough	Duration[3]
1974M7	1975M7	1.00	1974Q1	1975Q2	1.25
1979M10	1982M8	2.83	1980Q1	1982Q4	2.75
1990M9	1992M9	2.00	1992Q2	1993Q2	1.00

[1] Based on monthly data for Germany, UK, France, Italy, Austria, Spain,NL, Belgium, and Portugal

[2] Using quarterly GDP data for Germany, UK, France, Italy, Austria,and Spain:see Appendix A.

[3] Duration denotes the length of the recession in years

chain on the system. Rewriting (3) as $A(L)\Delta y_t = \nu(s_t) + \Sigma^{1/2}(s_t)\varepsilon_t$ where $\varepsilon_t|s_t \sim \mathsf{NID}(\mathbf{0}, \mathsf{I})$ and $A(L) = \mathsf{I} - A_1 L - A_7 L^7$ is the matrix polynomial in the lag operator $L,$ we get

$$\Delta y_t = A(L)^{-1}\nu(s_t) + A(L)^{-1}\Sigma^{1/2}(s_t)\varepsilon_t$$

where the second term has expectation zero. Figure 10 shows that the recessions after the oil-price shocks in 1974/75 and 1979-82 affected the European economies fairly synchronously. In contrast to these findings, the asymmetric shocks arising from the German unification result in a less synchronous outlook in the recession in the 1990s: while the UK already starts to recover in 1992, the German economy starts to contract.

4.5 Impulse response analysis

Many business cycle models following the SVAR approach derive stylized facts by making use of impulse response analysis. Impulse response analysis employs the MA representation and shocks the system with a one step innovation. Innovations are interpreted as cyclical shocks and the response of the variables is then analyzed. This has been criticized in terms of the interpretability of an one-and-for-all shock as a cyclical innovation. Krolzig and Toro (1998) introduced the idea that if the unobservable variable is to be interpreted

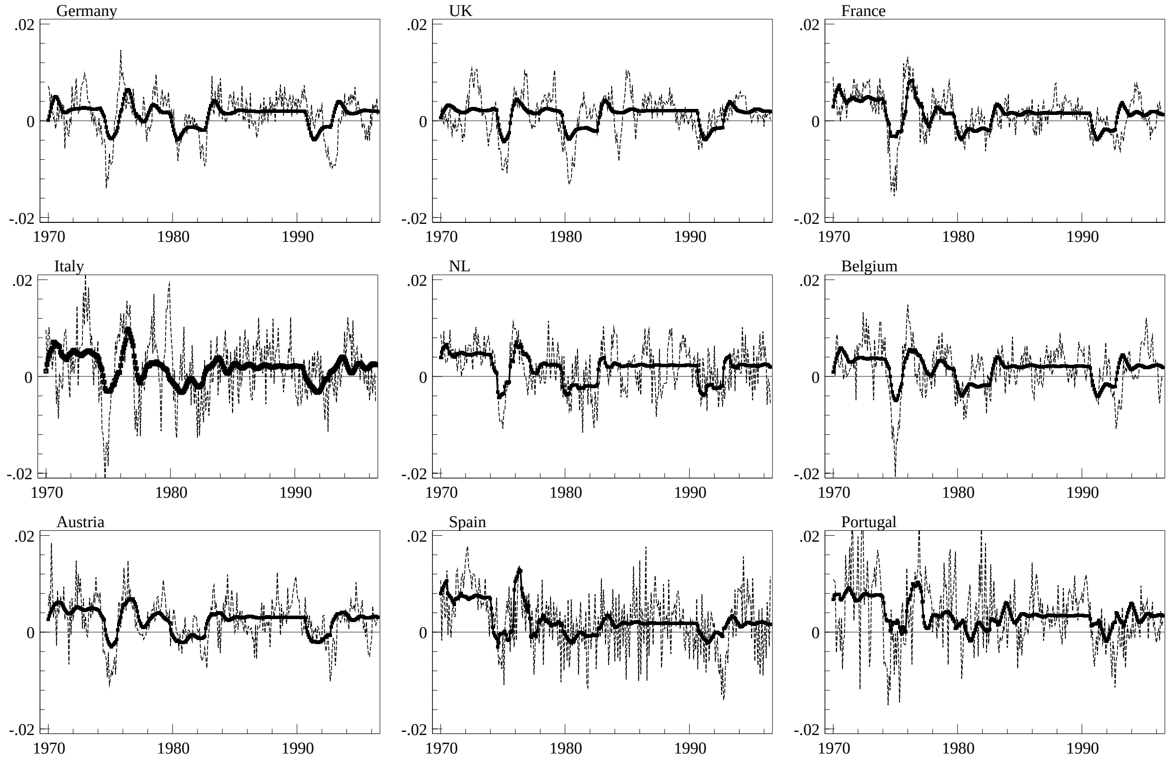

Figure 10 The Contribution of the European Business Cycle.

as the state of the business cycle, an alternative procedure is to look at cyclical fluctuation in terms of the response of the variables to changes in the regime of the state variable. Related to this topic there has been some recent interest in impulse response functions in non-linear models. Beaudry and Koop (1993) have investigated the persistence of output innovations when output has been modelled in a non-linear fashion. They show how previous results obtained by Campbell and Mankiw (1987) are biased. Their result show that the persistence of positive innovations had been underestimated whereas the persistence of negative innovations had been overestimated.Koop, Pesaran and Potter (1996) offer a more general analysis of impulse responses in non-linear models introducing the concept of generalized impulse response. The generalized impulse response differs from the traditional impulse response in respect of the conditional information set used in the dynamic analysis(that is, the type of shocks and the history).

These previous analysis had mainly focussed on the response of the system due to Gaussian innovations whereas Krolzig and Toro (1998) introduce a dynamic analysis when the system is subjected to non-Gaussian innovations. The methodology proposed in Krolzig and Toro (1998) takes into account the shock and the history of the system as in Koop *et al.* (1996). The history is represented by the given state from which we shock the system whereas the nature of the shock is given by the specific state to which we move.

One of the advantages of this new methodology is that non-Gaussian innovations(say, change in the phase of the cycle) might be what some economist have in mind when they refer to ”cyclical shocks”;that is, investigating the dynamics of some variables in the transition from boost to bust. Furthermore, this impulse response analysis is free from scaling criticism. In this section we follow this idea and analyze the response of industrial production in each country due to a change in regime. We focus mainly on two types of shocks, the response of industrial production in individual countries due to a European recession(shift from regime 1 to regime 2), and the effect of an expansionary period in Europe (shift from regime 2).

Facing an European recession (Figure 11), there are countries like France, UK, Germany, the Netherlands and Belgium which have a similar dynamic pattern, whereas Portugal and Spain show a different pattern. In terms of timing most of the countries (except for the three cases previously mentioned) reach the lowest point after five months. For Portugal, Spain and Italy it is not until approximately ten months that the recession reaches its trough. In terms of magnitude, most countries suffer a decline in industrial production of the same size. Here the exceptions are Austria, Spain and Italy, where recessions are milder.

On the other hand the response of industrial production in individual countries to an European boom presents very interesting results. Figure 12 gives the impulse responses to a shift to regime 2 from the unconditional distribution of the regimes: Spain, Portugal and France are the countries which react the most strongly, whereas the responses in the UK and Germany are relatively quite weak compared to the rest of the countries. These findings reflect

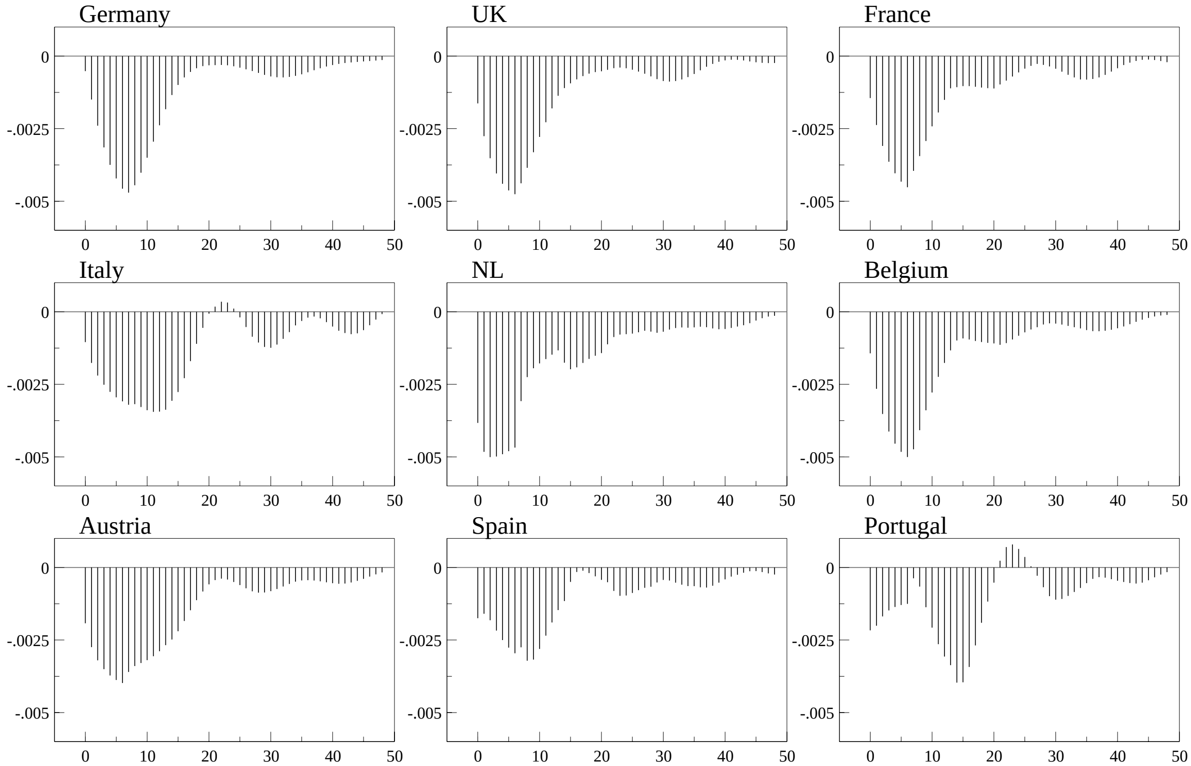

Figure 11 Effects of an European recession (shift from regime 2 to regime 1).

the different tendencies in the growth speed of the considered European countries in the early 1970s.

5 Conclusions

In this paper we use the approach innovated by Hamilton in his analysis of the US business cycle to identify cycles in a number of European economies. That approach consists in fitting a Markov-switching regime process to univariate data series for the economies in question. The regime identification preferred distinguishes between a low growth, high growth and very high growth regime. Inspection of the data indicates that the last of these three regimes corresponds, essentially, to the behaviour of two of the Southern economies

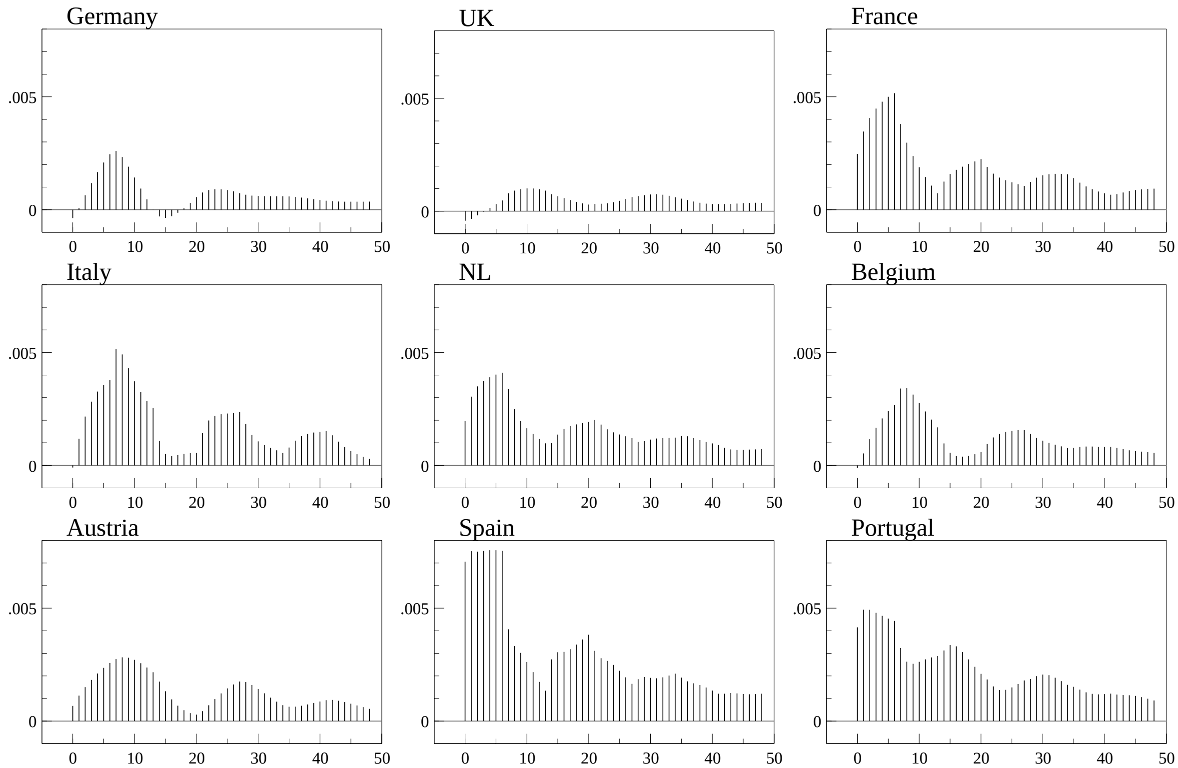

Figure 12   Effects of a regime shift towards the High-Growth regime.

(Spain and Portugal) at the beginning of the sample period employed here (1965:5 to 1997:6). The first two regimes correspond to the upturn and downturn phases of the growth cycle. The identification of the smoothed probabilities of regime-belonging which the procedure allows enables the calculation of cross-correlations of those probabilities, analogously to the synchronicity measures calculated on the basis of cyclical components identified through some trend-extraction technique. As in studies of that type for these economies, our method produces an indication of considerable synchronicity between the business cycles (the UK being a partial exception).

This suggests that the conception of a common or ’European’ business cycle is an intelligible one. In response to this we extended the procedure to fit an MS-VAR to the data, the individual country series making up the VAR. The method then identifies a European cycle, the contribution of which to the performance of individual countries can then be studied. In this study, in particular, we contribute to this task by examining the impulse response function of a regime change in the European cycle. An appendix considers the results (which are supportive) of an exercise of the same type centred on GDP rather than IP data.

In view of the criticisms that can be directed at conventional methods of business cycle identification, it is important to supplement those methods by others, especially in view of the policy significance of the type of results obtained. In particular, findings of business cycle synchronicity (or not) are an important indicator of the optimality of monetary union (or not) and hence deserve careful screening. The findings in this paper contribute to that end.

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A A GDP-based measurement of the European business cycle

In this appendix we investigate whether the cycle in industrial activity can also be found if one considers the economy as a whole, analyzing quarterly GDP data. Due to restricted data availability,our analysis is restricted to a subset of six European countries: Germany, UK, France, Italy, Austria, and Spain .

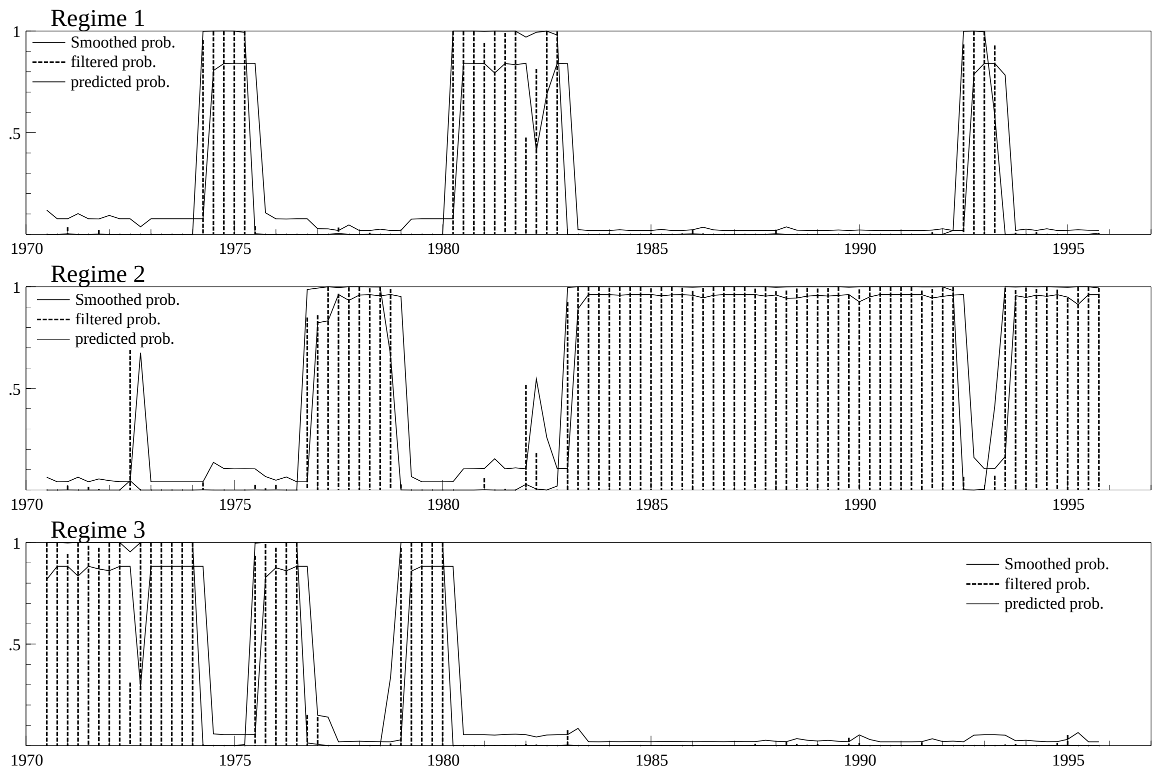

Figure A1 Regime-probabilities for the GDP–based European Business Cycle .

The presence of unit roots is underpinned by the results of augmented Dickey Fuller tests. Using 4 lags in the cointegration analysis gives no clear indication of the presence of cointegrating vectors (see table A1). Therefore we proceed as before with differencing the data.

Following the results in the main paper, a three-regime model was

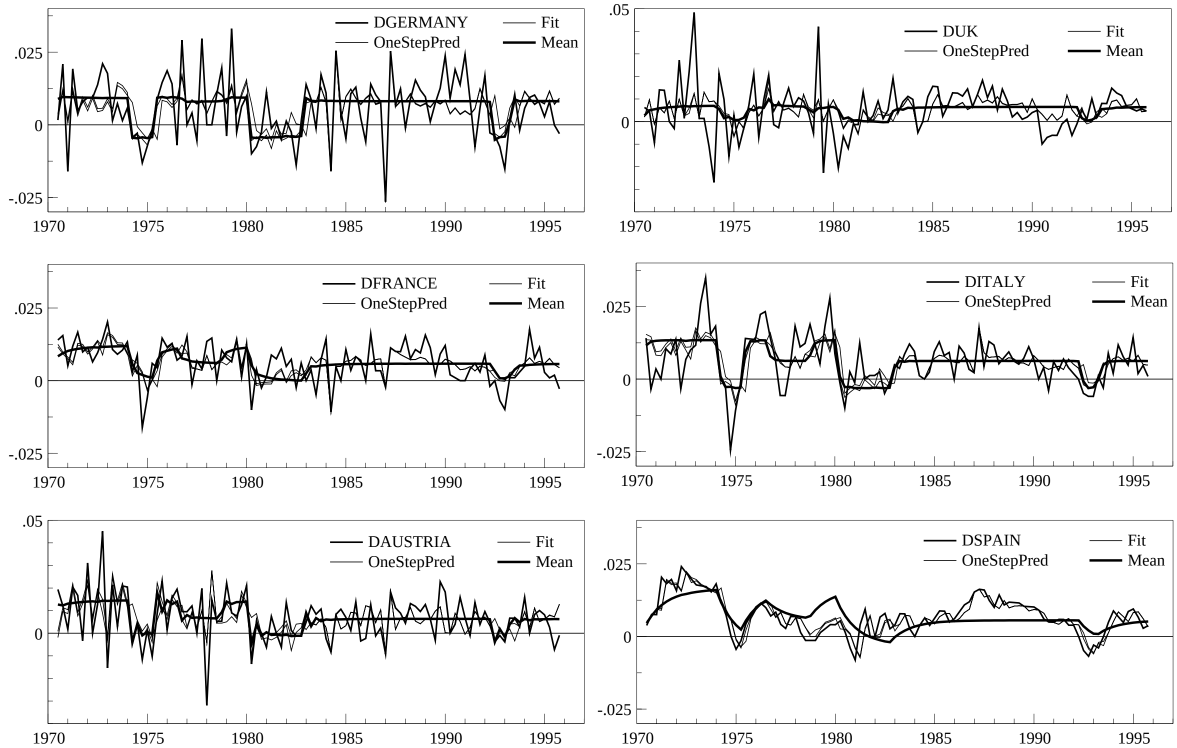

Figure A2 The contribution of the European Business Cycle to the country-specific GDP growth rates.

chosen which allows for changes in contemporaneous correlation structure. The estimation results for an MSIH(3)-VAR(1) model for the period from 1970:3 – 1995:4 are given in table A2. Outliers in 1984 and 1987 have been removed by including impulse dummies (and their first lags).

A comparison of these results with those obtained using industrial production data show very interesting insights in terms of the duration of the cycle, the transition probability matrix and the dating. Moreover figures A1 and A2 show that our findings are robust regarding the contribution of the European Business cycle to the country-specific business cycle, here measured by the GDP growth rate.

Table A1 Johansen Cointegration Likelihood Ratio Test.

	Maximal Eigenvalue Test			Trace Test		
H_0 : rank= r	-Tlog(1-μ)	$T-nm$	95%	-$T\sum$ log(.)	T-nm	95%
$p=0$	34.0	25.8	39.4	103.0*	78.3	94.2
$p\leq 1$	27.6	21.0	33.5	69.1*	52.5	68.5
$p\leq 2$	22.0	16.8	27.1	41.5	31.5	47.2
$p\leq 3$	10.8	8.2	21.0	19.4	14.8	29.7
$p\leq 4$	8.0	6.1	14.1	8.6	6.5	15.4
$p\leq 5$	0.6	0.4	3.8	0.6	0.4	3.8

** Significant at 1% level, * Significant at 5% level.

B Smoothing techniques

B.1 Symmetric moving averages

The choice of the seventh order centered moving average is made in order to smooth the series and free it from irregular components. Any non symmetric filter would have led to a shift in the phase of the individual series and the coherence in the frequency domain. The spectrum of a stationary series, x_t, can be represented as:

$$g_x\left(e^{-iw}\right)=\frac{1}{2\pi}\sum_{j=-\infty}^{j=\infty}\gamma_j e^{-iwj} \tag{B1}$$

where w is the frequency and γ_j the jth autocovariance.

If we apply a linear symmetric filter, in our case the centered seven term moving average,

$$A\left(L\right)=\frac{1}{7}\sum_{n=-3}^{3}L^n \tag{B2}$$

where L is the lag operator, the spectrum of the output series is given by

$$g_y\left(e^{-iw}\right)=g_x\left(e^{-iw}\right)A\left(e^{-iw}\right)A\left(e^{iw}\right) \tag{B3}$$

where $A\left(e^{iw}\right)$ is the spectrum of the filter.

The frequency response function of the 7MA is thus given by:

$$A\left(e^{-iw}\right)=\frac{\sin\left(7\frac{w}{2}\right)}{7\sin\left(\frac{w}{2}\right)} \tag{B4}$$

Table A2 Estimation Results: The MSIH(3)-VAR(1) Model of the European GDP Growth Rates.

	Germany	UK	France	Italy	Austria	Spain
Regime-dependent intercepts (10^{-2})						
Regime 1	-0.448	-0.033	0.078	-0.261	-0.194	-0.086
Regime 2	0.884	0.463	0.332	0.436	0.843	0.117
Regime 3	0.921	0.109	0.694	0.991	1.667	0.351
Autoregressive parameters at lag 1						
Germany	-0.268	-0.272	0.021	-0.038	-0.189	-0.025
UK	0.082	0.108	0.152	0.124	-0.034	0.021
France	-0.141	0.017	-0.106	-0.054	0.132	0.040
Italy	0.237	0.217	0.106	0.181	0.093	-0.018
Austria	0.101	0.244	0.067	0.119	-0.456	0.017
Spain	-0.069	0.061	0.159	-0.032	0.227	0.760
Dummies (10^{-2})						
D87q1	-3.409	0.051	-1.000	-0.395	-1.802	0.485
D87q2	1.000	0.033	0.522	1.250	-0.251	0.290
D84q2	-2.257	-0.935	-1.512	-0.465	-1.823	0.239
D84q3	1.210	-0.669	0.123	-0.404	-0.661	0.260

	log-likelihood 2311.37			(vs. linear 2227.19)		
	AIC -42.44	(-41.96)	HQ -40.91	(-41.06)	SC -38.66	(-39.73)

	p_{1i}	p_{2i}	p_{3i}	Duration	Ergodic Prob.	Observations
Regime 1	0.842	0.019	0.077	6.3	0.166	19.6
Regime 2	0.104	0.962	0.041	26.3	0.651	57.1
Regime 3	0.05	0.019	0.883	8.54	0.118	25.3

which is real because of the symmetry of the filter, and hence does not induce a change in the phase. A non symmetric filter would have lead to a change in the phase of the original series, altering the proper dating of the business cycle. The 7MA dampens irregular components and it further removes peaks at the fundamental frequency $\frac{2\pi}{7}$ and corresponding harmonic $\frac{4\pi}{7}$. It could further be shown that a symmetric linear filter applied to pairs of stationary series does not alter the coherence of the series at any frequency.

B.2 The unobserved component method:

The unobserved method is based on the decomposition of the time series into a trend,and a cycle and an irregular component ε_t[16].

$$y_t = \mu_t + \psi_t + \varepsilon_t$$

where μ_t is the trend component,ψ_t is the cycle and ε_t is the irregular component.

The trend component is specified as :

$$\mu_{t+1} = \mu_t + \beta_t + \eta_t \quad with \quad \eta_t \sim NID(0, \sigma_\eta)$$

$$\beta_{t+1} = \beta_t + \zeta_t \qquad with \quad \zeta_t \sim NID(0, \sigma_\zeta)$$

The cycle component can be specified as:

$$\begin{pmatrix} \psi_t \\ \psi_t^* \end{pmatrix} = \rho \begin{pmatrix} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{pmatrix} \begin{pmatrix} \psi_t \\ \psi_t^* \end{pmatrix} + \begin{pmatrix} \chi_t \\ \chi_t^* \end{pmatrix}$$

$$\begin{pmatrix} \chi_t \\ \chi_t^* \end{pmatrix} \sim NID\left(\begin{matrix} 0 \\ 0 \end{matrix} , \begin{matrix} 1 & 0 \\ 0 & 1 \end{matrix} \; \sigma_\psi^2 (1-\rho) \right)$$

where ρ is the dampening factor,$\lambda_c = \frac{2\pi}{c}$ is the frequency and c is the period.

This specification can be expressed in state form and the Kalman filter can be used to obtain the different components.

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[16] In order to simplify the explanation we have avoided the inclusion of a seasonal component.

A broad range of business cycle studies generate "stylized facts" of the business cycle using the Hodrick-Prescott (HP) filter which derives the trend component $\bar{y}_t$ of a univariate time series y_t as the result of the following algorithm:

$$\{\bar{y}_t\}_{t=1}^{T} = \arg\min \sum_{t=1}^{T}(y_t - \bar{y}_t)^2 + \lambda \sum_{t=2}^{T-1}(\Delta\bar{y}_{t+1} - \Delta\bar{y}_t)^2, \qquad \text{(B5)}$$

where $\Delta\bar{y}_t = \bar{y}_t - \bar{y}_{t-1}$. The FOC for $\bar{y}_t, 2 < t < T-2$ associated with the optimization problem (B5) is given by

$$(y_t - \bar{y}_t) = \lambda\left\{(\bar{y}_{t+2} - 2\bar{y}_{t+1} + \bar{y}_t) - 2(\bar{y}_{t+1} - 2\bar{y}_t + \bar{y}_{t-1}) + (\bar{y}_t - 2\bar{y}_{t-1} + \bar{y}_{t-2})\right\}$$

which can be simplified to the following inhomogeneous difference equation:

$$\lambda\bar{y}_{t+2} - 4\lambda\bar{y}_{t+1} + (1 + 6l)\bar{y}_t - 4\lambda\bar{y}_{t-1} + \lambda\bar{y}_{t-2} = y_t.$$

The system of first order conditions for $\{\bar{y}_t\}_{t=1}^{T}$ results in the following linear filter:

$$\begin{bmatrix} \bar{y}_1 \\ \bar{y}_2 \\ \bar{y}_3 \\ \vdots \\ \bar{y}_{T-2} \\ \bar{y}_{T-1} \\ \bar{y}_T \end{bmatrix} = \left(I_T + \lambda \begin{bmatrix} 1 & -2 & 1 & & & & 0 \\ -2 & 5 & -4 & 1 & & & \\ 1 & -4 & 6 & -4 & 1 & & \\ & \ddots & \ddots & \ddots & \ddots & \ddots & \\ & & 1 & -4 & 6 & -4 & 1 \\ & & & 1 & -4 & 5 & -2 \\ 0 & & & & 1 & -2 & 1 \end{bmatrix} \right)^{-1} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_{T-2} \\ y_{T-1} \\ y_T \end{bmatrix}.$$

The cyclical component is given by the residuum of this procedure, $y_t - \bar{y}_t$. Thus the cyclical component measures the deviation of the considered series from its local trend. The statistical properties of the filter have been criticized recently *inter alia* by King and Rebelo (1993), Harvey and Jaeger (1993), Cogley and Nason (1995) and Bårdsen, Fisher and Nymoen (1995). In particular, Cogley and Nason (1995) have shown that the HP filter can generate spurious cycles when the time series are integrated as in our case.