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ABSTRACT

The European Business Cycle*

This Paper deals with the existence and identification of a common European Growth Cycle. It has recently been argued that the formation of a monetary union creates in itself a tendency for business cycle symmetry to emerge. If this holds for the European monetary Union and the quasi-union of the Exchange Rate Mechanism of the European Monetary System, then we might already expect to be able to find an emergent ‘European cycle' which will become more dominant in future years. 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 possibility of inferring a common European cycle by jointly modelling the industrial production indices of the nine countries under study. An MS-VAR model is then 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. Two further issues are investigated. First we investigate the contribution of the European Business Cycle to the individual country cycles. Second, we undertake an impulse-response analysis where we investigate the response of each individual country to European expansions and recessions. We analyse 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 and the effect of an expansionary period in Europe. An appendix includes a similar analysis for GDP.

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NON-TECHNICAL SUMMARY

In this Paper we provide new measures of the business cycle in nine individual European countries and an estimate of the 'common' European business cycle. The main results are achieved using industrial production data. An appendix replicates the techniques applied and the main results, using data on GDP, which, however, is available only for a smaller set of six countries.

The principal motivations for the Paper are two-fold. First, at the technical level, the Paper features a relatively new method of identifying the business cycle. Second, at the substantive level, the Paper seeks to contribute to the literature that has grown up as a result of applying 'optimal currency area criteria' to the formation of the European Monetary Union. According to those criteria, a key positive indicator for countries contemplating a monetary union is that they should share, broadly, the same experience of shocks to their economies. The intuition is that only if this is the case will a single, undifferentiated monetary policy be acceptable for all the member countries of the currency area. An operational interpretation of a country's experience of economic shocks is provided by its business cycle. Thus, a positive indication for membership of a common currency area or monetary union is that the participating economies should be seen to experience a broadly similar business cycle. Recently, it has been indicated that an increased degree of business cycle symmetry could be expected to follow as a result of monetary union. Treating the experience of participation in the Exchange Rate Mechanism (ERM) of the European Monetary System (EMS) as a trial membership of monetary union, then, it might be expected that some evidence of a common European business cycle could already be found.

The Paper begins by identifying business cycles for each of nine European countries for which suitable data could be found: Germany, France, Italy, the Netherlands, Belgium, the UK, Spain, Portugal and Austria. The technique used to identify the cycle in these countries is that of the so-called 'Markov-switching' regime identification, first popularized in a business cycle setting by Hamilton who applied the technique to data for the US economy (for a clear exposition see Hamilton, 1994). The data (industrial production data are used in the main body of the Paper) can be sorted into growth regimes. In our context, three such regimes can be readily identified. One regime corresponds to negative growth (contraction or recession) and the other two to growth (expansion) and 'high growth' respectively. The period under study here (1970:1 to 1996:12) is long enough to incorporate a phase of exceptionally fast growth in the 'convergent' economies of Spain and Portugal (Austria shared a similar experience also) and a phase of 'secular decline' among the

more mature economies. This variation in growth experience is what makes the identification of three, rather than only two, regimes an optimal description of the data. Having identified the cycles, the next stage is to assess their symmetry across countries. An indicative assessment of the symmetry of the business cycle experience is reached in two ways. First, the correlations, for each pair of countries, of the probabilities of being in recession are examined; second, a test for independence is applied to each pair of countries. That is, if the cycles in country A and in country B are independent, there is no reason to expect that A will be in recession at the same time as B, other than by coincidence. Hence the data are examined for rejection of independence. On either method the indicative assessments of business cycle symmetry are positive, with the exception of the UK. For the UK correlations are low and the hypothesis of independence in business cycle experience cannot be rejected.

On the basis of these generally positive indications of business cycle symmetry, the next phase of the study was to apply the Markov-switching technique to the ensemble of the nine countries' industrial production series, with a view to identifying the 'common' or 'European' cycle. Peaks in the European cycle are identified at 1974:7, 1979:10 and 1990:9, with troughs at 1975:7, 1982:8 and 1992:9. A replication using GDP data (for the smaller sub set of six countries, omitting Portugal, Belgium and the Netherlands for data reasons) identifies rather similar dates. The contribution of the European cycle to the cycles in each of the nine countries is then examined graphically, to confirm the high degree of relevance of the European cycle to the individual countries' sequence of expansions and recessions.

The exercise as a whole reports the plausibility of a common European business cycle, which is significant in contributing to individual countries' cyclical experience. The principal exceptional country in this study (as in some other related studies) is the UK.

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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. An indication of a development of this type can be found in the cyclical cross-correlation analysis offered by Artis and Zhang (1997) and the analysis of the business cycle in the vein of the Burns and Mitchell (1946)'s methodology presented in Krolzig and Toro (1999). The current paper directly addresses the issues of identification and dating of an European business cycle using Markov-switching vector autoregressions.

We can usefully place the motivation for this paper within the context of preceding work that has focused on the identification of asymmetric shocks[1] within the member countries of the Union; and that which, more recently, has analyzed the relative importance of regional/industrial level factors, nation level factors and a common factor in explaining the variance of economic activity. Shock accounting was instigated, in the European context, by Bayoumi and Eichengreen (1993). In common with others, Bayoumi and Eichengreen (1993) employed a structural vector autoregression(SVAR) as their basic tool. 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 ex-

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

plained 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 those obtained for 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 employing alternative identification strategies with contradictory results.

Another strand of the literature has moved to a more disaggregated level of analysis. Studying the behavior of output at an industry level, this part of the literature analyzes the relative importance that industry-level factors, nation-level factors and the common factor have 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 adjustment mechanism and its dependence upon the industrial structure of the countries concerned. 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)[3] extend this analysis to a dynamic setup[4] and analyze behavior

[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. A more recent analysis is presented in Forni and Reichlin (1997).

[3] See also Forni and Reichlin (1997).

[4] 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.

across countries and industries in terms of industry-specific factors, nation-specific factors and the common factor. The set of countries comprises nine industrial economies and the sample extends from 1956:1 to 1992:4. Their analysis suggests that, in this 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, they seem to be a common across countries. 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.[5]

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. Their paper also offers what can be seen as an optimal "methodology" for extracting 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.[6]

The paper proceeds as follows: Section one gives a statistical character-

[5]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.

[6]Lumsdaine and Prasad (1998) use time-varying weights in order to identify a common component, where the weights are given by the conditional variance found by applying a univariate GARCH model to the index of industrial production series.

ization 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 two 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 three concludes.

2 The European affiliation: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 measure the US business cycle. There has 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 output 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 output, where the mean μ depends on the state or ”regime”, s_t. For example, μ_1 could be 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:

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

By inferring the probabilities of the unobserved regimes conditional on an available information set, it is then possible to reconstruct the regimes. [7] The

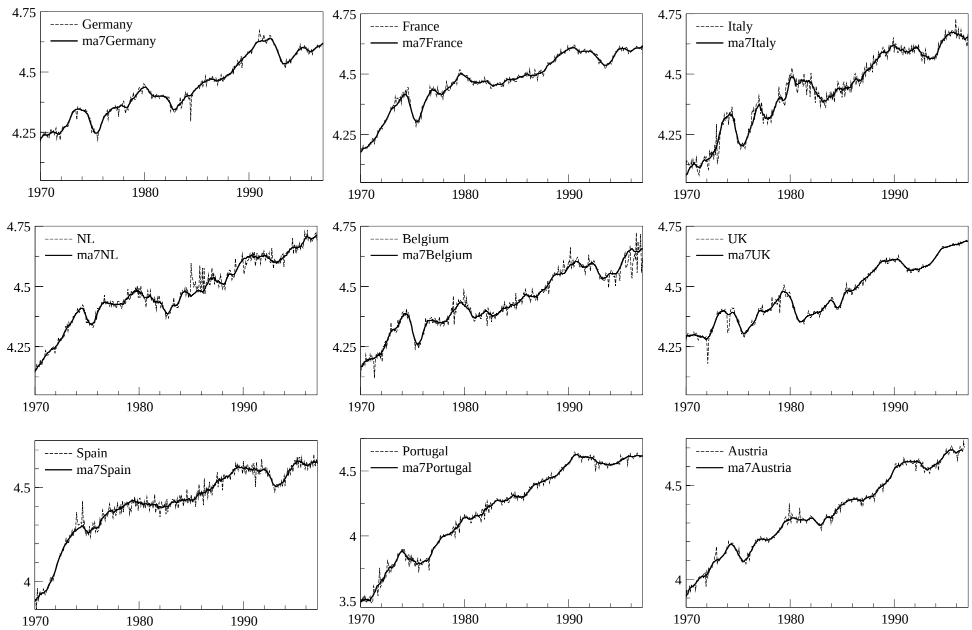

Figure 1 Industrial Production Index.

data used here are monthly industrial production indices for nine EU economies [8] 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 1. 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

[7] 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).

[8] Due to data availability considerations the analysis was restricted to these nine economies. But they can be seen as a very representative sample of the EU members.

analysis in section 3.1.

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 the 5 % level and hence y_t was found to have a stochastic trend. Prior to unit root testing the original series were purged of outliers and smoothed by taking seven-month moving averages.[9] The effect of this procedure is shown in Figure 1. 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 possess 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-AR model can then be carried out using the EM algorithm.

The estimation results are given in table 1 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. 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

[9] The programme TRAMO was employed in this process (Gomez and Maravall (1992))

Table 1 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

rates of most OECD countries in the post-Bretton Woods era (see also Krolzig (1997a) and Lumsdaine and Prasad (1998)). A two-regime model representing contractions and expansions is unable to reflect these two stylized facts of the postwar economic history of Western Europe. This is why the results reported in table 1 are based on an extended three regimes Markov-switching process. 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 time paths of the smoothed, filtered and predicted probabilities are presented in Figure 2. The smoothed probabilities are presented with the thick line, the filtered probabilities depicted by the shaded area and the predicted probabilities correspond to the thin line. 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, $\Pr(s_t = 1 \mid Y_T)$. Last, the predicted probability stands for the optimal inference on the regime at time t using all available information at time $t-1$, $\Pr(s_t = 1 \mid Y_{t-1})$. The univariate MS-AR models are not fully able to capture the different regimes in every case. 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 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 parts of the literature but the univariate models obviously cannot capture the idea of comovement among economic time 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. The contemporaneity of the regime shifts

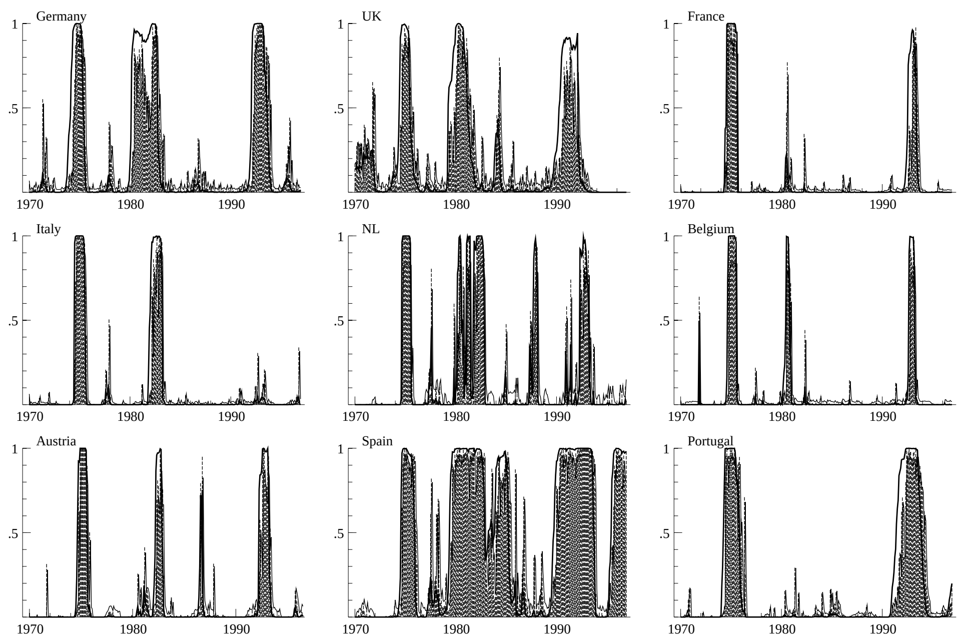

Figure 2 Probabilities of a Recession.

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 2, where the cross correlations at displacement zero of the smoothed probabilities of being in a recession are presented. Further information can be obtained from the cross correlations at different leads and lags of the same smoothed probabilities. This information is presented in table 3, where lagged cross correlations are to be read 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 2 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

In order to analyze further the synchronous nature of the European Business cycle we can employ a non-parametric procedure to investigate the cycle regime comovement across countries. We will analyze the direction of movement implied by our regime classification, and hence infer whether the cycles that we have uncovered are a European phenomenon. We will use a binary time series obtained from the classification regime, where 1 [10] will denote re-

[10] In the MS-AR fitted for some countries we have three states which correspond to growth, high growth and recession. For those countries with three regimes we make a dichotomous distinction between expansion and recession. So if the country is in recession we assign 1 and if it is a growth or a high growth state we assign it 0. The rule would thus be: if the smoothed probability of being in a recession is greater that 0.5 we give it the value 1 and if it is smaller than 0.5 we give it a value of 0.

Table 3 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

cession and 0 will denote expansion. We then obtain a contingency table that records expansion/recession frequencies (see table 4). We will use Pearson's contingency coefficient expressed as a percentage and corrected to take values in the range 0-100. Pearson's contingency coefficient is defined as:

$$CC = \sqrt{\frac{\widehat{\chi}^2}{N + \widehat{\chi}^2}}$$

where

$$\widehat{\chi}^2 = \sum_{i=0}^{1} \sum_{j=0}^{1} \frac{\left(n_{ij} - \frac{n_{i.}n_{.j}}{N}\right)^2}{\frac{n_{i.}n_{.j}}{N}}$$

In order to obtain a statistic that lies between 0 and 100 we correct the contingency coefficient by

$$CC_{corr} = \frac{CC}{\sqrt{0.5}}100.$$

The statistic CC_{corr} now lies in the range $0 - 100$. The results for our classification of regime probabilities are illustrated in table 5.

As it can be seen from table 5 there is a high degree of commonality for almost all countries with the exception of the UK. If we take 0.5 as a threshold

Table 4 Contingency table.

	Expansion	Recession	
Expansion	n_{00}	n_{01}	$n_{0.}$
Recession	n_{10}	n_{11}	$n_{1.}$
	$n_{.0}$	$n_{.1}$	N

Table 5 Corrected Contingency Coefficient.

	Germany	France	Italy	NL	Austria	Belgium	Spain	Portugal	UK
Germany	100.0								
France	59.18	100.0							
Italy	51.74	55.59	100.0						
NL	78.81	63.92	66.19	100.0					
Austria	62.71	79.33	69.52	78.54	100.0				
Belgium	60.84	87.32	52.12	65.50	74.25	100.0			
Spain	62.59	42.51	32.89	53.32	45.08	41.59	100.0		
Portugal	62.54	75.52	34.68	42.72	62.91	61.48	48.16	100.0	
UK	35.60	29.14	27.01	20.25	12.83	42.66	60.52	36.94	100.0

level, we see that UK's expansions and contractions do not show any commonality with any of their counterparts with the exception of Spain.[11] The highest correlation is found between France and Austria and Belgium and France. Apart from the UK, most countries record correlations higher than 0.6. Two countries have a special behavior: Spain and Portugal. Portugal has a correlation higher than 0.6 only *vis a vis* Germany and France whereas with respect to the other countries the correlation is just over 0.4. For the case of Spain its correlation goes beyond 0.6. We can conclude that overall there is a high degree of concordance that suggests moving to the MS-VAR in order to investigate the existence of one latent variable driving the Business Cycle in Europe.

[11] We emphasized previously how the univariate model for Spain had difficulties in distinguishing clearly between expansions and recessions and this high correlation of the smoothed probabilities of being in a recession of UK and Spain might just be due to the poor fit of the model for Spain.

3 An MS-VAR Model of the European Business Cycle

In this section an application of Hamilton's 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 also provides 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 of common cycles and the recent appreciation of empirical business cycle research, there has been little attempt to investigate cross-country effects with modern non-linear time series models. Moreover, most 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.

3.1 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

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

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). In 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

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
$p \le 1$	45.9	34.6	55.5	223.9**	168.9	182.8
$p \le 2$	45.6	34.4	49.4	178.0**	134.2	146.8
$p \le 3$	37.6	28.4	44.0	132.4**	99.9	114.9
$p \le 4$	34.9	26.3	37.5	94.8*	71.5	87.3
$p \le 5$	22.1	16.7	31.5	59.9	45.1	63.0
$p \le 6$	17.8	13.4	25.5	37.7	28.5	42.4
$p \le 7$	11.3	8.5	19.0	20.0	15.1	25.3
$p \le 8$	8.7	6.5	12.3	8.7	6.5	12.3

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

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 3). Some economic insight

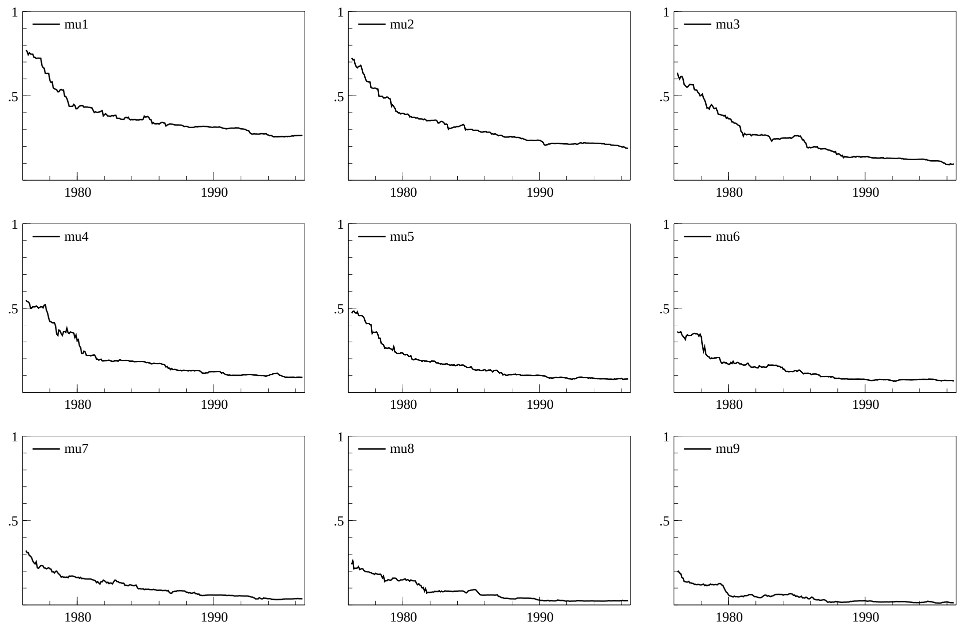

Figure 3 Eigenvalues from a Recursive Cointegration Analyis.

might help to interpret these results. An important economic feature of our period of investigation has been the convergence of the European economies. Convergence could be understood in at least two different ways: as relative convergence [13] and as convergence in the phase/coherence of the cycle. Convergence in cycle phase can be inferred from the statistical analysis conducted above; relative convergence is a more subtle issue. Some intuition about this type of convergence can be gained by looking at the change in the mean growth

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

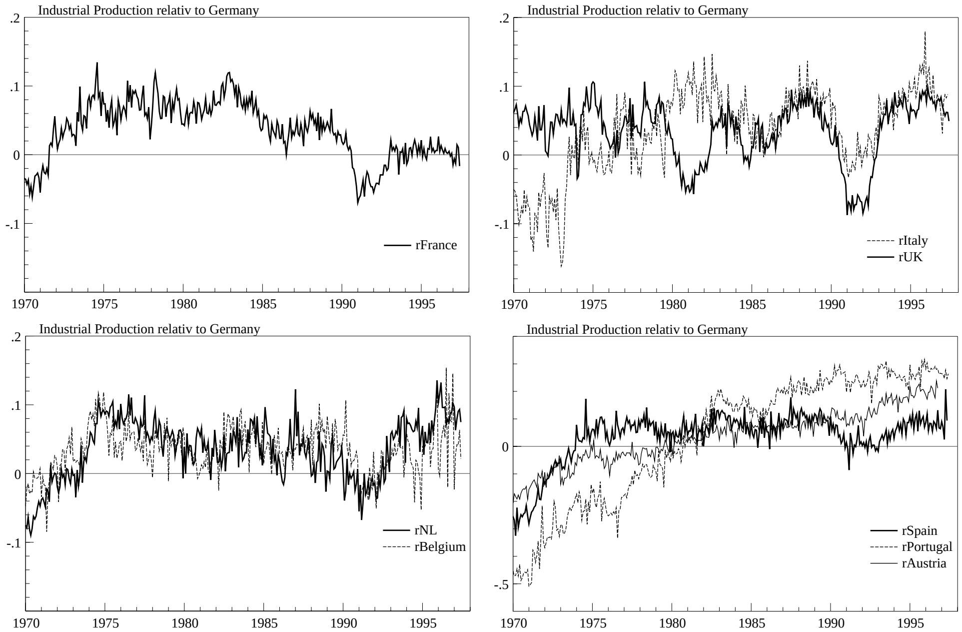

Figure 4 Cointegration Results.

of industrial production and the graphical representation of the series. More formally, one can approach the issue by considering 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,

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

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 present two types of relative convergence, type I and type II convergence. Type I convergence relates 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, i.e. a change in the rate of growth. We refer to type I convergence in the case of a shift in the equilibrium mean. Say a cointegrating relationship existed between the output of two countries at some time $t.$ If at some later period $t > 0$ there has been a shift in the equilibrium mean that has reduced it such that for $t > 0$, $\mu^* = \mu + \Delta\mu$, then we would have an instance of Type I convergence. On the other hand 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 takes 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 closely related to the concept of co-breaking(see Hendry (1995) and Toro (1999))

We are likely to have seen these two types of 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 1. Furthermore the equilibrium mean of any interpretable cointegrating relationship seems to have changed as well, as can be seen from figure 4. 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 4 shows how the equilibrium means of these relationships moved in time. Only after 1980 and

[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.

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.

3.2 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 passes all specification tests. The contribution of the European business cycle to the process of economic growth in the nine European countries is depicted in Figure 6. 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 of almost double this (42.7 months) and the “high growth” state tends to last 32.2 months. In the case of Germany and the UK, the values for the regime-dependent intercept are not in the ascending order (that is recession, growth,

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

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 recently observed . Figure 6 catches the contribution to the mean of the Markov chain, and can clarify this interpretation of the results. For all countries except the 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.

3.3 Dating the European business Cycle

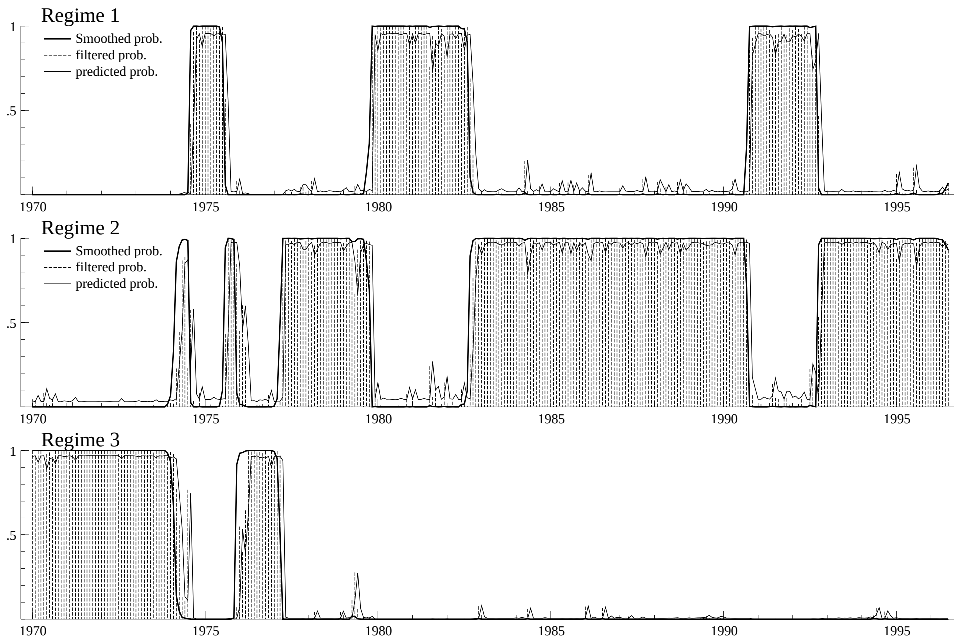

Figure 5 The European Business Cycle.

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

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 a 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.

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

The results are compared to a dating based on movements in GDP growth , which is modelled 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.

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

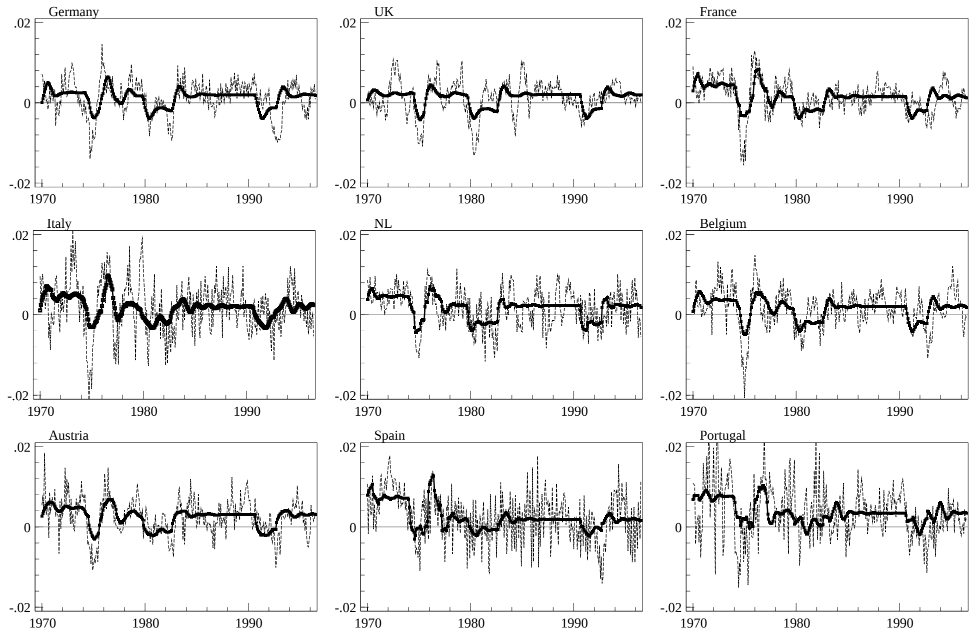

Figure 6 The Contribution of the European Business Cycle.

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 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 $A(L) = \mathsf{I} - A_1 L$ 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 6 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.

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 a once-and-for-all shock as a cyclical innovation. Krolzig and Toro (1998) introduced the idea that if the unobservable variable is to be interpreted as the state of the business cycle, an alternative procedure is to look at cyclical fluctuations 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. In particular, 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 the 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 analyses 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 economists have in mind when they refer to ”cyclical shocks”; that is, investigating the dynamics of some vari-

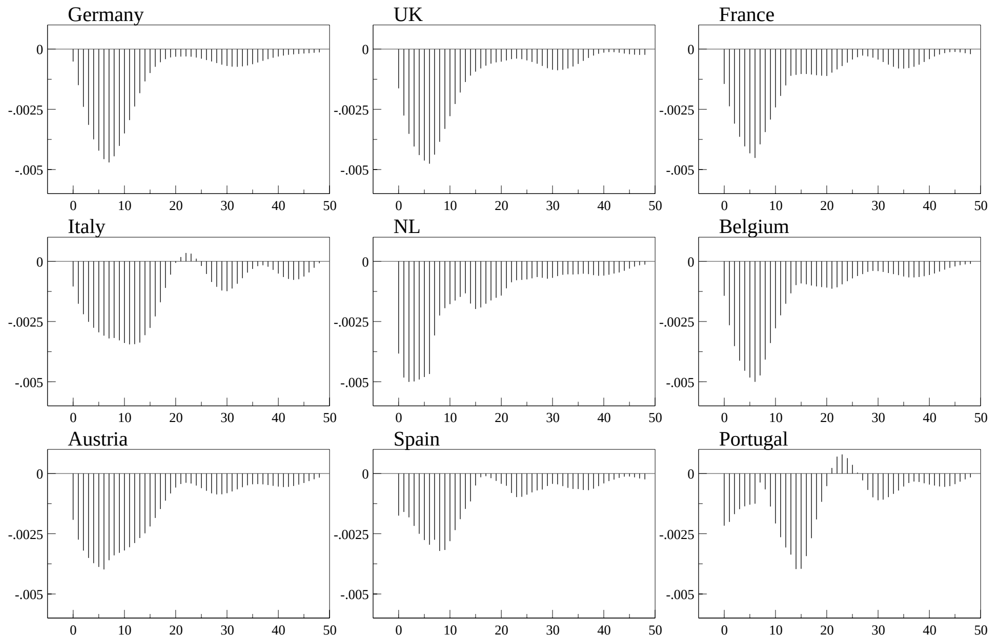

Figure 7 Effects of an European recession (shift from regime 2 to regime 1).

ables in the transition from boom 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 2 to regime 1), and the effect of an expansionary period in Europe (shift from regime 2).

Facing an European recession (Figure 7), there are countries like France, UK, Germany, the Netherlands and Belgium which have a similar dynamic pattern, whereas Portugal and Spain show a different one. 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 approximately until approximately ten months later that the recessions reaches its through. In terms of magnitude, most countries suffer a decline in industrial production of the same size. Here the exceptions are Austria, Spain and

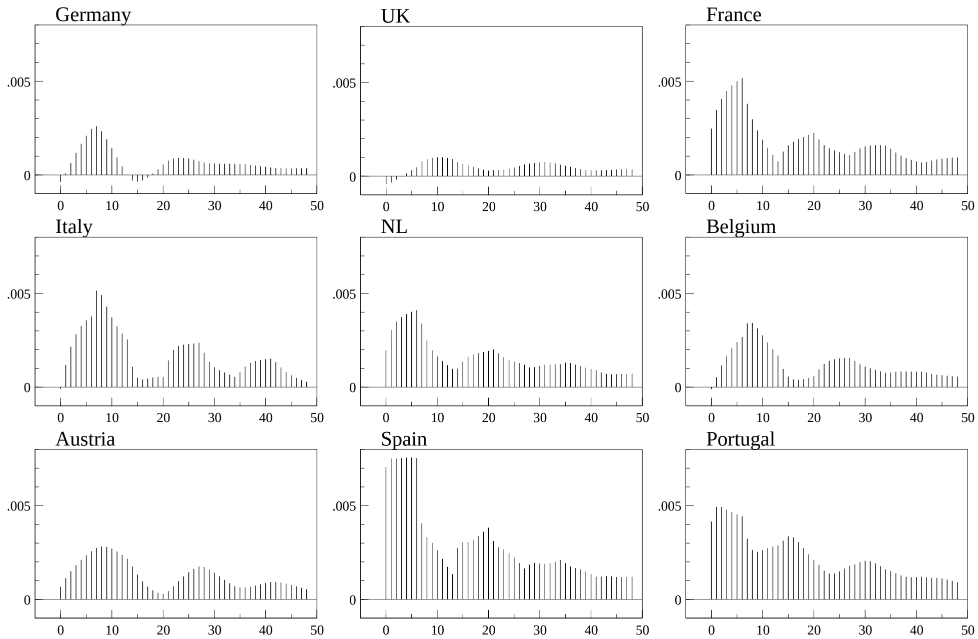

Figure 8 Effects of a regime shift towards the High-Growth regime.

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 8 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 other countries. These findings reflect the different tendencies in the rate of growth of the European countries under consideration in the early 1970s.

4 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 preferred regime identification 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 behavior of two of the Southern economies (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 centered on GDP rather than IP data.

In view of the criticisms that can be directed to conventional methods of business cycle identification, and more especially, in view of the policy significance of the type of results obtained, it is important to supplement those methods by others. 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 data availability considerations, our analysis is restricted to a subset of six European countries: Germany, UK, France, Italy, Austria, and Spain .

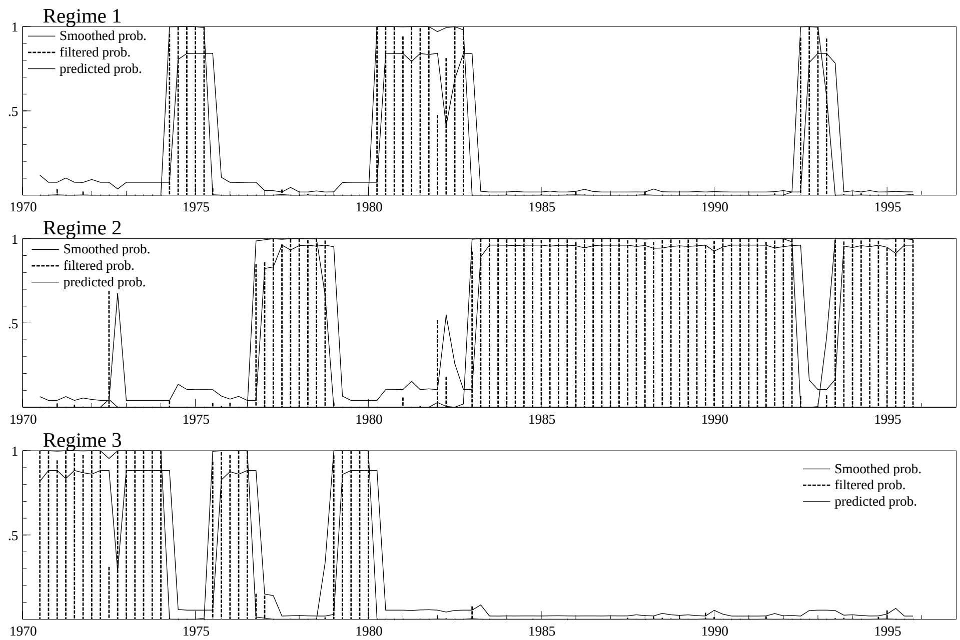

Figure A1 Regime-probabilities for the GDP–based European Business Cycle .

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 chosen which allows for changes in contemporaneous correlation structure. The estimation results for an MSIH(3)-VAR(1) model for the period from

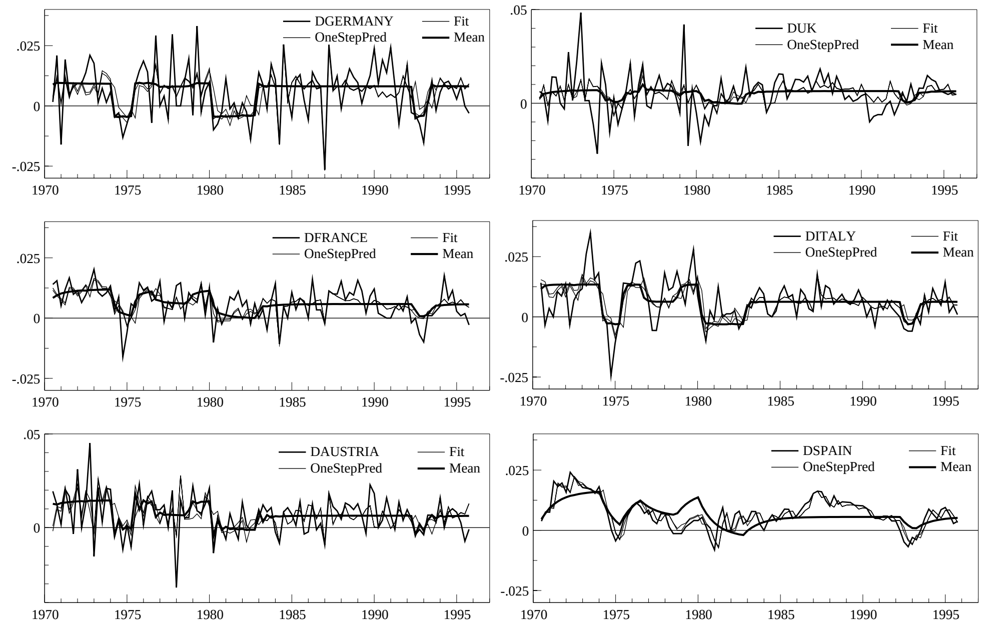

Figure A2 The contribution of the European Business Cycle to the country-specific GDP growth rates.

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.

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