The European business cycle

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This paper deals with the existence and identification of a common European growth cycle. Univariate Markov switching autoregressions are used for individual countries in order to detect changes in the mean growth rate of industrial production. A Markov switching vector autoregression model is then used to identify a common cycle in Europe. Three important results are obtained: we find a common unobserved component governing European business cycle dynamics, suggesting the existence of a common business cycle; we propose a dating of the business cycle, both for an index of industrial protection and GDP, and both chronologies appear to be consistent; and finally we retrieve an important set of stylized facts and relate these with those reported for the US. Finally two further issues are investigated: first, the contribution of the European business cycle to the individual country cycles; and second, we undertake an impulse response analysis to investigate the response of each individual country to European expansions and recessions.

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 would constitute a negative indicator in the optimal currency area literature for the formation of a monetary union. 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 condition holds for the European Monetary Union (EMU) and the quasi-union of the Exchange Rate Mechanism (ERM) of the European Monetary System, then we might expect to already find an emergent ‘European cycle’ which will become more dominant in future years.

This paper addresses the issue of identifying a common business cycle component for Europe. Once this common component is identified some stylized facts about the European business cycle are investigated. Three important results are obtained. First, we find a common unobserved component governing the business cycle dynamics in Europe, suggesting the existence of a common business cycle. Second, we propose a dating of the business cycle in Europe, both for an index of
industrial production (IIP) and gross domestic product (GDP); both chronologies appear to be consistent. Third, we retrieve an important set of stylized facts and relate these with those reported for the US economy (see, among others, French and Sichel, 1993; Warnock and Warnock, 2000; and Sichel, 1994). The main stylized facts are the following: (i) a structural break of the volatility of economic activity in the mid-eighties; (ii) higher variance of output around business-cycle booms, (iii) a specific transition dynamic from recessions to booms (in contradiction with the results reported by Sichel, 1994, for the US). The results of this paper complement earlier analysis on the business cycle behavior in the European area.

In relation to this issue, a strand of the literature has dealt with the issue of whether the EU has been subject to more asymmetric shocks than a monetary union such as the US.\(^1\) This work has focused on the identification of asymmetric shocks within the member countries of the Union; and, 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. Shocks accounting was instigated, in the European context, by Bayoumi and Eichengreen (1993), who employed a structural vector autoregression (SVAR) as their basic tool. For European data, Bayoumi and Eichengreen (1993) use the type of identification restrictions introduced by Blanchard and Quah (1989) in order to assess 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.

An alternative strand of the literature has moved to a more disaggregated level of analysis. 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, over all

\(^1\) Cochrane (1997) offers a critical review of the SVAR methodology.

sectors the relative importance of country-specific disturbances has declined in the 1980s. Norrbin and Schlaenhauf (1996) extend this analysis to a dynamic setup and analyze the behavior 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.

Another area of debate has been the extent to which the cyclical component of some measures of economic activity comoves across countries in the Union. An indication of a development of this type can be found in the cyclical cross-correlation analysis offered by Artis and Zhang (1997) and Artis and Zhang (1999), who examine whether the correlation between the business cycles in ERM countries and the cycle in Germany has increased since the formation of the ERM. Their results show that the cycles in the ERM countries became more synchronized with the German one, suggesting the emergence of a European business cycle. Christodoulakis et al. (1995) focus on the 12 EU countries (as of 1994). They analyze the time series of a set of key macroeconomic variables since the 1960s and find no evidence of a core-periphery distinction. In their study they find that business cycles are similar for the variables they call endogenous (such as income and consumption), whereas this is not the case for those variables they refer to as exogenous (i.e., variables controlled by the government such as government spending or variables dependent on national institutions, such as labour market variables). Contrary to the results in Artis and Zhang (1997) and Artis and Zhang (1999), Dickerson et al. (1998) find no evidence that the business cycles in the EU 12 have become more correspondent after the formation of the ERM. They use data from 1960 to 1993 on GDP, private final consumption expenditure and investment.

Within the 12 EU members they distinguish two groups of countries: a core (formed by Belgium, Germany, France, Luxembourg, and The Netherlands) and a periphery (formed by the remaining countries from the 12 EU members). They suggest the existence of a commonality in the business cycles for the core countries which is not shared by the 12 EU members as a whole. Wynne and Koo (2000) extend the cross-correlation of the cyclical component to the current 15 members of the EU. They reject the hypothesis of absence of pairwise correlation between the business cycle components of output for the original six EU members, but find lower correlation for those countries that joined EMU later. They also find empirical evidence for the hypothesis suggested by Frankel and Rose (1998), that countries with closer trade links tend to have more highly correlated business cycles. Wynne and Koo (2000) also report a notable difference in the volatility

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.
of the cyclical component of output across the EU countries. Further evidence of business cycle synchronization is provided by Inklaar and de Haan (2001). They use almost the same set of countries as in Artis and Zhang (1997) and Artis and Zhang (1999) but distinguish four subperiods rather than two (the reason being that the two periods distinguished by Artis and Zhang (1997) are not uniform with respect to exchange rate volatility). They show that for most ERM countries there is an increase in the correlation of the cyclical component of output during the period 1971–79, while in the period 1979–87 there is a decline in correlations. This sheds some doubts on the results of Artis and Zhang (1997) and Artis and Zhang (1999).

There are two sources of differing conclusions in this strand of the literature. The first source of the disagreement is the different detrending method used to calculate the cyclical component. Christodoulakis et al. (1995), Inklaar and de Haan (2001), and Dickerson et al. (1998) use the Hodrick-Prescott filter (Hodrick and Prescott, 1980). Artis and Zhang (1997) use three methods: the phase-average trend procedure used by the OECD; the Hodrick-Prescott filter; and a linear detrending. Wynne and Koo (2000) use a measure of the cyclical component based on the band-pass filter proposed by Baxter and King (1995). The second source of the disagreement stems from the question of how large correlations should be before we can talk of a European business cycle.

The most relevant conclusions of this strand of the literature can be summarized as follows. On the one hand, the factors that move output growth in the European countries seem to be common across countries, independently of whether they are supply or demand driven or of whether they are industry specific or nation specific. This commonality, which has been referred to as the European Business Cycle, opens up the possibility of a common monetary and fiscal policy.5 On the other hand, whereas correlations give a rough measure of comovement and guidance on the optimality of a monetary union, they do not give precise information about relevant business cycle stylized facts, such as whether these comovements take place at the relevant business cycle frequencies or the precise dating of peaks and troughs. A deeper look into the existence of a common European business cycle and the analysis of relevant stylized facts requires going beyond a cross-correlation or a shock-accounting analysis. Addressing these issues would require a statistical model where some relevant issues of the European business cycle can be addressed. Issues such as the identification of an unobserved component driving the rate of growth of all European economies, the identification and dating of the European business cycle, and the analysis of relevant stylized facts can only be addressed in the context of a statistical model where these relevant questions can be posed.

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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.
The current paper directly addresses the issues of identification and dating of a European business cycle using Markov-switching vector autoregressions. On the one hand, identification of a common business cycle sheds light on issues such as the optimality of a monetary union or business cycle synchronization across countries. Moreover, our statistical model is a framework in which many important business cycle stylized facts can be investigated. On the other hand, the precise dating of the business cycle has important policy implications. The optimal implementation of countercyclical policies needs a correct timing of booms and busts. Delays in spotting turning points could render many policies ineffective. The statistical model we propose might also be viewed as formalizing the statistical identification of a ‘turning point’ in an economic time series. Traditional methods of identifying turning points (see Diebold and Rudebush, 1987; Wecker, 1979; and Neftci, 1982) cannot provide the dates in real time.\footnote{Wecker (1979), for example, discusses the optimal forecast of an indicator function (e.g., $z_t = 1$ if both $y_{t-1} < y_t$ and $y_t < y_{t+1}$). Whereas Wecker’s (1979) indicator could be considered in some sense arbitrary, in our specification, by contrast, the turning point is a structural event inherent in the data generation process.} In the US, the NBER’s Business Cycle Dating Committee is responsible for identifying the different phases of expansion and recession occurring in the economy. The outcome is a set of reference chronologies for peaks (end of an expansion) and troughs (beginning of an expansion) that can be considered as a benchmark for testing economic hypotheses related to the business cycle. The absence of a similar committee in Europe, makes it even more important to provide tools that could supplement this work.\footnote{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 (see Lumsdaine and Prasad, 1997; and Norrbin and Schlaenauf, 1996) have tried to identify a common coincident composite indicator for a group of European countries, this is to our best knowledge, the first attempt to extract the common European cycle offering a joint statistical model for a relevant group of European economies.\footnote{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 applying a univariate GARCH model to the index of industrial production series.}

The main empirical facts established in this paper can be described succinctly. First, we offer a statistical model of output growth for a relevant group of EMU economies. This model favors the idea of a common unobserved component governing the business cycle dynamics in Europe. This offers evidence of the existence of a common business cycle in Europe. Second, the paper puts forward a dating of the business cycle in Europe. The business cycle dating is offered both for IIP and GDP, and both chronologies appear to be consistent. Third, an important set of stylized facts are retrieved from the modelling exercise. A relevant stylized fact
presented in this article refers to the transition dynamic of European activity from recessions to booms. These results are in contradiction with the evidence presented by Sichel (1994) for the US. Sichel (1994) documents that for the US during the post-war period, contractions have typically been followed by a high-growth recovery phase that quickly boosts output back to its pre-recession level. Another stylized fact that is in contradiction with the evidence presented by French and Sichel (1993) and Warnock and Warnock (2000) for the US is the different pattern of volatility in recessions and booms. We find that the variance of output is highest around business-cycle booms. A further important stylized fact documented in this paper is the structural break in the volatility of economic activity, which takes place in the early eighties. From a policy-making perspective this stylized fact has important implications. The reduction in the variance of output fluctuation should alter the interpretation policy-makers place on a specific realization of monthly industrial production. What might have been considered a moderate oscillation in activity prior to the break, may now be viewed as severe. This finding is in agreement with the results reported in Dickerson et al. (1998), who report that the amplitude of the cycle (measured as the mean absolute deviation from trend) has changed for the European countries in the early eighties.

The paper proceeds as follows. Section 2 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 3 presents the results from a Markov-switching vector autoregression (MS-VAR) exhibiting a common cycle consisting of three phases of the business cycle. Last, Section 4 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. In a Markov switching time series model, contractions and expansions are modelled as switching regimes of the stochastic process generating the growth rate of real output, \( \Delta y_t \). As a starting point we could postulate a simple model with no dynamics for the growth rate of real output, such as

\[
\Delta y_t = \mu_{s_t} + \varepsilon_t \\
\mu_{s_t} = \mu_1 (1 - s_t) + \mu_2 s_t
\]

(1)

where \( \varepsilon_t \sim N(0, \sigma^2) \), and \( s_t = 1 \) or \( 2 \) (Regime 1 or 2).
The general idea behind this class of regime-switching models is that a parameter of the modeled equation (μ, the growth rate of output in this case) depends upon a stochastic, unobservable regime variable s_t, which can take two values (s_t = 1 or 2). The regimes are associated with different conditional distributions of the growth rate of real output, and the mean μ depends on the state or ‘regime’, s_t. For example, μ_1 could be negative in the first regime (contraction), μ_1 < 0, and positive in the second regime (expansion), μ_2 > 0. The variance of the disturbance term, ε_t ~ NID(0, σ^2), is assumed to be the same in both regimes. The Hamilton (1989) model has become very popular, both because of its intuitive nature and because it fits well many time series that represent economic activity (see, among others, Filardo, 1994; and Goodwin, 1993). They capture the idea of a growth cycle as periods of acceleration and deceleration of the growth rates. In these models, the economy is characterized as moving between two states of high and low growth.

The stochastic process generating the unobservable regimes is an ergodic Markov chain defined by the transition probabilities

\[ p_{ij} = \Pr(s_{t+1} = j|s_t = i), \quad \sum_{j=1}^{2} p_{ij} = 1 \quad \forall i, j = 1, 2 \]  

where i, j = 1, 2. This model can be extended in different directions: we could allow other parameters of our model to vary, such as the variance; we could extend the number of states to M states s_t ∈ {1, . . . , M}; the model could be generalized to a vector process and we could model the dynamics of Δy_t. We could allow the variance to change across regimes to capture an important stylized fact reported in the literature that recessions and expansions are characterized by different volatilities (see French and Sichel, 1993; and Warnock and Warnock, 2000, for evidence of this stylized fact in the US). The extension to more than one regime can be used to capture another stylized fact documented by Sichel, 1994, for the US, the existence of three phases in the post-war US business cycle. The vector process generalization would allow us to investigate whether the set of endogenous variables under analysis share a common unobserved component that drives the changes in the means of output growth.

The data used here are monthly industrial production indices for nine EU economies from 1970:1 to 1996:12, and were drawn from the OECD Main Economic Indicators (updated monthly). The original series together with a seventh order moving average of the original series, are plotted in Fig. 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 important issue at the time of identifying the number of regimes when we move to the multivariate analysis in Section 3.

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9 The models we estimate are highly non-linear with a large number of parameters to estimate. These nine countries can be seen as a very representative sample of the EU members.
Fig. 1. Industrial production index
The presence of unit roots in the data can be checked with the augmented Dickey-Fuller test (the ADF test) proposed in Dickey and Fuller (1981). 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. First differences are then taken to achieve stationarity.

The baseline model estimated is

$$\Delta y_t = \nu_t + A_1 \Delta y_{t-1} + A_2 \Delta y_{t-2} + \varepsilon_t, \quad \varepsilon_t | s_t \sim \text{NID}(0, \Sigma(s_t))$$

with $s_t = 1, 2, 3$ (Regime 1, 2 or 3).

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 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. This is why the results reported in Table 1 are based on an extended three regimes Markov-switching process, except for Germany. For Germany, two regimes were sufficient on the basis of a likelihood criteria. Regime 1 correspond to recessions,

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10 The null hypothesis is $H_0: \psi_1 = 0$ in the regression:

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

11 Prior to unit root testing the original series were purged of outliers and smoothed by taking seven-month moving averages. The programme TRAMO was employed in this process (Gomez and Maravall, 1992). The effect of this procedure is shown in Fig. 1.

12 Note that the model presented in eq. 1 has no autoregressive dynamics and the parameter $\mu_{i,t}$ is the time-varying mean of the rate of growth of output. In the model presented in eq. 3 the parameter $\nu_{i,t}$ is a time-varying intercept, because of the presence of autoregressive dynamics. The mean is also time variant in this model. However the dynamics differ according as to whether we explicitly model the mean as time-varying or allow the intercept to be time-varying.

13 This convergence refers to the tendency for countries which are lagging behind in terms of living standards to catch up on the ‘centre’ countries, Germany and the UK.

14 An issue of considerable difficulty which arises when 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 $\chi^2$ distribution. One solution to this problem is to use the procedures proposed by Hansen (1992), Hansen (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($p^*, q^*$)–autoregressive moving average of order $p^*$ and $q^*$–representation of the MSM(M)-AR(p)-Markov (M) switching (S) mean (M) autoregressive (AR) process of order $p$ with $M$ states- or the MSI(M)-AR(p)- Markov (M) switching (S) intercept (I) autoregressive (AR) process of order $p$ with $M$ states. 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–Akaike Information Criterion–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.
Table 1 Univariate MS-AR models of the business cycle

<table>
<thead>
<tr>
<th>Regime-dependent intercepts (10^-2)</th>
<th>Germany</th>
<th>UK</th>
<th>France</th>
<th>Italy</th>
<th>NL</th>
<th>Belgium</th>
<th>Austria</th>
<th>Spain</th>
<th>Portugal</th>
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<tbody>
<tr>
<td>( \nu_1 )</td>
<td>-0.191</td>
<td>-0.115</td>
<td>-0.398</td>
<td>-0.699</td>
<td>-0.419</td>
<td>-0.563</td>
<td>-0.353</td>
<td>-0.091</td>
<td>-0.281</td>
</tr>
<tr>
<td>( \nu_2 )</td>
<td>0.131</td>
<td>0.069</td>
<td>0.014</td>
<td>0.073</td>
<td>0.114</td>
<td>0.066</td>
<td>0.086</td>
<td>0.511</td>
<td>0.222</td>
</tr>
<tr>
<td>( \nu_3 )</td>
<td>0.083</td>
<td>0.004</td>
<td>0.691</td>
<td>0.641</td>
<td>0.429</td>
<td>0.503</td>
<td>1.349</td>
<td>0.881</td>
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<tr>
<th>Regime-dependent variances (10^-6)</th>
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<tbody>
<tr>
<td>( \sigma^2_1 )</td>
<td>5.899</td>
<td>4.503</td>
<td>4.422</td>
<td>16.324</td>
<td>6.472</td>
<td>6.618</td>
<td>7.562</td>
<td>18.732</td>
<td>17.565</td>
</tr>
<tr>
<td>( \sigma^2_2 )</td>
<td></td>
<td>1.343</td>
<td></td>
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<tr>
<td>( \sigma^2_3 )</td>
<td></td>
<td>4.208</td>
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<tr>
<th>Regime dependent means (10^-2)</th>
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<tr>
<td>( E(\Delta y_t</td>
<td>s_t = 1) )</td>
<td>-0.44</td>
<td>-0.41</td>
<td>-0.63</td>
<td>-0.75</td>
<td>-0.41</td>
<td>-0.91</td>
<td>-0.50</td>
<td>-0.096</td>
</tr>
<tr>
<td>( E(\Delta y_t</td>
<td>s_t = 2) )</td>
<td>0.26</td>
<td>0.20</td>
<td>0.01</td>
<td>0.04</td>
<td>0.301</td>
<td>0.07</td>
<td>0.11</td>
<td>0.383</td>
</tr>
<tr>
<td>( E(\Delta y_t</td>
<td>s_t = 3) )</td>
<td>0.25</td>
<td>0.46</td>
<td>0.72</td>
<td>0.480</td>
<td>0.56</td>
<td>0.50</td>
<td>1.037</td>
<td>0.84</td>
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<tr>
<th>Persistence of Recessions (Regime 1)</th>
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<tr>
<td>Erg. Prob</td>
<td>0.206</td>
<td>0.004</td>
<td>0.079</td>
<td>0.087</td>
<td>0.175</td>
<td>0.078</td>
<td>0.119</td>
<td>0.513</td>
<td>0.161</td>
</tr>
<tr>
<td>Log Lik.</td>
<td>1473.60</td>
<td>1559.60</td>
<td>1497.60</td>
<td>1282.05</td>
<td>1393.77</td>
<td>1421.71</td>
<td>1403.85</td>
<td>1271.23</td>
<td>1279.48</td>
</tr>
<tr>
<td>LR Test</td>
<td>16.12</td>
<td>25.50</td>
<td>38.36</td>
<td>52.89</td>
<td>86.07</td>
<td>28.57</td>
<td>72.04</td>
<td>72.99</td>
<td>90.46</td>
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</table>
Regime 2 (which we will denote as growth regime) represents normal growth, while Regime 3 (which we will denote as high growth regime) characterizes high-growth episodes. One might also expect that recessions and expansions would be characterized by different volatilities. This stylized fact has been documented by French and Sichel (1993) and Warnock (2000) for the US. These authors find that the business cycle is asymmetrical with higher fluctuations in GDP in recessions than in expansions. 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.\(^{15}\)

The estimation results are given in Table 1. The first three rows in Table 1 report the state dependent intercept. The next three rows report the variance corresponding to each of the regimes identified. From row seven to nine we report the mean rate of growth prevailing in each state. The following two rows report measures of the persistence of recession: the expected number of months a recession prevails (duration) and the unconditional (ergodic) probability of recessions. The last two rows contain respectively the value of the maximized likelihood function and a likelihood ratio test statistic of linearity versus non-linearity (see footnote 14).\(^{16}\) By inferring the probabilities of the unobserved regimes conditional on an available information set, it is then possible to reconstruct the regimes.\(^{17}\) The time paths of the smoothed and filtered probabilities are presented in Fig. 2. The smoothed probabilities are presented with the thick line and the filtered probabilities are depicted by the dotted 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 \(t\), \(i.e.\) \(Pr(s_t = m | Y_t)\), where \(m\) stands for a given regime.\(^{18}\) The smoothed probability corresponds to the optimal inference on the regime at time \(t\) using the full sample information, \(Pr(s_t = m | Y_T)\). The continuous and dotted line in Fig. 2 represent, respectively, the inference obtained from the model on the recession state using information up to time \(t\) and using the full sample information.

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 and Portugal, the MS-AR misses the recession that took place in the early eighties.

\(^{15}\) The best model chosen based on a likelihood criterium considers three regimes \((s_t = 1, 2, 3)\) for all countries, except for Germany where a two regimes model \((s_t = 1, 2)\) was preferred. For France, Austria, and Portugal, a model with regime dependent variance was preferred \((\sigma_{s_t})\) whereas for the remaining countries we did not need to model a regime dependent variance \((\sigma_{s_t} = \sigma)\). Detailed output is available from the authors upon request.

\(^{16}\) Maximum likelihood (ML) estimation of the model is based on a version of the Expectation-Maximization (EM) algorithm discussed in Hamilton (1990) and Krolzig (1997). All the computations reported in this paper were carried out in Ox 1.20a, see Doornik (1996).

\(^{17}\) Hamilton (1989) proposes the probability smoother as an algorithm to date business cycles.

\(^{18}\) This statistic can provide real time information of the state of the business cycle and the occurrence of a turning point. This is not the case for the methods proposed by Diebold and Rudebusch (1987), Wecker (1979), and Neftci (1982) which cannot provide the dates of turning points in real time.
Fig. 2. Probabilities of a recession
and for Italy the 1990 recession is missed. The case of Spain probably delivers the worst fit, with difficulties in distinguishing clearly the recessionary periods. It is worthwhile stressing that Hamilton-type models capture only partially some of the stylized facts of business cycle fluctuations. Whilst they can capture the non-linearity or asymmetry stressed in some parts of the literature, the univariate model 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 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 contemporaneous cross correlations of the smoothed probabilities of being in a recession are presented.

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 will denote recession and 0 will denote expansion. We then obtain a contingency table that records expansion/recession frequencies (see Table A2). We will use Pearson’s contingency coefficient expressed as a percentage and corrected to take values in the range 0-100. The results for our classification of regime probabilities are illustrated in Table 3 (see Appendix 2 for a description of Pearson’s contingency coefficient).

As can be seen from Table 3 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 level, we see that UK’s expansions and contractions do not show any commonality with any of their counterparts with the exception of Spain. 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. Spain has a special behavior with a correlation higher than 0.6 only vis à vis Germany and the UK. 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.

19 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 in 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.

20 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.
Table 2  Contemporaneous cross-correlation of the smoothed probabilities of being in a recession for the sample period 1970:1-1996:7

<table>
<thead>
<tr>
<th></th>
<th>Germany</th>
<th>UK</th>
<th>France</th>
<th>Italy</th>
<th>Belgium</th>
<th>NL</th>
<th>Austria</th>
<th>Spain</th>
<th>Portugal</th>
</tr>
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<tbody>
<tr>
<td>Germany</td>
<td>1.0000</td>
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<td></td>
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<td></td>
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<tr>
<td>UK</td>
<td>0.314</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.0504)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>France</td>
<td>0.546</td>
<td>0.262</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.0392)</td>
<td>(0.0521)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Italy</td>
<td>0.463</td>
<td>0.187</td>
<td>0.491</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>(0.0439)</td>
<td>(0.0540)</td>
<td>(0.0424)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Belgium</td>
<td>0.730</td>
<td>0.229</td>
<td>0.536</td>
<td>0.556</td>
<td>1.00</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>(0.0260)</td>
<td>(0.0530)</td>
<td>(0.0398)</td>
<td>(0.0386)</td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>NL</td>
<td>0.559</td>
<td>0.355</td>
<td>0.827</td>
<td>0.409</td>
<td>0.593</td>
<td>1.00</td>
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<tr>
<td>(0.0384)</td>
<td>(0.0489)</td>
<td>(0.0176)</td>
<td>(0.0466)</td>
<td>(0.0362)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Austria</td>
<td>0.611</td>
<td>0.0987</td>
<td>0.737</td>
<td>0.648</td>
<td>0.707</td>
<td>0.657</td>
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<td>(0.0350)</td>
<td>(0.0554)</td>
<td>(0.0255)</td>
<td>(0.0324)</td>
<td>(0.0279)</td>
<td>(0.0317)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Spain</td>
<td>0.535</td>
<td>0.510</td>
<td>0.347</td>
<td>0.286</td>
<td>0.457</td>
<td>0.356</td>
<td>0.391</td>
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<tr>
<td>(0.0399)</td>
<td>(0.0414)</td>
<td>(0.0492)</td>
<td>(0.0513)</td>
<td>(0.0442)</td>
<td>(0.0488)</td>
<td>(0.0474)</td>
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<tr>
<td>Portugal</td>
<td>0.542</td>
<td>0.315</td>
<td>0.727</td>
<td>0.293</td>
<td>0.347</td>
<td>0.531</td>
<td>0.560</td>
<td>0.402</td>
<td>1.000</td>
</tr>
<tr>
<td>(0.0395)</td>
<td>(0.0504)</td>
<td>(0.0263)</td>
<td>(0.0511)</td>
<td>(0.0492)</td>
<td>(0.0401)</td>
<td>(0.0383)</td>
<td>(0.0469)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note: Standard errors in parentheses.*
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. 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) and Filardo and Gordon (1994). Phillips’s study of a two-country two-regime model was the very first multivariate Markov-switching analysis of all. Filardo and Gordon (1994) have extended this analysis to a trivariate two-regime model by using leading indicators for the prediction of turning points.

3.1 The MS-VAR

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

\[
\Delta y_t = \nu(s_t) + A_1 \Delta y_{t-1} + \varepsilon_t, \quad \varepsilon_t | s_t \sim \text{NID}(0, \Sigma(s_t))
\]

where \( \Delta y_t \) is the vector of growth rates (first differences smoothed by taking seven-month moving averages and controlled for outliers). Three vectors of regime-conditional mean growth rates of \( \Delta y_t \) are distinguished. The ML estimates of this model are given in Table 4. We found that this model passes all specification tests. The resulting smoothed and filtered probabilities are given in

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21 A cointegrating analysis revealed the absence of any cointegrating relationship and the model is fitted in first differences. See Appendix 1 for a discussion of this issue.
Table 4 Estimation results: the MS-VAR model of the European business cycle

<table>
<thead>
<tr>
<th>Regime</th>
<th>Germany</th>
<th>UK</th>
<th>France</th>
<th>Italy</th>
<th>NL</th>
<th>Belgium</th>
<th>Austria</th>
<th>Spain</th>
<th>Portugal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime-dependent intercepts (10^{-2})</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regime 1</td>
<td>-0.033</td>
<td>-0.073</td>
<td>-0.088</td>
<td>-0.025</td>
<td>-0.178</td>
<td>-0.073</td>
<td>-0.006</td>
<td>-0.011</td>
<td>0.048</td>
</tr>
<tr>
<td>Regime 2</td>
<td>0.017</td>
<td>0.088</td>
<td>0.051</td>
<td>0.086</td>
<td>0.213</td>
<td>0.069</td>
<td>0.193</td>
<td>0.142</td>
<td>0.271</td>
</tr>
<tr>
<td>Regime 3</td>
<td>-0.017</td>
<td>0.047</td>
<td>0.300</td>
<td>0.076</td>
<td>0.405</td>
<td>0.064</td>
<td>0.258</td>
<td>0.860</td>
<td>0.688</td>
</tr>
<tr>
<td>Regime-dependent means (10^{-2})</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$E(\Delta y_t</td>
<td>s_t = 1)$</td>
<td>-0.13</td>
<td>-0.26</td>
<td>-0.21</td>
<td>-0.11</td>
<td>-0.14</td>
<td>-0.18</td>
<td>-0.35</td>
<td>-0.11</td>
</tr>
<tr>
<td>$E(\Delta y_t</td>
<td>s_t = 2)$</td>
<td>0.13</td>
<td>0.21</td>
<td>0.12</td>
<td>0.14</td>
<td>0.18</td>
<td>0.17</td>
<td>0.25</td>
<td>0.19</td>
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<tr>
<td>$E(\Delta y_t</td>
<td>s_t = 3)$</td>
<td>0.36</td>
<td>0.27</td>
<td>0.56</td>
<td>0.65</td>
<td>0.53</td>
<td>0.47</td>
<td>0.55</td>
<td>0.73</td>
</tr>
<tr>
<td>Regime-dependent variance (10^{-4})</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
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</tr>
<tr>
<td>$\sigma_1$</td>
<td>0.0505</td>
<td>0.0390</td>
<td>0.0309</td>
<td>0.1699</td>
<td>0.1157</td>
<td>0.0672</td>
<td>0.0402</td>
<td>0.1698</td>
<td>0.3341</td>
</tr>
<tr>
<td>$\sigma_2$</td>
<td>0.0685</td>
<td>0.0339</td>
<td>0.0446</td>
<td>0.1753</td>
<td>0.1012</td>
<td>0.0687</td>
<td>0.0637</td>
<td>0.2346</td>
<td>0.1543</td>
</tr>
<tr>
<td>$\sigma_3$</td>
<td>0.0609</td>
<td>0.0464</td>
<td>0.0633</td>
<td>0.2166</td>
<td>0.0545</td>
<td>0.0988</td>
<td>0.1308</td>
<td>0.2261</td>
<td>0.4089</td>
</tr>
<tr>
<td>log-likelihood</td>
<td>12801.48</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>-78.19</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>HQ</td>
<td></td>
<td>-76.64</td>
<td></td>
<td></td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>SC</td>
<td></td>
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</tr>
</tbody>
</table>

log-likelihood: 12801.48 (vs. linear 12616.00)

$p_{1i}$ $p_{2i}$ $p_{3i}$ Duration Ergodic prob. Observations

<table>
<thead>
<tr>
<th>Regime</th>
<th>$p_{1i}$</th>
<th>$p_{2i}$</th>
<th>$p_{3i}$</th>
<th>Duration</th>
<th>Ergodic prob.</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime 1</td>
<td>0.955</td>
<td>0.018</td>
<td>0</td>
<td>22.2</td>
<td>0.249</td>
<td>70.3</td>
</tr>
<tr>
<td>Regime 2</td>
<td>0.045</td>
<td>0.977</td>
<td>0.031</td>
<td>42.7</td>
<td>0.633</td>
<td>184.6</td>
</tr>
<tr>
<td>Regime 3</td>
<td>0</td>
<td>0.006</td>
<td>0.969</td>
<td>32.2</td>
<td>0.118</td>
<td>65.1</td>
</tr>
</tbody>
</table>
Fig. 3. The upper, middle, and lower panels of Fig. 3 depict the smoothed probabilities of being in Regime 1, 2, and 3 respectively. Regime 1 (recessions) depicts very precisely the recessions of 1970, 1973/74, 1979/80, and 1990. Regime 2 (we will denote as ‘growth’ regime) represents normal growth, while Regime 3 (we will denote ‘high growth’ regime) characterizes high-growth episodes.

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 periods. 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.\(^{22}\) Table 4 also reports the state dependent means and state dependent variances. We find major differences in the mean rate of growth across regimes as well as significant differences in the mean rate of growth across countries within regimes. This points out two type of asymmetries: (i) across countries within regimes and (ii) within countries across regimes. As a measure of the asymmetry across countries within regimes we consider the standard deviation of the rates of growth across countries for each regime. These have values of \(10^{-2} \times 1.0190, 10^{-2} \times 0.60184\) and \(10^{-2} \times 1.4557\) respectively for Regime 1, 2, and 3. These results indicate that the dispersion of growth across countries is highest in Regime 3, whereas recent expansions (Regime 2) have registered a lower dispersion in the growth rates of the countries under analysis. This result is in agreement with the downward trend in the standard deviation of the cyclical component of output across countries reported in Wynne and Koo (2000). In Regime 3 the highest growth rates correspond to Italy, Spain and Portugal. This could be interpreted as implying that the third regime stands for high growth in the south and hence asymmetries in the European cycle. This 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. 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. If we compare the duration of each regime and consider the different state dependent means, these results point out to an interesting empirical finding: that expansions in the 70s were characterized by a shorter duration and higher amplitude.

The transition dynamics of the regimes can be observed by analyzing the transition probabilities. Note from the transition matrix given in Table 4, that the ‘high growth regime’ can only be reached through the ‘growth regime’ and not directly from a recessionary period \((p_{13} = 0)\). This differs with the evidence provided by Sichel (1994) for the US. For the US, contractions have typically

\(^{22}\) In the case of Germany and the UK, the values for the regime-dependent intercepts are not in the ascending order (that is recession, growth, high growth as we interpret them) that characterizes the other countries. Note that they are not means but intercepts.
Fig. 3. The European business cycle
been followed by a high growth recovery that quickly boosts output back to its pre-recession level. This corresponds to the ‘plucking model’ of fluctuations of Friedman (Friedman, 1969; and Friedman, 1993), where output is bumping along the ceiling of maximum feasible output and every now and then in plucked down by a cyclical contraction. When recovery sets in, it tends to return output to the ceiling.

An important feature of the model specified in eq. 4 is that it allows the covariance matrix to change according to the specific regime. As we mentioned before, this allows us to capture the fact that the volatility of economic growth could change according to the regime, as documented in French and Sichel (1993) and Warnock and Warnock (2000) for the US. In Table 4 we report the state dependent variance for each individual country.23 If we compare the recessionary regime with the ‘growth regime’, we can see that contrary to what has been found for the US (see French and Sichel, 1993; and Warnock and Warnock, 2000) we find that the business cycle is asymmetrical but with higher fluctuations in output during expansions (‘growth regime’) than in recessions. Only for the UK, the Netherlands, and Portugal do we find a higher volatility of output in recessions. For the other countries, the opposite holds. Moreover, if we compare the volatility of output in Regime 2 and 3, we can conclude that expansions after 1979 (Regime 2) are characterized by a reduced volatility of output. This coincides with the evidence documented for the US by Warnock and Warnock (2000) for employment and by McConnell and Perez-Quiros (2000) and Kim and Nelson (1999) for output growth. McConnell and Perez-Quiros (2000) and Kim and Nelson (1999) do not model the asymmetry in volatility reported in French and Sichel (1993), but document a structural change in the variance of output growth in the early eighties. Our model is rich enough to allow us to embed both empirical patterns reported above: the change in the volatility of output in the early eighties and the asymmetry in volatility in the business cycle phases. Regime 3 can only be observed until 1979, which might indicate a structural change in the phase structure of the business cycle. Expansions after 1979 (Regime 2) are characterized by a lower mean growth rate and lower variance relative to previous expansionary periods (Regime 3). So if we look at the post-80 period: we observe low growth and low volatility. We can thus report a structural break in the business cycle phase dynamics. This empirical finding is consistent with the results presented by Dickerson et al. (1998), who report a change in the amplitude of the cycle for the European countries in the early eighties (Dickerson et al., 1998, measure the amplitude as the mean absolute deviation from trend). The results suggested by our model can be summarized as follows: (i) during the seventies, business cycle dynamics in Europe were characterized by three phases: recessions (with low growth and low variance), ‘growth’ (with median growth and moderate variance), and ‘high growth’ (with high growth and high variance); (ii) from the early eighties, the third regime does not come up

23 The whole covariance matrices are available from the authors upon request.
anymore and business cycle dynamics are just characterized by two phases: recessions (with low growth and low variance) and ‘growth’ (with median growth and moderate variance).

In order to investigate the timing of the individual business cycle relative to the European business cycle, we analyze the synchronicity of the regime changes in each specific country with respect to the European business cycle. As a measure of the specific business cycle regime prevailing in each country, we use the smoothed probability of being in each regime obtained from the univariate models of Section 2 (we will denote by $S_{jt} = \Pr(I_t = 1 \mid Y_T)$, the smoothed probability of being in a recessionary state obtained from the univariate MS-AR fitted to each individual country in Section 2). A measure of the European business cycle is given by the smoothed probability of being in each regime obtained from the multivariate analysis (we will denote by $S_{rt} = \Pr(M = 1 \mid Y_T)$, the smoothed probability of being in a recessionary state obtained from the multivariate MS-VAR fitted previously, that is, the inference on the recessionary state of the European business cycle). As a measure of synchronicity, we have calculated the statistic suggested by Harding and Pagan (1999): the degree of concordance, defined as the fraction of time the reference cycle ($S_{rt}$) and the specific cycle ($S_{jt}$) are in the same state.  

Results in Table 5 indicate a high level of synchronicity of recessions and expansions between the country specific business cycle and the European business cycle, with the worst timing occurring in France, Spain, and Portugal.

3.2 Dating the European business cycle

Unlike the case of the US where a specific business cycle dating committee exists (the NBER Business Cycle Dating Committee), there is no such institution in Europe that offers guidance on the dates that recessions start and end. In the

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\[ DC_{jr} = T^{-1} \sum_{t=1}^{T} \{ I(S_{jt} = 1, S_{rt} = 1) + I(S_{jt} = 0, S_{rt} = 0) \} \]

or

\[ DC_{jr} = \frac{1}{n} \left[ \frac{1}{n} \left[ 2 \{ S_{jt} = 1, S_{rt} = 1 \} \right] + \frac{1}{n} \left[ 2 \{ S_{jt} = 0, S_{rt} = 0 \} \right] \right] \]

where the symbol $\{ S_{jt} = k, S_{rt} = k \}$ indicates the number of times in which both series, $j$ and $r$, are in the same state $k$. The above equation can also be written as

\[ DC_{jr} = \frac{1}{n} \left( \frac{T}{n} \sum_{t=1}^{T} S_{jt}S_{rt} + \frac{T}{n} \sum_{t=1}^{T} (1 - S_{jt})(1 - S_{rt}) \right) \]

where $j$ and $r$ are the indices for the different time series and $S_{jt}$ is the state of the time series $j$ at time $t$ ($S_{jt} = 1, 0$). The index should be between 1 and 0, where 1 indicates maximum concordance.
absence of a specific dating committee for Europe the model we propose in this paper could be used as an independent objective algorithm for generating such datings. Hamilton (1989) argues strongly in favour of this type of model as a reliable algorithm for the statistical identification of turning points. In Hamilton (1989), all the turning points estimated by the smoothed probabilities are within three months of those reported by the NBER, except for the 1957 and 1980 recessions that are dated two quarters in advance.

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 $\Pr(s_t = 1 \mid Y_T) \leq 0.5$. The latter procedure allows a corresponding dating of the European Business Cycle which is given in Table 6. The peak date denotes the period $t$ just before the beginning of a recession, i.e. $\Pr(s_t = 1 \mid Y_T) \leq 0.5$ and $\Pr(s_{t+1} = 1 \mid Y_T) > 0.5$; the trough is the last period of the recession.

<table>
<thead>
<tr>
<th>Table 5 Degree of concordance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
</tr>
<tr>
<td>$DC_{ij}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 6 Dating of the European business cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSVAR for IIP Growth*</td>
</tr>
<tr>
<td>Peak</td>
</tr>
<tr>
<td>1974M7</td>
</tr>
<tr>
<td>1979M10</td>
</tr>
<tr>
<td>1990M9</td>
</tr>
</tbody>
</table>

Note: *Based on monthly IIP data for Germany, UK, France, Italy, Austria, Spain, NL, Belgium, and Portugal. †Using quarterly GDP data for Germany, UK, France, Italy, Austria, and Spain: see Appendix 3. ‡Duration denotes the length of the recession in years.
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.

In Table 6 the results for IIP are compared to a dating based on movements in GDP growth, which is modelled in Appendix 3. An interesting fact that can be observed in Table 6 is that whereas the 1974/75 and 1979/82 recessions have similar durations both for IIP and GDP, the 1990/92 recession has a different duration depending on the measure of economic activity we consider. Whereas the recession in IIP lasted two years, that in GDP lasted a single year. This suggests that the recessions in GDP in the 90s have become shorter than those in IIP.\(^{25}\)

A further interesting fact can be spotted if we compare the troughs and peaks dating recorded in Table 6 with those reported by the NBER for the US economy\(^{26}\). The peaks are attained for the US economy well in advance of those in Europe. On the other hand the European troughs lag those reported for the US. An exception to this pattern is the 1980Q1-1982Q4 recession. Moreover, whereas for the early eighties the NBER reports a double dip recession, our model does not suggest for Europe a double dip pattern for the recession that took place in the early eighties, but just a single and long recession that lasted two years and three quarters.

\(^{25}\) Though it is somewhat risky to draw conclusions from the observation of a single recession, a similar feature has been documented for the US in McConnell and Perez-Quiros (2000). This stylized fact is related to the drop in GDP volatility that took place in the US in the mid-eighties and that has been reported in McConnell and Perez-Quiros (2000), Kim and Nelson (1999), and Warnock and Warnock (2000). Considering that recessions are defined as periods of absolute decline in economic activity, a reduction in output volatility implies that, keeping the product growth rate constant, we should observe fewer and shorter recessions, which is ultimately behind the longer business cycle expansions in the economy that we have recently observed in the US. Stock and Watson (2002) suggest that a potential explanation of this fact is the change in the structure of the economy. More specifically, they suggest a change in the sectorial composition of output away from durable goods. Since the services sector is less cyclically sensitive than the manufacturing sector, changes from manufacturing to services will contribute to diminish output volatility. Further research on this area for the European case is under way.

\(^{26}\) The dating for the business cycle in the US as reported by the NBER is as follows:

<table>
<thead>
<tr>
<th>Peak</th>
<th>Trough</th>
<th>Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>1973Q4</td>
<td>1975Q1</td>
<td>1.00</td>
</tr>
<tr>
<td>1980Q1</td>
<td>1980Q3</td>
<td>2.83</td>
</tr>
<tr>
<td>1981Q3</td>
<td>1982Q4</td>
<td>2.00</td>
</tr>
<tr>
<td>1990Q3</td>
<td>1991Q1</td>
<td>0.75</td>
</tr>
</tbody>
</table>

where duration denotes the length of the recession in years.
3.3 Contribution of the European business cycle to the country-specific cycles

The time series vector of the rate of growth of the nine countries under analysis can be decomposed into a non-Gaussian component and a Gaussian component. The first component would have a non-zero mean and would reflect the contribution of the European business cycle to the individual countries. The second term would have a zero mean and would pick up country specific shocks. Rewriting eq. 4 as

\[ A(L)\Delta y_t = v(s_t) + \Sigma^{1/2}(s_t)e_t, \]

where \( e_t|s_t \sim \text{NID}(0, \Sigma(s_t)) \) and \( A(L) = I - A_1L \) is the matrix polynomial in the lag operator \( L \), we get

\[ \Delta y_t = A(L)^{-1}v(s_t) + A(L)^{-1}\Sigma^{1/2}(s_t)e_t \] (5)

where the second term has expectation zero. In Equation 5, the two fundamental sources of randomness, \( s_t \) and \( e_t \), can have different implications for the future path followed by \( \Delta y_t \). \( s_t \) could be associated with the business cycle directly and \( e_t \) to other type of shocks contributing to changes in output. We will refer to the first term in eq. 5 as the contribution of the European business cycle to the individual countries (this is the non-Gaussian innovation, as the underlying source of randomness is exclusively the innovations coming from the unobserved component, \( s_t \), driving the common business cycle). We will refer to the second term as the Gaussian component. Note that whereas shocks from \( e_t \) are specific to each country, innovations coming from \( s_t \), are common to all of them. We could thus refer to \( A(L)^{-1}v(s_t) \) as the contribution of the European business cycle to the process of economic growth in each of the nine European countries. The term \( A(L)^{-1}v(s_t) \) can be seen as the time varying mean of the rate of growth, weighted by the corresponding probability of being in a given regime. This is depicted in Fig. 4. Figure 4 plots as a thick line the contribution of the European business cycle to each specific country (\( A(L)^{-1}v(s_t) \)) whereas the dashed line plots the rate of growth of the corresponding country (\( \Delta y_t \)). The contribution of the Markov chain to the mean of each individual country can be interpreted as follows. The contribution of the Markov chain (or thick line) can tell us how much of the behavior of the series is induced by a common component or European business cycle. The more closely the thick line (the contribution of the Markov chain to each individual’s country rate of growth) follows the dashed line (the rate of growth of industrial production of each individual country), the more the common component (or European business cycle) can explain the behavior of that country’s economic performance. An interesting finding that can be retrieved from Fig. 4 is that for all countries except the UK and Germany the contribution to the mean is higher for the period when the third regime is observed relative to the period when the second
Fig. 4. The contribution of the European business cycle
regime is observed. The third regime really picks up a catching up process taking place in the early 70s. The plot of these terms complements the information of the regime dependent means given in Table 4 and agrees with the previous discussion on the asymmetry observed in Regime 3. This plot together with the values recorded in Table 4, shed light on the different amplitude of booms and recessions across countries and gives information about the specific asymmetry of the business cycle in each European country. Figure 4 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.\textsuperscript{27}

In Section 2 we set up different univariate models for each of the countries under analysis. For each of these countries we could obtain the contribution of the business cycle to the fluctuation of economic activity. As this exercise only considers information corresponding to each specific economy under analysis, we could denote this term as the contribution to the economic fluctuation from the specific business cycle component. If we compare the contribution from the specific business cycle component with the contribution coming from the European business cycle component (the contribution extracted using the multivariate model) we can pick an important source of information on the specific and European business cycle contributions.\textsuperscript{28} This is plotted in Fig. 5, where the thin line corresponds to the contribution of the country specific business cycle and the thick line is the contribution of the European business cycle to the specific country. Interesting insights can be retrieved from this graph. We can see that for France, Italy and Belgium, the 1974Q1-1975Q2 recession was characterized by a deeper amplitude (deeper recession) and the country specific component dominated. A similar stylized fact arises in the 1992Q2-1993Q2 recession for France and Belgium. In terms of timing, the country specific component seems to lag the European component in the 1992Q2-1993Q2 recession in Germany, France, Belgium, and Austria. The information on the business cycle timing reported in Fig. 5 complements the information reported in Table 5 where the degree of concordance was recorded.\textsuperscript{29} A striking result is the behavior of the Netherlands and Portugal. Though in both countries, the recessions and expansions marked by the national business cycle seem to be followed closely by the European business cycle component, the volatility of the national business cycle component seems to

\textsuperscript{27} This seems also to be true of Italy and could probably be explained by the fact that both left the ERM in this year and benefited from the effects of a depreciation of their currencies.

\textsuperscript{28} We thank an anonymous referee for suggesting this idea.

\textsuperscript{29} The degree of concordance compares the individual dating of the business cycle with the dating corresponding to the European cycle whereas here we compare the contribution of the individual business cycle component with the contribution to each country of the European business cycle component.
Fig. 5. The contribution of the specific business cycle and the European business cycle
be much higher than that of the European component. In Table 7, we have reported the variance of each of these components for each country. The results in Table 7 show that the variance of the country specific component is much higher than that of the European component. From a policy-making perspective this suggests that there is a component of business cycle fluctuations than can be smoothed through common policies but there still remains a country specific component that needs country specific policies.

The duration of recessions reported in Table 4 differ from the results obtained for individual countries of Section 2. In Section 2, we recorded recessions of approximately two years for Spain and Portugal, whereas for Germany, UK, France, and Italy recessions have on average a duration of one year. For the Netherlands, Belgium, and Austria, we recorded very short recessions of over half a year. The results for each country obtained in Section 2 used only information corresponding to the individual country under analysis. In our multivariate analysis, the duration of regimes for the European business cycle uses information of all countries considered. These differences in duration are in agreement with the discussion above on the contribution of the individual and the European business cycle component to each country output fluctuation.

### 3.4 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 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

**Table 7 Variance of the individual business cycle component and the European business cycle component**

<table>
<thead>
<tr>
<th>Country</th>
<th>European</th>
<th>Country specific</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
<td>0.0431</td>
<td>0.0678</td>
</tr>
<tr>
<td>UK</td>
<td>0.0386</td>
<td>0.0462</td>
</tr>
<tr>
<td>France</td>
<td>0.0615</td>
<td>0.1032</td>
</tr>
<tr>
<td>Italy</td>
<td>0.0660</td>
<td>0.1768</td>
</tr>
<tr>
<td>NL</td>
<td>0.0656</td>
<td>0.1257</td>
</tr>
<tr>
<td>Belgium</td>
<td>0.0558</td>
<td>0.1378</td>
</tr>
<tr>
<td>Austria</td>
<td>0.0543</td>
<td>0.1050</td>
</tr>
<tr>
<td>Spain</td>
<td>0.0917</td>
<td>0.1133</td>
</tr>
<tr>
<td>Portugal</td>
<td>0.0649</td>
<td>0.1610</td>
</tr>
</tbody>
</table>
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 et al. (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 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, we suggest investigating the dynamics of some variables in the transition from boom to bust. Furthermore, this impulse response analysis is free from scaling criticisms. From eq. 5 we can see that the two fundamental sources of randomness, \( s_t \) and \( \varepsilon_t \), can have different implications for the future path followed by \( \Delta y_t \). We could associate \( s_t \) with the business cycle directly and \( \varepsilon_t \) to other factors contributing to changes in output. On the one hand, the permanent effect of the non-business component is given by

\[
\lim_{j \to \infty} \frac{\partial E_t(\Delta y_{t+j})}{\partial \varepsilon_t}
\]

where \( E_t(\Delta y_{t+j}) \) is the forecast of output growth at time \( t \), for the \( j \) periods ahead. On the other hand, if at a given date \( t \) the economy switches from a recession \( (s_t = 1) \) to a growth state \( (s_t = 2) \), the consequence for the long-run future level of output is given by

\[
\lim_{j \to \infty} \left[ E_t(\Delta y_{t+j}|s_t = 2) - E_t(\Delta y_{t+j}|s_t = 1) \right]
\]

where \( E_t(\Delta y_{t+j}|s_t = i) \) is the forecast of output growth at time \( t \), for \( j \) periods ahead given that we are in state \( i \). Hence, the effect on the rate of growth of each of the countries due to a change from Regime 2 \( (s_t = 2) \) to Regime 1 \( (s_t = 1) \), can be interpreted as the response of each individual country to a European recession.
Similarly we could measure the response of each country to an expansionary period induced by a change from Regime 2 (or state of normal growth) to Regime 3 (state of high growth regime).

In this section we follow this idea and analyze the response of industrial production in each country to a change in regime. We focus mainly on two types of shocks, the response of industrial production in individual countries to a European recession (shift from Regime 2 to Regime 1), and the effect of an expansionary period in Europe (measured as a shift from Regime 2 to Regime 3).

We can distinguish two groups of countries characterized by their dynamic response to a European recession. Facing a European recession (Fig. 6), there are countries like France, UK, Germany, the Netherlands, and Belgium which have a similar dynamic pattern, whereas Austria, 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 until approximately ten months later that 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. Hence, for the first group of countries (France, UK, Germany, the Netherlands, and Belgium) European induced recessions are deep and short, whereas for a second set of countries (Austria, Portugal, and Spain), recessions record smaller amplitude but tend to be more persistent.

On the other hand, the response of industrial production in individual countries to a European boom presents very interesting results. Figure 7 gives the impulse responses to a shift to Regime 3 from Regime 2. This would correspond to a shift from a ‘normal growth’ regime to a ‘high growth regime’. 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. A shift to a high growth regime increases the long-run level of output growth by 1% in countries like France, Spain, and Portugal. Smaller long run gains in output are recorded for the Netherlands, Belgium, and Austria, whereas for Germany, the UK, and Italy the gains are negligible. Given that Regime 3 is only observed till 1979, 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
Fig. 6. Effects of a European recession (shift from regime 2 to regime 1)
Fig. 7. Effects of a regime shift towards the high-growth regime
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 the IIP data.

In view of the criticisms that can be directed at 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.

Acknowledgements

We are grateful to David Cox, Natalia Fabra, Denise Osborn, Tommaso Proietti, and Paul Ruud for useful comments and discussions. Financial support from the Research Council of the European University Institute and from the TMR-NASEF project (administered through the CEPR) is gratefully acknowledged by the first and third authors. The research of the third author was also supported through a European Community Marie Curie Fellowship, contract HPMF-CT-2000-00761.

References


Appendix 1

Cointegration analysis
In order to investigate the cointegrating properties of our vector time series made up of the series of the index of industrial production of the nine countries under study, we depart from an intercept (I) Markov (M) switching (S) vector equilibrium correction (C) model. This is a Markov switching kth order vector autoregression with cointegration rank r and M regimes, $\text{MSCI}(M, r) - \text{VAR}(k)$. In this model both the drift term and the equilibrium mean of the cointegrating vectors are allowed to change. The analysis of this 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). 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 a vector process where $y_t$ is integrated of order one, such that $\Delta y_t$ is stationary. $y_t$ is said to be cointegrated if there is some vector $\beta$ such that $\beta' y_t$ is stationary. For a $p \times 1$ vector of variables we can find at most

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$^{30}$Krolzig (1996) discusses how the cointegration properties of the MS-VECM can be analyzed with a vector autoregression (VAR) of finite order.
\( p - 1 \) cointegrating relationships. We depart from a \( k \)th order VAR process with a Markov switching intercept and with \( y_t \sim I(1) \)

\[
y_t = \sum_{i=1}^{k} A_i y_{t-i} + \nu(s_t) + \varepsilon_t
\]

Then \( y_t \) admits a vector error correction representation

\[
\Delta y_t = \sum_{i=1}^{k-1} \Gamma_i y_{t-i} + \Pi y_{t-k} + \nu(s_t) + \varepsilon_t
\]

where \( \Gamma_i = -I - \sum_{j=1}^{i} A_j \) for \( i = 1, \ldots, k - 1 \) and \( \Pi = I_k - \sum_{i=1}^{k} \Gamma_i \). The rank of \( \Pi \) is called the cointegrating rank. If \( \Pi \) has rank \( r < p \), it then allows the following representation \( \Pi = \alpha \beta' \) where \( \alpha \) and \( \beta \) are \( p \times r \) full rank matrices. Table A1 shows the cointegrating results for a VAR(10), that could be seen as an approximation of the underlying MS-VAR process. The second column of Table A1 reports the maximum eigenvalue statistic \((-T \log(1-\mu_i))\), where \( \mu_i \) is the \( i \)th smallest eigenvalue of the eigenvalue problem that is solved in order to obtain the cointegrating relationships (see Johansen, 1995). The third column contains the same statistic with the small sample correction \((T - kp)\) suggested by Reinsel and Ahn (1992) and investigated by Reimers (1992), where \( k \) is the number of lags in the VAR model and \( p \) is the dimension of the multivariate model. The fourth column shows the 95% critical value. The next columns contain respectively the trace statistics \(-T \sum_{i=r+1}^{n} \log(1-\mu_i)\) (where \( r \) is the cointegrated rank tested), the same test with the small sample correction and the corresponding 95% critical value. On the one hand, the maximum eigenvalue statistic suggests the existence of a single cointegrating relationship, whereas the small sample corrected statistic suggests the absence of cointegration. On the other hand, the trace test seems to suggest four or five significant cointegrating relationships depending upon the level of significance chosen, but if we consider the small sample corrected statistic

<table>
<thead>
<tr>
<th>Maximal eigenvalue test</th>
<th></th>
<th>Trace test</th>
</tr>
</thead>
<tbody>
<tr>
<td>( H_0 : \text{rank} = r )</td>
<td>(-T \log(1-\mu))</td>
<td>(-T \sum \log(\cdot))</td>
</tr>
<tr>
<td>( T - nm )</td>
<td>95%</td>
<td>95%</td>
</tr>
<tr>
<td>( T - nm )</td>
<td>95%</td>
<td>95%</td>
</tr>
</tbody>
</table>

\begin{tabular}{cccccc}
  \( p = 0 \) & 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 \\
\end{tabular}

Notes: **Significant at 1% level, *significant at 5% level.
Fig. A1. Eigenvalues from a recursive cointegration analysis
we could reject the existence of cointegration. In Fig. A1 we have plotted the recursively estimated eigenvalues that are obtained from the eigenvalue problem that is solved when maximizing the likelihood function (see Johansen, 1995). These are plotted in decreasing order of magnitude. The stability of the cointegrated vectors is guaranteed by the constancy of the recursively calculated eigenvalues. 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 Fig. A1). Given that the approximation to the limit distribution is better with a correction for sample size (see Reimers, 1992), we can conclude that cointegration is absent from our VAR model.

The above analysis suggests the absence of any cointegrating relationship among the variables considered for the sample period under analysis. Some economic insight might help in interpreting this result. An important economic feature of our period of investigation has been the convergence of the European economies. We can say that two countries have converged if the difference between them is stable (that is, the difference between the series, call it $x_t$, is stationary). If the mean of $x_t$ is zero, the countries are in state of absolute convergence, whereas if the mean of $x_t$ is not zero, the countries have conditional or relative convergence. More formally, one can approach this issue by considering the following cointegrating VAR

$$
\Delta y_t = \tau + \alpha \beta' y_{t-1} + \varepsilon_t \tag{A1}
$$

We can separate the intercept term into the expectation of the growth rate and the equilibrium mean. In general, considering the drift and the equilibrium mean, the equation can be written as

$$
\Delta y_t - \gamma = \alpha (\beta' y_{t-1} - \mu) + \varepsilon_t
$$

where

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

and

$$
E[\Delta y_t] = \gamma
$$

Let us consider a bivariate model for the sake of simplicity. The long-run relationship between the output series of the two countries would be given by $\beta' y_{t-1}$. If we consider the relative output as the natural cointegrating relationship to investigate, then a structural break in the long-run relationship could have taken place because there has been a shift in the equilibrium mean ($\mu$) or a shift in the

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31 In a stationary series, one could also analyze the convergence of the dynamics of the cycle. Here, the interesting issue would be to look at the phase/coherence dynamics of the cycle and investigate whether the phase or the coherence of two stationary time series move closer during the sample period under analysis. Convergence of the cycle phase can be inferred from the statistical analysis conducted in Section 2. Artis et al. (1998), using spectral analysis, investigate whether the coherence at the business cycle frequencies have moved closer due to the European integration.
drift term ($\gamma$). In the first case, the gap in the relative output between two countries could have been reduced (or increased). In the second case, the relative output gap between two countries has remained stable (the equilibrium mean has not changed), though there has been a shift in the drift term, i.e. a change in the rate of growth. So we could have observed an structural break in the cointegrating relationship for two reasons: (i) there has been a transition to a convergence state (there has been a structural break in the equilibrium mean ($\mu$)); (ii) countries have remained in an state of relative convergence (the relative output of two countries have remained stable), but there has been a structural break in the drift term ($\gamma$).³⁴

³² Departing from,

$$\Delta y_t = \tau + \alpha \beta' y_{t-1} + \varepsilon_t$$

we want to decompose the intercept into the equilibrium mean and the drift term, such that $\tau$ can be written as

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

where

$$\gamma = \beta_L (\alpha_L' \beta_L)^{-1} \alpha_L' \tau$$

and

$$E(\Delta y_t) = \gamma$$

and

$$E[\beta' y_t] = \mu$$

We can thus rewrite the equation for $\Delta y_t$ as

$$\Delta y_t - \gamma = \alpha \beta' y_{t-1} - \alpha \mu + \varepsilon_t$$

For given initial conditions, it can be shown that

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

and

$$E(\Delta y_t) = \gamma = \beta_L (\alpha_L' \beta_L)^{-1} \alpha_L' \tau$$

Hence, in general, considering the drift and the equilibrium mean, eq. A1 can be written as

$$\Delta y_t - \gamma = \alpha (\beta' y_{t-1} - \mu) + \varepsilon_t$$

³³ If we were discussing convergence issues a natural cointegrating vector to consider would be $\beta' = (1 \quad -1)$.

³⁴ In the first case we can say that a cointegrating relationship existed between the output of two countries at some time $t_1$. At some later period $t > t_1$ there has been a shift in the equilibrium mean that has reduced the gap in their relative output. Such that for $t > t_1$, $\mu^* = \mu + \Delta \mu$. The convergence process induced a break in the equilibrium mean. In the second case we could say that at some time $t_1$, there existed a cointegrating relationship between a pair of countries which were growing at the same rate of growth. However for some $t > t_1$, a shift in the drift term took place as $\gamma^* = \gamma + \Delta \gamma$. This would have broken the previous long-run relationship.
Similar concepts are introduced in Harvey and Carvalho (2001), where the analysis is undertaken from an unobserved components time series approach. Harvey and Carvalho (2001) also show how the convergence concepts they introduce in the unobserved components framework can be parametrized in terms of a cointegrated VAR model. The resulting parametrization and convergence concepts follow closely the ideas introduced and discussed above.

In Europe, in the last 20 years, we are likely to have seen these two types of structural breaks in the output relationships among countries. In the early eighties some countries in Europe (Portugal and Spain) experienced rates of growth much higher than those of their European counterparts, showing a process of convergence. Moreover, the mean rate of growth declined in the early eighties for all countries. These two features are partly captured with the Markov switching model with three regimes discussed in Section 3.35

Appendix 2

Pearson’s contingency coefficient
The classification of regimes obtained from the smoothed probabilities consists of a binary time series for each country, denoting months during expansions by ones and contractions by zero. For a pair (country \(i\), country \(j\)) over the sample period, we obtain a \(2 \times 2\) contingency table recording expansion/contraction frequencies (see Table A2).

This table enable us to evaluate association between the business cycle phases defined by the smoothed probabilities. This association between the business cycle phases can be done using a conventional contingency table statistic, namely, Pearson’s contingency coefficient expressed as a percentage and corrected to lie in the range 0-100. Pearson’s contingency coefficient is defined as

\[
CC = \sqrt{\frac{\hat{\chi}^2}{N + \hat{\chi}^2}}
\]

Table A2 Contingency table

<table>
<thead>
<tr>
<th>Country (i)</th>
<th>Expansion</th>
<th>Recession</th>
<th>Subtotal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expansion</td>
<td>(n_{00})</td>
<td>(n_{01})</td>
<td>(n_0)</td>
</tr>
<tr>
<td>Recession</td>
<td>(n_{10})</td>
<td>(n_{11})</td>
<td>(n_1)</td>
</tr>
<tr>
<td>Subtotal</td>
<td>(n_0)</td>
<td>(n_1)</td>
<td>(N)</td>
</tr>
</tbody>
</table>

We acknowledge one referee for pointing out this fact.
where

$$\hat{\chi}^2 = \sum_{i=0}^{1} \sum_{j=0}^{1} \frac{(n_{ij} - (n_i n_j/N))^2}{(n_i n_j/N)}$$

Pearson’s contingency coefficient is related to a conventional correlation coefficient for continuous data. However, for a finite dimension contingency table it suffers from the disadvantage that the maximal attainable value is determined by the dimension of the table. For a $2 \times 2$ table, this maximal value is $\sqrt{0.5}$, and hence in order to obtain an statistic that lies between 0 and 100 we use the corrected contingency coefficient, $CC_{corr}$

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

The statistic $CC_{corr}$ now lies in the range 0–100. If the two binary series are independent and $n_{ij} = n_i n_j$ then $CC$ and $CC_{corr}$ both take value zero. With complete dependence, $n_{ij} = n_i n_j (i=0,1)$, $CC = \sqrt{0.5}$, and $CC_{corr} = 100$. In our case, independence indicates that there is no contemporaneous relationship between the business cycle regimes (expansions and contractions) for the two countries. At the other extreme, complete dependence implies that the two countries are in the same regime for every time period and hence have identical business cycle turning point dates.

**Appendix 3**

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. The quarterly series are taken from the OECD Quarterly National Accounts database. Due to data availability considerations, our analysis is restricted to a subset of six European countries: Germany, UK, France, Italy, Austria, and Spain.

The presence of unit roots is underpinned by the results of the augmented Dickey Fuller tests. Using four lags in the cointegration analysis, gives no clear indication of the presence of cointegrating vectors (see Table A3). Therefore we proceed as before, 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 1970:3–1995:4 are given in Table A4. Outliers in 1984 and 1987 have been removed by including impulse dummies (and their first lags).

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36 For a more detailed analysis on stylized facts in GDP data see Krolzig and Toro (2003).
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 A2 and A3 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 A3 Johansen cointegration likelihood ratio test

<table>
<thead>
<tr>
<th></th>
<th>Maximal eigenvalue test</th>
<th>Trace test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$-T \log(1-\mu)$</td>
<td>$T-nm$</td>
</tr>
<tr>
<td>$p = 0$</td>
<td>34.0</td>
<td>25.8</td>
</tr>
<tr>
<td>$p \leq 1$</td>
<td>27.6</td>
<td>21.0</td>
</tr>
<tr>
<td>$p \leq 2$</td>
<td>22.0</td>
<td>16.8</td>
</tr>
<tr>
<td>$p \leq 3$</td>
<td>10.8</td>
<td>8.2</td>
</tr>
<tr>
<td>$p \leq 4$</td>
<td>8.0</td>
<td>6.1</td>
</tr>
<tr>
<td>$p \leq 5$</td>
<td>0.6</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Notes:**significant at 1% level, *significant at 5% level.

### Table A4 Estimation Results: The MSIH(3)-VAR(1) Model of the European GDP Growth Rates

<table>
<thead>
<tr>
<th></th>
<th>Germany</th>
<th>UK</th>
<th>France</th>
<th>Italy</th>
<th>Austria</th>
<th>Spain</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Regime-dependent intercepts (10^{-2})</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regime 1</td>
<td>$-0.448$</td>
<td>$-0.033$</td>
<td>0.078</td>
<td>$-0.261$</td>
<td>$-0.194$</td>
<td>$-0.086$</td>
</tr>
<tr>
<td>Regime 2</td>
<td>0.884</td>
<td>0.463</td>
<td>0.332</td>
<td>0.436</td>
<td>0.843</td>
<td>0.117</td>
</tr>
<tr>
<td>Regime 3</td>
<td>0.921</td>
<td>0.109</td>
<td>0.694</td>
<td>0.991</td>
<td>1.667</td>
<td>0.351</td>
</tr>
<tr>
<td><strong>Autoregressive parameters at lag 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Germany</td>
<td>$-0.268$</td>
<td>$-0.272$</td>
<td>0.021</td>
<td>$-0.038$</td>
<td>$-0.189$</td>
<td>$-0.025$</td>
</tr>
<tr>
<td>UK</td>
<td>0.082</td>
<td>0.108</td>
<td>0.152</td>
<td>0.124</td>
<td>$-0.034$</td>
<td>0.021</td>
</tr>
<tr>
<td>France</td>
<td>$-0.141$</td>
<td>0.017</td>
<td>$-0.106$</td>
<td>$-0.054$</td>
<td>0.132</td>
<td>0.040</td>
</tr>
<tr>
<td>Italy</td>
<td>0.237</td>
<td>0.217</td>
<td>0.106</td>
<td>0.181</td>
<td>0.093</td>
<td>$-0.018$</td>
</tr>
<tr>
<td>Austria</td>
<td>0.101</td>
<td>0.244</td>
<td>0.067</td>
<td>0.119</td>
<td>$-0.456$</td>
<td>0.017</td>
</tr>
<tr>
<td>Spain</td>
<td>$-0.069$</td>
<td>0.061</td>
<td>0.159</td>
<td>$-0.032$</td>
<td>0.227</td>
<td>0.760</td>
</tr>
<tr>
<td><strong>Dummies (10-2)</strong></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D87q1</td>
<td>$-3.409$</td>
<td>0.051</td>
<td>$-1.000$</td>
<td>$-0.395$</td>
<td>$-1.802$</td>
<td>0.485</td>
</tr>
<tr>
<td>D87q2</td>
<td>1.000</td>
<td>0.033</td>
<td>0.522</td>
<td>1.250</td>
<td>$-0.251$</td>
<td>0.290</td>
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<tr>
<td>D84q2</td>
<td>$-2.257$</td>
<td>$-0.935$</td>
<td>$-1.512$</td>
<td>$-0.465$</td>
<td>$-1.823$</td>
<td>0.239</td>
</tr>
<tr>
<td>D84q3</td>
<td>1.210</td>
<td>$-0.669$</td>
<td>0.123</td>
<td>$-0.404$</td>
<td>$-0.661$</td>
<td>0.260</td>
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<tr>
<td>log-likelihood</td>
<td>2311.37</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>$-42.44$</td>
<td>$(-41.96)$</td>
<td>$-40.91$</td>
<td>$(-41.06)$</td>
<td>$-38.66$</td>
<td>$(-39.73)$</td>
</tr>
<tr>
<td>HQ</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>SC</td>
<td></td>
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</tr>
</tbody>
</table>

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 A2 and A3 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.
Fig. A2. The contribution of the European business cycle to the country-specific GDP growth rates
Regime 1

Regime 2

Regime 3

Fig. A3. Regime-probabilities for the GDP–based European business cycle.