European Business Cycles: New Indices and Analysis of their Synchronicity

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Abstract

This article presents a new type of business-cycle index that allows for cycle-to-cycle comparisons of the depth of recessions within a country, cross-country comparisons of business-cycle correlation and simple aggregation to arrive at a measure of a European business cycle. The paper examines probit-type specifications of binary recession/expansion variables in a Gibbs-sampling framework, wherein it is possible to incorporate time-series features to the model, such as serial correlation, heteroscedasticity and regime switching. The data-augmentation implied by Gibbs sampling generates posterior distributions for a latent coincident business-cycle index and extracts information from indicator variables, such as the slope of the yield curve. Sub-sample correlations between an aggregated "Europe" index and the national business-cycle indices from France, Germany, Italy are consistent with the claim that the European economies are becoming more harmonized over time, but there is no guarantee that this pattern will hold in the future. JEL classifications: **F42, C25, C22**

Key words: **Recessions, Gibbs sampler, cyclical indicators**

1. Introduction

In the run-up to the European Monetary Union (EMU), the eleven initial participating countries were judged to have achieved a sufficient degree of economic convergence to share a common currency and monetary policy decisionmaking. Notably absent, however, from the convergence criteria for the EMU is a test for synchronous business cycles. Instead, the criteria focus on fiscal and inflation attributes, perhaps because their measurement is more straightforward. Yet, the possibility of asynchronous business cycles likely poses challenges for the common currency area of the European Central Bank. Hallett and Piscitelli (1998) reach this conclusion based on simulations of a multi-country econometric model. Our article introduces a new method of calculating business-cycle indices that is well-suited to cross-country comparisons of business-cycle correlation. These indices are readily aggregated to arrive at a measure of a European business cycle. We also analyze whether intra-EMU business cycles appear more closely correlated with each other than with significant outside countries such as the United Kingdom and the United States.

We first discuss previous business-cycle indices and how our new measure differs. Nearly all existing indices show upward trends, e.g., the U.S. Commerce Department's indices of leading and coincident indicators and Stock and Watson's (1989, 1992) experimental leading index. The presence of a trend makes less than transparent the business-cycle component, comparisons of the business-cycle depth across time and business-cycle correlations across countries. Kim and Nelson (1998) add nonlinear regime switching to the drift coefficient in the construction of a Stock and Watson (1989) common component coincident index, and they find that the estimated regime probabilities closely match the recession dates defined by the National Bureau of Economic Research (NBER). While the Kim and Nelson

(1998) regimes help confirm the relevance of the NBER recession dates, their coincident index also trends upward and the regime switching provides "on/off" inferences regarding recessions, and does not directly provide information on the relative depths of recessions or their correlations across countries.

In effect, Kim and Nelson's (1998) regime-switching results bolster the approach of explaining or predicting recessions through probit analysis of recession dates, as in Estrella and Mishkin (1997, 1998), Bernard and Gerlach (1996) and others. The problem is that simple probit models are not well-suited to time series data consisting of dependent observations that are serially correlated and heteroscedastic. Estrella and Rodrigues (1998) deal with serial dependence by proposing autocorrelation-consistent standard errors to fit the probit case. But the coefficient estimates from simple probits still lack efficiency, even if the robust standard errors are valid. Because not much data are available for binary recession variables, we must strive to use the most efficient estimator. Therefore we aim for an estimator that directly incorporates time-series features into a probit model. Moreover, as discussed below, our time-series probit model generates a stationary business-cycle index through the data augmentation of the Gibbs sampler [Gelfand and Smith (1990)].

The business-cycle index that we propose based on time-series probit analysis of recession dates has several desirable properties. First, the prevalent use of the probit as a model of recession variables suggests that the latent variable in the probit, if it were recovered, would make an interesting business-cycle index. Second, unlike the coincident indices discussed above, our business-cycle index is stationary in that it does not have an upward trend. Thus, we do not have to extract the business-cycle component from a trending index variable. Third, within the probit framework, it is straightforward to evaluate candidate financial and macroeconomic indicators of the business cycle, as has been done previously using simple probits [e.g., Estrella and Mishkin (1998)]. Moreover, our time-series probit puts cyclical indicator variables to a stiffer test than does an ordinary probit. The only source of dynamics in the simple probit is the serial correlation in the explanatory variables, so any variable that displays generally appropriate swings can easily improve the fit relative to a constant-probability model. Our time-series probit contains built-in sources of dynamic behavior, so a financial indicator variable must do more to be significant than improve on the fit of a constant-probability model. Fourth, the autoregressive nature of the time-series probit business-cycle index means that many lags of the explanatory variables (with exponentially declining weights) influence the index variable. Fifth, the estimated business-cycle indices are comparable across countries and can readily be aggregated to form a European business-cycle index. We can then analyze the extent to which each country's business cycle now appears correlated with the European index.

2. Simple probit models

In a probit model, a continuous latent variable, y^*, determines the binary recession/expansion indicator variable, $y \in \{0,1\}$:

$$\begin{aligned} y = 0 \quad \text{iff} \qquad & y^* < 0 \\ y = 1 \quad \text{iff} \qquad & y^* \geq 0 \end{aligned} \tag{1}$$

A set of lagged explanatory variables, X_{t-1}, and a random disturbance determine the latent variable in the ordinary probit:

$$\begin{aligned} y_t^* &= X_{t-1}'\beta + \epsilon_t \qquad (2) \\ \epsilon_t &\sim N(0,1) \end{aligned}$$

The likelihood function for the observed y is then

$$l_t = \Phi(X_{t-1}'\beta)^{(1-y_t)} \times (1 - \Phi(X_{t-1}'\beta))^{y_t},$$

where $\Phi(.)$ is the normal cumulative density function. Most applications of probit models assume that the observations are independent, even for time-series data. Previous work that addressed serial correlation in probit models discussed inserting the expected value of the disturbance (ϵ) into first-order conditions for modified Generalized Least Square formulae for β [Poirier and Ruud (1988)]. Rather than take this rather uninformative approach, however, the Gibbs sampler allows us to study any aspect of the posterior density of the latent variable. The next section discusses data augmentation and the Gibbs sampler.

3. Data augmentation for time-series probits

A basic time-series probit model includes at least one autoregressive term on the right-hand side of the equation for the latent variable:

$$y_t^* = \rho y_{t-1}^* + X_{t-1}'\beta + \epsilon_t \tag{3}$$

The dynamic probit model of Eichengreen, Watson and Grossman (1985) serves as a time-series probit, because it allows for serial correlation. The maximum-likelihood estimation procedure of Eichengreen et al. (1985) requires numerical evaluation of an integral for each observation in order to obtain the density, h, of y_t^*, where ϕ is the standard normal density and I_t is the information available up to time t:

$$h(y_t^* \mid I_t) = 1/\sigma_\epsilon \int_{l_{t-1}}^{U_{t-1}} \phi(y_t^*/\sigma_\epsilon) h(y_{t-1}^* \mid I_t) dy_{t-1}^*, \tag{4}$$

where $\{l_t, U_t\} = \{-\infty, 0\}$ if $y_t = 0$, or else they equal $\{0, \infty\}$ if $y_t = 1$. Because numerical evaluation of these integrals is time-consuming and approximate, it is not tractable under direct maximum-likelihood estimation to extend the model to include additional features, such as regime-switching parameters.

In cases like the dynamic probit, where the joint density of y_t^* and y_{t-1}^* is difficult to evaluate, data augmentation via Gibbs sampling offers a tractable method to generate a sample of draws from a joint distribution through a sequence of draws from the respective conditional distributions. Data augmentation in the present context allows one to treat augmented values of $y_s^*, s \neq t$, as observed data when evaluating the conditional density of y_t^*. Thus, one conditions the density of y_t^* on a *value*, instead of a *density*, of y_{t-1}^*, making the problem much simpler than recursive evaluation of the integral in equation (4). Furthermore, once the latent variable has been augmented, it becomes straightforward to model any regime switching, such as conditional heteroscedasticity.

Because the serial dependence in y^* is likely to be strong, we re-write equation (3) as

$$\Delta y_t^* = (\rho - 1)y_{t-1}^* + X_{t-1}'\beta + \epsilon_t \tag{5}$$

As discussed below, we need sampling distributions for $(\beta, \rho - 1)$, and it is easier to work with normal distributions than with a near-unit root distribution that might pertain if ρ were close to one and we were to use equation (3), instead of equation (5), as the basis for regressions. Also, most of the explanatory variables must be differenced to render them stationary, so they are better suited to explaining incremental changes in the business-cycle index than in explaining its absolute level, which is another reason to employ equation (5).

We include two forms of regime switching in the latent variable from the time-series probit. First, the model allows for heteroscedasticity by way of Markov-switching variances. The binary variable that governs the variance switching is $S1$:

$$\sigma_{S1_t}^2 \in \{\sigma_0^2, \sigma_1^2\}.$$

Second, the model includes Markov switching in the intercept, β_0, which functions much like a drift term because ρ is not far from one. The binary variable that governs drift switching is $S2$:

$$\Delta y_t^* \quad = \quad (\rho - 1)y_{t-1}^* + \beta_0(S2_t) + X_{t-1}'\beta + \sigma_{S1_t} e_t \tag{6}$$

$$\begin{aligned} \beta_0(S2_t) &\in \{\beta_{0l}, \beta_{0h}\} \\ e_t &\sim N(0,1) \\ \epsilon_t &= \sigma_{S1_t} e_t \end{aligned} \tag{7}$$

The transition probabilities for the state variables, $S1$ and $S2$, are:

$$\begin{aligned} \text{Prob}(S1_t = 0 \mid S1_{t-1} = 0) &= p_1 \\ \text{Prob}(S1_t = 1 \mid S1_{t-1} = 1) &= q_1 \\ \text{Prob}(S2_t = 0 \mid S2_{t-1} = 0) &= p_2 \\ \text{Prob}(S2_t = 1 \mid S2_{t-1} = 1) &= q_2 \end{aligned} \tag{8}$$

The Gibbs sampler and conditional distributions

The Gibbs sampler is an attractive estimation procedure for the time-series probit, because the conditional distribution of the latent variable is easy to derive, given the other parameters and state variables $(\beta, \rho, S1, S2, p_j, q_j), j = 1, 2$, and the conditional distributions of the state variables are simple, given values for the latent variable and parameters. The key idea behind Gibbs sampling is that after a sufficient number of iterations, the draws from the respective conditional distributions jointly represent a draw from the joint posterior distribution, which often cannot be evaluated directly [Gelfand and Smith (1990)].

Gibbs sampling consists of iterating through cycles of draws of parameter values from conditional distributions as follows:

$$f(\varrho_1^{(i+1)} \mid \varrho_2^{(i)}, \varrho_3^{(i)}, \varrho_4^{(i)}, Y_T) \tag{9}$$

$$\begin{aligned} &f(\varrho_2^{(i+1)} \mid \varrho_1^{(i+1)}, \varrho_3^{(i)}, \varrho_4^{(i)}, Y_T) \\ &f(\varrho_3^{(i+1)} \mid \varrho_1^{(i+1)}, \varrho_2^{(i+1)}, \varrho_4^{(i)}, Y_Y) \\ &f(\varrho_4^{(i+1)} \mid \varrho_1^{(i+1)}, \varrho_2^{(i+1)}, \varrho_3^{(i+1)}, Y_T) \end{aligned} \tag{10}$$

where Y_T stands for the entire history of the data and superscript i indicates run number i through the Gibbs sampler. At each step, a value of ϱ is drawn from its conditional distribution. As discussed in the appendix and in Albert and Chib (1993), all of the necessary conditional distributions can be standard statistical distributions, given appropriate choices for prior distributions. Prior and posterior conditional distributions for $\varrho_j, j = 1, .., 4$ are in the appendix. The Gibbs sampler was run for a total of 8000 iterations in each estimation. The first 3000 iterations were discarded to allow the sampler to converge to the posterior distribution. For this application, parameters and latent data are sampled in the following groups:

$$\begin{aligned}
\varrho_1 &= \{y_t^*\}, t = 1, ..., T \qquad \text{latent variable} \\
\varrho_2 &= (\{S1_t\}, \{S2_t\}), t = 1, .., T \qquad \text{states} \\
\varrho_3 &= (\beta, \rho) \qquad \text{regression coefficients} \\
\varrho_4 &= (p_j, q_j), j = 1, 2 \qquad \text{transition probs.}
\end{aligned}$$

4. Data related to European business cycles

We estimate our new business-cycle index for the three largest countries participating in the EMU – Germany, France and Italy. Additionally, we investigate the United Kingdom, a European country which does not take part in EMU, and a non-European country, the United States. Data are monthly and range from January 1968 to April 1998 for the U.S. and from January 1973 to April 1998 for France, Germany, and the United Kingdom. For Italy the data end in December 1997.

The dependent variable is a 0/1 series to identify recessions and expansions, using NBER dates for the U.S. business cycle and Economic Cycle Research Institute (ECRI) dates for the business cycle in the European countries.[1] Of course, the reliability of the results hinges on the quality of the recession dates used. While the NBER dates are widely employed in the literature, it is much more difficult to obtain universally accepted dates for the turning points of the business cycle in European countries (see e.g., Bernard and Gerlach, 1996). As we want to compare our results across different countries, we chose the dates from the ECRI, because they come from a common methodology for all countries, one that is comparable to the NBER methodology.

The explanatory variables are the slope of the yield curve, a central bank interest rate, real money, unemployment, and industrial production.[2] In a number of studies the slope of the yield curve turned out to be a powerful predictor of economic activity [Bernard and Gerlach (1996), Estrella and Mishkin (1997, 1998), and others]. We therefore included the difference between the interest rate on 10-year government bonds and the 3-month treasury bill rate. In addition, we used short-term interest rates thought to be administered by the central bank and real money growth as explanatory variables. We use the repurchase rates from Germany and France as the central-bank rates. For the U.S. and the U.K, overnight interbank rates are used, with the federal funds rate as the U.S. rate. For Italy, we use the money market rate, because some data for the repo rate were missing. Also the choice of the monetary aggregate was dictated by data availability. For the U.S. and Germany we use broad money, while for the other countries only a narrow definition of money was available. Money is deflated with the consumer price index because it is known that real money growth is a useful element of the U.S. Commerce Department's Index of Leading Indicators. Finally, we included industrial production growth and changes in the unemployment rate as macroeconomic variables that indicate the state of the economy. For the

[1] The data were obtained at http://www.businesscycle.com/products/table2.html.

[2] We thank Arturo Estrella and Frederic Mishkin for providing their data set with monthly data covering the years 1973 to 1994 and the Deutsche Bundesbank for providing us with a break-adjusted series for M3. Details on the data and the sources can be found in the appendix.

U.S. case, the unemployment rate appears stationary, but did not prove to have significant explanatory power and was omitted. Since we are concerned with finding consistent indicators of the business cycle across time, we decided to focus on West Germany only, leaving aside East Germany's structural transformation from a planned to a market economy. For Germany, therefore, prices and unemployment refer to West Germany only, while money and industrial production are for unified Germany but have been linked to the series for western Germany.

The explanatory variables, X_{t-1}, are all lagged one period to avoid simultaneous determination of the explanatory variables and the dependent variable. Except for the slope of the yield curve, all variables are in logarithmic changes. For real money, industrial production and the central-bank rate the change between the previous month and the month before is included in the estimation. For unemployment the change in the previous quarter is used since month-to-month changes are often zero. From the indicator variables, we would expect negative coefficients on the central-bank interest rate changes and the unemployment rate changes, because these would suggest either coming weakness or recent weakness in the economy. For the slope of the yield curve, industrial production growth and real money growth, a positive coefficient is expected, meaning that high values of these variables suggest cyclical strength in the economy.

5. Posteriors for European business cycles and their indicators

The posterior means for the regression coefficients, together with their empirical 95% confidence intervals from the Gibbs sampling procedure, are shown in Table 1. Variances are set to 0.05 for the low and 0.25 for the high-variance state. These variance levels are arbitrary, just as the normalization of unit variance is arbitrary in the ordinary probit model. We could double both variances and not change the results, other than the scale of the regression coefficients.

For all countries except for Italy, the yield curve has a significant, positive coefficient, though only marginally so for the United Kingdom. This implies that an inverted yield curve indicates that a recession is more likely and confirms the findings in the literature on the yield curve as a business-cycle predictor [Bernard and Gerlach (1996), Estrella and Mishkin (1997, 1998), Dueker (1997)]. Increases in the central-bank rates are a negative indicator for the business cycle in Germany, the U.K., and Italy. For France and the U.S., the coefficients on central-bank interest rate changes are insignificant. The coefficient on the central-bank rate is by far the largest for Germany, so the cyclical indicator property of monetary-policy actions is strongest in Germany. Real money growth has the expected positive sign for all countries except for Italy, but it is significant only in the U.S. and France. Though one would expect that industrial production would be a good indicator of the state of the economy, it is significant only for Italy. This variable might contain information that is already captured by other variables. Unemployment changes are almost always insignificant. The reason may be that unemployment in general is found to be a lagging indicator (Fiorito and Kollintzas, 1994) and therefore is not of much use in predicting recessions.

The lower part of Table 1 shows the other parameters of the model. The switching constants are significantly different from each other, indicating that switching between upward and downward regimes is important, but the regimes are not persistent. The sum of the transition probabilities ($p_2 + q_2$) barely exceeds one, which suggests independent state switching. The autoregressive coefficients, ρ, range from 0.91 to 0.96 across countries, implying significant persistence in the business cycle. This persistence confirms our expectation that the switching constants would act much like drift terms. The transition probabilities (p_1, q_1) also sum to about one, so the variance state switching does not uncover evidence of persistent periods of high or low variance. The high-variance periods occur randomly across time.

The posterior inferences for the latent variable determine the level of the business-cycle index. We take the posterior means of the 5000 Gibbs-sampling draws of the latent variable as the business-cycle index. The index value at time t is

$$1/5000 \sum_{i=1}^{5000} y_t^{*(i)},$$

where i is run number i through the Gibbs sampler. Figures 1 to 5 show the latent business-cycle index for France, Germany, Italy, the United Kingdom and the United States. Shaded areas indicate recessionary periods. By the construction of the model, the latent variable crosses zero at business-cycle turning points. The distance from zero at all other times provides information regarding the relative strength of an expansion or severity of recession.

At the beginning of the sample period, the oil crises affected all countries with relatively severe recessions. Figure 5 for the United States illustrates the stop/go nature of the business-cycle in the 1970s, where the economy shot up to unsustainable peaks before succumbing to recession. The U.S. index also shows why some observers claim that the U.S. economy had only one long recession in the early 1980s, rather than two distinct ones: the economy never reached a true recovery stage between the two recessions. All countries experienced recessions in the early 1980s and the early 1990s, but the turning points differ by several years. In the early 1980s and 1990s, the U.S. and the U.K. were the first countries to experience recession, as the other European countries followed later.

Looking only at the EMU members, the business cycles are much more correlated. The largest divergence occurs with the French "Mitterand experiment" in 1982-83, which delayed the consequences of the second oil shock and led at the time to different business-cycle behavior in France. The recession that followed German Unification in the early 1990s did not induce idiosyncratic business-cycle behavior in Germany; instead, the shock was transmitted by the fixed exchange rate system into the other European countries. These observations are reflected in the correlation coefficients in Table 2. The correlation between Germany and Italy is especially high, whereas the correlation between Germany and France is markedly lower. In accordance with the literature (Artis and Zhang, 1997, Forni and Reichlin, 1997), we find that ERM members share closely affiliated business cycles with Germany, whereas the business cycle in the U.K. is more closely connected with the business cycle in the U.S. than with the other European countries.

Granger causality tests

To investigate the cross-country business-cycle dynamics in more detail, we performed bilateral Granger causality tests. That is, we test whether lagged values of the business-cycle index for one country contain significant information for the business cycle of the other country. The tests were performed with six different lag lengths. Too few lags may lead to the problem that not all relevant past information is considered. Too many lags result in too many insignificant coefficients and an associated loss of efficiency. We tried lag lengths of 6, 12, 18, 24, 30 and 36 months. In most cases, the results are independent of the lag length chosen. The results differ with respect to the lag length only for the U.S. versus the U.K. in both directions and for the test of whether the U.K. causes Italy. We always obtain uni-directional causality among the significant relationships. Germany causes the European countries' business cycles, but not the business cycle in the United States. The U.S. has only slight influence on Europe. To save space, we only report the significance levels for the tests with 18 lags in Table 3. The figure below Table 3 illustrates the causal directions, where we emphasize that the U.S. causality to France is marginal.

Construction of a European index

These national business-cycle indices are readily aggregated across countries to create a cyclical indicator for Europe or the EMU. This European index can also be used to investigate the harmonization of the European business cycles. The European index is constructed as a GDP-weighted average of the national indices, which are first scaled by their respective sample standard deviations. The aggregate index, Europe 3 or EU3, consists of Germany, France, and Italy.[3] Figure 6 shows the European business-cycle index. One use of an index like EU3 would be to define "European" recessions to be those periods in which EU3 lies below zero. We can also look at the correlations between the national business-cycle indices and EU3, assuming that the European Central Bank will generally set monetary policy according to EMU-wide business-cycle conditions implied by EU3. Low degrees of correlation might suggest that a national economy would not be well served if monetary policy were set according to EU3. If an EMU country's business cycle diverges significantly from the EU3 average, the European Central Bank is likely to face contentious policy decisions.

Table 4 shows the correlation between the European and the national indices. The first column gives the correlation over the whole sample period. Germany and Italy are highly correlated with the European index, while the correlation of France with the European index is lower. To look at how the correlation evolves over time, we split the sample into different subperiods. The first subperiod ranges from the start of the sample to the foundation of the European Monetary System (EMS) in March 1979, and the last runs from

[3]With GDP weights, the average weight over the sample period for the three largest countries in the EMU is 33% for France, 38% for Germany, and 29% for Italy.

the EMS crisis in September 1992 to the end of our sample. The time between these two events is split into a turbulent phase (see Gros and Thygesen, 1998) from March 1979 to March 1983, a calmer intermediate phase from March 1983 to January 1987, and the phase of the "hard" EMS where no realignment took place from January 1987 to September 1992.

The correlation rises over time for the EMU members, reflecting increased policy coordination and economic integration in Europe. This result generally matches Lumsdaine and Prasad (1998), who find that the business cycle in the European countries has a common component, especially in the post-Bretton Woods period. They conclude that there is a distinct European business cycle.

The effects of the French "Mitterrand experiment" are mirrored in the lower correlation in the second subperiod, whereas German Unification did not lead to economic divergence. These findings indicate that the inception of EMU is not likely to exacerbate cyclical problems to an extent greater than German Unification already did. Like Guha and Banerji (1998), who use employment time series, we find that Italy is consistently correlated with the European cycle. Unlike the employment data, however, our indices do not find that the correlation of Germany and France is weak. While the correlation of the United Kingdom with the European index is relatively high in the last two subperiods, it is somewhat negative during the 1980s. The United States, in contrast, shows a higher correlation with the European average in the 1980s, but the correlation is negative in the 1990s.[4]

6. Conclusions

This article presents a new type of business-cycle index that allows for cycle-to-cycle

[4]When interpreting the numbers in Table 4, one has to keep in mind that the European index is constructed from the French, German and Italian indices. The correlations for these three countries therefore cannot be compared directly to the correlations of the United Kingdom or the United States.

comparisons of the depth of recessions within a country, cross-country comparisons of business-cycle correlation and simple aggregation to arrive at a measure of a "European" business cycle. Data augmentation via the Gibbs sampler allows us to derive posterior inferences of the latent variable behind a probit model of a recession dummy variable. This latent variable, which by definition is positive in expansions and negative in recessions, serves as our business-cycle index.

Our time-series probit model includes features to address time-series properties of business cycles, such as serial correlation, regime switching and heteroscedastic shocks. In the framework of this time-series probit model, the explanatory variables do not have to provide all of the business-cycle dynamics. Much previous work has demonstrated in simple probit models that readily-available financial indicators are good predictors of recessions. The slope of the yield curve has received particular notice in this regard. Our re-examination of indicator variables takes place in a context where explanatory variables must supplement the fit provided by lagged dependent variables, as opposed to serve as the only source of fit. We find that the slope of the yield curve contributes significant explanatory power to that provided by the lagged dependent variable for all countries but Italy.

Inspection of the business-cycle indices for five countries over the post-Bretton Woods period shows that the business cycles are closely correlated among France, Germany and Italy, and much less so among the United Kingdom and the United States. Granger causality tests among the national indices suggest business-cycle causality running from Germany to the other three European countries, but not to the United States. In addition, we aggregated the business-cycle indices from the three EMU countries and examined the correlations between the indices from the individual EMU countries and the "Europe" index across sub-sample periods. The sub-sample correlations are consistent with the claim that the European economies are becoming more harmonized over time, but there is no guarantee that this pattern will hold in the future. At present, however, our results give little reason to argue that the European Central Bank will face completely disparate cyclical exigencies from the member countries. It is possible that past coordinated, but individually tailored, fiscal and monetary policies worked to absorb shocks in the past. If looser policy coordination was better able to dampen economic shocks, then the common monetary policy – in combination with the Growth and Stability pact – could lead to more divergence among national business cycles in Europe in the future [Schuberth and Wehinger (1998)].

Appendix A1: Data

The slope of the yield curve is defined as the difference between the interest rate on 10-year government bonds and the 3-month treasury bill rate. Interest rates are from the International Financial Statistics (IFS) of the International Monetary Fund and from the Main Economic Indicators (MEI) of the OECD for the European countries, and from the Federal Reserve Bulletin for the United States. For Italy, missing data for the treasury bill rate were supplemented with information from the Annual Reports of the Banca d'Italia.

For Germany and France the repo rate is obtained from the respective central-bank reports. For Germany, the repo rate had to be supplemented by the lombard rate before July 1983 as the Bundesbank did not use repos until then. The federal funds rate for the U.S. and the overnight interbank rate for the U.K. are from the IFS. For Italy, the money market rate from the IFS is used instead of the central-bank rate because of missing values for the repo rate.

The monetary aggregate is currency in circulation for Italy, M0 for the U.K., M1 for France, M2 for the U.S., and M3 for Germany. Data for Italy, the U.K. and the U.S. are from the respective central-bank reports. M1 in France is from the IFS (national definition) and adjusted for a break due to a change in definition in 1978. M3 for Germany is from the Deutsche Bundesbank and is adjusted for the break in the time series due to German Reunification. Money is deflated with the consumer price index (CPI). For Germany, the CPI refers to West Germany only and is from the Monthly Reports of the Deutsche Bundesbank. The CPI data for the other countries are from MEI of the OECD.

The unemployment data for Germany relate to West Germany only and are from the Monthly Reports of the Deutsche Bundesbank. No monthly unemployment data were available for Italy and France. For the other countries, the unemployment rate of the OECD is used.

Industrial production data are from the OECD. Industrial production for Germany is for unified Germany, but it has been linked to the series for western Germany (OECD, 1997).

Appendix A2: Gibbs sampling distributions

Several of the parameters regarding the Markov switching were drawn in accordance with the procedures from Dueker (1998). In all cases the Markov state variables, $S1$ and $S2$, were treated symmetrically, so in the following description we drop references to a particular state variable.

Priors and posteriors for transition probabilities

The likelihood function for a discrete binary random variable that is governed by a first-order Markov process is

$$L(p,q) = p^{n_{00}}(1-p)^{n_{01}} q^{n_{11}} (1-q)^{n_{10}} \tag{11}$$

where n_{ij} is the number of transitions between $S_{t-1} = i$ and $S_t = j$.

The prior is to assign parameters u_{ij}, where the ratio between u_{00} and u_{01}, for example, represents a prior guess for the ratio between the corresponding numbers of actual transitions, n_{00}/n_{01}. The magnitudes of the u_{ij} relative to the sample size indicate the strength of the prior. As a weak prior, we set $u_{00} = 4, u_{01} = 1, u_{10} = 1$, and $u_{11} = 4$, such that the sum of the u_{ij} is low relative to the sample size.

The beta distribution is conjugate to itself, so the posterior is also beta and is the product of the prior and the likelihood of the observed transitions, so that we may draw transition probabilities from

$$p \mid \tilde{S}_T \sim \text{beta}(u_{00} + n_{00}, u_{01} + n_{01}) \tag{12}$$

$$q \mid \tilde{S}_T \sim \text{beta}(u_{11} + n_{11}, u_{10} + n_{10}), \tag{13}$$

where $\tilde{S}_T = \{S_t\}, t = 1, ..., T$. The initial values for p and q at the start of the Gibbs sampling were $p = 0.8$ and $q = 0.6$.

Priors and posteriors for Markov state variables

We wish to sample the states in reverse order from the following probability, where Υ_T stands for the entire history of the observed and latent data and υ_t is the observed and latent data at a point in time:

$$P(S_t = 0 \mid S_{t+1}, ..., S_T, \Upsilon_T) \tag{14}$$

By Bayes theorem, and as outlined in Chib (1996),

$$P(S_t = 0 \mid S_{t+1}, ..., S_T, \Upsilon_T) \quad \propto \quad f(\upsilon_{t+1}, ..., \upsilon_T, S_{t+1}, ..., S_T \mid \upsilon_1, ..., \upsilon_t, S_t) \times P(S_t \mid \upsilon_1, ..., \upsilon_t)$$

$$
\begin{aligned}
&\propto f(\upsilon_{t+1}, ..., \upsilon_T, S_{t+2}, ..., S_T \mid \upsilon_1, ..., \upsilon_t, S_t, S_{t+1}) \times \\
&\quad P(S_{t+1} \mid S_t) \times P(S_t \mid \upsilon_1, ..., \upsilon_t) \\
&\propto P(S_{t+1} \mid S_t) \times P(S_t \mid \upsilon_1, ..., \upsilon_t).
\end{aligned} \tag{15}
$$

The first and second proportions in equation (15) are simply applications of Bayes' theorem. Because the density $f(\upsilon_{t+1}, ..., \upsilon_T, S_{t+2}, ..., S_T \mid \upsilon_1, ..., \upsilon_t, S_t, S_{t+1})$ is independent of S_t, it can be subsumed into the constant of proportionality, which can easily be recovered in order to draw states. As shown in equation (15), the only necessary inputs are the transition probabilities and the filtered probabilities conditional on the contemporaneous data.

Priors and posteriors for β coefficients

Following Albert and Chib (1993), the prior for β is diffuse and the initial value for β in the first cycle of the Gibbs sampler is the ordinary least square estimate from the regression of the initial draw of y^* on the right-hand variables. Like Albert and Chib (1993, p. 671), we use a flat uninformative prior for β, because our initial draw of y^* is uninformative. For this reason, we do not wish to allow a prior distribution around the starting OLS estimate to influence the posterior distribution.

With Σ_T denoting the diagonal matrix with entries from the vector $(\sigma^2_{S1_t}, t = 1, ..., T)$, the posterior distribution for β is the multivariate normal distribution for generalized least squares coefficients:

$$\beta \sim N((X'\Sigma_T^{-1}X)^{-1}X'\Sigma_T^{-1}y^*, (X'\Sigma_T^{-1}X)^{-1}),$$

where the matrix X is understood to include the lagged dependent variable and intercept dummies for $S2$ and $(1 - S2)$. Hence the β coefficients described here include the autoregressive and drift coefficients.

Generating latent variables, y_t^*

The initial values of $y_t^*, t = 1, .., T$ are drawn from $f(y_t^* \mid y_{t-1}^*, y_t \in \{0, 1\}), y_0^*$ is drawn from a uniform distribution on the interval (0,2) if no recession pertains to the beginning of the sample, which was true. In this case,

$$y_t^* \sim N(\rho y_{t-1}^* + X_{t-1}'\beta, \sigma^2_{S_t})$$

with truncation such that $y_t^* \in (c_{j-1}, c_j)$, where the vector $c = (-\infty, 0, \infty)$. These expressions imply that the disturbance, ϵ_t, is in the interval $[-\rho y_{t-1}^* - X_{t-1}'\beta + c_{j-1}, -\rho y_{t-1}^* - X_{t-1}'\beta + c_j)$. Denote this interval as $[l_t, u_t)$. The standardized shock, ϵ_t/σ_{S1_t}, is in the interval $[l_t/\sigma_{S1_t}, u_t/\sigma_{S1_t})$. Let Φ denote the cumulative normal density function. To sample from the truncated normal, we first draw a uniform variable, υ_t, from the interval $[\Phi(l_t/\sigma_{S1_t}), \Phi(u_t/\sigma_{S1_t}))$. The truncated normal draw for the standardized shock is then $\Phi^{-1}(\upsilon_t)$.

We take subsequent draws from

$$f(y_t^{*(i+1)} \mid {y_{t-1}^*}^{(i+1)}, {y_{t+1}^*}^{(i)}, y_t \in \text{cat}.j), \tag{16}$$

where, as in equation (9), superscript i denotes the i^{th} cycle of the Gibbs sampler. We use the density from equation (16), because sampling the entire vector jointly from $f(y_1^*, ..., y_T^* \mid Y_T)$ would require evaluation of a density equivalent to the cumbersome likelihood function from equation (4). To draw from (16), we note that unconditionally $(\epsilon_t, \epsilon_{t+1})$ are distributed as independent, bivariate normals with mean zero:

$$f(\epsilon_t, \epsilon_{t+1}) = \frac{1}{2\pi\sigma_{S_t}\sigma_{S_{t+1}}} \exp\left\{-.5\epsilon_t^2/\sigma_{S_t}^2 - .5\epsilon_{t+1}^2/\sigma_{S_{t+1}}^2\right\}. \tag{17}$$

Given equation (3), we can write

$$\begin{aligned} y_{t+1}^* &= \rho y_t^* + X_t'\beta + \epsilon_{t+1} \\ &= \rho^2 y_{t-1}^* + \rho X_{t-1}'\beta + \rho\epsilon_t + X_t'\beta + \epsilon_{t+1}. \end{aligned} \tag{18}$$

Conditional on values for y_{t-1}^* and y_{t+1}^*, we know the particular value, denoted r_0, of $\rho\epsilon_t + \epsilon_{t+1}$. Substitute $r_0 - \rho\epsilon_t$ for ϵ_{t+1} in the joint density of equation (17) and we find after some algebra that

$$y_t^* \sim N\left(\rho y_{t-1}^* + X_{t-1}'\beta + \frac{\rho r_0 \sigma_{S_t}^2}{\rho^2\sigma_{S_t}^2 + \sigma_{S_{t+1}}^2}, \frac{\sigma_{S_{t+1}}^2 \sigma_{S_t}^2}{\rho^2\sigma_{S_t}^2 + \sigma_{S_{t+1}}^2}\right). \tag{19}$$

We then draw y_t^* as a truncated normal as described above.

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Table 1: Posterior distributions of parameters for data spanning 1973-98 (1969-98 for USA) time-series probit from equation 5

parameter	France	Germany	Italy	U.K.	U.S.
Posterior means of coefficients on explanatory variables					
yield curve	.099	.120	-.047	.069	.127
95 % region	(.025, .188)	(.032, .212)	(-.176, .056)	(-.007, .192)	(.047, .240)
interest rate	-.012	-1.152	-.416	-.523	.103
95 % region	(-.430, .505)	(-2.293, -.126)	(-.638, -.155)	(-.946, -.119)	(-.106, .348)
real money	.151	.201	-.019	.079	.307
95 % region	(.023, .306)	(-.193, .588)	(-.124, .063)	(-.196, .380)	(.030, .727)
unemp.		-.463		-.381	
95 % region		(-2.362, 1.276)		(-1.719, .825)	
indust. prod.	.080	-.010	.111	.150	-.004
95 % region	(-.089, .240)	(-.181, .152)	(.016, .206)	(-.035, .328)	(-.193, .173)
Autoregressive coefficient on business cycle index					
$\rho - 1$	-.062	-.039	-.038	-.063	-.093
95 % region	(-.129, -.017)	(-.075, -.012)	(-.065, -.015)	(-.142, -.015)	(-.163, -.043)
Markov switching drift coefficients					
$\beta_0(S2 = 0)$	.274	.235	.626	.819	.110
95 % region	(-.024, .796)	(-.154, .641)	(.139, 1.102)	(.168, 1.772)	(-.075, .477)
$\beta_0(S2 = 1)$	-.266	-.392	-.488	-.516	-.204
95 % region	(-.695, -.004)	(-.730, -.110)	(-.907, -.043)	(-1.099, .078)	(-.539, -.014)
Markov transition probabilities					
p_1	.673	.674	.672	.673	.672
95 % region	(.621, .725)	(.623, .724)	(.416, .723)	(.620, .723)	(.625, .719)
q_1	.342	.341	.344	.342	.342
95 % region	(.267, .413)	(.269, .414)	(.270, .416)	(.271, .416)	(.275, .407)
p_2	.670	.671	.671	.672	.670
95 % region	(.619, .720)	(.620, .721)	(.621, .721)	(.622, .721)	(.624, .716)
p_2	.344	.342	.344	.344	.343
95 % region	(.272, .415)	(.273, .411)	(.273, .414)	(.271, .417)	(.276, .408)
Variances $\sigma^2_{S1=0}, \sigma^2_{S1=1}$ are fixed at 0.05 and 0.25, respectively.					

Table 2: Correlations of national business-cycle indices

	France	Germany	Italy	U.K.	U.S.
France	1.00				
Germany	0.51	1.00			
Italy	0.58	0.86	1.00		
U.K.	0.05	0.55	0.37	1.00	
U.S.	0.14	0.66	0.55	0.61	1.00

Table 3: Granger-causality tests

	France	Germany	Italy	U.K.	U.S.
France		0.021	0.395	0.080	0.044
Germany	0.279		0.195	0.252	0.117
Italy	0.021	0.000		0.041	0.082
U.K.	0.334	0.030	0.170		0.188
U.S.	0.429	0.648	0.326	0.621	

Note: Values are p-values for an F-test of the null hypothesis that lagged values of the business-cycle index for the country listed on top of column does not have an influence on the business-cycle index of the country listed in the respective row.

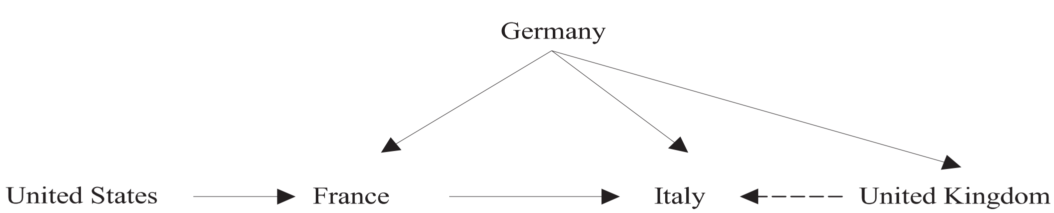

Figure: Causal structure

Table 4: Correlation of national indices with the EU3 index

	1973:01 -1998:04	1973:01 -1979:02	1979:03 -1983:02	1983:03 -1986:12	1987:01 -1992:08	1992:09 -1998:04
France	0.78	0.89	0.82	0.96	0.94	0.99
Germany	0.91	0.91	0.88	0.94	0.98	0.98
Italy	0.92	0.91	0.96	0.90	0.97	0.98
U.K.	0.38	0.80	-0.39	-0.09	0.73	0.74
U.S.	0.53	0.85	0.60	0.88	0.47	-0.73

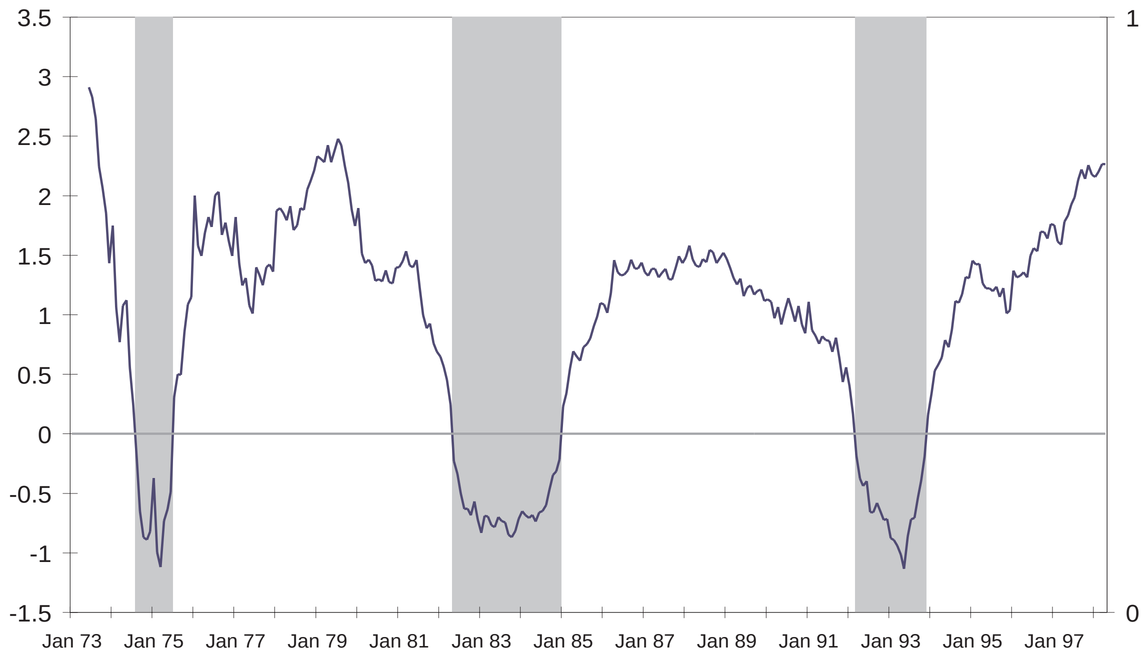

Figure 1: Business-cycle index – France

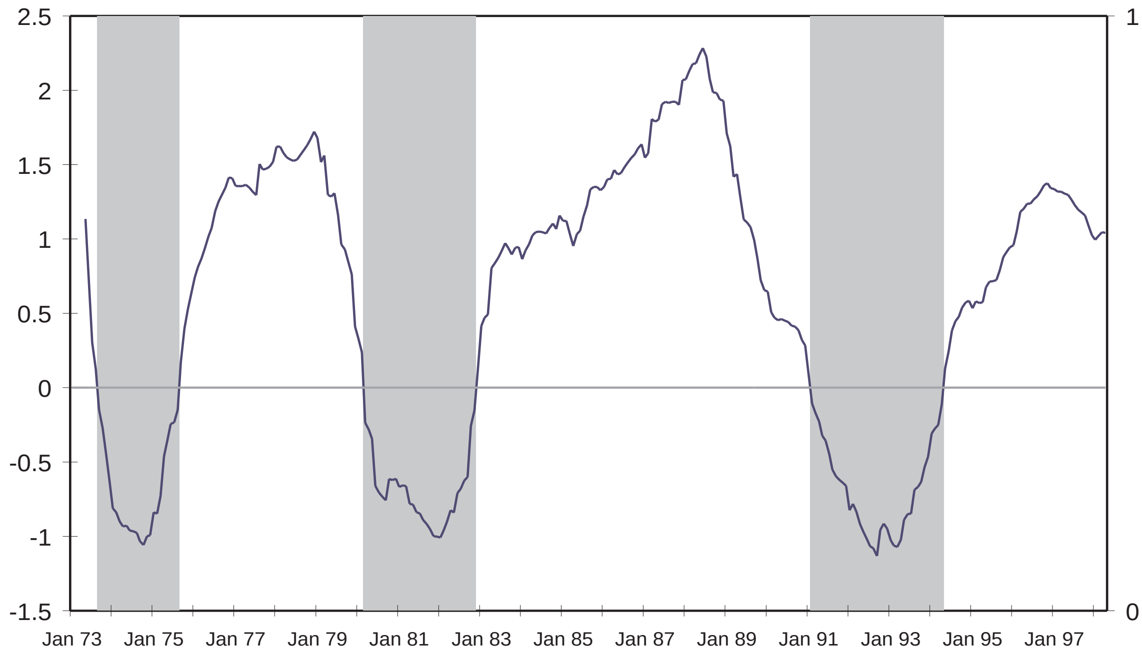

Figure 2: Business-cycle index – Germany

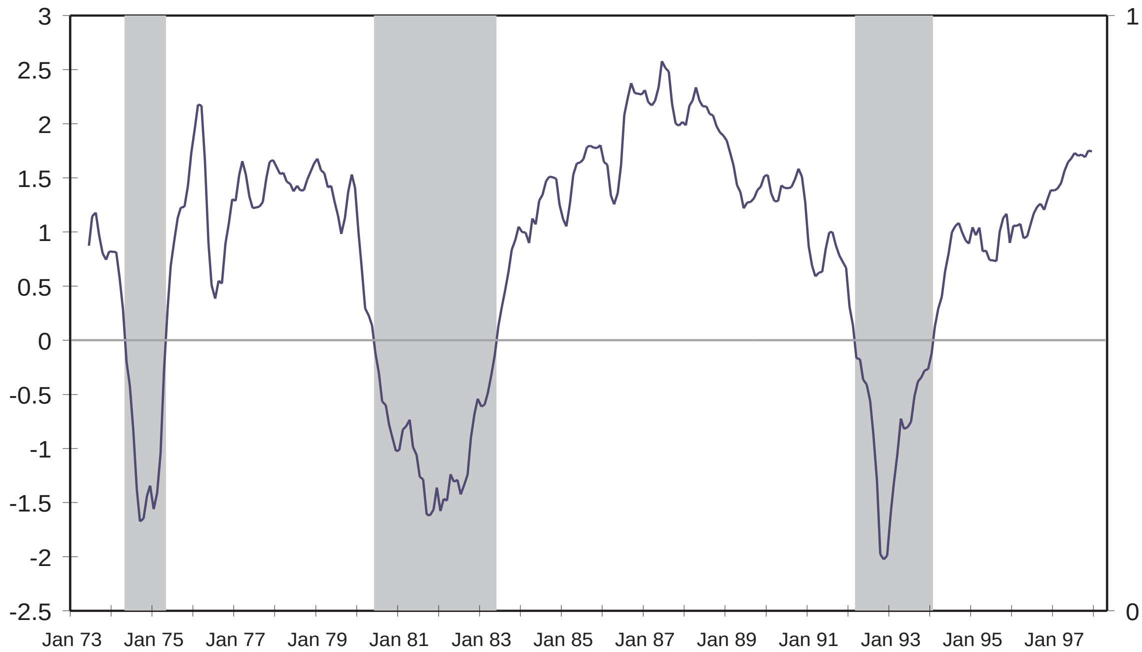

Figure 3: Business-cycle index – Italy

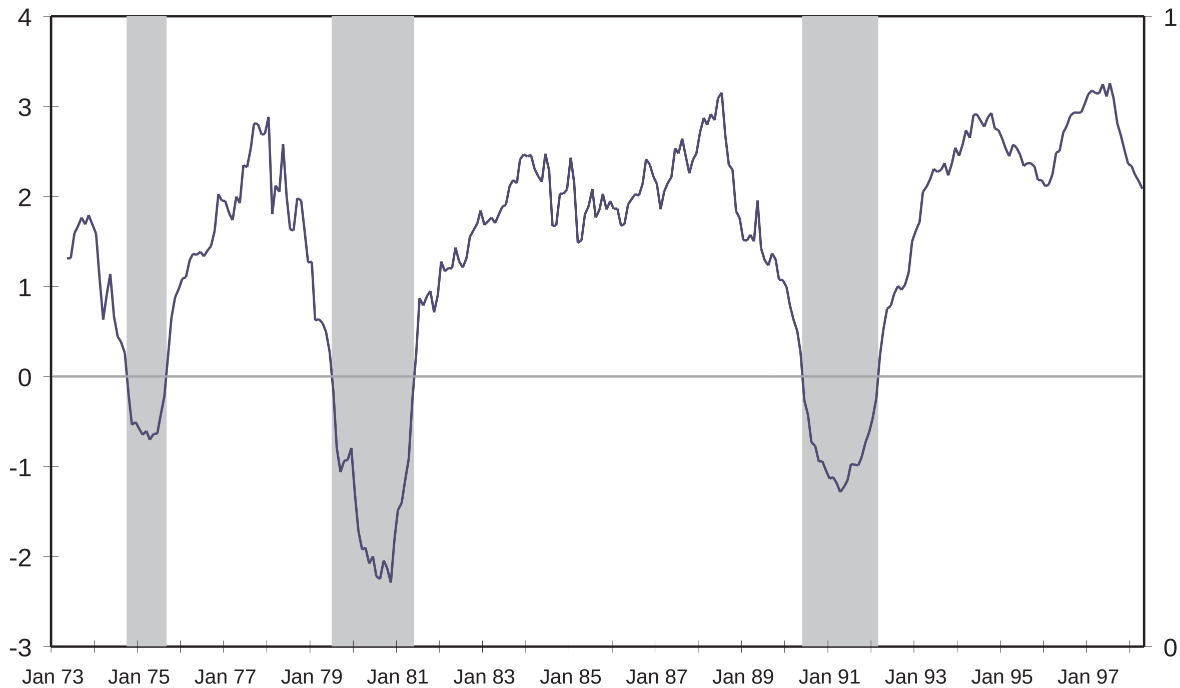

Figure 4: Business-cycle index – United Kingdom

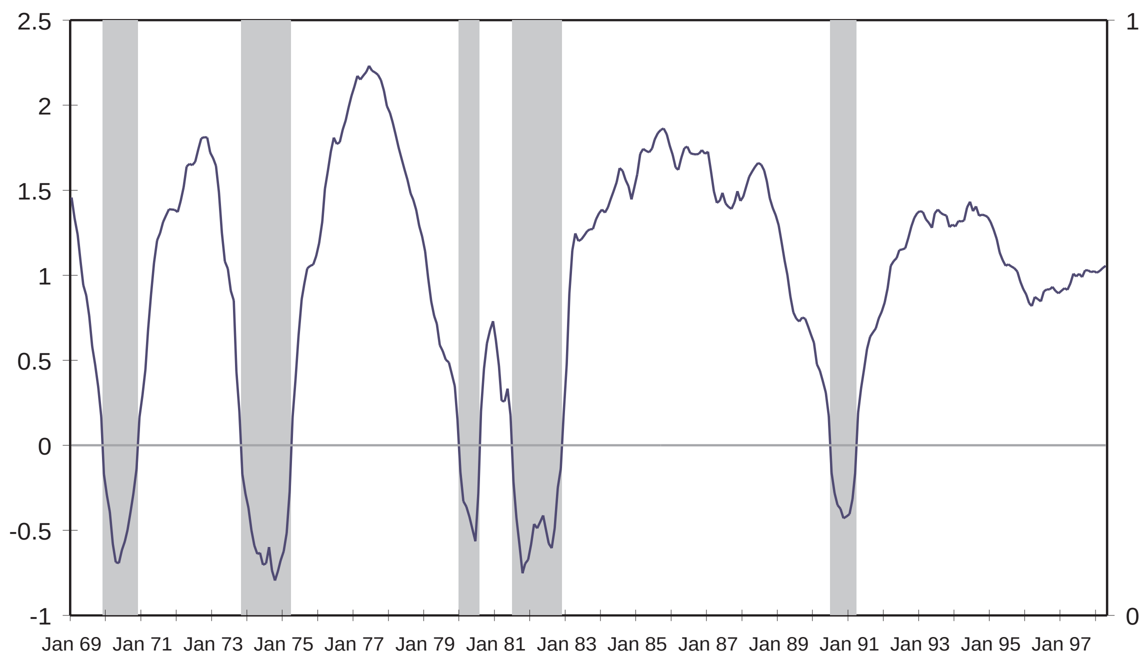

Figure 5: Business-cycle index – United States

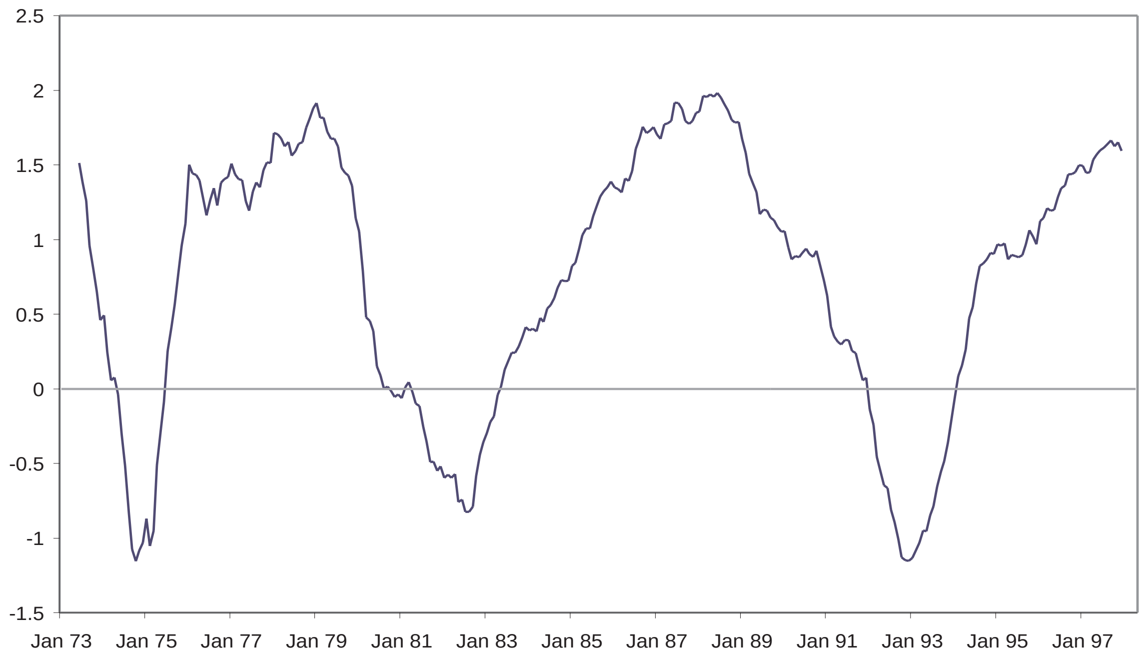

Figure 6: European business-cycle index