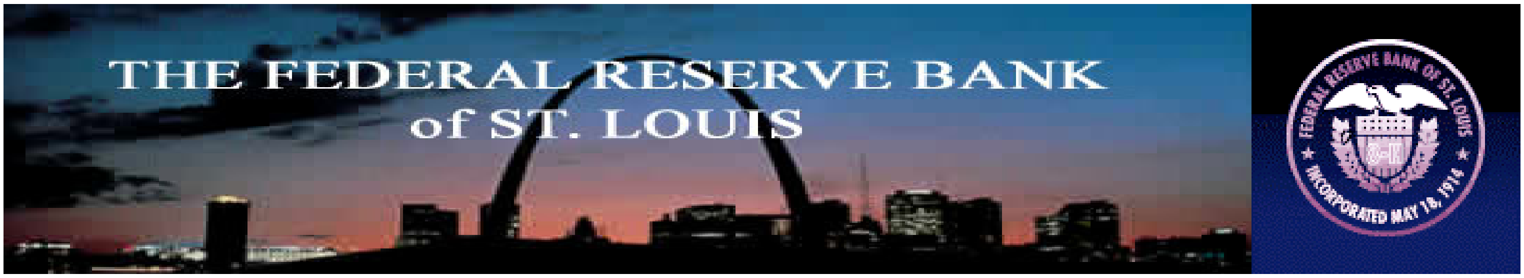


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# European Business Cycles: New Indices and Analysis of their Synchronicity

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# European Business Cycles: New Indices and Analysis of their Synchronicity

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# European Business Cycles: New Indices and Analysis of their Synchronicity


**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 output, income, sales, and employment. 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 (1999) 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.

Our analysis stems from the popular approach of analyzing binary recession variables with probit models, as in Estrella and Mishkin (1997, 1998), Bernard and Gerlach (1998) and others. We extend the probit model to include time-series features such as autoregressive variables and Markov regime switching. Simple probit models, in contrast, 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 lack efficiency, even if the robust standard errors are valid. Because macroeconomic data sets include few business cycle turning points, we aim for an estimation procedure that directly incorporates time-series features into a probit model to make efficient use of the available data. In addition, because simple probits lack time-series features, only the current values of the explanatory variables are used to infer the current state of the business cycle. The autoregressive nature of the time-series probit, in contrast, means that past movements in the explanatory variables are used in conjunction with their current values to better reflect the persistent nature of business cycles and macroeconomic data.

The business cycle index that we propose based on time-series probit analysis of recession dates has several desirable properties. First, the index comes from a model with autoregressive dynamics to reflect the strong serial dependence found in expansions and recessions. Second, unlike other coincident indices that are integrated of order one, $I(1)$, with upward drift, our business cycle index is stationary and does not have an upward trend. Standard filtering methods for business cycle analysis, such as band pass filters or the Hodrick-Prescott filter, presume that the business cycle component (of possibly $I(1)$ data) is stationary or $I(0)$. This view immediately calls into question the use of an $I(1)$ index to measure an $I(0)$ business cycle components. Moreover, with our $I(0)$ index, we can readily calculate cross-country correlations. With upward-trending, $I(1)$ coincident indices —such as the Conference Board's Index of Coincident Indicator and Stock and Watson's (1989) coincident common component from the Kalman filter— the index has to be differenced prior to calculating its correlation with other variables. First differencing leads to a loss of information about the level of the series. For example, the indices for two countries may be growing at the same rate when one country is in a boom and the other country is recovering from a bad recession. A growth rate correlation does not reflect this difference in circumstances. Alternatively, one could take the deviation between an upward-trending coincident index and a measure of its trend and calculate correlations across countries [Mintz (1969)]. Such growth cycles, however, can have downturns that are much more protracted than recession chronologies, yet recessions are when public pressure for policy responses is most intense. For example, the output gap between actual and potential GDP measured by the U.S. Congressional Budget Office and the cyclical component from Hodrick-Prescott-filtered GDP both remained negative until early 1997, whereas the National Bureau of Economic Research dated the end of the preceding recession to be March 1991. Third, our index is symmetric in terms of measuring both the depths of recessions and the heights of booms. Beaudry and Koop's (1993) index measures the cumulative depth of recessions (cumulated over a period that includes the recovery following the recession), but provides no information about the strength of expansions. Similarly, Markov switching models of output growth are designed to discriminate clearly between high and low growth states [Hamilton (1989); Hansen (1992); Filardo (1994)]. Hence, smoothed probabilities of the high-growth state in these Markov switching models tend to remain extremely close to unity for a wide range of expansionary conditions and close to zero throughout recessions. Thus, these models do not provide much information about the relative strength of expansions or depth of recessions. Moreover, if one were to add intermediate growth states to a Markov switching model of output growth, it is not clear that the intermediate state would be comparable across countries, so correlations of the smoothed probabilities would be hard to interpret. Fourth, our 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 appears correlated with the European index.

Our approach extends to time series Albert and Chib's (1993) methods of sampling the latent variable that lies behind a probit model. We propose that the posterior mean of the latent variable is an interesting coincident business cycle index. This approach takes the binary categorical data (business cycle turning points) as given and implies that the latent variable has a truncated posterior distribution: it cannot be positive during recessions and it cannot be negative during expansions. Hence, our posterior inferences about the latent variable are not predictions about future recessions; instead, they represent an inference of how deep was the recession that occurred, or how strong was the expansion that occurred.

The next section presents our time-series probit model.

## 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 ($\epsilon$) into first-order conditions for modified Generalized Least Square formulae for $\beta$ [Poirier and Ruud (1988)]. Rather than limiting oneself to using the expected value of the residual, the Gibbs sampler allows for inference of any aspect of the posterior density of the latent variable. The next section discusses the Gibbs sampler and its data augmentation.

# 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:

$$y_t^* = \rho y_{t-1}^* + \beta_0 + X_{t-1}'\beta + \epsilon_t \tag{3}$$

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 $\phi$ 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, Gibbs sampling offers a tractable method to generate a sample of (i.e., augment the observed data with) draws of the latent variable $y^*$ through a sequence of draws from its conditional distribution. Data augmentation in the present context allows one to treat drawn 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.

Given that business cycle conditions, even in the healthiest expansion, never become arbitrarily distant from recessionary conditions, the business cycle index, $y^*$, must be constructed to be stationary. For this reason, we need to ensure that no nonstationary variable appears in levels on the right side of equation (3). Only cointegrating linear combinations and first differences ought to be used:

$$\Delta y_t^* = \beta_0 + (\rho - 1)y_{t-1}^* + \sum_{j=1}^{J} \Delta X'_{t-j}\beta_j + \gamma(\alpha X_{t-1}) + \epsilon_t, \tag{5}$$

where there are $n$ cointegrating linear combinations among the $X$ variables, $\alpha$ is an $n \times k$ matrix of cointegrating vectors, and $\gamma$ is $1 \times n$. Note that equation (5) is an error-correction mechanism for a variable that is stationary in a system with nonstationary variables $X$, provided that $\rho$ is less than one.

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 $S1$:

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

Second, the model includes Markov switching in the intercept, $\beta_0$. The binary variable that governs drift switching is $S2$:

$$\begin{aligned} \Delta y_t^* &= (\rho - 1)y_{t-1}^* + \beta_{0,S2_t} + \sum_{j=1}^{J} \Delta X'_{t-j}\beta_j + \gamma(\alpha X_{t-1}) + \sigma_{S1_t} e_t \qquad (6) \\ \beta_{0,S2_t} &\in \{\beta_{0l}, \beta_{0h}\} \\ e_t &\sim N(0,1) \\ \epsilon_t &= \sigma_{S1_t} e_t \end{aligned}$$

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

$$\begin{aligned} \text{Prob}(S1_t = 0 \mid S1_{t-1} = 0) &= p_1 \\ \text{Prob}(S1_t = 1 \mid S1_{t-1} = 1) &= q_1 \\ \text{Prob}(S2_t = 0 \mid S2_{t-1} = 0) &= p_2 \\ \text{Prob}(S2_t = 1 \mid S2_{t-1} = 1) &= q_2 \qquad (7) \end{aligned}$$

## 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 $(\beta, \rho, S1, S2, p_j, q_j), j = 1, 2$; in turn, 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:

$$\begin{aligned}
&f(\varrho_1^{(i+1)} \quad | \quad \varrho_2^{(i)}, \varrho_3^{(i)}, \varrho_4^{(i)}, Y_T) \\
&f(\varrho_2^{(i+1)} \quad | \quad \varrho_1^{(i+1)}, \varrho_3^{(i)}, \varrho_4^{(i)}, Y_T) \\
&f(\varrho_3^{(i+1)} \quad | \quad \varrho_1^{(i+1)}, \varrho_2^{(i+1)}, \varrho_4^{(i)}, Y_T) \\
&f(\varrho_4^{(i+1)} \quad | \quad \varrho_1^{(i+1)}, \varrho_2^{(i+1)}, \varrho_3^{(i+1)}, Y_T)
\end{aligned} \tag{8}$$

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 $\varrho$ 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:

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

## 4 Data related to European business cycles

We estimate our business cycle index for the three largest countries participating in the EMU —Germany, France and Italy— as well as the United Kingdom and the United States. In this way, we can compare business cycle correlation within the EMU and also between EMU countries and significant outside countries.

The dependent variable is a 0/1 series that defines a chronology of recessions and expansions. For the European countries, we use chronologies from the Economic Cycle Research Institute (ECRI), whereas for the United States, we use the well-known chronology from the National Bureau of Economic Research (NBER). 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 [cf. Bernard and Gerlach (1998)]. As we want to compare our results across different countries, we chose the dates from the ECRI, because they come from a common methodology that is comparable to the NBER methodology.

For explanatory variables, we use a broad set of macroeconomic indicators. In their classic work on business cycles, Burns and Mitchell (1946: p. 3) define business cycles as fluctuations that occur at about the same time in many economic activities. Business cycles consist of comovement of series like output, income, employment and sales. Stock and Watson (1989), for instance, use industrial production, personal income less transfers, manufacturing and trade sales, and the number of hours worked to compute their index of coincident economic indicators. Correspondingly, the variables entering our business cycle index are industrial production, real personal income, real retail sales, and employment. Although these variables are available on a monthly basis for the United States, data on employment and personal income exist only at a quarterly frequency for the European countries. Using quarterly data, we are able to include real GDP as an additional measure of output. Since the available employment data for the European countries cover only employment in the manufacturing industry, we also include the unemployment rate as a broader measure of labor market conditions in European countries. Our sample period spans the first quarter of 1970 to the last quarter of 2000. Except for the unemployment rate, all series are in logarithms.[1]

German reunification brought a structural transformation to a market economy in East German that differed from a typical business cycle downturn [see Sachverständigenrat (1993)]. For this reason, the German data series are adjusted by the OECD for the break due to German Unification, except for the unemployment rate which covers West Germany throughout the sample period.[2] In addition, we included a post-1990 dummy variable in the cointegration analysis of the German variables to pick up shifts in the long-run relationships between the variables.

Because the business cycle index is stationary, the cointegrating vectors, $\alpha$, that enter equation (6) do not depend on the latent variable and can be estimated prior to the Gibbs draws. Hence, before estimating the business cycle index, we perform a cointegration analysis of the series that enter the index. Not surprisingly, Dickey-Fuller tests are unable to reject the hypothesis that each time series is individually integrated of order one. We use the Johansen procedure with four lags and an unrestricted constant to test for coin-

[1] The precise definition of the time series for each country was dictated by data availability. Details on the data and the sources can be found in Appendix A1.

[2] We linked the personal income series using the one-period link method; the methodology that is also used by the OECD, see OECD (2000: p. 296).

tegration among the nonstationary explanatory variables. The absence of the stationary latent variable does not contaminate the Johansen estimates of the cointegrating vectors because, according to the superconsistency theorem, the stationary dynamic terms have no influence on the asymptotic distribution of the estimators of the cointegrating vectors (see Banerjee et al., 1993). Therefore, the cointegrating vector can estimated consistently without including the latent variable among the short-run regressors. The residual from the cointegrating relations, i.e., the deviation from the long-run relation, is then included in the time-series probit model. We normalize this series by its mean and standard deviation, which makes the coefficient in the probit equation independent of the normalization of the cointegration vector.

In the probit model of equation (6), we include four lagged changes (one year of data) of the explanatory variables and the residual from the cointegrating regression to garner information from the levels of the series. The explanatory variables, $\Delta X_{t-1}$, are all lagged at least one period to avoid simultaneous determination of the explanatory variables and the dependent variable. 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.

Table 1 shows the results from likelihood ratio tests for cointegration. For France, Germany, and the United States, two cointegrating vectors are found at the 5 percent significance level, while Italy and the United Kingdom have one cointegrating vector.[3]

[3]For brevity, we do not report here the coefficients in the cointegrating vectors.

# 5 Posteriors for European business cycles

## Coefficient estimates

We report in Table 2 posterior means for the $\rho$ coefficients, the Markov switching intercepts, $\beta_{0,S2_t}$, and the transition probabilities for the Markov processes. We do not report the $\beta$ or $\gamma$ coefficients because these are reduced-form coefficients, lacking any structural interpretation. The specification of the time-series probit in equation (6) with four lags on $\Delta X$ implies a set of distributed lag coefficients:

$$\sum_{j=1}^{4} \beta_j \Delta X_{t-j} + \gamma\alpha X_{t-1} \quad = \quad \Gamma(L) X_{t-1}, \tag{9}$$

where the sum of the distributed lag coefficients is $\Gamma(1) = \gamma\alpha$. The signs of the sum of distributed lag coefficients , $\Gamma(1)$, are not easy to interpret. For example, suppose that real GDP and industrial production had a cointegrating vector of (1,-1), with zeros on the other variables. In this case, GDP and industrial production would have equal and opposite values of $\Gamma(1)$, yet this would not mean that GDP was good and industrial production was bad for the state of the business cycle. We could only say that a period when GDP is high relative to industrial production tends to preced a period of improvement in the state of the business cycle. Even this level of interpretation is not applicable when we have five variables in the cointegrating vector and have more than one cointegrating vector. Moreover, a set of assumptions sufficient to transform the reduced-form coefficients to structural vector error correction model (VECM) parameters is beyond the scope of this paper. Note that the structural parameters would be especially difficult to disentangle in this system, where the variables —GDP, industrial production, personal income, sales and employment— are so closely related. The Data Appendix shows which variables were used for each of the five countries.

The lower part of Table 2 shows the other parameters of the model. The switching constants are significantly different from each other for France, Italy, and the United States, indicating that switching between regimes with upward and downward drift is important. The regimes are not persistent, however, as the sum of the transition probabilities $(p_2+q_2)$ barely exceeds one, which suggests independent state switching. The autoregressive coefficients, $\rho$, range from 0.42 for the U.K. to 0.97 for Italy, implying significant persistence in the business cycle and validating a time-series probit approach to business cycles. The transition probabilities $(p_1, q_1)$ also sum to about one, so the variance state switching does not uncover evidence of volatility clustering.

## Posterior means for business cycle index

The most important results concern the estimated business cycle index that comes from posterior inferences of the latent variable $y^*$, which can come from estimation of equation (6). 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 superscript $i$ denotes run number $i$ through the Gibbs sampler. Figures 1 to 5 show the latent business cycle indices for France, Germany, Italy, the United Kingdom and the United States, scaled by their respective sample standard deviation. Shaded areas indicate recessionary periods. As discussed in the introduction, the latent variable crosses zero at business cycle turning points by the construction of the model. The distance from zero at all other times provides information regarding the relative strength of an expansion or severity of recession.

The recession induced by the first oil crisis in the early 1970s was most severe in Germany and Italy. Figure 3 for Italy illustrates the relative instability of the Italian business cycle prior to the mid-1980s. After exiting the EMS in 1992, Italy achieved a strong expansion much sooner than either France or Germany after the end of the recession in 1993. For Germany, the recession following German Unification in 1991 stands out with respect to its duration and severity. Though France experienced a shorter downturn in the early 1990s, it was equally severe. In contrast, the recession at the beginning of the 1990s was relatively mild in the U.S. and Italy. The current expansion in the United States showed no sign of weakening until the economy appeared to be cyclically overheated by the middle of 1999, after which the cyclical index began to drop quickly. France was the only European country whose cyclical index was unusually strong by the late 1990s.

Looking only at the EMU members, the business cycles are closely correlated. The largest divergence occurs with the French “Mitterand experiment” in 1982-83, where an expansive fiscal policy delayed the consequences of the second oil-price 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.

To assess the co-movement of the business cycle we compute the cross-correlation between the indices for the five countries in Table 3. The correlation between the EMU countries —especially between Germany and Italy— is high, whereas the correlation with the non-EMU countries is markedly lower. In accordance with Artis and Zhang (1997, 1999) 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. In contrast to Dickerson, Gibson and Tsakalotos (1998), who conclude that France and Germany but not Italy belong to a core set of European countries that share a common business cycle, we find a high correlation between Italy and Germany.

### Granger causality tests

To investigate the cross-country business cycle dynamics in greater detail, we perform Granger causality tests on the business cycle indices. 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 bivariate system in which the Granger causality tests are performed is not meant as a representation of the true data-generating process but serves as part of a data-description exercise. The tests were performed with four different lag lengths. Too few lags may lead to the problem that not all relevant past information is considered. Too many lags result in many insignificant coefficients and an associated loss of efficiency. We tried lag lengths of 2, 4, 6, and 8 quarters. To save space, in Table 4 we only report the significance levels for the tests with 6 lags. Figure 7 illustrates the causal directions from Table 4. In most cases, the results are independent of the lag length chosen. Only the causal relation between the U.K. and Italy, and the U.S. and the U.K. vanishes if fewer lags are employed, and is therefore marked by a broken line in Figure 7. We always obtain uni-directional causality among the significant relationships. Germany causes the French and the Italian business cycle but not the business cycle in the United Kingdom and the United States. France and Italy do not cause the business cycle in any other country.

### Construction of a European index

The 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.[4] The aggregate index, Europe 3 or EU3,

[4] This means that weights change for each observation, but changes are small and have almost no influence on the resulting EU3 index. Real GDP is converted with base-year purchasing power parities.

consists of Germany, France, and Italy and is plotted in Figure 6.[5] One use of an index like EU3 would be to define "European" recessions to be those periods in which EU3 lies below zero. Peak dates for the European business cycle thus are 1974:1, 1980:1, and 1991:4, whereas the troughs occur 1975:2, 1983:1, and 1993:3. Between 1979 and 1983, the European index turns positive for 3 quarters in 1981 without a real recovery taking place. For the recessions in the 1970s and 1980s the business cycle turning points for EU3 correspond closely to those in the United States, whereas in the 1990s Europe experiences a later and longer recession.

We can also look at the correlations between the national business cycle indices and EU3. If one assumes that the European Central Bank will generally set monetary policy according to the EMU-wide business cycle conditions implied by EU3, a low degree of correlation between a member nation and EU3 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.

Figure 8 shows the rolling correlation over a window of 8 years between the European and the national indices. For France, Germany and Italy, the correlation is computed for an aggregate index where the respective country is excluded. The effects of the French "Mitterrand experiment" are mirrored in the lower correlation during the 1980s for France. The idiosyncratic shock due to German Unification is reflected in a sharp drop of the correlation coefficients, but did not lead to long-lasting economic divergence among the EMU countries. In the second half of the 1990s the EMU countries show a consistently high correlation with the European aggregate, whereas the correlation between EU3 and the U.K. and the U.S. indices fluctuates around zero. Given that the correlation of the

[5] Though we consider only three of the eleven countries comprising the EMU, more than 70% of EMU GDP is covered, with France and Italy each accounting for about 20% and Germany for 30% of total EMU GDP (figures for 1997).

U.S. and U.K. indices with the European business cycle is low during the 1990s, it seems that the close coherence between cycles is a European phenomenon rather than a general feature of business cycles in industrial countries. These findings indicate that the inception of EMU is not likely to exacerbate cyclical problems to an extent greater than German Unification already did. The findings for the U.K. also highlight that conditions were not ripe for the U.K. to join the European Exchange Rate Mechanism in 1990.

The high correlation for the EMU members reflects increased policy coordination and economic integration in Europe. This result generally matches Lumsdaine and Prasad (1997), 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. Vijselaar and Albers (2001) also find that the correlation of the U.K. with a European business cycle is lower than for the other European countries. 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, except for the time following the "Mitterand experiment" and German Unification. The United States, in contrast, show a relatively high correlation with the European average in the 1980s, but the correlation is negative in the 1990s.

# 6 Conclusion

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. Data augmentation via the Gibbs sampler allows us to derive posterior inferences of the latent variable behind a time-series 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, as the autoregressive structure of the model, together with the switching constants, allows for a flexible dynamic structure.

Inspection of the business cycle indices for five countries over the post-Bretton Woods period shows that the business cycles are closely correlated among the EMU countries —France, Germany and Italy— and much less so between the EMU countries and the United Kingdom or the United States. Granger causality tests among the national indices suggest business cycle causality running from Germany to France and Italy but not to the United Kingdom or the United States. In addition, we aggregate the business cycle indices from the three EMU countries and examine the correlations between the indices from the individual EMU countries and the "Europe" index across time. The evolution of correlation is 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 policy constraints from the Growth and Stability pact — could lead to more divergence among national business cycles in Europe in the future.

## Appendix A1: Data

| Variable | Source | Definition |
|---|---|---|
| FRSALES | MEI | retail sales, volume, SA, 1995 = 100 |
| FRIP | MEI | production, industry excluding construction, SA, 1995 = 100 |
| FRGDP | MEI | gross domestic product, SA, 1995 Ffr bn, annual rate |
| FRUNEMP | MEI | unemployment rate, SA, % of total labor force (ILO def.) |
| GRSALES | MEI | retail sales, volume, SA, 1995 = 100 |
| GRIP | MEI | production, industry excluding construction, SA, 1995 = 100 |
| GRGDP | MEI | gross domestic product, SA, 1995 DM bn, annual rate |
| GRPINC | BIS | household disposable income, SA, DM mil, deflated with the OECD GDP deflator |
| GREMPL | MEI | employment, manufacturing: employees in '000 persons |
| GRUNEMP | BBK | unemployment rate, West Germany, % of dependent civilian labor force |
| ITSALES | MEI | retail sales, major outlets, volume, SA, 1995 = 100 |
| ITIP | MEI | production, industry excluding construction, SA, 1995 = 100 |
| ITGDP | MEI | gross domestic product, SA, 1995 Lit '000 bn, annual rate |
| ITEMPL | MEI | employment, industry incl. construction, employees and self employed, in '000 persons |
| ITUNEMP | MEI | unemployment rate, SA, % of total labor force, which excludes conscripts |
| GBSALES | MEI | retail sales, volume, SA, 1995 = 100 |
| GBIP | MEI | production, industry excluding construction, SA, 1995 = 100 |
| GBGDP | MEI | gross domestic product, SA, 1995 GBP bn, annual rate |
| GBPINC | BIS | household disposable income, SA, GBP mil, deflated with the OECD GDP deflator |
| GBEMPL | MEI | employment total: employees and self employed, 1995 = 100 |
| GBUNEMP | BBK | unemployment rate, SA, % of total labor force |
| USSALES | FRED | real retail sales, deflated using the consumer price index for all urban consumers (1982-84=100), mil, SA |
| USIP | FRED | industrial production index, 1992=100, SA |
| USGDP | FRED | real gross domestic product, chained 1996 USD bn, SA, annual rate |
| USPINC | FRED | real disposable personal income, chained 1996 USD bn, SA, annual rate |
| USEMPL | FRED | total nonfarm payrolls: all employees, '000 persons, SA |

*Note: MEI: Main Economic Indicators of the OECD, BIS: Bank for International Settlements data base, BBK: Deutsche Bundesbank, FRED: Federal Reserve Bank of St. Louis Economic Time-Series Data Base. SA: Seasonally adjusted.*

The dependent variable is a 0/1 series to identify recessions and expansions. Dating of the business cycle turning points was obtained from the Economic Cycle Research Institute at http://www.businesscycle.com/research/intlcycledates.asp.

Personal income was not available for France and Italy. The series for unified Germany have been linked to the series for West Germany to eliminate the break from German Unification.

## Appendix A2: Gibbs sampling distributions

Several of the parameters regarding the Markov switching were drawn in accordance with the procedures from Dueker (1999). 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

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

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

$$p \mid \tilde{S}_T \sim \text{beta}(u_{00} + n_{00}, u_{01} + n_{01}) \tag{11}$$

$$q \mid \tilde{S}_T \sim \text{beta}(u_{11} + n_{11}, u_{10} + n_{10}), \tag{12}$$

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 $\Upsilon_T$ stands for the entire history of the observed and latent data and $\upsilon_t$ is the observed and latent data at a point in time:

$$P(S_t = 0 \mid S_{t+1}, ..., S_T, \Upsilon_T) \tag{13}$$

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

$$
\begin{aligned}
P(S_t = 0 \mid S_{t+1}, ..., S_T, \Upsilon_T) &\propto f(\upsilon_{t+1}, ..., \upsilon_T, S_{t+1}, ..., S_T \mid \upsilon_1, ..., \upsilon_t, S_t) \times \\
&\quad P(S_t \mid \upsilon_1, ..., \upsilon_t) \\
&\propto f(\upsilon_{t+1}, ..., \upsilon_T, S_{t+2}, ..., S_T \mid \upsilon_1, ..., \upsilon_t, S_t, S_{t+1}) \times \\
&\quad P(S_{t+1} \mid S_t) \times P(S_t \mid \upsilon_1, ..., \upsilon_t) \\
&\propto P(S_{t+1} \mid S_t) \times P(S_t \mid \upsilon_1, ..., \upsilon_t). \qquad (14)
\end{aligned}
$$

The first and second proportions in equation (14) 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 (14), the only necessary inputs are the transition probabilities and the filtered probabilities conditional on the contemporaneous data.

### Priors and posteriors for $\beta$ coefficients

Following Albert and Chib (1993), the prior for $\beta$ is diffuse and the initial value for $\beta$ 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 $\beta$, 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 $\Sigma_T$ denoting the diagonal matrix with entries from the vector $(\sigma^2_{S1_t}, t = 1, ..., T)$, the posterior distribution for $\beta$ 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 $\beta$ 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, $\epsilon_t$, 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, $\epsilon_t/\sigma_{S1_t}$, is in the interval $[l_t/\sigma_{S1_t}, u_t/\sigma_{S1_t})$. Let $\Phi$ denote the cumulative normal density function. To sample from the truncated normal, we first draw a uniform variable, $\upsilon_t$, 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

$$f(y_t^{*(i+1)} \mid {y_{t-1}^*}^{(i+1)}, {y_{t+1}^*}^{(i)}, y_t \in \{0,1\}), \tag{15}$$

where, as in equation (8), superscript $i$ denotes the $i^{\text{th}}$ cycle of the Gibbs sampler. We use the density from equation (15), 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 (15), we note that unconditionally $(\epsilon_t, \epsilon_{t+1})$ are distributed as independent, bivariate normals with mean zero:

$$f(\epsilon_t, \epsilon_{t+1}) = \frac{1}{2\pi\sigma_{S_t}\sigma_{S_{t+1}}} \exp\left\{-.5\epsilon_t^2/\sigma_{S_t}^2 - .5\epsilon_{t+1}^2/\sigma_{S_{t+1}}^2\right\}. \tag{16}$$

Given equation (3), we can write

$$\begin{aligned} y_{t+1}^* &= \rho y_t^* + X_t'\beta + \epsilon_{t+1} \\ &= \rho^2 y_{t-1}^* + \rho X_{t-1}'\beta + \rho\epsilon_t + X_t'\beta + \epsilon_{t+1}. \end{aligned} \tag{17}$$

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 $\epsilon_{t+1}$ in the joint density of equation (16) and we find after some algebra that

$$y_t^* \sim N\left(\rho y_{t-1}^* + X_{t-1}'\beta + \frac{\rho r_0 \sigma_{S_t}^2}{\rho^2\sigma_{S_t}^2 + \sigma_{S_{t+1}}^2}, \frac{\sigma_{S_{t+1}}^2\sigma_{S_t}^2}{\rho^2\sigma_{S_t}^2 + \sigma_{S_{t+1}}^2}\right). \tag{18}$$

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

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**Table 1: Likelihood-ratio tests for cointegration**

| 5 % Critical Value | France | Germany | Italy | UK | US |
|---|---|---|---|---|---|
| 94.15 | | 149.93* | | 102.32* | |
| 68.52 | | 75.46* | 93.12* | 54.20 | 88.74* |
| 47.21 | 65.51* | 39.24 | 45.08 | 31.77 | 50.62* |
| 29.68 | 30.08* | 15.24 | 17.45 | 13.20 | 25.61 |
| 15.41 | 14.08 | 5.86 | 6.89 | 3.85 | 8.94 |
| 3.76 | 0.87 | 0.18 | 0.01 | 0.91 | 0.12 |

*Note: An asterisk signifies significant cointegrating relations. The test statistic is the so-called trace statistic (see Johansen and Juselius, 1990). Critical values are from Osterwald-Lenum (1992).*

Table 2: **Posterior distributions of parameters**

| *parameter* | France | Germany | Italy | UK | US |
|---|---|---|---|---|---|
| | | | *Autoregressive coefficient on business cycle index* | | |
| $\rho$ | 0.77 | 0.45 | 0.97 | 0.42 | 0.71 |
| 95 % region | (0.66, 0.85) | (0.25, 0.68) | (0.95, 0.99) | (0.21, 0.67) | (0.60, 0.83) |
| | | | *Markov switching drift coefficients* | | |
| $\beta_{0,S2=0}$ | 10.78 | 10.99 | 6.44 | 13.13 | 7.02 |
| 95 % region | (8.14, 13.89) | (5.44, 19.84) | (5.36, 7.96) | (4.45, 19.15) | (4.82, 10.76) |
| $\beta_{0,S2=1}$ | -0.19 | 7.84 | -0.08 | 5.54 | 0.98 |
| 95 % region | (-2.80, 1.59) | (3.57, 14.87) | (-0.95, 0.89) | (1.36, 9.79) | (-0.78, 3.43) |
| | | | *Markov transition probabilities* | | |
| $p_1$ | 0.67 | 0.67 | 0.67 | 0.68 | 0.67 |
| 95 % region | (0.60, 0.76) | (0.59, 0.75) | (0.59, 0.76) | (0.60, 0.76) | (0.60, 0.76) |
| $q_1$ | 0.36 | 0.36 | 0.36 | 0.36 | 0.36 |
| 95 % region | (0.25, 0.47) | (0.25, 0.47) | (0.25, 0.47) | (0.25, 0.47) | (0.25, 0.47) |
| $p_2$ | 0.70 | 0.68 | 0.71 | 0.68 | 0.67 |
| 95 % region | (0.63, 0.77) | (0.60, 0.75) | (0.64, 0.78) | (0.60, 0.75) | (0.60, 0.73) |
| $q_2$ | 0.32 | 0.37 | 0.34 | 0.31 | 0.40 |
| 95 % region | (0.22, 0.43) | (0.27, 0.48) | (0.24, 0.45) | (0.21, 0.44) | (0.30, 0.49) |

*The table shows the posterior distribution of parameters for the time-series probit model from equation (6). Variances $\sigma^2_{S1=0}, \sigma^2_{S1=1}$ are fixed at 0.05 and 0.25, respectively. Data span the period from 1970 to 2000.*

**Table 3: Correlation of national business cycle indices**

| | France | Germany | Italy | U.K. | U.S. |
|---|---|---|---|---|---|
| France | 1.00 | | | | |
| Germany | 0.37 | 1.00 | | | |
| Italy | 0.38 | 0.55 | 1.00 | | |
| UK | 0.08 | 0.30 | 0.20 | 1.00 | |
| US | 0.31 | 0.33 | 0.29 | 0.24 | 1.00 |

**Table 4: Granger-causality tests**

| | France | Germany | Italy | U.K. | U.S. |
|---|---|---|---|---|---|
| France | | 0.07 | 0.62 | 0.41 | 0.32 |
| Germany | 0.60 | | 0.22 | 0.20 | 0.56 |
| Italy | 0.16 | 0.03 | | 0.02 | 0.00 |
| U.K. | 0.46 | 0.11 | 0.16 | | 0.01 |
| U.S. | 0.93 | 0.94 | 0.14 | 0.42 | |

*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 do not have an influence on the business cycle index of the country listed in the respective row.*

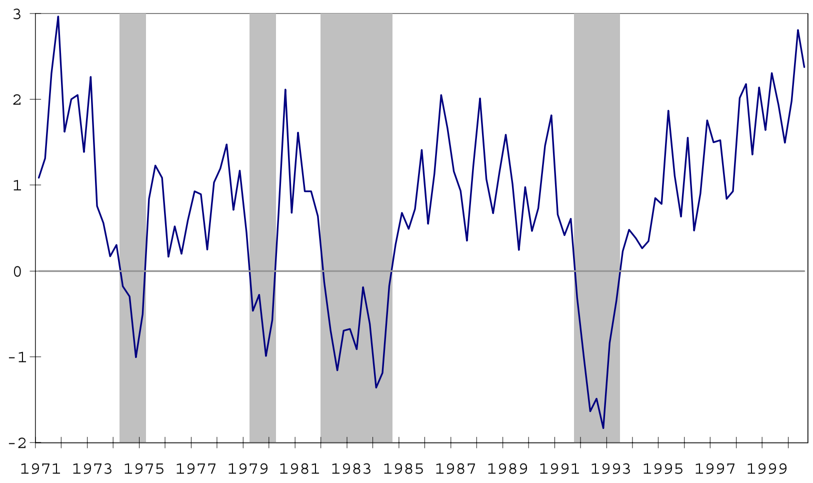

**Figure 1:** Business cycle index – France

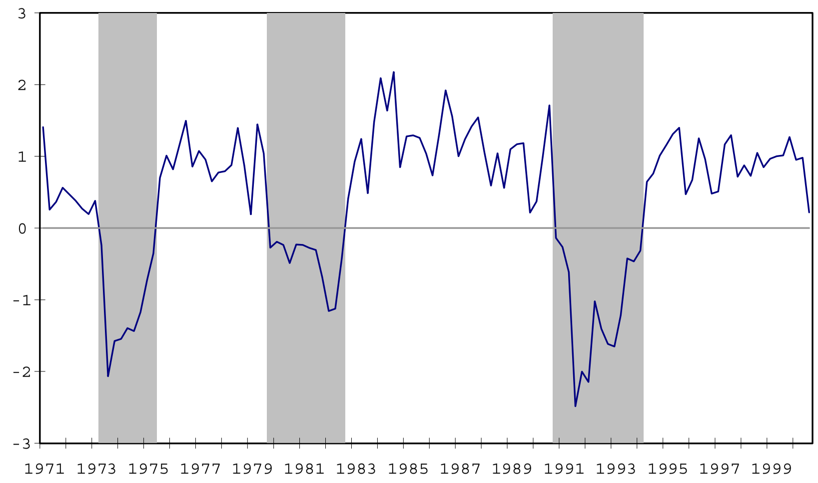

**Figure 2:** Business cycle index – Germany

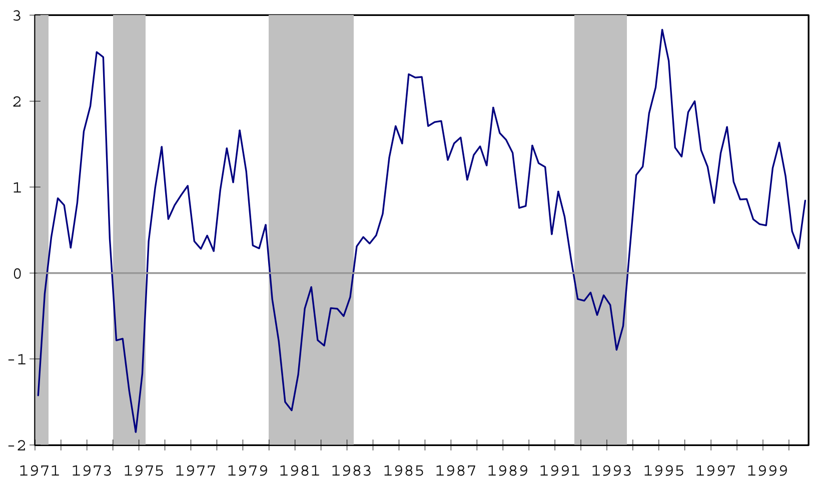

**Figure 3:** Business cycle index – Italy

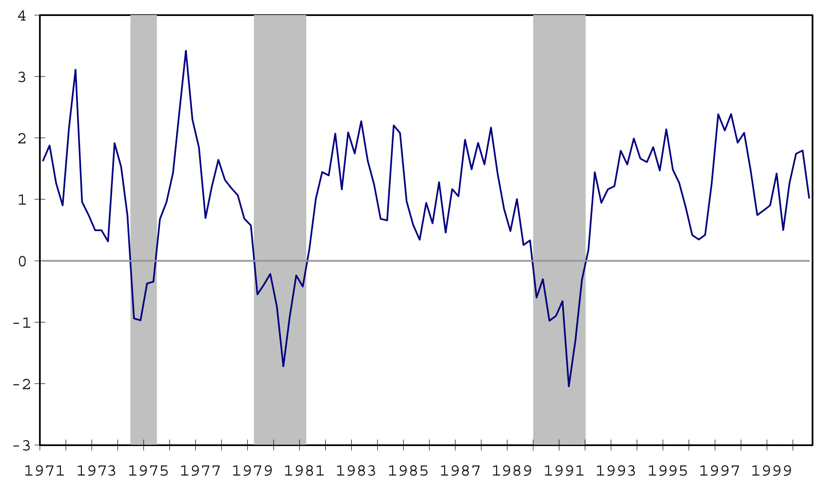

**Figure 4:** Business cycle index – U.K.

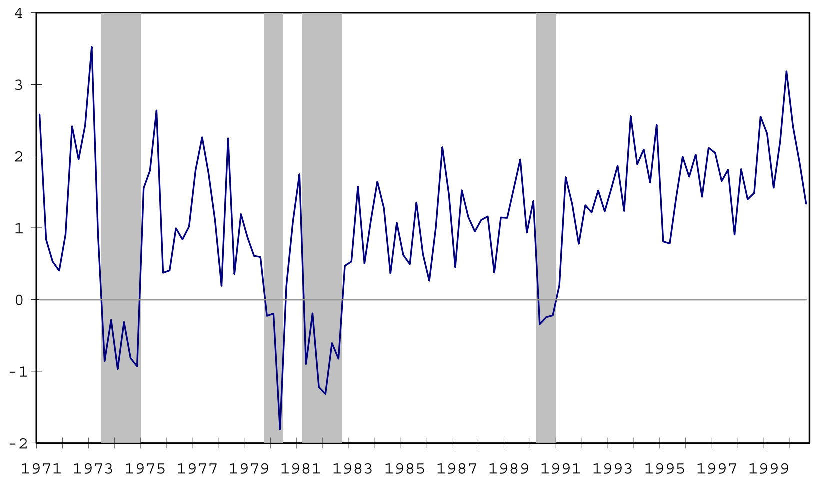


**Figure 5:** Business cycle index —U.S.

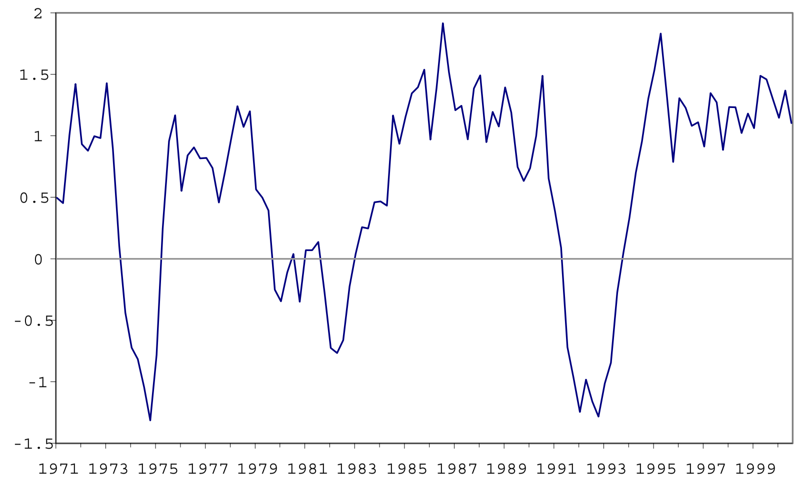


**Figure 6:** European business cycle index

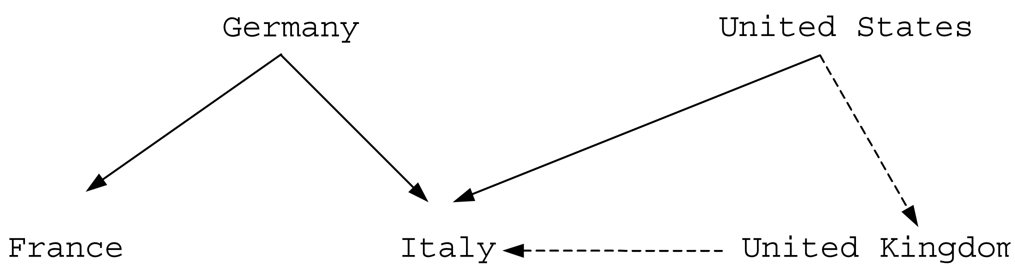


**Figure 7:** Causal structure

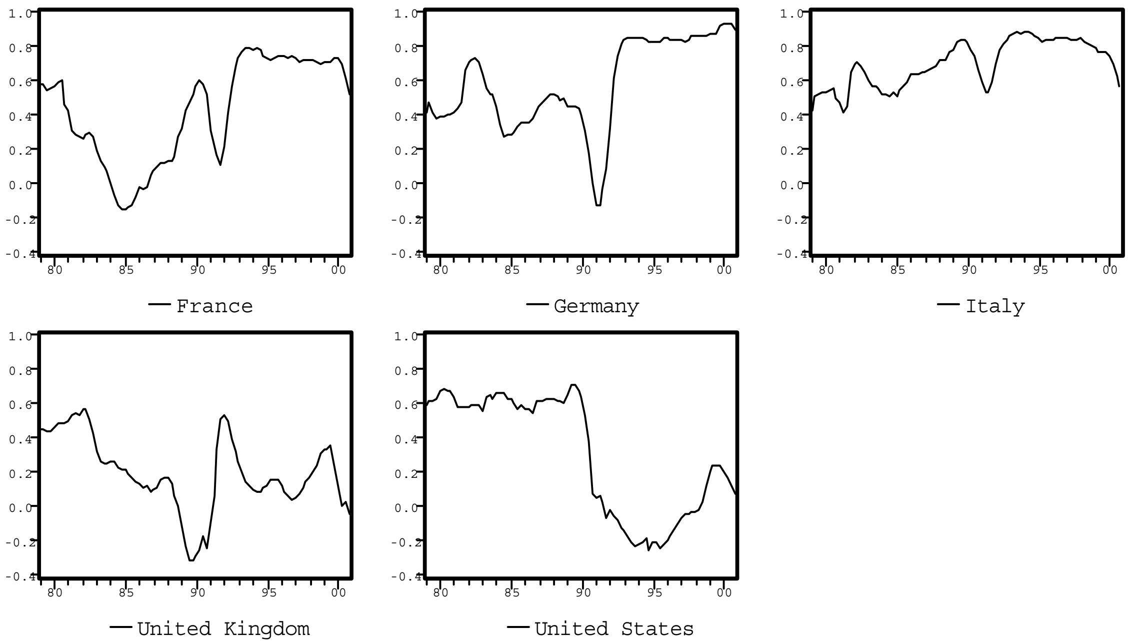


**Figure 8:** Correlation of national indices with the European index