Synchronisation of national business cycles in Europe?
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Synchronisation of national business cycles in Europe?

Gebhard Flaig, *ifo Institute for Economic Research, Munich, Germany*
Jan-Egbert Sturm, *ifo Institute for Economic Research, University of Munich, Germany*
Ulrich Woitek, *University of Munich, Germany*
Synchronization of National Business Cycles in Europe?

Gebhard Flaig†, Jan-Egbert Sturm†‡ and Ulrich Woitek‡

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Abstract

This paper explores the extent to which co-movement in business cycles in European countries has changed over the last fifty years. Several complementary methods are applied to check the robustness of the findings. The most important result is that the correlation between the national business cycles was already quite high during the fifties and early sixties of the last century, declined in the late sixties to in some cases even negative values and reached a peak after the first oil price shock. Since the eighties we observe a stable or even steadily increasing co-movement of the national business cycles.

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† ifo Institute for Economic Research, Munich, Germany.
‡ University of Munich, Germany.
1. Introduction

In an open economy, business cycle developments not only depend upon internal supply and demand factors, but also from shocks originating in other countries. The European integration of goods, capital and factor markets suggests that economic dynamism in a European country is more responsive to external influences as used to be the case. This suggests increasing business cycle affiliations at least within Europe. On the other hand, however, economic and financial integration allows countries to exploit comparative advantage through specialization, which leads to increased macroeconomic asymmetry (Krugman, 1991). This paper explores the extent to which co-movement in business cycles in European countries has changed over the last fifty years. Several complementary methods will be applied to check the robustness of our findings.

The degree of synchronization depends upon the correlation of the external shocks between countries and the intensity to which single markets are internationally integrated. For instance, changes in oil prices affect countries simultaneously, but to a different extent. It is also possible that shocks that originate in one particular country expand across border and affect other countries as well. Following the European Commission (2001, p. 7), the transmission channels can be grouped into four: international trade, the corporate channel, confidence effects and financial linkages. Ideally, one needs a structural model to be able to differentiate between these channels and to test whether at least one of these channels has changed over time. There is a general feeling that all four channels have indeed become more important in recent history. Removal of trade barriers has boosted international trade, especially between European countries. Recent years have witnessed exponentially increasing flows of foreign direct investment. Confidence indicators throughout the world have moved in tandem in recent years. As confidence influences business cycles, the increased international co-movement of confidence indicators could suggest a larger transmission of shocks. Finally, linkages through financial markets have become stronger as investors have increased the international diversification of their portfolio.

The often mentioned intensification of international business cycle co-movement has clear implication for economic policy. For instance, many economists argue that divergence among the EMU member countries still is so high and the flexibility of labor markets so low, that the euro-zone common currency area is not optimal from an economic point of view (De Grauwe, 2000; Eijffinger and De Haan, 2000). Various studies have, in that respect, pointed out that business cycles in the euro-zone countries diverged considerably in the past (see, e.g.
However, in assessing the economic case for EMU the crucial question is how likely it is that business cycles will diverge in the future.\(^1\)

This paper explores to which extent co-movement of business cycles in Europe actually has increased over time and should therefore be seen as an – in our view – first and necessary step in a larger project on European business cycle synchronization. The next section will discuss the data and present some descriptive statistics. Section 3 uses rolling correlation coefficients for the cyclical component generated by an Unobserved Components Model, whereas Section 4 applies spectral analysis to the problem at hand. We end with some conclusions.

### 2. Data

In order to analyze business cycles across countries and over time, we need to observe the evolution of a measure of production both comparable across countries and over time. The latter implies focusing on a measure like real GDP. Cross-country comparison forces us to convert real GDP into one unit of measure. As we do not want the data to be influenced by the relatively volatile movements of exchange rates, we turn to Purchasing Power Parities (PPPs). We use GDP measures based on constant PPPs. This approach to generate time series of PPPs is to fix a ‘base’ year and to extrapolate PPPs for other years. Extrapolation is done by applying the relative rates of inflation observed in different countries to the base year PPPs. GDP series in national currency and at current prices can now be converted with these PPPs to yield volume measures that are comparable across countries. The resulting measures of GDP comparisons are volume indices at constant prices and PPPs.\(^2\)

These time series have a very convenient property: they replicate exactly the relative movements of volume GDP growth of each country, which facilitates the use and interpretation of PPPs over time. Another advantage is that the resulting series is unaffected by methodological changes relating to the calculation of PPPs.\(^3\) For these reasons, the OECD

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\(^1\) Arthis and Zhang (1999) found evidence that business cycles are becoming more synchronous across Europe. This view is challenged by Inklaar and De Haan (2001).

\(^2\) The same result would have been achieved by applying volume growth rates of GDP to the comparative GDP levels of the base year.

\(^3\) A drawback of this approach is that it is assumed that price structures do not change over time. Economic reality has it, however, that relative prices do change over time and it is well known that ignoring these shifts
recommends indices based on constant PPPs for the analysis of relative business cycle performance between countries and over time.\(^4\)

The GDP data comes from the GGDC Total Economy Database at the University of Groningen and The Conference Board.\(^5\) This database is strongly rooted in the work of Angus Maddison. For most countries trends in GDP before 1990 are derived from Maddison (2001) as well as some of Maddison’s other publications. GDP series since 1990 are constructed by researchers of the Groningen Growth and Development Centre and The Conference Board. In some cases the long-run series were revised when new estimates came available. We use the tables for OECD countries expressed in 1999 US dollars, for which ‘EKS’ purchasing power parities (as published by the OECD, 2002) have been used. For all European countries, data covers the period 1950 until 2002.\(^6\) Figure 1 shows the GDP growth rates for (the sum of) these countries.

[Insert Figure 1 about here]

To analyze the issue of business cycle synchronization, it is necessary to determine the cyclical component of output. The problem we face here is that the widely used filtering methods cause artificial cyclical structure when applied to a series based on a data generating process different from the assumptions underlying the chosen filter.\(^7\) Following Canova (1998), we chose the pragmatic way of comparing the results for different filters, e.g., the difference filter, the Hodrick-Prescott filter (HP, Hodrick and Prescott, 1997), the Baxter-
King filter (Baxter and King, 1999) and the filter generated by an Unobserved Components Model.⁸

2.1 Correlation Coefficients

Arguably the most commonly used measure of co-movement is correlation analysis.⁹ Correlation analysis is used to summarize the extent to which the cyclical components exhibit co-movements across countries. A high coefficient of correlation indicates that countries tend to be in similar states of cyclical movement. The degree of synchronization itself is determined on the basis of contemporaneous cross-correlation, while the overall linkage between cyclical movements is measured by the maximum coefficient, which emerges from cross-correlation at different lags and leads. This allows for a fairly comprehensive analysis. Developments in synchronization over time are examined on the basis of the contemporaneous cross-correlation coefficients for rolling 10-year periods.¹⁰

While evidence of increasing or decreasing synchronization may emerge, there is uncertainty as to whether this is due to generally higher or lower linkages in cyclical developments or simply to a phase shift of the cycles, effectively reducing the number of lag and lead periods during which the maximum correlation occurs. Evidence of increased synchronization may thus be considered most convincing if the contemporaneous correlation is increasing over time and tends to be equal to the maximum correlation at a zero lag or lead (ECB, 1999).

There are drawbacks when using ‘moving windows’. For instance, the results might be quite dependent on the size of the window. For example, if the moving window covers a common shock (such as the oil price shock in the 1970s), correlation is very high, and immediately drops once this common shock is no longer covered.

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⁸ Note that, Arthis and Zhang (1997, 1999) and De Haan et al. (2002) report that their results are not dependent on the choice of the detrending method.

⁹ Recently, Harding and Pagan (2002) proposed a new ‘concordance’ measure as new indicator for economic convergence. We will not focus on this new measure.

¹⁰ For our purpose, to determine the evolution of co-movement over time subsamples need to be examined. This makes the measure sensible to the length of the samples.
In this section we restrict our attention to a correlation analysis for the period 1950 until 2002. In a first step we explore the association between the growth rate of GDP of each country and the growth rate of GDP of the rest of the European countries.

The left-hand side of Table 1 shows the highest cross-correlation coefficients between the growth rates of single countries versus the growth rate of the remaining European countries. As the first column indicates, except for Greece, Spain and the United Kingdom the contemporaneous correlation coefficient is the highest among all lead/lag-relationships. Whereas the United Kingdom leads the European business cycle by one year, Spain and Greece have a lag of respectively one and two years. Strikingly low correlations we observe for Ireland and Norway. Also the United Kingdom, Greece and Denmark have correlation coefficients below 0.5. Except for maybe Denmark, this list is not really surprising. The United Kingdom and Ireland have traditionally rather strong economic relationships with the U.S. and other Common Wealth nations. Norway – as an oil-producing non-EU country – has probably been affected by oil price developments – which underlie most major international business cycle shocks – in a rather different way than most European countries. Greece’s peripheral location within the EU together with its relatively low degree of economic development might be able to explain its low business cycle correlation with the rest of Europe.

[Insert Table 1 about here]

Using the cyclical component extracted by using the Hodrick-Prescott-filter the picture changes slightly. The right-hand side of Table 1 shows that in this case Norway, Denmark, Finland and the UK lead the other European countries by respectively four, three and one year; Germany on the other hand lags the other European countries by one year. Except for Ireland and the United Kingdom, the differences in correlation coefficients are not large. Whereas Belgium, France, the Netherlands, Portugal and Spain all report correlation coefficients of around 0.8, for Germany, Ireland and Norway its magnitude is below 0.5. With the clear exception of Germany, the initiators of European integration (by founding the European Coal and Steel Community (ECSC), the European Atomic Energy Community (EURATOM) and the European Economic Community (EEC) in respectively 1951 and 1957) all belong to the group of countries with the highest correlations.
3. Synchronization of Business Cycles in the Time Domain

3.1 The Unobserved Components Model

In this section we employ an Unobserved Components Model in order to extract the cyclical component from the yearly GDP series for single countries and the rest of the European countries, respectively. In a second step, we use rolling correlation coefficients to analyze the changing pattern of synchronization between the national and international business cycles.

The basic assumption underlying Unobserved Components Models is that an observed time series \( y_t \) can be decomposed into several interpretable components (for a general discussion see Harvey, 1989; Maravall, 1995). In the following, we decompose the logarithm of the yearly GDP series into the unobserved components trend \( T \), cycle \( C \), and the irregular \( I \):

\[
(1) \quad y_t = T_t + C_t + I_t.
\]

The trend component represents the long-run development of GDP and is specified as a random walk with a possibly time-varying drift rate \( \mu_t \):

\[
(2) \quad T_t = T_{t-1} + \mu_{t-1} + \epsilon_t.
\]

The level impulse \( \epsilon_t \) is a white noise variable with mean zero and variance \( \sigma^2_\epsilon \). The drift rate \( \mu_t \) is allowed to vary over time and is also defined as a random walk:

\[
(3) \quad \mu_t = \mu_{t-1} + \xi_t.
\]

The drift impulse \( \xi_t \) is a white noise variable with variance \( \sigma^2_\xi \).

The model specified in equations (2) and (3) implies that the trend component follows an IMA(2,1)-process. Special cases emerge when we set the variance of the shocks to zero. If both are zero, we get a deterministic linear trend. If \( \sigma^2_\xi \) is zero and \( \sigma^2_\epsilon \) is strictly positive, the model collapses to a random walk with a constant drift rate. The opposite case – with a strictly positive \( \sigma^2_\xi \) and \( \sigma^2_\epsilon \) equal to zero – gives an integrated random walk with a usually smooth trend component.

The cycle \( C_t \) captures the business cycle fluctuations around the trend component and is modeled as the sum of \( M \) subcycles with different frequencies:
The specification of the total cycle as the superposition of subcycles with different frequencies is able to represent some ideas of classical business cycle theory (e.g., the existence of Kitchin or Juglar cycles) and to capture several forms of business cycle asymmetries (for some alternative specifications see Harvey, 2002, and Harvey and Trimbur, 2001).

Each subcycle is specified as a vector AR(1) process:

\[
\begin{pmatrix}
C_{t, i} \\
C^*_{t, i}
\end{pmatrix} = \rho_i \begin{pmatrix}
\cos \lambda^C_i & \sin \lambda^C_i \\
-\sin \lambda^C_i & \cos \lambda^C_i
\end{pmatrix} \begin{pmatrix}
C_{t-1, i} \\
C^*_{t-1, i}
\end{pmatrix} + \begin{pmatrix}
\kappa_{t, i} \\
\kappa^*_{t, i}
\end{pmatrix},
\]

\(C^*\) appears only by the construction of the recursion and has no intrinsic interpretation.

The period of subcycle \(i\) is \(2\pi / \lambda^C_i\) with \(\lambda^C_i\) the frequency in radians. The damping factor \(\rho_i\) with \(0 < \rho_i \leq 1\) ensures that \(C_{t, i}\) is a stationary ARMA(2,1) process with complex roots in the AR-part (see Harvey, 1989). This guarantees a quasi-cyclical behavior of \(C_{t, i}\). The shocks \(\kappa_{t, i}\) and \(\kappa^*_{t, i}\) are assumed to be uncorrelated white noise variables with common variance \(\sigma^2_{\kappa}\). They induce a stochastically varying phase and amplitude of the wave-like process. The total cycle \(C_t\) is an ARMA(2M,2M-1) process with restricted MA-parameters.

The irregular component is specified as a pure white noise process:

\[
I_t = u_t.
\]

It is assumed that all disturbances are normally distributed and are independent of each other. This is the usual assumption to assure the identification of the parameters (see, e.g., Watson, 1986).

Estimation of the model parameters is carried out by maximum likelihood in the time domain. The initial values for the stationary cycle components are given by the unconditional distribution and for the nonstationary trend and drift components by a diffuse prior. The filtered and smoothed values of the unobserved components are generated by the Kalman filter (for details see Harvey, 1989).
3.2 Empirical results

After an intensive specification search we choose a model with two subcycles. This model passes all specification tests and delivers plausible estimates for the trend and cycle components. The short subcycle varies between 3.5 and 5 years, the long subcycle between 9 and 12 years.

Using the cyclical components of both the Unobserved Components Model and the Hodrick-Prescott filter (as used in Section 2), we then calculate the rolling contemporaneous correlation coefficients between each country and the rest of Europe. Each value of the correlation coefficient is computed over a window of the past 10 years. Due to lack of space, we do not comment in detail the results for each individual country. However, by graphical inspection we are able to distinguish five groups within our set of 16 European countries. Within each group the time pattern of the correlation coefficients is rather similar. Furthermore, the results are quite robust across the different filtering techniques we apply.

[Insert Figures 2 to 6 about here]

Figure 2 depicts the contemporaneous cross-correlation coefficients for Belgium, France and the Netherlands. In general, these three countries show correlation coefficients well above 0.5 throughout. Furthermore, these three countries show a relatively stable pattern over time.

The second group consists of the two oil-producing countries in our sample, i.e. United Kingdom and Norway. In the fifties and early sixties, these two countries move in clear concordance with the rest of Europe. This abruptly changed at the end of the sixties. Especially for Norway, its correlation with the rest of Europe remained low – and often even negative – until the end of the nineties. Only in recent years, both countries have witnessed a sharp increase in concordance with other European countries.

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11 In Appendix A we show the estimated cyclical component results using the Unobserved Components Model for each individual country and the rest of the European countries together with their rolling contemporaneous correlation coefficients. In order to capture some phase shifts between the cycles of different countries we also report a centered three year moving average of each cycle component.

12 Besides an Unobserved Components Model and the Hodrick-Prescott filter, we have also used annual growth rates and the Baxter-King filter. The results are much alike to ones presented and are available upon request.
Austria, Denmark and Germany, i.e. the third group we distinguish, depict a steady increase in correlation until the seventies, after which it starts deteriorating again – reaching their low at the end of the eighties / early nineties. Since, there we observe that these countries start moving in line with the rest of Europe again. For Germany we can identify the sluggish behavior of the German economy between 1982 and 1987, when other countries experienced a more or less strong recovery from the 1981/82 recession and the idiosyncratic unification boom in Germany in the years 1990/91.

The countries in the fourth group, i.e. Belgium, Finland, Ireland, Sweden and Switzerland, start of from a level above 0.6 in the fifties. However, these cross-correlation coefficients then slowly decline and – except for Sweden – reach their lows during the late seventies, early eighties. When using the Unobserved Components Model, Sweden’s turning point was already in the early seventies. During the nineties, all correlation coefficients are on a high and relatively stable level again.

The last group, containing the southern European countries Greece, Italy, Portugal and Spain, show lows in the late sixties and early eighties. Except for Portugal – which already started from a very high level – we see a clear rise in concordance of these countries with the rest of Europe. For Portugal and Spain this pattern is interrupted during the late seventies and early eighties. In recent years, we see some slight regress for all countries within this group.

Figure 7 summarizes the business cycle synchronization in Europe by showing both (GDP-) weighted and unweighted average contemporaneous cross-correlations across our group of 16 European countries using the Unobserved Components Model and the Hodrick-Prescott filter. It reveals that the correlation between the national business cycles was already quite high during the fifties and early sixties. For countries from group 2 and 5 we observe a sharp decline in the business cycle synchronization during the late sixties, sometimes even leading to negative correlations. The first oil price shock induced a high synchronization between the national business cycles. Consequently, the correlation coefficients show a sharp increase from the mid-seventies to the early eighties and remain then fairly stable on a high level. There is some evidence – especially when focusing on the Unobserved Components Model – that the strength of the co-movement of national business cycles has further increased during the nineties of the last century.
The last few years exhibit a tendency to a stronger co-movement of especially the British and German business cycles with those of remaining European countries. So – except for the southern European countries (group 5) in which European integration has probably indeed led to a higher business cycle concordance with the rest of Europe – we have a convergence to a situation which is ‘normal’ for most other countries – in particular those from the first (and third) group – over the last two or three decades. ‘Normal’ means that we observe a correlation coefficient in the range of 0.5 to 0.8 between the national and the European business cycle, respectively. There is a significant association among the cycle in different countries, but the co-movement is far from a perfect synchronization.

4. Synchronization of Business Cycles in Frequency Domain

To go a step further and check the results in time domain for robustness, we employ spectral analysis techniques. This method has the advantage that it allows to derive a measure for synchronization frequency by frequency, which enables us to focus on the relevant business cycle frequency intervals. The measures are based on those developed in A’Hearn and Woitek (2001). We focus on three cycle ranges: the 7-10 years range (Juglar cycle), the 5-7 years range, and the 3-5 years range (Kitchin cycle). The dominant cycle band is identified by calculating the share of total variance attributable to cycles in these intervals. To address the issue of synchronization, we decompose the variance for each frequency band into an explained and an unexplained part. In addition, we adopt the dynamic correlation measure suggested by Croux, Forni and Reichlin (2001) to distinguish between in-phase and out-of-phase movements.

To derive these measures, consider two stationary time series, \( tX \) and \( tY \). The spectrum is defined as the Fourier transform of the covariance function \( \Gamma_{xy} (\tau) \), \( \tau = 0, \pm 1, \pm 2, \ldots \).\(^{14}\)

\(^{13}\) An example for potential weaknesses of the correlation coefficient in time domain as a measure of synchronization is the result in Backus and Kehoe (1992), who report a very low correlation coefficient (0.01) between the US and the UK cycle before World War I. Based on this result, one would have to conclude that the ‘Atlantic Economy’ did not exist. Both the state space approach (Solomou, 1998) and spectral analysis (A’Hearn and Woitek, 2001), however, reveal that there is a strong relationship between cycles with periods in the range 7-10 years.

The diagonal elements of the spectral density matrix $F_{xy}(\omega)$ are called autospectra. Integrating the autospectra over the frequency band $[-\pi, \pi]$, we obtain the variance of the respective series. After dividing the autospectrum by the variance, we can calculate the contribution of cyclical components in a frequency band $[\omega_1, \omega_2]$. The off-diagonal elements or cross-spectra are complex numbers and given by

$$ f_{xy}(\omega) = c_{xy}(\omega) - iq_{xy}(\omega), \quad \omega \in [-\pi, \pi], $$

where $c_{xy}(\omega)$ is the cospectrum and $q_{xy}(\omega)$ is the quadrature spectrum. The cospectrum measures the covariance between the ‘in-phase’ components of $X_t$ and $Y_t$, whereas the quadrature spectrum measures the covariance between the ‘out-of-phase’ components. Together with the autospectra, the cross spectrum can be used to calculate a measure similar to $R^2$ in linear regression analysis. This measure is the squared coherency $sc(\omega)$:

$$ sc(\omega) = \frac{|f_{xy}(\omega)|^2}{f_x(\omega)f_y(\omega)}, \quad 0 \leq sc(\omega) \leq 1. $$

This measure assesses the degree of linear relationship between two series, frequency by frequency. If we are interested in the extent to which the variance of cyclical components of the series $X_t$ in the frequency band $[\omega_1, \omega_2]$ can be attributed to corresponding cyclical components in series $Y_t$, we can use $sc(\omega)$ to decompose the fraction of overall variance in this interval into an explained and an unexplained part:

$$ \int_{\omega_1}^{\omega_2} f_x(\omega)d\omega = \int_{\omega_1}^{\omega_2} sc(\omega)f_x(\omega)d\omega + \int_{\omega_1}^{\omega_2} f_u(\omega)d\omega. $$

We will use this decomposition to compare the degree of linear relationship between cycles in the aggregate of the European countries and each of the member countries in the three business cycle frequency intervals mentioned above.

As pointed out by Croux, Forni and Reichlin (2001), a measure like the squared coherency presented above is not suited for analyzing the co-movement of time series, because it does not contain information about possible phase shift between cycles in the series $X_t$ and $Y_t$. In
this sense, the correlation coefficient in time domain used in the previous sections is more informative, since it is calculated lag by lag, providing both information on the lead-lag structure and the degree of linear relationship between the two series. Croux, Forni and Reichlin (2001) propose an alternative measure, the so-called dynamic correlation $\rho(\omega)$, which measures the correlation between the ‘in-phase’ components of the two series at a frequency $\omega$:

\[
(11) \quad \rho(\omega) = \frac{c_{xy}(\omega)}{f_x(\omega)f_y(\omega)}, \quad -1 \leq \rho(\omega) \leq 1.
\]

Using

\[
(12) \quad sc(\omega) = \frac{\left| f_{xy}(\omega) \right|^2}{f_x(\omega)f_y(\omega)} = \frac{c_{xy}(\omega)^2 + q_{xy}(\omega)^2}{f_x(\omega)f_y(\omega)},
\]

we can use this idea to further decompose explained variance:

\[
\int_{\omega_1}^{\omega_0} f_x(\omega)d\omega = \int_{\omega_1}^{\omega_0} sc(\omega)f_x(\omega)d\omega + \int_{\omega_1}^{\omega_0} f_u(\omega)d\omega \quad \text{“explained” variance “unexplained” variance}
\]

\[
= \int_{\omega_1}^{\omega_0} \frac{c_{xy}(\omega)^2 + q_{xy}(\omega)^2}{f_y(\omega)}d\omega + \int_{\omega_1}^{\omega_0} f_u(\omega)d\omega
\]

\[
= \int_{\omega_1}^{\omega_0} \frac{c_{xy}(\omega)^2}{f_y(\omega)}d\omega + \int_{\omega_1}^{\omega_0} \frac{q_{xy}(\omega)^2}{f_y(\omega)}d\omega + \int_{\omega_1}^{\omega_0} f_u(\omega)d\omega.
\]

Thus, it is possible to decompose explained variance into the ‘in-phase’ component and the ‘out-of-phase’ component, adding some information on the importance of the phase shift in a frequency interval to the $R^2$ interpretation of the decomposition in equation (10) above.

To estimate the spectra, we fit VAR models in time domain, and calculate the spectra of the estimated models.\(^{15}\) With a VAR model of order $p$, the spectral density matrix is given by

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\(^{15}\)This method is based on the seminal work by Burg (1967), who shows that the resulting spectrum is formally identical to a spectrum derived on the Maximum Entropy Principle. This is seen to be a more reasonable approach than the normally used periodogram estimator. The periodogram employs the assumption that all the covariances outside the sample period are zero. Given that economic time series are notoriously short, this seems to be a problematic assumption (see the discussion in Priestley, 1981, 432 and 604-607).
\[ F(\omega) = \frac{1}{2\pi} A(\omega)^\dagger \Sigma A(\omega)^{-\dagger}, \ \omega \in [-\pi, \pi]. \]

The error variance-covariance matrix is denoted by \( \Sigma \), and \( A(\omega) \) is the Fourier transform of the matrix lag polynomial \( A(L) = I - A_1 L - A_2 L^2 - \cdots - A_p L^p \).\(^{16}\) But before we can actually estimate the spectrum, we have to solve the problem that the series under consideration are not stationary. Since it is widely used in the literature, we present the results for the Hodrick-Prescott (1997) filter.\(^{17}\)

‘Synchronization’ describes a process; hence, we need the measure in equation (13) to be time-varying. Since the estimator for the spectrum is parametric, it is straightforward to obtain a time dependent measure: we re-cast the VAR-model into state-space form, treating the parameters as unobservables. The starting point is a VAR of order \( p \)

\[
x_t = c + \sum_{j=1}^{p} A_j x_{t-j} + u_t,
\]

\[= (c \ A \ ... \ A_p) \begin{pmatrix} x_{t-1} \\ x_{t-p} \\ z_{t-4} \end{pmatrix} + u_t,
\]

\[= AZ_{t-4} + u_t,
\]

where \( u_t \) is iid\((0,H)\). Vectorizing the above equation and treating the parameters of the VAR as state variables, results in

\[ x_t = (Z' \otimes I) \text{vec } A_t + u_t = (Z' \otimes I) \alpha_{t-1} + u_t, \]

which is the measurement equation in the state-space version of equation (15).\(^{18}\) The transition equation describes the time path of the VAR parameters and is given by

\[ \alpha_t = T \alpha_{t-1} + \eta_t, \]

---

\(^{16}\) \( L \) is the backshift operator, and the superscript \(^*\) denotes the complex conjugate transpose.

\(^{17}\) As smoothing weight we use 6.25 as suggested by Ravn and Uhlig (2002).

\(^{18}\) For the following, see Harvey (1989).
where $\eta_i$ is iid$(0, Q)$. We assume the matrix $T$ to be a diagonal matrix with elements $\rho = 0.9$ on the diagonal, forcing the time path of the parameters to be a damped AR(1) process. The elements in the covariance matrices $H$ and $Q$ are treated as hyperparameters, and the likelihood function based on the cumulated prediction errors of the Kalman filter applied to equations (16) and (17) is maximized with respect to these parameters. The solution implies a time path for $\alpha_i$, thus allowing the measures in equation (13) to be time dependent.

[Insert Figure 8 about here]

The time path for the in-phase proportion of explained variance for the European countries is displayed in Figure 8 (data in logs). Explained variance is calculated as the proportion of variance of a European member explained by the variance of the rest in the business cycle intervals (7-10 years, 5-7 years, and 3-5 years). The results are summarized for the five groups identified above by taking averages over the group members. Note that the time paths are smoothed to facilitate the identification of overall patterns.

It is obvious that for Belgium, France and the Netherlands, in-phase explained variance is highest, i.e. above 50 per cent in all three business cycle intervals for almost the entire observation period, with the exception of the 7-10 years range, where it is below 50 per cent before 1955. Compared with the other 4 groups, the United Kingdom and Norway exhibit the lowest link to the European cycle: explained variance is constantly below 50 per cent. Austria, Germany and Denmark have an average explained variance above 50 per cent, with the exception of short periods at the end of the 60s and the beginning of the 90s. Group 4 (Finland, Ireland, Sweden and Switzerland) starts with explained variance above 50 per cent. After 1965, the measure declines, and increases again after 1985, at least in the 3-5 years range. Finally, Greece, Italy, Portugal and Spain start with an average explained variance below 50 per cent, which, in the 5-7 and 7-10 years range, decreases until about 1965. After 1965, the measure increases again to reach values above 50 per cent around 1980 in the 7-10 years range. For the other two business cycle ranges, it crosses the 50 per cent line not before the start of the 90s. A comparison with the outcome for the difference filter shows that with the exception of Group 4, these results are robust.

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19 Group 1: Belgium, France, the Netherlands; Group 2: United Kingdom, Norway; Group 3: Austria, Germany, Denmark; Group 4: Finland, Ireland, Sweden, Switzerland; Group 5: Greece, Italy, Portugal, Spain.
Ahmed, Levin, and Wilson (2002) interpret synchronization in the high frequency ranges as due to converging business practices like improved inventory management, while synchronization in the lower frequency range is caused by fiscal and monetary policies aimed at smoothing out the business cycle. Reducing the variance of innovations would affect all frequencies. Since our results do not favor a particular range, and are also not entirely the same over all three ranges, there seems to be a mixture of causes responsible for the synchronization process of the European cycles.

5. Concluding remarks

This paper presents an exploratory study concerning the strength of business cycle co-movement of the European countries from 1950 to 2002. Special emphasis is given to the question of whether the correlation between the national business cycles has changed over time. We find that the association between the national and the European business cycle was already quite high during the fifties and early sixties. Since the mid-sixties we see a dramatic decrease in the strength of co-movement with even negative correlation coefficients for some countries. The first oil price shock induced a closer co-movement of the national cycles. Since then we observe over more than 20 years a stable or even steadily increasing correlation. However, there is no clear evidence that the co-movement is higher than in the fifties or seventies. These findings are generally corroborated by an analysis in the frequency domain. Looking at co-movement in three different frequency bands (7-10 years, 5-7 years, 3-5 years) reveals additional insight. It turns out especially Norway can be seen as an outlier with respect to synchronization with the aggregate European business cycle. For the most part of the observation period, the Norwegian cycle is not in phase with the European cycle.
References


Table 1: Maximum cross-correlations for single countries versus European countries

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Figure 1: Growth rates for European GDP
Figure 2: Rolling Correlation Coefficients for Group 1

Unobserved Components Model  Hodrick-Prescott filter

<table>
<thead>
<tr>
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<td>bel</td>
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Figure 3: Rolling Correlation Coefficients for Group 2

Unobserved Components Model  Hodrick-Prescott filter

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Figure 4: Rolling Correlation Coefficients for Group 3

Unobserved Components Model  Hodrick-Prescott filter

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<tr>
<td>aut</td>
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</table>
Figure 5: Rolling Correlation Coefficients for Group 4

Unobserved Components Model

Hodrick-Prescott filter

Figure 6: Rolling Correlation Coefficients for Group 5

Unobserved Components Model

Hodrick-Prescott filter

Figure 7: Average Correlation Coefficients across European Countries

Unobserved Components Model

Hodrick-Prescott filter
Notes:

Averages of in-phase proportions of explained variance. Smoothing weight for the Hodrick-Prescott filter is 6.25 (Ravn and Uhlig, 2002).

Group 1: Belgium, France, the Netherlands; Group 2: United Kingdom, Norway; Group 3: Austria, Germany, Denmark; Group 4: Finland, Ireland, Sweden, Switzerland; Group 5: Greece, Italy, Portugal, Spain.
Appendix A

Figure A.1: Austria

Figure A.2: Belgium
Figure A.3: Denmark

Figure A.4: Finland
Figure A.5: France

Figure A.6: Germany
Figure A.9: Italy

Figure A.10: Netherlands
Figure A.13: Spain

Figure A.14: Sweden
Figure A.15: Switzerland

Figure A.16: United Kingdom