Perspectives on productivity and business cycles in Europe

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Chapter 3 Business cycle synchronization[34]

3.1 Introduction

One of the main determinants of the success of the European monetary union will be whether the common monetary policy set by the European Central Bank (ECB) is suitable for all member countries. This suitability in turn depends on the degree to which business cycles are synchronized across countries. In setting monetary policy, the ECB can only respond to the average level of economic activity, which can lead to economic and political difficulties for countries that are performing better than the average, but especially, for those that perform worse than the average. The original literature on optimal currency areas (OCAs) argued that if countries are prone to asymmetric shocks, their economies should be flexible enough to absorb these shocks. Mundell (1961) argued that labour migration could be such an absorption mechanism but labour mobility is still less than perfect in Europe.

As a result, research in recent years has examined whether economic and monetary integration will make asymmetric shocks more or less likely. Krugman (1991) argued that with increasing economic integration, specialization would lead to a regional concentration of industries due to agglomeration benefits. In that case, industry-specific shocks will affect some countries more strongly than others. In contrast, the European Commission has argued that more economic and monetary integration will lead to more synchronous business cycles (Emerson *et al.*, 1992), due to, for example, more similar monetary and fiscal policies.

With the increased interest in the determinants of business cycles synchronization, there has also been a growing literature on the measurement of synchronization. Before presenting new empirical results, this chapter starts off by giving an overview of this

[34] This chapter builds on Inklaar and de Haan (2001), de Haan, Inklaar and Sleijpen (2002), de Haan, Inklaar and Jong-A-Pin (2005) and Inklaar, Jong-A-Pin and de Haan (2005). See the acknowledgements for further details.

literature. Part of the overview deals with what types of data have been used, but most attention is devoted to discussing measures of business cycles and synchronization.

To gauge the prospects of Europe's common currency, an obvious starting point is to see whether monetary integration in itself contributes to more similar cycles. Specifically, since the breakdown of the Bretton-Woods system of fixed exchange rates in the early 1970s, there has been a trend towards greater monetary integration within Europe, starting with the Exchange Rate Mechanism (ERM) in 1979 and culminating in the introduction of the euro in 1999. If monetary integration is a dominant determinant of synchronization one would expect the cycles of European countries to have become more similar with no similar development amongst other countries. This issue is taken up in Section 3.2.

To examine the impact of increased economic integration, the United States provides a useful test case. The U.S. has been a monetary union for a long time. Therefore, trends in business cycle synchronization among U.S. states can be revealing about how similar cycles are within a monetary union over time and as a result, it can give some indication of Europe's prospects (Section 3.3).[35]

Up to this point, the discussion about economic and monetary integration has been relatively abstract, while in practice it is a multi-faceted concept reflecting similarities in economic policies, structural features and closeness of trade links. To draw conclusions that are relevant for policy, these different dimensions should be disentangled and their relative importance for business cycle synchronization evaluated. In their seminal paper, Frankel and Rose (1998) show that countries with more intensive trade links have more similar business cycles. Since then, this topic has received increasing attention and a large number of potential determinants has been considered and tested. Section 4 of this chapter analyzes a large set of such variables. The goal is to come up with a robust set of explanatory variables and estimate how monetary union will affect synchronization in Europe.

[35] This is no strict comparison since the period before the U.S. became a monetary union is not analyzed. As a result, differences in the U.S. economic structure relative to the euro area can lead to differences in the eventual synchronization patterns. For example, the greater degree of labour mobility between U.S. states could be an important determinant of synchronization. Despite this, the U.S. experience should still be informative.

The main findings of these analyses are that there is no clear trend in synchronization over time, neither in Europe nor in the United States. This stands in contrast to some earlier studies for Europe, notably Artis and Zhang (1997, 1999), who conclude that a European business cycle is emerging over time. More recently though, research by, e.g. Massman and Mitchell (2004) has shown that periods of greater and lesser synchronization alternate. The U.S. experience is also revealing as it has been a monetary union throughout the period. Indeed, Clark and van Wincoop (2001) established that there is a greater degree of synchronization within the U.S. than within Europe, and this finding is confirmed. Again however, synchronization tends to fluctuate over time. Some economic episodes are shared by nearly all states, such as the Great Depression of the 1930s or the effects of the oil crises of the 1970s but there are also periods of wide divergence in the economic experience of U.S. states. A recent study by Partridge and Rickman (2005) shows that a decline in synchronization among U.S. states in recent decades can be traced to a decline in the volatility of the aggregate U.S. cycle. However, other U.S. research by Kim (1995) shows that specialization across U.S. regions has decreased in recent periods due to more mobile production factors, which presumably has had a positive impact on business cycle co-movement.

The analysis of the determinants of synchronization has more encouraging news for euro enthusiasts. Not only trade intensity, but the similarity of monetary and fiscal policies, the degree of financial integration and the similarity of trade also has a robust positive effect on synchronization and the impact of each of these factors is at least as large as that of trade intensity. Scenarios show that under monetary union these factors will contribute to a greater degree of synchronization. Caution is in order though, as even the most optimistic projections show less than perfect synchronization and there are important uncertainties regarding the similarity of fiscal policy and changes in specialization patterns in the future. This suggests that a reform agenda focusing on flexibility and mobility of production factors is still important and might even stimulate further synchronization due to decreasing specialization.

3.2 Measuring business cycle synchronization

Various studies have looked at the issue of synchronization of business cycles in the euro area, often reaching very different conclusions. Part of these differences can be related to differences in variables used, diverging business cycle measures and methods to assess synchronization. This section therefore deals in turn with the different economic variables that have been considered in previous studies, the differences in the measurement of relevant cyclical information, and different measures of cyclical synchronization.

Data

One obvious reason for differences between studies on business cycle synchronicity is different data sources. The two most important sources are quarterly data on GDP and monthly data on industrial production. In addition, GDP is sometimes decomposed into expenditure categories such as consumption and investment.[36] Annual data is usually avoided to capture more of the high-frequency fluctuations.

Studies of business cycle synchronization should focus on the broadest possible output variable, GDP. In addition, expenditure components can provide further useful information. If, for example, consumption is highly synchronized across countries but government expenditure is not, then one can hypothesize that a large degree of risk sharing between consumers is already taking place, but that fiscal policies are very different. Similarly, correlations between consumption in country A and exports in country B can elucidate the importance of trade links between country A and B.

The conceptual reasoning behind using industrial production is less convincing. First of all, manufacturing activity represents less than 20 percent of aggregate output in the euro zone so a priori it would not seem to be representative of total output. Second, manufacturing output is much more volatile than aggregate output, so the claim to being representative seems even less credible.[37] One could argue that movements in the manufacturing sector are likely to have a more than proportionate impact on GDP since

[36] Some studies, like Angeloni and Dedola (1999), not only look at common output cycles, but also study cyclical movements in consumer prices or stock prices. As the main topic is the level of economic activity, price cycles are not treated here.
[37] Using annual data on value added growth from the GGDC 60-industry database, it can be shown that the standard deviation of annual output growth in the manufacturing sector is more than twice as large as the standard deviation of GDP growth for the euro zone over the period 1979-2003.

sectors such as transport and trade earn their revenues from transporting and trading manufactured goods.[38] Furthermore, the higher frequency at which industrial production data is available, as well as the longer time series is appealing. Still, analysis based on more comprehensive output measures seems preferable to using industrial production.

Measuring business cycles

As discussed in Section 2.2, an important distinction that has to be made is between classical business cycles and growth (or deviation) cycles. In the work by Burns and Mitchell (1946), (classical) business cycles are defined in terms of absolute expansions and contractions of economic activity. Many of the more recent studies, however, look at deviation cycles, or the deviation of economic activity from a 'trend'.

Harding and Pagan (2002, 2005) discuss some of the arguments for both cycle concepts, concluding that the classical cycle should be the relevant measure to be explained by researchers. First, classical cycles are less subjective since no trend has to be identified and second, policymakers are more interested in recessions instead of slowdowns relative to a trend. There is a relationship between classical and deviation cycles since slowdowns generally precede a recession but not every slowdown leads to a recession. However, a practical reason why most researchers focus on deviation cycles is that most (parametric) measures used to describe the cycle need stationary series as input.

Most studies in this literature focus on growth cycles in European countries and a variety of filtering techniques is used to separate trend and cycle. This makes it useful to describe the salient features of these techniques.[39] The most straightforward filtering technique is calculating first differences.[40] Usually, this is sufficient to render the series of interest stationary.[41] However, as, for example, Baxter and King (1999) point out, first differencing does remove a trend from a series, but at the cost of a shift in the peaks and

[38] Indeed, the correlation between manufacturing output growth and GDP growth from the GGDC 60-industry database is 0.9 for the euro zone over the period 1979-2003.
[39] See also, for example, Canova (1998), Zarnowitz and Ozyildirim (2002), and Massmann and Mitchell (2004) for an overview of various filtering methods.
[40] If the original series is expressed in natural logs, first differencing yields growth rates. Various studies employ growth rates (e.g. Frankel and Rose, 1998, Otto *et al.*, 2001 and Kose *et al.*, 2003).
[41] In other words, the moments (mean, variance, etc.) of the series do not depend on time.

troughs of the differenced series and a larger volatility.[42] The phase shift may not be too important when comparing cycles across countries since this phase shift is the same for both countries. However, the larger weight on higher frequencies in the series emphasizes the irregular 'noise' over the cyclical movements.

Canova (1998) and Massmann and Mitchell (2004) discuss a number of parametric methods such as the Beveridge-Nelson decomposition, unobserved component models and simple linear time trends. Since such methods are hardly used in the literature on business cycle synchronization, these will not be discussed in depth. Most studies apply non-parametric filters such as the Hodrick-Prescott (HP, 1997) filter; the Baxter-King (BK, 1999) and Christiano-Fitzgerald (CF, 2003) band pass filters and the phase average trend (PAT, Boschan and Ebanks, 1978).

In general, filters can be viewed as weighted moving averages. For example, first differencing can be interpreted as applying a filter with a weight of one on the current observation and a weight of minus one on the previous observation. Usually, the filters are two-sided, which means that the current value of the trend depends on both past and future values of the series under observation. The use of a two-sided, symmetric filter ensures that there is no phase shift between the original and the filtered series.[43] However, as a result, the trend value near the beginning and end of the sample will be less reliable since part of the moving average cannot be calculated. Quite often this problem is ignored, although the standard programs to calculate the BK filter automatically remove a certain number of observations at the start and end of the series. Another alternative is to forecast and backcast the original series using, for example, an AR process.

Probably the most widely used filter is the Hodrick-Prescott filter. This filter estimates the trend component by minimizing deviations from trend, subject to a predetermined smoothness of the resulting trend:

[42] In other words, first differencing induces a phase shift and puts a larger weight on higher frequencies of the time series.
[43] See, for instance, Baxter and King (1999).

(3.1) $$\min_{y_t^{tr}} \sum_{t=1}^{T} \left(y_t - y_t^{tr}\right)^2 + \lambda \sum_{t=2}^{T} \left(\left(y_{t+1}^{tr} - y_t^{tr}\right) - \left(y_t^{tr} - y_{t-1}^{tr}\right)\right)^2 .$$

In this equation y_t is the original series, y_t^{tr} the estimated trend and λ is the smoothness parameter. Note that this is a two-sided filter in that the current deviation from trend is minimized, subject to the change in the trend from the current period to the next and the change from the previous period to the current. Note also that if λ is set to zero, the 'trend' will simply follow the original series, while if λ is set to infinity, a linear time trend will be estimated.

For quarterly data, Hodrick and Prescott (1997) argue that a standard deviation of the cyclical component of 5 percent is moderately large, just as an 1/8th of a percent standard deviation of the quarterly trend growth rate. Based on these priors, they set λ to 1600 for quarterly frequencies on the assumption that trend and cycle are identically and independently distributed.[44] The problem of choosing appropriate smoothness parameters for data at frequencies other than quarterly has in the past mostly been solved by keeping the 5 percent variability in the cyclical component fixed and scaling the variability of the trend component up or down. So the appropriate λ for annual data becomes 100 and for monthly data 14,400.[45] However, using frequency-domain techniques, Ravn and Uhlig (2002) have shown that the same amount of smoothing is achieved by scaling the quarterly lambda by one over the frequency change to the fourth power. So for annual data, λ becomes $(1/4^4)*1600=6.25$.

As noted before, the HP filter can be viewed as a moving average filter. Specifically, as pointed out by Prescott (1986), the HP filter can be interpreted as a high-pass filter that removes fluctuations with a frequency of more than 32 quarters or 8 years and puts those fluctuations in the trend. Baxter and King (1999) argue that the combination of such a high-pass filter on the one hand and a low-pass filter (which removes high frequencies) on the other is another improvement since the HP filter still leaves much of the high-frequency noise as part of the cycle.[46] The resulting cyclical

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[44] The calculation is $\lambda = (5/0.125)^2$.
[45] Calculated as $(5/0.5)^2$ and $(5/0.0417)^2$, respectively.
[46] Zarnowitz and Ozyildirim (2002) argue that such high-frequency fluctuations are important to determine the exact date of a business cycle peak or trough. This consideration does not seem to be too important for measuring cycle synchronization, though.

component does not contain any fluctuations with high or low frequencies beyond predetermined cut-off points, and this defines a band pass filter. Baxter and King (1999) and Christiano and Fitzgerald (2003) derive approximate band pass filters, using somewhat different assumptions.[47] Although different in details, in both cases the weights for the filter are estimated using frequency domain arguments, but the standard Baxter and King (1999) filter is two-sided, while Christiano and Fitzgerald (2003) advocate a one-sided filter. Christiano and Fitzgerald (2003) also point out though that both filters are quantitatively similar when looking at cyclical statistics.

Baxter and King (1999) suggest using a band pass filter isolating frequencies between 6 and 32 quarters, based on the observation in Burns and Mitchell (1946) that business cycles are generally confined to these frequencies. The analogy is somewhat problematic, however, as the 6 to 32 quarter interval refers to classical cycles, not to growth cycles. Economic variables generally trend upwards, so classical cycles between 6 and 32 quarters will conform to a smaller frequency band for growth cycles (Zarnowitz and Ozyildirim, 2002).

Finally, the Phase Average Trend (PAT) is closely related to the method used to calculate business cycle turning points. The PAT filter, originally proposed by Boschan and Ebanks (1978) and more recently described in Zarnowitz and Ozyildirim (2002), starts off by estimating a 25-quarter moving average. The turning points of the deviations from this trend are dated using the Bry and Boschan (1971) algorithm, which generates classical cycle turning points that closely approximate those selected by the NBER Business Cycle Dating Committee. Finally, the trend is estimated by connecting the mean values between each cyclical peak. Although the OECD uses this filter for their business cycle indicators, not many studies apply this filter. However, Zarnowitz and Ozyildirim (2002) show that the PAT filter gives similar turning points as other filters such as the HP and the BK band pass filter. Artis and Zhang (1997) and Calderon *et al.* (2002) also conclude that the choice of filtering method is not crucial for their conclusions. Massmann and Mitchell (2004, p. 303), who consider the largest number of filtering methods, conclude that "our examination of convergence between euro area business

[47] An ideal band pass filter would need a time series of infinite length, so an approximation is always necessary.

cycles indicates that there are substantive similarities across alternative measures of the business cycle." This finding is remarkable since Canova (1998) concluded that different cycle filtering methods lead to different conclusions regarding business cycle facts in the U.S. These findings are not mutually exclusive, since Canova compares different filters within a country, while Massmann and Mitchell and others compare the results from different filters across countries. So although the various filters may indeed "extract different types of information" (Canova 1998, p. 475), the findings are similar when comparing this information across countries.

In summary, studies that use standard filters such as the HP, BK and CF filters are likely to yield similar results as long as the same data are used. These three filters also perform reasonably well in isolating fluctuations in the data of certain frequencies, which after all is the most important goal of filtering. Using first differences is likely to lead to larger problems, as it puts too much weight on high-frequency fluctuations.

A quite different approach to extracting cyclical information is by estimating Markov switching models. These models, first used in this setting by Hamilton (1989) allow the economy to 'switch' between expansions and recessions. The probability of being in recession can then be compared across countries to gauge the commonality of business cycles across countries. This methodology is relatively less established for comparing business cycles across countries, but Artis, Krolzig and Torro (2004) implement this method in a recent study.

Another comparatively new method is the one proposed by den Haan (2000). His approach to analyzing the co-movement between series is to study the forecast errors from a VAR that includes (at least) the two series of interest. This way, the dynamics and possible cointegration of the series can be taken into account. Up until now, only Camacho *et al.* (2005) have used this method.

Synchronization measures

Given a certain measure of the cycle, the important question arises to what extent these cycles move together across countries. Most studies use simple (Pearsson) correlation coefficients of the cyclical part of GDP to answer this question, but other measures have been suggested in the literature as well, like the dynamic correlation measure of Croux, Forni and Reichlin (2001), the phase-adjusted correlation of Koopman and Azevedo (2003) and the concordance index of Harding and Pagan (2002).[48]

The measures suggested by Croux *et al.* (2001), Koopman and Azevedo (2003) and Harding and Pagan (2002) require some more discussion. The dynamic correlation measure of Croux *et al.* (2001) is defined as the co-spectrum between two series over the product of the spectra of each series. The authors then go on to define this measure over a certain frequency band, i.e. fluctuations in the series with a certain period. They show that for time series with an infinite number of observations, the dynamic correlation between two series over a frequency band is equal to the regular correlation between two band pass filtered series. For finite time series this equality does not hold in general as both the band pass filter and the dynamic correlation are estimated imperfectly. Despite this, it is likely that the two measures will be quite close in practice. Croux *et al.* (2001) suggest that for more than two series, one should look at the cohesion of these series. The authors define cohesion as the (weighted) average of the binary dynamic correlation coefficients. This measure provides a useful summary statistic on the degree of co-movement within a group of countries by avoiding the problem of choosing a base country. Still, the full distribution of correlation coefficients as for example plotted in Massmann and Mitchell (2004) provides even more useful information.[49]

Koopman and Azevedo (2003) estimate an unobserved components model that accounts for time-varying phase differences as well as a time-varying relation between cycles. Although unobserved components models can also be used to distinguish trend and cycle, Koopman and Azevedo (2003) take band pass filtered series as input. Their method refines standard contemporaneous correlations between cyclical components in two ways, first by separating the contemporaneous correlation into a part due to differences in the position on the cycle of two countries (phase shift) and a 'phase-shift'

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[48] Belo (2001) also applies Spearman rank correlations. Camacho *et al.* (2005) use the simple average of various measures (including those of Forni *et al.* (2001), Harding and Pagan (2002) and den Haan (2000)), yielding what they call a comprehensive measure of distance.

[49] More recently, Hughes Hallett and Richter (2004) discuss a measure of business cycle coherence that is similar in spirit to the dynamic correlation of Croux *et al.* (2001). The main innovation is that Hughes Hallett and Richter (2004) allow for time variation in their estimated spectra. This not only allows them to judge how strongly two countries co-move at a certain frequency, but also how this degree of co-movement changes over time. The drawback is that it is as yet hard to gauge how statistically important some of these changes are.

adjusted correlation. Second, they allow for time variation in both the phase shift and the phase-shift adjusted correlation. Although this last innovation seems valuable, they can only practically implement their method by imposing a monotone time function. In other words, the correlation can either go up over the sample period, or it can go down. While this provides useful information, visual inspection of their cyclical component series suggests that periods of stronger and weaker correlation alternate. Furthermore, the finding that the correlation between the cyclical components of each country versus the euro area is around 0.90 near the year 2000 seems puzzling when compared to the results using other methods in studies like Massman and Mitchell (2004), or the estimates presented in the next section.

The concordance index proposed by Harding and Pagan (2002) is a non-parametric co-movement measure that uses a binary indicator variable of recessions and expansions. Referring to this indicator variable for country *x* at time *t* as S_{xt}, the concordance index is defined as:

(3.2) $$I_{x,y} = \frac{1}{T}\left(\sum_{t=1}^{T} S_{xt}S_{yt} + \sum_{t=1}^{T}(1-S_{xt})(1-S_{yt})\right).$$

Put differently, this index measure the percentage of the time where the two series are in the same state. The index is in some ways more flexible than the correlation coefficient since any method for distinguishing between recessions and expansions can be chosen. While the correlation between series of GDP levels will in general be spurious due to the strong trend in those series, classical recessions can be dated from these level series and the concordance index can be calculated. A drawback is that analyzing a binary variable throws away potentially useful information. Still, the concordance index can be a useful complement to correlation measures between detrended series as well as providing a useful measure to analyze classical cycles. Artis, Marcellino and Proietti (2002) provide a related perspective by looking at diffusion indexes. Such a diffusion index for say the euro area, measures the share of countries that are in a recession if the euro area as a whole is in recession. Such indexes can also be modified to measure the share of above-trend countries or countries with positive growth. While the concordance index seems useful to summarize bilateral co-movement between two series, diffusion indexes can provide insight in the co-movement within an aggregate at each point in time.[50]

Most co-movement measures are judged by their characteristics and not so much by economic reasoning. An exception is the work by Kalemli-Ozcan, Sørensen and Yosha (2001), who compare utility under autarky, where the consumption possibilities are constrained by the country's own GDP, and utility under full cross-country risk sharing. In the latter case, consumption possibilities are equal to a fraction of total GDP in the area in which risk sharing takes place.[51] Moving from autarky to full risk-sharing will generally bring utility gains and Kalemli-Ozcan *et al.* (2001) derive the following measure for these gains when assuming log-utility:[52]

$$(3.3) \qquad G^i = \frac{1}{\delta}\left(\frac{1}{2}\sigma^2 + \frac{1}{2}\sigma_i^2 - \mathrm{cov}^i\right),$$

where δ is the intertemporal discount rate, σ^2 is the variance of output growth in the entire economic area, excluding country *i*, σ_i^2 is the variance of output growth in country *i* and cov^i is the covariance between output growth in country *i* and the rest of the economic area. This measure states that the gains from risk-sharing for country *i* will be larger when the standard deviation of GDP growth in country *i* is higher, when the standard deviation of GDP growth in the rest of the risk-sharing area is larger and when the covariance between country *i* and the rest of the area is smaller. The interpretation of this negative sign on the covariance is straightforward as joining an area with largely unrelated fluctuations will provide more insurance by stabilizing aggregate output. Furthermore, the higher the standard deviations of growth, the more is gained by sharing risk.

This measure also focuses attention on an issue that is often ignored when looking at business cycle synchronization. Asynchronous business cycles are assumed to be costly for a monetary union since the common monetary policy will not fit all countries. However, as the analysis by Kalemli-Ozcan *et al.* (2001) makes explicit, transfers of

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[50] Note that diffusion indexes are also used widely in the study of business cycles within a country, amongst others by The Conference Board for the U.S. Leading Index.

[51] In the first case consumption possibilities are equal to GDP_i, and in the second case they are equal to a (long-run) share of total GDP in the currency area.

[52] The authors also consider a constant relative risk aversion (CRRA) functional form for utility. The resulting expression for risk-sharing gains is more complicated, but the intuition is similar.

income across countries could increase aggregate utility and more so with asynchronous business cycles.[53] Interestingly, equation (3.3) bears close resemblance to the correlation coefficients that are often used in the study of business cycle synchronicity since the standard deviations of the two series and the covariance between the series are the main components of both equation (3.3) and of the standard correlation coefficient.

A related problem is how to judge the change in co-movement between cycles over time. The simplest solution is to compare correlations in two periods, for example, before and after the establishment of the ERM (Artis and Zhang, 1997, 1999), or for multiple periods as in Inklaar and de Haan (2001). A more general and less arbitrary approach is to use rolling windows as in Massmann and Mitchell (2004).

Summing up, depending on the purpose, many different methods can be used to measure the amount of co-movement between two countries. In the introduction it has already been spelled out that the main issue is to see whether business cycles in the euro area are similar enough to justify a common monetary policy, whether the similarity has increased over time and which factors can help predict the similarity in the future. Indeed, the simplicity of the correlation coefficient is one its strongest advantages: the main question of interest is whether monetary policy will be suited to a currency area at a point in time. Decomposing co-movement into in-phase and out-of-phase components as in Koopman and Azevedo (2003) may provide interesting information, but it is not very useful from the point of view of the suitability of a common monetary policy.

3.3 Synchronization trends in OECD countries

Although the previous section demonstrated that there are many ways to analyze the co-movement of economic activity across countries, for the empirical analysis it makes sense to consider a more manageable set of indicators. The most commonly used indicator is the correlation coefficient between detrended measures of economic activity. The choice of detrending method is generally not crucial for the results, so here the Baxter-King band pass filter is used.[54] Following the discussion in the previous section

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[53] This obviously abstracts from political considerations that could hamper the adoption and operation of such a risk-sharing scheme.

[54] Following Baxter and King (1999), cyclical frequencies are defined as fluctuations between 6 and 32 quarters.

about selecting a measure of economic activity, there is a clear trade-off between GDP and the index of industrial production (IIP) in terms of the scope of coverage and the frequency and length of the time series. Therefore, results based on both measures will be presented.

As the ECB takes the business cycle of the euro area into account when making monetary policy decisions, the most obvious first question is how similar the business cycles of euro area countries are to the aggregate euro area cycle. The analysis is performed using data on quarterly GDP and monthly industrial production for 21 OECD countries between 1970 and 2003, including all euro area countries except Luxembourg.[55] Most of the GDP series are directly from the OECD *Quarterly National Accounts*. These data were supplemented with series from Eurostat and national statistical offices to get the maximum number of observations.[56] The source of the industrial production data is the OECD *Main Economic Indicators* publication. Chapter 1 already showed those results for the period 1999-2003, but the next step is to see whether the degree of synchronization has changed over time, especially compared to countries that are not part of the euro area. One complication for comparisons of EMU members to the euro area aggregate is that these countries are part of the aggregate. To avoid this bias, correlations are calculated relative to the aggregate excluding the country in question.[57]

While the degree of monetary integration has generally increased since 1970, a number of periods can be distinguished with relatively distinct exchange rate behaviour. In the early 1970s, the Bretton-Woods system of fixed exchange rates broke down and until 1979, only relatively informal exchange rate arrangements were in place. From 1979 onwards, the Exchange Rate Mechanism (ERM) started to function, but especially in early years there were still frequent changes in parities. From about 1987 onwards, these

[55] In addition to these eleven euro area countries, Australia, Canada, Denmark, Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom and the United States are included. In the case of Australia, New Zealand and Switzerland, only quarterly industrial production data is available. Therefore, all correlations for these countries are calculated using quarterly data.

[56] Specifically, Eurostat data was used for Denmark, Italy, Norway, Sweden and Switzerland. For Japan data was used from the Cabinet Office (SNA68 series), for Spain from INE (SNA68 series) and for Canada from Statistics Canada.

[57] To facilitate this, changes in the euro area aggregate are defined as changes in the GDP-weighted average of the individual countries for both quarterly GDP and industrial production. In case of GDP, there are missing observations for a considerable number of countries in the early 1970s. For estimating the aggregate, the OECD estimate of quarterly euro area GDP is substituted for these countries.

occurred much less often, with the exception of the currency upheavals of 1992. The obvious starting point for the final period is 1999, at the introduction of the euro.

Table 3.1 Business cycle synchronization of 21 OECD countries with euro area aggregate, 1970-2003

	All countries				*Euro area countries*			
	1970:Q1-1979:Q2	1979:Q3-1987:Q3	1987:Q4-1998:Q4	1999:Q1-2003:Q4	1970:Q1-1979:Q2	1979:Q3-1987:Q3	1987:Q4-1998:Q4	1999:Q1-2003:Q4
A: Summary statistics								
GDP								
Average	0.68	0.58	0.45	0.52	0.61	0.68	0.70	0.65
Standard deviation	0.13	0.27	0.36	0.43	0.14	0.21	0.18	0.36
Minimum	0.43	-0.28	-0.20	-0.57	0.43	0.38	0.34	-0.26
Maximum	0.83	0.90	0.88	0.98	0.83	0.90	0.88	0.98
Industrial production								
Average	0.74	0.55	0.52	0.65	0.73	0.53	0.62	0.76
Standard deviation	0.20	0.29	0.30	0.35	0.24	0.33	0.24	0.29
Minimum	0.36	-0.08	-0.26	-0.11	0.36	-0.08	0.25	0.02
Maximum	0.97	0.87	0.92	0.99	0.95	0.87	0.92	0.99
B: Number of significant changes over previous period								
GDP								
Increases		1	4	3		1	3	3
Decreases		0	2	2		0	0	2
Industrial production								
Increases		0	3	9		0	2	5
Decreases		9	5	1		6	2	0

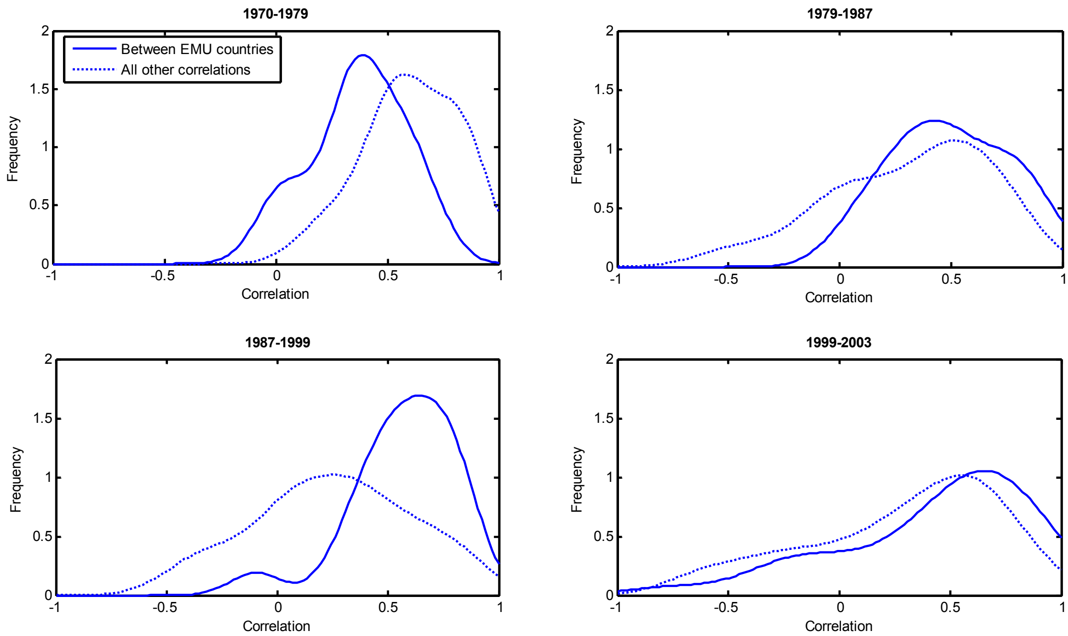
Notes: Based on correlations between detrended output in 21 OECD countries, including all euro area countries except Luxembourg, and the euro area aggregate. The non-EMU countries are Australia, Canada, Denmark, Japan, New Zealand, Norway, Sweden, Switzerland, United Kingdom and United States. In case of euro area countries, the correlation is computed excluding the country itself. In panel B, a correlation changes significantly when the 95% confidence intervals in two periods do not overlap.

Table 3.1 shows the resulting development of synchronization with the euro area over time. Panel A presents some summary statistics, both for all countries and for the subset of euro area countries. To get an indication about the importance of some the changes, Panel B shows how many countries had significantly higher or lower correlations compared with the previous period.[58] As the table makes clear, there is no clear trend in synchronization over time for either measure of output and while the correlations are generally positive, some are quite small. The correlations for the euro

[58] To be precise, a correlation coefficient changes significantly from one period to the next if the 95% confidence intervals do not overlap.

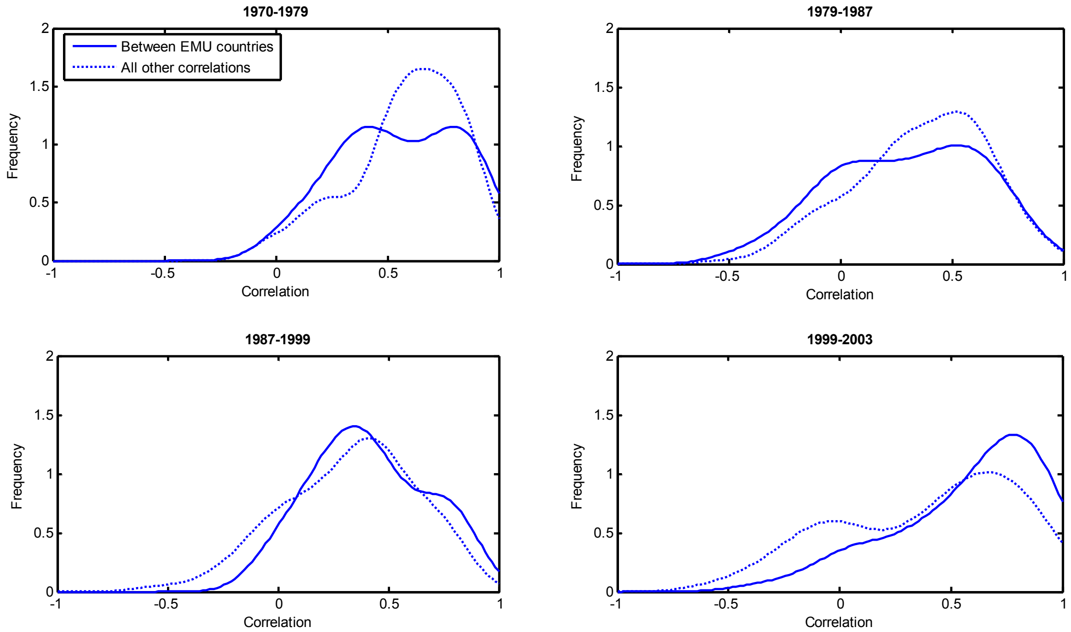
area countries are somewhat higher than the overall average, but the differences are not very large and there has only been a modest increase in the difference over time. In this respect it is remarkable that the GDP-based correlation has gone down after the start of EMU, while the correlation based on industrial production has gone up. As further evidence, the number of significant increases is not clearly larger than the number of decreases. For example, after 1999, the correlations based on industrial production increased significantly in five euro area countries, but also in four non-EMU countries. These results are akin to the conclusions by Artis (2003), who finds that there is no clear, overwhelmingly European business cycle.

Figure 3.1 Density estimates of bilateral output correlations, GDP 1970-2003



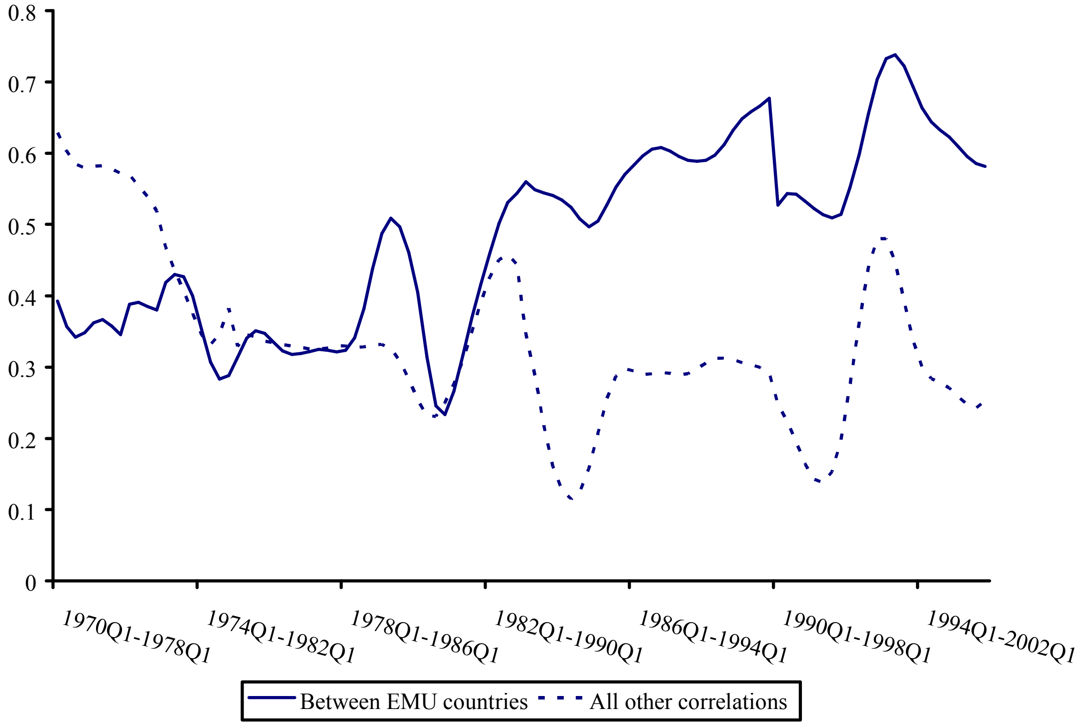
There are two obvious objections to the analysis underlying Table 3.1. First of all, although the correlations with the euro area as a whole may not show a clear pattern, a core group of euro area countries may have similar business cycles (see e.g. Forni and Reichlin, 2001). The other potential problem is that the results in Table 3.1 may not be robust to changes in the periodisation. To address the first issue, Figures 3.1 and 3.2 show kernel density estimates of bilateral correlations for the same periods as Table 3.1, while Figures 3.3 and 3.4 plot the average bilateral correlation for a moving window. The estimated densities are basically refined histograms, showing the frequency of different values of correlation coefficients.

Figure 3.2 Density estimates of bilateral output correlations, industrial production 1970-2003



If there is a core group of countries with high bilateral correlations, or if this group developed over time, a bimodal distribution for the correlations between EMU countries would show up in Figures 3.1 and 3.2. These figures show the distribution of bilateral correlations for country couples that are both EMU members, and the distribution for all other country couples (i.e. couples where at least one country is not an EMU member). However, the evidence for bimodality is by no means obvious. What does stand out in both figures is that in the period from 1970 to 1979, correlations amongst EMU countries were generally lower than all other correlations. This picture changed during the late 1980s. In the 1987-1999 period for GDP (Figure 3.1), the EMU countries were clearly more correlated amongst each other, than country couples that were not both EMU members, but for industrial production (Figure 3.2) the picture is not so clear. The pattern for GDP also did not hold clearly after 1999.

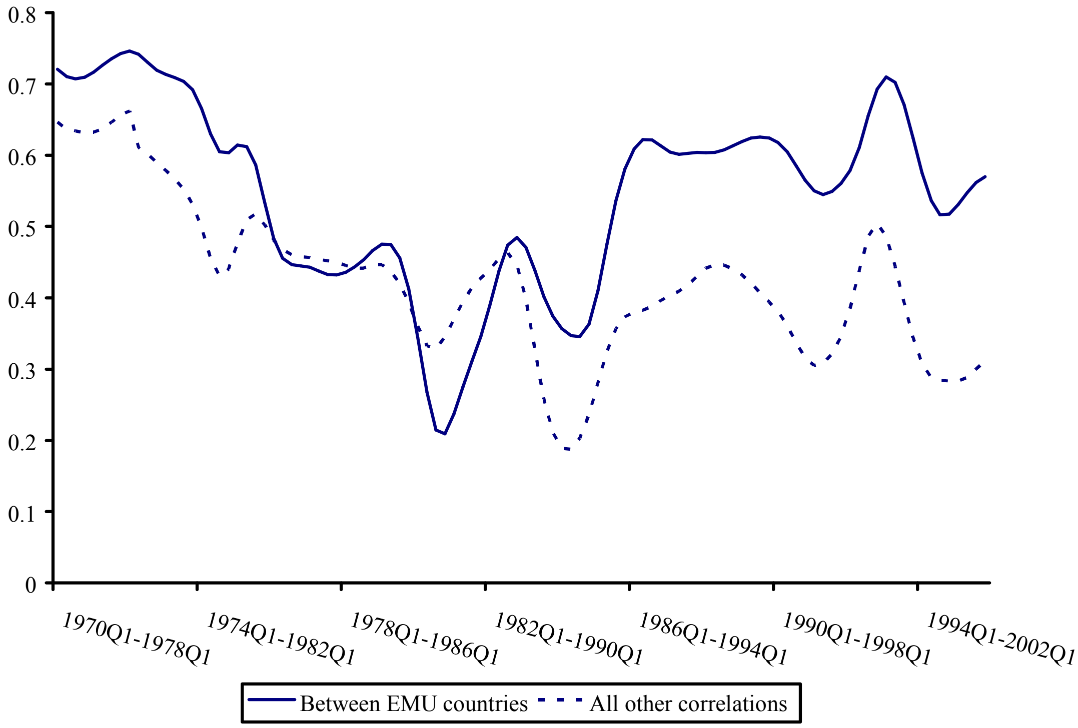
Figure 3.3 Average bilateral correlation between EMU countries and all other correlations for an 8-year moving window, GDP 1970-2003



Figures 3.3 and 3.4 provide somewhat clearer evidence. Both figures chart the average bilateral correlation for 8-year moving windows, Figure 3.3 for GDP and 3.4 for industrial production. Again, a distinction is made between correlations of EMU countries and all other correlations. The average correlation fluctuates, sometimes substantially, but since the mid-1980s, EMU correlations have on average been higher than non-EMU correlations for both output measures.[59] Still, Figures 3.1 and 3.2 showed that the distribution of correlations is quite wide and even an average correlation of 0.60 means that there has been quite some heterogeneity in the cyclical experience of euro area countries.

[59] The average correlation for EMU countries in Figure 3.3 dropped substantially around 1990. This can be traced to Portugal, which did not have a long enough time series of quarterly GDP data for earlier periods. These sample imbalances are less an issue for industrial production, as only data for Denmark and Ireland do not stretch back to 1970, but 1974 and 1975, respectively.

Figure 3.4 Average bilateral correlation between EMU countries and all other correlations for an 8-year moving window, industrial production 1970-2003



3.4 Synchronization trends in U.S. states

The past experience of euro area countries may not be representative for the future. For much of the period since 1970, monetary policy has not been coordinated and exchange rates fluctuated wildly at times. Also, the period since 1999 may simply be to short as no full business cycle has occurred since then. Indeed, the full effects of a monetary union will take even longer to materialize, as, for example, production may take a long time to concentrate geographically. To evaluate the effects of monetary union, we need to turn to an area that has already been a monetary union for many decades.

The United States is a good candidate as it is similar in size to the euro area and it is also a developed country. Ever since 1935, all monetary policy decisions have been in the hands of the Federal Reserve and before that, a common currency was in use and individual states could not hamper inter-state commerce. Technological progress over the past century has reduced the cost of transport and communications, which may have made regional specialization more attractive over time.[60]

To analyze long-run trends in business cycle synchronization, state personal income is the only available measure. Gross state product (the state analogue of GDP) is only available from 1977 onwards on a consistent basis, while employment data go back to 1969. In contrast, the personal income data from the U.S. Bureau of Economic Analysis (BEA) are available from 1929 onwards.[61] No price data is available at the state level, so instead the implicit GDP deflator is used.

Table 3.2 Business cycle synchronization of personal income in U.S. states with U.S. aggregate personal income, 1929-2004

	1929-1947	1948-1966	1967-1985	1986-2004	1929-1966	1967-2004
Summary statistics						
Average	0.88	0.67	0.76	0.68	0.85	0.72
Standard deviation	0.08	0.22	0.19	0.22	0.09	0.18
Minimum	0.61	0.11	0.17	0.07	0.54	0.25
Maximum	0.97	0.93	0.96	0.94	0.96	0.92
Number of significant changes over previous period						
Increases		0	3	0		0
Decreases		5	0	0		7

Notes: Based on correlations of annual state personal income for U.S. states excluding Alaska and Hawaii, including the District of Columbia. Personal income is deflated using the U.S. GDP deflator and detrended with the Baxter-King band pass filter (fluctuations between 1 and 8 years). Each state's cycle is correlated to the U.S. aggregate, excluding the state in question. A correlation changes significantly when the 95% confidence interval of the coefficients in one period does not overlap the interval in the next period.

Table 3.2 shows the results for a number of different periods. As there have been no major shifts in the degree of monetary integration, the period is first divided into four periods of equal length and next divided into two periods. As the table makes clear, the average correlation was highest in the first period, 1929-1947, which included both the Great Depression and the wartime economic boom. The minimum correlation of 0.61 in this period is another indication that this was a period of relatively homogenous

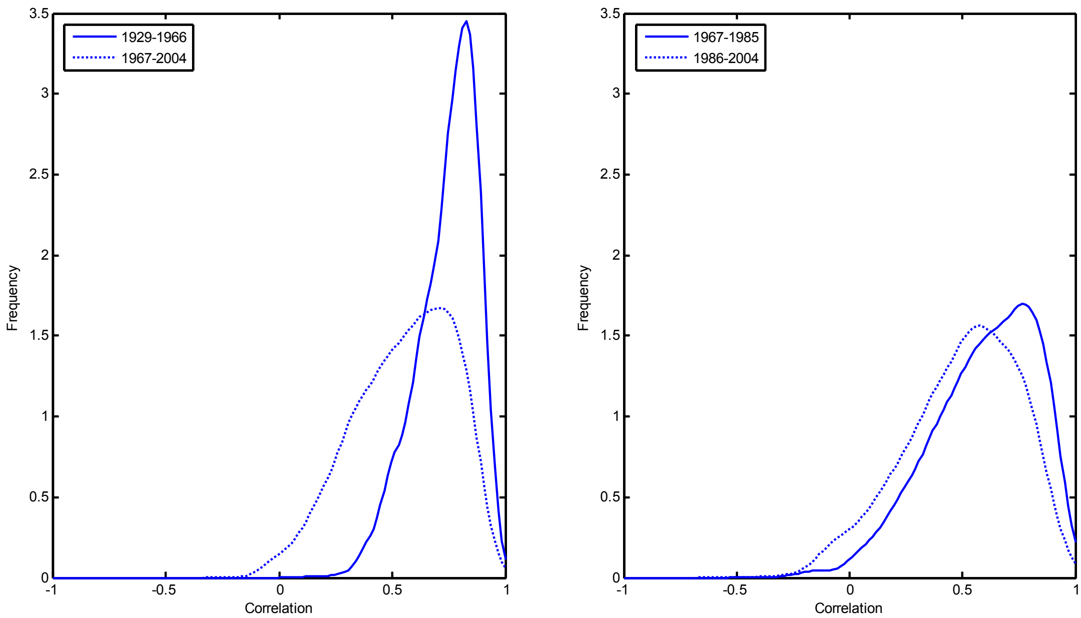
[60] See also Sleijpen (2001) for more on the United States as a monetary and fiscal union.

[61] The personal income measure in the U.S. national accounts includes household income from all sources, including government transfers as well as income of non-profit institutions. As such, it covers around 80 percent of GDP.

economic performance across states. The post-war periods shows much greater divergence with a lower average correlation and a greater spread. The bottom panel of the table shows that there have been relatively few significant changes in correlation: of the 49 states covered,[62] only seven or eight showed a significant change. Compared to the results in Table 3.1, the cycles of U.S. states after 1948 are not much more similar than the business cycles of countries in the euro area.

Again, similar criticisms can be raised about the possible cluster formation (for example in certain regions) and the arbitrary periodisation. Figure 3.5 shows density estimates of the correlations for each couple of states. The chart on the left-hand side compares the period up to 1966 to the period afterwards, and the right-hand side divides the 1967-2004 period in two. These charts show a comparable pattern to that seen in Table 3.2 with a very high degree of synchronization in early periods and lower synchronization from around 1970 onwards. Compared to Figures 3.1 and 3.2 though, the spread of bilateral correlations is smaller in case of the U.S. states.

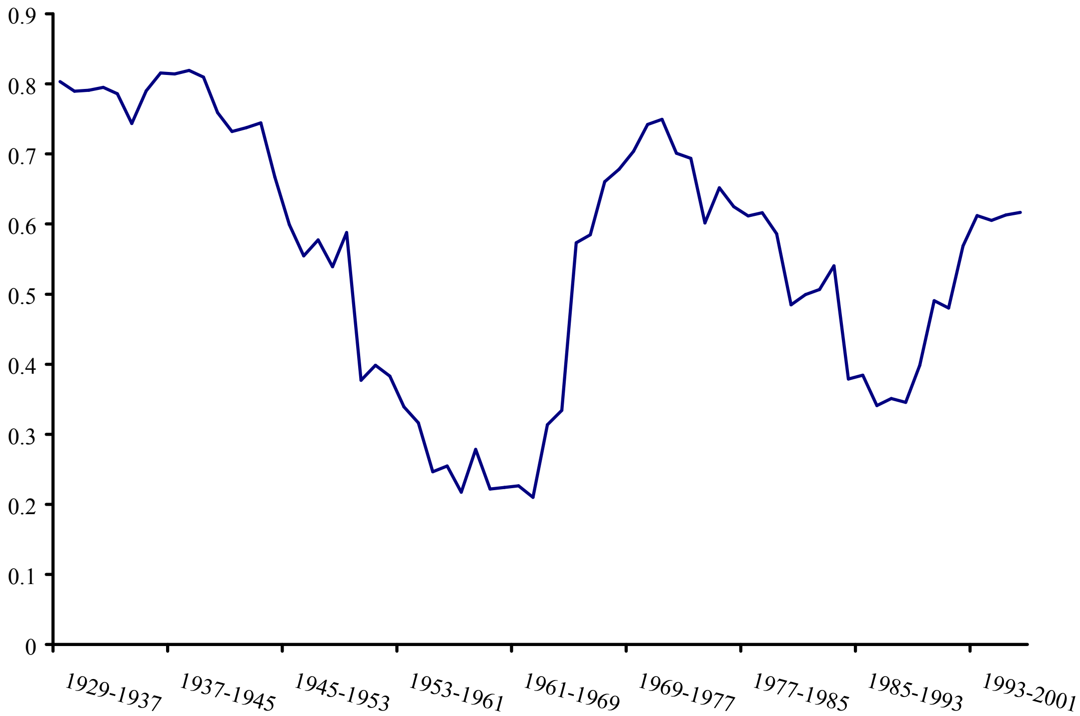
Figure 3.5 Density estimates of the bilateral personal income correlations, 1929-2004



[62] Alaska and Hawaii are excluded because they have not been part of the Union since 1929. The District of Columbia is included.

Figure 3.6 addresses the issue of periodisation. All bilateral correlations are calculated for each 8-year period between 1929 and 2004 and the average is plotted. The figure shows considerable variation with average correlations fluctuating between 0.2 and 0.8. The pattern is also broadly comparable to that shown in Table 3.2. The figure suggests economy-wide developments, such as the Great Depression and the following wartime boom, or the oil crises and economic stagflation in the 1970s and early 1980s have similar effects across most states. However, there are also periods where divergence is much greater.

Figure 3.6 Average bilateral correlation between U.S. states for an 8-year moving window, personal income 1929-2004



In summary, the U.S. experience suggests that a monetary union is no guarantee for perfectly synchronized business cycles and economic integration does not inexorably lead to more similar business cycles. Even though the average correlation seems to be somewhat higher amongst U.S. states than between euro area countries, the differences are not large. The development over time suggests that there are periods where U.S.-wide developments dominate, such as the Great Depression, but also that there are periods of greater divergence across states. This is in line with the results of Partridge and Rickman

(2005), who find that co-movement between states has decreased since the late 1960s due to a less volatile aggregate economy.[63]

3.5 The determinants of synchronization

Since the seminal paper of Frankel and Rose (1998), the search for determinants of business cycle synchronization has taken a great flight. However, these studies cannot agree on more than the original finding by Frankel and Rose (1998) that more intensive trade links between two countries stimulates synchronization.[64] The analysis in this section builds on this literature and first focuses on finding a set of robust explanatory variables. This analysis is comparable to the Extreme Bounds Analysis of Baxter and Kouparitsas (2004), but covers 21 OECD countries and considers a more extensive list of potential explanatory variables. Furthermore, instead of the very restrictive criterion for robustness of Leamer (1983), the criterion of Sala-i-Martin (1997) is followed.[65]

Once a set of robust explanatory variables is identified, the remainder of the section focuses on estimating a model for synchronization that incorporates these variables and analyzing the implications for EMU. This analysis makes a number of contributions to the literature. First of all, as the density estimates of Figures 3.1 and 3.2 already showed, correlation coefficients are skewed and hence, not normally distributed. For valid inference in the regressions, the correlation coefficients are transformed, so that they are no longer bounded between -1 and 1.

Second, the issue of endogeneity of trade is dealt with in a more substantive way than in previous studies. The basic problem here is that countries with intense trade relations are more likely to link their currencies, either explicitly or implicitly. This implies that these countries will have similar monetary policies – and possibly other policies – that may synchronize their business cycles. So it is not only trade that causes the business cycles to be correlated but also the similarity of economic policies. Neglecting these other variables in the regression specification renders the trade

[63] The correlation of output between two states will *ceteris paribus* be lower if shocks that are common to both states, such as U.S.-wide shocks are less common. See e.g. McConnell and Perez-Quiros (2000) or Stock and Watson (2003) for more on the decreased volatility of the U.S. economy.
[64] For a survey of research into the determinants of synchronization, see de Haan, Inklaar and Jong-A-Pin (2005).
[65] See Appendix 3.A for more details.

coefficient biased and inconsistent. Frankel and Rose (1998) and most subsequent studies therefore employ instrumental variables estimation, using gravity variables as instruments. However, this is not an adequate solution, since the gravity variables are likely to affect other variables that influence business cycle synchronization as well, like participation in a currency union. This problem is avoided by estimating a multivariate model, including policy variables as well as structural characteristics.

The third topic is the effect of specialization on business cycle synchronization. If the degree of specialization between two countries is high, most trade will be inter-industry, and industry-specific shocks will lead to diverging business cycles. However, a dominant role for intra-industry trade can explain the positive association between trade and synchronization that has been found in the literature. Despite these theoretical arguments, this issue has received only scant empirical attention. Gruben *et al.* (2002) include inter-industry and intra-industry trade in their business cycle synchronization model and claim that the effects of both variables are different. However, this conclusion is based on unreliable estimates as the correlation between inter- and intra-industry trade is very high. Imbs (2004) accounts for the effect of inter-industry trade by including a measure of industrial specialization. The approach taken here is similar, but in addition to industrial structure, the structure of overall exports and the share of (bilateral) intra-industry trade are used to test the theoretical foundations of the trade relationship more directly.

The final issue is to what extent the relationship between trade intensity and business cycle synchronization is robust across different country pairs. Is the effect of trade on business cycle synchronization the same for country pairs that are already highly synchronized, like Germany and the Netherlands, and countries which are not, like for example Germany and Japan? Or is the effect of trade on business cycle correlations driven by (outlying) country pairs such as the US and Canada? To examine the importance of sample heterogeneity and outliers, the methods of quantile regressions and least-trimmed squares are employed, respectively.

The main findings are the following. Trade intensity is found to affect business cycle synchronization, but the effect is much smaller than reported by Frankel and Rose (1998) and Hausman (1978) tests show that in the multivariate models, estimation using ordinary least squares is no longer inconsistent. Furthermore, apart from the level of trade, specialization has a strong impact on business cycle synchronization. In addition, similar monetary and similar fiscal policies have a positive impact on business cycle synchronization. The impact of these factors on business cycle synchronization is about as large as the impact of trade intensity. Finally, the results suggest that the effect of trade on business cycle synchronization does not suffer from sample heterogeneity and is robust for outlying observations.[66]

The remainder of the section is organized as follows. First, the methodology and the data sources and methods are described. Thereafter, the estimation results are presented and the economic relevance of the findings is discussed. The final part shows the results of the quantile and least trimmed squares regressions.

Methodology

Theoretically, trade intensity has an ambiguous effect on the co-movement of output. Standard trade theory predicts that openness to trade will lead to increased specialization in production and inter-industry patterns of international trade. If business cycles are dominated by industry-specific shocks, trade-induced specialization leads to decreasing business cycle correlations.[67] However, if trade is dominated by intra-industry trade industry-specific shocks may lead to more symmetric business cycles. Furthermore, in case of intensive trade relations economy-wide shocks in one country will generally have an effect on demand for goods from the other country.

The question how to disentangle the effect of intra-industry and inter-industry trade has been dealt with in different ways in the literature. Imbs (2004) includes an industrial specialization measure to capture the impact of inter-industry trade. Gruben *et al.* (2002)

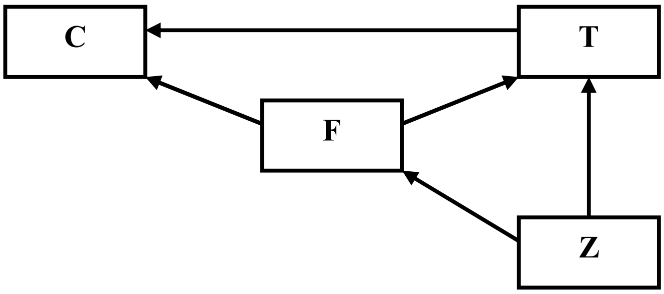
[66] The paper that comes closest to the analysis here is Imbs (2004), who also finds that the effect of trade on business cycle synchronization is less than that reported by Frankel and Rose (1998). There are, however, a number of important differences between both studies. The methodology is quite different as the primary interest is in the effect of trade intensity on output correlation. Furthermore, a much longer list of potential determinants of business cycle synchronization is analyzed here. Imbs (2004), for instance, does not take the role of monetary and fiscal policy into account, which is found to be important. Imbs also does not examine how sensitive his findings are for sample heterogeneity and outliers.

[67] However, as pointed out by Frankel (2004), a positive shock at one point in the chain of value added in a country will tend to have positive spillover effects at the other points along the chain in other countries. Thus trade in intermediate products gives rise to positive correlations but may be recorded as inter-industry trade.

take a more direct approach and split up trade in inter- and intra-industry trade. In a regression in which both intra-industry and inter-industry trade are included, they find that intra-industry trade has a positive effect and that the effect of inter-industry is insignificant. An important problem with this approach is that intra-industry trade is highly correlated with inter-industry trade; in the dataset used here, this correlation is 0.82. This means that including both variables simultaneously leads to serious multicollinearity problems. Therefore the approach of Imbs (2004) is followed and his solution is taken one step further. Instead of relying only on specialization measures based on industrial structure, measures based on the structure of exports, and the share of intra-industry trade are also used. These measures will be discussed in more detail below.

Frankel and Rose (1998) acknowledge the possible contrasting effects of inter- and intra-industry trade on business cycle synchronization, but focus on the net effect of total trade on output co-movement. However, even identifying the net effect of trade is not straightforward since trade intensity is endogenous, which makes an OLS regression of business cycle synchronization on trade intensity inappropriate. Frankel and Rose (1998) deal with this problem by using gravity variables (distance, border dummy, common language dummy) as instruments to identify the effect of trade on business cycle correlation. However, as pointed out by Gruben *et al.* (2002), this is not appropriate if the gravity variables (Z) not only affect bilateral trade intensity (T) but are also possibly related to some other variables (F) that affect business cycle synchronization (C), as illustrated in Figure 3.7. For instance, neighbouring countries are more likely to coordinate their monetary policies, or even to have a common currency, than countries that are further away from each other. In turn, the introduction of a single currency will contribute to reducing trading costs both directly and indirectly, e.g., by removing exchange rate risks (and the cost of hedging) and diminishing information costs (De Grauwe and Mongelli, 2005).

Figure 3.7 The Relationship between business cycle correlation (*C*), trade (*T*), gravity variables (*Z*) and other variables (*F*)



The regression model that corresponds to the figure above is:

$$\begin{aligned} &C = \beta_1 T + \beta_2 F + \varepsilon \\ (3.4)\quad &T = c_1 Z + c_2 F + \nu \;. \\ &F = c_3 Z + \omega \end{aligned}$$

The model shows that the business cycle correlation depends on bilateral trade as well as other policy-related and structural variables. Some of these variables may be influenced by the exogenous gravity variables, while in turn affecting trade intensity. Broadly speaking, these variables can be grouped into the following categories: (1) specialization (see, e.g., Imbs, 2004); (2) monetary integration (see, e.g., Rose and Engel, 2002); (3) financial integration (see, e.g., Imbs, 2004); and (4) similarity of fiscal policies (see, e.g., Clark and van Wincoop, 2001). Apart from these variables many others have been suggested that may be related to business cycle synchronization (see chapter 6 in De Haan, Eijffinger and Waller (2005) for an extensive discussion).

To identify the other variables to be included in the model, an Extreme Bounds Analysis is used to examine which variables are robustly related to business cycle synchronization in the OECD area, following Baxter and Kouparitsas (2004). Using a much longer list of potential explanatory variables than examined by Baxter and Kouparitsas a number of robust variables are identified, including the similarity of monetary policy (proxied by the correlation of short-term interest rates) and the similarity of fiscal policy (proxied by the correlation of cyclically-adjusted budget deficits). In contrast to Baxter and Kouparitsas (2004) the robustness criteria of Sala-i-Martin (1997) are used since Leamer’s (1983) EBA is extremely restrictive. Appendix Table 3.1 shows the variables that have been used in the analysis and whether they are robust explanatory variables of the business cycle correlation between two OECD countries. When testing for the robustness of these variables, care was taken not to include other proxies for the same "driving force" in the set of control variables. This is especially relevant for financial integration and specialization, since three measures of financial integration and specialization are under consideration (see below for more details on these measures).

Once a suitable set of explanatory variables has been identified, the appropriate method to estimate the model above depends on the correlation between the error terms of the three equations. Given the exogeneity of gravity variables, it is crucial whether ν and ε are correlated. If so, using OLS for the first equation results in inconsistent estimates and instrumental variables estimation should be preferred. If not, OLS estimates are consistent and at least as efficient. A Hausman (1978) test is used to test whether IV estimates are significantly different from OLS estimates. If there is no significant difference between these estimates, we can conclude that OLS gives consistent results.

Data sources and methods

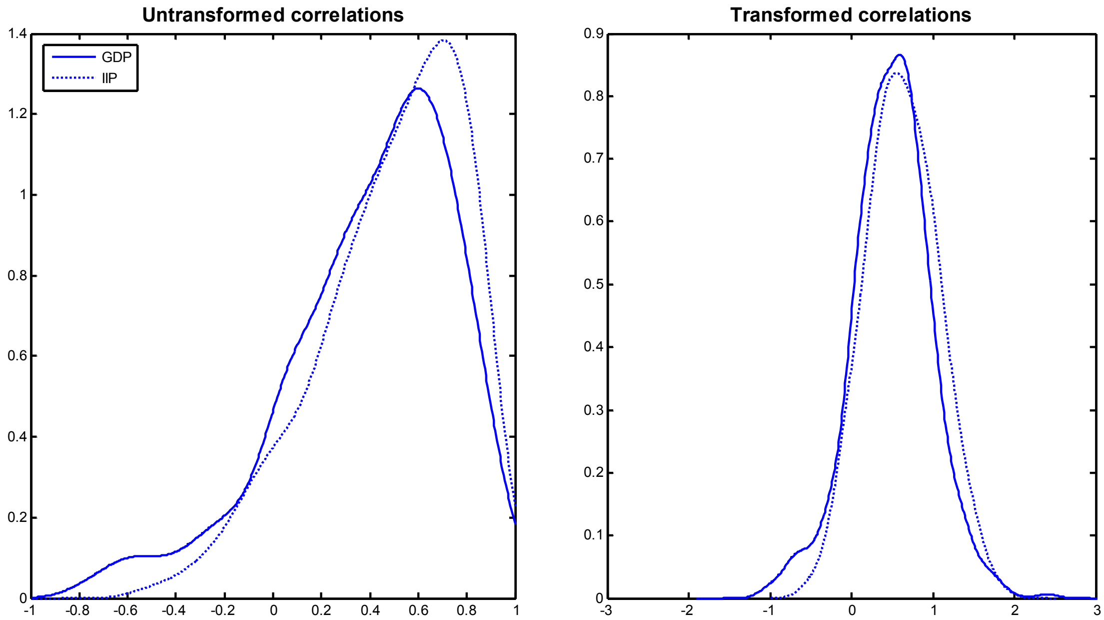
As in Section 3.3 on synchronization trends in the OECD, both GDP and industrial production are used as measures of economic activity and both variables are detrended using the Baxter-King band pass filter. As Figures 3.3 and 3.4 showed, synchronization tends to fluctuate over time and there is no obvious way to split the sample period in relatively homogenous sub-periods. For the regression analysis, the sample is therefore split into three periods of equal length (i.e. 11 years: 1970-1981, 1981-1992 and 1992-2003), resulting in a maximum of 630 observations (0.5*(3*21*20)).[68] For the quantile regression results shown below, the sample is split in eight periods of equal length in order to increase the number of observations.[69]

As Figures 3.1 and 3.2 showed, the set of correlations is generally not normally distributed. Up to here, this was not problematic, but the residuals in the regression need to be normally distributed for valid inference. To resolve this, Fisher's *z*-transformation of the correlation coefficients is used as the dependent variable. The transformed correlation coefficients are calculated as $C^t = 1/2\ln((1+C)/(1-C))$, where *C* is the pair-

[68] Frankel and Rose (1998) followed a similar approach, using four periods of about 9 years.
[69] The results are generally robust to distinguishing from two up to eight different periods.

wise correlation coefficient for each country couple. After transformation, the correlation coefficient is no longer bounded at -1 and 1, but unbounded instead. As a result the transformed correlations will be normally distributed (see David, 1949). This issue has not been addressed in most previous papers using these types of model, presumably under the assumption that the deviation from normality is sufficiently small. Figure 3.8 shows density estimates of all untransformed correlations (left-hand side) and the transformed correlations. While the untransformed correlations are clearly skewed, the *z*-transformation mostly removes this.

Figure 3.8 Estimated density plots of untransformed and transformed business cycle correlations



In previous studies on the determinants of business cycle synchronization various indicators of trade intensity have been used.[70] For instance, Frankel and Rose (1998) employ total trade (i.e. exports X and imports M) between two countries (i,j) scaled by total GDP (Y) or total trade.[71] Instead of using the sum of trade or GDP of the two

[70] The source for all the trade data in this study is the new database by Feenstra *et al.* (2005).
[71] As pointed out by Otto *et al.* (2001), the first measure suffers from obscuring one-way interdependence, the second suffers from not measuring the relative importance of trade in the total economy. Note that when using GDP as a scaling factor, GDP at current national prices is converted to U.S. dollars using

countries as scaling factor, some authors prefer scaling by the product of GDP or trade of the two countries concerned (see, for instance, Clark and van Wincoop, 2001) as this indicator is not size-dependent. An alternative indicator is suggested by Otto *et al.* (2001), who take the maximum of:

(3.5) $$\sum_t \frac{X_{ijt} + M_{ijt}}{Y_{it}}, \sum_t \frac{X_{ijt} + M_{ijt}}{Y_{jt}}.$$

They argue that what matters is whether or not at least one country is exposed to the other. In this measure, total trade can also be used for normalization. As a result, six different trade intensity measures have been calculated. Table 1 shows the correlation matrix of these indicators. As these measures are (imperfect) proxies for trade intensity and it is not obvious which one is to be preferred, they are combined into a single measure using principal component analysis. The preferred trade intensity measure is therefore based on the common variation in the six individual trade intensity measures. This combined measure is based on the largest eigenvalue, which accounts for 64 percent of the total variance.[72]

Table 3.3 Correlation coefficients between trade intensity measures

	TINT2	TINT3	TINT4	TINT5	TINT6
TINT1	0.52*	0.84*	0.73*	0.27*	0.58*
TINT2		0.58*	0.52*	0.60*	0.48*
TINT3			0.57*	0.29*	0.78*
TINT4				0.64*	0.57*
TINT5					0.51*

Notes: * denotes correlation significantly different from zero at 5% level.
TINT1: bilateral trade, normalised by total trade of the two countries.
TINT2: normalised by minimum of total trade of the two countries,
TINT3: normalised by the product of total trade of the two countries.
TINT4-6: same, but with GDP.

As discussed in the previous section, three indicators of *specialization* are distinguished, namely measures based on industrial specialization, export similarity and the share of intra-industry trade. Imbs (2004) suggests the following measure for industrial specialization:

purchasing power parities from the OECD (2002a) to take price differences between countries into account. All trade data are already converted using current exchange rates.

[72] The first eigenvalue is four times larger than the second. Furthermore, a measure based on the largest two eigenvalues has a correlation of 0.99 with the measure based on only the largest eigenvalue.

(3.6) $$\frac{1}{T}\sum_{t}\sum_{n=1}^{N}|\, s_{tni} - s_{tnj} \,|,$$

where s_{tni} denotes the GDP share of industry n at time t in country i. Apart from the index suggested by Imbs, the squared difference instead of the absolute difference of output shares can be used. Following Baxter and Kouparitsas (2004), these specialization measures are recast as similarity measures by subtracting the specialization measure from one. In addition, the correlation of output shares is used. These three industrial similarity indicators are constructed using the 60-industry database of the Groningen Growth and Development Centre (GGDC, 2005b), which has data on 56 industries covering the entire economy at the 2-digit and sometimes 3-digit level of industry detail (according to the ISIC revision 3 classification).[73] As might be expected, the three measures of output similarity are highly correlated (between 0.87 and 0.96), so following similar reasoning and criteria as for the trade intensity measures, the first principal component is used in the regressions as the first indicator of specialization.[74]

Furthermore, following Baxter and Kouparitsas (2004), the similarity of exports is used as the second main indicator of specialization. As these authors point out, countries with similar baskets of traded goods will be affected similarly in the event of sector-specific shocks hitting their export and/or import sectors. Using the trade data by commodity (at the 4-digit SITC level of detail) of Feenstra *et al.* (2005), export shares are calculated for each country. The same three similarity measures as for output shares are calculated for export shares. The correlation between these export similarity measures varies between 0.54 and 0.84, and the first principal component accounts for 78% of the variance. Therefore, this measure is used as the second specialization indicator.

The final indicator of specialization is the share of bilateral trade that can be attributed to intra-industry trade, *IIT*. This index is defined as:

[73] See www.ggdc.net for a more thorough documentation of this database, as well as the most recent version.
[74] The first principal component accounts for 94 % of the variance.

$$(3.7) \quad IIT_{ij} = 1 - \frac{\left| \sum_k \left(E_{ij}^k - E_{ji}^k \right) \right|}{\sum_k \left(E_{ij}^k + E_{ji}^k \right)}.$$

The share of intra-industry trade is calculated as one minus the absolute difference between exports of industry *k* from country *i* to country *j* and exports from country *j* to country *i*, divided by total bilateral trade (see Grubel and Loyd, 1971). The trade data by commodity of Feenstra *et al.* (2005) are allocated to industries using a detailed concordance.[75]

Financial linkages could result in a higher degree of business cycle synchronization by generating large demand side effects. For instance, a decline in a particular stock market could induce a simultaneous decline in demand in other countries if investors in these countries have invested in this particular stock market. Furthermore, contagion effects that are transmitted through financial linkages could also result in heightened cross-country spillover effects of macroeconomic fluctuations. However, international financial linkages could also stimulate specialization of production through the reallocation of capital in a manner consistent with countries' comparative advantages. Three indicators of *financial integration* are considered: the correlation of changes in stock market indexes, a dummy for capital account restrictions, and the (absolute) difference between the net foreign asset (NFA) positions of a country couple.[76]

The stock market data are from the IMF's *International Financial Statistics* and the measure that is used is the correlation of annual growth rates. The capital account variable is based on information provided by Lane and Milesi-Ferretti (2001) and updated using the IMF publication *Exchange arrangements and exchange restrictions*, which gives an overview of capital and current account restrictions for each country. The indicator equals one if at least one of the two countries had capital account restrictions during the period considered. The source of the NFA data is again Lane and Milesi-Ferretti (2001). They present two estimates, one based on cumulated current account data and one based on cumulated capital accounts. As the capital account-based measure is

[75] Industries are defined at the 4-digit level of the international standard classification (ISIC rev. 2). See http://www.macalester.edu/research/economics/PAGE/HAVEMAN/Trade.Resources/TradeConcordances.html.
[76] The latter two measures are also employed by Imbs (2004).

available for fewer years in most countries and (in theory) they should measure the same phenomenon, the cumulated current accounts are used.

Estimation results

The first two rows of Panel A of Table 3.4 shows a replication of the main results of Frankel and Rose (1998), i.e. the OLS and instrumental variables (IV) estimates of the effect of trade on business cycle correlations using the same trade measures as in their study. In addition to the instruments used by Frankel and Rose (1998), i.e. distance, an adjacency dummy, and a dummy for common language, a variable measuring geographical remoteness and a dummy for common legal origin are also included.[77]

The OLS and IV estimates of the trade coefficient are positive and highly significant and comparable for the two measures of economic activity. Like Frankel and Rose, the coefficients are smaller and less significant when bilateral trade intensity is normalized by output. The IV estimates are similar in magnitude as those reported by Frankel and Rose (1998) and considerably higher than the OLS estimates. Indeed, Hausman (1978) tests show that the IV estimates are significantly different from the OLS estimates, suggesting that the OLS estimates are biased.

[77] All these instruments are highly significant in explaining trade intensity and the F-statistic from the test of the joint significance of all variables in the first-stage regression with gravity variables explaining trade is 157. Legal origin has also been used to directly explain output co-movement (e.g. Otto *et al.*, 2001) but it can be argued that the main effect of a common legal origin is via trade: the correlation between legal origin and trade intensity is 0.40, while the correlation with the GDP and IP correlations are 0.23 and 0.11, respectively. As the 95% lower bound of the legal origin-trade intensity correlation is 0.27, the link with trade is significantly stronger than the link with output correlations. From a conceptual point of view, it also seems reasonable that a common legal system will facilitate trade links, while the direct link with synchronization is more elusive.

Table 3.4 The effect of trade on business cycle synchronization, replication of the Frankel-Rose model with the current dataset

	OLS		*IV*	
	IIP	GDP	IIP	GDP
Panel A, Estimation results				
(1) Bilateral trade, normalised by total trade	0.031*	0.025*	0.060*	0.061*
	(0.005)	(0.006)	(0.008)	(0.011)
(2) Bilateral trade, normalised by total GDP	0.009*	0.010*	0.016*	0.016*
	(0.001)	(0.002)	(0.002)	(0.003)
(3) Bilateral trade, factor score	0.074*	0.086*	0.125*	0.140*
	(0.010)	(0.014)	(0.015)	(0.021)
(4) Bilateral trade, factor score, transformed correlation	0.127*	0.125*	0.204*	0.203*
	(0.018)	(0.021)	(0.024)	(0.030)
Hausman test (H0: OLS is consistent)				
Bilateral trade, normalised by total trade			21.0*	18.3*
Bilateral trade, normalised by total GDP			24.6*	11.4*
Bilateral trade, factor score			22.2*	13.3*
Bilateral trade, factor score, transformed correlation			24.5*	14.5*
Panel B, Standardized coefficients				
Bilateral trade, normalised by total trade	0.081	0.072	0.070	0.077
Bilateral trade, normalised by total GDP	0.080	0.089	0.079	0.081
Bilateral trade, factor score	0.074	0.084	0.100	0.106
Bilateral trade, factor score, transformed correlation	0.126	0.123	0.160	0.151
95% confidence interval of standardized coefficient [Lower bound – Upper bound]				
Bilateral trade, normalised by total trade	[0.06 - 0.11]	[0.04 - 0.10]	[0.05 - 0.09]	[0.05 - 0.11]
Bilateral trade, normalised by total GDP	[0.06 - 0.10]	[0.06 - 0.12]	[0.06 - 0.10]	[0.06 - 0.11]
Bilateral trade, factor score	[0.05 - 0.09]	[0.06 - 0.11]	[0.08 - 0.12]	[0.08 - 0.14]
Bilateral trade, factor score, transformed correlation	[0.09 - 0.16]	[0.08 - 0.16]	[0.12 - 0.20]	[0.11 - 0.19]

Note: * denotes significantly different from zero at 5% level (coefficients) or null hypothesis rejected at 5% level. Dependent variable are the bilateral output correlations. Heteroscedasticity-consistent standard errors are in parentheses. The standardized coefficients are calculated by dividing the coefficient by the standard deviation of the underlying data series. The number of observations is 630 for the IIP regressions and 472 for the GDP regressions.

Row (3) of panel A of Table 3.4 shows the results using the preferred indicator of trade intensity (the first principal component of six different measures of trade), while row (4) presents the results after transforming the output correlations. The coefficients of the preferred trade indicator are highly significant, which suggests that the qualitative conclusion that trade intensity is positively related to business cycle correlation is not sensitive to the measurement of trade intensity. Transforming the dependent variable yields higher coefficients, but due to the transformation it is not straightforward to compare the coefficients with the estimates of rows (1)-(3). In order to make a meaningful comparison, Panel B of the table presents the standardized coefficients, calculated by dividing the coefficients in Panel A by the standard deviations of the respective trade series. This gives the effect on the business cycle correlation from a change in trade intensity of one standard deviation, evaluated at the mean. The effect for the model with transformed correlation coefficients is calculated by running the reverse z-transformation on the estimated effect. Below the point estimates, the 95% upper and lower bound are shown. These results suggest that the use of the transformed dependent variable leads to a somewhat stronger impact of trade on business cycle synchronization.

Table 3.5 shows the estimation results for the model outlined in Figure 3.7. For the variables to be included in F, the results of the Extreme Bounds Analysis (EBA) as described in Appendix 3.A are used. A separate analysis is run for each combination of financial integration and specialization measures. For the financial integration measures only the correlation of stock returns turns out to be a robust explanatory variable for synchronization while the capital account restrictions and NFA measures fail to pass the test. Therefore only regressions with the stock market indicator are shown. In contrast, all three specialization measures appear robustly related to business cycle synchronization and are therefore each included in a separate regression model.[78]

It follows from Appendix Table 3.1 that apart from the correlation of stock market returns and the specialization measures, other variables are also considered robust in the sense that in regressions with different control variables, the sign and significance of the coefficients remains stable.[79] The correlation of short-term interest rates and the correlation of cyclically-adjusted budget deficits are robustly related to business cycle synchronization for both GDP and industrial production correlations. For the GDP-based measure of synchronization, exchange rate variability is also robust.[80] It follows from Table 3.5 that almost all explanatory variables are significant with the expected sign. So a higher correlation between monetary policy or fiscal policy, more similar industrial and export structures, a higher share of intra-industry trade, and less exchange rate variability are related to more similar business cycles.

[78] The measure of industrial similarity is not robust with GDP as the dependent variable, but it is included to facilitate the comparability of results across specifications.
[79] See the Appendix for a more precise definition.
[80] For the industrial production correlations, measures reflecting differences in capital stocks and arable land are also robust for some combinations of financial integration and specialization measures. Since they frequently fail this test and are also not robustly related to the GDP-based measure of synchronization, they are not included here.

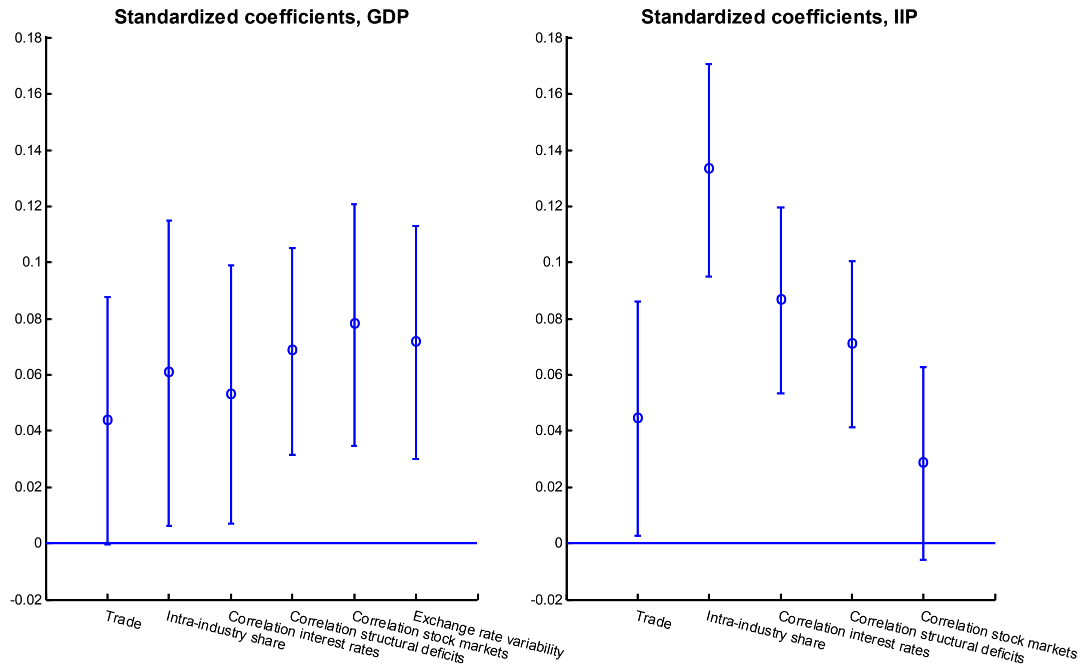
Table 3.5 Effect of trade on business cycle synchronization in a multivariate model

Specialisation measure:	*Industrial similarity*		*Export similarity*		*Share of intra-industry trade*	
GDP	OLS	IV	OLS	IV	OLS	IV
Trade	0.043*	0.054*	0.053*	0.121*	0.044	0.115*
	(0.020)	(0.026)	(0.021)	(0.036)	(0.023)	(0.040)
Specialisation measure	0.032	0.031	0.064*	0.050*	0.346*	0.177
	(0.024)	(0.024)	(0.021)	(0.021)	(0.159)	(0.175)
Correlation of short-term interest rates	0.239*	0.236*	0.124*	0.112	0.129*	0.130*
	(0.055)	(0.057)	(0.057)	(0.059)	(0.057)	(0.058)
Correlation of cyclically-adjusted budget deficits	0.172*	0.171*	0.143*	0.137*	0.136*	0.133*
	(0.036)	(0.036)	(0.038)	(0.038)	(0.037)	(0.038)
Correlation of stock markets	0.308*	0.303*	0.214*	0.202*	0.225*	0.216*
	(0.080)	(0.080)	(0.065)	(0.064)	(0.064)	(0.063)
Exchange rate variability	-1.600*	-1.513*	-1.552*	-1.089*	-1.548*	-1.165*
	(0.483)	(0.497)	(0.46)	(0.487)	(0.458)	(0.478)
Number of observations	335	335	459	459	459	459
Industrial production						
Trade	0.080*	0.088*	0.069*	0.113*	0.043*	0.080*
	(0.021)	(0.026)	(0.019)	(0.023)	(0.021)	(0.026)
Specialisation measure	0.070*	0.069*	0.118*	0.105*	0.761*	0.657*
	(0.018)	(0.018)	(0.016)	(0.016)	(0.111)	(0.117)
Correlation of short-term interest rates	0.374*	0.372*	0.221*	0.217*	0.211*	0.214*
	(0.042)	(0.042)	(0.042)	(0.043)	(0.041)	(0.041)
Correlation of cyclically-adjusted budget deficits	0.125*	0.126*	0.157*	0.155*	0.143*	0.143*
	(0.034)	(0.034)	(0.030)	(0.030)	(0.030)	(0.030)
Correlation of stock markets	0.161*	0.156*	0.064	0.057	0.082	0.077
	(0.060)	(0.059)	(0.052)	(0.052)	(0.050)	(0.050)
Number of observations	378	378	556	556	556	556
Hausman test (H0: OLS is consistent, critical 5% value: 12.6)						
GDP		0.32		6.83		5.00
Industrial production		0.28		8.51		3.90

Notes: The dependent variable is the transformed output correlation. * denotes coefficient significantly different from zero at 5% level. Heteroscedasticity-consistent standard errors are in parentheses. IV includes gravity instruments (distance, geographical remoteness and dummies for a common border, language and legal origin) and all explanatory variables except trade.

The main finding in Table 3.5 is that the trade coefficients are much smaller than those previously found: the coefficient of trade intensity with GDP correlation as dependent variable is only half as large as in Table 3.4 for both the OLS and IV specification. In addition to the gravity variables that were used as instruments in Table 3.4, the other explanatory variables are included as instruments too (except trade); this specification corresponds to the second line of equation (3.4). The Hausman tests show that OLS and IV estimates are not significantly different so the consistency of OLS can no longer be rejected. Because Frankel and Rose (1998) did not specify a full model, they overestimated the impact of trade on output correlation.

Figure 3.9 Standardized coefficients of explanatory variables with 95% confidence intervals



Note: The standardized coefficients are based on the OLS regressions, using intra-industry trade as the measure of specialization.

Figure 3.9 shows the standardized coefficients of all the variables included in the model with intra-industry trade as the specialization measure. The point estimate, as well as the 95% upper and lower bounds are shown. It follows that the point estimates of almost all standardized coefficients – like the correlation of short-term interest rates or of cyclically-corrected budget deficits – is larger than the impact of trade intensity. The upper and lower bounds show that these differences are mostly not significant. Still, the evidence suggests that variables that reflect common economic policies and specialization are at least as important as strong trade ties for synchronization.

Finally, Figure 3.10 compares the standardized coefficients of the three specialization measures that are used. Again, the point estimate as well as the 95% upper and lower bounds are shown. In this figure, industrial similarity has the lowest impact. In view of the upper and lower bounds of the coefficients one has to be careful in drawing too strong conclusions, but the evidence suggests that trade-based specialization measures have a larger impact on business cycle synchronization than industry-structure-based specialization measures. This is most visible for the coefficients of the models based on industrial production.

Figure 3.10 Standardized coefficients of specialization measures with 95% confidence intervals

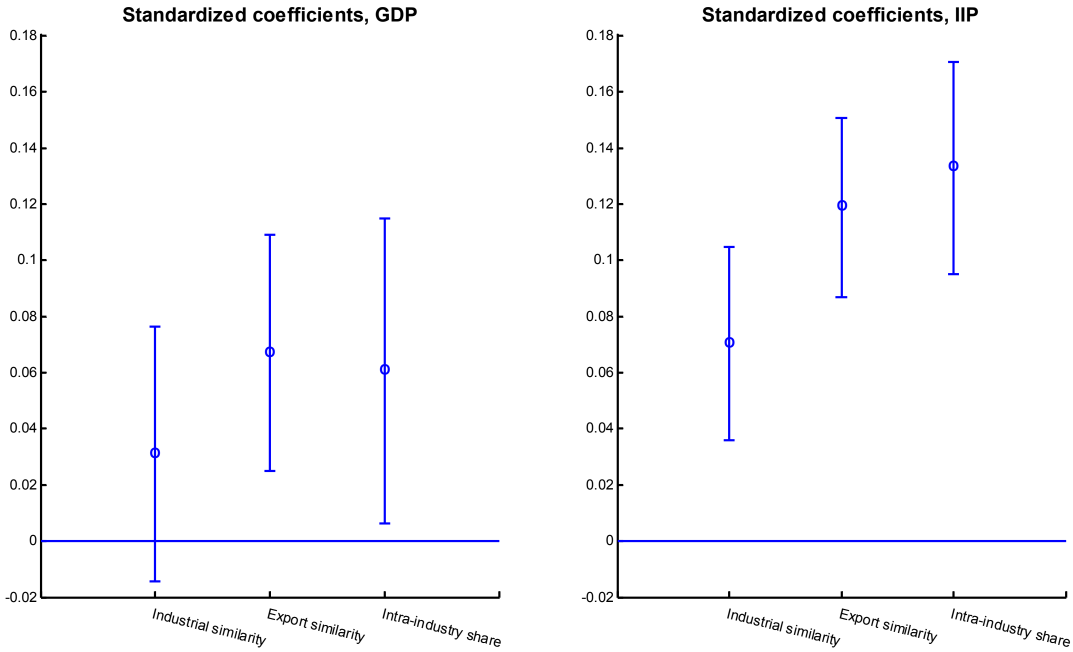


Figure 3.9 showed the economic significance of the determinants of synchronization, but this does not yet give an indication of the prospects for synchronization in the euro area. Table 3.6 examines this issue by looking at three scenarios. The first column shows the actual average correlation between EMU countries, the second shows the correlation predicted by the regression.[81] The last three columns show projected correlations according to three scenarios. The first scenario is cautious and assumes that the monetary union, with perfectly correlated monetary policy and no exchange rate variability, is the only difference compared to the 1970-2003 period. The other variables are set equal to the average for EMU countries over the period 1970-2003. The second scenario sets all other variables equal to the average for the period 1992-2003. The third scenario is the most speculative and assumes that (cyclically-adjusted)

[81] The intra-industry OLS regressions from Table 3.5 are used for the predication and projections. The predicted value is lower than the actual average since EMU countries have a correlation that is higher than the average in the full sample. Regression to the mean leads to the lower prediction.

fiscal policy will be perfectly correlated. As the table shows, each of the scenarios implies an economically significant, but not implausible, rise in the predicted correlation. The rise in the projected correlation from Scenario II relative to Scenario I shows that in the period between 1992 and 2003, the explanatory variables favoured higher synchronization. Part of this effect can be traced to more correlated monetary policy, fiscal policy and stock market returns. In addition, a rise in the average intra-industry share, from 40 percent between 1970 and 1981 to 52 percent after 1992, made a notable contribution. In comparison, export similarity also increased, but by less than the intra-industry share and industrial similarity decreased modestly. This confirms the importance of looking at trade-based measures of specialization and that based on those measures, specialization has actually decreased in recent decades. Note also that the range of projections, from 0.64 to 0.75, corresponds to the range of post-war average correlations of states within the U.S. from Table 3.2.

Table 3.6 Actual, predicted and projected output correlations between EMU countries based on the intra-industry regressions

	Actual average (1970-2003)	Predicted value (1970-2003)	Projections		
			Scenario I	Scenario II	Scenario III
GDP	0.62	0.58	0.65	0.71	0.74
Industrial production	0.63	0.59	0.64	0.70	0.75

Scenario I: correlation of monetary policy is 1, exchange rate variability is 0. All other variables are equal to the 1970-2003 average for EMU countries.

Scenario II: correlation of monetary policy is 1, exchange rate variability is 0. All other variables are equal to the 1992-2003 average for EMU countries.

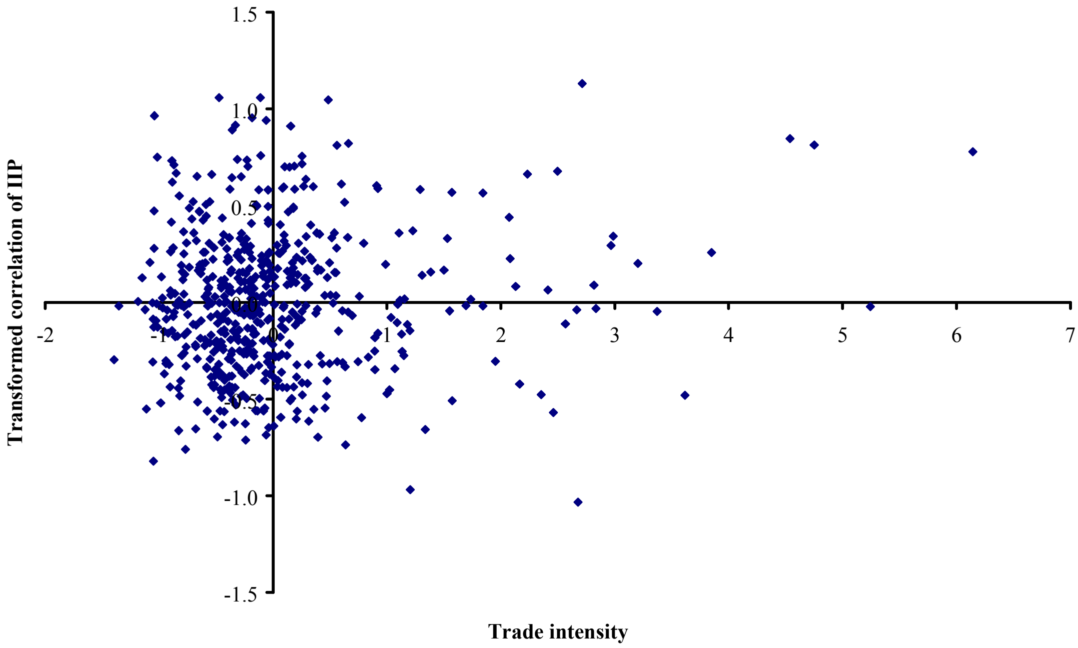
Scenario III: correlation of monetary policy is 1, exchange rate variability is 0 and correlation of fiscal policy is 1. All other variables are equal to the 1992-2003 average for EMU countries.

Predictions and projections are based on the intra-industry regressions from Table 3.5.

Sample heterogeneity and outliers

There are two potential problems with the OLS results. First of all, outlying observations may influence the results and second, the identified relationships may not be the same for different groups of observations. Figure 3.11 shows the residuals of the regression of business cycle correlation for industrial production on the control variables against the residuals of the regression of bilateral trade on these same control variables. This figure suggests that there are various observations that are quite far away from the bulk of the observations and these may drive the results. This section reports the estimation results using the Least Trimmed Squares (LTS) estimator of Rousseeuw (1984, 1985) to identify outlying observations. Furthermore, quantile regressions are used to examine sample heterogeneity.[82]

Figure 3.11 Scatter diagram of industrial production correlations and trade (after conditioning on other explanatory variables)



The basic principle of LTS is to fit the majority of the data, after which outliers may be identified as those points that lie far away from the robust fit. LTS typically minimizes the sum of squares over half the observations, the chosen half being the set that gives the smallest residual sum of squares. Although this method is particularly suited for identifying leverage points, it is not suited for inference. As proposed by Rousseeuw (1984), this can be resolved by using re-weighted least squares (RWLS). A simple, but effective, way is to give a weight of zero to all observations identified as outliers and a weight of one to all other observations (Sturm and De Haan, 2005).

Table 3.7 shows the results of the LTS/RWLS estimates. For comparison purposes, the OLS results of Table 3.5 are also shown. Overall, there are no large differences

[82] See Koenker and Basset (1978) for the seminal contribution or Koenker and Hallock (2001) for a non-technical overview.

between the OLS estimates and the robust estimates. However, there are exceptions. In the models for the GDP-based correlations, the bilateral trade coefficient loses significance in some specifications. This is quite remarkable, as almost all other variables remain significant at the 5% level. Still, in the models for the industrial production correlations, the significance of the trade variable increases. This suggests that in general, the effect of trade on business cycle synchronisation is not driven by outliers.

Table 3.7 The effect of trade on business cycle synchronization, OLS versus LTS/RWLS estimation

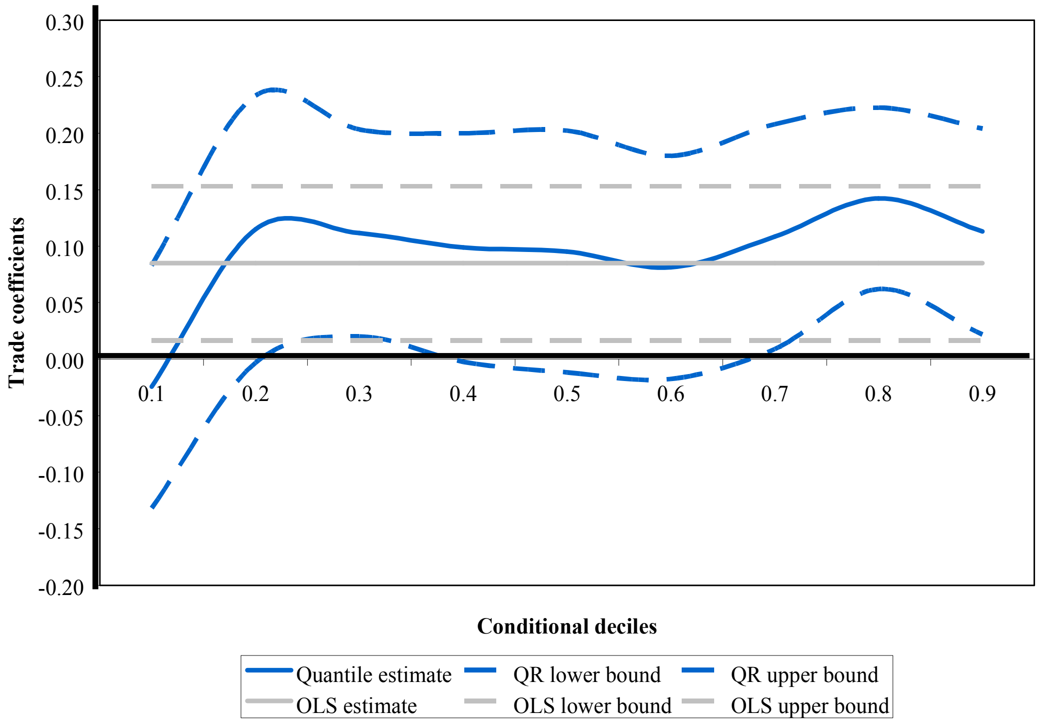
Specialisation measure:	*Industrial similarity*		*Export similarity*		*Share of intra-industry trade*	
GDP	OLS	LTS/RWLS	OLS	LTS/RWLS	OLS	LTS/RWLS
Trade	0.043*	0.044*	0.053*	0.033	0.044	0.022
	(0.020)	(0.020)	(0.021)	(0.018)	(0.023)	(0.020)
Specialisation measure	0.032	0.041*	0.064*	0.059*	0.346*	0.354*
	(0.024)	(0.021)	(0.021)	(0.018)	(0.159)	(0.122)
Correlation of short-term interest rates	0.239*	0.274*	0.124*	0.207*	0.129*	0.177*
	(0.055)	(0.050)	(0.057)	(0.045)	(0.057)	(0.045)
Correlation of cyclically-adjusted budget deficits	0.172*	0.191*	0.143*	0.161*	0.136*	0.16*
	(0.036)	(0.036)	(0.038)	(0.034)	(0.037)	(0.034)
Correlation of stock markets	0.308*	0.266*	0.214*	0.138*	0.225*	0.158*
	(0.080)	(0.068)	(0.065)	(0.051)	(0.064)	(0.051)
Exchange rate variability	-1.600*	-1.373*	-1.552*	-1.920*	-1.548*	-1.768*
	(0.483)	(0.416)	(0.460)	(0.392)	(0.458)	(0.393)
Industrial production						
Trade	0.080*	0.092*	0.069*	0.074*	0.043*	0.048*
	(0.021)	(0.017)	(0.019)	(0.015)	(0.021)	(0.016)
Specialisation measure	0.070*	0.056*	0.118*	0.136*	0.761*	0.838*
	(0.018)	(0.017)	(0.016)	(0.016)	(0.111)	(0.100)
Correlation of short-term interest rates	0.374*	0.392*	0.221*	0.267*	0.211*	0.268*
	(0.042)	(0.041)	(0.042)	(0.039)	(0.041)	(0.039)
Correlation of cyclically-adjusted budget deficits	0.125*	0.117*	0.157*	0.186*	0.143*	0.141*
	(0.034)	(0.032)	(0.030)	(0.030)	(0.030)	(0.029)
Correlation of stock markets	0.161*	0.223*	0.064	0.047	0.082	0.101*
	(0.060)	(0.057)	(0.052)	(0.044)	(0.050)	(0.043)

Notes: The dependent variable is the transformed output correlation. * denotes coefficient significantly different from zero at 5% level. Heteroscedasticity-consistent standard errors are shown in parentheses. LTS/RWLS shows regressions robust for outliers.

Quantile regression is an appropriate tool to address sample heterogeneity as shown by Koenker and Basset (1978). OLS focuses on the mean of the dependent variable given the explanatory variables. Quantile regressions are used to analyze other parts of the conditional distribution, such as the (conditional) median or specific deciles. The difference between the OLS and the median regression can help clarify this. In OLS, the sum of squared residuals is minimized, while for the median regression, the sum of absolute residuals is minimized. Regressions for other deciles can be run by giving a greater weight to positive or negative residuals. In order to increase the degrees of freedom, the sample period 1970-2003 is divided into eight periods of uniform lengths after which the same regressions as for Table 3.5 are run.

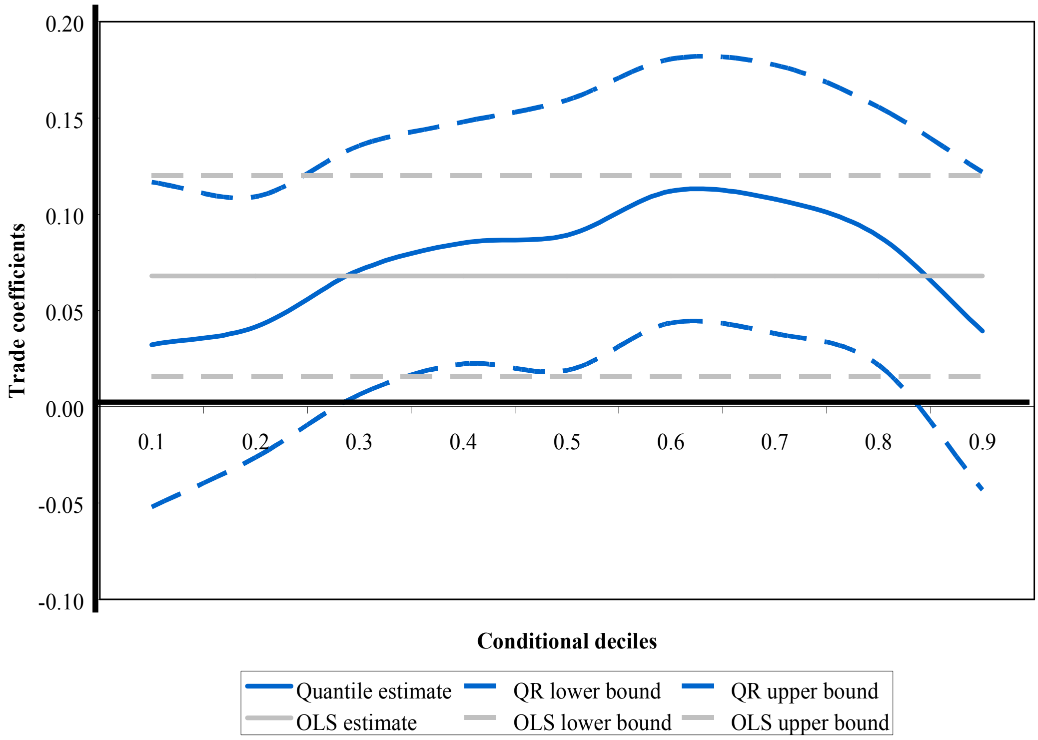
Figures 3.12 and 3.13 show the estimated coefficients of the trade intensity variable for each decile, using the model in which intra-industry trade is used as specialization measure.[83] It follows that the relationship between the correlation of business cycles and bilateral trade is fairly robust across deciles. The estimates for each conditional decile are almost always significant at the 5% significance level. More importantly, the figures show that the quantile regression estimates are very similar to the OLS estimates and almost always lie within the 95% confidence band of the OLS estimates. This indicates that the relationship between business cycle correlations and bilateral trade does not differ across the sample.

Figure 3.12 Quantile regression estimates of the effect of trade on synchronization, GDP correlations



[83] For brevity, only the estimates across deciles for bilateral trade are shown.

Figure 3.13 Quantile regression estimates of the effect of trade on synchronization, industrial production correlations



3.6 Concluding remarks

One of the main long-run challenges to the euro is the possible lack of similarity of business cycles in the member countries. If the degree of synchronization is low, the ECB's common monetary policy will not be suitable for all countries. In other words there is a risk is that 'one size does not fit all'. Monetary policy will be too restrictive for countries that face a recession while the rest of the euro area flourishes or too accommodating for economies that perform better than the average.

Since the late 1970s, monetary integration within Europe has increased steadily with the introduction of the euro as the high mark. However, synchronization is not solely determined by monetary integration as synchronization within Europe has fluctuated over time. Furthermore, the dispersion around the mean is quite sizeable, suggesting a great degree of heterogeneity. Still, since the mid-1980s, synchronization between EMU countries has been higher on average than between other countries.

The experience of the U.S. suggests that even decades of monetary union is no guarantee of perfect synchronization. The average correlation between state cycles and the aggregate cycle is somewhat higher than among EMU countries, but not much. The dispersion of cyclical correlations is notably smaller though, with fewer negative correlations between states. Synchronization between states also varies over time, and this variation is larger than between EMU countries. An important factor in this variation seems to be the aggregate U.S. business cycle. In periods of great volatility, such as the Great Depression, the national cycle plays a dominant role and synchronization is high. In contrast, the volatility of the U.S. economy has been relatively low in the past two decades, resulting in lower levels of synchronization.

Comparing patterns of synchronization over time is useful to capture broad trends, but for specific policy recommendations, the determinants of synchronization need to be examined. A set of robust explanatory variables was identified from a large set of variables using Extreme Bounds Analysis (EBA). The robust variables include trade intensity, measures of specialization, financial integration as given by the correlation of stock market returns, the similarity of monetary and fiscal policy and exchange rate variability. The resulting multivariate model is able to account for the endogeneity of trade. The main problem in estimating the effect of trade on synchronization is that other policy-related and structural variables affect both trade and synchronization. It turns out that once the variables identified using EBA are added to the regression, the hypothesis of OLS consistency is no longer rejected. This suggests that the endogeneity of trade is no longer a major problem.

In the multivariate model, trade is still an important explanatory variable, but in terms of economic significance, the other explanatory variables are equally important. Projections of future output correlations between EMU countries suggest that synchronization is likely to increase to similar levels as between U.S. states. The main uncertainties in these projections are the degree of coordination of fiscal policy and the development of specialization. Resistance against the rules of the Stability and Growth Pact suggests that the appetite for fiscal policy coordination is limited. It should be noted though that strict adherence to deficit limits is not crucial for synchronization. Instead, the main factor is the similarity of policy. So a unilateral spending spree is likely to reduce synchronization, but a large deficit in response to adverse cyclical developments is unlikely to have such an effect.

The future direction of specialization is harder to gauge. In part, this is because different specialization measures show different patterns in Europe. On the one hand, there has been a modest decrease in industrial similarity in recent decades, but on the other hand, both the similarity of export bundles and the intra-industry share have increased. The U.S. experience suggests that the trade-based measures may be most relevant. Kim (1995) showed that the industrial structure of U.S. regions has become more homogenous in the past decades due to more mobile production factors. As Europe has been working towards a single market for capital and labour, specialization could decrease further, increasing synchronization. This issue might also become more important as other evidence for the U.S. suggests that the national cycle has become less volatile, leading to a larger effect of region-specific and industry-specific shocks on synchronization.[84] If similar developments occur in Europe, changes in specialization patterns will become even more important in determining future synchronization.

These uncertainties strengthen the case for more flexibility, following De Grauwe and Mongelli (2005). Specifically, it should be easier for Europeans to take jobs in other countries. Blanchard and Katz (1992) show that economic shocks in U.S. states induce notable migration out of that state in addition to higher unemployment and lower wages. In contrast, Puhani (2001) argues that even within a number of European countries, labour mobility is not a very effective adjustment mechanism. Currently, there are not just language and cultural barriers, but, for example, pension and insurance systems are also not compatible. Reforms aimed at reducing these barriers are likely to decrease the degree specialization as well as making it easier for countries to absorb asymmetric shocks. Both developments would reduce the costs of having a common currency. In addition, as the next chapter will argue, more flexible labour markets will also stimulate productivity growth.

[84] See Partridge and Rickman (2005). See also Clark and Shin (2000) for more on identifying different types of shocks.

Appendix 3.A Extreme bounds analysis

Appendix Table 3.1 Robustness of potential explanatory variables for synchronization

Variable:	Source:	Suggested by:	Robust in model for:	
			GDP correlation	*IIP correlation*
Correlation of short-term interest rates	IMF, International Financial Statistics (IFS)	Otto *et al.* (2001)	Yes	Yes
Correlation of cyclically-adjusted budget deficits	OECD Economic Outlook (vol. 76)	Camacho *et al.* (2005)	Yes	Yes
Correlation of stock market returns	IFS	Otto *et al.* (2001)	Yes	Yes
Absolute difference in net foreign asset positions	Milesi-Feretti and IMF	Imbs (2004)	No	No
Capital account restrictions	Milesi-Feretti and IMF	Imbs (2004)	No	No
Industrial similarity	GGDC 60-industry database	Imbs (2004)	No	Yes
Export similarity	Feenstra *et al.* (2005)	Baxter and Kouparitsas (2004)	Yes	Yes
Share of intra-industry trade (IIT)	Feenstra *et al.* (2005)		Yes	Yes
Exchange rate variability	IFS	Otto et al. (2001)	Yes	No
Arable land difference	WDI	Baxter and Kouparitsas (2004)	No	No
Human capital difference, secondary education	OECD Labour Force Statistics	Baxter and Kouparitsas (2004)	No	No
Human capital difference, tertiary education	OECD Labour Force Statistics	Baxter and Kouparitsas (2004)	No	No
Physical capital difference	GGDC Total Economy Growth Accounting Database	Baxter and Kouparitsas (2004)	No	No
Import similarity	Feenstra *et al.* (2005)	Baxter and Kouparitsas (2004)	No	No
Average openness	IFS & GGDC Total Economy Database	Baxter and Kouparitsas (2004)	No	No
Relative financial structure credit/stock	Beck et al. (1999)	Artis (2003)	No	No
Relative labour productivity level	GGDC Total Economy Database	Baxter and Kouparitsas (2004)	No	No
Correlation of inflation rates	IFS	Camacho *et al.* (2005)	No	No
Average oil import share	World Bank, World Development Indicators (WDI)	Artis (2003)	No	No
Difference in national savings ratio	OECD National Accounts	Camacho *et al.* (2005)	No	No

Note: A more detailed description of the variables and sources, as well as the data is available at www.rug.nl/economics/inklaarrc

The Extreme Bounds Analysis (EBA) as suggested by Leamer (1983) and Levine and Renelt (1992) is used to determine the list of variables to be included in the structural model outlined in the main text. EBA has been widely used in the economic growth literature.[85] Baxter and Kouparitsas (2004) also use this methodology (using a different set of countries and a more limited set of potential explanatory variables than in the present analysis) to examine which variables are robustly related to business cycle synchronization. The EBA can be exemplified as follows. Equations of the following general form are estimated:

(3.A1) $$C = \alpha M + \beta F + \gamma Z + u,$$

where C is the dependent variable (output correlation); M is a vector of 'standard' explanatory variables; F is the variable of interest; Z is a vector of up to three (Levine and Renelt, 1992) possible additional explanatory variables, which according to the literature may be related to the dependent variable; and u is an error term. In this analysis only trade intensity is included in the M vector. As explained in the main text, the various proxies for financial integration and specialization are not considered simultaneously. Following Sala-i-Martin (1997), the criterion for the robustness of the sign of the coefficient is the fraction of the cumulative distribution function lying on one side of zero (CDF(0)). In addition, the percentage of the regressions in which the coefficient of the variable of interest differs significantly from zero is used to distinguish robust variables. Following Sturm and De Haan (2005), a variable is considered to be robust if the CDF(0) test statistic is larger than 0.95 and if the variable has a significant coefficient (at the 5% significance level) in 90% of all regressions.

[85] See Sturm and De Haan (2005) for a further discussion