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Máximo Camacho, Gabriel Pérez-Quirós
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Máximo Camacho
UNIVERSIDAD DE MURCIA

Gabriel Pérez-Quirós (**)
BANCO DE ESPAÑA

Lorena Saiz
BANCO DE ESPAÑA

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(**)Corresponding Author: Banco de España, Servicio de Estudios, Alcala 50, Madrid 28014. email: gabriel.perez@bde.es.

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Abstract

We propose a comprehensive methodology to characterize the business cycle comovements across European economies and some industrialized countries, always trying to "leave the data speak". Out of this framework, we propose a novel method to show that there is no an "Euro economy" that acts as an attractor to the other economies of the area. We show that the relative comovements across EU economies are prior to the establishment of the Monetary Union. We are able to explain an important proportion of the distances across their business cycles using macro-variables related to the structure of the economy, to the directions of trade, and to the size of the public sector. Finally, we show that the distances across countries that belong to the European Union are smaller than the distances across newcomers.

Keywords: Business Cycle Synchronization, Economic Integration, European Union Enlargement .

JEL Classification: E32, F02, C22

1 Introduction

The academic literature and the press are full of references to the importance of globalization and the links across economies. Several economists talk about the "world business cycle" and, assuming from the beginning that this cycle exists, estimate it and calculate its importance in explaining country specific movements. Recent examples are Lumsdaine and Prasad (2003), Canova, Ciccarelli and Ortega (2003), or Gregory, Head and Raynauld (1997). At the same time, many other economists talk about the "European business cycle", also assuming that there exist European-specific business cycle driving forces, or Euro-area specific factors. Supporting this view, significant examples are Mansour (2003), Del Negro and Ottrok (2003), Artis, Krozlig and Toro (1999), and obviously all the literature behind the well known coincident indicator for the Euro-area economies by Forni, Hallin, Lippi and Reichlin (2001a and 2001b). Most of the previous papers, when dealing with international business cycle movements, spend serious amount of effort in explaining how much or how little the common business cycle explains the cyclical behavior of the different economies. In addition, an important part of those papers deal with estimating the law of motion for the unobserved common business cycle that better fits the individual economies data.

The purpose of our paper is to go behind the assumptions of this literature. We want to analyze the comovements across economies without previously assuming that they should or should not move together. We want to "leave the data speak" without imposing any kind of *a priori* restrictions. This approach will allow us to draw a map of comovements across economies where we can check which economies are close together and which are further away from each other. At the same time, this approach will allow us to answer the leading question about the existence of either a world or an European attractor: Do the economies move according to a common driving force? We think that our answer to this question is more careful than any that we can previously find in other papers of the literature and require serious investment in applying and mixing different techniques to the data, much more when we do not pretend to impose a particular model or a particular framework to the data. To that extend, we think that we present different contributions to the literature. First, we propose a two by two comparison across economies without taking any of them as "reference" for the others. Second, we calculate different measures of comovements across economies, in order to check for the robustness of our results and not to condition our findings to a given framework. Third, we propose new measures of business cycle synchronization. Finally, we analyze the role of macroeconomic and policy variables in explaining distances across economies.

To deal with these questions, we will concentrate in this paper on European economies, although we will extend the usual European sample of countries in two different ways. On the one hand, we will include a set of industrialized economies that will allow us to understand how close or how far European economies are from those major industrialized countries. On the other side, we will include the Eastern European economies which represent most of the enlargement of the European Union. Extending the sample in this way allow us to address additional questions which are key to measure the gains and costs of the enlargement of the Union (and the future enlargement of the Euro-area) for both the accession and the existing countries. When countries join a monetary union they leave to a supranational decision maker traditional instruments for the control of the business cycles. Obviously, the optimality of this delegation of the decisions to a higher authority will be a direct function of the similarities across these economies. If the economies move together, we might think that they need the same type of economic policy decisions at the same time. If, there is no synchronization of their business cycle comovements, we might think that different solutions are optimal for different economies and probably, the costs associated to an economic union might be higher than the gains. In this context, little has been written about the business cycles of emerging economies and even less about Euro-accessing countries. All the literature about these economies have to do with convergence criteria and convergence tests as in Brada, Khutan and Zhou (2003). Other authors like Babetski, Boone and Maurel (2002), and Frenkel and Nickel (2002) try to identify demand and supply shocks, with the identification restrictions that this specific purpose implies. Finally, other authors take as given a "leading" economy and analyze the transmission of shocks from this economy to the accessing economies as in Boone and Maurel (2002), but we do not find in any paper a careful analysis of the comovements of each of the accessing economies with each of the European and other major industrialized economies.

In addition, with this European focus in mind, there is an additional set of economic questions that we can address; for example, so far, the European economies linked their decisions together without any major trauma in their economies, but was the link across these economies not traumatic because these economies had previous linkages? Have these economies increased their comovements since they decided to join their policies? Is there an attractor across these economies? Is there a limit to the expansion of the EU? Finally, a more general question is analyzed in the last section of the paper; is there a role for macroeconomic variables in explaining the possible links across these countries' business cycles?

We think that an appropriate answer to these questions is necessary to understand deeply the benefits and the costs that for different economies imply leaving traditional instruments for controlling aggregate demand to a supranational decision maker.

The paper is structured as follows. Section 2 characterizes the concept of business cycles synchronization and checks whether the economies move together and how far are these economies from each other. Section 3 analyzes the existence of a common attractor or leader among European economies. Section 4 relates all these distances across economies with macroeconomic variables. Section 5 concludes.

2 Business cycles synchronization

2.1 Data

In our business cycle analysis, we have used the monthly (seasonally adjusted) Industrial Production series as an indicator of the general economic activity. We understand that choosing the Industrial Production as a measure of aggregate activity could be controversial. Obviously we are measuring only one sector and only the supply side of the economy. However, there is a trade off between the statistical reliability of the series and how representative this series is of the overall economic activity. We tried to use a more comprehensive measure activity using aggregate GDP. However, the frequency of this series is quarterly, not monthly, the sample is shorter and, for most of these countries, the GDP is not calculated from national accounts on a quarterly basis but the series is annual and converted into a quarterly frequency using indicators.[1] We have also tried to create

[1] In a preliminary version of this paper, we also constructed a composite index for each country by using a Kalman filter specification of the type proposed by Stock and Watson (1991), with the series of

a diffusion index for each economy, following the diffusion index approach of Stock and Watson (1999). However, the results were disappointing when we analyzed the calculated series, probably due to the small number of series available for the accessing economies.

The sample of the countries include all the European Union countries, all the accession countries but Malta, and all the negotiating countries but Bulgaria.[2] Finally, we also include some industrialized countries: Canada, US, Norway and Japan. The source of the data is the OECD Main Economic Indicators and the IMF International Financial Statistics. In the analysis of European and industrialized countries we use data from 1965.01 to 2003.01. The exercises including the accession countries use data from 1990.01.[3] In order to facilitate a quick visual inspection of our data set, given the big number of countries, we plot the industrial production index for each country in Figure A1 of Appendix A.[4]

2.2 Correlation as measure of comovements

We will spend a serious amount of time and effort computing the degree to which the economies move together. However, as a preliminary approach, we think that a few pictures could help the reader to understand the nature of the problem. Figure 1 plots the the industrial production series of Italy, Spain, Romania and Ireland as well as the first difference of the logs of the industrial production series of Italy and Spain. Looking at the pictures in levels, it seems that the industrial production of some, but not all, of these countries move together. A first glance to the picture would say that Italy and Spain (both of them, Mediterranean countries) industrial productions present synchronized busi-

Industrial Production, Total Sales, Employment and a measure of income for the different economies. However, this specification gave in many cases a weight of 0.99 to the Industrial Production series and almost 0 to the others. In addition, we found in the all cases very high correlation with the GDP quarterly series of the country.

[2] The accession countries are Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, the Slovak Republic and Slovenia. The negotiating countries are Bulgaria, Romania and Turkey.

[3] Even though we have statistical information for most of the accession countries from 1990, we do not use the first two years of observations. Blanchard (1997) or The World Bank (2002) point out the atypical characteristics of the transition period in which falls experienced in output can not be considered as sign of a conventional recession.

[4] See Appendix D for a more detailed description of data sources, missing data, and the nomenclature used for the different countries.

ness cycles, which lead us to think that they should not have major problems linking their economies. However, in the case of Italy and Romania or Italy and Ireland the synchronization of their industrial production business cycles do not seem to be so evident, which leads us to think that joining these economies with a supranational decision maker should reduce the optimality of the stabilization policies for at least one of the economies.

Figure 1 also raises an additional question. The most standard measures to deal with the comovements across time series are the correlations among the series. However, what it is not so obvious is to choose between the correlations in levels (or log levels) and the correlations in rates of growth. For example, using the industrial production of Italy and Spain, the correlation between the log levels of the series is 0.94 whereas the correlation between their growth rates is 0.09. That is, the log levels of the series seem to show that the comovements of the series are very important, while the first differences lead to the opposite conclusion. In order to illustrate why this puzzling result occurs, let us to propose the following clarifying example. Let us assume that the data generating process for the series x_t and y_t be equal to

$$x_t = a + x_{t-1} + \phi(y_{t-1} - y_{t-2}) + e_t, \tag{1}$$

$$y_t = b + y_{t-1} + u_t, \tag{2}$$

with serially uncorrelated errors, $e_t \sim N(0, \sigma_e^2)$, $u_t \sim N(0, \sigma_u^2)$, and with $E(e_t, u_t) = 0$. Finally, let us assume that both x_1 and y_1 are zero. Using these assumptions, the correlation between the series in log levels is

$$Corr(x_t, y_t) = Corr\left((a + \phi b)(t-1) + \phi \sum_{j=1}^{t-1} u_j + \sum_{i=2}^{t} e_i, b(t-1) + \sum_{j=2}^{t} u_j\right), \tag{3}$$

which clearly tends to unity because it is dominated by the trend effect. However, the correlation between the first differences of the log levels is

$$Corr(x_t - x_{t-1}, y_t - y_{t-1}) = Corr(a + \phi(b + u_{t-1}) + e_t, b + u_t), \tag{4}$$

which is cero. This example illustrates a general problem in defining the correlation across industrial productions as a measure of business cycle comovements: we can not use series in levels or log levels because in these series dominates the long-term rather than the business cycle correlation. In addition, we can not simple take first differences of the logs because the correlation between these transformations is dominated by the short-term noise. Thus, it is clear that we need some kind of filtering (more sophisticated that just taking the differences) in order to extract the information of the series about the short term movements (and comovements) of the series. Obviously, the chosen filter will affect the shape of the cycle, and, of course, the comovements across economies. In order to give robustness to our results we propose three different measures of comovements. The first is based on VAR estimations, following Den Haan (2000); the second, based on spectral analysis, following Reichlin, Forni and Croux (2001); and the third, based on business cycle dummy variables, following Harding and Pagan (2002). Our first definition tries to relate the business cycle comovements with the "rate of growth cycle", the second definition relates to the "growth cycle" and the third definition is close to the "classical cycle". A good review of these definitions can be found in Harding and Pagan (2002).

2.3 Synchronization of cycles. Measure 1. Den Haan (2000)

Den Haan (2000) argues that unconditional correlation coefficients lose important information about the dynamic aspects of the comovement across variables. In addition, in the case of non-stationary variables (as the ones in the previous example), the unconditional correlation produces spurious estimates. In order to solve these problems he proposes to use the correlations of the VAR forecast errors at different horizons as a measure of comovements of the series.

He proposes the following identification scheme:

$$Z_t = \mu + \sum_{j=1}^{N} A_j Z_{t-j} + \varepsilon_t, \tag{5}$$

where Z_t represents in our case, the logs differences of the industrial production indexes for each pair of countries at time t, A_j is a (2×2) matrix of regression coefficients, μ is a vector of constants, N is the number of necessary lags, and ε_t are serially uncorrelated errors with zero mean and covariance matrix Ω.[5] Out of this specification, the k-period ahead forecast error is

$$Z_{t+k} - Z_{t+k/t} = \sum_{j=0}^{k-1} \Theta_j \varepsilon_{t+k-j}, \tag{6}$$

[5]Den Haan presents a more general model by allowing for both linear and quadratic deterministic trends. In our case, for the sample considered, these trends were not necessary for most of the countries. In addition, he shows that the results are robust to estimate the model in level and in first differences. We present the results of the estimation in first differences but the results using the leves are very similar.

where $Z_{t+k/t}$ is the k-period ahead forecast, and Θ_j may be obtained recursively from $\Theta_j = \sum_{i=1}^{N} A_i \Theta'_{j-i}$, with $\Theta_0 = I$, and $\Theta_\tau = 0$ for any $\tau < 0$. Therefore, the covariance matrix of this k-period ahead forecast error $\widetilde{Z}_{t+k/t} = Z_{t+k} - Z_{t+k/t}$ becomes

$$E\left(\widetilde{Z}_{t+k/t}\widetilde{Z}'_{t+k/t}\right) = \sum_{j=0}^{k-1} \Theta_j \Omega \Theta'_j. \tag{7}$$

Finally, the correlation between the k-period ahead forecast error between the two variables that form Z_t will be the element $(2,1)$ of the previous matrix divided by the product of the two forecasted standard deviations for the two series (elements $(1,1)$ and $(2,2)$ of the previous matrix).

To facilitate comparisons, we present the empirical results by using distances instead of correlations. These distances are measured by one minus the value of the correlations. In this respect, Table A1 of Appendix A shows all the distances computed from the correlation of 48 months ahead forecasting errors.[6] Of special interest is the correlation of 0.60 computed for Italy and Spain (distance of 0.40), which represents a less extreme value than the correlations of almost one (using the logs levels) and of almost cero (using first differences). In order to illustrate this point, let us consider the correlation computed from the 2 months ahead forecast error in the example outlined in equations (1) and (2). In this case, the VAR representation of the 2-period ahead forecast error is:

$$\begin{pmatrix} \widetilde{Z}^x_{t+2/t} \\ \widetilde{Z}^y_{t+2/t} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} e_{t+2} \\ u_{t+2} \end{pmatrix} + \begin{pmatrix} 1 & \phi \\ 0 & 1 \end{pmatrix} \begin{pmatrix} e_{t+1} \\ u_{t+1} \end{pmatrix}, \tag{8}$$

where $\widetilde{Z}^x_{t+2/t}$ and $\widetilde{Z}^y_{t+2/t}$ represent the 2-period ahead forecast errors for the logs of the industrial production series x and y, respectively. For $k = 2$, the correlation of the forecast errors would be

$$Corr\left(\widetilde{Z}^x_{t+2/t}, \widetilde{Z}^y_{t+2/t}\right) = \frac{\phi\sigma_u^2}{\sqrt{2\left[\sigma_e^2 + \sigma_u^2\left(1+\phi^2\right)\right]}}, \tag{9}$$

that is clearly between the extreme values of zero and one for any reasonable values of ϕ, σ_e^2, and σ_u^2.

Table 1 shows a summary of the distances (one minus correlation coefficient) computed from the industrial production series since the nineties.[7] The table shows that the Euro

[6] Hence, we consider business cycle horizons of four years.

[7] The correlation between two variables in a sample is not the average correlation of the subsamples.

economies are more interlinked across them than with the accession countries economies (distances of 0.61 versus 0.82). In fact, if we test the null hypothesis of no correlation with respect the alternative of positive correlation, we reject the null in more than 50% of the occassions in the case of Euro countries with themselves, but only in 27% in the case of accession countries with themselves.[8] However, according to this measure, this link is previous to the creation of the Eurozone (the distance computed from series since the sixties to the eighties is 0.56, and the null of no correlation is rejected in 73% of cases). A summary of the information about all the pair of cross correlation across European economies is displayed in Figure 2. This figure plots the kernel estimation of the density function of the distances for two groups of countries, the Euro economies and the accession countries. The former countries presents a distribution of the distances more concentrated around a smaller mean than the latter countries. In addition, and as explained in the figure, a test of equality of the correlation mean of these two groups clearly rejects the null of equality for any standard critical value.

2.4 Synchronization of cycles. Measure 2. Forni et al. (2001)

It is well-known that a time series can be expressed as a sum of infinite sinusoidal functions or waves with different frequencies and amplitudes. This is what is called the *spectral decomposition* of a time series. This decomposition allows the disaggregation of a time

Therefore, the correlation across the Euro-area economies is not the average of the correlations between each pair of countries. There is one transformation in the statistical literature, the hyperbolic tangent, that allows us to obtain a statistic with a known distribution for the correlation and combine several correlation coefficients. It consists on:

$$\zeta = \tanh^{-1}(r) = \frac{1}{2}(\ln(1+r) - \ln(1-r)),$$

where $\zeta \backsim N(r, 1/n)$, r is the correlation coefficient and n is the sample size. This is also call the Fisher's z-transformation (David, F. N, 1949). When we want to combine different correlations coefficients (e.i. two correlations r_1 and r_2), we operate in the following way:

$$\zeta' \backsim N(\frac{1}{n_1+n_2}(n_1 \tanh^{-1}(r_1) + n_2 \tanh^{-1}(r_2)), \frac{1}{n_1+n_2}).$$

Hence, we undo the transformation to get a correlation coeffcient which summarizes both ($r = \tanh(\zeta')$). In the case of correlation coefficients, this is a more suitable form of combination than a simple average.

[8] We have bootstrapped the VAR forecasts errors for different forecast horizons. With this distribution, we are able to calculate a 90% confidence interval for each correlation coefficient.

series into components of different periodicities. The study of business cycles is based on the components with periodicities ranging from 1.5 to 8 years. In terms of frequencies, this implies frequencies from 0.07 to 0.35 radians.

If we want to know the explanatory power of each component in the behaviour of the original series, it is possible to use the spectral and cross-spectral density functions. Thus, the spectral density would be a function that assigns the variance of variable x_t to intervals of frequencies (ω). This function has the following form,

$$S_x(\omega) = \frac{1}{2\pi} \sum_{h=-\infty}^{\infty} e^{-ih\omega} \gamma_x(h) = \frac{\gamma_x(e^{i\omega})}{2\pi}, \tag{10}$$

where $\gamma_x(h)$ is the autocovariance function, ω holds $-\pi \leq \omega \leq \pi$, and $\gamma_x(e^{i\omega})$ is the autocovariance generating function. In the bivariate case, the spectral function is known as the cross-spectral density function, which assigns the covariance between two variables to different frequencies,

$$S_{x,y}(\omega) = \frac{1}{2\pi} \sum_{h=-\infty}^{\infty} e^{-ih\omega} \gamma_{x,y}(h) = \frac{\gamma_{x,y}(e^{i\omega})}{2\pi}, \tag{11}$$

where $\gamma_{x,y}(h)$ is the cross-covariance function, ω again holds $-\pi \leq \omega \leq \pi$, and $\gamma_{x,y}(e^{i\omega})$ is the cross-covariance generating function.

Using this decomposition of variance, through both functions calculated in the frequency band of the business cycle, we are able compute the correlation in frequency domain. In particular, we choose the measure of correlation defined by Forni et al (2001) that is called *dynamic correlation*:

$$\rho_{x,y}(\omega) = \frac{\text{Real}\left(S_{x,y}(\omega)\right)}{\sqrt{S_x(\omega) S_y(\omega)}}. \tag{12}$$

The main advantages of this measure of correlation is that it is a real number, takes values between -1 and 1, incorporating the sign of the relation and that it permits to calculate the correlation for each band of frequencies.[9]

We need some final remarks concerning the estimation of the spectrum. First, Granger and Hatanaka (1964) showed that the spectral and cross-spectral methods applied to non-stationary series should be used with caution, since the variance of these series tends to

[9]This measure overcomes some problems of other measures used in the literature. The "coherency" can take imaginary values and the "squared coherence" does not keep the sign of the relation. See Forni et al. (2001) for further details.

infinite. In these cases, the spectrum should be estimated as an approximation (pseudo-spectrum) and the series should be transformed to stationary. Hence, before estimating the spectrum, we need some filter to reduce or eliminate the lower frequencies of the series. The filter used for removing trends depends on what subsequent analysis one intends to perform. If, for example, one is interested in studying long cycles, the first differences appear to be inappropriate as although they attenuate the power of low frequencies, they give a lot of importance to the high frequencies. The resulting distortion may obscure important features of the original series. In order to be as general as possible, we use the most popular filter to remove low frequency movements of the data, the Hodrick Prescott (HP) filter (see Hodrick and Prescott, 1980 and 1997). The HP filter is a symmetric linear filter that decomposes a time series into two components: a long-term trend and a stationary cycle. This filter requires the specification of one parameter (usually called lambda) which penalizes the bad fit and the lack of smoothness in the trend component. This parameter depends on the periodicity of the data and the band of frequencies which we are interested in.[10] Second, to overcome the asymptotic inconsistency of the estimates, we use the standard Barlett's lag spectral window (this weights the sample covariance in the spectral estimator and reduces the variance). Third, as it is impossible to calculate the sum of infinite terms, we truncate it with a truncation parameter equals to the sample size to the power of one third.[11]

The dynamic correlations for all the pairwise combination of countries are collected in the Appendix A, Table A2, and they are summarized in Table 2. These tables confirm the results of the previous section. The Euro area countries are closer than accession countries (distances of 0.55 versus 0.66). Besides, if we test the null hypothesis of no correlation with respect the alternative of positive correlation, we reject the null in more than 65% of the occassions in the case of Euro countries with themselves, and 45% in the case of

[10]We have applied the most commonly used lambda for monthly series of $14,400$.. However, we have come to similar results using other values which extract longer cycles as, for example, the lambda of $129,119$ proposed by Maravall and del Río (2001).

[11]Whichever lag window function is used, either if the truncation parameter M tends to infinite or if it is a function of the sample size T, the asymptotic unbiasedness is guaranteed (see Priestley, 1981). Andrews (1991), proposes using $M = O(T^{1/3})$ when we work with Bartlett window. In our work we employed values from 3 to 6, according to the formula $M = T^{1/3}$.

accession countries with themselves.[12] And, with respect the Euro Area countries, this link is also previous to the creation of the EMU (distance of 0.44 since the sixties to the eighties, and 83% of rejections of the null of no correlation among Euro countries). As in the previous section, we complete the description of the results in Figure 3 where we also present the test that clearly reject the equality of means.

2.5 Synchronization of cycles. Measure 3. Harding and Pagan (2002)

In this section, we describe a third approach to assess the degree of synchronicity among the countries' business cycle. In this respect, Harding and Pagan (2002) propose to consider the pairwise correlation coefficient among their reference cycles, that is a binary variable having value one when the country is in recession and zero otherwise.[13] Unfortunately, with the exception of the US economy, for which the NBER dates its official peaks and troughs, no generally accepted reference cycles appear to be available for the other countries. In this paper, we follow the well-known procedure of Bry and Boschan (1971) to identify the countries' business cycle turning points.[14] These authors develop an algorithm that isolates the local minima and maxima in a series, subject to reasonable constraints on both the length and amplitude of expansions and contractions. Table B in Appendix B shows the output results (classified by decades) of this dating procedure applied to the thirty industrial production series. Note that the NBER reference dates, also shown in the table, provides an obvious standard of comparison for the results of our procedure applied to US data. This shows that the Bry-Boschan procedure identifies US turning points that are either identical or close to the official NBER turning points.[15]

[12] We use, as in the previous section, the Fisher transformation in order to obtain a standard error for the correlation coefficient. Obviously, after calculating the Fisher transformation, we use the delta method to obtain the standard errors of the correlation coefficients.

[13] These authors show the advantages of using the correlation index instead of the concordance index of Artis et. al (1997) to analyze business cycle synchronicity.

[14] Several authors propose slightly different versions of the Bry-Boschan dating rule. In this respect, Garnier (2003) finds that they lead to similar turning points for most of the industrialized countries.

[15] One noticeable exception is the peak in the last eighties. This seems to be a characteristic of non-parametric dating rules based on industrial production indexes, as documented by Artis et al. (1997) and Garnier (2003).

Having a look at these tables, it is easy to anticipate two conclusions about the business cycle synchronization. First, as noted by Massmann and Mitchel (2003), the timing of the European business cycle phases is more synchronous during the period before 1990 than in the period from this date. For example, all of the countries that experienced the first recession of the seventies showed the peak in 1974. However, it does not happen with the first recession of the nineties which depending on the country starts in a range from 1989 to 1992. Second, the synchronization between European and accessing countries is rather limited. In this respect, while more than 80% of the European countries experienced the first recession of the new century, this percentage is less than 40% for the group of accessing countries.

Harding and Pagan (2002) measured the degree of business cycles synchronicity between country i and country j with the sample correlation between their reference cycles. A simple way to obtain this measure is by the regression

$$\sigma_i^{-1} D_{it} = a_{ij} + \rho_{ij} \sigma_j^{-1} D_{jt} + u_t, \tag{13}$$

where D_i is the reference cycle of country i, σ_i is its standard deviation, and ρ_{ij} is the sample correlation between the reference cycle of countries i and j. Table 3 shows the mean distance estimated among each of the countries within the Euro area and the accessing countries. With respect to the Euro countries, the distance across Euro economies has not decreased with the implementation of the EMU. At the same time, as in the other previous measures, distances across Euro economies are slightly smaller than distances across accessing countries (0.7 versus 0.73) although in this case, it is remarkable the big distances from accessing countries to the Euro economies (0.93). Information in Table 3 is complemented with the display in Figure 4, where it is clear that, by contrast with the previous distances, it is in the dispersion, and not in the mean where the differences between Euro and accession countries are more evident. Table A3 in the appendix A shows all the individual correlations.

In contrast to the previous measures of business cycle correlations, Harding and Pagan (2002) propose a simple test of the null of no business cycle synchronization by using the t-ratios of the null that the correlation coefficient is zero, allowing for heteroskedasticity and serial correlation. However, we think that this test may be biased to reject the null of no correlation simply because there are more zeroes than ones in the countries' reference cycles since expansions are typically longer than recessions. In this respect, we propose a new approach to develop the test of no business cycle synchronization between countries i and j based on the bootstrap approximation of the t-ratio's true distribution. First, we compute the countries' reference cycles D_{it} using the Bry-Boschan dating procedure. Second, for each country we estimate the probability of being in recession, the probability of being in expansion, and the probability of switching the business cycles phase. Third, given these estimates, we generate $10,000$ reference cycle variables sharing the same business cycles characteristics than these two countries. Finally, we compute the p-value associated to the null of zero correlation coefficient. The results of applying this test show that correlation has decreased since the 60s in the Euro area. The percentage of rejections of the null of no correlation is 52% since the sixties, becoming 46% in the nineties. As detected by Garnier (2003), the business cycle phases in the EU countries have become more idiosyncratic. At the same time, the results of the comparison Euro area and accessing countries confirm previous results, correlation across accessing countries is smaller than across Euro countries (46% of rejections of the Euro versus 27% of the accessing) and the same happens with the average rejection in the correlation across Euro and accessing countries (9.84%).

2.6 A comprehensive measure of distance

The result from the previous sections is a collection of distances among countries, applying three different methodologies, which measure the degree of business cycle synchronization among several European and Non-European countries. However, despite the heterogeneity of the approaches, they come to the same two conclusions: synchronization between Euro-zone countries with themselves is higher than synchronization between accession countries with themselves, and there are no appreciable gains in synchronization between EMU countries in the last decade.

As frequently stated in the literature, a mixing of techniques should give more robust results than individual measures by themselves. Given that we do not have any a priori on which is the most accurate measure,we again follow the Fisher transformation to combine them into a comprehensive measure of distance.[16] Following this strategy, Table

[16]The reader could think of ways to give more weight to some measure versus the others. However, it is worth mention, that potential ways of weighting the measures as could be the dispersion of rates (more weight to the measure with less dispersion) do not help in this case because the standard error of the

A4 (in Appendix A) displays all distances across all the economies. We summarize these combined distances in Table 4 and Figure 5. A test of the null hypothesis that the mean or the volatility of distances across Euro and accessing economies are equal rejects both hypothesis. Again, the conclusion is that Euro economies seem to be more homogeneous and closer together than the accession countries.

We explore the combined distances in the following subsections by using both *multi-dimensional scaling* techniques, that are designed to represent distance measures among objects on a plane (such as a map), and *cluster analysis* techniques, that are designed to classify objects into groups. The former is concerned with the geometric representation, while the latter is concerned with the group identification.

2.6.1 Multidimensional Scaling

Multidimensional Scaling (MDS) techniques (Cox and Cox, 1994) seek to find a low dimensional coordinate system to represent n-dimensional objects and create a map of lower dimension (k) which gives approximate distances among objects. The k-dimensional coordinates of the projection of any two objects, r and s, are computed by minimizing a measure of the squared sum of divergences between the true distances ($d_{r,s}$) and the approximate distances ($\widehat{d}_{r,s}$) among these objects.[17] That is,

$$min_{\widehat{d}_{rs}} \frac{\sum_{r,s}(d_{r,s} - \widehat{d}_{r,s})^2}{\sum_{r,s} d_{r,s}^2}, \tag{14}$$

with

$$\widehat{d}_{r,s} = (||z_r - z_s||^2)^{1/2} = \left[\sum_{i=1}^{k}(z_{ri} - z_{si})^2\right]^{1/2}, \tag{15}$$

where z_r and z_s are the k-dimensional projection of the objects r and s, and z_{ri} and z_{si} are the k dimensions of each object. It is noticeable that MDS is equivalent to using k principal components.[18]

In the case of 2-dimensional representations, the resulting picture is much easier to interpret than distances in higher dimensional spaces because it allows plotting the distances in a plane. In the resulting map, countries which present big dissimilarities have representations in the plane which are far away from each other. Figure 6 represents the

distribution of distances for each measure is the same.

[17] This measure is usually called the *Stardardized Residual Sum of Square* (STRESS).

[18] We refer the reader to Kruskal (1964) and Timm (2002) for more details.

map of the average distances (mean of distances among countries obtained with the above three methods) using MDS. This representation gives us a glimpse of the how close are the cycles among countries. It can be seen, for example, that United Kingdom cycles are closer to those of Canada and United States than to the Euro area countries. Euroarea countries are closer to each other than to any other group of countries, and the accessing countries are far from each other.

2.6.2 Cluster analysis of business cycle synchronization

In this section, we try to identify clusters of countries attending to their business cycle synchronization. Countries in the same cluster will have more syncronization across them than countries in other groups. There are different methods to do this grouping. First, we use *hierarchical clustering* algorithms, which enable us to determine the number of clusters (explanatory method). Secondly, we use this information to apply *non-hierarchical clustering* or *partitioning* algorithms (confirmatory method), which search the best partition given the number of clusters.[19]

1st step: Hierarchical clustering.

Hierarchical algorithms are used to generate groups from a set of individual items. The algorithms begin with each item forming its own cluster. Then, the clusters are combined iteratively with the two "most similar" clusters employing some criteria, until all of them form a single cluster.[20]

When we represent the sequence of cluster solutions in a plot we obtain a *tree diagram or dendogram*. The tree starts with the leaves at the bottom, which are the original items. Then, the pair with the lowest distance forms the first group. In the following steps, the items or clusters are successively combined, forming the branches of the tree until we get at the top of the graphic. The height of the tree represents the level of dissimilarity at which observations or clusters are merged. The higher the height of the tree, the more dissimilar are the observations contained in the clusters. When a great jump has to be given to join two groups, it implies a big intergroup dissimilarity. The optimal number of

[19] In this section we just describe an overview of clustering methods. For a more detailed view, see chapter 9 in Timm (2002).

[20] We use the "most similar" criterium of Ward (1963) that is based on the minimal increment of within-group sum of squares.

groups is often situated at those junctures.

Figure 7 shows the dendogram for our set of distances among countries.[21] This algorithm joins items or clusters based upon minimizing the increase in the sum of squares of distances within clusters. Looking at the figure, we can observe big jumps in forming two, three and four groups. We do not have a clear tool to decide which is the optimal number of groups. We will try in the next step these three possible options. However, just looking at the tree, we can observe a group formed by most of the EU countries, another group formed by the US and relatives, a third group with most of the accession countries, and a fourth group with three "atypicals", Cyprus, Greece and Portugal.

2nd step: Non-hierarchical clustering.

These algorithms try to find a "good" partition, in the sense that objects of the same cluster should be closed to each other, whereas objects of different clusters should be far away. They classify the data into k groups (k is given by the user) satisfying the requirements that each group must contains at least one object, and that each object must belong to exactly one group. These methods are usually called partitioning methods since they make a clear-cut decision. In this paper, we follow Kaufman and Rousseeuw (1990) to employ the k-medoid method.[22]

In the previous step, the data have revealed us that there may be between two and four clusters of countries. Hence, we start by considering four groups. The fact that one of the cluster includes countries that are basically atypicals implies that once we decide four groups, these atypicals do not form a group but they get integrated in the other groups, because the distance across them is too big to link themselves together. On the other side, allowing just for two groups make one group too big, including the atypicals, all the EU countries and the US and others, with very high heterogeneity across them. Therefore, we try three groups, obtaining the most sensible characterization of the data with the first cluster that includes Euro Area economies (except Finland) plus Denmark, Sweden, Cyprus, Lithuania, Slovenia and Hungary, the second cluster includes the United States and other industrialized economies as Canada, United Kingdom, Japan and Finland. The

[21] For robustness, we constructed the dendograms for two other criteria, the average link and complete link methods, leading to similar results.

[22] These authors show the advantages of the k-medoid method of Vinod (1969) with respect to others clustering method as the k-means method of McQueen (1967).

last cluster is the cluster of accession countries: Latvia, Estonia, Slovakia, Czech Republic, Romania, Turkey, Norway and Poland. Figure 8 displays the resulting clusters from the k-medoid method when imposing three groups.[23]

3 Is there a European attractor?

Most of the papers cited in the introduction that deal with the problem of European business cycle comovements or even world business cycle comovements, consider a leading economy or an attractor formed by a weighted average of all the economies of the area. In this section we want to check if this attractor matches with what we find in the pictures and maps previously showed in the paper. The papers that analyze how important is an attractor in defining the comovements across economies usually try to decompose the idiosyncratic and common components in each of the series analyzing how much of the variance can be explained from each of them.[24] In order to check if a common attractor could explain the comovements across economies we propose a new methodology that, to our knowledge has not been used in the previous literature.

The idea is the following: If there exist an attractor, most of the distances between the leading country and the rest of countries would be small, and we would observe a great amount of small distances and a very few large ones. In practical terms, looking at Figure 6, the question to ask is: are those points (countries) in the map randomly distributed or is there any kind of attractor that keep them together? In order to answer this question, we propose the following exercise. First, we normalize the distances to include them in a square of dimensions 1 by 1. Second, we generate 27 observations (30 countries minus Japan, US and Canada) from a bivariate uniform distribution and we calculate the distances between each pair of points.[25] We repeat this exercise $10,000$ times and we

[23] A word of caution must be said when interpreting Figure 8. Even though we plot three groups, the average similarities between groups are very small in all cases. We have computed the "silhouette width" (Rousseeuw, 1987), a measure of cohesion within a cluster with respect to the neighbour clusters. A value close to one means that countries are well clustered. A small coefficient means poor clustering structure. In our case we have obtained silhouette width values of 0.2 or 0.3 for each cluster. Special mention deserves the case of Hungary with a high negative value for its silhouette width which suggest that the methodology has trouble in assigning this economy to any of the existing groups.

[24] Bordo and Helbling (2003) is a good example.

[25] For this exercise, we consider all the European economies in order to maximize the number of obser-

generate the density function of those distances between each pair of countries (Figure 9 top). The plotted distribution represents the distances across economies when there is no attractor across them (they have been generated by a uniform distribution).[26] Third, we generate 27 observations with the same support space but coming from a bivariate normal distribution, where an attractor is clear. We repeat the exercise $10,000$ times and show the distribution of the distances (Figure 9 middle). As we can see, in the case of one attractor, there is a concentration of small distances across the points, implying a higher value for the skewness than in the case of the uniform distribution.

Additionally, we consider the possibility of the existence of two attractors. In order to simulate economies with two attractors we consider a mixture of bivariate normals. If this is the data generating process of the data and the distances between the two attractors is big enough, we will expect a bimodal distribution as the one plotted in Figure 9 (bottom). We have generated the plot by extracting $10,000$ times observations from a mixture of normals. The bimodality comes from the fact that there is a set of short distances associated with observations that are generated by the same normal and a set of long distances associated with observations that has been extracted from different normals.[27]

We then represent the estimated distribution of the distances of the actual data, plotted in Figure 10. There are a few basic statistics that could help us to distinguish which is the distribution that best describe the data generating process of the observations. High values of the skewness will imply evidence of the existence of one attractor and bimodality will be evidence of two attractors. Table 5 presents the basic statistics of the different distributions of the simulated and observed data. Even though we concentrate our explanation on the combined measure of distance, the results are extremely robust to any of the three other measures, as shown in Table 5. We can observe that the estimated skewness of the observed data is -0.08, which is statistically different than the estimated value for one attractor, 0.65 (p-value of equality of the coefficients is 0.00) but not different from the value estimated for the uniform, 0.20 (p-value 0.15). With respect to the existence of

vations used for the kernel density estimation.

[26] The plot represents the density function of the distances across the 27 points, generated $10,000$ times. The density function has been approximated with a kernel estimator following Silverman (1986).

[27] We use a 0.5 probability for mixing the two normals.

two attractors, the bimodality index of the data is 0.41, below the critical value of 0.55.[28] However, the hypothesis of two attractors implies an estimated modality index of 0.59. Out of this experiment, we obtain no evidence of the existence of one or two attractors in the comovements across European economies. The null of no attractor can not be rejected.

4 Can distances across economies be explained?

In the paper, we have shown that some economies are closer than others. However, as economists, we might want to understand what is behind those distances. Are there any macroeconomic variables that could help us to explain these distances? The attempt to answer these questions is not new in the literature. Some papers have tried to explain these facts but in different contexts. A seminal paper in this literature is Frankel and Rose (1998), where they introduce the importance of trade in explaining the correlations across economies, carefully considering the endogeneity of this variable in the regression of correlation measures and trade. Clark and Van Wincoop (2001) analyze correlations across regions in the US and Europe, with a different measure of correlations (basically annual rates of growth). Bordo and Helbling (2003) analyze annual data from 1880 to 2001, trying to measure the effect of the exchange rate regime on the correlations.[29] The results are mixed but they all coincide that trade linkages are relevant in explaining comovements.

We want to explain comovements using our measures trying to incorporate in the analysis as much variables as we can with the only restriction that they should be available for all the countries in the sample. We careful explain in Appendix D the data sources and the exact definition of each variable used. After trying different specifications, the most successful one is displayed in Table 6.[30] In this table, all the variables represent differences

[28] The bimodality index Timm (2002, pag. 535) is defined by:

$$BM = (m_3^2 + 1)/[m_4 + 3(n-1)^2/(n-2)(n-3)],$$

where m_3 is the skewness coefficient, m_4 is the kurtosis coefficient, and n is the number of observations.

[29] They use also three different measures of the correlations, different to ours because they concentrate more on the static correlations rather than in the dynamics concepts that we consider. In their case, it makes more sense to contemplate different measures of static correlations because they observe long series of annual data.

[30] Table 6 presents the results for the combination of distances. Just for completeness, the results for each of the individual distances are displayed in Appendix C.

from country i to j. For example, the variable called percentage of industry means the differences in percentage of industry output divided by total output in country i and country j. As we can see, the distances can be explained, partially by the specialization of the economy, captured by differences in the percentage of industry production in total production and percentage of agriculture in total production. Other significant variables are differences in average saving ratio and average labor productivity. These variables are basically related to the structure of the economy, both, on the production side (the productivity) and on the consumer's side (the saving ratio).

Obviously, the trade variable is fundamental in explaining the relations across economies. We move slightly away from the standard measures of trade linkages in the literature.[31] We want to capture the transmission of the business cycle comovements through trade. We assume that a country i can export or import its cycle to another country j if the proportion of imports or exports coming in or going to the other country is high. In order to account for those relations, we create the trade variable as the maximum of two different averages (over the sample): the proportion of exports of country i that go to country j and the proportion of exports of country j to country i.[32] For example, in the case of Austria and Germany, the average proportion of exports of Austria going to Germany is 37%. The average proportion of exports of Germany going to Austria is 5%. Therefore, for this pair of countries we will use 37% as the trade linkages across them.[33]

However, the trade variable presents a serious problem of endogeneity.[34] We solve this problem by estimating the equation by instrumental variables. We use the standard

[31] We also include the definition of trade linkage proposed by Frankel and Rose (1998) in terms of the sumation of exports and imports from country i to country j, divided by the total amount of export and imports of country i plus country j, with very similar results.

[32] We tried the same measure with imports with extermely similar results. Actually, the correlation between both measures is 0.93.

[33] The idea behind using the maximum is that, if business cycles are linked to trade, when a small economy has strong trade linkages with a big economy, we will observe that the business cycle of the small economy is linked to the business cycle of the big one.

[34] It might be a problem for some other variables used in the estimation, particularly the policy ones. However, we think that the problem is partially solved by taking averages at the beginning of the sample as explanatory variables for future comovements. This caveat do not apply so clearly to trade because trade structures and trade relations are deeply related with business cycle comovements.

instruments in the literature for explaining trade, a border dummy, a Euro dummy, a European Union dummy, the log of geographical distances, and the absolute difference of the log population.[35] The results of Table 6 show that this is a very important variable in explaining the business cycle comovements and with the appropriate (negative) sign. Pairs of countries with a high level of this variable are closer together, which implies that there is a transmission of the cycle through trade. Countries that are more linked by trade are more linked in their business cycles.

Finally, it is important to remark the role of the policy variables. Fiscal variables are significant (the size of the public balance on the GDP) but monetary policy related variables seem not to explain any of the cyclical differences. We tried lots of possible combinations to include monetary policy variables (inflation differentials, inflation correlations, etc), but the results were not very satisfactory. In all cases, the macro variables used as explanatory variables are sample means for the longer period of information available. We pretend to capture "structure" of the economy and avoid as much as possible all the cyclical variation in the variables. We consider that our results are fundamentally different from the previous results found in the literature where most of the variables but trade were non significant. We find a role for different macro-variables in explaining the comovements across economies.

5 Conclusion

We think that this paper has different lessons according to the interest of the reader. Much of the papers that analyze international links among economies usually assume that there is an "European business cycle", which is usually associated to some economies with a leading role in the area. This paper tries to go further by testing if such business cycle attractor actually exists. For this attempt, we present a comprehensive methodology to characterize the comovements across the economies. In addition, we propose a new method to test for statistical support of the supposed attractor. Using this test, we show that there is no evidence of the existence of neither one nor two attractors in the comovements across

[35] The dummies take the value 1 when both countries share a common border or both belong to the Euro-area or EU, respectively. Sargan test for the correct specification of the orthogonality restrictions accepts the null of correct specification (p-value 0.33).

European economies. Obviously, this result put a question mark in those papers that either implicitly or explicitly assume that it exists.

In addition, we consider two features of the international business cycles. The first one, is related to the evolution of the business cycle synchronization. As Stock and Watson (2003) have recently documented, we show that the international economies seem to be less (rather than more) synchronized in the last fifteen years. The second one, is related to the role of trade in explaining international business cycle transmissions. In contrast to the standard results in the literature, we find that, apart from trade, there is a significant role for other macroeconomic variables (structural and some economic policy variables) to explain business cycle comovements.

Finally, due to the imminent incorporation of ten new members to the European Union, we think that the analysis of similitudes and differences among the actual members and the newcomers is going to be a source of many studies. In the context of the business cycles, this is the first paper that proposes a systematic analysis of these countries' linkages. We show that the distances across Euro economies are more closely linked than distances across newcomers, and these newcomers are on average further away from the Euro countries than across themselves. Finally, we have shown that the linkages across Euro economies are prior to the establishment of the union, showing that the smooth transition towards a more integrated economic area could be due to previous strong business cycles correlations, fundamentally through trade. This is not the case of the current enlargement because the differences among the newcomers and the current members (and among themselves) seem to be much more important than the differences that the actual members exhibited prior to the establishment of the union.

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Distances across economies

(Sample: 1990.1-2003.01)*

Table 1
Measure 1: Distances based on VAR estimations

	Euro	Candidates
Euro	0,61 *(0.06)*	0,83 *(0.05)*
Candidates	-	0,82 *(0.04)*

The distance across the Euro area countries from 1965.1-1989.12 is 0.56 (0.04).

Table 2
Measure 2: Distances based on the Spectrum

	Euro	Candidates
Euro	0,55 *(0.06)*	0,7 *(0.06)*
Candidates	-	0,66 *(0.05)*

The distance across the Euro area countries from 1965.1-1989.12 is 0.44 (0.05) .

* The sample starts in 1992 for all the accession countries but Turkey and Cyprus , because the first two years after the fall of the communist regimen had exceptional characteristics (see footnote 3 in the main text).

Distances across economies (cont.)

(Sample: 1990.1-2003.01)*

Table 3
Measure 3: Distances based on Harding and Pagan (2002)

	Euro	Candidates
Euro	0,7	0,93
	(0.05)	*(0.05)*
Candidates	-	0,73
		(0.04)

The distance across the Euro area countries from 1965.1-1989.12 is 0.65 (0.04).

Table 4
Distances based on a combination of the before three measures

	Euro	Candidates
Euro	0,62	0,82
	(0.06)	*(0.05)*
Candidates	-	0,73
		(0.04)

The distance across the Euro area countries from 1965.1-1989.12 is 0.55 (0.05).

Notes:

Tables 1 to 4 describe the combined distance across economies.

Distance is measured as 1 minus the correlation. Standard errrors are in parenthesis.

* The sample starts in 1992 for all the accession countries but Turkey and Cyprus , because the first two years after the fall of the communist regimen had exceptional characteristics (see footnote 3 in the main text).

Table 5
Is there an European Attractor? Some important statistics

		Mean	Median	Min	Max	Std. Dev	Skewness	Kurtosis	BM(*)
SIMULATED	no attractor	0,52	0,51	0,00	1,36	0,25	0,20	-0,68	0,44
	one attractor	0,36	0,33	0,00	1,28	0,19	0,65	0,26	0,42
	two attractors	0,44	0,41	0,00	1,18	0,24	0,19	-1,19	0,59

	Our Sample	Mean	Median	Min	Max	Std. Dev	Skewness	Kurtosis	BM(*)
OBSERVED	Measure 1	0,79	0,81	0,03	1,40	0,26	-0,15	-0,44	0,40
	Measure 2	0,68	0,67	0,11	1,47	0,27	0,24	-0,41	0,40
	Measure 3	0,84	0,84	0,05	1,47	0,27	-0,16	-0,45	0,40
	Combined Dist.	0,76	0,77	0,18	1,31	0,23	-0,08	-0,56	0,41

(*) BM refers to the bimodality index. Values bigger than 0.55 indicate the existence of bimodal or multimodal distributions.

Notes: The table collects the summary of most relevant statistics for the distributions of our three measures of business cycles distances and for the combination of these three measures. We have only into account the sample of european countries (all the countries considered except US, Canada and Japan). At the top of the table there are those statistics for the simulation exercises of distances associated with the existence of no attractors, one and two attractors. (More details in the main text.)

Table 6

Can distances be explained?

Dependant variable:
Combined Distances of Business Cycles

	OLS	IV
Constant	0,578	0,583
	(0.0249)	*(0.0311)*
%Industry	0,839	0,830
	(0.1825)	*(0.1863)*
%Agriculture	1,547	1,549
	(0.259)	*(0.2591)*
Saving Ratio	0,362	0,356
	(0.1665)	*(0.1680)*
Labor Productivity	0,080	0,078
	(0.0441)	*(0.0446)*
Public Balance	0,557	0,545
	(0.2356)	*(0.2412)*
Trade (%Exports)	-0,585	-0,638
	(0.1371)	*(0.2656)*
R squared	30%	

Notes: The table shows the estimated coefficients for the OLS and instrumental variables (IV) regression of the distances across business cycles in different economies and distances of those economies in each of the macroeconomic variables.The instruments employed to solve the possible endogeneity problem of trade variable are: log of the geographical distance between countries, border dummy, euro dummy, EU dummy and the absolute differences between the logs of population.

The results for each of the alternative measures of distances are displayed in the tables of Appendix C.

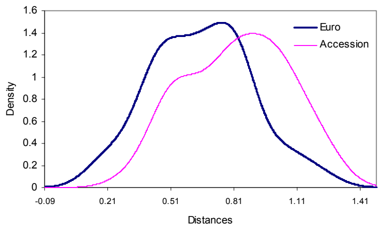
All the explanatory variables are explained in Appendix D.

Standard errors are in parenthesis.

Figure 1
A first graphical approach

Note: The top left figure plots the levels of the Industrial Production series for Italy and Spain and the top right, for Italy and Romania. The bottom left figure represents the rates of growth of the Industrial Production for Italy and Spain, and the bottom right the levels for Italy and Ireland.

Figure 2
Distribution of distances based on *VAR estimations*.



H_o: Euro mean = Acces. mean

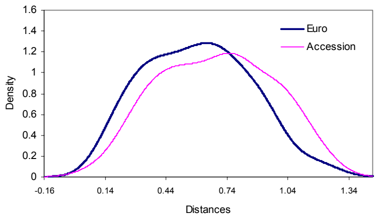
p-value: < 0.01

H_o: Euro variance = Acces. variance

p-value: 0.90

Note: The figure plots the estimated density function of the distribution of distances. The dark line represents the Euro area data, the clear line is the accessing countries data.

Figure 3
Distribution of distances based on *Spectrum*.

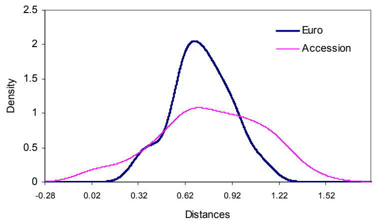


H_o: Euro mean = Acces. mean
p-value: 0.03

H_o: Euro variance = Acces. variance
p-value: 0.68

Note: The figure plots the estimated density function of the distribution of distances. The dark line represents the Euro area data, the clear line is the accessing countries data.

Figure 4
Distribution of distances based on *Harding and Pagan, 2002*.

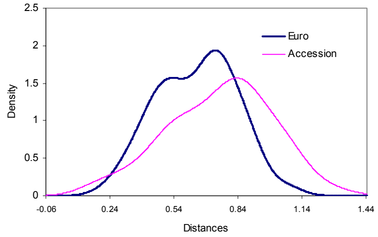


H_o: Euro mean = Acces. mean
p-value: 0.12

H_o: Euro variance = Acces. variance
p-value: 0.00

Note: The figure plots the estimated density function of the distribution of distances. The dark line represents the Euro area data, the clear line is the accessing countries data.

Figure 5
Distribution of distances based on *Combined distances*

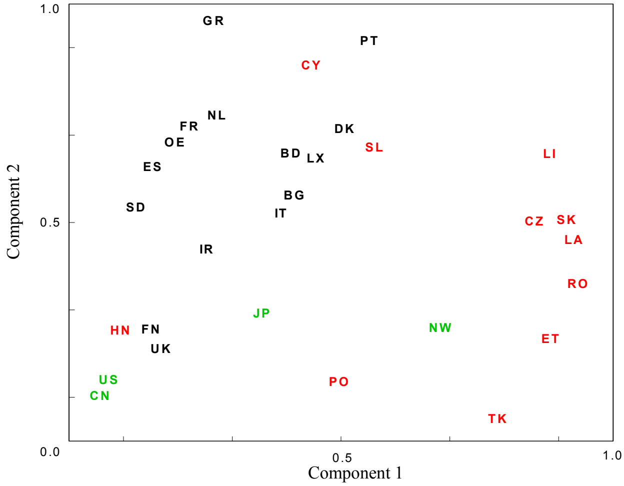


H_o: Euro mean = Acces. mean
p-value: <0.01

H_o: Euro variance = Acces. variance
p-value: 0.02

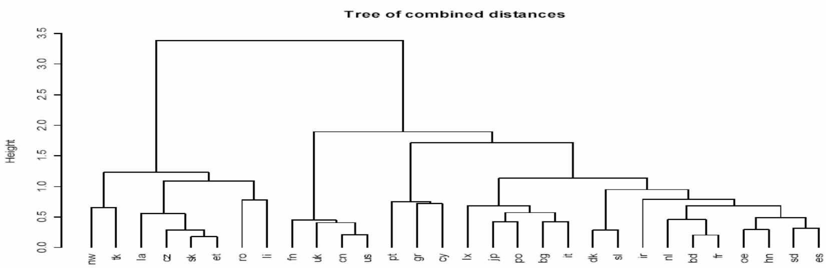
Note: The figure plots the estimated density function of the distribution of distances. The dark line represents the Euro area data, the clear line is the accessing countries data.

Figure 6
Map of average distances (Multidimensional Scaling)



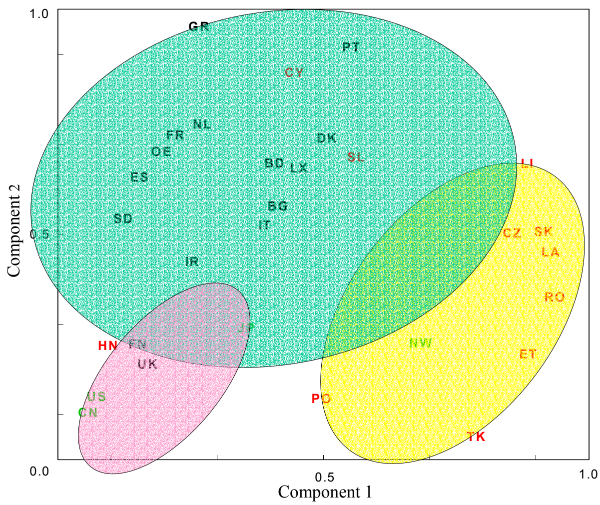
Note: The figure plots in a two dimensional scale the distances across the economies.
* The symbols used to represent countries are collected in Appendix D.

Figure 7
Hierarchical clustering (Timm, 2002)



Note: The graph plots a tree where the height represents the level of dissimilarity at which observations or clusters are merged.
* The symbols used to represent countries are explained in Appendix D.

Figure 8
Non-hierarchical clustering (Kaufman and Rousseeuw, 1990)



1- **Group " Europeans":** All EMU countries (except Finland), Denmark, Sweden, Cyprus, Lithuania, Slovenia and Hungary.

2- **Group "United States and relatives":** US, Canada, United Kingdom, Japan and Finland.

3-**Group"Accession countries":** Estonia, Slovakia, Czech Republic, Romania, Turkey, Norway, Latvia and Poland.

Note: The figure plots in a two dimensional scale the distances across the economies. And the circles represent the groups obtained in the clustering analysis.
* The symbols used to represent countries are explained in Appendix D.

Figure 9

Density functions of distances across 27 points

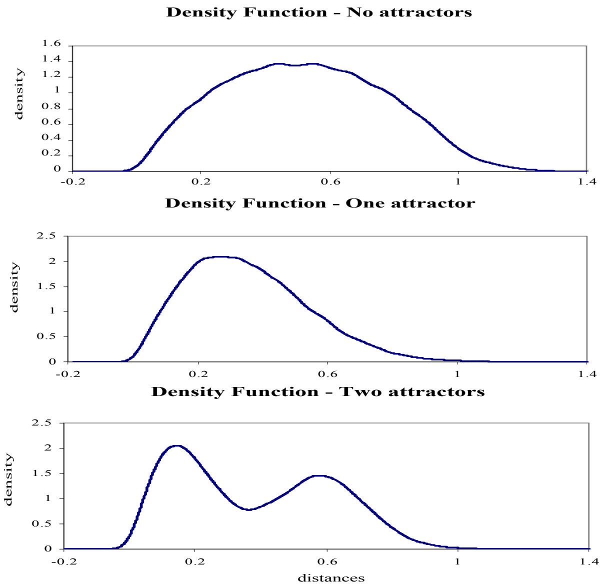
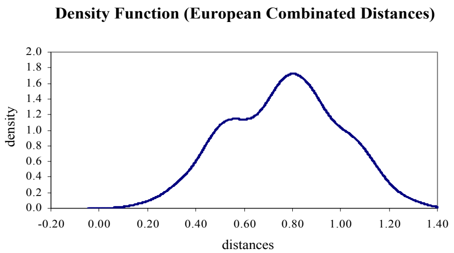


Figure 10

Density function of distances across 27 European countries



Note: The density function has been approximated with a Kernel estimator developed in more detail in Silverman, 1986.

Appendix A

Table A1: ***Measure 1 - Distances across countries based on VAR (4-years forecast errors)***

	Austria	Belgium	Germany	Greece	Finland	France	Italy	Luxemburg	Netherland	Portugal	Sweden	UK	Canada	Norway	Japan
Austria	-	0,27	0,15	0,45	0,73	0,49	0,53	0,87	0,45	0,98	0,27	0,86	0,37	0,97	0,64
Belgium		-	0,36	0,57	0,59	0,51	0,42	0,43	0,49	0,49	0,52	0,82	0,85	0,62	0,35
Germany			-	0,72	0,68	0,18	0,61	0,80	0,40	0,87	0,47	0,62	0,86	0,84	0,40
Greece				-	0,86	0,38	0,84	0,68	0,83	1,02	0,73	0,81	1,03	1,04	0,96
Finland					-	0,58	0,65	0,89	1,18	0,84	0,25	0,70	0,23	0,77	0,46
France						-	0,45	0,67	0,41	0,80	0,82	0,59	0,54	0,95	0,57
Italy							-	0,74	0,41	0,76	0,69	0,48	0,44	0,78	0,35
Luxemburg								-	0,84	0,82	1,03	0,80	0,64	0,83	0,64
Netherland									-	1,10	0,68	0,63	0,79	0,93	0,59
Portugal										-	1,25	1,11	0,85	0,95	0,86
Sweden											-	0,58	0,76	0,77	0,45
UK												-	0,22	0,69	0,53
Canada													-	0,92	0,22
Norway														-	1,07
Japan															-
USA															
Spain															
Denmark															
Ireland															
Cyprus															
Czech															
Hungary															
Latvia															
Poland															
Slovenia															
Turkey															
Romania															
Slovakia															
Estonia															
Lithuania															

Table A1 (cont.): ***Measure 1 - Distances across countries based on VAR (4-years forecast errors)***

	USA	Spain	Denmark	Ireland	Cyprus	Czech	Hungary	Latvia	Poland	Slovenia	Turkey	Romania	Slovakia	Estonia	Lithuania
Austria	0,52	0,26	0,43	0,36	1,15	0,95	0,21	1,02	0,46	0,41	0,80	1,29	0,87	0,81	0,03
Belgium	0,45	0,40	0,57	0,51	1,13	1,18	0,54	0,80	0,59	0,54	0,82	1,15	0,62	0,75	0,35
Germany	0,55	0,58	0,47	0,75	0,90	0,78	0,65	0,75	0,87	0,40	1,00	1,40	0,70	0,38	0,45
Greece	0,68	0,82	0,92	0,48	0,85	0,96	0,91	1,11	0,88	0,95	1,19	1,18	1,21	1,16	0,48
Finland	0,49	0,50	0,83	1,00	0,84	1,02	0,22	0,88	0,84	0,77	0,69	1,37	0,73	0,77	0,99
France	0,46	0,47	0,35	0,77	1,09	0,79	0,46	0,93	0,89	0,55	0,94	1,35	0,88	0,81	0,94
Italy	0,56	0,40	0,61	0,64	0,97	0,54	0,56	0,46	0,51	0,67	0,86	1,11	0,69	0,55	0,69
Luxemburg	0,82	0,76	0,81	0,83	0,99	0,77	0,83	0,64	0,60	1,09	1,13	1,22	0,83	0,59	1,20
Netherland	0,79	0,45	0,56	0,81	0,83	0,89	0,61	0,92	0,94	0,68	1,11	1,14	0,89	0,81	1,31
Portugal	0,92	0,97	1,01	0,89	0,83	0,90	1,09	0,85	0,88	1,14	0,87	1,12	0,87	0,91	1,31
Sweden	0,68	0,31	0,59	0,58	0,99	1,24	0,80	1,19	0,82	0,41	0,96	0,95	0,74	1,15	1,14
UK	0,34	0,77	0,71	0,62	0,93	1,06	0,58	1,14	0,25	0,65	1,04	1,11	1,05	0,85	1,05
Canada	0,19	0,71	0,71	0,61	0,98	0,79	0,26	1,02	0,29	0,77	0,98	1,03	0,88	0,72	1,11
Norway	0,87	0,92	0,85	0,94	1,01	0,96	0,98	0,77	0,79	0,97	0,78	1,11	0,80	0,81	1,18
Japan	0,30	0,46	0,84	0,68	1,17	0,67	0,60	0,85	0,33	0,81	0,65	0,65	1,02	0,58	0,78
USA	-	0,59	0,66	0,59	0,82	1,13	0,32	1,07	0,35	0,74	0,70	1,42	0,90	0,59	0,97
Spain		-	0,35	0,63	0,94	0,77	0,43	0,60	0,68	0,42	0,84	1,35	1,02	0,68	1,16
Denmark			-	0,79	0,66	0,84	0,70	0,74	0,55	0,29	1,15	0,98	0,65	0,62	1,15
Ireland				-	1,14	0,89	0,86	0,95	0,96	0,78	0,86	1,09	0,89	1,14	1,06
Cyprus					-	0,90	0,63	1,01	1,19	0,75	1,00	1,20	0,72	0,61	1,19
Czech						-	0,84	0,54	0,60	0,65	1,01	0,97	0,80	0,49	1,29
Hungary							-	1,11	0,80	0,72	0,91	1,12	0,85	0,64	1,17
Latvia								-	0,86	0,82	1,07	1,01	0,68	0,53	1,28
Poland									-	0,50	0,76	1,02	0,83	0,46	1,06
Slovenia										-	1,04	0,90	0,53	0,79	0,95
Turkey											-	1,06	0,95	0,90	0,93
Romania												-	0,48	0,77	0,54
Slovakia													-	0,31	0,41
Estonia														-	0,49
Lithuania															-

Table A2: ***Measure 2 - Distances across countries based on Spectrum (Dynamic correlation at business cycle periodicities)***

	Austria	Belgium	Germany	Greece	Finland	France	Italy	Luxemburg	Netherland	Portugal	Sweden	UK	Canada	Norway	Japan
Austria	-	0,39	0,21	0,82	0,44	0,21	0,31	0,60	0,45	0,77	0,16	0,52	0,55	0,86	0,48
Belgium		-	0,38	0,94	0,63	0,44	0,33	0,62	0,57	0,77	0,45	0,74	0,68	0,63	0,55
Germany			-	0,93	0,67	0,16	0,29	0,64	0,26	0,68	0,31	0,70	0,84	0,82	0,41
Greece				-	1,06	0,76	0,89	0,93	0,95	0,87	0,90	0,98	1,00	1,30	1,28
Finland					-	0,56	0,53	0,85	0,78	1,23	0,35	0,20	0,26	0,77	0,69
France						-	0,17	0,54	0,38	0,73	0,28	0,57	0,66	0,97	0,65
Italy							-	0,50	0,36	0,77	0,31	0,54	0,51	0,81	0,52
Luxemburg								-	0,72	0,90	0,67	0,67	0,60	0,75	0,59
Netherland									-	0,56	0,40	0,61	0,95	0,78	0,53
Portugal										-	0,77	1,16	1,36	0,97	0,93
Sweden											-	0,42	0,57	0,68	0,53
UK												-	0,29	0,87	0,62
Canada													-	0,98	0,56
Norway														-	0,82
Japan															-
USA															
Spain															
Denmark															
Ireland															
Cyprus															
Czech															
Hungary															
Latvia															
Poland															
Slovenia															
Turkey															
Romania															
Slovakia															
Estonia															
Lithuania															

Table A2 (cont.): ***Measure 2 - Distances across countries based on Spectrum (Dynamic correlation at business cycle periodicities)***

	USA	Spain	Denmark	Ireland	Cyprus	Czech	Hungary	Latvia	Poland	Slovenia	Turkey	Romania	Slovakia	Estonia	Lithuania
Austria	0,52	0,26	0,44	0,55	0,62	0,71	0,18	0,83	0,39	0,33	0,95	0,99	0,67	0,58	0,96
Belgium	0,60	0,42	0,40	0,46	0,59	0,64	0,47	0,63	0,36	0,45	0,67	0,80	0,52	0,49	0,92
Germany	0,74	0,21	0,33	0,66	0,45	0,50	0,32	0,56	0,30	0,20	1,05	0,79	0,61	0,37	0,79
Greece	1,07	0,77	0,86	0,78	0,64	1,11	0,98	1,19	1,18	0,86	1,42	1,33	1,07	1,47	1,00
Finland	0,27	0,58	0,65	0,65	0,97	0,80	0,20	0,82	0,56	0,48	0,87	1,06	0,77	0,59	0,98
France	0,63	0,13	0,29	0,59	0,47	0,48	0,33	0,46	0,38	0,25	1,21	1,01	0,59	0,48	0,61
Italy	0,54	0,19	0,34	0,39	0,55	0,46	0,29	0,47	0,30	0,41	0,98	0,87	0,48	0,46	0,80
Luxemburg	0,65	0,53	0,70	0,86	0,72	0,70	0,68	0,81	0,33	0,73	1,12	1,03	0,88	0,65	1,34
Netherland	0,90	0,47	0,50	0,60	0,55	0,68	0,51	0,78	0,57	0,49	1,26	0,65	0,57	0,82	0,83
Portugal	1,28	0,83	0,96	0,66	0,74	0,97	1,21	0,92	1,05	1,04	1,04	0,79	0,68	1,35	0,86
Sweden	0,60	0,27	0,42	0,58	0,59	0,71	0,34	0,87	0,50	0,31	1,08	0,83	0,73	0,62	0,94
UK	0,30	0,62	0,70	0,73	0,94	0,89	0,29	0,97	0,50	0,55	1,22	0,90	0,83	0,70	1,18
Canada	0,10	0,58	0,77	0,72	1,00	0,91	0,27	1,04	0,50	0,67	0,84	1,08	0,95	0,74	1,45
Norway	0,93	0,94	0,68	0,89	0,72	0,62	0,87	0,71	0,60	0,75	0,63	0,83	0,87	0,58	1,05
Japan	0,54	0,59	0,75	0,82	0,97	0,78	0,49	0,98	0,29	0,72	0,73	0,54	0,80	0,60	1,39
USA	-	0,63	0,72	0,69	0,87	0,82	0,26	0,96	0,40	0,70	0,70	1,16	0,87	0,65	1,30
Spain		-	0,34	0,70	0,48	0,68	0,37	0,71	0,47	0,27	1,16	1,02	0,78	0,58	0,94
Denmark			-	0,75	0,43	0,42	0,48	0,47	0,41	0,24	1,09	0,92	0,68	0,41	0,67
Ireland				-	0,77	0,68	0,54	0,75	0,71	0,79	0,80	1,00	0,59	0,92	0,87
Cyprus					-	0,77	0,80	1,08	0,71	0,59	1,18	1,17	0,83	0,97	1,05
Czech						-	0,71	0,11	0,36	0,53	0,79	1,01	0,48	0,27	0,42
Hungary							-	0,77	0,38	0,42	0,87	0,94	0,75	0,53	0,96
Latvia								-	0,49	0,63	0,63	1,03	0,32	0,27	0,30
Poland									-	0,47	0,79	0,81	0,56	0,24	1,03
Slovenia										-	1,18	0,78	0,69	0,43	0,64
Turkey											-	1,00	0,84	0,55	0,98
Romania												-	0,66	0,77	1,01
Slovakia													-	0,35	0,38
Estonia														-	0,53
Lithuania															-

Table A3: ***Measure 3 - Distances across countries based on Harding-Pagan (2002)***

	Austria	Belgium	Germany	Greece	Finland	France	Italy	Luxemburg	Netherland	Portugal	Sweden	UK	Canada	Norway	Japan
Austria	-	0,75	0,57	0,80	0,87	0,36	0,66	0,54	0,33	0,69	0,64	0,94	0,86	0,89	0,62
Belgium		-	0,57	0,74	0,86	0,62	0,54	0,71	0,70	0,65	0,43	0,69	0,70	1,02	0,64
Germany			-	1,16	0,94	0,29	0,75	0,92	0,56	0,93	0,80	0,96	0,78	1,00	0,67
Greece				-	0,95	1,08	0,82	0,58	0,85	0,38	0,58	0,81	1,02	1,15	1,06
Finland					-	0,82	0,63	0,86	0,93	1,11	0,74	0,71	0,32	1,07	1,26
France						-	0,74	0,74	0,41	0,82	0,62	1,06	0,63	1,15	0,52
Italy							-	0,54	0,65	0,78	0,60	0,85	0,84	0,81	0,65
Luxemburg								-	0,76	0,40	0,63	0,94	1,07	1,05	0,72
Netherland									-	0,74	0,63	0,67	0,94	0,78	0,63
Portugal										-	0,64	1,01	1,22	1,20	0,75
Sweden											-	0,63	0,61	1,15	0,62
UK												-	0,71	0,56	1,10
Canada													-	1,06	1,09
Norway														-	0,95
Japan															-
USA															
Spain															
Denmark															
Ireland															
Cyprus															
Czech															
Hungary															
Latvia															
Poland															
Slovenia															
Turkey															
Romania															
Slovakia															
Estonia															
Lithuania															

Table A3 (cont.): ***Measure 3 - Distances across countries based on Harding-Pagan (2002)***

	USA	Spain	Denmark	Ireland	Cyprus	Czech	Hungary	Latvia	Poland	Slovenia	Turkey	Romania	Slovakia	Estonia	Lithuania
Austria	0,91	0,49	0,57	0,73	0,70	0,91	0,64	1,31	0,97	0,62	1,20	1,19	0,94	1,21	1,11
Belgium	0,76	0,41	0,74	0,77	0,98	0,55	0,61	0,90	0,68	0,53	0,87	0,92	0,46	0,62	1,00
Germany	0,92	0,57	0,63	0,70	1,09	0,59	0,70	0,75	0,81	0,62	1,03	1,00	0,53	0,75	0,99
Greece	0,95	0,76	0,79	1,14	0,69	1,08	1,15	1,37	1,23	0,67	1,31	1,11	1,15	1,19	1,28
Finland	0,68	0,57	1,11	0,76	0,79	1,28	0,61	0,84	0,94	1,20	1,21	1,41	1,29	1,28	0,94
France	0,78	0,36	0,81	0,69	0,97	0,84	0,62	1,19	0,95	0,77	1,22	1,16	0,85	1,18	1,19
Italy	0,86	0,55	0,66	0,82	0,81	0,58	0,73	0,74	0,60	0,46	1,02	0,87	0,60	0,69	1,04
Luxemburg	1,12	0,70	0,67	1,14	0,56	0,62	1,17	0,97	1,00	0,38	1,18	0,98	0,64	0,85	0,85
Netherland	0,79	0,62	0,50	0,70	0,88	0,89	0,63	1,39	0,95	0,61	1,22	1,21	0,93	1,20	1,30
Portugal	1,10	0,84	0,67	1,13	0,72	0,82	1,16	1,30	1,23	0,52	1,24	1,10	0,82	1,15	1,07
Sweden	0,55	0,40	1,04	0,72	1,18	1,06	0,49	1,27	0,83	0,81	1,06	1,01	1,15	1,14	1,21
UK	0,43	0,89	0,82	0,75	0,98	0,96	0,61	1,18	0,63	0,90	0,79	1,11	0,89	0,79	1,24
Canada	0,47	0,34	1,24	0,68	1,12	1,20	0,46	1,18	0,81	1,30	0,99	1,29	1,21	1,19	1,21
Norway	0,95	1,18	0,68	0,84	1,08	0,75	0,87	1,01	0,45	0,64	0,55	0,70	0,71	0,56	1,08
Japan	0,94	0,77	0,89	0,76	1,15	0,66	0,68	1,25	0,72	0,68	1,05	0,73	0,69	0,82	1,31
USA	-	0,63	1,18	0,58	1,00	1,18	0,38	1,33	0,75	1,26	0,94	1,25	1,18	1,17	1,25
Spain		-	0,92	0,74	0,97	0,94	0,58	1,23	0,91	0,79	1,14	1,11	0,98	1,17	1,11
Denmark			-	1,08	0,67	0,51	1,12	0,94	0,87	0,34	0,99	1,03	0,52	0,64	1,11
Ireland				-	1,15	1,09	0,22	1,16	0,59	1,13	1,00	1,12	1,09	1,08	1,12
Cyprus					-	0,90	1,19	0,95	1,28	0,93	1,31	1,47	0,99	1,25	0,97
Czech						-	1,11	0,68	0,53	0,36	0,70	0,76	0,07	0,05	0,99
Hungary							-	1,20	0,61	1,16	0,97	1,16	1,11	1,10	1,15
Latvia								-	0,88	0,73	0,72	0,87	0,61	0,64	0,47
Poland									-	0,72	0,50	0,71	0,55	0,33	1,14
Slovenia										-	0,78	0,61	0,26	0,33	0,89
Turkey											-	0,65	0,61	0,37	0,64
Romania												-	0,65	0,49	0,83
Slovakia													-	0,05	0,90
Estonia														-	0,98
Lithuania															-

Table A4: ***Distances across countries (Combination of the before three measures)***

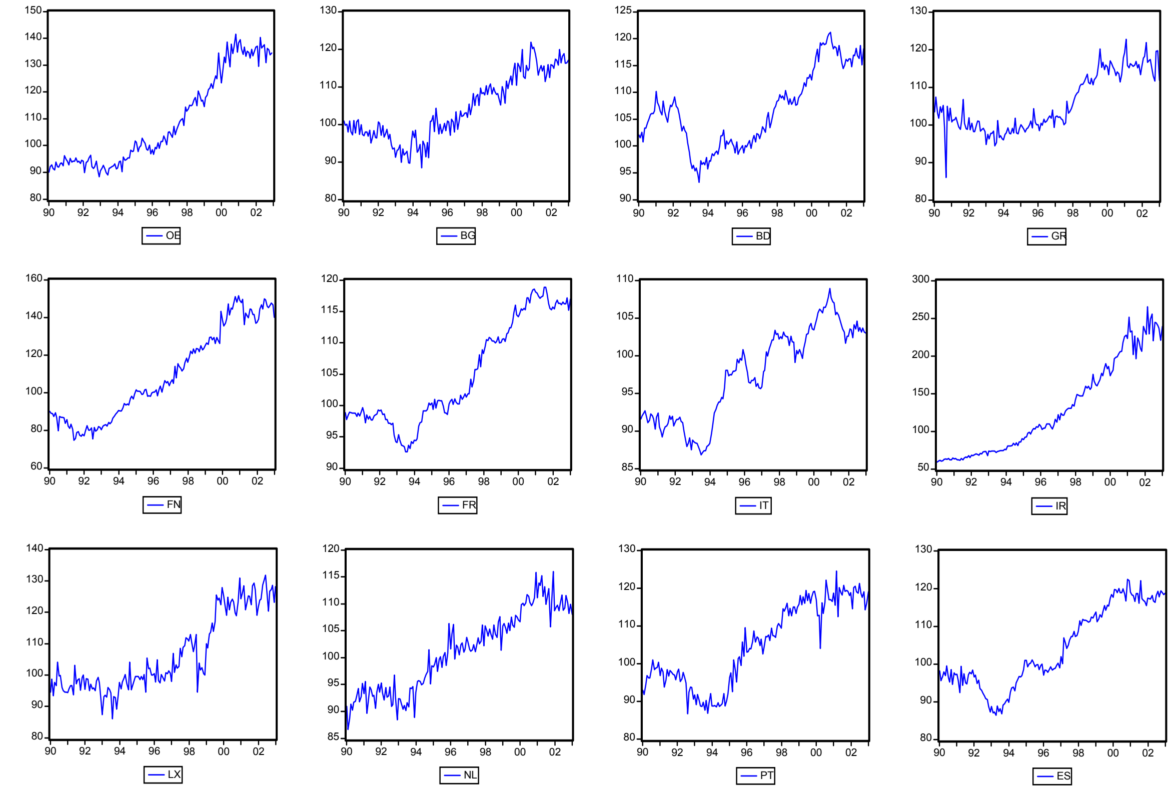
	Austria	Belgium	Germany	Greece	Finland	France	Italy	Luxemburg	Netherland	Portugal	Sweden	UK	Canada	Norway	Japan
Austria	-	0,44	0,27	0,68	0,67	0,34	0,48	0,66	0,41	0,81	0,31	0,76	0,57	0,91	0,58
Belgium		-	0,43	0,75	0,69	0,52	0,43	0,58	0,58	0,63	0,46	0,75	0,74	0,75	0,50
Germany			-	0,93	0,76	0,20	0,53	0,78	0,39	0,83	0,50	0,75	0,83	0,89	0,48
Greece				-	0,96	0,71	0,85	0,73	0,88	0,73	0,73	0,87	1,02	1,16	1,10
Finland					-	0,65	0,60	0,87	0,96	1,06	0,41	0,49	0,27	0,87	0,78
France						-	0,40	0,65	0,40	0,78	0,54	0,73	0,61	1,03	0,58
Italy							-	0,59	0,46	0,77	0,51	0,61	0,58	0,80	0,50
Luxemburg								-	0,77	0,69	0,77	0,80	0,76	0,88	0,65
Netherland									-	0,79	0,56	0,64	0,89	0,83	0,58
Portugal										-	0,88	1,09	1,15	1,04	0,85
Sweden											-	0,54	0,64	0,87	0,53
UK												-	0,37	0,70	0,74
Canada													-	0,99	0,56
Norway														-	0,95
Japan															-
USA															
Spain															
Denmark															
Ireland															
Cyprus															
Czech															
Hungary															
Latvia															
Poland															
Slovenia															
Turkey															
Romania															
Slovakia															
Estonia															
Lithuania															

Table A4 (cont.): ***Distances across countries (Combination of the before three measures)***

	USA	Spain	Denmark	Ireland	Cyprus	Czech	Hungary	Latvia	Poland	Slovenia	Turkey	Romania	Slovakia	Estonia	Lithuania
Austria	0,64	0,32	0,48	0,53	0,81	0,86	0,30	1,05	0,58	0,44	0,98	1,16	0,82	0,86	0,39
Belgium	0,60	0,41	0,56	0,57	0,89	0,78	0,54	0,77	0,53	0,51	0,79	0,96	0,53	0,62	0,73
Germany	0,73	0,42	0,46	0,71	0,79	0,62	0,53	0,68	0,62	0,38	1,03	1,07	0,61	0,48	0,73
Greece	0,90	0,78	0,86	0,78	0,72	1,05	1,02	1,23	1,10	0,83	1,31	1,21	1,15	1,28	0,91
Finland	0,46	0,55	0,86	0,80	0,86	1,04	0,31	0,84	0,77	0,80	0,92	1,28	0,93	0,88	0,97
France	0,62	0,29	0,45	0,68	0,83	0,69	0,46	0,84	0,71	0,49	1,13	1,18	0,77	0,80	0,91
Italy	0,64	0,36	0,52	0,60	0,77	0,53	0,50	0,55	0,46	0,50	0,95	0,95	0,59	0,56	0,84
Luxemburg	0,86	0,66	0,72	0,94	0,75	0,70	0,89	0,80	0,61	0,70	1,14	1,08	0,78	0,69	1,14
Netherland	0,83	0,51	0,52	0,70	0,75	0,82	0,58	1,04	0,81	0,59	1,20	1,00	0,79	0,94	1,15
Portugal	1,10	0,88	0,88	0,89	0,76	0,90	1,15	1,02	1,06	0,89	1,05	1,00	0,79	1,14	1,08
Sweden	0,61	0,32	0,66	0,62	0,91	1,00	0,52	1,11	0,71	0,48	1,03	0,93	0,87	0,97	1,10
UK	0,36	0,76	0,74	0,70	0,95	0,97	0,47	1,10	0,44	0,69	1,02	1,04	0,92	0,78	1,16
Canada	0,22	0,53	0,90	0,67	1,03	0,97	0,32	1,08	0,50	0,91	0,94	1,14	1,02	0,88	1,26
Norway	0,92	1,02	0,73	0,89	0,93	0,77	0,90	0,83	0,60	0,78	0,65	0,88	0,79	0,64	1,11
Japan	0,56	0,60	0,83	0,75	1,10	0,70	0,59	1,03	0,42	0,73	0,81	0,64	0,84	0,66	1,17
USA	-	0,61	0,85	0,62	0,90	1,04	0,32	1,12	0,48	0,89	0,78	1,28	0,98	0,80	1,18
Spain		-	0,50	0,69	0,78	0,79	0,45	0,84	0,67	0,46	1,05	1,16	0,92	0,80	1,07
Denmark			-	0,87	0,58	0,57	0,75	0,70	0,59	0,29	1,08	0,97	0,62	0,55	0,97
Ireland				-	1,02	0,88	0,49	0,95	0,75	0,90	0,89	1,07	0,85	1,05	1,01
Cyprus					-	0,86	0,87	1,01	1,06	0,75	1,17	1,29	0,84	0,94	1,07
Czech						-	0,88	0,37	0,49	0,50	0,83	0,91	0,32	0,20	0,88
Hungary							-	1,02	0,58	0,75	0,92	1,07	0,90	0,74	1,09
Latvia								-	0,73	0,73	0,80	0,97	0,52	0,46	0,63
Poland									-	0,56	0,68	0,85	0,64	0,34	1,08
Slovenia										-	1,00	0,76	0,47	0,50	0,82
Turkey											-	0,90	0,80	0,58	0,84
Romania												-	0,59	0,67	0,78
Slovakia													-	0,18	0,54
Estonia														-	0,65
Lithuania															-

Appendix A

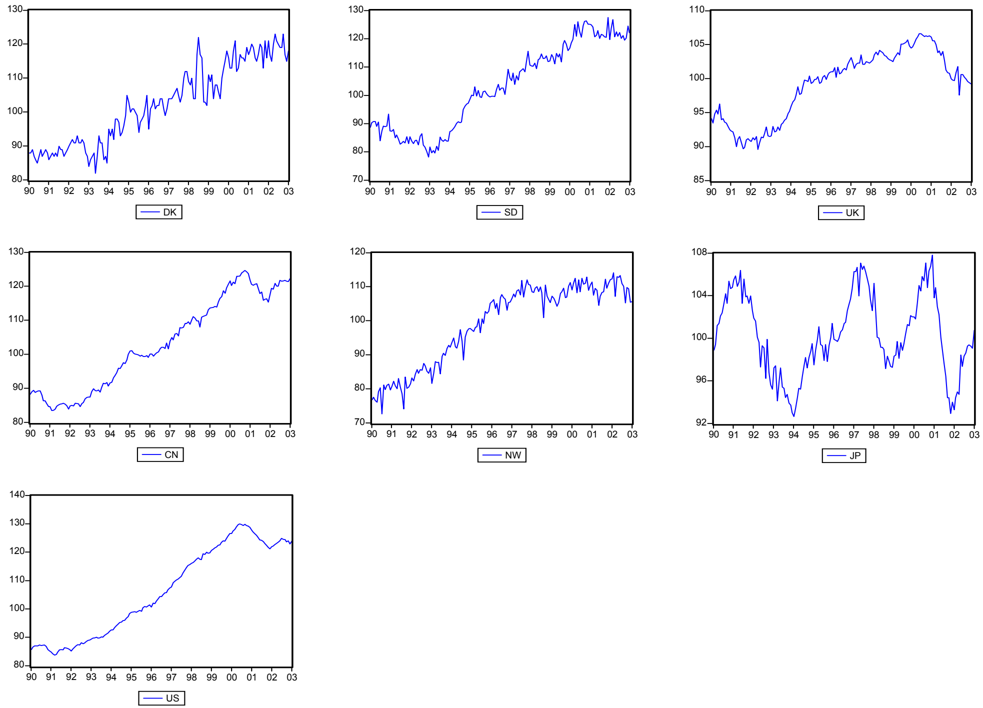
Figure A1- Industrial Production Index Euro Area Countries



Levels of monthly Industrial Production Index (S.A.)
Source: OECD Main Economic Indicators.

* The symbols used to represent countries are collected in Appendix D.

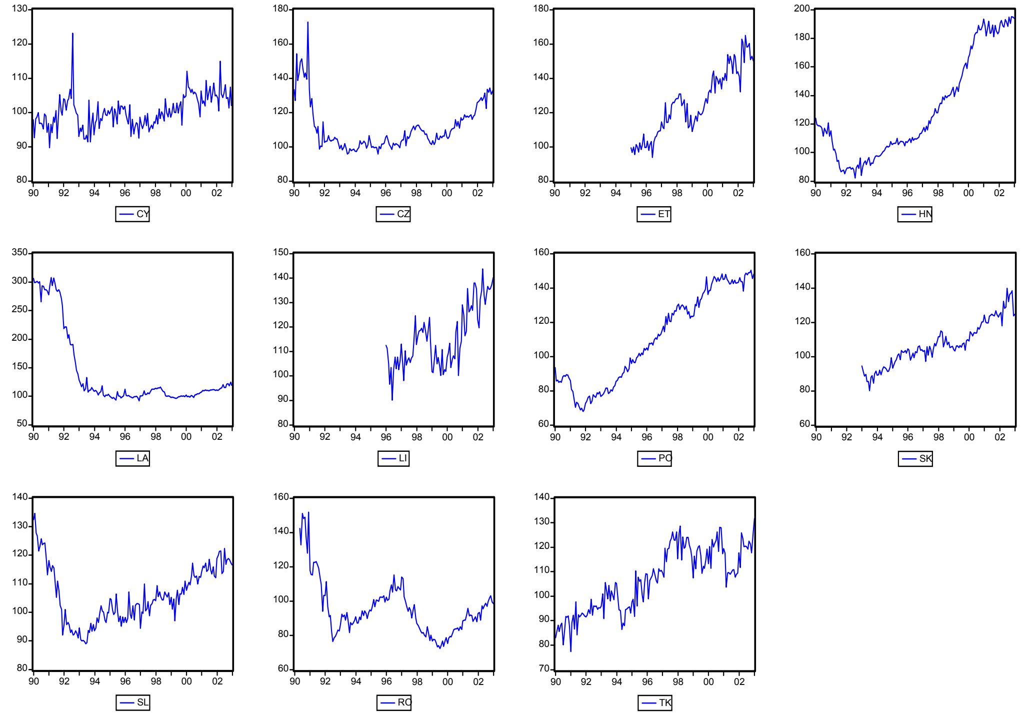
Figure A1 (cont.)- Industrial Production Index Rest of the EU and other industrialized countries



Levels of monthly Industrial Production Index (S.A.)
Source: OECD Main Economic Indicators.

* The symbols used to represent countries are collected in Appendix D.

Figure A1 (cont.)- Industrial Production Index Accession and negotiating countries



Levels of monthly Industrial Production Index (S.A.)

* The symbols used to represent countries are collected in Appendix D.

Source: OECD Main Economic Indicators and IMF International Financial Statistics.

Appendix B

Table B. Classical business cycle chronologies of Euro-area countries.

	OE	BG	BD	GR	FN	FR	IT	IR	LX	NL	PT	ES
60's												
T									62.05		62.04	
P			66.03			64.04	64.01		65.02		66.04	
T			67.05			64.12	64.08		67.08		67.02	
70's												
P					70.07				70.01			
T					71.03				70.10			
P	74.06	74.06	73.08	74.02	74.07	74.07	74.06		74.08	74.08	74.03	74.08
T	75.10	75.04	75.07	74.07	75.09	75.05	75.04		75.08	75.08	75.08	75.04
P		76.11				76.09	77.01		76.05	76.09		
T		77.09				77.12	77.11		77.08	77.11		
P	79.12	79.12	79.12			79.07		79.09	79.12	79.11		79.08
T	81.07	80.12	82.11			81.04		80.12	81.04	82.11		82.08
80's												
P	82.01	82.04		80.04	81.07	81.12	80.03		82.02			
T	83.01	82.12		81.04	82.07	82.08	83.05		82.12			
P	86.03	85.11		82.05						84.06		
T	86.11	87.01		83.05						86.05		
P		89.07		85.12	89.07		89.12			87.01		89.07
T		91.08		87.06	91.06		91.04			88.04		91.03
90's												
P	91.08	92.01	92.02	89.04		91.12	91.09		90.06	92.01	90.08	91.12
T	93.06	93.11	93.07	93.01		93.08	93.07		93.08	93.06	93.10	93.04
P	95.06		94.12		95.01	95.03	95.12		95.08			95.05
T	96.02		95.10		95.11	95.12	96.12		96.05			96.01
P		98.07	98.07	99.08			97.10		98.02		99.06	
T		99.02	99.02	00.10			98.12		98.07		00.04	
00's												
P	00.11	00.11	01.02		00.12	00.12	00.12	01.02		00.12		00.11
T	01.09	01.09	01.11		01.12	01.12	01.11	01.07		-		01.12
P	02.04			02.04	02.06		02.07		02.06		02.07	
T	-			-	-		-		-		-	

Table B (cont.). Classical business cycle chronologies of other European and non-European countries.

	DK	SD	UK	CN	NW	JP	US	NBER
60's								
P			66.03	69.03	68.05	-	69.08	69.12
T			66.11	70.10	69.04	62.12	70.11	70.11
70's								
P		71.01	70.10		71.07			
T		71.09	72.02		72.03			
P	-	74.06	74.06	74.03	76.08	74.01	73.11	73.11
T	75.03	78.06	75.08	75.05	77.05	75.03	75.05	75.03
P	78.04							
T	79.01							
P	79.10	79.12	79.06	79.07				
T	80.11	82.11	81.05	80.06				
80's								
P				81.04	80.02	80.02	80.01	80.01
T				82.10	80.07	80.08	80.07	80.07
P					81.07	81.10	81.07	81.07
T					82.10	82.10	82.12	82.11
P	86.09	85.09	84.01	86.01		85.05		
T	87.10	86.04	84.08	86.08		86.08		
P	88.12						89.01	
T	89.08						89.07	
90's								
P	92.06	90.04	90.06	89.04		91.05	90.09	90.07
T	93.05	92.12	91.08	91.02		94.01	91.03	91.03
P				95.02				
T				95.12				
P	98.07		98.06		97.10	97.05		
T	98.12		99.02		99.04	98.08		
00's								
P		00.11	00.06	00.10	00.10	00.12	00.06	01.03
T		02.01	-	01.12	01.05	01.11	01.12	-
P	02.05				02.02			
T	-				-			

Table B (cont.). Classical business cycle chronologies of acceding countries.

	CY	CZ	ET	HN	LA	LI	PO	SK	SL	RO	TK
90's											
P	-	90.12		-			-			-	
T	91.02	91.09		91.12			91.11			92.07	
P	92.08	92.09			-			-	-		93.12
T	93.10	93.07			95.06			93.07	93.06		94.05
P	95.08				96.01	-					
T	96.12				96.12	96.06					
P		98.02	98.03		98.05	98.11	98.02	98.03	98.02	97.01	98.03
T		99.01	99.01		99.05	99.08	98.11	99.02	99.04	99.07	99.08
00's											
P	00.02			01.01			00.12				00.10
T	00.12			01.09			01.06				01.03
P	02.04								02.07		
T	-								-		

Appendix C

Can distances be explained?

Table C1 *Dependant variable: VAR Distances of Business Cycles*

	OLS	IV
Constant	0,557	0,555
	(0.0288)	*(0.0360)*
%Industry	1,214	1,218
	(0.211)	*(0.2153)*
%Agriculture	1,704	1,704
	(0.2993)	*(0.2995)*
Saving Ratio	0,372	0,374
	(0.1925)	*(0.1941)*
Labor Productivity	0,053	0,054
	(0.051)	*(0.0516)*
Public Balance	0,625	0,630
	(0.2723)	*(0.2787)*
Trade (%Exports)	-0,477	-0,455
	(0.1585)	*(0.3069)*
R squared	28%	

Table C2 *Dependant variable: Spectral Distances of Business Cycles*

	OLS	IV
Constant	0,503	0,523
	(0.0296)	*(0.0371)*
%Industry	0,698	0,658
	(0.217)	*(0.2221)*
%Agriculture	2,042	2,050
	(0.3079)	*(0.3088)*
Saving Ratio	0,420	0,397
	(0.1980)	*(0.2002)*
Labor Productivity	0,001	-0,006
	(0.0524)	*(0.0532)*
Public Balance	0,956	0,901
	(0.2801)	*(0.2874)*
Trade (%Exports)	-0,685	-0,929
	(0.163)	*(0.3165)*
R squared	28%	

Table C3 *Dependant variable:*
Harding Pagan Distances of Business Cycles

	OLS	IV
Constant	0,708	0,704
	(0.0314)	*(0.0393)*
%Industry	0,536	0,544
	(0.2306)	*(0.2353)*
%Agriculture	0,779	0,777
	(0.3271)	*(0.3273)*
Saving Ratio	0,349	0,354
	(0.2103)	*(0.2122)*
Labor Productivity	0,175	0,177
	(0.0557)	*(0.0564)*
Public Balance	-0,024	-0,013
	(0.2976)	*(0.3046)*
Trade (%Exports)	-0,461	-0,411
	(0.1732)	*(0.3354)*
R squared	16%	

Notes: The tables C1, C2 and C3 show the estimated coefficients for the OLS and instrumental variables (IV) regression of the distances across business cycles in different economies and distances of those economies in each of the macroeconomic variables.The instruments employed to solve the possible endogeneity problem of trade variable are: log of the geographical distance between countries, border dummy, euro dummy, EU dummy and the absolute differences between the logs of population.

All the explanatory variables are explained in Appendix D.
Standard errors are in parenthesis.

Appendix D

Countries and data availability

Industrial Production Index (S.A.)

Euro-area

Country		Sample	Source
Austria	OE	62.01-02.12	OECD -MEI
Belgium	BG	62.01-03.01	OECD -MEI
Germany	BD	62.01-03.01	OECD -MEI
Greece	BR	62.01-03.01	OECD -MEI
Finland	FN	62.01-03.01	OECD -MEI
France	FR	62.01-03.01	OECD -MEI
Italy	IT	62.01-03.01	OECD -MEI
Ireland	IR	75.07-03.01	OECD -MEI
Luxembourg	LX	62.01-03.01	OECD -MEI
Netherlands	NL	62.01-03.01	OECD -MEI
Portugal	PT	62.01-03.01	OECD -MEI
Spain	ES	65.01-03.01	OECD -MEI

European Union

Country		Sample	Source
Denmark	DK	74.01-03.01	OECD - MEI
Sweden	SD	62.01-03.01	OECD - MEI
United Kingdom	UK	62.01-03.01	OECD - MEI

Acceding (by 2007)

Country		Sample	Source
Bulgaria	--	--	--
Romania	RO	90.05-03.01*	OECD - MEI

Negotiating

Country		Sample	Source
Turkey	TK	90.01-03.01	OECD - MEI

Candidates (1st May 2004)

Country		Sample	Source
Cyprus	CY	90.01-03.01	IMF - IFS
Czech Republic	CZ	90.01-03.01*	OECD - MEI
Estonia	ET	95.01-03.01	OECD - MEI
Hungary	HN	90.01-03.01*	OECD - MEI
Latvia	LA	90.01-03.01*	OECD - MEI
Lithuania	LI	96.01-03.01	OECD - MEI
Malta	--	--	--
Poland	PO	90.01-03.01*	OECD - MEI
Slovak Republic	SK	93.01-03.01	IMF - IFS
Slovenia	SL	90.01-03.01*	OECD - MEI

Other countries

Country		Sample	Source
Canada	CN	62.01-03.01	OECD - MEI
Norway	NW	62.01-03.01	OECD - MEI
Japan	JP	62.01-03.01	OECD - MEI
USA	US	62.01-03.01	OECD - MEI

Macro variables

Variable	Smp Aver (1)	Source	Observation
Trade Variable	1989-1998	IMF, Dir Trade	Explained in text.
Saving Ratio	1995	Penn World Table	
%Public Sector	1998-2002	Eurostat	(2)
Inflation	1998-2002	Eurostat	(3)
Labor productiv.	1995-1999	Eurostat	(4)
%Industry	1996-2000	World Devel Report	
%Agriculture	1996-2000	World Devel Report	

(1) The sample average is, in all cases, the maximum allowed by the data

(2) Public balance - Net borrowing/lending of consolidated general government sector as a percentage of GDP

(3) Inflation rate - Annual average rate of change in Harmonized Indices of Consumer Prices (HICPs)

(4) Labour productivity - GDP in PPS per person employed relative to EU-15 (EU-15=100)

* The sample used in the estimation starts in 1992.01.