ONE MONEY WITH SEVERAL CYCLES?
EVALUATION OF EUROPEAN BUSINESS CYCLES USING CLUSTER ANALYSIS

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One Money with Several Cycles?

Evaluation of European business cycles using cluster analysis

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Abstract

Optimal currency area theory suggests that business cycle comovement is a sufficient condition for monetary union, particularly if there are low levels of labour mobility between potential members of the monetary union. Previous studies of co-movement of business cycle variables (mainly authored by Artis and Zhang in the late 1990s) found that there was a core of member states in the EU that could be grouped together as having similar business cycle comovements, but these studies always used Germany as the country against which to compare. In this study, the analysis of Artis and Zhang is extended and updated but correlating against both German and euro area macroeconomic aggregates and using more recent techniques in cluster analysis, namely model-based clustering techniques.

Keywords: Business cycles, co-movement, optimal currency areas, model-based cluster analysis, Bayesian variable selection.

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1 Introduction

Following the signing of the Maastricht Treaty in mid-1992, the transition to Economic and Monetary Union (EMU) has been completed, euro notes and coins were introduced into circulation (in 2002), the European Central Bank (ECB) has successfully operated a single monetary policy in the euro area for over 10 years. The number of participants in the euro area began with 11 member states in January, 1999 but since then Greece, Cyprus, Slovenia, Malta and the Slovak Republic have been added to the euro area, bringing the current number of member states in the euro area to 16.

Given the developments described above, and the lingering doubts that many economists had prior to the launch of the euro about its sustainability, it seems appropriate to review whether business cycles in euro area member states have further converged after the inception of EMU, and to see whether the new member state business cycles are also synchronized with those of the existing euro area member states. Here we only consider business cycle comovement as a measure of synchronization, as optimal currency area (OCA) theory suggests that business cycle synchronicity is the most important measure as to the suitability of a country to join an existing monetary union (- despite the fact that OCA theory states that if other mitigating factors are in place, a country might still be theoretically eligible to join an existing monetary union).

The issue of Central and Eastern European Country (CEEC) membership in EMU is also important, as the 1993 Copenhagen criteria for accession to European Union (EU) was that new EU members would not have any opt-out provision from EMU (unlike existing EU member states), so joining the EU will eventually necessitate joining the euro area. Because of this, the economic convergence criteria take on additional *gravitas* for the 12 new accession countries. So the further issue of which CEEC countries might also already possess synchronous business cycles is also addressed, in addition to whether any CEEC member state groupings are already emerging.

The paper seeks to evaluate which member states, potential member states, and other European countries might be most suited as candidates for EMU, in the sense that i) synchronicity of (GDP) business cycles with Germany or the euro area is achieved and ii) countries have similar experience with movements in other business cycle variables, specifically interest rates, inflation and unemployment. As noted above, both labor mobility and trade intensity are ignored, as labor mobility is rather small in the EU, and although trade intensity clearly matters for the possibility of achieving convergence (usually through the endogenous OCA route), there is a considerable amount of debate in the economics literature as to the nature and size of the relationship between a single currency and the growth in trade.

From a methdological viewpoint, the paper takes as its starting point the work done by Michael Artis and Wenda Zhang using cluster analysis in the 1990s (now published as Artis and Zhang (2001) and Artis and Zhang (2002)) and updates these studies, not only temporally, but also using more recently developed clustering techniques, specifically the model-based cluster approach which uses Bayesian methodology with maintained hypotheses about the distribution of data within clusters.

The paper is divided into five sections. Section 2 gives a brief overview of the voluminous literature on EMU and business cycle synchronization, while section 3 outlines the methodology to be used. Section 4 describes the data and provides justification for the time periods chosen. Section 5 presents the results of model-based cluster analysis, while section 6 gives some general results and section 7 then concludes.

2 EMU and business cycle synchronization

The empirical literature on business cycle convergence originated as an empirical by-product of the literature on OCAs[1] and has largely focused on time-series methodology that uses structural vector autoregressions (SVAR) to identify demand and supply shocks (see for example, Bayoumi and Eichengreen (1994) for the EU and North America). The main approach here is to look at the correlation of shocks across countries or regions. Following the work of Gerlach (1988) and Baxter and Stockman (1989) on business cycle correlations, there has been considerable research devoted to the propagation of business cycles, and the existence of a world business cycle in the pre- and post- Bretton Woods periods. Recent research on business cycles has focused on the effects of trade in propogating business cycles and on new measures of co-movement of output data for different regions or countries. In the EU context a specific strand of the literature evaluated the synchronicity of business cycles across prospective currency union members (Baxter and Stockman (1989) and Artis and Zhang (1997)) and the full arsenal of techniques, both time-series (see De Haan, Inklaar, and Sleijpen (2002) and Altavilla (2004) for example) and frequency domain (see Valle e Azevedo (2002) and Hughes Hallett and Richter (2006) for example) have been used to address this

[1] See Mundell (1961), McKinnon (1963), Gerlach (1988), Tavlas (1993) and Bayoumi (1994) for the seminal paper on OCA theory.

issue post-EMU inception, as endogenous OCA considerations come into play. Indeed much of the recent research has gone beyond simply trying to measure synchronization and is exploring the determinants of business cycle synchronicity (see de Haan, Inklaar, and Jong-a Pin (2008) for a critical survey and for more recent contributions see Giannone and Reichlin (2006),and Böwer and Guillemineau (2006)). More recent work (notably Stavrev (2007) using a VAR methodology) has noted that although the incidence of common shocks has increased under EMU, dispersions in inflation and growth rates remain and will persist, largely (the authors claim) due to idiosyncratic shocks. Although there is general agreement that convergence has taken place, there is no firm evidence as to whether this has increased, remained constant, or declined for EMU members.

Clearly, despite the general agreement on a European business cycle, there is recognition of regional variations and "core-periphery" effects, which are undoubtedly a factor in both the EU and within the euro area. Artis and Zhang (1999) explored the idea of group-specific business cycles after the inception of the ERM of the EMS in 1979, positing a distinctly European business cycle, but noting significant divergences from this cycle. In these earlier studies, cyclical components of industrial production were obtained using several de-trending methods, and then the cross-correlations of the cyclical components of these series with the US series and the German series were calculated before using hierarchical cluster analysis. A European business cycle was confirmed, but the cycle was confined to members of the ERM of the EMS, as might have been expected. Artis and Zhang (2002) then went on to extend the analysis using fuzzy clustering techniques.

Here a similar methodology is employed, with two differences. First, in the European context, Artis and Zhang (2001) justified using the cyclical component of the German series as a basis for evaluating whether a European business cycle existed, predicated on other research which clearly showed Germany to be the largest and most influential economy in the EU, and the Bundesbank to be a “leader” in terms of the setting of monetary policy in the ERM of the EMS (the “German dominance” hypothesis). In the context of this paper the German aggregates are again used as one appropriate “target” variables for the purposes of calculating cross-correlations for European member states/countries - but the analysis is extended by also evaluating the correlation of cycles with a euro area aggregate as well. Second, the methodology adopted is not the same as the (hierarchical) cluster analysis that has been used in most research up until 1999, but instead uses a new clustering technique developed by statisticians based in the US through the 1990s.

3 Methodology

3.1 Basic Approach

First, cyclical components of real GDP movements are estimated using a band-pass filter (see Baxter and King (1985) and Stock and Watson (1998)). Then the cyclical component of real GDP is correlated for each member state/country with the cyclical component of a) German real GDP and b) euro area real GDP. Other business cycle variables are then also correlated with German and euro area equivalents to obtain a dataset of correlations. Note that this methodology does not rely on a consistent set of data across countries, which is an important consideration for Central and East European countries, where for several of these countries, reliable data does not exist before 1997.

Obviously a high degree of correlation of business cycle variables with Germany or the euro area aggregates is taken to imply that the country may benefit from membership in EMU (or certainly won't be adversely affected by membership). The time period under consideration is also a factor here, as before 1999 high correlations with Germany were deemed to be more important in terms of indicating suitability for membership in EMU, but after 1999 clearly a high correlation with the euro area aggregate is likely more appropriate given the fact that German GDP growth did not reflect the average growth in the euro area, and this is now the focus of the European Central Bank (ECB), not any individual member state economic conditions[2].

But evaluating correlations does not identify which countries might be classified as potential candidates for EMU, or which countries fit well (or otherwise) inside EMU. For this purpose cluster analysis is used. In economics cluster analysis has been applied to EU data by several authors, notably Jacquemin and Sapir (1995), Artis and Zhang (2001), Artis and Zhang (2002) and most recently by Camacho, Perez-Quiros, and Saiz (2006) with interesting results. The cluster analysis done in the 1990s on the EU has largely corroborated the evidence on suitability for membership of EMU gained from the aforementioned empirical methods used in the OCA literature. The methodology has also started to appear more frequently in the economics literature, with Galbraith and Jiaqing (1999), Honohan (2000), Frühwirth-Schnatter and Kaufmann (2004) and Camacho, Perez-Quiros, and Saiz (2006) applying different cluster analysis methods to various economic problems and data. Here we use model-based clustering, a relatively recent technique that was developed at the University of Washington by Adrian Raftery and Chris Fraley.

[2] As one German finance minister found out to his cost!

Cluster analysis aims to determine the intrinsic structure of data when no information other than the observed values is available - the data is to be partitioned into meaningful subgroups. Clustering methods range from those that are largely heuristic to more formal procedures based on statistical models, and they are hierarchical or based on allocating observations among tentative clusters (such as k-means clustering). Hierarchical methods fall into two categories: "agglomerative" and "divisive" - with agglomerative denoting the merging of clusters at each stage and divisive denoting the splitting of clusters at each stage - in most cases agglomerative and divisive methods give similar clusterings. At each stage some criterion (often a similarity or dissimilarity index) is optimized and used to determine which clusters should be combined or split - most methods use single link (nearest neighbor), complete link (farthest neighbor) or sum of squares. Useful references for these heuristic clustering methods are Anderberg (1993), Kaufman and Rousseeuw (1990) and Hartigan (1975).

Unfortunately, although the traditional clustering methods are appealing, none of them addresses the issue of how many clusters there should be. Various strategies have been put forward to choose the number of clusters, but up until recently none of these methods has been satisfactory from a computational or methodological point of view. The alternative that has been presented by Fraley and Raftery (2002) and Fraley and Raftery (2006) is computationally relatively straightforward, and is also intuitively appealing, so this methodology is adopted here[3]. In contrast to hierarchical methods, in model methods a maximum likelihood based on specific distributional assumptions is used to find the best groupings of the observations.

3.2 Model-based cluster analysis

In probability based clustering, each observation is assumed to be generated by a mixture of underlying probability distributions where each component in the mixture represents a different cluster. Given a set of data $\mathbf{x} = (\mathbf{x}_1, ...\mathbf{x}_n)$, then the likelihood function for a mixture model with G components is:

$$\mathcal{L}_{MIX}\left(\theta_1, \theta_2, ..., \theta_G; \tau_1, ..., \tau_G | \mathbf{x}\right) = \prod_{i=1}^{n} \sum_{k=1}^{G} \tau_k f_k(\mathbf{x}_i | \theta_k) \tag{1}$$

[3]The methodology was developed over a number of years, and the main references are Banfield and Raftery (1993), Fraley and Raftery (1998), Fraley (1998) and Fraley and Raftery (2003).

where f_k and θ_k are the density and parameters of the kth component in the mixture and τ_k is the probability that an observation belongs to the kth component (- the mixing proportion). Generally f_k is the multivariate normal (Gaussian) density which has parameters mean μ_k and covariance matrix Σ_k. These clusters will be ellipsoidal with geometric features (shape, volume, orientation) determined by the covariances Σ_k.

Banfield and Raftery (1993) propose a general framework for geometric cross-cluster constraints by parametrizing covariance matrices through an eigenvalue decomposition of the form:

$$\Sigma_k = \lambda_k D_k A_k D_k^T \tag{2}$$

where D_k is an orthogonal matrix of eigenvectors, A_k is a diagonal matrix whose elements are proportional to the eigenvalues, and λ_k is a constant scalar. This leads to a geometric interpretation of the ellipsoidal clusters - D_k determines the orientation, A_k determines the shape of the density contours and λ_k specifies the volume. These characteristics can then be allowed to vary between clusters, or constrained to be the same for all clusters. This approach actually subsumes many previous approaches at model-based clustering - more details can be located in Fraley and Raftery (2002). The range of models used has now been expanded from the original 1998 software, and the new 2006 MCLUST library uses a more extensive set of models within the same framework following Celeux and Govaert (1995). In the approach taken here, the parameterizations ("models") of the covariance matrix considered by the model-based clustering method are detailed in table 1. These parameterizations are essentially maintained hypotheses which are then compared in terms of their likelihood. Given these different model parameterizations for the distribution of correlations, the optimal number of clusters is determined by hierarchical clustering so as to maximize the resulting likelihood as specified in equation (1) above.

3.3 Clustering algorithms

The algorithm used for maximizing the likelihood function here is the EM (Expectation-Maximization) algorithm (see McLachlan and Krishnan (1997)). The EM algorithm was designed for maximum likelihood estimation with n multivariate observations $\mathbf{y}_i$ recoverable from $(\mathbf{x}_{i,}\mathbf{z}_i)$, in which $\mathbf{x}_i$ is observed and $\mathbf{z}_i$ is unobserved. If the $\mathbf{x}_i$ are iid according to a probability distribution f with parameters θ then the complete-data likelihood is given by:

Identifier	Model	Distribution	Volume	Shape	Orientation
EII	λI	Spherical	equal	equal	NA
VII	$\lambda_k I$	Spherical	variable	equal	NA
EEI	λA	Diagonal	equal	equal	coordinate axes
VEI	$\lambda_k A$	Diagonal	variable	equal	coordinate axes
EVI	λA_k	Diagonal	equal	variable	coordinate axes
VVI	$\lambda_k A_k$	Diagonal	variable	variable	coordinate axes
EEE	λDAD^T	Ellipsoidal	equal	equal	equal
VVV	$\lambda_k D_k A_k D_k^T$	Ellipsoidal	variable	variable	variable
EEV	$\lambda D_k A D_k^T$	Ellipsoidal	equal	equal	variable
VEV	$\lambda_k D_k A D_k^T$	Ellipsoidal	variable	equal	variable

Table 1: Parameterizations of the Covariance matrix for Model-based Clustering

$$\mathcal{L}_C(\mathbf{x}_i|\theta) = \prod_{i=1}^{n} f(\mathbf{x}_i|\theta) \tag{3}$$

If we assume that the unobserved variable depends only on the observed data $\mathbf{x}$, and not on $\mathbf{z}$, then we can integrate out the unobserved variable from the likelihood to get the observed-data likelihood, or $\mathcal{L}_O$:

$$\mathcal{L}_O(\mathbf{x}_i|\theta) = \int \mathcal{L}_C(\mathbf{x}_i|\theta) d\mathbf{z} \tag{4}$$

The EM algorithm iterates between an "E" step, which computes a matrix $\mathbf{z}$ such that $\mathbf{z}_{ik}$ is an estimate of the conditional probability that observation i belongs to group k given the current parameter estimates, and an "M" step, which computes maximum likelihood parameter estimates given $\mathbf{z}$. In mixture models, the complete data are considered to be $\mathbf{y} = (\mathbf{x}, \mathbf{z})$ where $\mathbf{z} = (\mathbf{z}_{i1}, \mathbf{z}_{i2}, ..., \mathbf{z}_{iG})$ represents the unobserved portion of the data, which in turn refers to cluster membership. In the limit, under certain regularity conditions the parameters usually converge to the maximum likelihood values for the Gaussian mixture model and the sums of the columns of $\mathbf{z}$ converge to n times the mixing proportions tk, where n is the number of observations (i.e. the numbers of clusters, $\mathbf{G}$.should reflect the number of distributions in the mixture model.

The EM algorithm is not without its problems though. Fraley and Raftery (2002) detail several problems notably i) a slow rate of convergence, ii) the number of conditional probabilities associated with each observation equals the number of components in the mixture, so that the EM algorithm may not be suitable for large datasets and iii) when the covariance matrix becomes singular or nearly singular (otherwise known as "ill-conditioned") the

EM algorithm breaks down. The latter problem was evident but not a decisive issue in this study - it usually relates to clusters which only contain a few observations where the observations contained are almost co-linear.

3.4 Model selection

The mixture model approach allows the use of approximate Bayes factors and posterior model probabilities to compare models (see Kass and Raftery (1995)). If there are several different contender models, $M_1, M_2, ..., M_K$ with prior probabilities $p(M_k); k = 1, ..., K$ then by Bayes's theorem the posterior probability of model M_k given data D is proportional to the probability of the data given model M_k times the model's prior probability:

$$p(M_k|D) \propto p(D|M_k)p(M_k) \tag{5}$$

When there are unknown parameters, by the law of total probability, we integrate over the parameters:

$$p(D|M_k) = \int p(D|\theta_k, M_k)p(\theta_k|M_k)d\theta_k \tag{6}$$

where $p(\theta_k|M_k)$ is the prior distribution of θ_k, and $p(D|M_k)$ is known as the integrated likelihood of model M_k. The Bayes factor is then defined as the ratio of the integrated likelihood between two models:

$$B_{12} = \frac{p(D|M_1)}{p(D|M_2)} \tag{7}$$

with the comparison favoring M_1 if $B_{12} > 1$.

The main problem in calculating the Bayes factor is the numerical evaluation of the integral in equation 6. But this can be approximated as:

$$2 \ln p(D|M_k) \approx 2 \ln p(D|\widehat{\theta}_k, M_k) - \upsilon_k \ln(n) = BIC \tag{8}$$

where υ_k is the number of independent parameters to be estimated and model M_k Thus we can now determine which is the most appropriate model by taking differences in BIC values:

$$2 \ln(B_{12}) = 2 \ln p(D|\widehat{\theta}_1, M_1) - 2 \ln p(D|\widehat{\theta}_2, M_2) = BIC_1 - BIC_2 \tag{9}$$

A standard convention for calibrating BIC differences is that differences of less than 2 correspond to weak evidence, differences between 2 and 6 to positive evidence, differences between 6 and 10 to strong evidence, and differences greater than 10 to very strong evidence.

3.5 Clustering strategy

The general strategy adopted here is similar to that of Fraley and Raftery (2002)
The strategy comprises 3 core elements:

i) initialization using model-based hierarchical agglomerative clustering,

ii) then maximum likelihood estimation using the EM algorithm, and lastly

iii) selection of the model and the number of clusters via the approximate Bayes factors using the BIC

Model-based agglomerative hierarchical clustering proceeds by successively merging pairs of clusters corresponding to the greatest increase in the classification likelihood, where the classification likelihood is defined as:

$$\mathcal{L}_{CL}(\theta_1, ..., \theta_G; \ell_1, ..., \ell_n|\mathbf{x}) = \prod_{i=1}^{n} f_i(\mathbf{x}_i|\theta_i) \tag{10}$$

where $\ell_i = k$ indicates a unique classification of each observation if x_i belongs to the kth component. Note that if the probability model in equation 10 is λI then the selection criterion reverts to a sum-of-squares.

The estimation process thus consists of the following steps:

a) determine a maximum number of clusters to consider, and a set of candidate parameterizations of the model to use.

b) use agglomerative hierarchical clustering for the unconstrained Gaussian model, to obtain classifications for up to M groups.

c) do EM for each parameterization and each number of clusters, starting with the classification from hierarchical clustering.

d) compute the BIC for the one cluster model for each parameterization and for the mixture likelihood with optimal parameters from EM for other clusters.

e) plot the BIC - this should hopefully indicate a local maximum and a specific model.

f) determine cluster membership and the uncertainty relating to cluster membership for all the data.

4 Time segmentation and data preparation

To use cluster analysis for classifying business cycle correlations with Germany or the euro area, data is needed that corroborates the degree of synchronicity in business cycles and associated variables. In this analysis the following variables were used:

i) real cyclical GDP correlations, transformed into log quarterly change (CGDP)

ii) inflation rate correlations, tranformed into log quarterly change (CPI)

iii) unemployment rate correlations (UN)

iv) short-term interest rate correlations (SINT)

v) long-term interest rate correlations (LINT)

The data was sourced from the IMF International Financial Statistics or from the ECB's Area-Wide Model database and extends to 2008. Exact details of data used is detailed in annex A. The above gives 5 pieces of economic data to use for cluster analysis for each of a total sample of 29 countries, giving a data set of 145 observations. But the unevenness of the data did not lend itself to analysis of the entire dataset, because availability of interest rates varied through time and also many of the CEECs had limited data series, most notably most of the IMF data begins in 1993 when these countries began collecting data after the fall of the Berlin Wall in late 1991. Clearly, any analysis done with these countries included should only use more recent data, even though more data exists for EU member states. In addition, to expand the dataset when only a limited amount of data was available so as to allow the cluster algorithms to converge, the US, Canada and Japan were added to all datasets. Using a maximum of 32 countries, four different clustering exercises were undertaken, based on different sets of data and different time periods[4]. In each case

[4] The rationale for these breakpoints detailed above is as follows; 1982/1983 is chosen as the first breakpoint for the Western European countries as in 1983 the ERM of the EMS became more stable and at that point many economists declared that a "new" EMS had begun to emerge; the 1991/1992 breakpoint marks the end of the narrow band ERM, as the political and economic landscape altered so drastically in 1991

a separate dataset was constructed for correlations with i) Germany and ii) with the euro area, leading to 12 different correlation exercises:

a) 1970-1982 for only West European countries (using CGDP, CPI, and LINT);

b) 1983-1991 for only West European countries (using CGDP, CPI, UN and SINT);

c) 1992-1998 for only West European countries (using CGDP, CPI, UN and SINT);

d) 1999-2004 for only West European countries (using CGDP, CPI, UN and SINT);

e) 1992-1998 for all European countries (using CGDP, CPI, UN and SINT); and

f) 1999-2008 for all European countries (using CGDP, CPI, UN and SINT).

Several of these clustering exercises encountered problems though, and these problems were of 3 types: convergence onto only one cluster, convergence onto n clusters, where n is the number of countries in the sample, and no convergence in the algorithm. These clustering exercises are excluded from the results.

As this is a large amount of data to summarize, the focus will be placed on the two more recent periods (- as this is likely to attract most interest). Correlations against the euro area for Western European countries are shown in appendix B for the period from 1992-98 and for the period from 1999-2008, while the same correlations for the CEE countries are shown in table 7 for the period from 1992-98 and in table 8 for the period from 1999-2004. The country codes used in the tables are listed in appendix A.

The tables clearly show a wide variation of correlations between countries. Between the 1992-98 and 1999-2008 periods, the average correlations for CGDP rose from 0.55 to 0.70, while for CPI average correlations fell from 0.334 to -0.037, for UN average correlations rose from 0.47 to 0.53, and not unexpectedly, average correlations for SINT stayed roughly constant, falling slightly from from 0.92 to 0.88. For the extended sample of countries average correlations for CGDP rose from -0.06 to 0.05, average correlations for CPI rose from -0.07 to 0.45 and correlations for UN fell from 0.25 to -0.11 and lastly average correlations for SINT increased from 0.22 to 0.57.

and 1992 (Maastricht, the collapse of the Berlin Wall, the single market, etc.); 1992 to 1998 marked the run-up period before the inception of EMU, and was marked by convergence among the current euro area member states; and lastly the period from 1999 to 2005 was the period when a single monetary policy was in operation.

5 Results

Following usual conventions in cluster analysis, all the correlation distributions were normalized for the clustering exercises. The results of the clustering exercises area shown in tables 2, 3 and 4. The cluster ordering refers only to the sequence of formation, and bears to significance in terms of magnitude of correlations. Any missing observations were replaced with an average value[5]. The rest of this section is devoted to detailing and illustrating these results.

5.1 1970-82: Western Europe vs Germany

This was the period when the ill-fated "snake" was in operation (1973-1979), and also the period covers the inception of the ERM of the EMS in 1979 and the early volatile years of the system. Figure 1 shows the BIC profiles for the different models, and although one particular model clearly is favoured (EEV) with a distance greater than 10 from the next highest alternative, there is only one particular country which has any uncertainty in this classification, and that is Italy - the alternative cluster for Italy would have been cluster 1[6]. Table 2 shows the cluster configuration, and figure 2 shows the 4 dimensional clusters in 2 dimensional space (here CGDP vs CPI) with the circles representing one standard deviation from the centre of each cluster. The result here roughly corroborates the result obtained in Holmes (2002) who shows that economic convergence occurred during this period for the core member states.

[5] Only one missing observation for each country was allowed, as inclusion could have led to problems of matrix singularity in the EM algorithm.

[6] The cluster numbers indicate the order in which the cluster form, so reflects only the proximities within groups and is independent of the magnitude of correlation values.

Cluster	70-82 vs GER	83-91 vs GER	92-98 vs GER	92-98 vs euro area	99-08 vs euro area (EA)
1	AUS BEL FRA GRE NET	AUS ICE ITA NOR	AUS GRE LUX POR	All other countries	AUS BEL DEN FIN ICE IRE, LUX NOR SWI UK
2	LUX SWI	BEL DEN FRA LUX NET SWE SWI	BEL FRA SPA SWI	ICE SWI UK	FRA GRE ITA NET POR SPA SWE
3	FIN POR	FIN UK	DEN UK		GER
4	ICE NOR	GRE IRE POR SPA	FIN ICE NET SWE		
5	DEN IRE ITA SWE UK		NOR		

Table 2: Cluster membership of Western European Countries

Cluster	92-98 vs GER	92-98 vs EA incl SINT	92-98 vs EA excl SINT
1	AUS BEL FIN GRE LAT LIT LUX NET POR SLO SPA SWE SWI	AUS BEL FIN FRA GER LUX NET POR SWE	AUS BEL FRA GER GRE LUX NET POR SPA LAT
2	Rest of Europe	DEN IRE ITA NOR POL	Rest of Europe
3		CRO LIT SLR SLO	
4		GRE IRE SPA SWI LAT	
5		UK BUL HUN	
6		EST TUR	
		CZR ROM	

Table 3: Cluster membership of Western Europe + CEE countries: 1992-98

Cluster	99-08 vs GER	99-08 vs EA	99-08 vs EA excl SINT
1	AUS BEL FIN FRA ITA LUX	AUS BEL FIN LUX	Western Europe CZR LAT SLO
2	DEN SWE SWI CZR	DEN IRE NOR	GER SWI + other CEECs
3	NET BUL POR	FRA GRE ITA NET POR SPA SWE	
4	GRE LIT	GER CRO HUN	
5	ICE LAT EST	ICE UK CZR LAT SLO	
6	NOR SPA UK	SWI BUL POL	
7	CRO HUN ROM TUR	EST TUR	
8	IRE POL SLR SLO	LIT	

Table 4: Cluster membership of Western Europe + CEE countries: 1999-2005

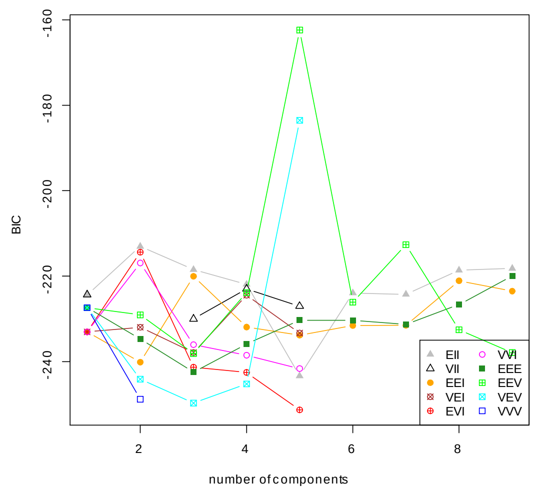

Figure 1: BIC for 70-82 vs Germany

5.2 1983-91: Western Europe vs Germany

This period has been termed the "New EMS" (see Giavazzi and Spaventa (1990)) as the initial turbulence in the ERM settled down with much less frequent realignments following France's u-turn in economic policy in 1983. Figure 3 shows the BIC profiles for the different models, with once again the EEV model being selected as optimal with 4 clusters. There is some low levels of uncertainty in terms of this classification, with Denmark having by far the highest level of uncertainty. Table 2 shows the cluster configuration and figure 4 shows this in map form. The clustering clearly corroborates previous cluster analysis studies of Jacquemin and Sapir (1995) and Artis and Zhang (2001), showing a "core" cluster which contains nearly all of the ERM member states (- Italy falling outside of this core here), and a definite periphery, with Ireland, the Iberian peninsula and Greece falling into a more disparate "periphery" cluster (- although there is a low level of uncertainty associated with Italy and Ireland's cluster classification).

5.3 1992-98: Western Europe

5.3.1 vs Germany

After the signing of the Maastricht Treaty convergence occurred in Europe as ERM members struggled to meet the convergence criteria for EMU. Here the growth dynamics are likely

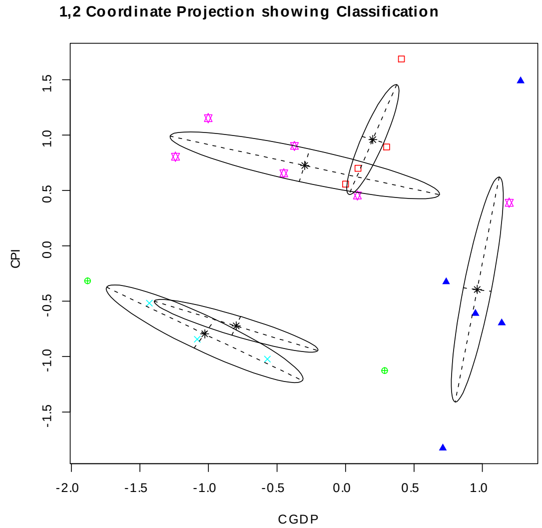

Figure 2: Cluster classification for 70-82 vs Germany

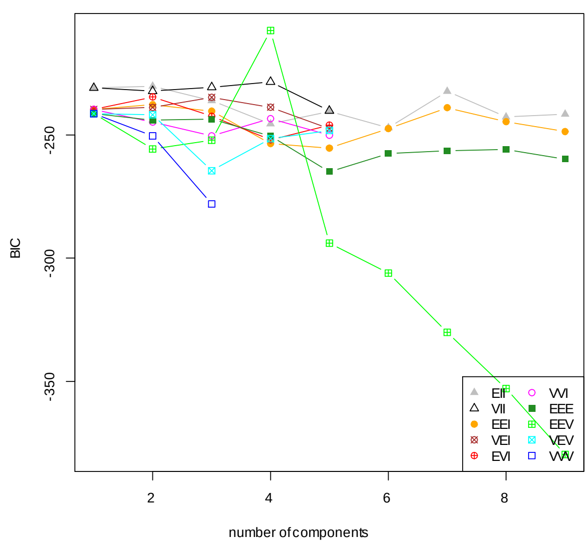

Figure 3: BIC for 83-91 vs Germany

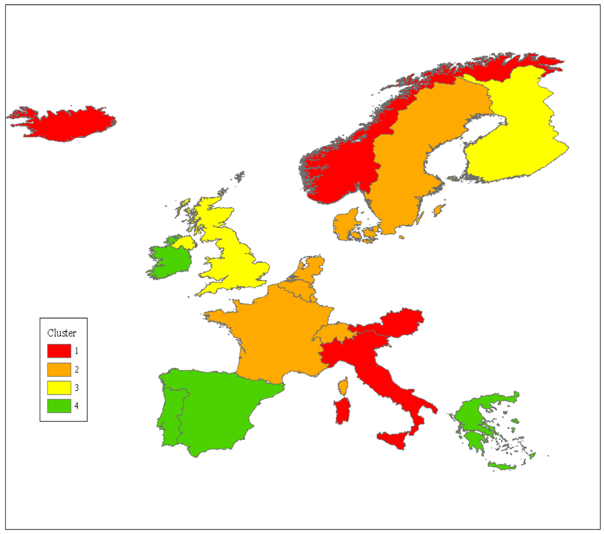

Figure 4: Cluster map for 83-91 vs Germany

to dominate, with convergence occurring at different rates across Western Europe. Figure 5 shows the BIC profiles for the different models, and here once again the EEV model dominates, with 6 clusters being optimal - although here one of these clusters just contains the US so for our purposes for Europe there are only 5 clusters. There is no uncertainty in this classification. Table 2 shows the cluster configuration and figure 6 shows this in a hatchplot. One of the issues regarding this classification relates to German reunification, as here correlating against Germany may not be appropriate given that Germany's business cycle would inevitably be impacted by the "shock" of German reunification, a shock that was idiosyncratic and not common to all EU member states.

Here there are clearly issues with the normalization of the short term interest rate correlation variable.as the US correlation is so low in comparison with the other correlations - this appears to be driving the cluster classifications. Indeed if the interest rate correlations are dropped the cluster classification collapses into just 2 clusters, with Denmark, Ireland, Italy, Norway and the UK in one cluster and all other countries in the other. This suggests that different dynamics to reduce inflation and interest rates to meet the Maastricht criteria in comparison with Germany are apparent, but that when interest rates are excluded there were essentially two different business cycle dynamics in Europe over this period[7]. Figure

[7] It is noteworthy that both Denmark and the UK were not in the "core" cluster as both these countries opted out of EMU. Italy and Ireland are the only apparent "misfits", but Italy does have a moderate degree of uncertainty associated with this classification (- Ireland does not).

7 shows the geographical clustering when interest rates are dropped.

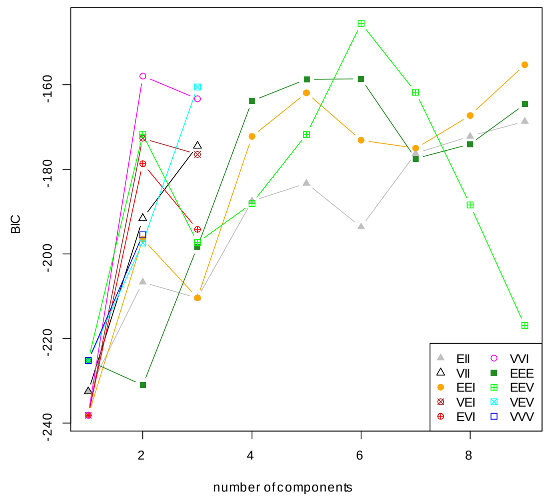

Figure 5: BIC for 92-98 vs Germany: Western Europe

5.3.2 vs euro area

Interestingly, although prior to 1992 no results are obtained when correlating against the euro area aggregates because of convergence problems, results are obtained after 1992, signifying perhaps that only when economies were forced to converge because of the Maastricht criteria did any discernable groupings of countries appear against a(n) (albeit "constructed") European aggregate. Here, only 2 clusters are apparent, with the EEV model once again maximizing BIC. Figure 8 shows the BIC plot and figure 9 the clusters, where only Iceland, Switzerland and the UK lie in the left hand smaller cluster[8]. Dropping the short term interest rate variable leads to the migration of Denmark, Ireland, Italy and Norway to the smaller cluster, but otherwise the results are identical with just 2 clusters maximizing the likelihood but the optimal model changes to EEI.

[8]This illustrates much lower cyclical GDP correlations for these 3 countries than for other countries, although there is a moderate degree of uncertainty about membership of Finland, Ireland and Sweden in the main (right hand) cluster.

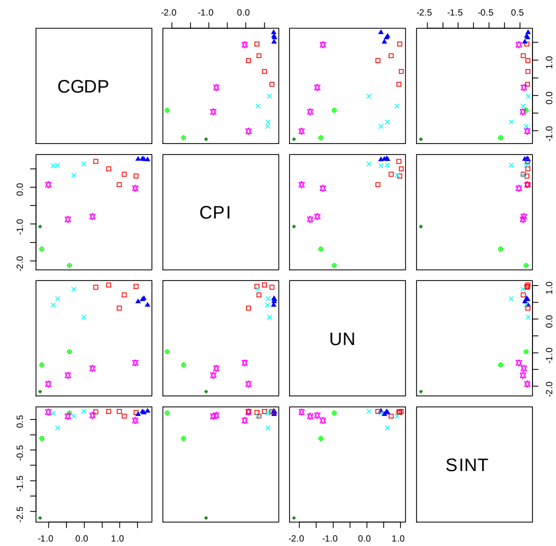

Figure 6: Hatchplot for 92-98 vs Germany: Western Europe

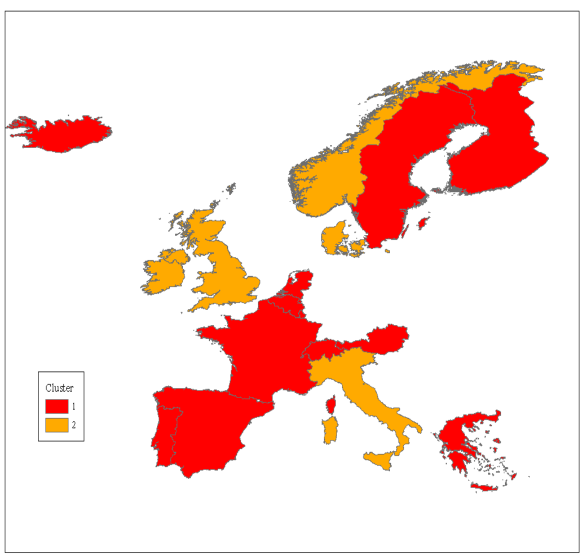

Figure 7: Cluster map for 92-98 vs Germany excluding SINT

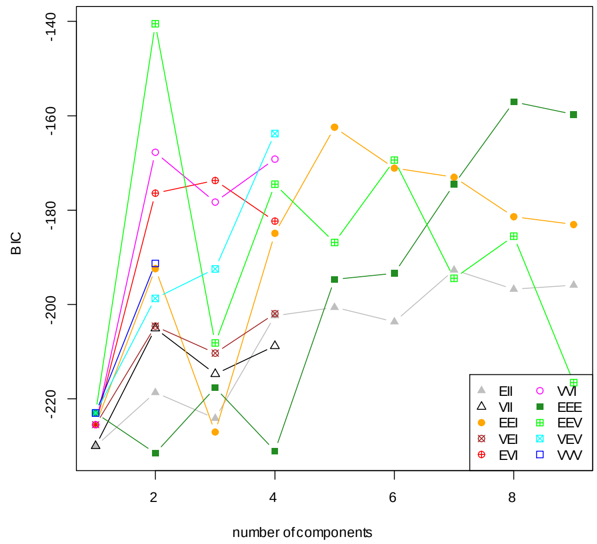

Figure 8: BIC for 92-98 vs euro area aggregate: Western Europe

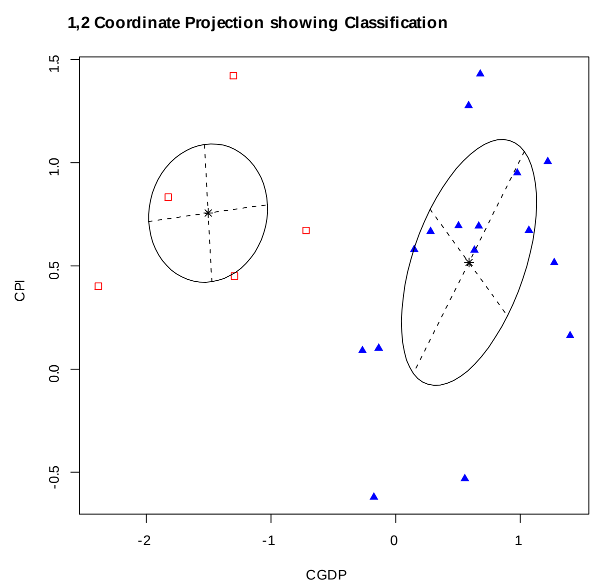

Figure 9: Cluster classification for 92-98 vs euro aggregate

5.4 1999-2008: Western Europe

5.4.1 vs euro area

When correlating all variables, we now obtain 3 clusters[9], this time just marginally better a 4 cluster configuration, with the EEE being the model (in either case). Figure 10 shows the BIC plots by model, table 2 shows the cluster classification and figure 11 shows this geographically. Germany is clearly outside of the main euro area cluster, which is perhaps hardly surprising given the economic problems that have Germany faced over the early period of the decade.

At first this appears to be a curious result, as it implies that under a single monetary policy there are more, not less individually identifiable business cycles. Part of the reason could be temporal: that of a differing response to the economic downturn experienced by the US in the early part of the 2000s, or it could be differing adjustment channels as the single monetary policy was introduced[10]. Another interesting observation is that (as table 2 shows) there is a north-south divide within the euro area, with northern euro area member states tending to fall into cluster 1 (with the exception of the Netherlands) and southern euro area member states falling into cluster 2. The hatchplot is reproduced in figure 12 and shows that although the growth correlations appear to be very similar, the unemployment and inflation correlations seem to define these groupings.(second row, third box from left).

5.5 1992-1998: Western Europe + CEECs

Here the CEE countries are now added to the mix, with the important difference that we now encounter missing values in the dataset, and these have been set to an average value for the class of countries being considered (- so in the case of a missing value for a CEE country, this would be set as the normalized value for the average of all CEE countries).

5.5.1 vs Germany

In this first instance, excluding the interest rate variable turns out not to make any difference: the VII model is chosen with 2 clusters, as is shown in table 3 and figure 13. Compared with the earlier clustering exercise including only Western European countries,

[9] If the SINT variable is dropped we obtain 2 clusters.

[10] Hoeller, Giorno, and de la Mainneuve (2004) and Stavrev (2007) discuss some of the issues as to why a single monetary policy might not generate a single cycle in all business cycle-related variables. Specifically they mention the financial sector and the housing sector as areas where national differences can cause differential responses to a commont monetary policy.

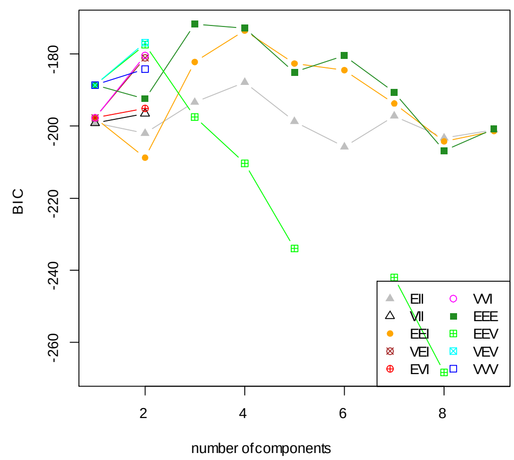

Figure 10: BIC for 99-08 vs euro area aggregate: Western Europe

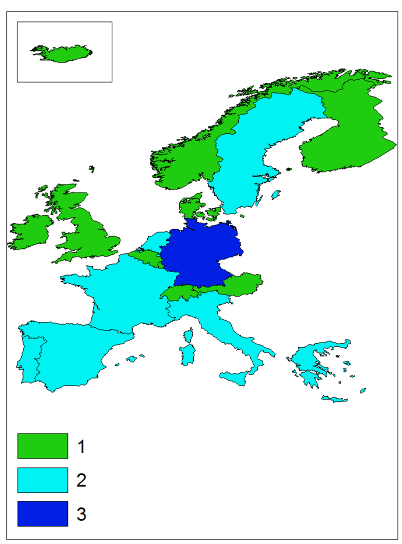

Figure 11: Cluster map for 99-08 vs euro aggregate for Western Europe

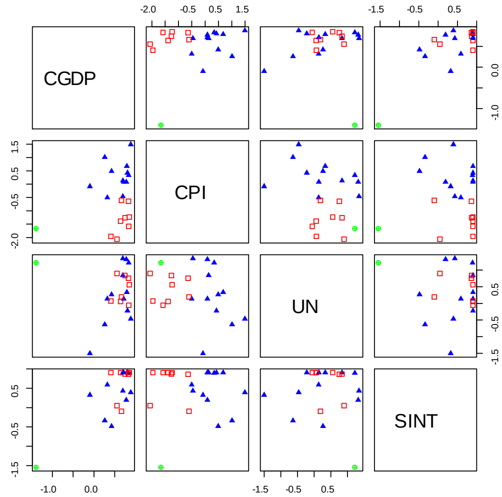

Figure 12: Hatchplot for 1999-08 vs euro aggregate

those Western European countries that lie outside the main cluster include those countries from the exercise with just Western Europe, but two of the Baltic countries plus Slovenia now join the main Western European bloc. The latter is noteworthy, as the Baltic countries plus Slovenia all undertook to maintain exchange rate stability against the German mark during this period, so this likely accounts for this similarity in correlations of business cycle variables[11]. Figure 14 shows the geographical dispersion of the clusters.

5.5.2 vs euro area - including SINT

When clustering against the euro area aggregate the EEV model dominates with 7 clusters (as shown in figure 15), but interestingly with a high degree of uncertainty for Germany. The clustering configuration is shown in figure 16 and table 3 with the geographical representation in figure 17. Here the map reveals a definite "core-periphery" effect, with the "soon-to-be" EMU countries falling into 3 clusters, one main "hard core" cluster (cluster 1) and two peripheral clusters (clusters 2 and 4).

5.5.3 vs euro area - excluding SINT

When interest rates are excluded, as table 3 details, the sorting is much more obvious - there is a clear demarcation between a "core" and the others. BIC was maximized for VII with 2

[11] It is notable that Estonia, however, is not included in this grouping.

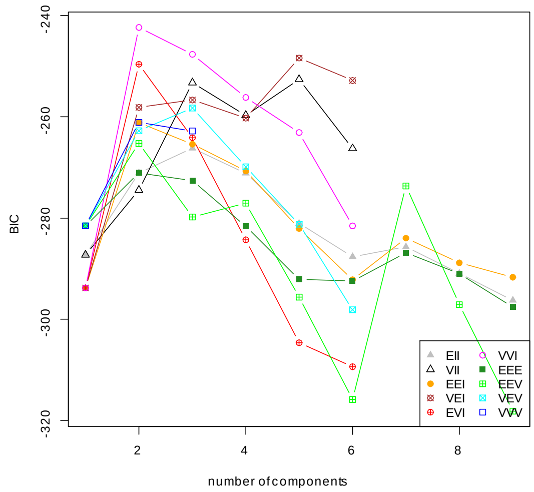

Figure 13: BIC for 92-98 vs Germany

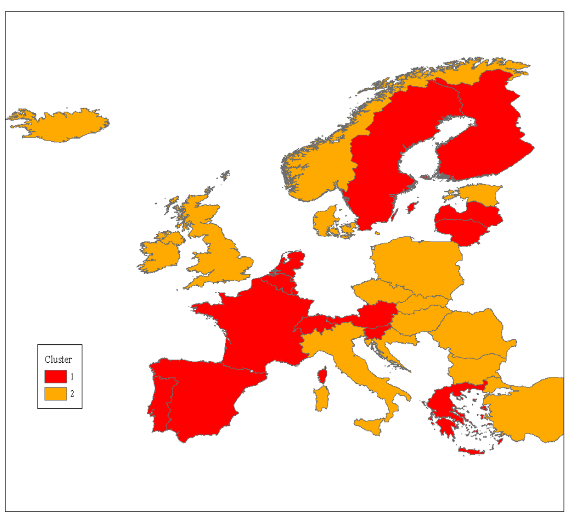

Figure 14: Cluster map for 92-98 vs Germany

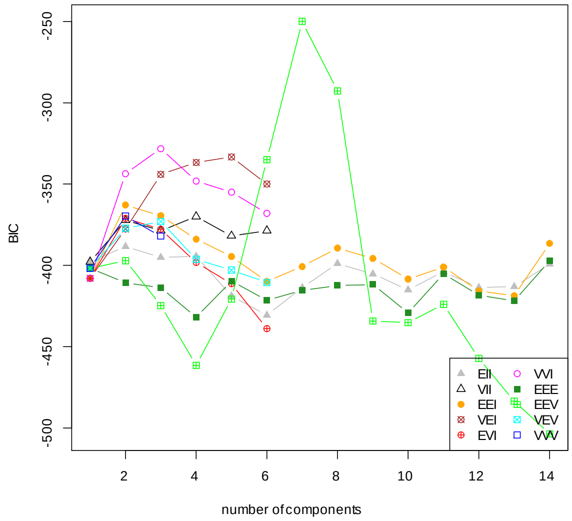

Figure 15: BIC for 92-98 vs euro aggregate: including SINT

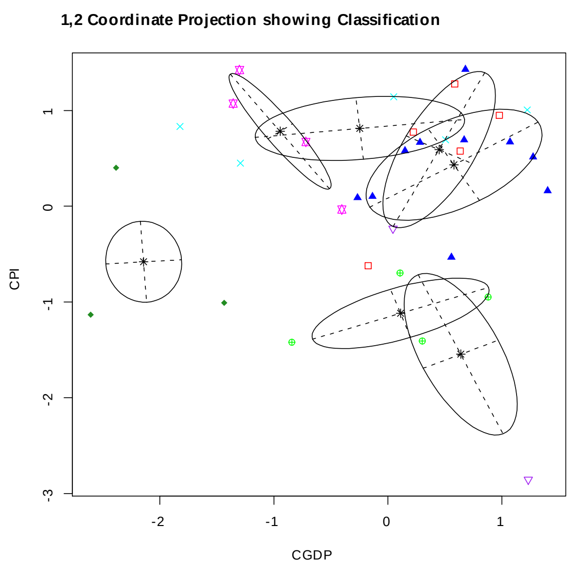

Figure 16: Cluster classification for 92-98 vs euro aggregate: including SINT

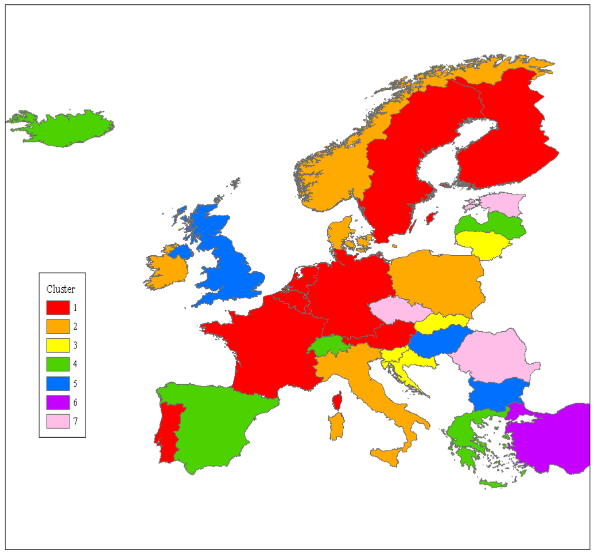

Figure 17: Cluster map for 92-98 vs euro aggregate: including SINT

clusters as is shown in figure 18. Figure 19 shows the appropriate cluster configuration plot with a geographical interpretation in figure 20. Latvia, Luxembourg and the Netherlands have relatively high levels of uncertainty in their classifications. The only current EMU members not classified in the first cluster are Finland, Ireland and Italy, suggesting that their macroeconomic behaviour was somewhat different to the other EMU members over this period. The reasons are likely diverse, as Ireland was in the midst of an unprecedented economic boom, Finland underwent a severe recession after a banking crisis and losing its trade with former Soviet Union, and perhaps Italy was the biggest victim of the ERM crisis of 92/93. It is interesting to note though that clearly with Finland inclusion of interest rate correlations makes a difference as the inclusion of a monetary policy variable puts Finland into the "core" cluster[12].

5.6 1999-2008: Western Europe + CEECs

5.6.1 vs Germany - including SINT

In this instance, as table 4 shows, BIC was maximized with 8 clusters with an VVI model, although this was not decisive in that the BIC difference from a 7 cluster configuration was less than 10. Figure 21 gives a BIC plot, figure 22 a cluster plot and figure 23 shows a map

[12] This is clearly related to interest rate targeting which was introduced in 1994 and also the political commitment to join the EU which then occurred in 1995.

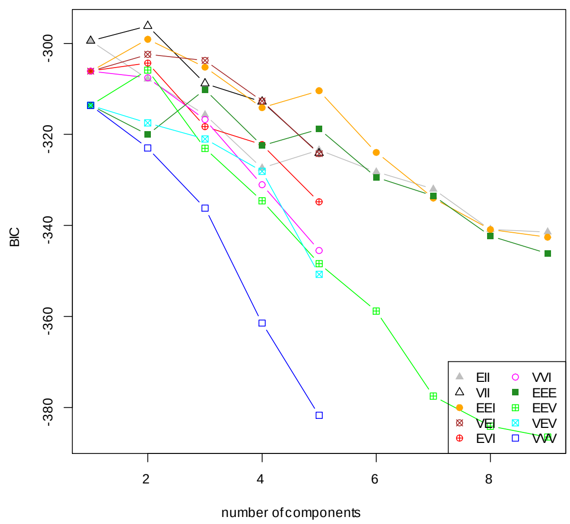

Figure 18: BIC for 92-98 vs euro area aggregate

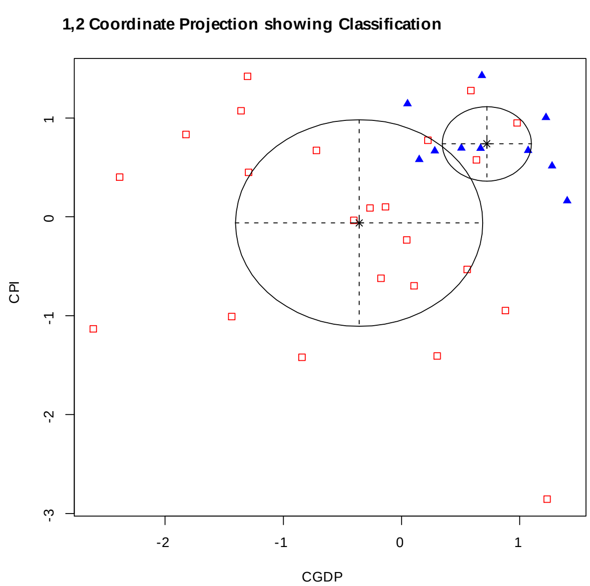

Figure 19: Cluster classification for 92-98 vs euro aggregate

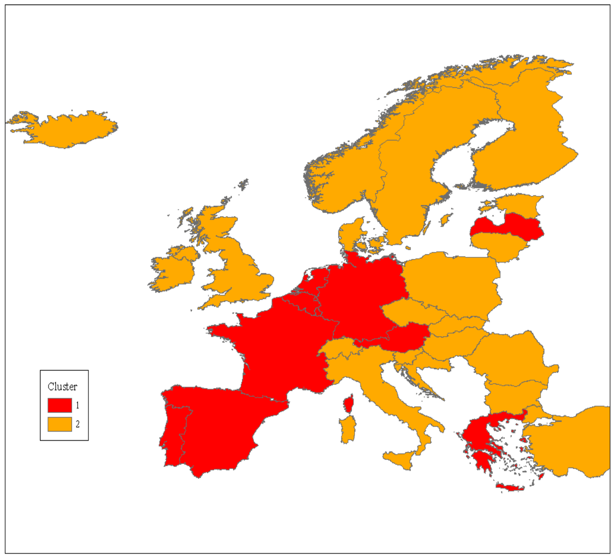

Figure 20: Cluster map for 92-98 vs euro aggregate

of this configuration. As the map shows, the classification is interesting as cluster 1 contains euro area member states (with some uncertainty surrounding Finland's membership), and the rest of the euro area is scattered between 4 other clusters.

5.6.2 vs Germany - excluding SINT

Here, there was no convergence.

5.6.3 vs euro area - including SINT

Here once again the EEV model dominates, with 8 clusters maximizing the likelihood but not highly significantly so over 2 clusters with the same model. What is interesting about this particular exercise, aside from the fact that Germany, Ireland and Slovenia appear in separate clusters, is that there are now apparently two distinctive cycles (in clusters 1 and 3) within the euro area, one consisting of a core of countries (cluster 3) and one consisting of the smaller countries Austria, Belgium, Finland and Luxembourg (cluster 1 - see table 4 for cluster details). Looking at the cluster configuration in figure 25 it is clear that CPI and business cycle correlations are largely determining the cluster classifications. It is also clear that looking at the close configurations to the right of the figure in figure 25 that these could be combined into one single cluster which actually leads to the two cluster configuration shown in figure 24. Another factor is likely the differing interest rate profiles

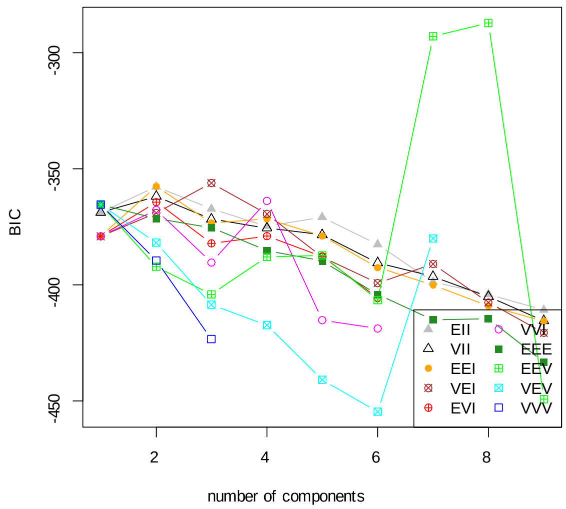

Figure 21: BIC for 1999-08 vs Germany

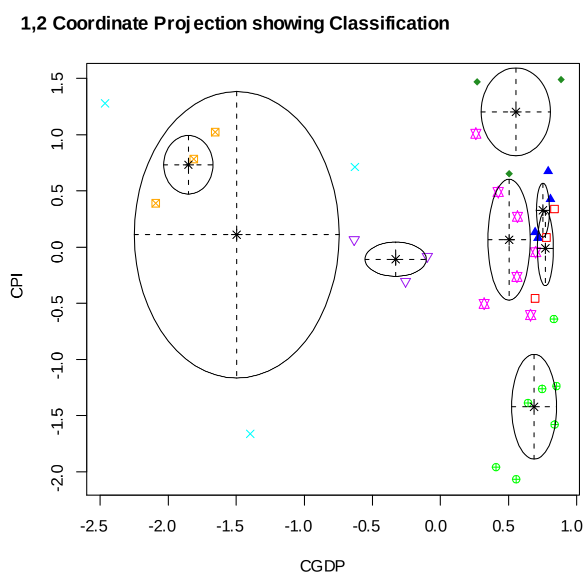

Figure 22: Cluster configuration for 1999-08 vs Germany

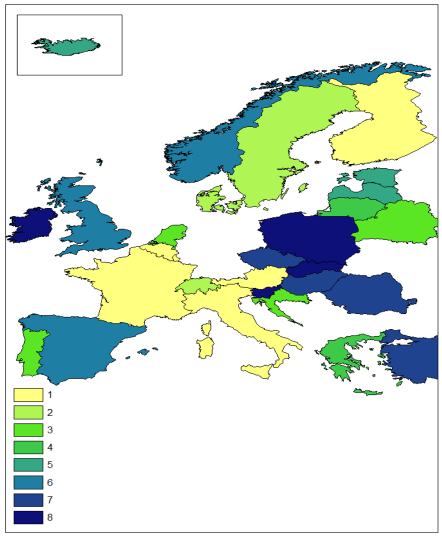

Figure 23: Cluster map for 99-08 vs Germany

given the differing fiscal policy reactions to the most recent economic downturn - clearly this might account for the large number of clusters found in this exercise.

5.6.4 vs euro area - excluding SINT

As table 4 shows, here the results were consistent with those obtained earlier for correlations including only the Western European countries. 2 clusters are obtained with an VVI model, with both Switzerland and Iceland having the largest degree of uncertainty associated with their classification but this is clearly a significant finding as the value of the next nearest classification BIC is roughly 20. What is confirmed here once again is the unique behaviour of Germany within the euro area, as it is the only euro area member state to now belong to the main Western European cluster (cluster 1). What is also of note is that the Czech Republic, Latvia and Slovenia (which is already a member of the euro area) fall into cluster 1. The BIC plot is shown in figure 27 with the graphical representation in figure 28 and the geographical representation of the VVI clusters shown in figure 29.

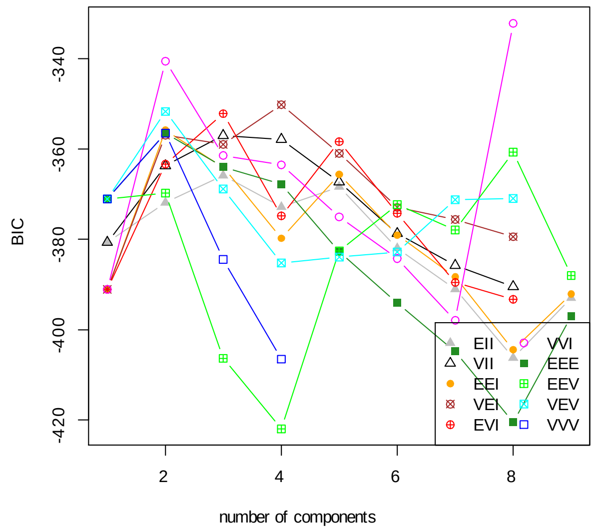

Figure 24: BIC for 1999-08 vs euro area

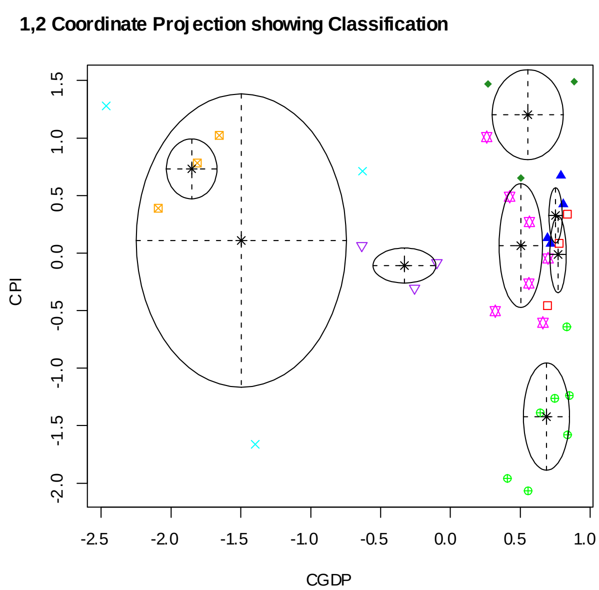

Figure 25: Cluster configuration for 99-08 vs euro area

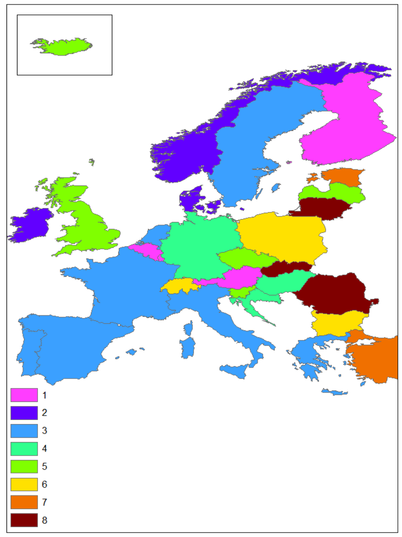

Figure 26: Cluster map for 99-08 vs Euro area aggregate

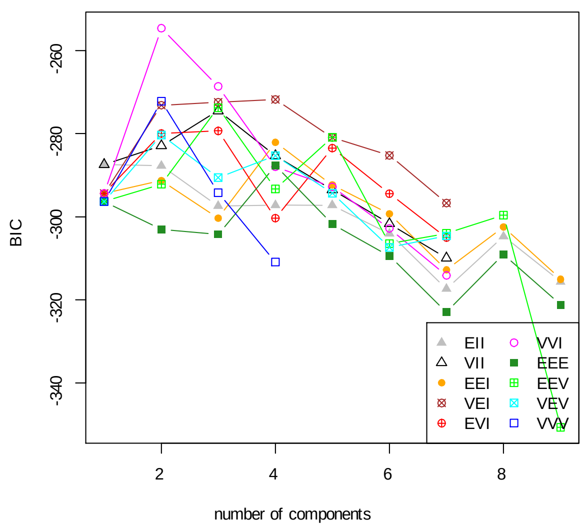

Figure 27: BIC for 1999-08 vs euro aggregate excluding SINT

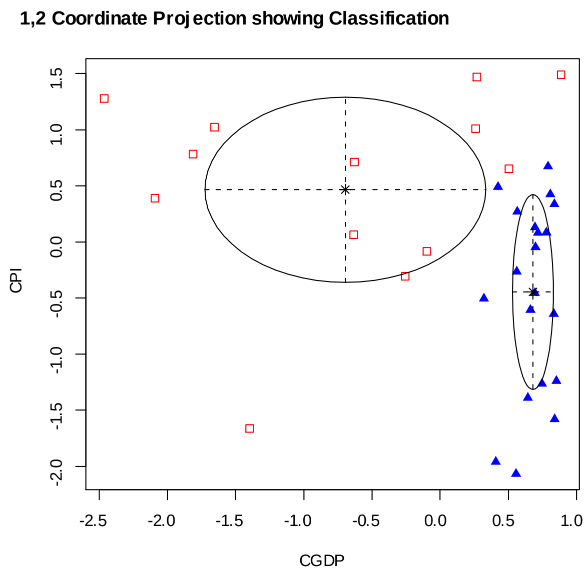

Figure 28: Cluster classification for 99-08 vs euro aggregate: excluding SINT

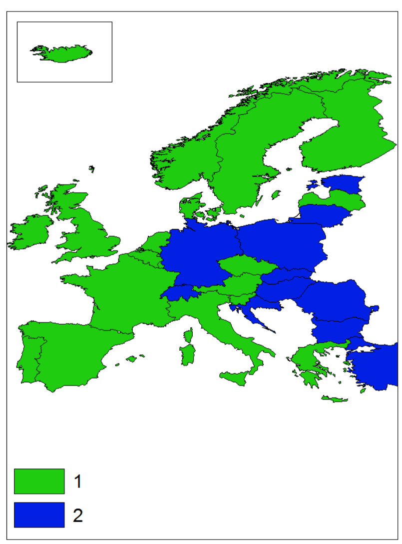

Figure 29: Cluster map for 99-08 vs euro aggregate: excluding SINT

6 Discussion

Five general results stem directly from this study.

i) The first result corroborates that of Crowley and Lee (2005) in that growth cycles in the euro area (- and in general as well) occur at frequencies that are shorter than the business cycle. Hence the time periods under consideration in this study do not always include a full business cycle, and yet they show variations between growth cycles in member states/countries which can yield groupings of countries which largely follow what one might expect. Hence in the 1992-98 period, although this period does not cover a complete business cycle, the results reveal that countries still split into sensible groupings in terms of the growth and behaviour of macroeconomic variables.

ii) Excluding CEE countries, the number of clusters for euro area members when correlating against a euro area aggregate has increased from 1 to 3 between the 92-98 period and the 99-08 period, signifying less business cycle comovement than prior to 1999. This could be due to a variety of reasons, most notably different growth dynamics in response to the US downturn and the introduction of the single monetary policy.

iii) When CEE countries are included, there are two stories dependent on whether correlations against Germany or the euro area are used. Against Germany, the euro area goes from 2 clusters in the 92-98 period to 5 clusters for the 99-08 period, but in the 92-98 period Ireland and Italy lie outside the main "soon-to-be" EMU cluster, while in the 99-08 period, Italy moves into the EMU cluster but Greece moves out and Ireland stays out. Against the euro aggregate, the euro area member states are located in 3 clusters (out of a total of 7) before EMU, with Greece, Ireland, Italy and Spain outside the main grouping before EMU, while after 1999 current euro area members are located in 5 different clusters out of a total of 8.

iv) The next general result is that clearly geography matters. The clusters usually tend to form around member states/countries in the centre of Europe, with many clusters consisting of contiguous member states/countries while clusters consisting of member states/countries on the periphery of Europe tend to belong to more disparate clusters. This is hardly a surprising result: the endogenous OCA theory states that trade within a common currency area is likely to synchronize business cycles, and so as contiguous or nearby member states are likely to trade more, the more neighbours participate in EMU the more likely they are to be in the same cluster.

v) Lastly, with regard to the CEE countries, apart from Slovenia (which now falls outside the main euro area member state clusters), the evidence here points to Hungary and Croatia being the best future candidates to join EMU[13].

There are two major issues that arise from this research.

First, points ii) and iii) appear to be in contradiction, as with the smaller dataset, there appears to be a larger number of clusters for euro area member states, whereas for the larger dataset the number of euro area member state clusters actually falls. One might argue that part of the reason for this is technical and due to the normalization of the datasets: normalizing a small number of observations will separate the values of the correlations more than normalizing on a larger dataset with more dispersion in the original data.

Second, which is the most appropriate target for correlating these business cycle variables.against - Germany or the euro area? Here there is no single correct answer. Clearly the euro aggregate is most relevant for ECB monetary policy, but on the other hand, the euro area aggregate doesn't represent the macroeconomic variable of a single socio-political entity, and so is just a "construct" aggregate. Given the dispersed nature of the euro area, there are bound to be different macroeconomic cycles within it, in particular due to the trade linkeages that the peripheral euro area member states will maintain with their non-euro area neighbours[14]. Conversely, Germany is the largest single member state in the euro area, in terms of both its economy and population, so any significant divergence in terms of business cycle correlations by a single euro area member state could have undesirable consequences, but a divergence by a group of euro area member states would be balanced by ECB monetary policy in terms of being reflected in the aggregate. In this sense the results in iii) should raise concerns for European central bankers.

7 Conclusions

The paper used model-based cluster analysis to group European member states/countries according to correlations with Germany and the euro area, over different periods, given data availability, and also over a consistent periods from 1970 through until 2008. This methodology originated in the literature on optimal currency areas, where it was able

[13] Based on 1999-2008 business cycle correlations.

[14] Finland is a good example here, as all of its neighbours are non-euro area countries.

to suggest which countries are most suited to adoption of a common currency. Model-based clustering was used to identify the number and membership of clusters during several subperiods of relevance to European integration.

The results showed that there is some divergence within the euro area in terms of the evolution of macroeconomic variables, and that this follows roughly a geographical "core-periphery" model. Nonetheless, when viewed against the backdrop of the CEE countries there appears to have been a sustained increase in convergence from 1992-99, although this appears to have fragmented once the euro area came into operation. Several caveats must be made regarding these results, which relate to the limits to interpreting the correlations, the correlation against Germany (which has experienced much higher unemployment rates since reunification), and the lack of any data to portray trade between member states (which according to the endogeneity of OCAs, should induce further convergence).

Future research will explore other variables of interest for this methodology, perhaps incorporating some measure of the government fiscal policy, and will also compare correlations of business cycle variables with other aggregates when and if they become available.

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Appendices

A Country abbreviations

Country abbreviations used in tables:

AUS = Austria

BEL = Belgium

DEN = Denmark

FIN = Finland

FRA = France

GRE = Greece

ICE = Iceland

IRE = Ireland

ITA = Italy

LUX = Luxembourg

NET = Netherlands

NOR = Norway

POR = Portugal

SPA = Spain

SWE = Sweden

SWI = Switzerland

UK = United Kingdom

BUL = Bulgaria

CRO = Croatia

CZR = Czech Republic

EST = Estonia

HUN = Hungary

LAT = Latvia

LIT = Lithuania

POL = Poland

ROM = Romania

SLR = Slovak Republic

SLO = Slovenia

TUR = Turkey

B Correlation database

	CGDP	CPI	UN	SINT
AUS	0.709	0.372	0.697	0.983
BEL	0.888	0.318	0.921	0.972
DEN	0.406	0.593	-0.260	0.946
FIN	0.118	0.164	0.478	0.974
FRA	0.865	0.649	0.959	0.988
GER	0.884	0.341	0.764	0.984
GRE	0.892	0.382	0.696	0.918
ICE	-0.125	0.295	0.645	0.682
IRE	0.687	0.340	-0.359	0.931
ITA	0.806	0.475	-0.014	0.921
LUX	0.395	0.190	0.858	0.962
NET	0.444	0.375	0.442	0.980
NOR	0.122	-0.092	-0.409	0.894
POR	0.810	0.382	0.896	0.989
SPA	0.990	0.495	0.682	0.954
SWE	0.561	-0.061	0.872	0.946
SWI	0.671	0.433	0.931	0.990
UK	-0.221	0.374	-0.334	0.481

Table 5: Correlations for Western Europe against the euro area: 1992-98

	CGDP	CPI	UN	SINT
AUS	0.93	0.43	0.44	0.99
BEL	0.88	0.21	0.68	0.99
DEN	0.96	0.30	0.86	0.99
FIN	0.94	0.33	0.17	0.99
FRA	0.97	-0.35	0.54	0.99
GER	0.90	-0.35	0.68	0.99
GRE	-0.32	-0.52	0.86	0.36
ICE	0.66	-0.05	0.34	0.92
IRE	0.88	-0.03	0.92	0.88
ITA	0.85	-0.40	0.31	0.99
LUX	0.89	0.19	0.34	0.99
NET	0.96	-0.49	0.25	0.99
NOR	0.92	0.19	0.91	0.81
POR	0.71	-0.64	0.31	0.99
SPA	0.95	-0.10	0.64	0.99
SWE	0.77	-0.69	0.70	0.78
SWI	0.99	0.76	0.06	0.87
UK	0.72	0.36	0.40	0.64

Table 6: Correlations for Western Europe against the euro area: 1999-2005

	CGDP	CPI	UN	SINT
BUL	-0.184	0.119	-0.575	-0.044
CRO	0.445	-0.120	0.166	0.809
CZR	0.258	-0.901	0.196	-0.597
EST	-0.221	-0.279	0.848	-0.579
HUN	-0.104	0.520	-0.026	0.222
LAT	-0.167	0.545	0.752	0.915
LIT	0.271	-0.377	0.622	0.796
POL	-0.298	0.411	-0.105	0.906
ROM	-0.346	0.047	-0.043	-0.779
SLR	0.366	-0.211	0.715	0.222
SLO	-0.489	-0.382	0.849	0.957
TUR	-0.216	-0.233	-0.454	-0.168

Table 7: Correlations for CEEC against the euro area: 1992-98

	CGDP	CPI	UN	SINT
BUL	0.76	0.42	-0.68	0.89
CRO	-0.93	0.68	-0.91	0.12
CZR	0.80	0.27	0.26	0.74
EST	0.33	0.03	-0.28	0.88
HUN	0.12	0.45	0.72	0.14
LAT	0.88	0.14	0.63	0.46
LIT	-0.72	0.32	-0.86	0.41
POL	0.63	0.76	-0.24	0.94
ROM	-0.56	0.48	-0.02	0.47
SLR	-0.47	0.57	-0.51	0.90
SLO	0.80	0.05	0.45	0.77
TUR	0.11	0.18	0.00	0.79

Table 8: Correlations for CEEC against the euro area: 1999-2008