Has the EU Become an OCA?
Evaluation using Model-based Cluster Analysis

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PRELIMINARY

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1. Introduction

The euro was formally launched on January 1, 1999. Since that time, the transition period has been completed, the European Central Bank (ECB) has now been in operation with a single currency for over a year, and accession negotiations have been concluded for 10 new member states to join the European Union (EU) as of 2004. The countries currently subject to ECB monetary policy (here we label them the 13 "eurozone" member states), have also been under some economic strains as the fiscal counterpart to Economic and Monetary Union (EMU), namely the Stability and Growth pact (SGP) has come under scrutiny and has been ignored by some member states. Also the subject of the accession of the Central and Eastern European countries (CEECs) has recently been widely discussed in the discipline of economics, partly because of the extensive changes that the European Union (EU) will have to undergo, but also because of the implications in terms of successful integration of the Central and Eastern European countries for regional growth and further integration.

Given the developments 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 EMU constitutes an optimal currency area (in the sense that applying a single monetary policy is appropriate for each country/member state), and to apply such criteria to the CEECs to see if they are suited yet to membership of EMU.

This paper, rather than discussing the political and economic merits or otherwise of EMU, 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 business cycles with Germany is achieved and ii) countries have similar experience with movements in interest rates, inflation and unemployment. Unlike with optimal currency area considerations, 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[1].

The issue of CEEC membership in EMU is also important, as the 1993 Copenhagen criteria for accession to 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 also necessitate joining EMU - so the economic convergence criteria take on additional meaning for the accession countries. This also leads to additional weight being placed on economic convergence with the rest of the EU, as newly joining member states will also have their exchange rate and monetary policies removed in addition to restrictions being placed on their fiscal policy, on top of the already heavy burden of implementation of other EU policies. So this paper also addresses the further issue of which CEEC countries might also already possess synchronous business cycles, in addition to a high degree of correlation in other important macroeconomic variables.

The paper is divided into five sections. Section 2 evaluates the literature on EMU and CEEC integration, as well as the literature on business cycle synchronicity, while section 3 outlines the methodology to be used. Section 4 describes the data and provides the results of model-based cluster analysis, while section 5 concludes.

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[1] The author plans to add trade data at a future date.

2. EMU and Business Cycles

a. EMU and the CEEC countries

The two seminal papers on optimal currency areas (Mundell (1961) and McKinnon (1963)) outlined the conditions under which several administrative jurisdictions might be suitable to be subject to the same monetary policy. Further refinements of this approach were subsequently made by Kenen (1969). Bayoumi (1994) also offered a formal model of optimal currency areas (OCAs) with microeconomic foundations to underscore Mundell's original thesis. The conditions for an OCA are that members of the currency union should, for the most part, experience symmetric shocks and that economic cycles should be synchronous. If countries experience asymmetric shocks or have asynchronous business cycles then the costs of being subject to a single monetary policy may be significant, and may outweigh the costs. To offset asymmetric shocks or asynchronous business cycles, then certain currency area characteristics may ameliorate costs, notably i) a significant degree of labour mobility, ii) fiscal transfers through a "federal" level of government and iii) flexible wages and prices.

A recent development in the OCA literature has also been recognition that ex-ante evaluations of which countries constitute an OCA might ignore the Lucas critique, in that new members of an OCA might a) modify policy to be better suited to an OCA (see Tavlas, G. (1993)) or b) be more suited to being in an OCA *ex-post* (Frankel and Rose (1997)). The latter approach takes into consideration factors which usually do not appear in the *ex-ante* OCA approach, such as trade intensity, real interest rate cycles, and fiscal policy coordination[2]. Clearly, in terms of EMU, trade intensity and real interest cycles can, *ex-post*, be important factors, and fiscal policy coordination is also clearly a factor, although because of the SGP its use in low-growth situations would be limited not only by the rules inherent in the SGP, but also by the large public debt burden that many European member states/countries already face.

The issue of CEEC membership should also be dealt with here. As Boreiko (2002) points out, there are in fact two economic conditions that need to be met in order to join the EU. The first is the Maastricht Treaty economic criteria, which have been well documented and argued over elsewhere, but nevertheless this does imply exchange rate stability and both the fiscal criteria and monetary criteria specified in the other criteria. These are of course in addition to the acquis communitaire and the political criteria which together make up what has been labelled the "Copenhagen criteria". As has been argued elsewhere, the Maastricht criteria themselves bear little resemblance to what should constitute the conditions for an OCA, so can only be considered a proxy for suitability for membership in a currency union. Therefore, from an economic view, it can be argued that the Maastricht criteria should not really be deciding factors in terms of whether a country is really a good candidate for EU membership and by extension EMU.

In fact, since 2002 several historic changes have occurred, with the negotiations and timetable for accession being completed with the countries that were deemed to qualify for EU membership. The culmination of the negotiations with the qualifying members of both the 1998 and 2000 accession groups gave rise to the agreements at Copenhagen in December which

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[2] Neumeyer (1998) also considers the notion that political shocks could be incorporated as another variable contributing to the factors which might suggest an optimal currency area.

culminated in 10[3] new members being admitted to the EU, subject to ratification of the Treaty of Accession in all present and prospective member states. Some work has already been done on whether Central and Eastern European countries should be part of the EMU: notably Boone and Mathilde (1999) and De Grauwe and Aksoy (1999). Both concluded that at present none of the CEEC applicants could be said to be part of an OCA with the current eurozone members - but also that after joining the EU it is likely that greater trade linkages and membership of ERMII should lead to greater convergence with the current eurozone members. Cahlík (2002) reviews what some scenarios for what is likely to happen after the CEEC become members of the EU.

b. Synchronicity of Business Cycles

The empirical literature on OCAs has largely focused on methodology that uses structural vector autoregression (SVAR) time series methodology to identify demand and supply shocks (see for example, Bayoumi and Eichengreen (1994a) for the EU and North America) and then look at the correlation of these shocks across countries or regions. But another strand of the literature evaluates the synchronicity of business cycles across prospective currency union members (Baxter and Stockman (1989) and Artis and Zhang (1997a)) and this is used as the basis for this paper.

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

[3] The countries are the Czech Republic, Estonia, Poland, Hungary, Slovenia, Latvia, Lithuania, Slovak Republic, Cyprus and Malta (the first five constitute the 1998 Accession group).

research on business cycles has focussed on the effects of trade in propogating business cycles (see Imbs (1999)) and on new measures of co-movement (see Croux, Forni and Reichlin (1999)) of output data for different regions or countries.

Artis and Zhang (1997a) 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[4]. In this study, cyclical components of industrial production were obtained using several de-trending methods[5], and then the cross-correlations of the cyclical components of these series with the US series and the German series were calculated. A European business cycle was confirmed, but the cycle was confined to members of the ERM of the EMS, as might have been expected. The results were shown to be robust to the detrending method employed.

Here a similar methodology is employed, with two differences. First, in the European context, Artis and Zhang (1997a) 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 the appropriate "target" variables for the purposes of calculating cross-correlations for European member states/countries. Second, the methodology adopted is not the same as the cluster analysis that has been used in most research up until 1999, but instead uses a combination of techniques to construct an integrated strategy towards cluster identification.

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[4] Further research by Artis, Krolzig and Toro (1999) has analysed the phasing of the European business cycle.

[5] The methods used were phase-average trend (PAT) detrending, a linear trend and a Hodrick-Prescott filter.

3. Methodology

a. Basic Approach

The analysis was undertaken by estimating cyclical components of real GDP movements using a band-pass filter (Baxter and King, 1985; Stock and Watson 1998). Cyclical real GDP is then correlated for each member state/country to German real GDP. Other business cycle variables are then also correlated with German equivalents to obtain a set 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 the Germany is taken to imply that the country may benefit from membership in EMU, or certainly wouldn't be adversely affected by membership. But this does not identify which countries might be classified as potential candidates for EMU. For this purpose cluster analysis is used[6]. In economics cluster analysis has been applied to EU data by several authors, notably Jacquemin and Sapir (1995) and Artis and Zhang (1997b and 1998a and b), 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 is also started to infiltrate into the economics profession in North America, with Galbraith and Jiaquing (1999), Honohan (2000) and also Maharaj and Inder (1999)[7]. Most

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6 Cluster analysis was first applied by Fisher (1936) to classifications of irises (found by Anderson (1935)) indigenous to the Gaspé peninsula in Québec.

7 In other disciplines, cluster analysis is frequently used - applications range from astrophysics (Mukerjee, Feigelson, Babu et al (1998)) to microbiology (van Ooyen (2001)).

recently Boreiko (2002) applied fuzzy cluster analysis to both fiscal data, nominal and real data to assess which countries tended to be in the forefront for EU membership and which also could be selected to be appropriate members of EMU[8].

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 is optimized 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. In model methods, however, usually a maximum likelihood based on specific distributional assumptions is used to merge or divide groups. Useful references for these heuristic clustering methods are Anderberg (1993), Kaufman and Rousseeuw (1990) and Hartigan (1975).

Unfortunately, although these 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[9], but up until recently none of these methods has been satisfactory

[8] This is a notable difference with Boreiko (2002), who uses traditional fuzzy cluster analysis. Most statisticians view model-based cluster analysis as superior to traditional fuzzy cluster analysis, as model-based cluster analysis is already in a sense "fuzzy", as it does look at the possibility of certain data points having membership of different clusters.

[9] Usually, as with Boreiko (2002), Silhouette widths and Dunn's coefficient is used to "select" the appropriate number of clusters.

from a computational point of view, or from a methodological point of view (see Bock (1996) for a survey of this issue and related research). The alternative that has been presented by Fraley and Raftery (1998a and b, updated in 2002) is computationally relatively straightforward, and is also intuitively appealing, so this methodology is adopted here.

b. 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 observations $\boldsymbol{x} = (\boldsymbol{x}_1,....,\boldsymbol{x}_n)$, then the density of an observation $\boldsymbol{x}_i$ from the kth component in a total number of G components, is $f_k(\boldsymbol{x}_i \,/\, \theta_k)$, where θ_k are the parameters. In most cases, $f_k(\boldsymbol{x}_i \,/\, \theta_k)$ is assumed to be multivariate normal (Gaussian), so in this instance the parameters θ_k consist of a mean vector μ_k and a covariance matrix Σ_k. The clusters will then be ellipsoidal, with center at μ_k, and the covariance matrix will determine the other characteristics.

The mixture likelihood approach then maximizes the criterion:

$$\lambda_M(\theta_1,...,\theta_G:\tau_1,...,\tau_G|x)=\prod_{i=1}^{n}\sum_{k=1}^{G}\tau_k f_k(x_i|\theta_k) \tag{1}$$

where τ_k is the probability that an observation belongs to the kth component.

Banfield and Raftery (1993) developed a model-based framework for clustering by expressing the covariance matrix in terms of its eigenvalue decomposition, which is of the form

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

where D_k is the orthogonal matrix of eigenvectors, A_k is a diagonal matrix where the elements of the diagonals are proportional to the eigenvalues of Σ_k, and λ_k is a 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 (1998a). The range of models used has now been expanded from the original 1998 software, and the new 2002 MCLUST library uses a more extensive set of models within the same framework following Celeux and Govaerts (1995).

In the approach taken here, the parameterizations of the covariance matrix are detailed in table 1 below:

Table 1

Parameterizations of the Covariance Matrix

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

Source: Banfield and Raftery (2002)

Given the different model parameterizations above, agglomerative hierarchical clustering can be used by merging clusters so as to maximize the resulting likelihood as specified in equation (1) above.

c. Clustering algorithms

The algorithm used for maximizing the likelihood function here is the EM (Expectation-Maximization) algorithm (see McLachlan and Krishnan (1997)). EM iterates between an "E" step, which computes a matrix z such that 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 z. In the limit, under certain conditions the parameters usually converge to the maximum likelihood values for the Gaussian mixture model and the sums of the columns of z converge to n times the mixing proportions τ_k, where n is the number of observations.

The EM algorithm is not without its problems though. Fraley and Raftery (1998a) 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 an issue in this study - and it usually relates to clusters which only contain a few observations where the observations contained are co-linear.

d. Model selection

The mixture model approach allows the use of approximate Bayes factors to compare models (see Kass and Raftery (1995)). The Bayes factor is the posterior odds for one model against the other assuming neither is favored a priori. With the EM algorithm twice the log Bayes factor is used to determine the number of clusters in hierarchical clustering based on the mixture likelihood.- this measure is also known as the Bayesian Information Criterion (BIC) and is specified as:

$$2\log p(x|M) + const \approx 2\lambda_M \log(n) - m_M \log(n) \equiv BIC \qquad (3)$$

where $p(x|M)$ is the likelihood of the data for the model M, $l_M(x|\theta)$ is the maximized mixture log likelihood for the model and m_M is the number of independent parameters to be estimated in the model. The larger the value of the BIC, the stronger the evidence for the model[1].

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.

e. Clustering strategy

The general strategy adopted here is similar to that of Fraley and Raftery (1998a). The steps of strategy are as follows:

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

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

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

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

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

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

4 Data and Empirical Results

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

i) real cyclical GDP correlations (GDP)

ii) inflation rate correlations (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. Exact details of data used is detailed in annex A. The above gives us 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 of two different problems with the data. First, many of the CEEC countries had very 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. Second, there was clearly a high degree of correlation between short-term and long-term interest rate movements, so as outlined above in the methodology section, this led to problems in algorithm convergence. As there appeared to be less IMF data available for long term interest rates, short term interest rates were used in all the exercises that follow[10]. Four different clustering exercises were undertaken, based on different sets of data and different time periods.

[10] It could be argued, along the lines of the original Maastricht criteria, that long-term interest rates are more appropriate as a measure for EMU membership, and that is perhaps correct. But the reader should be aware that the correlations presented here are correlations of movements in short-term interest rates and not indicative at all of levels of interest rates. Many economists would also likely argue that if one interest rate had to be included it should be short-term rates as these are more indicative of monetary policy. Another possibility if more long-term data is located is to use a yield curve slope measure (long- minus short-term interest rates).

In each case these are described below:

a) 1983-1992 for only West European countries (using CGDP, CPI, and SINT);

b) 1992-2001 for only West European countries (using CGDP, CPI, and SINT)

c) 1992-2001 for only West European countries (using CGDP, CPI, UN and SINT)

d) 1993-2001 for all European countries (using CGDP, CPI, UN, and SINT)

The rationale for using 1983 for the starting point for the Western European countries was that 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 rationale for the 1992 break point was that this was essentially the end of the narrow band ERM, and that as political and economic landscape altered so drastically in 1991 and 1992 (Maastricht, the collapse of the Berlin Wall, the single market, etc.), it was not sensible go beyond 1992. Correlations for each of these exercises are documented in tables 2a, 2b and 2c below.

Table 2a

Correlations with West Germany: 1983-1992

	CGDP	CPI	SINT
AUS	0.557	0.593	0.973
BEL	0.272	0.438	0.774
DEN	-0.041	-0.018	0.443
FIN	-0.724	0.204	0.283
FRA	0.063	0.247	0.481
ICE	-0.109	-0.192	-0.904
IRE	-0.117	0.294	0.461
ITA	0.141	0.304	0.204
NET	0.305	0.743	0.965
NOR	0.063	-0.555	-0.368
POR	0.133	0.168	-0.064
SPA	0.208	0.149	0.141
SWE	-0.413	0.058	0.744
SWI	-0.029	0.521	0.630

See appendix A for abbreviations used for countries.

See appendix B for frequencies and time periods.

Table 2b

Correlations with Germany for Western European Countries: 1992-2001

	CGDP	CPI	SINT
AUS	0.548	0.884	0.999
BEL	0.381	0.747	0.994
DEN	0.068	-0.438	0.970
FIN	-0.423	0.411	0.966
FRA	0.321	0.698	0.976
GRE	0.883	0.756	0.947
ICE	0.063	0.186	0.272
IRE	0.052	0.033	0.912
ITA	0.375	0.555	0.788
LUX	-0.472	0.827	0.989
NET	0.136	0.387	0.999
NOR	-0.071	0.052	0.825
POR	0.311	0.824	0.966
SPA	0.463	0.709	0.872
SWE	-0.012	0.795	0.905
SWI	-0.089	0.786	0.960
UK	-0.660	-0.143	0.537

See appendix A for abbreviations used for countries.

See appendix B for frequencies and time periods.

<u>**Table 2c**</u>

Correlations with Germany for All European Countries: 1993-2001

	CGDP	CPI	UN	SINT
AUS	0.819	0.860	0.680	0.998
BEL	0.859	0.773	0.253	0.999
DEN	0.676	-0.244	-0.606	0.982
FIN	0.663	0.309	-0.177	0.966
FRA	0.869	0.683	0.582	0.957
GRE	0.395	0.597	0.799	0.947
ICE	0.431	0.303	0.000	-0.055
IRE	0.022	0.178	-0.265	0.773
ITA	0.693	0.460	-0.806	0.590
LUX	0.401	0.798	0.767	0.990
NET	0.500	0.503	0.826	0.998
NOR	-0.083	0.027	-0.349	0.486
POR	0.459	0.738	-0.807	0.929
SPA	0.783	0.660	-0.170	0.810
SWE	0.762	0.796	0.134	0.761
SWI	0.746	0.622	-0.104	0.902
UK	0.560	-0.148	0.408	-0.351
BUL	0.992	0.011	-0.635	0.085
CRO	-0.298	0.715	0.000*	0.834
CZR	0.382	0.233	0.238	-0.148
EST	-0.283	0.618	0.026	-0.185
HUN	0.337	0.192	-0.519	0.000*
LAT	0.326	0.652	0.688	0.743
LIT	0.051	0.711	0.207	0.696
POL	0.237	0.547	-0.858	0.548
ROM	0.134	0.671	-0.786	-0.826
SLR	-0.493	0.272	-0.529	0.000*
SLO	0.669	0.827	-0.712	0.881
TUR	-0.212	0.022	-0.532	0.138

Note: * = no data available, so the value was set to zero.
See appendix A for abbreviations used for countries.
See appendix B for frequencies and time periods.

The tables clearly show a wide variation of correlations between countries. In tables 2a and 2b, the average correlations for CGDP rose from -0.035 to 0.130, but for the ERM member states the average rose from 0.148 to 0.256. The increase in correlations for short and long term interest rates were also particularly notable. The average correlation for ERM member states with short-term interest rates rose from 0.573 to 0.945. With table 2c, comparisons can be made more on a cross-sectional basis. Here, average correlations for CGDP were 0.611 for the eurozone member states compared with 0.196 for all of those outside the eurozone. As might be expected for eurozone countries the averages for short-term interest rates were high at 0.884 compared with 0.273 for those outside the eurozone.

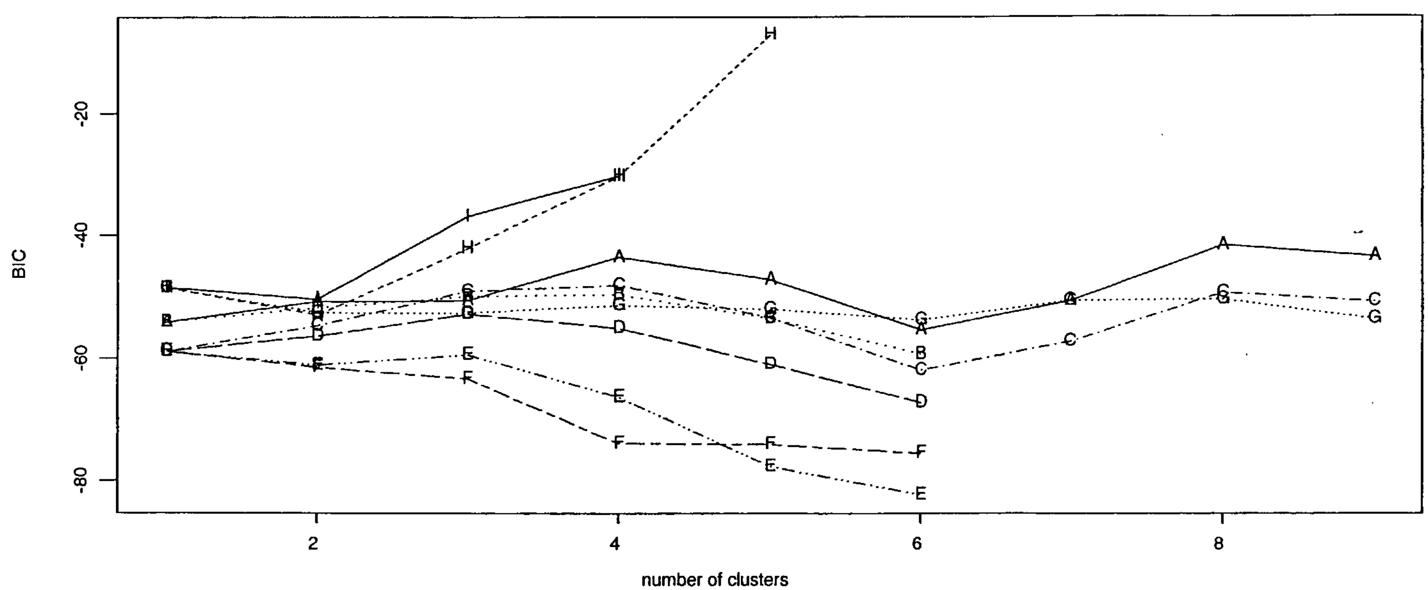
As section 3 e) detailed, cluster analysis is adopted here to classify these member states/ countries into groups. In all cases the EM algorithm was initialized using hierarchical clustering using the unconstrained model (VVV) detailed in table 1 above. The maximum number of clusters was chosen to be M=9. From this point BIC values were calculated from an initial parameterization for all other possible models presented in table 1. Table 4 gives the BIC for each of the candidate models for each of the cluster groups specified, and the BIC is then plotted against the number of clusters. Some BIC estimates were not available, as the covariance matrix associated with one or more of the mixture components is ill-conditioned, so that the log likelihood and hence the BIC cannot be computed. Once again clustering is done for all three exercises detailed above.

Table/Figure 3a

BIC Values by Number of Clusters using the EM algorithm for Western Europe: 1983-1992

# of clusters	EII	VII	EEI	VEI	EVI	VVI	EEE	EEV	VEV	VVV
1	-54.1694	-54.16942	-58.9021	-58.9021	-58.9021	-58.9021	-48.5816	-48.5816	-48.5816	-48.582
2	-50.759	-51.79145	-54.7099	-56.4033	-61.121	-61.4839	-52.574	-52.9841	-50.4112	NA
3	-50.5966	-49.94076	-49.1098	-52.8585	-59.4101	-63.3327	-52.6806	-42.1296	-36.8874	NA
4	-43.5436	-49.67943	-48.1231	-55.1117	-66.3306	-73.9182	-51.3831	-30.2556	-30.2004	NA
5	-47.1374	-53.51414	-53.4049	-61.0017	-77.6809	-74.0552	-52.0098	-7.01721	NA	NA
6	-55.3815	-59.33163	-61.9528	-67.2475	-82.3246	-75.5337	-53.7875	NA	NA	NA
7	-50.6182	NA	-57.2654	NA	NA	NA	-50.5645	NA	NA	NA
8	-41.5713	NA	-49.2587	NA	NA	NA	-50.3939	NA	NA	NA
9	-43.3451	NA	-50.733	NA	NA	NA	-53.5181	NA	NA	NA

NA = ill-conditioned matrix



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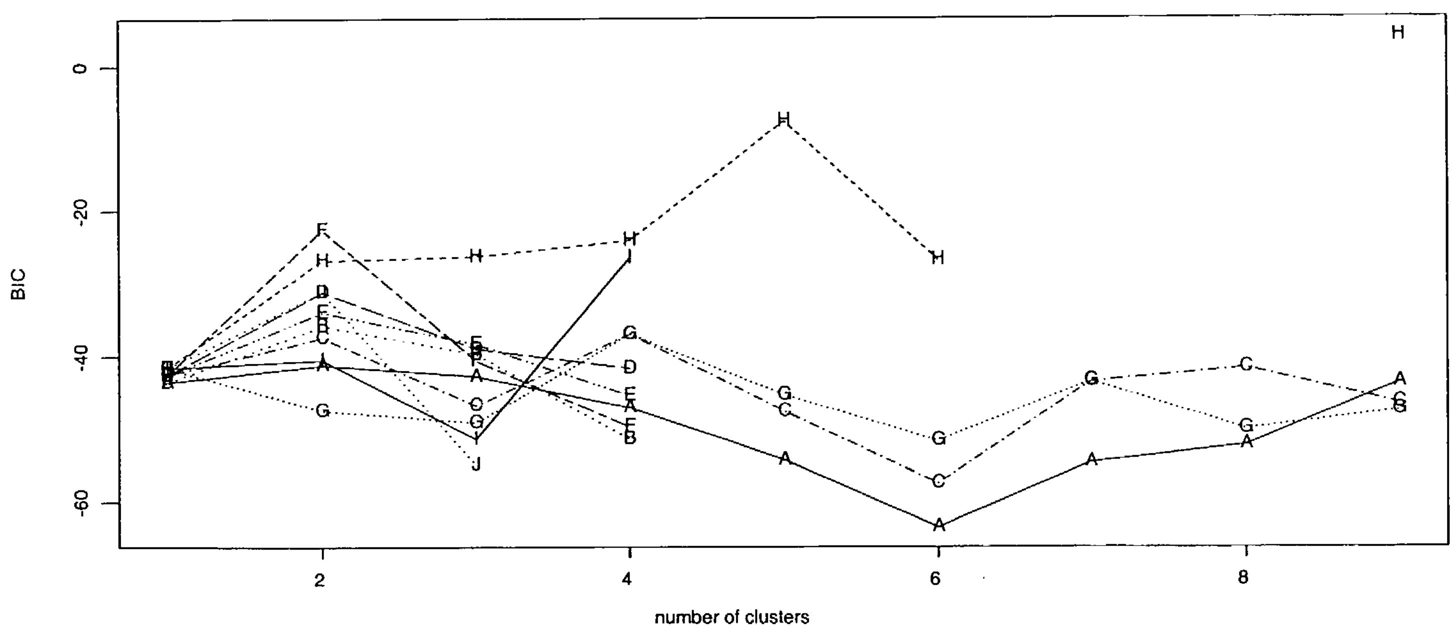
Table/Figure 3b

BIC Values by Number of Clusters using the EM algorithm for Western Europe: 1992-2001

# of clusters	EII	VII	EEI	VEI	EVI	VVI	EEE	EEV	VEV	VVV
1	-43.52	-43.522	-42.55	-42.55	-42.55	-42.55	-41.58	-41.58	-41.58	-41.58
2	-41.19	-35.825	-37.44	-31.19	-33.95	-22.67	-47.45	-26.87	-40.52	-31.17
3	-42.73	-39.68	-46.74	-38.98	-38.33	-40.62	-49.1	-26.32	-51.35	-54.93
4	-47	-51.355	-36.96	-41.64	-45.36	-49.66	-36.98	-24.12	-26.51	NA
5	-54.24	NA	-47.53	NA	NA	NA	-45.29	-7.653	NA	NA
6	-63.53	NA	-57.46	NA	NA	NA	-51.59	-26.84	NA	NA
7	-54.59	NA	-43.47	NA	NA	NA	-43.35	NA	NA	NA
8	-52.17	NA	-41.58	NA	NA	NA	-49.98	NA	NA	NA
9	-43.6	NA	-46.44	NA	NA	NA	-47.42	3.8241	NA	NA



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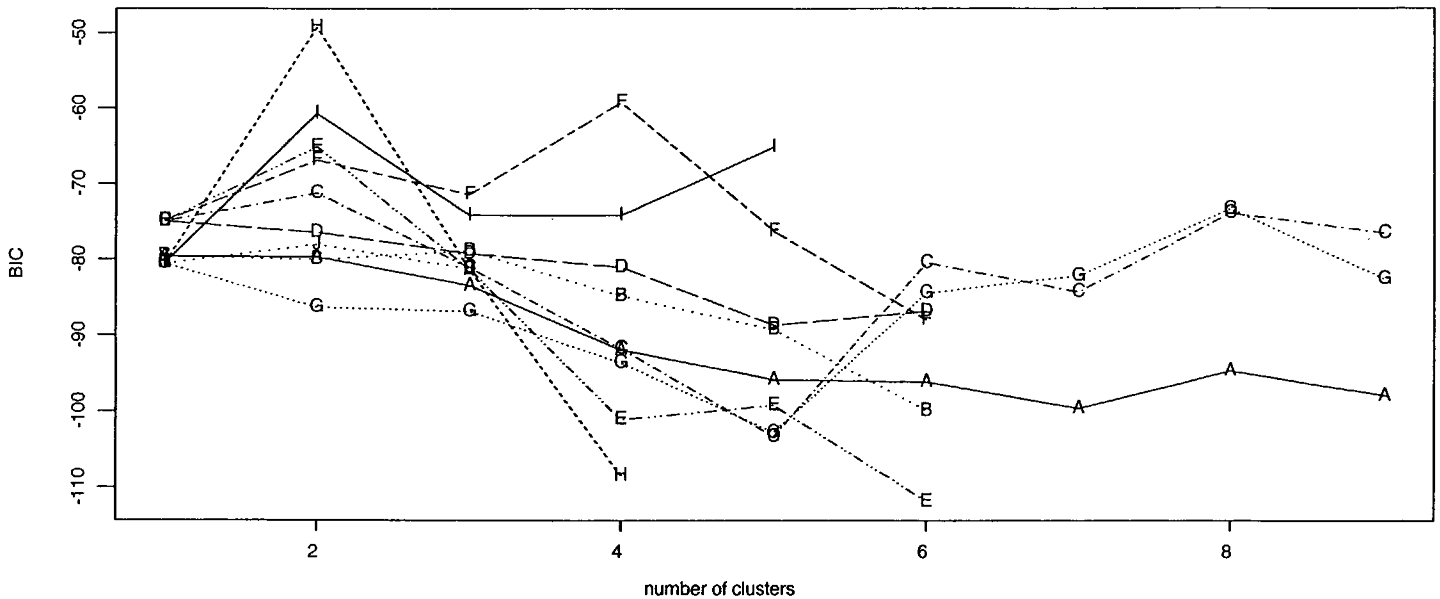
<u>**Table/Figure 3c**</u>

BIC Values by Number of Clusters using the EM algorithm for Western Europe (including UN): 1992-2001

# of clusters	EII	VII	EEI	VEI	EVI	VVI	EEE	EEV	VEV	VVV
1	-79.593	-79.5934	-74.9906	-74.991	-74.9906	-74.991	-80.563	-80.563	-80.563	-80.563
2	-79.699	-80.0596	-71.3181	-76.484	-65.1849	-66.936	-86.323	-49.338	-60.752	-78.088
3	-83.46	-78.9189	-81.1117	-79.276	-81.3266	-71.484	-86.881	-81.43	-74.233	-81.262
4	-91.951	-84.8137	-91.7967	-81.05	-101.107	-59.288	-93.677	-108.55	-74.187	NA
5	-95.85	-89.2493	-103.373	-88.69	-99.2521	-76.328	-102.82	NA	-65.145	NA
6	-96.165	-99.9494	-80.4763	-86.86	-111.867	-87.979	-84.441	NA	NA	NA
7	-99.648	NA	-84.3179	NA	NA	NA	-82.188	NA	NA	NA
8	-94.713	NA	-73.8891	NA	NA	NA	-73.353	NA	NA	NA
9	-97.966	NA	-76.5831	NA	NA	NA	-82.617	NA	NA	NA



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Table/Figure 3d

BIC Values by Number of Clusters using the EM algorithm for All of Europe: 1993-2001

# of clusters	EII	VII	EEI	VEI	EVI	VVI	EEE	EEV	VEV	VVV
1	-157.61	-157.61	-161.03	-161.03	-161.03	-161.03	-163.76	-163.76	-163.76	-163.76
2	-154.72	-137.58	-154.8	-145.64	-150	-134.98	-163.65	-157.07	-163.67	-163.34
3	-152.3	-137.15	-155.09	-144.02	-167.6	-144.04	-173.12	-160.38	-169.49	NA
4	-162.66	-142.66	-164.17	-152.78	-175.65	-160.92	-182	-191.4	-173.61	NA
5	-175.2	-149.18	-185.85	-160.07	-190.58	-186.15	-183.83	-209.8	-178.83	NA
6	-174.23	-157.76	-183.55	-171.4	-223.86	-206.93	-191.15	-166.33	-160.3	NA
7	-175.27	-175.02	-189.99	-184.31	-211.75	-217.62	-192.52	-158.08	NA	NA
8	-189.98	-173.98	-202.96	-180.43	-236.19	-229.98	-206.97	NA	NA	NA
9	-181.01	NA	-196.34	NA	NA	NA	-198.02	NA	NA	NA

NA = ill-conditioned matrix

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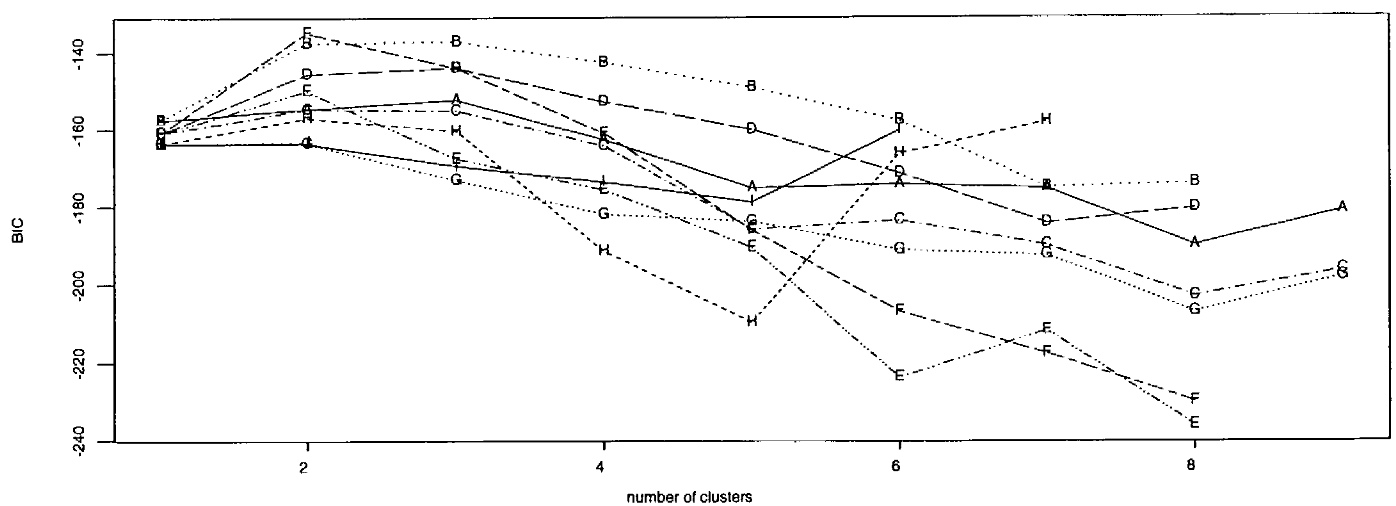

For the three projects table 3a, 3b, 3c and 3d shows the results in each instance. For the time period from 1983-1992, the results indicate that the best classification of the countries falls into 5 clusters, with the most appropriate model being the EEV model (ellipsoidal distribution, equal volume and shape, but variable orientation). Given the rule of thumb used with BICs outlined above, this appears to be a much superior classification to the next best classification of 4 clusters under VEV. In table and figure 3b, the data for the later period of 1992-2001 is clustered, and once again the most appropriate model is an EEV model with 5 clusters. Nevertheless, despite this, table 4a and 4b below shows how cluster membership changes between the two time periods. In table and figure 3c, the unemployment rate is added to the data, and the result is surprising - now only 2 clusters are found with the model once again EEV. Table 4c below details this result. When the CEEC and other countries are added in for the 1993-2001 time period, the number of clusters stays the same, although the model changes to VVI (diagonally distributed, variable shape and volume). The configuration of clusters is given in table 4d below.

Table 4a

EEV Model with 5 Clusters: Cluster Membership 1983 to 1992

Cluster number	Countries
1	Austria, Belgium, Netherlands, Switzerland
2	Denmark, France, Ireland
3	Finland, Sweden, UK
4	Iceland, Norway
5	Italy, Portugal, Spain

Uncertainty:	0%	25%	50%	75%	100%
	0	0	0	0	0.009286943

Table 4b

EEV with 5 clusters: 1992-2001

Cluster number	Countries
1	Belgium, France, Italy, Netherlands, Spain
2	Denmark, Ireland, Norway
3	Finland, Sweden
4	Austria, Greece, Luxembourg, Portugal, Switzerland
5	Iceland, UK

Uncertainty:	0%	25%	50%	75%	100%
	0	0	0	0	0.009286943

Table 4c

EEV with 2 clusters: 1992 to 2001 with Unemployment added to dataset

Cluster	Countries
1	Austria, Belgium, Finland, France, Greece, Ireland, Luxembourg, Netherlands, Spain, Sweden, Switzerland
2	Denmark, Iceland, Italy, Norway, Portugal, UK

Uncertainty:	0%	25%	50%	75%	100%
	0	0	0	0.00001063384	0.09154122

Table 4d
VVI with 2 clusters: 1993-2001 with all European countries

Cluster	Countries
1	Austria, Belgium, France, Greece, Ireland, Luxembourg, Netherlands, Portugal, Spain, Sweden, Switzerland, Croatia, Latvia, Lithuania, Slovenia
2	Denmark, Finland, Iceland, Italy, Norway, UK, Bulgaria, Czech Republic, Estonia, Hungary, Poland, Romania, Slovak Republic, Turkey

Uncertainty:	0%	25%	50%	75%	100%
	0	0	0.0002922603	0.004654643	0.06155675

Table 4e
VII with 3 clusters: 1993-2001 with all European countries

Cluster	Countries
1	Austria, Belgium, France, Spain, Sweden, Switzerland
2	Denmark, Finland, Iceland, Ireland, Italy, Norway, Portugal, UK, All CEECs, Turkey,
3	Luxembourg, Netherlands, Latvia

The clusters for table 4a show the configuration of member states/countries from 1983-1992, and the uncertainty measure underneath shows the probability of mis-classification, given that the methodology allocates data to the nearest cluster (- in this sense the methodology is "fuzzy"). The uncertainty indicates the likelihood that any country is mis-classified, by ranking the data according to how well any piece of data belongs to a particular cluster. The total sum of all these probabilities of mis-classifications is less than one percent, and given that there are only 15 member states/countries, this indicates that the classification is extremely good. The clusters themselves are formed from ellipsoidal distributions, with equal volume and shape, but variable orientation (- the EEV model from table 1). The classification itself falls into the groups that might be expected for this period. The cluster number indicates the order in which the groups are formed, and clearly the so-called "hard core" of the ERM of the EMS form the first cluster. These are member states/countries that have a history or shadowing German monetary policy.

Interestingly, other member states form another cluster, with France - these member states did not follow German monetary policy as closely in the 1980s, and similarly cluster 3 and 5 consist of other member states that either were not members of the EU during much of the 1980s, or member states that devalued frequently within the ERM given that their monetary policies differed significantly with German monetary policy. Notably two of the countries which still remain outside the EU, Norway and Iceland, form their own cluster.

Table 4b shows the cluster formed when the same variable correlations with Germany are clustered for the 1992-2001 period. The number of clusters remains the same, and the distribution and uncertainty doesn't alter either, but the membership is significantly different. Belgium and the Netherlands remain in the first group to form, but Austria and Switzerland drop out into another group. France joins this group as does both Italy and Spain. This is likely because these countries maintained very their monetary policies closely aligned to those of Germany during this time. Denmark and Ireland remain in the second grouping, but Norway now joins this group. Finland and Sweden form the third grouping, but the UK clearly used significantly different monetary policy and experienced different business cycles during this time (- the UK left the ERM in 1993, and has showed little intent to rejoin the mechanism since), and consequently drops out into a cluster with Iceland, a non-member of the EU. The fourth cluster has a rather surprising membership and appears to be a group of countries that loosely followed German monetary policy, but perhaps was less constrained to do so, either because of not wanting to tighten monetary policy to the extent that Germany did after reunification, or because of not being in the EU (Switzerland).

Table 4c repeats 4b, but adds unemployment to the correlations. The configuration changes quite drastically, but the model does not, and the number of clusters reduces to two. The uncertainty does increase significantly, however. What is interesting about this configuration though is that most of the EU member states are in the first cluster, and that with the exception of Italy and Portugal, both countries that have experienced difficulties in EMU sticking to the Stability and Growth pact, the second group contains countries that are outside EMU or the EU. This clustering configuration suggests that adding the unemployment correlations tends to introduce other elements into the analysis.

Table 4d now clusters all the member states/countries over the period 1993-2001. Once again the optimal clustering configuration is for two clusters. Although there is more uncertainty about more cluster memberships than before, the total uncertainty falls compared to table 4c. Also the model used for the clustering also changes to a diagonal distribution with both variable volume and shape. When adding the CEEC countries, it is noteworthy that only Croatia, Latvia, Lithuania and Slovenia join the main EU grouping, and then another cluster forms with the rest of the CEEC countries and Denmark, Finland, Iceland, Italy, Norway and the UK. This is fairly consistent with the table 4c except that Portugal now joins the first grouping and Finland drops out to join the second grouping.

As table 3d suggests that this model is only just significantly better than the next best model choice (- recall that the BIC needs to be greater than 2 for a "significant" difference according to the rule of thumb that statisticians use, and here the difference is 2.17), the exercise is repeated with the second best model, a VII (spherical distribution with variable volume and equal shape) with 3 clusters. In this case cluster one effectively splits into two, with only Latvia leaving the rest of the CEEC countries to form a grouping with the Netherlands and

Luxembourg. The remaining CEEC group remains with much of the periphery of the EU plus those member states remaining outside of EMU.

To illustrate the kinds of grouping obtained in this exercise, several figures are reproduced for the 2 cluster configuration of table 4d, and are shown below as figures 4, 5, and 6.

Figure 4

VVI with 2 clusters: 1993-2001

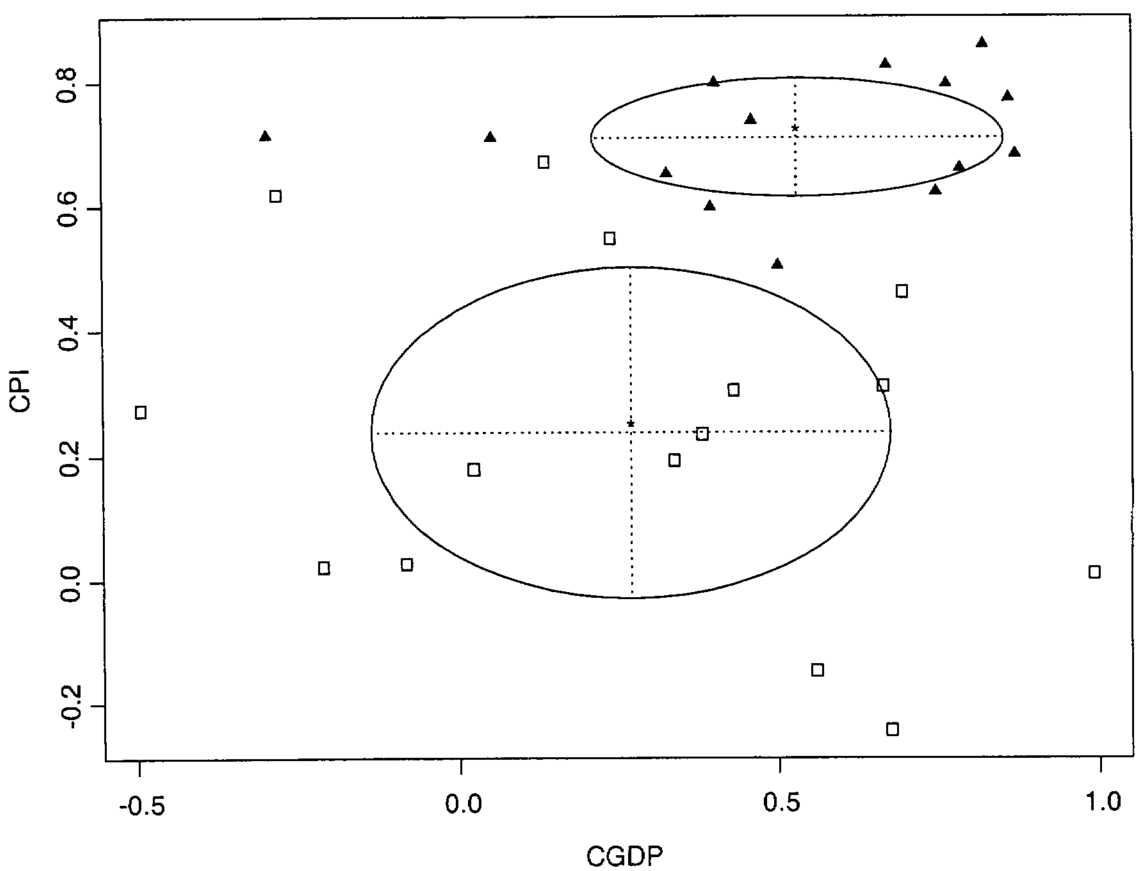

Figure 5

VVI, 2 Cluster plots with uncertainty measures: 1993-2001

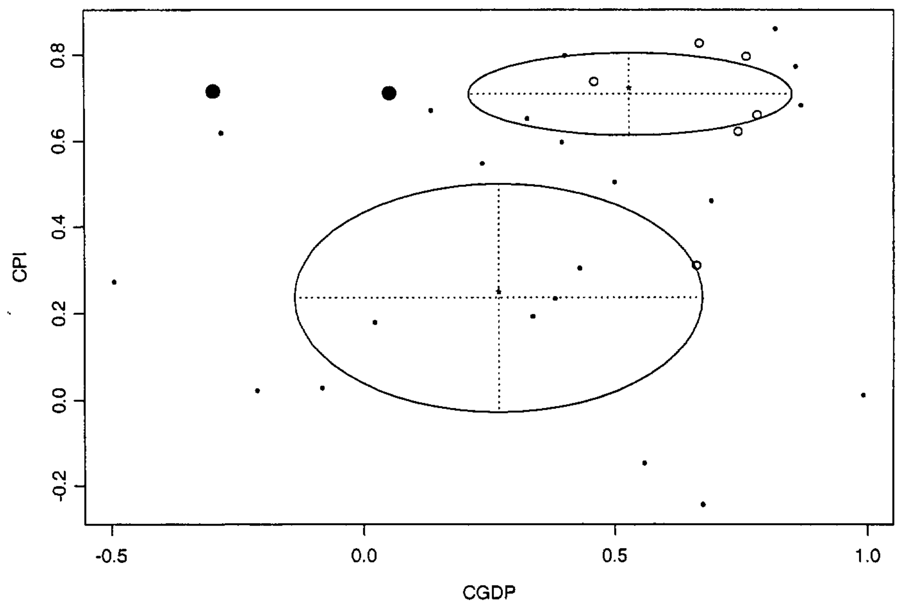

Figure 6

Hatch plot of all correlations indicating cluster membershi: VVI, 2 for 1993-2001

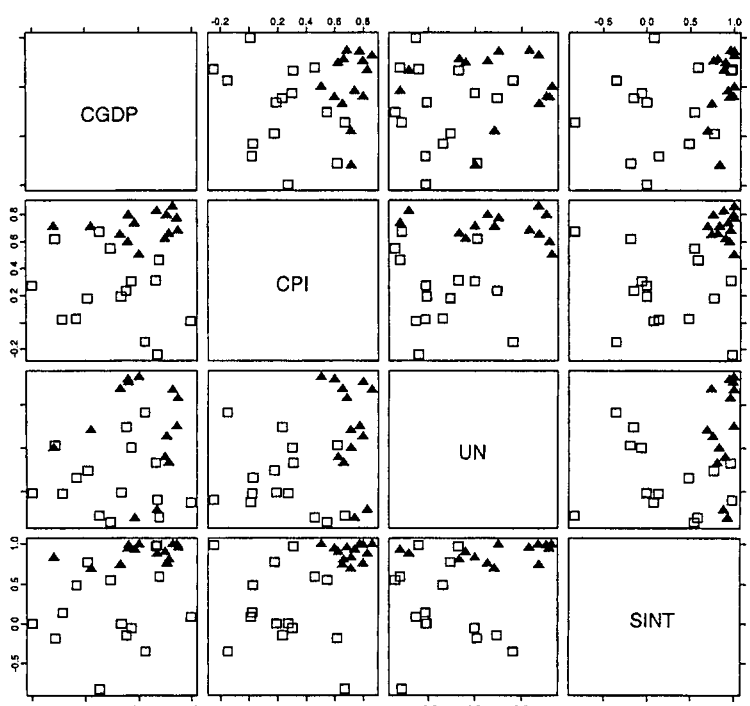

Figure 4 shows the two clusters using CGDP and CPI as plotting variables. The centre of the clusters is represented by a dot, and one standard deviation distance is represented by a elliptical line. Figure 5 now superimposes the uncertainty for each variable, with dots indicating less than one percent uncertainty, round circles greater than one percent uncertainty and blackened circles representing greater than 2 percent uncertainty. The two blackened circles represent Croatia and Lithuania, both countries that are both included in the main EU grouping (in table 4d) but then drop out and join the other cluster when the model is changed (in table 4e). Lastly, figure 6 shows all the data with the cluster memberships indicated by either triangles (cluster 1) or squares (cluster 2). What is interesting about this hatch plot is that it is clear that for certain variables the groupings are quite stark (for example CPI against SINT), but for other plots the distinction is not so clear (for example, UN against CGDP).

To conclude the analysis, geographical plots from GIS software are used to show the configurations of clusters in figures 7, 8, 9 and 10 below.

<u>Figure 7</u>

Cluster Memberships for Western European Member States/Countries: 1983-1992

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Figure 8

Cluster Membership for West European Member States/Countries: 1992-2001

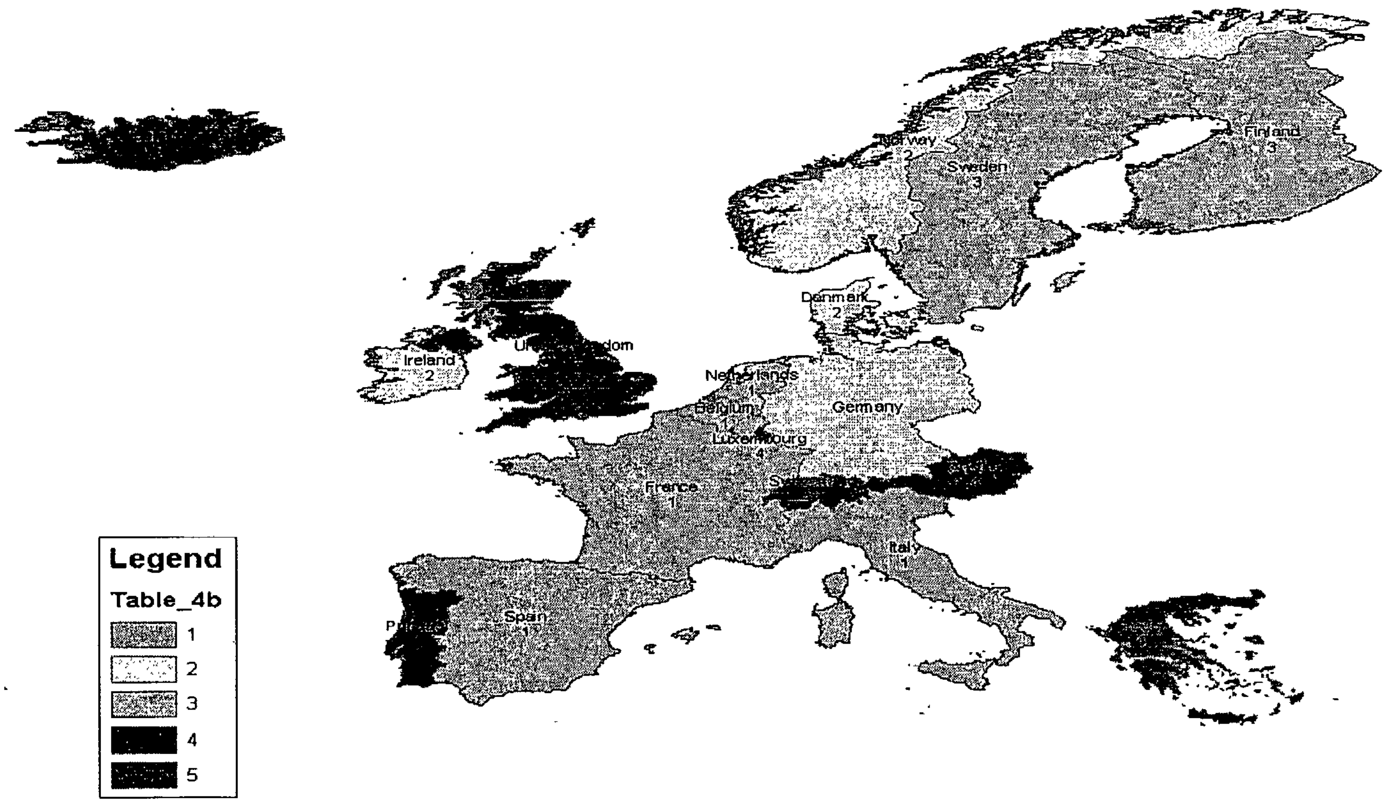

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Figure 9

Cluster Membership for West European Member States/Countries: 1992-2001 including UN

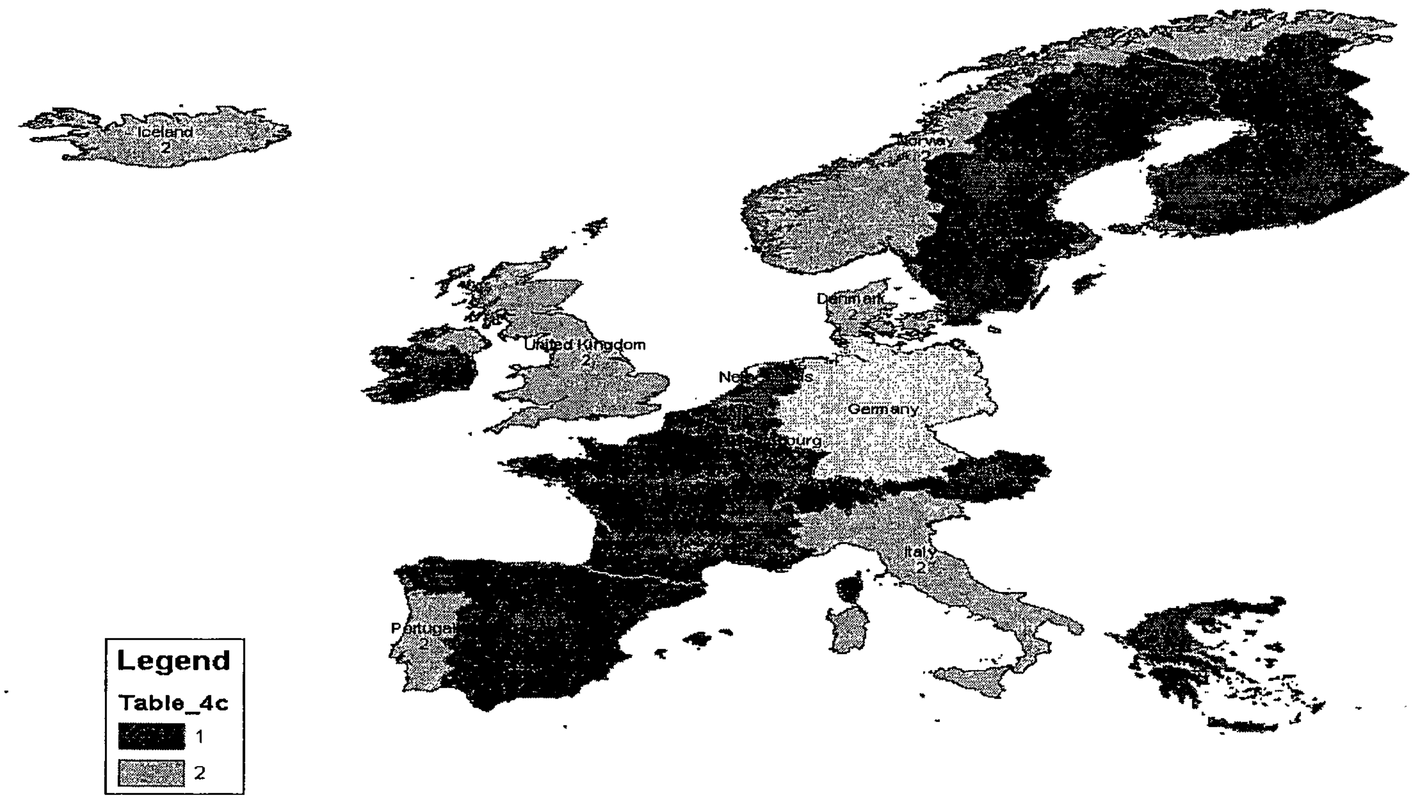

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Figure 10

Cluster Membership for All of Europe: 1993-2001

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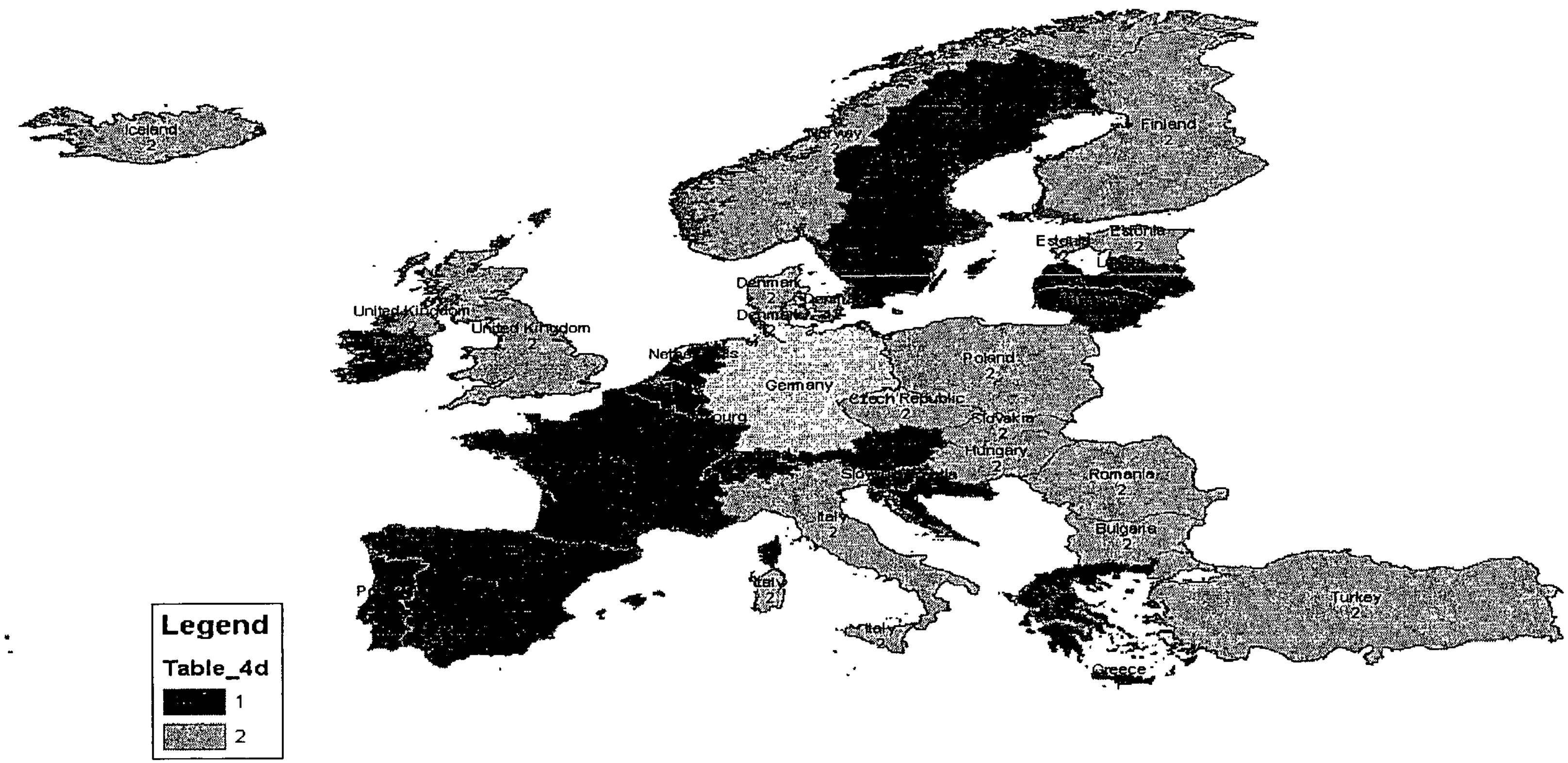

5. Conclusions

The paper used model-based cluster analysis to group European member states/countries according to the business cycle correlations with Germany, over different periods, given data availability, and also over a consistent period from 1993 to 2001 including CEEC countries. This methodology originated in the literature on optimal currency areas, where it was able to suggest which countries are most suited to adoption of a common currency.

The results showed that:

i) in the 1983-1992 period Western Europe consisted of five groupings, with the EU forming four of these groupings. A "hard core" of member states was identified, confirming the results of previous contributions to this literature;

ii) in the 1992-2001 period Western Europe again formed five groupings again, although the lines between the EU and other countries now blurred somewhat, with the non-EMU member states mixing with the non-EU countries;

iii) in the 1993-2001 period Europe as a whole formed two clusters, with only Croatia, Latvia Lithuania and Slovenia joining the main EU bloc of member states;

iv) in a secondary exercise, during the 1993-2001 period Europe as a whole again formed two clusters but this time only Latvia appeared to be grouped with other EU member states. The grouping containing the other CEECs also included the other member states in Western Europe that remain outside EMU.

The conclusions of the above analysis suggest that neither EMU or the EU formed an optimal currency area during the period 1993-2001, although most of the EMU countries did fall into the same cluster (- Finland, Italy and Portugal did not). This suggests that in fact the EU is fast becoming an optimal currency area, as results for previous time periods showed that the EU split into many more groupings. The corollary is then that even prior to 2001, the shadowing of German monetary policy in addition to the economic convergence achieved through the Maastricht convergence criteria prior to 1999 has fostered circumstances that are closer to an optimal currency area than ever before.

As for the addition of new member states to the EU, the analysis undertaken here shows that the addition of new member states should not impede EMU in the sense that several of the countries already can be grouped with existing member states outside of EMU.

Several caveats must be made regarding these results, which relate to the limits to interpreting the correlations, the correlation against only 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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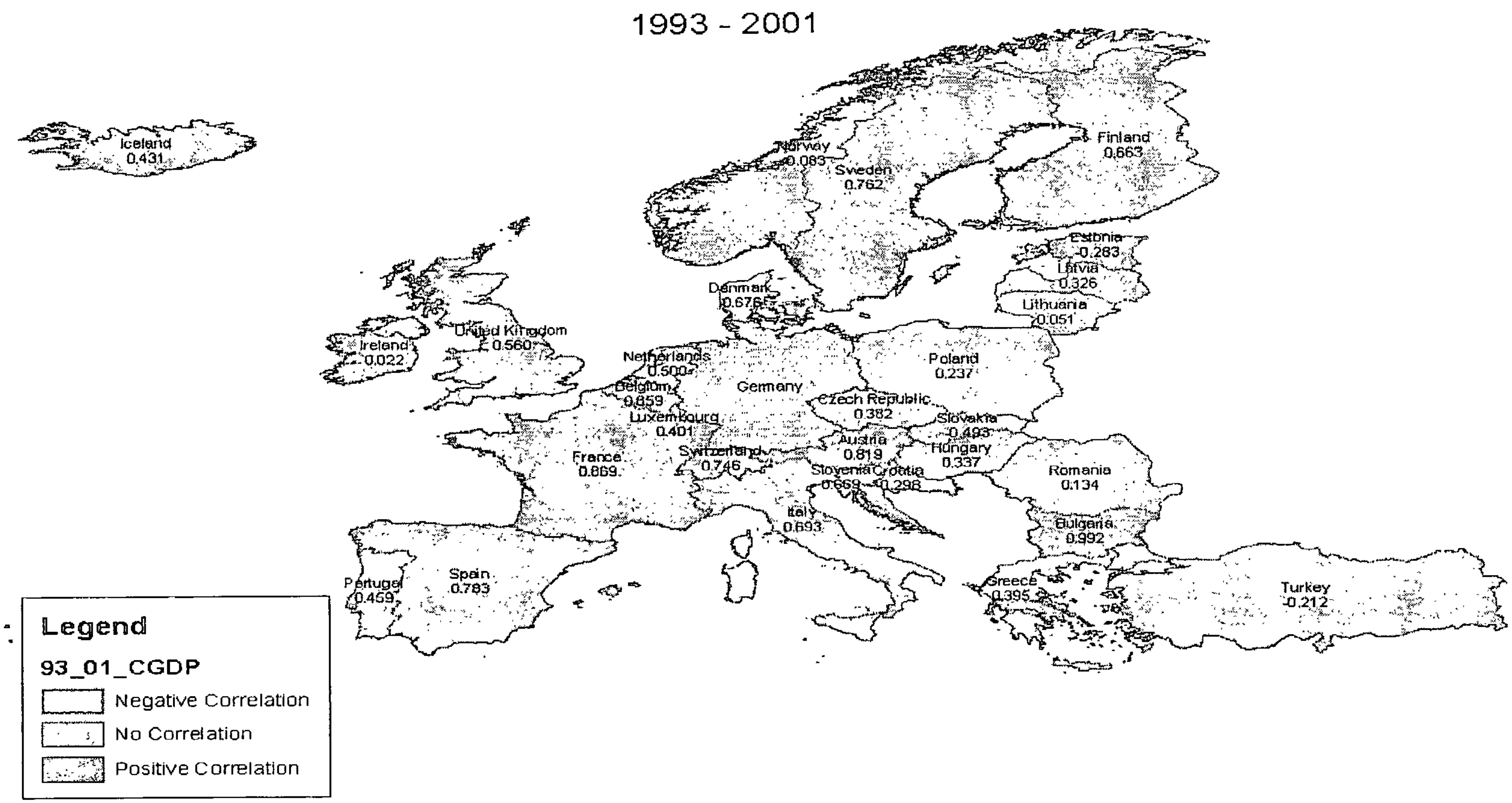
Annex A

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

Annex B

i) CGDP Correlation



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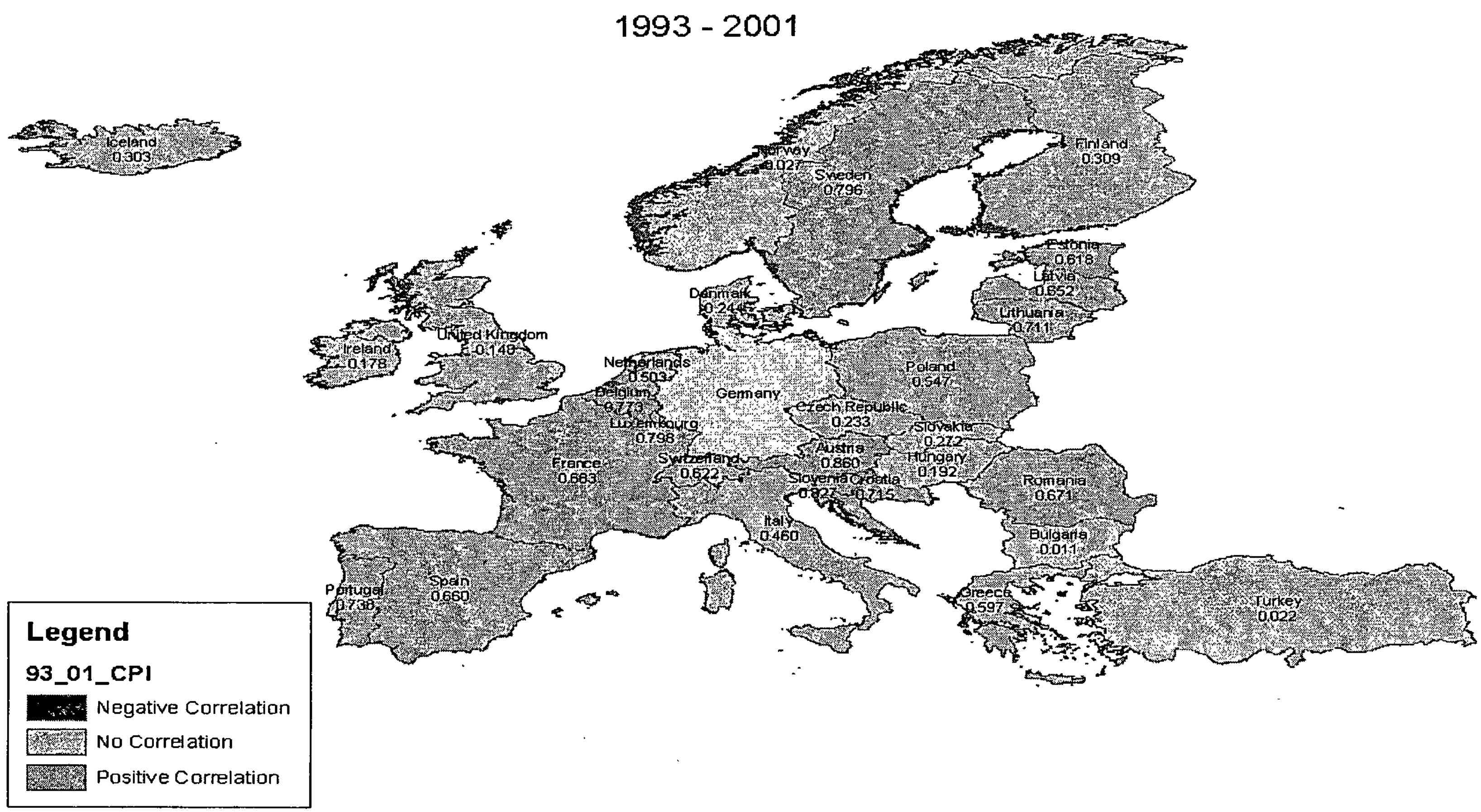
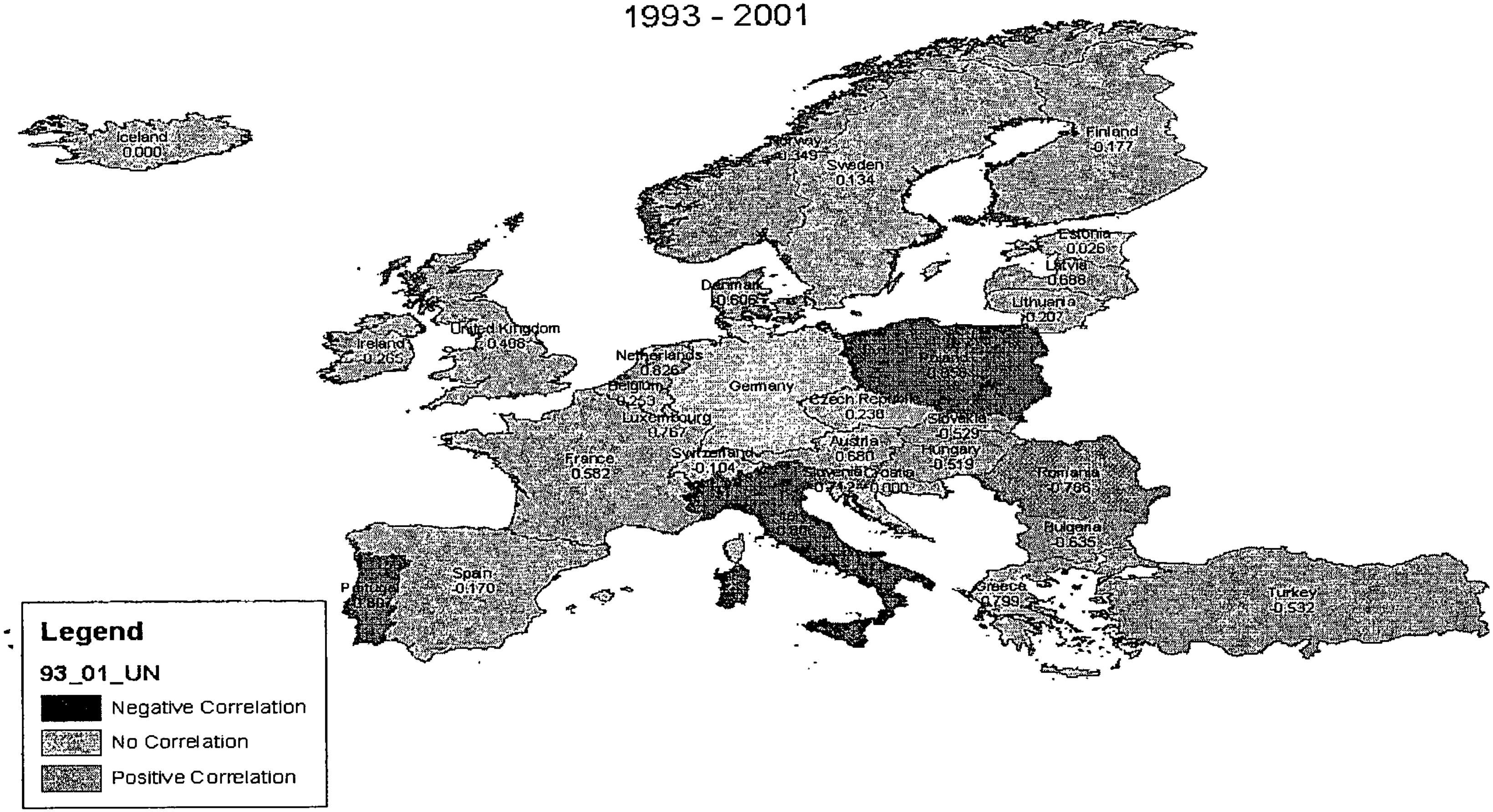
ii) CPI Correlation



iii) UN Correlation

1993 - 2001



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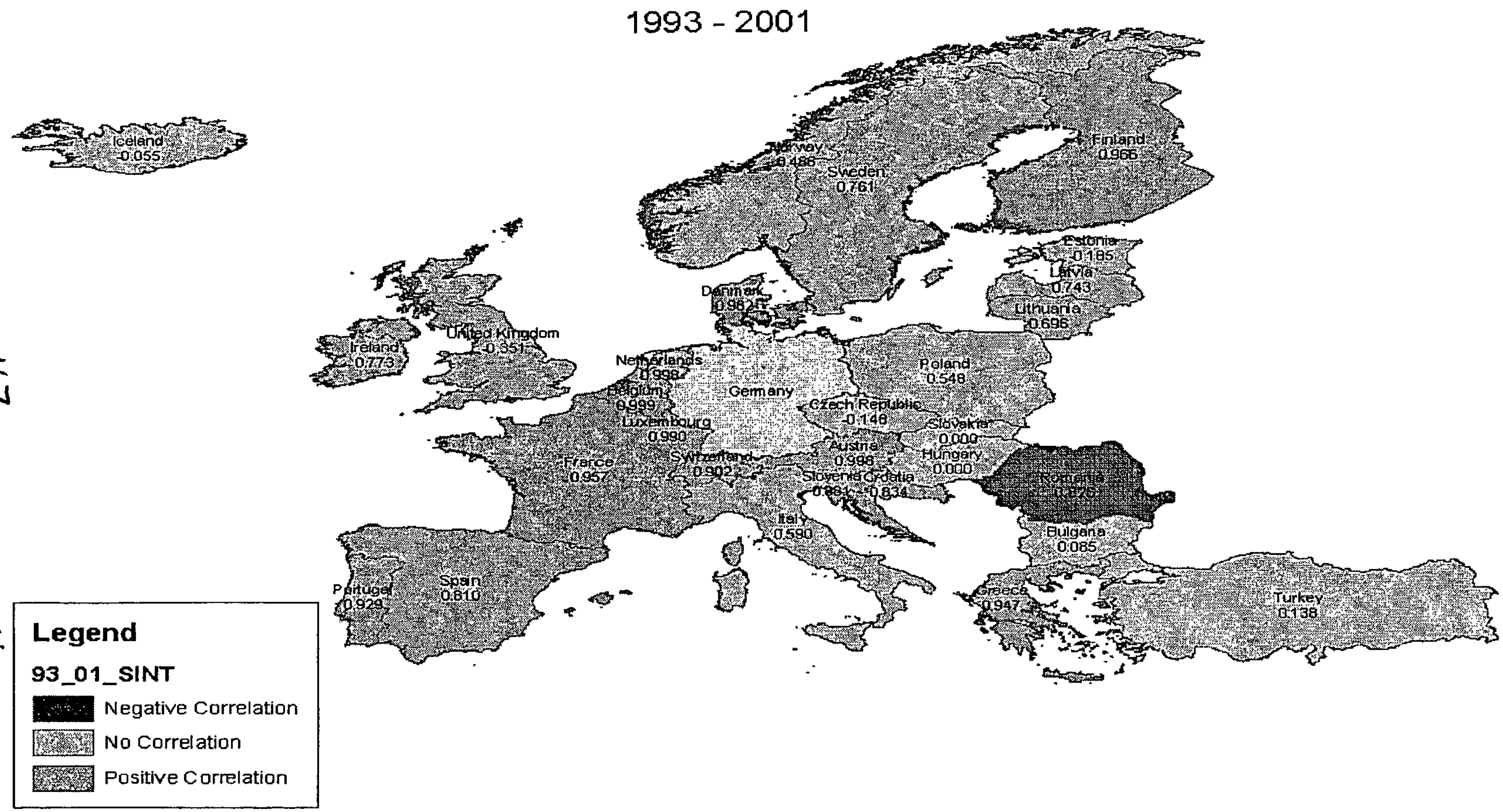
iv) SINT Correlation



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