Does the Comovement of Cycles in the EU suggest an OCA?

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1 Introduction

Economic convergence during the 1990s and to a lesser extent the 1980s (due to ERM) is an accepted fact by most economists;

If endogenous OCA theory to be believed, launch of the euro in 1999 should have caused further convergence in euro area member states in more recent years;

Many new and aspirant member states also want to tie their business cycles more closely with the euro area - some because of trying to import price stability from the euro area and some as a by-product of exchange rate policies (e.g. currency boards)

Leads to several questions:

- Have business cycles converged in the EU after the introduction of the euro?

- Has there been convergence in new and aspirant member states/countries?

- Does the periphery of the euro area form a separate OCA compared with the core of the euro area?

In this paper the results of Artis and Zhang from the late 1990s are updated to address these questions

2 EMU and Business Cycles

2.1 OCA literature

OCA literature well established - with seminal papers by Mundell (1961), McKinnon (1961) and Kenen (1969)

Main gist is that business cycles should move together, but divergence can occur as long as wage or price flexibility can act as an offsetting factor (e.g. through labour mobility), or if there is some form of co-insurance or federal transfers to compensate.

Recent innovations: a) endogenous policy modifications (Tavlas (1993)) and b) endogenous OCAs (Frankel and Rose (1997))

Interesting in the the EU case, as there is also the limits placed on domestic fiscal policy by SGP, which may, in turn, constrain automatic stabilizers.

2.2 EMU and CEEC countries

New CEEC member states have to be members of the ERM for at least 2 years before joining EMU

Also interesting is the fact that the Maastricht convergence criteria bear little resemblence to any criteria that might arise out of OCA theory.

Lots of criticisms of Maastricht limits as applied to CEEC member states, particularly from Buiter (2003).

Several of the new accession member states are hoping to join euro area in 2007.

Assessment by Boreiko (2002) using similar methodology to that used here although he sticks more closely to the Maastricht criteria.

2.3 Business cycle synchronicity

Most research in this area uses time series methodology.

Research using business cycle correlations stems from work of Gerlach (1988) and Baxter and Stockman (1989)

SVAR [Bayoumi and Eichengreen (1994)] probably best known for assessing OCAs around the world.

Jacquemin and Sapir (1995) first used cluster analysis to analyse possibility of "hard core" in potential EMU.

Method extended by Artis and Zhang (1997, 1998) in a series of papers using cluster analysis - found that there appeared to be a "hard-core" but also a "soft core"

Boreiko (2002) expanded this to CEECs, but used Maastricht type measures and more recently Camacho, Perez-Quiros and Saiz (2006) extended this by clustering features of business cycles rather than correlations, more as a taxonomical strategy.

3 Methodology

3.1 Basic approach

Basis of approach is that high degree of correlation with Germany or the euro area aggregates tends to suggest greater likelihood of an OCA.

In short: i) use band-pass filter on GDP to obtain cyclical component of GDP; ii) Correlate this and other key business cycle variables with a) German equivalents and b) euro area equivalents; then iii) cluster.

Cluster analysis used extensively in other disciplines (e.g. astronomy, medical sciences, marketing, biology, zoology), but not common in economics.

Other papers that use cluster analysis in economics - Galbraith and Jiaquing (1999), Honohan (2000), Fruhwirth-Schattner and Kaufmann (2004)

Originally developed to try to classify objects - 2 basic approaches - agglomerative (combining observations) and divisive (splitting down a dataset) - problem: no way to decide on the number of clusters apart from using visual tools ("dendgrograms") or distance measures (e.g. Ward's criterion)

3.2 Model-based cluster analysis

Approach taken here follows JASA paper of Fraley and Raftery (2002). 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:

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

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 $\mathbf{\Sigma}_k$ where $\mathbf{\Sigma}_k$.can be written as an eivgenvalue decomposition in the form:

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

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.

By imposing restrictions on these parameters, this leads to an interpretation of these parameters as follows:

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	varialbe
VEV	$\lambda_k D_k A D_k^T$	Ellipsoidal	variable	equal	variable

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

4 Clustering algorithms

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:

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

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.

4.1 Model selection

Here we use approximate Bayes factors and posterior model probabilities to compare models (see Kass and Raftery (1995)). Imagine several different contender models, $M_1, M_2, ..., M_K$ with prior probabilities $p(M_k); k = 1, ..., K$ then by Bayes's theorem:

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

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 $B_{12} > 1$. An approximation to the Bayes factor is used here:

$$2\log(B_{12}) = 2\log p(D|\widehat{\theta}_1, M_1) - 2\log p(D|\widehat{\theta}_2, M_2) = BIC_1 - BIC_2 \qquad (8)$$

where BIC is known as the "Bayesian information criterion". Convention is that a difference of less than 2 is not significantly different, but greater than 2 is significant.

4.2 Clustering strategy

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.

5 Data and time segmentation

5 variables used to study business cycles:

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)

Data are sourced from IMF-IFS and from ECB AWM for euro area aggregates.

6 different time segments/datasets analysed:

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

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

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

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

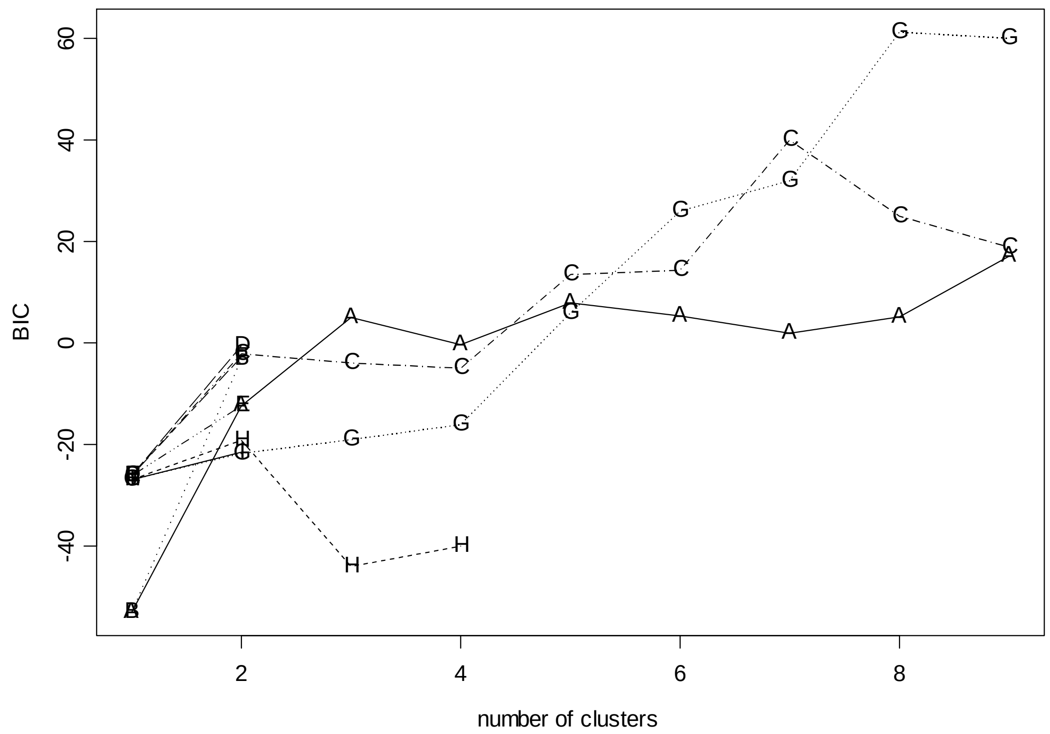
e) 1992-1998 for all European countries (using CGDP, CPI and UN)

f) 1999-2004 for all European countries (using CGDP, CPI and UN)

in each case vs I) Germany and II) euro area aggregate.

6 Results

a) 70-82 vs Germany

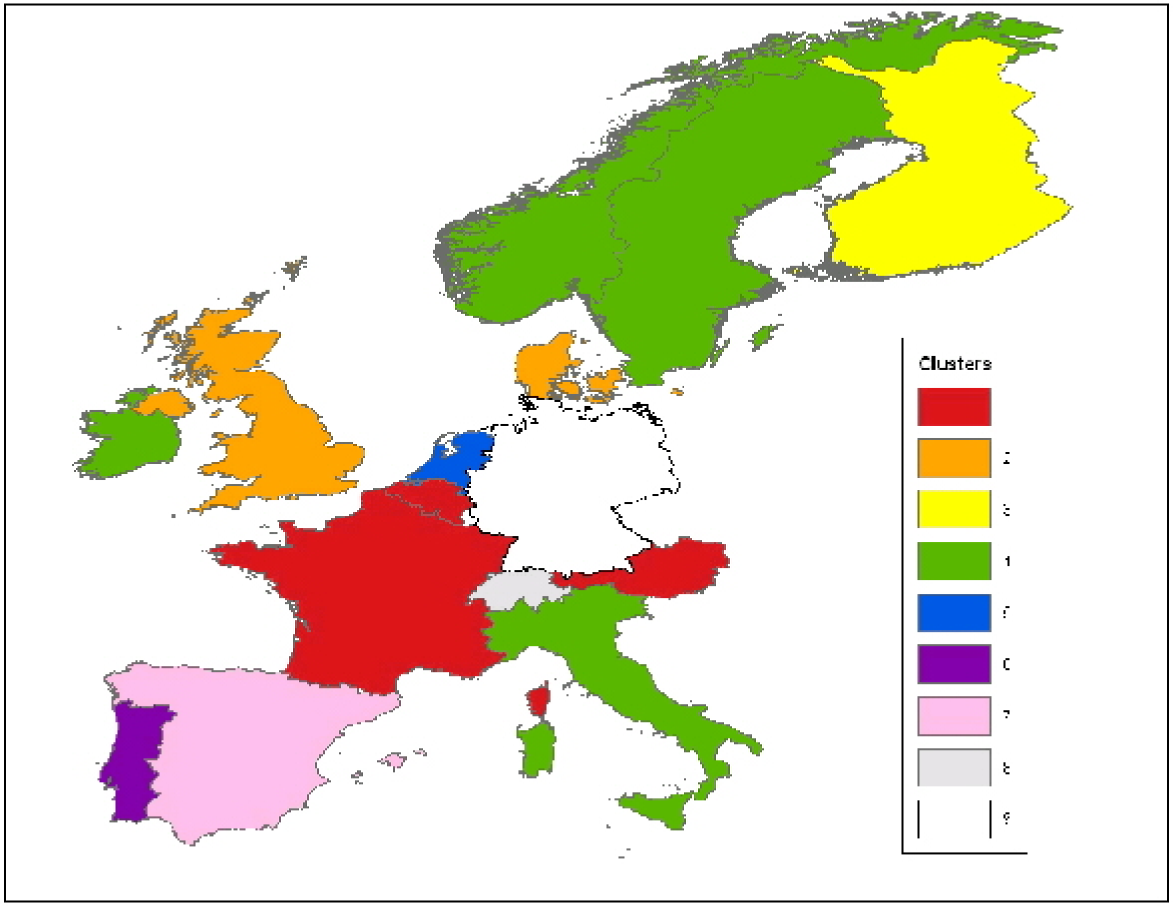


BIC for 70-82 Correlations vs Germany

G = EEE model

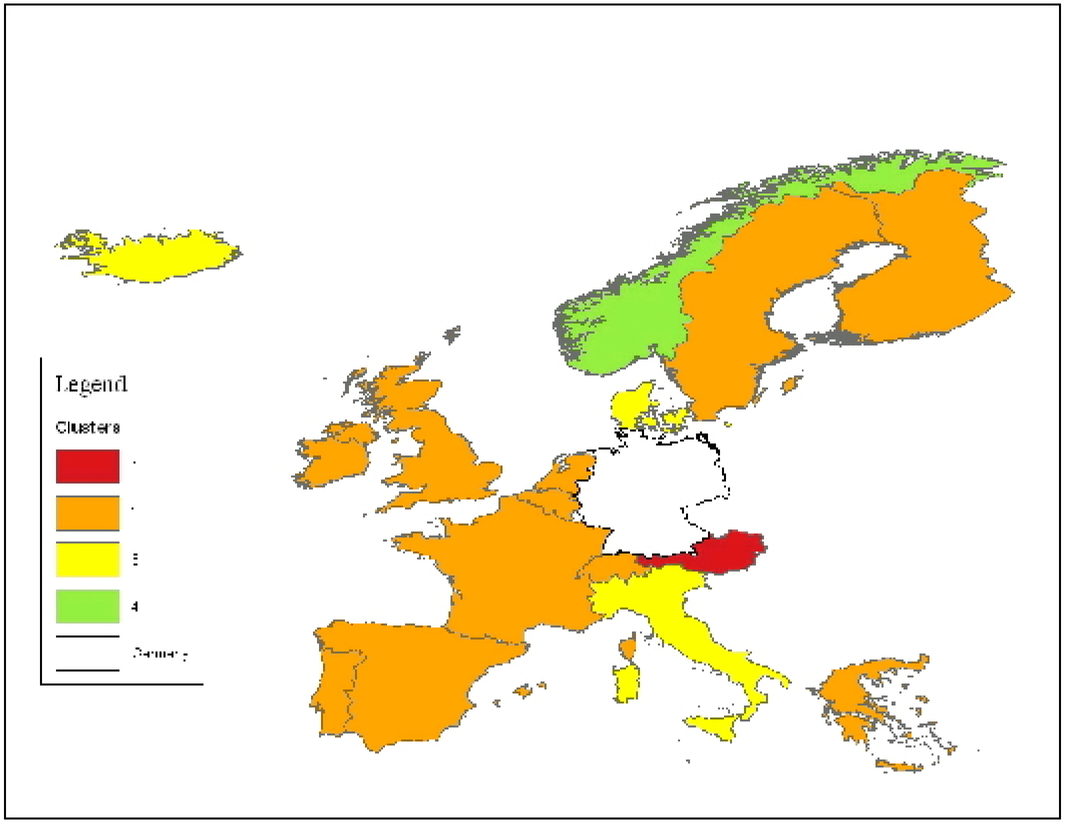
Cluster	Members
1	AUS, BEL FRA
2	DEN, UK
3	FIN
4	IRE, ITA NOR SWE
5	NET
6	POR
7	SPA
8	SWI

Table 2: Clusters for 70-82 vs Germany



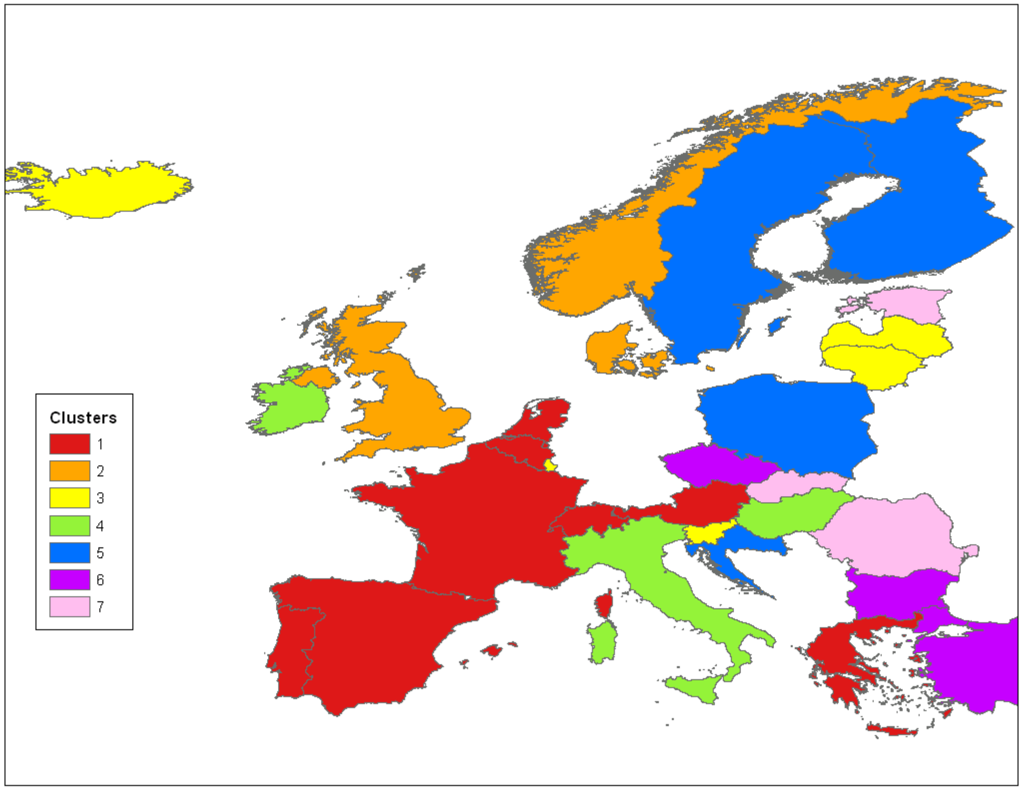
Map of 70-82 clusters vs Germany

b) 83-91 vs Germany



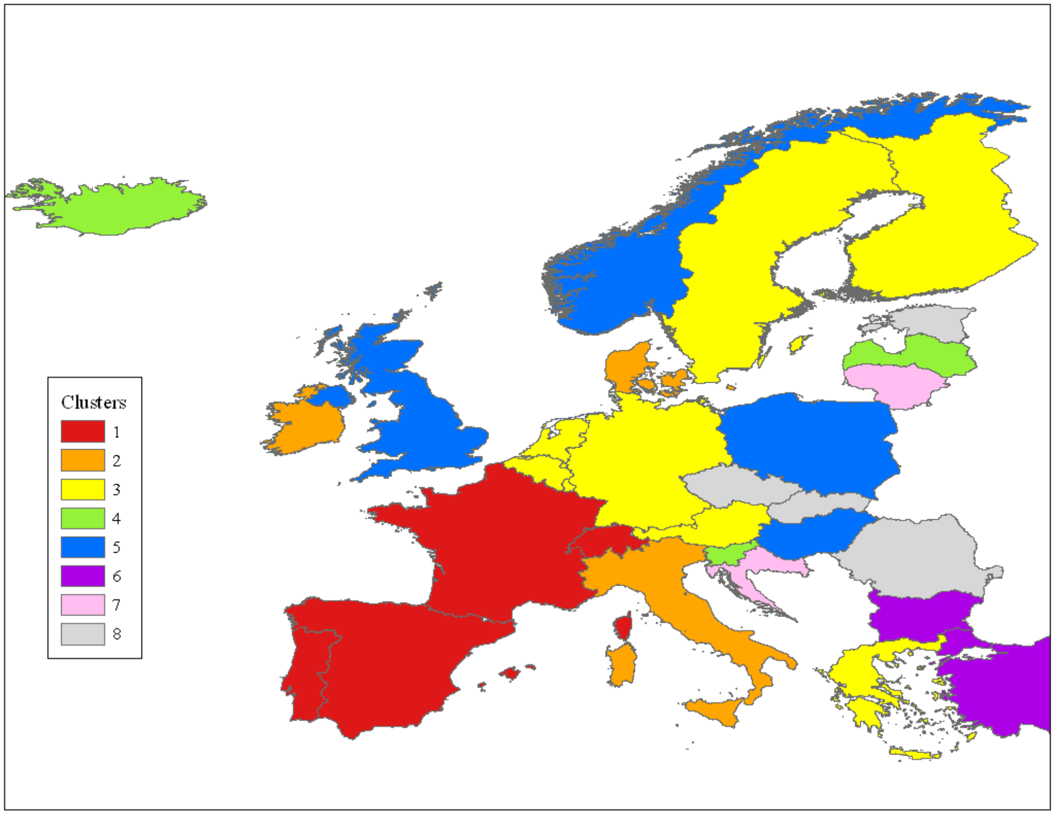
Map of 83-91 clusters vs Germany

e) 92-98 EU + CEEC vs I) Germany



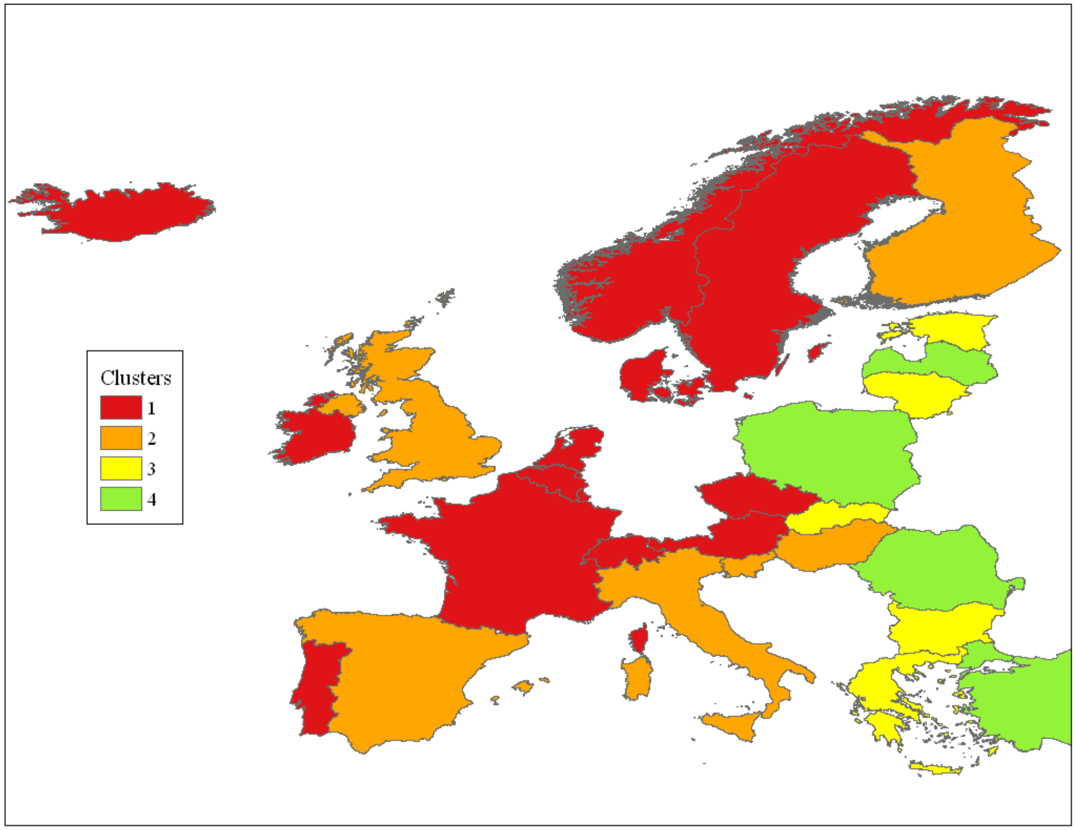
Map of 92-98 clusters with CEEC vs Germany

e) 92-98 EU + CEEC vs II) euro area



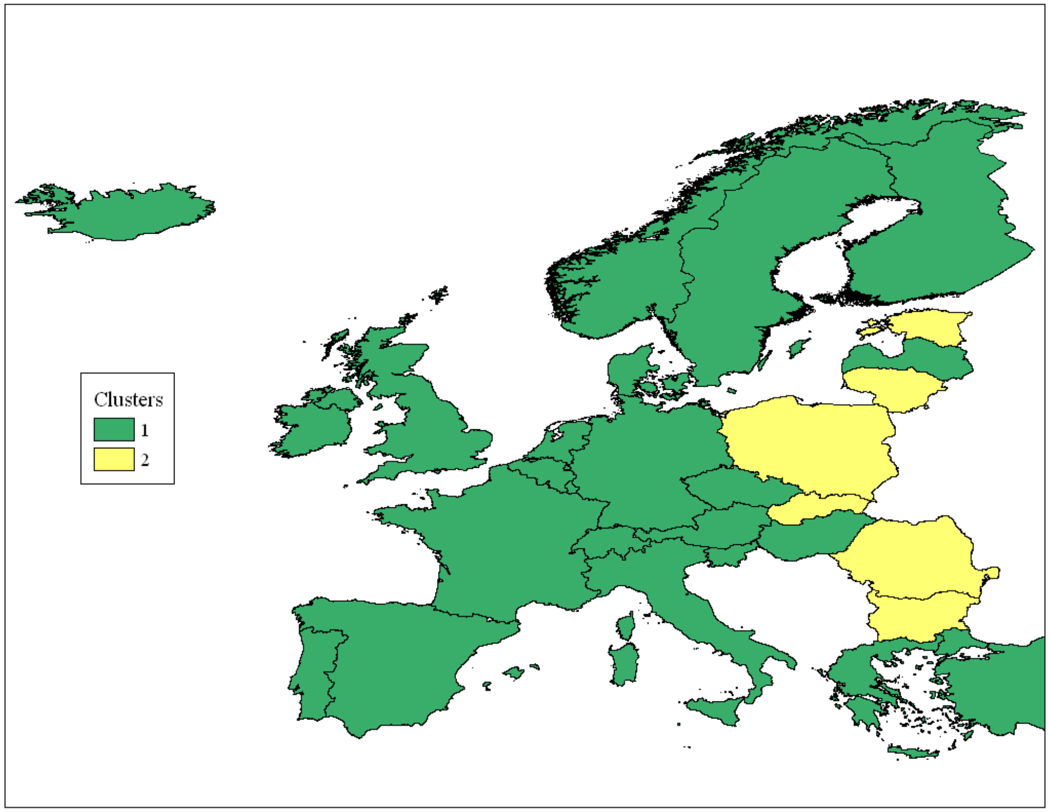
Map of 92-98 clusters with CEEC vs euro area

f) 99-04 EU + CEEC I) vs Germany



Map of 99-04 clusters with CEEC vs Germany

f) 99-04 EU + CEEC I) vs euro area



Map of 99-04 clusters with CEEC vs euro area

7 Discussion and some tentative conclusions

Clustering exercises produced some surprising results, prompting several questions:

a) we are making the assumption that if model-based clustering implies that the correlations can be characterized by a single Gaussian distribution then this would represent an OCA. Is there any evidence to support this? Doing this type of exercise with the US or Canada does show a small number of clusters, so the implication is "yes".

b) is it appropriate to correlate against the euro area for member ststes which are already in the euro area? Obviously the correlation coefficient is automatically biased upwards.

c) Is the "target" state-dependent? Maybe euro area member states should "target" Germany while non-euro area member states and outsiders target the euro area?

Also the results give rise to several tentative conclusions:

i) Time periods that are shorter than a business cycle can yield interesting results - reflects the results of Crowley and Lee (2005) using wavelets that showed that growth cycles are at work in GDP growth;

ii) Germany clearly the "target" (following the German dominance hypothesis) prior to 1992, but after 1999 this is no longer clearly the case. Certainly CEEC and other aspirant member states target the euro area, not Germany alone.

iii) These results tend to suggest that either Tavlas's view or the endogenous OCA theory has some validity - number of groupings among euro area member states appear to have fallen through time. Because of events concerning SGP, more likely to be endogenous OCA theory.

iv) Geography matters.