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IDENTIFYING AND INTERPRETING REGIONAL CONVERGENCE CLUSTERS ACROSS EUROPE*

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In this paper we test for regional convergence clusters across the EU. We utilise a methodology that allows for the endogenous selection of regional clusters using a multivariate test for stationarity, where the number and composition of clusters are determined by the application of pairwise tests of regional differences in per capita output over time. To interpret the composition of the resulting convergence clusters, the latter are tested against a number of possible groupings suggested by recent theories and hypotheses of regional growth and convergence. Further, our method allows regional convergence clusters to vary over time.

Since the mid-1980s, the study of long-term growth has made a major re-appearance on the research agenda in economics. An important stimulus for this revival has been the renewed interest in the empirics of growth, and especially the evidence that rates of long-run convergence of per capita output and incomes between nations, and even between regions within nations, appear to be much slower and far more variable than predicted by the standard Solow-Swan neoclassical growth model (Abramovitz, 1986; Boltho and Holtham, 1992). One consequence has been the emergence of a 'new' growth theory that incorporates increasing returns and technical change within the production function as determinants of the (endogenous) long-term growth rate (Romer, 1986; Lucas, 1988; Grossman and Helpman, 1994; Barro and Sala-i-Martin, 1997). Although several variants of this new endogenous growth theory have been developed, all permit a wider set of possibilities with regard to convergence behaviour. Some variants predict 'conditional' convergence of national (regional) per capita incomes to different long-run steady states that depend on initial national (regional) differences in institutional set-up, economic structure, tastes and so on. Others allow for so-called 'club' convergence among countries (regions) with similar structural and related conditions. Still others, including models that assume that technological advance is highly localised and its diffusion slow, predict persistent or even divergent differences in national (or regional) per capita output and incomes as long run outcomes (Bertola, 1993).

At the same time, the emergence over the past decade or so of the so-called 'new economic geography' models of industrial location and agglomeration has highlighted how many sources of increasing returns are associated with Marshallian-type external localisation economies (such as access to specialised local labour inputs, local market access and size effects, local knowledge spillovers, and the like). These models provide a rich set of possible long-run regional growth patterns that depend, among other things, on the relative importance of transport costs and localisation economies (Fujita *et al.*, 1999; Brackman *et al.*, 2001; Fujita

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and Thisse, 2003; Baldwin *et al.*, 2003). Thus some new economic geography models predict a persistent core-periphery pattern of regional per capita incomes; others predict divergent regional income paths; and yet others predict initial divergence of regional per capita incomes, followed by convergence, as centrifugal forces (such as congestion diseconomies and excessive costs in the core) come to outweigh the centripetal attraction of localisation economies.

These theoretical developments are of more than just academic interest, for they have figured prominently in discussions of the regional implications of increasing economic integration in the European Union. Regional convergence – or what the European Commission calls 'regional cohesion' – is a primary policy objective in the EU, and is seen as vital to the success of other key policy objectives, such as the single market, monetary union, EU competitiveness and enlargement (European Commission, 2004). But equally, increasing economic integration (EMU) and enlargement themselves impose major shocks on the European regions, and potentially threaten the achievement of regional convergence (Martin, 2001, 2002). As a result, the theory of and the evidence on long-run trends in regional per capita incomes and output are of critical relevance to the EU regional convergence and regional policy debate (Boldrin and Canova, 2001). Indeed, according to Fujita *et al.* (1999), the implications of increasing economic integration for the EU regions have been one of the factors behind the development of the 'new economic geography' models of regional growth. To date, however, very few of these models have been tested empirically on EU evidence. Instead, an extensive econometric literature[1] has accumulated that uses both Barro-style growth regressions and time-series methods to estimate the speed of regional convergence across the EU (Barro and Sala-i-Martin, 1991; Armstrong, 1995; Button and Pentecost, 1999). Results have differed according to the period for which regressions are estimated, the dependent variable used, and the geographical scale of regions analysed, although most studies suggest that regional convergence across the EU is slow (Martin and Sunley, 1998).

Against this background, our aim in this paper is to examine the evidence for regional convergence clusters across the European Union, on the basis of per capita Gross Value Added (GVA)[2] trends over the period 1975–99. We base our analysis on an extension of the cluster method introduced by Hobijn and Franses (2000) which allows for an endogenous identification of the number and membership of regional convergence clusters (or 'clubs') using a pairwise test for stationarity of regional differences in per capita GVA. Cluster or club convergence in this context implies that regional per capita differences between the members of a given cluster converge to zero (in the case of perfect or absolute convergence) or to some finite, cluster specific non-zero difference (in the case of relative convergence). Regional similarities in structural, institutional, and technological conditions, on the one hand, and the impact of inter-regional dependencies on the other, are likely to lead to distinct regional convergence clusters.

[1] For an analysis of the methodological implications of the new growth evidence see Temple (1999).
[2] GVA has the comparative advantage with respect to GDP per capita of being the direct outcome of various factors that determine regional competitiveness.

The novelty of our analysis is that to circumvent the problem of how to interpret the composition of the resulting convergence clusters, the latter are tested against a number of hypothetical groupings suggested by recent theories of regional growth and convergence. For example, one hypothesis is that regional convergence takes the form of a core-periphery dichotomy, with regions in the core converging to a different long-run steady state per capita output from those in the periphery. Based upon this hypothesis, it is possible to construct a square matrix with rows and columns equal to the number of regions, where cell entries, say m_{ij}, are either zero or one; $m_{ij} = 1$ indicates that regions i and j are part of a core region. We also entertain the hypothesis that regional convergence clusters are based on spatial proximity (contiguity) effects, associated, for example, with localised knowledge spillovers and interfirm demand-supply networks. An additional set of hypotheses postulates that regional convergence clusters are formed around major urban agglomerations.

The paper is organised as follows. Section 1 introduces the existing approaches used to evaluate the extent and composition of convergence clubs. We also examine one of the most critical questions in the literature on convergence and growth: the appropriate level of aggregation of cross-sectional units, both at the geographical and at the industrial level. Section 2 describes the cluster methodology adopted and introduces a time-varying version of the cluster method. By allowing the cluster composition to be time-varying, we are able to examine how the number and the size of clusters vary over time. Section 3 describes the data. The next three Sections analyse the cluster outcomes, and test these against the hypothesised patterns. Some conclusions are offered in Section 7.

1. Identifying and Interpreting Convergence Clubs

Given that economic theory offers little guidance in determining both the number and composition of clubs within a given cross-section of countries or regions, several approaches have been used to evaluate the extent and composition of convergence clubs in models of economic growth. Durlauf and Johnson (1995), using cross-country data over the period 1960–85, employ a regression tree approach to locate different groups endogenously. The authors discretise the support over a number of conditioning variables which reflect initial conditions, specifically initial output and literacy rates, and locate a sequence of thresholds governing groups of economies. Given that they find the first threshold is determined by output, the authors interpret this as suggestive of the fact that output dominates literacy in locating multiple convergence clubs.

Canova (2004) utilises a predictive density framework to search for the number of convergence clubs in European regional per capita income data. In contrast to Durlauf and Johnson (1995), Canova allows for both inter and intra-regime heterogeneity. An obvious disadvantage of both approaches is that although the use of conditioning information provides automatic and model consistent information for interpreting the resultant clusters, the methodology is reliant on both a correct identification of the mean equation and the set of variables controlling the clustering of regions. For example, if we wish to emphasise the importance of location, then we would order regions on the basis of geographical proximity. As Canova states, a subsequent problem is that for regional data there are few usable indicators on which to order units. In addition, since both approaches are heavily parametric, limits on the maximum number of clusters are imposed. This follows since as the number of clusters increases, there will be as many statistical models as groups, resulting in a large number of parameters to be estimated, with obvious consequences for precision and inference. In adopting a somewhat different approach, Desdoigts (1999) goes some way in addressing these problems by first identifying clusters using a large number of both initial conditions and structural characteristics, and then utilising information on the cluster composition to evaluate differences in income convergence patterns across the different groups of economies.

In contrast, the method proposed by Hobijn and Franses (2000) tests whether countries' log per capita income levels are identical in the long-run or whether their difference is converging to a cluster specific finite constant. The principal drawback of this approach follows immediately from one of its advantages, namely that the clustering model uses no conditioning variables and simply uses information contained in output differences. In this respect, although the approach is not dependent upon the choice of conditioning variables and attendant problems of misspecification, there is a real difficulty of interpretation, especially as the number of regions increases. Islam (2003) also makes this point, noting that omitting factors which determine the clustering (by utilising endogenised grouping) is unsatisfactory since it is not informative in terms of policy prescriptions. Hobijn and Franses (2000) acknowledge this fact, noting that beyond making references on the effect of country and contiguity (which is observed), there is no additional information to evaluate the composition of the cluster groups. The approach adopted in this study avoids the pitfalls of methods which utilise conditioning information to generate clusters but facilitates interpretation by confronting the resulting cluster compositions with a set of clusters generated by hypotheses constructed using a set of economic, socio-demographic and political indicators suggested by economic theory.

By considering two time periods we are also able to determine whether the effect of these factors on the degree of convergence and cluster composition is constant. This information represents a critical output of our study. For example, in the case of the manufacturing sector, we might postulate that given increasing globalisation and increasing trade links, the effect of geographical attributes such as country membership and peripherality will fall over time. This provides useful information from a policy perspective, in the sense of assessing whether the set of region-specific factors, which help determine a region's performance (in terms of real per capita GVA), are changing over time.

1.1. *A Question of Aggregation*

There is some evidence that the degree of convergence varies according to the scale at which regional differences (contrasts) are measured.[3] For example, it is

[3] See, for example, Arbia (1986; 1989), Armhein (1995), Anselin and Cho (2002).

possible to find convergence at one spatial level but a lack of convergence (or even divergence) at another. This is not just a statistical (aggregation) issue, since it raises the basic question of how economic convergence/divergence growth processes operate at different geographical and sectoral levels (Martin and Sunley, 1998). In a study on cross-province convergence for China, Jian *et al.* (1996) find that divergence in the post reform period is entirely explained by the variance between regions defined on the basis of coastal and interior provinces. However, within both of these regions there was no evidence of divergence. A related issue is that the extent of regional differences at different scales may not be stable over time. In the UK, for example, the between-region contribution to the total variance of unemployment rates has steadily declined over the past 15 years, while the intra-region contribution has remained more or less constant (Gregg and Wadsworth, 1999).

In an examination of the extent of inequality and convergence across Europe, the question of geographical scale is obviously central. Boldrin and Canova (2001) criticise the European Commission for utilising inappropriate regional units (the so-called Nomenclature of Statistical Territorial Units or NUTS). The principal reason for their comments is that NUTS1, NUTS2 and NUTS3 regions are neither uniformly large nor sufficiently internally homogeneous such that a finding of income divergence across regions can unequivocally be taken as evidence for the existence of endogenous, cumulative growth processes. In fact, the smaller the geographical scale, the more incomplete and fragmented is the available statistical information. These difficulties become more severe if we further disaggregate the information among industries and sectors of production. In conducting our analysis at the NUTS1 level we achieve a compromise between the need for a reliable set of information at a regional level, which is sufficiently homogeneous, and the need to move beyond national borders to depict the true process of convergence.

The question of scale is also important in terms of the appropriate level of aggregation of productivity measurement. For example, Bernard and Jones (1996) pose the question of whether trends in aggregate productivity are also revealed at the industry level. Relative to a finding of convergence at the aggregate national output level, the authors find that whereas the manufacturing sector has not exhibited signs of convergence, the service sector shows strong evidence of convergence. One possible explanation is that international spillovers, associated mostly with manufacturing, may not be contributing substantially to convergence either through capital accumulation or technological transfer. In a world with specialisation and spillovers, the non-tradable sectors will behave very much like an aggregate growth model and per capita output will converge over time as the technological diffusion process spreads. As a result, in the service sector factor productivity will most probably converge since public services are invariant across countries and the information and communications based technologies used to offer the same services are potentially similar. In contrast, within the manufacturing sector comparative advantage leads to specialisation, and since different countries or regions produce different goods, there is no reason to expect convergence in multifactor productivity.

2. A Cluster Methodology

In motivating our approach we first acknowledge and differentiate between a number of different concepts of convergence. As Bernard and Durlauf (1996) note, the formation of testable hypotheses depends critically on the precise form of the data and, related, how convergence is defined. For example, if initial conditions are unimportant and the objective is to test for convergence across regions for a single developed economy, then the appropriate question to ask is whether these regional economies have converged; in this case we may frame our test around a null of the stationarity of output gaps since we require that the data under analysis are near their long-run equilibria and that initial conditions are not important.[4] Such a test is appropriate if the expectation is that differences in log per capita income levels should be level stationary in the long run.[5]

The concept of *absolute* convergence implies that, independent of the current income levels, regions i and j converge to the same income levels. Hence, regions i and j are perfectly converging to the same level of income if

$$\lim_{s\to\infty} \mathrm{E}(y_{i,t+s} - y_{j,t+s} \mid I_t) = 0 \quad \forall i \neq j \in F, \tag{1}$$

where $i, j \in F$ index regions, F denotes the set of regions (R in total), t is the time index, y denotes the logarithm of per capita income and I_t denotes the information set at time t. Asymptotic *relative* convergence implies that the difference between log per capita income for i and j converges to a finite constant. Two regions are converging relatively if

$$\lim_{s\to\infty} \mathrm{E}(y_{i,t+s} - y_{j,t+s} \mid I_t) = \mu_{ij} \quad \forall i \neq j \in F, \tag{2}$$

where μ_{ij} denotes a specific mean difference for regions i and j. Equation (2) is satisfied if $y_{i,t+s} - y_{j,t+s}$ is level stationary. The necessary and sufficient conditions for countries i and j to have converged are that the log of their per capita incomes are cointegrated with cointegrating vector $(1, -1)$, and that the regions share common trends. We consider the definition in (2) as a more reasonable definition of convergence in the sense that, unlike (1), it allows the process of convergence to stop within a neighbourhood of zero mean stationarity. Such a definition is consistent with the existence of increasing costs of convergence and possible barriers to perfect convergence.

In considering more than two series, we may also think of the degree of convergence as measured by how many countries share a common trend and form a convergence club. There is a large literature on different approaches to this problem,[6] highlighting for example, whether system wide cointegration

[4] See Harvey and Bates (2003) and Pesaran (2004) for a useful discussion of the advantages of constructing tests of convergence on output gaps (over individual output series) and also of stationarity over unit root tests.

[5] Bernard and Durlauf (1996) also propose the notion of *convergence as catching-up* as appropriate in situations where initial conditions are important, and it is necessary to take account of the fact that countries are in a process of transition and far from their respective (or shared) steady states. In this case, since the series will not satisfy the property of stationary output differences, it is more appropriate to test for the presence of a unit root in the difference between the individual series.

[6] Other critical issues include the importance of cross-sectional dependence in determining the power of multivariate common trends tests addressed by Nyblom and Harvey (2000). See Pesaran (2004) for a discussion on the merits of using a pairwise approach.

techniques should be applied to individual series, as in Bernard and Durlauf (1995); or whether tests of convergence should be based upon pairwise differences of the form $y_{i,t} - y_{j,t}$ (Hobijn and Franses, 2000; Pesaran, 2004). However, given the focus of our analysis, namely the identification of *both* the number and composition of convergence clubs, the fundamental problem which plagues the multivariate approach is that the null hypothesis, typically the joint existence of $R - 1$ cointegrating and co-trending vectors of the form $(1, -1)$, is applied to a group of pre-selected countries. Subsequently, this form of test and null hypothesis is not useful if the analyst is seeking to determine both the number and composition of convergence clubs.[7] In seeking to test for the existence of more than a single convergence club to be revealed endogenously, we employ the recursive multivariate test of stationarity proposed by Hobijn and Franses (2000) and describe the procedure below.

Denoting the asymptotic relative convergence test statistic by τ^{ij} and its corresponding p-value by p^{ij}, the formation of clusters is described by the following procedure.[8] We first initialise the algorithm by associating the R regions in F with N_c clusters. In the first iteration, a univariate version of the KPSS (Kwiatkowski *et al.*, 1992) test of the null hypothesis of level stationarity of $y_{i,t} - y_{j,t}$ is conducted for all i, j region pairs in F;[9] empirical p-values are collected in the vector $\widehat{\mathbf{p}}_1$. Since we do not reject the null of level stationarity for $p^{ij} > p_{\min}$, where $p_{\min}$ is the critical value, the first cluster, say $G_1 = \{l, k\}$, is formed by selecting that pair of regions l and k where $p_1^{lk} = \max_{i,j \in F}(\widehat{\mathbf{p}}_1)$; over all regions in F, l and k are then the most likely to have converged.

We now iterate this process with the corresponding p-values collected in a new vector, $\widehat{\mathbf{p}}_2$; the maximum p-value in $\widehat{\mathbf{p}}_2$ identifies the new set of regions for which convergence occurs. These regions may form either another two-region cluster or a three-region cluster if one of the single-region clusters in F is convergent with cluster G_1. We collect the results of our tests in a $R \times R$ matrix $\mathbf{M} = \{m_{ij}\}$, where m_{ij} equals 1 if regions i and j belong to the same cluster (zero otherwise).

2.1. *An Alternative Time-varying Framework*

Both the number and composition of clusters may be time varying. For example, it may be the case that, in the initial part of a sample, a subset of countries are in the process of converging and only converge to the same cluster-specific level of output at the end. To establish whether the number of clusters and the composition of the convergence clubs vary over time, we employ a time-varying stationarity test. Specifically, we utilise a n-year rolling window that shifts year by year from the beginning, t_0, until the end of the sample period, T, is reached; for

[7] See, for example, Bernard and Durlauf (1995). In testing for the presence of convergence and common trends, the authors consider three separate groupings of countries. The reason for this is to determine whether the failure to reject a null of no convergence for a particular group of countries is dependent upon the size of the group.

[8] Hobijn and Franses (2000) describe a procedure which combines tests for both asymptotic perfect and asymptotic relative convergence.

[9] Test statistics τ^{ij} are invariant to the ordering over which the recursive tests are conducted. This implies that the convergence clubs are independent of the ordering.

$1 < n < T - t_0$ we can generate at most $T - t_0 - n + 1$ time windows.[10] For starting period $t_s \in [t_0, T - n]$, the cluster membership in each time window is, again, generated by the application of pairwise tests on differences of the form $y_{i,t} - y_{j,t}$. For interval $(t_s, t_s + n)$ regions i and j are converging relatively if

$$\lim_{n\to\infty} \mathrm{E}(y_{i,t_s+n} - y_{j,t_s+n} \mid I_{t_s}) = \mu_{(ij),t_s} \quad \forall i \neq j \in F. \tag{3}$$

The formation of clusters in each interval $(t_s, t_s + n)$ is described by the same algorithm outlined in Section 2. In focusing on the difference in the composition of our cluster outcomes over time, we note that the composition of clusters is now represented by the matrix $\mathbf{M}_{t_s} = \{m_{(ij),t_s}\}$, where $m_{(ij),t_s}$ equals 1 if, in the time interval $(t_s, t_s + n)$, regions i and j belong to the same cluster (zero otherwise).

2.2. *Parameter Choices*

In operationalising the recursive multivariate stationarity test we need to make decisions on the choice of two key parameters: the choice of the critical p-value, $(p_{\min})$, and the bandwidth parameter, ω.[11] The choice of $p_{\min}$ has a direct effect on the cluster size since, as we reduce $p_{\min}$, the less likely is the rejection of the null hypothesis of convergence and the larger are the resultant clusters. The choice of the bandwidth, ω, as demonstrated by Hobijn and Franses (2000) and Hobijn *et al.* (1998), does not have a direct impact on the size of the clusters. However, Monte Carlo results reveal that in small samples ω influences the size of the test and, as a result, the composition of the clusters.

In the Appendix we examine the robustness of the time-varying cluster algorithm over different values of ω, focussing on both the degree of convergence (the sensitivity of the number of clusters with respect to the bandwidth) and the composition of the convergence clubs. To analyse the sensitivity of cluster composition to changes in the bandwidth we follow Hobijn and Franses (2000) and use a cluster correlation coefficient which measures the degree of overlap between the outcomes associated to different values of ω. The higher the correlation coefficient the less sensitive are the results to the choice of the bandwidth. The test outcomes indicate that the composition of the convergence clubs is quite sensitive to the choice of the bandwidth. Our analysis suggests that setting $\omega = 2$ results in a greater level of robustness relative to other bandwidth choices. As demonstrated in Table A1, cluster correlations with other competing bandwidth choices exceed, in most cases, 0.50. Finally, we note that as demonstrated by Hobijn and Franses (2000), the recursive multivariate stationarity test is consistent in the sense that for large time horizons the tests will reveal the true underlying convergence clubs. However, since the stationarity test is known to be oversized in small samples, this bias will generate inference towards finding less

[10] In this study we choose an eighteen-year rolling window spanning the years 1975–99. Subsequently given the initial period ($t_0 = 1975$), the final period ($T = 1999$), and the window size ($n = 18$) we can generate up to seven different time windows.

[11] The bandwidth parameter ω defines the truncation lag for the estimation of the long-run variance-covariance matrix.

convergence. We counter this by setting $p_{\min}$ to be quite small namely $p_{\min}$ equal to 0.01.[12]

3. Data

EUROSTAT has established an administrative map of the European Union called Nomenclature of Statistical Territorial Units. The present NUTS nomenclature subdivides the economic territory of the EU-15 plus Norway using four regional levels. The levels are: NUTS3, consisting of 1,031 regions; NUTS2, consisting of 206 regions; and NUTS1 consisting of 77 regions. NUTS0 represents the delineation at the national level and comprises France, Italy, Spain, UK, Ireland, Austria, Netherlands, Belgium, Luxemburg, Sweden, Norway, Portugal, Greece, Finland, Denmark and West Germany.[13] A complete list of NUTS1 regions is given in Table 1.

We use regional data on Gross Value Added[14] per worker for the period 1975 to 1999 for agriculture, manufacturing and services. The service sector has been further sub-divided into market and non-market services: market services comprise distribution, retail, banking, and consultancy; non-market services comprise education, health and social work, defence and other government services. This disaggregation encompasses the information of more general aggregate indicators which are based upon measures of total factor productivity, thereby ignoring the possible differential contribution to convergence of different sectors.

The regional characteristics employed to help interpret our cluster outcomes consist of a number of indicators which may be considered as fixed effects.[15] These fall into three broad groups, as detailed in Table 2. *Geographical* effects comprise country-membership, the geographical location of the region and its distance with respect to core European regions. Country-membership defines the institutional setting; geographical location, which classifies regions on a 5 point scale, is a measure of contiguity and institutional similarity; the periphery-core indicator is a measure of accessibility and classifies regions according to their relative distance with respect to core regions. As an additional indicator of accessibility, we also consider the intensity of transport infrastructure which classifies regions on a 5 point scale according to the length of the transportation network. The *socio-demographic* effects are indicators of regional-urban agglomeration and classify

[12] The asymptotic properties of multivariate stationarity tests, including the KPSS extension of Nyblom and Harvey (2000), are usually derived under the assumption of a large number of time periods. Further work in this area is required and might explore the use of bootstrap generated critical values so as not to be reliant on the use of asymptotic results when faced with small time horizons; and also to facilitate inference in cases where R is large so as not to be reliant on fixed R asymptotics.

[13] For Portugal, Luxemburg and Ireland, data are only available at the NUTS0 level. For Norway we have no data at the NUTS1 level. Time series data for the sample period considered are not available for East Germany, which is therefore excluded from the analysis.

[14] Regional data on GVA per-capita at the NUTS1 level for agriculture, manufacturing, market and non-market services, have been kindly supplied by Cambridge Econometrics, and are taken from their European Regional Database. All series have been converted to constant 1985 prices (ECU) using the purchasing power parity exchange rate.

[15] The exception here is population change which is averaged across the years 1991–5 for all the NUTS1 regions.

Table 1

NUTS1 Codes

Code	Country	Code	Country
AT	*Austria*	IE	*Ireland*
AT1	Ostosterreich	IT	*Italy*
AT2	Sudosterreich	IT1	Nord Ovest
AT3	Westosterreich	IT2	Lombardia
BE	*Belgium*	IT3	Nord Est
BE1	Region Bruxelles-Capital-Brussels	IT4	Emilia-Romagna
	Hoofdstedelijke Gewest	IT5	Centro
BE2	Vlaams Gewest	IT6	Lazio
BE3	RegionWallonne	IT7	Abruzzo-Molise
DE	*Germany*	IT8	Campania
DE1	Baden-Wurttemberg	IT9	Sud
DE2	Bayern	ITA	Sicilia
DE3	Berlin	ITB	Sardegna
DE5	Bremen	LU	*Luxembourg*
DE6	Hamburg	NL	*Netherlands*
DE7	Hessen	NL1	Noord-Nederland
DE9	Niedersachsen	NL2	Oost-Nederland
DEA	Nordrhein-Westfalen	NL3	West-Nederland
DEB	Rheinland-Pfalz	NL4	Zuid-Nederland
DEC	Saarland	PT	*Portugal*
DEG	Thuringen	PT1	Continente
DK	*Denmark*	SE	*Sweden*
ES	*Spain*	UK	*United Kingdom*
ES3	Comunidad de Madrid	UKC	North East
ES4	Centro	UKD	North West
ES5	Este	UKE	Yorkshire and
ES6	Sur		Humber
ES7	Canarias	UKF	East Midland
F1	*Finland*	UKG	West Midlands
FR	*France*	UKH	East of England
FR1	Ile de France	UK1	London
FR2	Bassin-Parisien	UKJ	South East
FR3	Nord Pas de Calais	UKK	South West
FR4	Est	UKL	Wales
FR5	Ouest	UKM	Scotland
FR6	Sud-Ouest		
FR7	Centre-Est		
FR8	Mediterranee		
GR	*Greece*		
GR1	Voreia Ellada		
GR2	Kentriki Ellada		
GR3	Attiki		
GR4	Nisia Aigaiou, Kriti		

regions according to their settlement structure and population growth.[16] For agriculture we also use an indicator of regional agricultural specialisation which groups regions on a 5 point scale according to the percentage of land utilisation under agriculture.

[16] The population growth indicator classifies regions on a 5 point scale. For example, regions in the North-Western part of Germany, Belgium, Central Spain and Northern Italy have the highest levels of population growth.

Table 2

Data Source and Description

	Factors	Mechanism	Year	Source	Comments
Geographic	Country	Institutional Setting			Manual classification
	Core-Periphery	Accessibility		BBR*	1 Peripheral core, 2 Central and central metropolitan regions, 3 Tourist regions, 4 Brussels and Bremen, 5 German New Lander, 6 Central and Eastern UK, 7 Nordic countries, 8 Peripheral Southern Europe, 9 Mediterranean plus Ireland, 10 Northern Italy.
	Geographic location	Contiguity and Institutional Similarity		BBR	Manual classification according to geographic location: 1 The North, 2 Atlantic, 3 Mediterranean, 4 Eastern EU-border, 5 Centre.
	Length of transport routes	Accessibility	1996	University of Trier	1 Very low, 2 Low, 3 Medium, 4 High, 5 Very High.
	Agricultural intensification	Specialisation	1989–96	Greek and Dutch NFPs	Composite indicator of percentage growth of agricultural accounts, percentage of agricultural holdings > 50 and percentage of land use by total area. The classes are: 1 High pressure, 2 Important pressure, 3 Eventual presence of pressure, 4 Neutral pressure, 5 Negative pressure.
Socio-demographic	Population growth by total area	Agglomeration	1991–95		1 Very Low, 2 Low, 3 Medium, 4 High, 5 Very High. No data for Madeira, Acores, Canarias, Ceuta y Melilla.
	Settlement structure	Agglomeration		BBR	I. Agglomerated regions with a centre > 300,000 inhabitants and a population density >(I.1) or <(I.2) 300 inhabitants/km^2; II. Urbanised regions with a centre >150,000 inhabitants with a population density >(II.1) or <(II.2)150 inhabitants/km^2; III. Rural regions with a population density < 100 inhabitants/km^2 and a centre >(III.1) or <(III.2) 125,000 inhabitants.

Table 2
Continued

	Factors	Mechanism	Year	Source	Comments
Political	Type of EU Structural and Cohesion Funds	Externalities-Inducing Policies		Eurostat	0 = No special status 1 = Objective 1 status only 2 = Objective 2 status only 5 = Objective 5b status only 6 = Objective 6 status only 7 = Partially Objective 5b 8 = Partially Objective 2 9 = Partially Objective 2 and 5b 10 = Partially Objective 2, 5b and 6 11 = Partially Objective 1 and 5b 12 = Partially Objective 1 and 2 13 = Partially Objective 1, 2 and 5

Data coverage for all variables is at the EU15 level. *German Federal Office for Building and Planning.

Finally, regions are classified according to the degree and nature of public assistance in terms of their designation under the specific EU Cohesion and Structural Fund objective assigned (*political* effect).

In Section 4 we begin with an informal analysis of how the extent and composition of convergence clubs within Europe differ both across economic sectors and over time. We note that in line with other studies (Hobijn and Franses, 2000), our endogenously derived clusters are difficult to interpret, other than in simple geographical terms. Thus in Sections 5 and 6 we construct a number of hypothetical cluster patterns, and examine the extent to which cluster patterns generated by the application of our multivariate stationarity tests, are consistent with a number of alternative models of convergence processes.

4. The Observed Clusters

In Table 3 we report results based upon a test of asymptotic relative convergence at the country level (NUTS0). The largest clusters in agriculture and manufacturing comprise four countries, whereas non-market services exhibit the highest degree of convergence with a five country cluster. This confirms the findings of Quah

Table 3
Asymptotic Relative Convergence: NUTS0

Agriculture	Manufacturing	Market Services	Non-Market Services
1. FR IE LU BE	1. LU AT UK NO	1. ES IE PT NO	1. DK DE ES AT UK
2. IT PT UK	2. DK FR PT	2. GR SE BE	2. IT LU NL
3. DK NL	3. ES IE BE	3. DE UK	3. IE FI BE
4. GR SE	4. GR NL	4. IT AT	4. SE NO
5. FI NO	5. DE FI	5. FR FI	
Single Country Clusters			
AT	SE	DK	FR
ES	IT	LU	GR
DE		NL	PT

(1996) and Bernard and Jones (1996) that convergence is easier to find in the service sector perhaps because most countries (and regions) tend to have similar types of basic market and non-market services.

Since aggregate national level data may mask the extent of the convergence processes operating at the sub-national level, we also analyse the process of convergence at the regional level (NUTS1). Given the large number of EU regions we choose to present the results for asymptotic relative convergence in mapped form rather than in tables. Clusters with the highest number of member regions are indicated with a darker shade on each map. Regions which belong to two-country clusters or do not cluster with any other region have no shading. In the key to the maps, the first number indicates the cluster size and the second letter denotes the cluster identifier.

The full sample results (1975–99) for the four sectors are displayed in Figures 1 to 4. In agriculture (Figure 1), we find a five region cluster which comprises regions located in the North-Western, and Eastern parts of England and in the South-Western part of Germany. Note that regions located in Southern Italy, and the South and East of Spain belong to the same cluster (4B). This confirms that agricultural regions with similar climate and technological endowments tend to cluster together (Wichmann, 1996). A similar result is also present in Durlauf and Johnson (1992).

AGRICULTURE 1975-1999

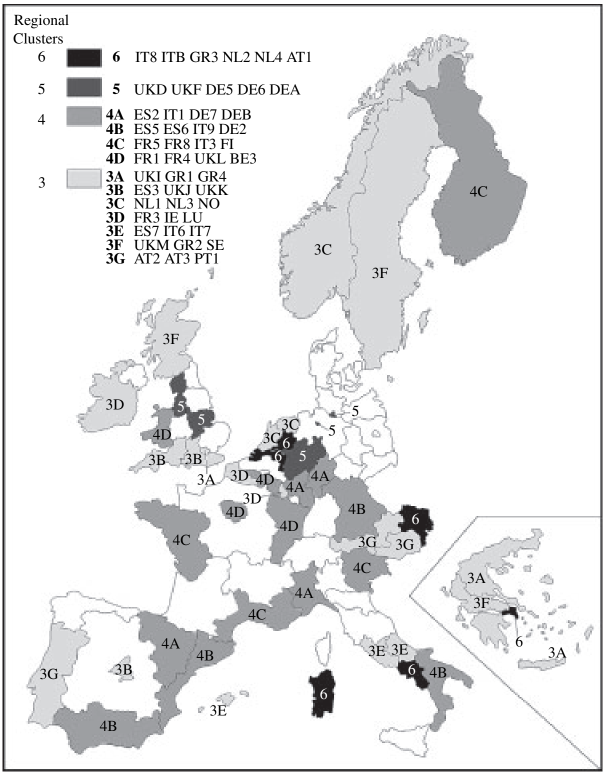

Fig. 1. *Relative Convergence in Agriculture*

MANUFACTURING 1975-1999

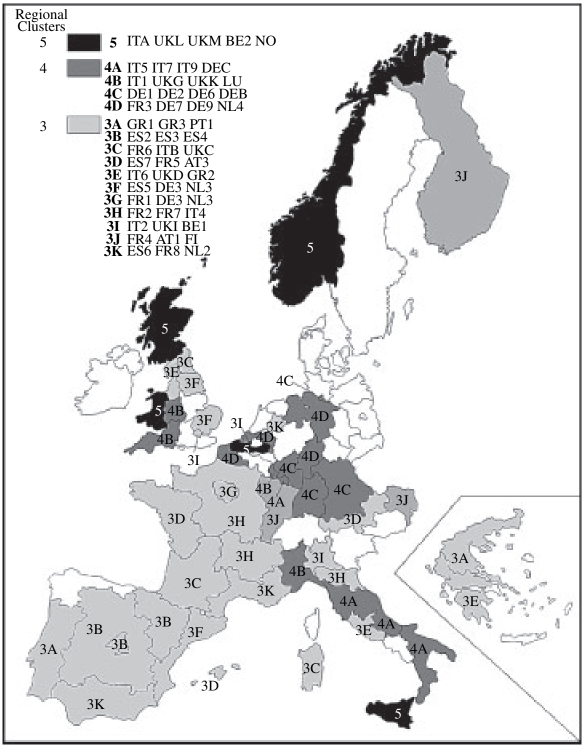

Fig. 2. *Relative Convergence in Manufacturing*

In the case of manufacturing (Figure 2) there is a single five region cluster and in general we have less convergence than in the other sectors. This is also consistent with the findings of Bernard and Jones (1996) who detect little evidence of labour productivity[17] convergence in manufacturing. A higher degree of convergence is found for the service sector (Figures 3 and 4) where there are seven region clusters both for market and non-market services. It could be argued that the extent of convergence would be expected to be more prevalent in manufacturing than in services, because this sector is mainly traded, whereas most services are driven by demands of a local population. On the other hand, the degree of convergence in services most likely reflects the systemic shift towards a more service based economy and society.

4.1. *Time-varying Results*

In analysing the time varying results we will consider two out of the seven windows referred to in Section 2.1. Specifically we examine the initial (1975–93) and final window (1981–99). This choice is useful for two reasons. First, we are able to assess

[17] Our focus is on labour productivity which does not allow for the identification of the contribution of technology and capital. As such a broader measure of multifactor productivity may lead to different results.

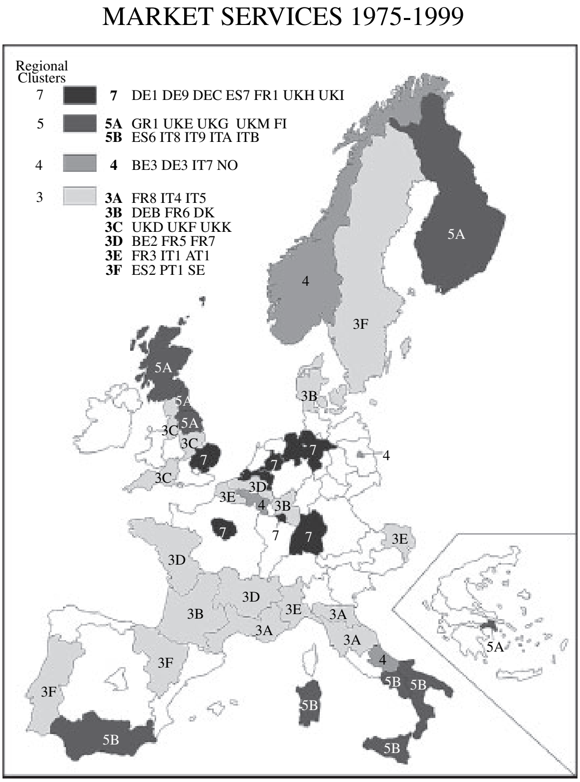

Fig. 3. *Relative Convergence in Market Services*

whether the initial size and composition of clusters have changed over the sample period considered. Second, in focusing on these two sub-periods, we examine whether and how far major developments in economic integration and intervention have been reflected in regional convergence patterns. The first period, for example, captures the years following the creation of the European Regional Development Fund in 1975. The second includes the reform of the Fund in 1986 and the creation of the Single Market in 1987. Some other studies have suggested that regional convergence slows down after the mid-1980s (Martin, 2001, 2002). Thus, our two sample sub-periods should also throw some light on this issue.

Table 4 presents summary information for each economic sector. The full-sample (1975–99) results are displayed in the top panel and indicate that the largest clusters are in the service sector (one seven region cluster in each sector), whereas in the agricultural and manufacturing sector there are mostly middle size (three and two) clusters. The time-varying results are displayed in the middle and lower panel of the Table. For agriculture there is evidence of a reduction in the size of the largest cluster from seven to five regions and an increase in clustering at a smaller scale. In the manufacturing sector there is a fall in the size of the largest cluster from eight to five regions and an increase in the number of middle-size clusters. In the market-service sector there is no change in the size of the largest cluster. However, there is a reduction in the number of middle size clusters from

NON-MARKET SERVICES 1975-1999

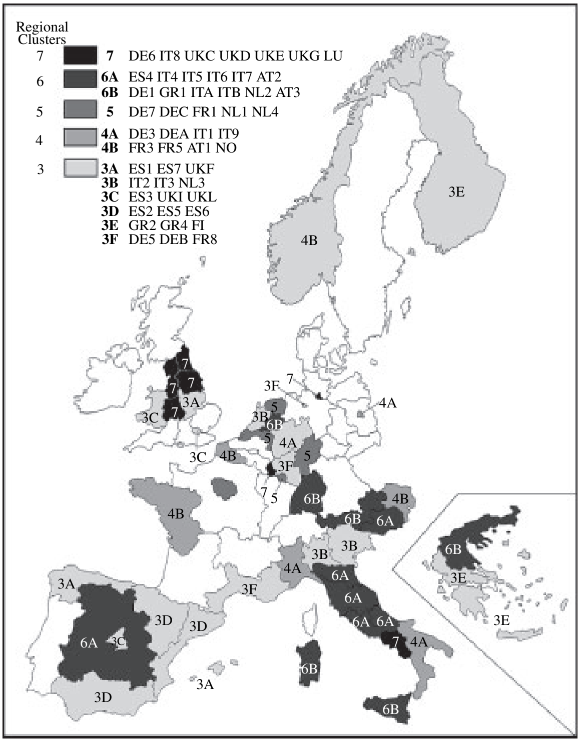

Fig. 4. *Relative Convergence in Non-Market Services*

Table 4

Cluster Summary Information

	Number of Clusters								
Cluster size	1	2	3	4	5	6	7	8	Total Clusters
1975–99									
Agriculture	1	9	7	4	1	1	0	0	23
Manufacturing	2	7	11	4	1	0	0	0	25
Market Service	6	11	6	1	2	0	1	0	27
Non-market Service	1	8	6	2	1	2	1	0	21
1975–93									
Agriculture	2	5	4	6	0	2	1	0	20
Manufacturing	1	7	6	4	2	0	0	1	21
Market Services	1	10	4	2	4	1	0	0	22
Non-market Services	2	10	6	3	3	0	0	0	24
1981–99									
Agriculture	2	8	8	5	1	0	0	0	24
Manufacturing	3	7	4	7	2	0	0	0	23
Market Services	1	14	5	3	1	1	0	0	25
Non-market Services	1	7	8	4	1	0	1	0	22

the initial to the final period and an increase in clustering at the smaller scale. For non-market services there is an increase in the size of the largest cluster from five to seven regions, and an increase in clustering at the medium and lower scale.

Examining the final period (1981–99) we observe that there are no clusters comprising more than five regions in both the agricultural and manufacturing sector, whereas in the market services we have one cluster with six regions, and in the non-market service sector there is one cluster comprising seven regions. Note that the non-market service sector in the initial sample period (1975–93) does not have any cluster comprising more than five regions.

Overall, two key features stand out from Table 4. First, regional convergence clusters across the EU are small in size: there are few clusters (clubs) having five or more members. Second, this situation does not appear to change significantly over time. Thus our results suggest that regional convergence dynamics across the EU are complex and vary markedly across regions: certainly there is no evidence of generalised regional convergence.

A number of studies have detected a slowing down of overall regional convergence across the EU regions from the mid-1980s onwards. Our findings suggest that this does not hold when sectoral disaggregations are examined; and that somewhat different processes are at work in manufacturing as compared to services. Although this issue obviously warrants further investigation, beyond casual observations as to the importance of spatial proximity and national (country) effects in influencing the convergence process, the clusters are difficult to interpret. In exploring the factors which underlie changes in cluster size and membership over time, we construct testable hypotheses that examine the difference between observed cluster patterns as generated by our testing methodology, and hypothetical clusters generated by a number of specific socio-geographical and politico-institutional factors.

5. Comparing Cluster Outcomes with Hypothetical Cluster Patterns

In evaluating the cluster outcomes against one or more hypothetical cluster patterns it is instructive to think of the clusters (and regions therein) as *data* generated by the outcome of a recursive sequence of stationarity tests. We collect this data in a $R \times R$ matrix $\widehat{\mathbf{M}} = \{\widehat{m}_{ij}\}$, where typical element $\widehat{m}_{ij}$ equals 1 if regions i and j belong to the same cluster and zero otherwise. $\mathbf{M}^h = \{m_{ij}^h\}$ denotes the artificially constructed cluster matrix based on hypothesis h.

Table 5 describes the features of the indicators used in the formation of the hypothesised cluster patterns. All of them are central components in the new economic geography growth models since they justify the presence of increasing returns and comparative advantage at the sectoral and/or regional level (Fujita *et al.*, 1999; Fujita and Thisse, 2003). The first set of *geographic* factors group regions on the basis of country-membership, peripheral-core distribution of the final market, location and the intensity of the transportation network. In their earlier work on regional convergence, Barro and Sala-i-Martin (1997) argued that regional convergence is more likely amongst regions within a given nation than it is between regions in different nations. Their argument is that institutional frameworks, regulatory systems, consumer tastes, and technologies are much more similar across regions within a given country than they are between different countries. This line of reasoning would lead us to hypothesise a significant country (national) effect on regional convergence clustering.

Table 5

Geographic, Socio-demographic, and Political Indicators

Factors	Description
Geographical	
Country membership	Regions cluster solely on the basis of their nation-state membership. The associated mechanisms include a shared institutional framework and a well defined geographic boundary.
Core-Periphery	Regions are classified according to their relative distance with respect to a core of European regions.
Geographic location	Regional clusters are determined by a broader geographical classification of regions: Northern European, Atlantic, Mediterranean, Central or Eastern European. Here, it is assumed that contiguity and institutional similarity may affect regional convergence.
Transportation network by total area	Regions are classified according to the intensity of the transportation network.
Agricultural intensification	Regions are classified according to a composite indicator of percent growth of agricultural accounts, percent of agricultural holdings greater than 50% and percentage of land use by total area.
Socio-demographic	
Population growth by area	Regions are classified according to the average of population growth between 1991 and 1995. Changes in population growth and population density capture the role of urban agglomeration in shaping real GVA per capita convergence.
Settlement structure	Regions are classified according to the number of inhabitants and population density. This may reflect, for example, different levels of urbanisation and agglomeration dynamics.
Political	
EU Structural Funds Objectives	Regions are classified according to the following EU Cohesion and Structural Fund objectives: Objective 1. To promote the development and structural adjustment of underdeveloped regions. Objective 2. To redevelop regions or areas within regions (local labour markets or urban communities) seriously affected by industrial decline. Objective 3. To combat long term unemployment, to provide career prospects for young people (aged under 35) and to reintegrate persons at risk of being excluded from the labour market. Objective 4. To facilitate the adoption of workers to industrial change and developments in the production system. Objective 5a. To speed up the adoption of production, processing and marketing structures in agriculture and forestry and to help modernise and restructure the fisheries and aquaculture sector. Objective 5b. To promote the development of rural areas. Objective 6. To promote the development of northern regions in the new Nordic member states. (since 1995 Finland and Sweden).

At the same time, recent work on the application of endogenous growth theory to regional development suggests that growth effects arising from knowledge creation and spillovers, on the one hand, and the accumulation of skilled human capital on the other, tend to exhibit spatial concentration. Strong spatial proximity effects are held to operate, implying a significant degree of spatial dependence in the geographical pattern of growth performance. In other words, we should expect convergence clusters to comprise sets of neighbouring or spatially proximate regions. Another important factor for the location of activity is the intensity of the transportation network. Since production in our four sectors differs in the intensity of transportation costs and in their relative distance from the final markets, then regions with a better transport infrastructure might be expected to attract sectors which produce transport intensive commodities. This approach is developed in a trade theory framework in Louveaux *et al.* (1982) and Fujita and Thisse (2002). On a larger geographical scale, it is often argued that the regional patterns of growth and development in the EU are characterised by a strong and persistent core-periphery structure, in which a core of leading growth regions encompassing the South East region of the UK, parts of the Netherlands, the Paris region, the Brussels region, Southern Germany and Northern Italy, is contrasted with a periphery of slower growing regions. The implication is that regional convergence dynamics should reflect this core-periphery dichotomy.

The second set of *socio-demographic* factors group regions on the basis of population growth and agglomeration effects. Along these lines Martin and Ottaviano (2001) show that growth and geographical agglomeration are self-reinforcing processes. In fact, agglomeration increases with growth since it is always more convenient to locate the activity where the final market is bigger or the production of knowledge is higher. At the same time growth increases with agglomeration since agglomeration reduces the cost of innovating in those regions where economic activity concentrates. Finally, the third set of *political* factors group regions on the basis of political intervention (within the EU) which are designed to encourage and guide structural adjustment of poorer regions (Martin, 2001). The instruments used include the European Development Fund, the European Social Fund and the European Agricultural Guidance and Guarantee Fund (Martin and Tyler, 2000).

Given that we would expect each effect to explain a relatively small fraction of the cluster outcome, we also test whether the degree of convergence and the cluster composition in the four sectors are affected by the *joint* interaction of some of the geographical, socio-demographic and policy indicators.

6. The Univariate and Multivariate Cluster Correlations

In assessing whether the generated cluster patterns are consistent with one or more of the artificially constructed cluster patterns based upon the hypotheses outlined above, we calculate the following cluster correlations. We write the correlation parameter, ζ^h, between the hypothesised cluster pattern, $\mathbf{M}^h$, and the generated cluster pattern, $\widehat{\mathbf{M}}$, as

$$\zeta^h = \left[\frac{\sum_{i=1}^{R} \sum_{j \neq i}^{R} m_{ij}^h \times \widehat{m}_{ij}}{\left(\sum_{i=1}^{R} \sum_{j \neq i}^{R} m_{ij}^h \right)^{1/2} \left(\sum_{i=1}^{R} \sum_{j \neq i}^{R} \widehat{m}_{ij} \right)^{1/2}} \right]^{1/2}. \tag{4}$$

We write the multivariate cluster correlation, ζ^{h_m}, as

$$\zeta^{h_m} = \left[\frac{\sum_{i=1}^{R}\sum_{j\neq i}^{R} m_{ij}^{h_1} \times m_{ij}^{h_2} \times m_{ij}^{h_3} \times \widehat{m}_{ij}}{\left(\sum_{i=1}^{R}\sum_{j\neq i}^{R} m_{ij}^{h_1}\right)^{1/2} \left(\sum_{i=1}^{R}\sum_{j\neq i}^{R} m_{ij}^{h_2}\right)^{1/2} \left(\sum_{i=1}^{R}\sum_{j\neq i}^{R} m_{ij}^{h_3}\right)^{1/2} \left(\sum_{i=1}^{R}\sum_{j\neq i}^{R} \widehat{m}_{ij}\right)^{1/2}} \right]^{1/2}, \quad (5)$$

where h_m represents a multivariate hypothesis which, in this example, combines the three univariate hypotheses h_1, h_2, h_3. ζ^{h_m} is the correlation coefficient between our generated outcome and the multivariate hypothesis h_m.

Tables 6 and 7 report the results of the univariate and multivariate cluster correlation analysis. In testing whether the correlation between our observed and hypothesised clusters has changed over time, we test for the significance in the difference of the correlation coefficients ζ_1 and ζ_2, where the subscripts 1 and 2 refer, respectively, to the sub-periods 1975–93 and 1981–99. To do this we first convert each correlation coefficient into a Z-score using Fisher's Z transformation

$$Z_l = \frac{1}{2}\ln\frac{1+\zeta_l}{1-\zeta_l} \; (l = 1, 2). \quad (6)$$

Using the statistic $z = (Z_1 - Z_2)/\sigma_{Z_1-Z_2}$ we test whether the difference in the two correlation coefficients is significantly different from zero.[18] Tables 6 and 7 report the correlation coefficients in the two sub-periods and the z statistics. A positive (negative) value of the statistic indicates that the correlation coefficient is decreasing (increasing) over time.

With respect to the univariate results, several points are worthy of note. First, location factors emerge as relevant in all sectors. In particular, with the exception of market services, our observed clusters are correlated with hypothesised clusters derived on the basis of country membership – no doubt reflecting the importance of national level effects on regional growth patterns. Likewise, the local intensity of the transportation network yields cluster groups that show a significant correlation with our observed clusters (although in this case with the exception of manufacturing). For both agriculture and manufacturing there is evidence of correlation with a pattern based on a core-periphery distribution of regions, while for all sectors other than market services, a cluster pattern based on geographical contiguity also correlates with our observed clusters. Not surprisingly, for agriculture there is a statistically significant correlation between our observed clusters and groupings defined on the basis of local relative specialisation in agriculture. The general suggestion from these findings is that geographic factors – whether of a broad core-periphery nature, of accessibility, proximity, or common national membership – have a role in explaining our observed regional clusters across the EU.

Second, socio-demographic factors also appear to be of importance. Hypothetical clusters based on population growth and population density correlate with

[18] The statistic z is normally distributed with standard error $\sigma_{Z_1-Z_2} = \sqrt{\sigma^2_{Z_1} + \sigma^2_{Z_2}}$. Since the sample size for the two periods are equal then $\sigma_{Z_1-Z_2}$ is equal to $\sqrt{2/[n(n-1)-3]}$ (Cohen and Cohen, 1983).

Table 6
Univariate Analysis

	Agriculture	Manufacturing	Market Services	Non-Market Services
Geographical				
Country Membership				
(1975–93)	0.363	0.346	0.340	0.431
(1981–99)	0.295	0.297	0.316	0.352
z	(3.59)**	(2.57)**	(1.26)	(4.40)**
Core-Periphery				
(1975–93)	0.349	0.380	0.308	0.354
(1981–99)	0.382	0.272	0.318	0.359
z	(−1.79)*	(5.70)**	(−0.52)	(−0.27)
Geographic Location				
(1975–93)	0.384	0.351	0.318	0.394
(1981–99)	0.392	0.284	0.321	0.364
z	(−0.44)	(3.51)**	(−0.15)	(1.65)*
Transportation Network				
(1975–93)	0.296	0.279	0.292	0.338
(1981–99)	0.229	0.266	0.329	0.293
z	(3.39)**	(0.66)	(−1.93)*	(2.35)**
Agricultural Intensification†				
(1975–93)	0.402	–	–	–
(1981–99)	0.348	–	–	–
z	(2.96)**			
Socio-Demographic				
Population Growth by Area				
(1975–93)	0.371	0.312	0.340	0.324
(1981–99)	0.270	0.350	0.316	0.321
z	(5.31)**	(−2.01)**	(1.26)	(0.15)
Settlement Structure				
(1975–93)	0.363	0.317	0.302	0.304
(1981–99)	0.297	0.267	0.321	0.321
z	(3.49)**	(2.57)**	(−0.99)	(−0.88)
Political				
EU Structural Fund Objectives				
(1975–93)	0.393	0.310	0.342	0.335
(1981–99)	0.358	0.320	0.334	0.312
z	(1.92)*	(−0.52)	(0.42)	(1.21)

**(*) denotes significance at the 5% (10%) level. †Data are available only for the agricultural sector. A positive (negative) value of z indicates that the correlation coefficient is decreasing (increasing) over time.
Note: All correlation coefficients for each period were tested and were found to be significantly different from zero at the 5% level.

our observed cluster groupings for both agriculture and manufacturing, suggesting that local market-demand factors and dense labour markets may be of importance for these two sectors respectively.

Third, in general we find little evidence that regional convergence has been strongly influenced by the provision of the EU Structural and Cohesion Funds. Grouping regions according to their Objective funding status, only the agricultural sector shows any significant correlation between our observed clusters and those based on Objective funding type. Other studies have found mixed evidence that EU regional policy has contributed to regional convergence (Braunerhjelm *et al.*, 2000; Boldrin and Canova, 2001; Puga, 2002) and our results tend to confirm this ambiguity.

Table 7

Multivariate Analysis

	(1975–93)	(1981–99)	z	(1975–93)	(1981–99)	z
	$C \cap L \cap AG$			$C \cap L \cap EU$		
Agriculture	0.294	0.284	(0.51)	0.258	0.253	(0.25)
	$C \cap L \cap CP$			$C \cap L \cap EU$		
Manufacturing	0.296	0.162	(6.68)**	0.275	0.244	(1.56)
	$C \cap L \cap P$			$C \cap L \cap EU$		
Market Services	0.264	0.236	(1.40)	0.242	0.279	(−1.87)*
Non-Market Services	0.237	0.296	(−2.99)**	0.331	0.243	(4.52)**

**(*)denotes significance at the 5% (10%) level.
A positive (negative) value of z indicates that the correlation coefficient is decreasing (increasing) over time.
$C \cap L \cap AG$ = Combination of Country Membership (C), Geographical Location (L) and Agricultural Intensification (AG)
$C \cap L \cap CP$ = Combination of Country Membership (C), Geographical Location (L) and Core-Periphery (CP)
$C \cap L \cap P$ = Combination of Country Membership (C), Geographical Location (L) and Population Growth by Area (P)
$C \cap L \cap EU$ = Combination of Country Membership (C), Geographical Location (L) and EU Structural Funds Objectives (EU)

Table 6 also suggests that the underlying dynamics of regional convergence have been changing over time. For all three types of clustering hypotheses – on the basis of location and socio-demographic factors, and policy status – there is a tendency for the correlation between the hypothesised cluster types and our observed clusters to decline over the two sample sub-periods. The decline in the role of geographic location factors is of particular interest, since it suggests – somewhat in contrast to new economic geography models – that increasing economic integration in the EU may not be intensifying the spatial agglomeration (clustering) of economic activity, but rather is being accompanied by a certain degree of geographical dispersal. The declining correlations (in agriculture and manufacturing) in the case of population growth and density would also suggest this. Clearly, this issue raises key questions for the regional convergence debate, and would repay further investigation.

We now analyse the multivariate correlation coefficients between the observed cluster outcomes and hypothesised cluster patterns, which in this instance are generated by a composite indicator based upon a number of the quasi-fixed factors. These effects have jointly combined to reduce or increase convergence. In the case of agriculture we examine the extent to which country membership (C), location (contiguity) (L) and the degree of agricultural intensification (AG) can explain, jointly, the observed set of cluster outcomes. This multivariate correlation coefficient allows us to establish whether regions with similar intensity of land utilisation, climate and physical conditions, and institutional settings, are aligned in terms of per capita GVA. For manufacturing, we examine the extent to which regional cluster outcomes relate to the canonical 'new economic geography view' of joint interaction between country membership (C), spatial proximity (L) and the core-periphery distribution (CP) of industrial activity. For market and non-market services we examine the joint interaction of country membership (*C*), location (*L*) and population growth (*P*) in explaining cluster outcomes (for example, the geographical distribution of market and non-market services might be hypothesised as being strongly influenced by nearness to large population centres). Finally, for all four sectors we analyse the joint interaction between country-membership (*C*), location (*L*) and the policy intervention at the EU level (*EU*).

Our findings are presented in Table 7. A particularly noteworthy result is observed in the case of manufacturing. The multivariate correlation results confirm the point made above in relation to the univariate correlations, namely that the regional distribution of production (per capita output) is becoming less clustered and more geographically fragmented. The joint effect of country membership, location and core-periphery pattern falls substantially between the two sample sub-periods (from 0.30 to 0.16). As noted above, this possibly suggests that agglomeration economies have in fact been declining in importance, and that (as some evidence for individual countries supports), a relative geographical shift in the location of manufacturing has taken place over the past two decades or so, away from established industrial-urban regions (which have tended to experience deindustrialisation), towards less industrialised rural areas.

For market services the correlation between the observed outcome and the composite indicator based on country membership, location and the provision of EU Structural Funding increases over the two subperiods, whereas that for non-market services declines. In the case of market services (which includes retail, distribution and banking) the high correlation between the observed clusters and the EU indicator may possibly be explained by the fact that in recent years this sector has been targeted by the allocation of Cohesion Funds, with the result that regions eligible for these Funds have tended to move closer together in terms of per capita GVA levels in this sector.

In the case of non-market services, the correlation of the observed cluster outcome with the hypothesised joint indicator comprising country membership, location and population, increases between the two subperiods. Since this sector comprises major public services such as education and health, it is not surprising that country membership and location, combined with high population densities and growth, are important correlates of the change in the observed relative convergence clusters in this sector of the economy.

7. Conclusion

There is a wide debate whether the rejection or non rejection of stationarity tests is informative about the process of convergence. However, there is as much interest in *how* these patterns evolve over time and space, as in the general question of whether or not convergence has taken place. We have addressed this issue by examining the pattern of European convergence using pairwise stationarity tests over the period 1975–99 and across the two sub-samples 1975–93 and 1981–99. We use a methodology that selects convergence clusters (clubs) endogenously, that is without any prior constraints on either the number or composition of clusters. Our results suggest that processes of regional convergence across the EU are complex and that they also vary over time. All four sectors reveal quite large numbers of regional convergence clusters (Table 4), suggesting that there is no single EU-wide convergence process but rather different convergence paths in different economic sectors and different parts of the EU.

To examine this idea, our observed clusters were then compared with a number of hypothesised regional groupings based on different theories and models of regional growth and development. We provide estimates of the correlations between our observed outcomes and these hypothesised cluster patterns, using both univariate and multivariate approaches.

Geographical location factors are correlated with the observed cluster outcomes for all four sectors. For both agriculture and manufacturing, there is evidence of correlation with a pattern based on a core-periphery distribution of regions, and for all sectors other than market services, a cluster pattern based on geographical contiguity also correlates with our observed clusters. These results confirm the importance of geographical proximity – whether country membership, spatial contiguity, relative core-periphery location, accessibility – in shaping individual regional convergence paths.

Socio-demographic characteristics also appear to be relevant. Hypothetical clusters based on similar population growth and population density correlate with our observed cluster groupings for both agriculture and manufacturing but less so for services. Somewhat contrary to the official view of the European Commission, we find little evidence that the pattern of regional convergence across the EU correlates with regional policy intervention, as measured by the provision of Structural and Cohesion Fund assistance.

Finally, and importantly, our results suggest that the underlying dynamics of regional convergence across the EU have been changing over time. For all three main types of clustering hypothesis – on the basis of geographical factors, socio-demographic characteristics, and policy status – the correlations between the hypothesised cluster types and the observed clusters decline between our two sample sub-periods. The decline in the relevance of geographical location is perhaps of special interest, since it suggests – in contrast to many of the new economic geography models – that increasing economic and monetary integration in the EU may not be intensifying the geographical agglomeration of economic activity.

Appendix: Robustness Results

We examine the robustness of the cluster algorithm with respect to the choice of ω, and assess both the degree of convergence (the sensitivity of the number of clusters with respect to the bandwidth) and the composition of the convergence clubs. To analyse the sensitivity of cluster composition we follow Hobijn and Franses (2000) and use a cluster correlation index which measures the degree of overlap between the two outcomes. To this end we construct a matrix $\mathbf{M}^* = \{m_{ij}\}$, $i, j = 1, \ldots, R$, where m_{ij} is 1 if regions i and j belong to the same cluster and zero otherwise. Let $\mathbf{M}^a$ denote a particular value of $\mathbf{M}$ generated by a sequence of pairwise tests of stationarity with bandwidth parameter $\omega = a$; $\mathbf{M}^b$ is similarly defined. In varying the bandwidth parameter, $m_{ij}^{a} \times m_{ij}^{b \neq a}$ equals 1 if countries i and j are in the same convergence club for values of the bandwidth parameters a and b. The statistic $\zeta \in (0, 1)$, given below, represents the correlation parameter between the two sets of outcomes.

$$\zeta = \left[\frac{\sum_{i=1}^{R} \sum_{j \neq i}^{R} m_{ij}^{a} \times m_{ij}^{b \neq a}}{\left(\sum_{i=1}^{R} \sum_{j \neq i}^{R} m_{ij}^{a} \right)^{1/2} \left(\sum_{i=1}^{R} \sum_{j \neq i}^{R} m_{ij}^{b \neq a} \right)^{1/2}} \right]^{1/2} \quad \text{for } a, b \in (1, 2, 3, 4, 5, 6). \tag{A.1}$$

Table A1 reports the sensitivity results for all the sectors in the time-varying cluster algorithm considering a bandwidth parameter value ranging from 1 to 6 for the initial (1975–93) and final window (1981–99). The first row in each matrix for the two sub-samples reports the number of clusters in the two sub-periods considered. The cluster correlations show that the number of convergence clubs is not very sensitive to the choice of the bandwidth, but this is not the case for the composition of the convergence clubs as the outcomes are never identical. Therefore, given that there is no evidence of any outperforming outcome, the strategy is to choose a bandwidth whose cluster correlation with other competing bandwidth choices remains relatively high and substantially stable. In this respect a bandwidth $\omega = 2$ is confirmed to be robust with respect to various choices of ω. These results are in line with those reported by Hobijn and Franses (2000) for the Penn World Table convergence clusters, described in Summers and Heston (1991). The Penn World Table includes data for 112 countries for the period 1960–89 and, as in our case, presents the same small-sample problem with a cluster correlation between the various outcomes never exceeding 0.66.

Table A1

Sensitivity Results: Relative Convergence

Agriculture

			1975–93			
clubs	19	21	21	22	25	27
ω=	1	2	3	4	5	6
1	–	0.701	0.667	0.526	0.569	0.604
2	–	–	0.572	0.584	0.540	0.575
3	–	–	–	0.529	0.517	0.474
4	–	–	–	–	0.627	0.440
5	–	–	–	–	–	0.598
			1981–99			
clubs	24	24	24	25	27	28
ω=	1	2	3	4	5	6
1	–	0.612	0.522	0.622	0.587	0.579
2	–	–	0.650	0.588	0.549	0.553
3	–	–	–	0.6325	0.502	0.549
4	–	–	–	–	0.575	0.631
5	–	–	–	–	–	0.520

Manufacturing

			1975–93			
clubs	23	22	26	26	29	27
ω=	1	2	3	4	5	6
1	–	0.385	0.524	0.376	0.374	0.436
2	–	–	0.501	0.467	0.474	0.517
3	–	–	–	0.389	0.563	0.354
4	–	–	–	–	0.693	0.492
5	–	–	–	–	–	0.549
			1981–99			
clubs	25	23	25	26	26	32
ω=	1	2	3	4	5	6
1	–	0.499	0.536	0.435	0.452	0.403
2	–	–	0.615	0.539	0.514	0.424
3	–	–	–	0.598	0.497	0.399
4	–	–	–	–	0.564	0.474
5	–	–	–	–	–	0.476

Market Services

			1975–93			
clubs	21	22	22	25	27	28
ω=	1	2	3	4	5	6
1	–	0.639	0.614	0.373	0.428	0.467
2	–	–	0.605	0.412	0.569	0.504
3	–	–	–	0.418	0.500	0.511
4	–	–	–	–	0.604	0.386
5	–	–	–	–	–	0.570
			1981–99			
clubs	24	24	25	27	28	30
ω=	1	2	3	4	5	6
1	–	0.747	0.662	0.582	0.502	0.584
2	–	–	0.728	0.648	0.510	0.551
3	–	–	–	0.613	0.503	0.545
4	–	–	–	–	0.539	0.598
5	–	–	–	–	–	0.744

Non-Market Services

			1975–93			
clubs	23	24	25	27	27	29
ω=	1	2	3	4	5	6
1	–	0.584	0.461	0.544	0.453	0.540
2	–	–	0.686	0.667	0.602	0.540
3	–	–	–	0.576	0.595	0.586
4	–	–	–	–	0.731	0.593
5	–	–	–	–	–	0.583
			1981–99			
clubs	22	22	22	24	26	26
ω=	1	2	3	4	5	6
1	–	0.421	0.423	0.541	0.458	0.540
2	–	–	0.491	0.628	0.465	0.479
3	–	–	–	0.499	0.454	0.482
4	–	–	–	–	0.563	0.470
5	–	–	–	–	–	0.535

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