UNIVERSITÀ DEGLI STUDI DI FERRARA
DIPARTIMENTO DI ECONOMIA ISTITUZIONI TERRITORIO
Via Voltapaletto, 11 – 44100 Ferrara

Quaderno n. 7/2008

March 2008

Identifying regional convergence clubs through a mapping structure

Rosa Bernardini Papalia

Silvia Bertarelli

Identifying regional convergence clubs through a mapping structure

Rosa Bernardini Papalia[1]

Silvia Bertarelli[2]

Abstract:

This work aims at developing a two stage strategy which employ information on clustering schemes identified by a mapping analysis with the purpose of estimating a club convergence model. At the first stage, unobserved TFP differentials across regions are identified by introducing a mapping structure in a conditional convergence growth model. Since estimation of this class of convergence models in the presence of regional heterogeneity poses both identification and collinearity problems, we develop an entropy-based estimation procedure which simultaneously takes account of ill-posed and ill-conditioned inference problems. At the second step of the analysis, we estimate a two-club spatial convergence model, where clubs correspond to subsets of total observations, as identified at the first stage of the analysis and spatial dependence is modeled. The two step strategy is applied to assess the existence of conditional convergence across Italian regions over the period 1960-1999.

Keywords: club convergence, mapping models, maximum entropy estimation, spatial dependence.

JEL classification: C130, C210, C230, O180, O470

[1] Dipartimento di Scienze Statistiche, Università di Bologna, Via Belle Arti, 41 - 40126 Bologna, e-mail: bernardini@stat.unibo.it
[2] Correspondent author: Dipartimento di Economia Istituzioni Territorio, Università di Ferrara, Via Voltapaletto, 11 – 44100 Ferrara, e-mail: silvia.bertarelli@unife.it

1. Introduction

Empirical evidence suggests that regions and countries are not homogenous and not independent units. Using different statistical methodologies, Durlauf and Johnson (1995), Quah (1996), Desdoigts (1999), and Canova (2004), among others, argue that the assumption of homogeneity across countries is incorrect. In light of these findings, it is desirable to incorporate heterogeneity in growth empirical analysis, by making a further distinction between the concepts of absolute and relative location, as suggested by Abreu *et al*. (2004), that can be related to spatial heterogeneity and spatial dependence, respectively. Spatial heterogeneity occurs when different patterns of economic development emerge across space. In a regression model, spatial heterogeneity can be reflected by non uniform coefficients, i.e. structural instability, or by varying error variances across observations, i.e. heteroskedasticity[1]. What matters is the location at a particular point in space, which is an absolute location concept. The absolute location concept refers to the impact of being located at a particular point in space and has been empirically investigated in non spatial econometrics literature. Spatial heterogeneity can be linked to the concept of convergence clubs. The economy is characterized by the possibility of multiple, locally stable, steady state equilibria. A convergence club is a group of economies whose initial conditions are near enough to converge toward the same long-term equilibrium. Under such circumstances there might be convergence among similar types of economies (club convergence), but little or no convergence among clubs. Spatial dependence states that similar values of a random variable measured on various locations tend to cluster in space. In this case, the concept of location is that of relative location and models of spatial dependence are proposed in the growing spatial econometrics literature (Rey and Montouri, 1999; Fischer and Stirbock, 2004; Ertur *et al*., 2006; Le Gallo and Dall'Erba, 2006).

This work aims at developing a two stage strategy to estimate a spatial club convergence model, which employs information on clustering schemes identified by a mapping analysis.

At the first stage, we admit the presence of multiple spatial regimes or "clubs", whose identification is pursued by means of a mapping analysis. The proposed approach draws from the choice of a mapping methodology to model the existing unobserved heterogeneity related to interregional inequalities in unobservable TFP levels within a conditional growth model (Islam, 1995; Caselli *et al*., 1996). In particular, our approach proceeds by: (i) introducing spatial heterogeneity across regions (absolute location effects) at the level of unobserved and explanatory variables, and (ii) explicitly producing a location map for unobserved components from the growth theory. The multidimensional scaling technique models spatial autocorrelation for unobserved variables in a non-parametric way. The use of mapping results for potential regimes identification allows for an endogenous selection of regional clusters and facilitates the interpretation of the cluster outcomes, providing a measure of the role (weight) of different unobserved dimensions. Since in the presence of regional heterogeneity, estimation of this class of convergence models poses both identification and collinearity problems, we develop a generalized maximum entropy (GME) based estimation procedure (Golan *et al*., 1996), which simultaneously takes account of ill-posed and ill-conditioned inference problems.

[1] Spatial heterogeneity in terms of structural instability and group-wise heteroskedasticity has been empirically investigated, among others, by Tsionas (2000). The treatment of heterogeneity in panel data analysis has been proposed by Lee *et al*. (1995) and Pesaran and Smith (1995) with Mean Group and Pooled Mean Group estimators.

At the second step of the analysis, our objective is to incorporate parametrically spatial effects or externalities into the spatial regime specification. The growth analysis is extended to take account of relative location effects by explicitly modeling spatial dependence within a spatial econometrics framework. We specify a multiple club spatial convergence model, with clubs corresponding to subsets of total observations, which are identified at the first stage of the analysis. The proposed strategy is applied to assess the existence of club convergence across Italian regions over the period 1960-1999.

The paper is organized as follows. Section 2 presents convergence concepts, and related issues connected to spatial heterogeneity and spatial dependence. Section 3 introduces the approach used to identify convergence clusters by a mapping structure. A generalized maximum entropy estimation procedure is also developed and discussed in section 3.2. Section 4 introduces alternative two-club_spatial convergence model specifications. Data description and results of an application to Italian regional data are reported in section 5. Finally, section 6 concludes and lists some potential advantages and investigations of the proposed approach.

2. Club convergence analysis

The existence of a negative relationship between the initial GDP per capita/per worker and subsequent growth is a phenomenon, called β-convergence[2], largely documented in the empirical literature with reference to both cross-country and cross-region analysis. If convergence derives by physical and human capital accumulation, initial capital-poor regions have higher marginal productivity of capital, hence faster growth than rich regions. This view is grounded by the Solow (1956) neoclassical model and its extended version by Mankiw, Romer and Weil (1992) or by endogenous growth models that display transitional dynamics, such as the two-sector growth models of Lucas (1988)[3]. The convergence issue has been extensively debated in the growth and regional science literature, giving rise, from a theoretical point of view, to different concepts, such as absolute and conditional β-convergence, and club convergence. We briefly outline the former two concepts and then concentrate on the latter definition since our focus is on the analysis of heterogeneous countries/regions.

If we assume that all the economies are structurally similar, characterized by the same steady state, and differ only by their initial conditions, we define the concept known as absolute (or unconditional) β-convergence. It is only in this case that poor countries grow faster than rich ones and eventually catch them up in the long run. If we assume that the growth rate of an economy is positively related to the distance that separates it from its own steady state, we consider the concept known as conditional β-convergence. If economies have different steady states, this concept is compatible with a persistent high degree of inequality among economies[4].

To account for the presence of relative location effects, spatial externalities are introduced in growth models yielding convergence equations with spatial autocorrelation. These theoretical models have been derived by Lopez-Bazo *et al.* (2004), Vaya *et al*. (2004), Ertur and Koch (2006).

When the neoclassical growth model is augmented so as to capture additional (empirically significant) elements such as human capital, income distribution, capital market

[2] For a complete survey see, for example, Barro and Sala-i-Martin (2004).

[3] However, the fact that poor countries grow faster than rich countries may be also (or only) the effect produced by a process of technological diffusion (Abramovitz, 1986; Barro and Sala-i-Martin, 1997).

[4] See Islam (2003) for a detailed survey.

imperfections, externalities, and imperfectly market structures, club convergence emerges under plausible scenarios (Galor, 1996). More specifically, in the presence of factors related to the concept of absolute location, if heterogeneity is permitted across individuals, the dynamical system of the Solow model may be characterized by multiple, locally stable, steady-state equilibria. An economy will be reaching one of these different equilibria depending on the range to which its initial conditions belong. The set of variables whose initial levels are relevant depends on the theoretical models considered (Galor, 1996)[5].

In such a framework, club convergence means that economies, similar in their structural characteristics, converge to one another if their initial conditions guarantee the attraction to the same steady state equilibrium. When convergence clubs exist, one (conditional) convergence equation should be estimated per club, corresponding to different regimes. If for simplicity we have two different regimes, A and B, we consider the following system:

$$\begin{aligned} \ln y_{it} - \ln y_{it-1} &= \beta_A \ln y_{it-1} + \gamma_A^{'} X_{it-1}^{A} + \mu_i^{A} + \upsilon_t^{A} + u_{it}^{A} \qquad i \in \text{regime A} \\ \ln y_{it} - \ln y_{it-1} &= \beta_B \ln y_{it-1} + \gamma_B^{'} X_{it-1}^{B} + \mu_i^{B} + \upsilon_t^{B} + u_{it}^{B} \qquad i \in \text{regime B} \end{aligned} \tag{1}$$

There is club convergence when β_A and β_B are significantly negative[6]. The vector $X_{it-1} = (sk_{it-1}, sh_{it-1}, ndx_{it-1})$ gives the determinants of the steady state output and consists of a set of region-specific explanatory variables suggested by the theory, including sk_{it-1} the investment rate in physical capital, and ndx_{it-1} the sum of the population growth rate, the exogenous technological growth rate, and the depreciation rate. In addition, we also consider sh_{it-1}, the investment rate in human capital measured by the enrollment ratio at the secondary school. Time effects control for the presence of a time trend component and of a common stochastic trend (the common component of technology). Individual effects capture total factor productivity (TFP) differences and other omitted variables.

3. Step I – Procedure: identification of convergence clubs by a mapping structure

Several approaches have been performed to evaluate the composition of convergence clubs in models of economic growth, since economic theory does not provide guidance as to (i) the number of groups of regional economies that interact more with each other with those outside; and (ii) the way in which the explanatory variables defining the initial conditions determines clubs.

Exogenous and endogenous techniques have been proposed with the aim of determining those clubs. The former class of exogenous procedures comprises: (i) a priori criteria, like the belonging to a geographic zone or some per capita GDP cut-offs or exogenous core periphery division; and (ii) an exploratory spatial data analysis (ESDA), based on several measures of global and local spatial autocorrelation of the explanatory variables as per capita GDP, human and physical capital measures (Basile *et al*., 2003).

[5] Heterogeneity across economies is essential in creating ambiguity between club convergence and conditional convergence (Galor, 1996), that is to say that evidence of conditional β-convergence may be interpreted as evidence of club convergence as well. The importance of initial conditions within the convergence club hypothesis may be mined in the presence of international capital mobility. However, human capital is not perfectly mobile across countries, so club convergence remains a plausible hypothesis. However, in the presence of technological progress, conditional convergence may be observed in the long run, preceded by polarization and clustering in the medium run (Galor and Tsiddon, 1997). In this case, we observe a non monotonic evolution of the distribution of income across countries, and clustering schemes are to be interpreted as transitory phenomena. For a unified review of theories examining the process of development through different stages, see Galor (2005).

[6] The system (3) describing the convergence process can be generalized to the case of a number C > 2 of clubs.

The latter ones enclose all the statistical techniques that endogenously determine clubs of regions on the basis of a number of conditioning variables which reflect initial conditions, structural characteristics, economic activity and other effects associated with physical and human capital stocks. When multiple control variables are used it is possible to identify the variable that dominates as an element useful in identifying multiple regimes. Within the endogenous approaches, several techniques have been developed, as the regression tree method (Durlauf and Johnson, 1995), projection pursuit technique (Desdoigts, 1999) or techniques based on polynomial functions (Durlauf *et al*., 2001) or based on multivariate test for stationary (Corrado *et al*., 2005),

3.1. The mapping model

Our idea is to analyze spatial association within all observed explanatory variables, which define the initial conditions, by means of a mapping representation. The approach aims at investigating regional spatial heterogeneity by also capturing the contribution of omitted variables such as the unobserved quality of institutions, and the determinants of regional technological and structural characteristics. In addition, this type of information on initial conditions is recovered in an endogenous way, without any *ex ante* (and somewhat subjective) selection.

The method draws from the choice of a mapping methodology to model the existing unobserved heterogeneity related to interregional inequalities in unobservable TFP levels and proceeds by: (i) introducing spatial heterogeneity at the level of the unobserved variables, and (ii) explicitly producing a location map for unobserved components from the growth theory. The use of mapping results for potential regimes identification allows for an endogenous selection of regional clusters and facilitates the interpretation of the cluster outcomes, providing a measure of the role (weight) of different unobserved dimensions.

More specifically, the individual-effect term in the standard conditional growth model specification is estimated and used to define the spatial position of a region's TFP level in terms of different unobserved dimensions weighted by the variables' features. The variability in both cross-region specific unobserved characteristics and time invariant components is considered and, as in the choice map, the position of the unobserved variables on the M-dimensional map and the country's importance weights for these dimensions are derived. In this framework, the interpretation of the dimensions of maps is aimed at endogenously identifying the determinants of technological and structural differences. The resulting location map can be obtained by using a two-stage process. First, the parameters of the growth model (eq. 1) are estimated and the covariance matrix of unobserved components μ_i's is computed. Then this matrix is used as an input in multidimensional scaling to obtain their locations in a multi-attribute space. As in the choice map representation we assume that the time-invariant effect for region i, μ_i, is a linear function of the region's time invariant attributes which lie within a two-dimension map, such as:

$$\mu_i = w_1 z_{1i} + w_2 z_{2i} + \xi_i \tag{2}$$

where the parameters w_1 and w_2 are modeled as a function of country's characteristics, (z_{1i}, z_{2i}) are the coordinates representing the location (to be estimated) of the unobserved effect on the map, and ξ_i is a random error with zero mean.

It should be noted that this approach presents the advantage over the more traditional approaches to simultaneously identify the main spatial factors that provide an indirect measure of unknown invariant TFP (dis)similarities across regions, without imposing an a priori spatial structure on the growth model.

3.2. A Maximum Entropy-based estimation approach

In the presence of regional heterogeneity, estimation of convergence models poses both identification and collinearity problems. In this phase of the analysis we then proceed by developing a generalized maximum entropy (GME) based estimation procedure (Golan *et al*., 1996) which simultaneously takes account of ill-posed and ill-conditioned inference problems. Our approach retains the flexibility of the SUR approach in allowing for correlated shocks across regions and can be implemented (i) when the number of time periods, T, is not sufficiently large, (ii) when the number of regions N is lower than the number of time periods, T, and/or (iii) in presence of small samples.

The entropy-based estimation procedure shares some of the characteristics of Stein Rule estimators and Bayesian approaches to estimation (see Judge *et al*., 1988 and Zellner, 1997). There is now a considerable body of work, which has given an application of the entropy criterion to a wide class of models (Golan *et al*. 1996, 1997). As regards traditional estimation techniques, the formulation of the constrained maximization problem in the maximum entropy view does not require: (i) the use of restrictive parametric assumptions on the model; (ii) the formulation of hypotheses regarding the form of the distribution of the objective variables. Restrictions expressed in terms of inequality can be introduced and it is possible to calibrate the precision in the estimation. Good results are produced in the case of small-sized samples, in the presence of high numbers of explanatory parameters and variables (highly correlated).

We start by considering the maximum entropy formulation relative to a seemingly unrelated system of N equations which allows for covariance between the disturbances across different regions where the i-th model (equation) is given by:

$$Y_i = X_i\beta_i + \varepsilon_i \tag{3}$$

for i=1,..,N, where Y_i and ε_i are of dimension (T×1), X_i is (T×K_i) and β_i is (K_i×1). Here $Y_i = lnY_i$ and X_i includes sk_i, sh_i, ndx_i and $lny_{i,t-1}$.

Stacking all the equations, the system approach considers the N equations, of the form (3) for each region as:

$$Y = X\beta + \varepsilon$$

$$\text{where}\quad Y \equiv \begin{bmatrix} y_1 \\ \dots \\ \dots \\ y_N \end{bmatrix} \quad X \equiv \begin{bmatrix} X_1 & 0 & .. & 0 \\ 0 & X_2 & .. & 0 \\ .. & & .. & .. \\ 0 & 0 & .. & X_N \end{bmatrix} \tag{4}$$

$$\beta \equiv \begin{bmatrix} \beta_1 \\ \dots \\ \dots \\ \beta_N \end{bmatrix} \quad \varepsilon \equiv \begin{bmatrix} \varepsilon_1 \\ \dots \\ \dots \\ \varepsilon_N \end{bmatrix} \quad \text{with}\quad i = 1,\dots N \qquad k = 1,\dots, K$$

where *Y* and ε are each of dimension (NT×1), X is a block diagonal matrix of dimension (NT×K) with K = Σ K_i and β = (β_1, β_2,.. β_N)' is an unknown vector of dimension (NK×1).

Under the GME framework we recover simultaneously the unknown parameters β, the unknown errors by defining an inverse problem, which is based only on indirect, partial or incomplete information. We also assume that the equation error are contemporaneously correlated, but uncorrelated over time. Consequently, the covariance matrix for ε may be written as:

$$\Phi = \Sigma \otimes I_T \tag{5}$$

where Σ is an (N×N) positive definite symmetric matrix, ⊗ is the Kronecker product operator and I_T is an identity matrix of dimension T.

In the GME estimation the objective is to recover the probability distributions for unknown parameters and errors. Each parameter is treated as a discrete random variable with a compact support and M possible outcomes, 2 ≤ M ≤ ∞. The uncertainty about the outcome of the error process is represented by treating each error as a finite and discrete random variable with *J* possible outcomes, 2 ≤ J ≤ ∞. To this end, we start by choosing a set of discrete points, the support space $v = [v_1, v_2, \dots, v_M]'$ of dimension $M \geq 2$, that are at uniform intervals and symmetric around zero. Each error term has corresponding unknown weights $w_j = [w_{j1}, w_{j2} \dots, w_{jM}]'$ that have the properties of probabilities $0 \leq w_{jm} \leq 1$ and $\sum_m w_{jm} = 1$.

Re-parameterizing the set of equations (4), so that $\beta = Zp$ and $\varepsilon = Vw$, yields:

$$\begin{bmatrix} y_1 \\ \dots \\ \dots \\ y_N \end{bmatrix} = \begin{bmatrix} X_1 & & & \\ & X_2 & & \\ & & \dots & \\ & & \dots & X_N \end{bmatrix} \begin{bmatrix} Z_1 p_1 \\ \dots \\ \dots \\ Z_N p_N \end{bmatrix} + \begin{bmatrix} V_1 w_1 \\ \dots \\ \dots \\ V_N w_N \end{bmatrix} \tag{6}$$

where p = (p_1, p_2, .., p_K)'and w = (w_1, w_2, .., w_N)' are the unknown signal and noise probabilities we wish to recover; Z and V are the corresponding parameter supports for β and ε as previously defined.

Given the data consistency (6) and the covariance's relationship (5) the GME objective function relative to our formulation problem may be formulated as:

$$\max_{p_i, w_i} H(p, w) = -p' \ln p - w' \ln w \tag{7}$$

for i = 1,2,..,N , subject to:

(*i*) data consistency conditions (6):

(*ii*) adding-up constraints:

$$\begin{aligned} &1_{K_i}(\mathrm{I}_{K_i} \otimes 1'_M)\, p_i, \qquad \text{for} \quad i = 1,2,..N;\ K = \sum_i K_i; \\ &1_{T_i}(\mathrm{I}_{T_i} \otimes 1'_J)\, w_i, \qquad \text{for} \quad i = 1,2,..N;\ T = \sum_i T_i. \end{aligned} \tag{8}$$

where p = (p_1, p_2, .., p_K)'and w = (w_1, w_2, .., w_N)'.

The solution to the system of equations related to the first-order conditions produce the following point estimates:

$$\hat{\beta}_k = \sum_{m=1}^{M} \hat{p}_{km} z_m \qquad k = 1,\dots, K \qquad \hat{\varepsilon}_i = \sum_{j=1}^{J} \hat{w}_{ij} v_i \qquad i = 1,\dots, N. \quad . \tag{9}$$

To allow the possibility of non-zero covariances for errors it is possible to specify, within the GME formulation, an additional set of restrictions which is based on a particular error covariance structure and incorporates the known *a priori* information of contemporaneous

correlations among the disturbance terms in the equations of the system (Bernardini Papalia, 2002).
For the empirical analysis on regional convergence three points of interest should be noted here. First, the system estimation approach facilitates testing of hypotheses involving cross equation restrictions such as testing the equality of total factor productivities in two neighboring regions. Second, by using the GME procedure it is possible to derive an estimator even if the number of regions involved, N, is more than the number of time periods, T, and the corresponding variance-covariance matrix for errors is singular. Third, estimates are computed without imposing strong distributional assumptions.

4. Step II - Procedure: specification of the spatial multiple regimes model

The second step of our approach is focused on the specification of a spatial multiple regimes model in which the sample is divided into groups identified by the first step results and the spatial dependence is incorporated into the model.
In spatial process models, one proceeds by specifying the spatial process and by choosing an appropriate spatial weights matrix that must not contain any of the exogenous or endogenous variables used in the growth regression.
Let us consider two clubs only, indicated by the indices A and B. Clubs correspond to subsets of regions identified by means of the mapping analysis. Each club may be represented by a cross-sectional equation. By considering the system of two equations, one for each regime, A and B, the *two-club growth regression model* can formally be represented as:

$$\begin{bmatrix} Y_A \\ Y_B \end{bmatrix} = \begin{bmatrix} X_A & 0 \\ 0 & X_B \end{bmatrix} \begin{bmatrix} \beta_A \\ \beta_B \end{bmatrix} + \begin{bmatrix} \varepsilon_A \\ \varepsilon_B \end{bmatrix} \tag{10}$$

where Y_A and Y_B are the dependent variables; X_A and X_B include the explanatory variables, β_A and β_B are the coefficients, and ε_A and ε_B are the errors in the respective clubs A and B of regions. Let N_A and N_B denote the number of regions in club A and club B, respectively, so that $N = N_A + N_B$. Here Y_A and Y_B are $(N_A T\times 1)$ and $(N_B T\times 1)$ vectors of observations on the dependent variable (per capita GDP growth rate) for the N_A and N_B regions and t = 1, ..,T time periods, respectively. *X* is a set of explanatory variables suggested by the theory, comprising, the lag of per capita GDP level, the investment rate in physical capital and in human capital, the sum of the population growth rate, the exogenous technological growth rate, and the depreciation rate.
The single block structure of the two-club model (10) expressed by a single equation results:

$$Y^* = X^* \beta^* + \varepsilon^* \tag{11}$$

where the variables without subscript refer to combined variables, coefficients and error matrices.
The model with a constant error variance over the whole set of observations:

$$\Phi = \sigma^2 I_N \tag{12}$$

refers to the *classical two-club convergence model* that we indicate with M_0 model.
The *two-club convergence model with groupwise heteroskedasticity* (M_1) assumes an error variance that is different in each of the clubs of regions:

$$\Phi = \begin{bmatrix} \sigma_A^2 I_A & 0 \\ 0 & \sigma_B^2 I_B \end{bmatrix} \tag{13}$$

where σ_A^2 and σ_B^2 denote club-specific constant error variances, I_A and I_B are identity matrices of dimensions N_A and N_B.

In both model specifications, a spatial error dependence (spatial autocorrelation) can represent a problem in the situation where the error term at each region is correlated with values of the error term at other regions. In these cases, the above two-club convergence models are misspecified and it is necessary to specify a spatial process for the disturbance terms ε*.
The most common specification is a spatial autoregressive process in the error terms ε*, Spatial Error Model (SEM), which leaves unchanged the systematic component and models the error term by assuming (Anselin-Bera, 1998):

$$\varepsilon^* = \lambda \omega \varepsilon^* + \mu^* \tag{14}$$

Where ω is the spatial weights matrix of dimension NT by NT, λ is a scalar spatial autoregressive coefficient for the spatial error ε*, and μ^* is a $(NT\times 1)$ vector of iid errors with variance $\sigma^2_{\mu^*}$.
This specification allows the convergence process to be different across regimes and in the same time it deals with spatially autocorrelated errors. However, spatial effects are assumed to be identical within each club, but all the regions are still interacting spatially through the spatial weight matrix W. Note that model M_1 assumes that spatial effects are identical also across spatial clubs[7].
In this case, it is observed how a random shock in a region affects growth rates in that region and additionally impacts all the other regions through the spatial transformation by recognizing the presence of global externalities associated solely with random shocks.
Depending on the structure of the error variance in club A and club B, we can specify different *two-club spatial error convergence models*.
Assuming a constant spatial structure for error variance in clubs A and B we have (M^0_{SEM} model):

$$E\left[\mu^* \mu^{*\prime}\right] = \sigma^2_{\mu^*} I_N$$

and the overall variance-covariance matrix takes the form:

$$\Phi = \sigma^2_{\mu^*} \left(A'A\right)^{-1}, \tag{15}$$

where:

$$\varepsilon^* = A^{-1}\mu^*, \qquad A = \left(I_N - \lambda\omega\right). \tag{16}$$

Assuming that the two clubs have different error variances $\left(\operatorname{var}\left[\mu^*_A\right] = \sigma^2_{\mu^*_A} \neq \operatorname{var}\left[\mu^*_B\right] = \sigma^2_{\mu^*_B}\right)$ then (M^1_{SEM} model):

$$E\left[\mu^* \mu^{*\prime}\right] = \Omega = \begin{bmatrix} \sigma^2_{\mu^*_A} I_A & 0 \\ 0 & \sigma^2_{\mu^*_B} I_B \end{bmatrix}. \tag{17}$$

The spatial weights matrix W is a N by N positive and symmetric matrix which expresses for each observation (row) those regions (columns) that belong to its neighborhood set as non-zero elements, that is: for pairs of locations (i, j), $w_{ij} \neq 0$ for ‘neighbors’ and $w_{ij} = 0$ for others. It is common practice in the empirical growth studies to derive spatial weights from the location and spatial arrangements of observation by means of a geographic information system. In this case, regions are defined ‘neighbors’ when they are within a given distance of each other, i.e. $w_{ij} = 1$ for $d_{ij} \leq \delta$ and $i \neq j$, where d_{ij} is the great circle distance between the capital cities of region i and j, and δ is a critical cut-off value (distance-based contiguity), above which all interactions are assumed to be negligible.

[7] However, it is also possible to investigate the potential for differentiated spatial effects in modeling convergence, that is, a different λ coefficient for each regime.

More specifically, a spatial weights matrix W* is defined as follow:

$$w_{ij}^{*}=\begin{cases}0 & \text{if} \quad i=j \\ 1 & \text{if} \quad d_{ij}\le\delta, i\ne j \\ 0 & \text{if} \quad d_{ij}>\delta, i\ne j\end{cases}. \tag{18}$$

The elements of the row-standardized spatial weights matrix W (with elements of a row sum to one) result:

$$w_{ij}=\frac{w_{ij}^{*}}{\sum_{j=1}^{N}w_{ij}^{*}}, \qquad i,j=1,..,N. \tag{19}$$

An alternative way to incorporate the spatial effects on growth and convergence is through spatial autoregressive models (SAR), where a spatial lag of the dependent variable is included on the right hand side of the model. If W is a row-standardized matrix of spatial weights describing the structure and intensity of spatial effects, equation (11) is re-specified as follow:

$$Y^{*}=\gamma^{*}X^{*}+\rho WY+u \quad u\sim N(0,\sigma_{u}^{2}I), \tag{20}$$

where ρ is the parameter associated to the spatially lagged dependent variable WY that captures the spatial interaction effect indicating the degree to which the growth rate of per-capita GDP in one region is determined by the growth rates of its neighboring regions, after conditioning on the effect of X. The error term is assumed normally distributed and independently of X and WY, under the assumption that all spatial dependence effects are captured by the lagged term. In this case, it is observed how the performance of the dependent variable impacts all the other (neighbor) regions through the spatial transformation by recognizing the presence of global spillovers associated to GDP growth rates.

Finally, two other models are described only for completeness reasons. Another way to deal with spatial dependence is to introduce a set of exogenous spatial lag variables B that can include or not the lag of initial income per capita (spatial cross-regressive model, SCRM). This approach has the advantage of confining the spatial effects to selected explanatory variables and maintaining a strong link to theory. The SCRM formulation is a model which is local in scope.

$$Y^{*}=\gamma^{*}X^{*}+\rho WB+u^{*} \quad u^{*}\sim N(0,\sigma_{u^{*}}^{2}I), \tag{21}$$

In this case, the model gives estimates of both a direct and a spatially lagged effects of initial per capita GDP levels on the growth rates, besides estimates of spatially lagged effects of other explanatory variables. Another model, which is also local in scope, is the spatial moving average model (SMAM), where the error term for each region *i* is a function of a random error term for *i*, and the average of the error term for the neighbors of *i*:

$$Y^{*}=\gamma^{*}X^{*}+e \quad e=\tau W\xi+\xi, \tag{22}$$

where τ is the spatial moving average parameter.

5. Application: club convergence across Italian regions

The procedure developed in previous sections is employed in order to analyze conditional club convergence across Italian regions. The analysis is based on CRENOS data set covering the period 1960-1999 (details are reported in Appendix). Per capita GDP and other economic aggregates at constant 1995 prices are used. Real per capita GDP is calculated as a ratio of real GDP and population, the saving rate in physical capital is given by the ratio of total investment and GDP, and the investment rate in human capital is the ratio of enrollment in secondary school and population of age 14-19. Moreover, we add to the population growth rate, a constant value of 0.05 to take account of the exogenous technological growth rate and the depreciation rate. The district variable is a measure of the local degree of industrial district diffusion over the Italian regions; specifically, we consider the relative number of district identified by ISTAT in a region over the total number of Italian districts in 1991. All final data are expressed in logs and are calculated as 5-year averages to eliminate the business cycle component[8].

5.1 Step 1 - results

In the analysis of convergence across Italian regions a mapping analysis is implemented with the aim of identifying multiple regimes. Following the step I procedure, presented in section 3.1, we model the relationship which describes the evolution of regional per-capita GDP through a system of seemingly unrelated regression equations (SUR) with reference to the dynamic model (1) [9]. In order to overcome problems connected to collinearity of regressors and to the singularity of the error covariance matrix, a generalized maximum entropy approach, developed in section 3.2, is used.

Results obtained with the generalized maximum entropy (GME) approach are summarized for all regions in table 1. We consider the vector X_{it-1} = (sk_{it-1}, sh_{it-1}, ndx_{it-1}, *district*) to determine the steady state output, which consists of a set of region-specific explanatory variables suggested by the theory, including sk_{it-1} the saving rate in physical capital, ndx_{it-1} the sum of the population growth rate, the exogenous technological growth rate, and the depreciation rate. In addition, we also consider sh_{it-1}, the investment rate in human capital, by following the extended version by Mankiw, Romer and Weil (1992) and *district*, the district variable used as a *proxy* of the local degree of industrial district diffusion over the Italian regions.

With reference to the mapping analysis, we find geographic localisation to have a prevailing role after taking account of differences in human capital and of the uneven distribution of economic activities (see figure 1). Maps show two separated groups of regions, located in the North-Center and South of Italy with a bi-modal distribution of real per capita GDP (sigma convergence)[10]. Besides the result of two different regimes, we also observe that convergence clubs are spatially concentrated. Our mapping analysis contributes to the identification of two regimes in accordance with other studies focusing on Italian regions (Mauro and Podrecca, 1994; Cellini and Scorcu, 1995). For details on regional groupings see Table 2.

It is interesting to highlight that the dimensions of the map indicate groups of regions with 'homogeneous' rates of convergence. Such evidence related to the estimated regional rates of convergence indicates some empirically significant differences across groups of regions, and

[8] Other studies have taken averages over 5-*year* periods, like Islam (1995) and Caselli *et al*. (1996) among others.

[9] In SUR specification complete heterogeneity across regions is assumed and $(1+\lambda)$ and γ in eq. (1) become $(1+\lambda)_i$ and γ_i, respectively.

[10] The first dimension, the vertical axe in figure 1, can be interpreted as a separation between the Northern-Central and Southern regions, apart for Lazio. The second dimension (see below the horizontal axe in figure 1) contributes to isolate the regions that present some anomalies (Sicilia, Basilicata, Val D'Aosta, and Lazio), showing the relevance of the geographical location of a region as a source of (dis)advances in a context where economic activity is not homogenously distributed in space, but is concentrated in some areas.

the richest regions of Northern Italy attain the lowest growth convergence rates, while Southern regions experience the highest speeds of convergence (see table 1).

5.2 Step II - results

Having identified two different sub-groups of Italian regions, our objective is now the estimation of a system of two convergence equations, one for each regime. In addition, the presence of some residual spatial correlation is tested. We estimate the two-club growth regression model (12) by assuming a model specification in terms of per capita GDP growth rate (equation 2) for each regime. Again, as in section 5.1, X_i is a set of explanatory variables, comprising ln y_{it-1} the lag of per capita GDP level, sk_{it-1} the saving rate in physical capital, sh_{it-1} the investment rate in human capital, ndx_{it-1} the sum of the population growth rate, the exogenous technological growth rate, and the depreciation rate.

As a preliminary analysis to detect spatial correlation within regimes we have estimated a system of seemingly unrelated (SUR) equations (system 3a) without spatial effects, for the period 1960-1999. OLS estimates of the non spatial model shows significant coefficients of the lagged income (*ly*) and also supports the hypothesis of conditional convergence within each regime. This finding seems to favor the two-club convergence model rather than a single steady-state conditional convergence model[11].

In addition, by splitting the sample into four groups with a time span of ten years, ‘60s, ‘70s, ‘80s, ‘90s, we obtain diversified results[12]. More specifically, estimated rates of convergence are always different between regime A and B for all sub-periods. In the ‘60s, for regime B, the coefficient for *ly* is negative, supporting the hypothesis of conditional convergence, but it is not significant for regime A. In the ‘70s and ‘80s, the same coefficient is not significant for regimes A and B so this finding does not provide support for the hypothesis of conditional convergence, while in the 90s the coefficient for of the lagged income is negative and significant for regime A, and not significant for regime B[13]. Provided that the relative short time span may contribute to weaken our findings and previous evidence based on Italian data (Paci and Pigliaru, 1995; Cellini and Scorcu, 1995; Arbia *et al*., 2003) points in favor of a structural break at the beginning of the ‘70s, we focus our analysis on the period 1970-1999 and maximum likelihood estimates of the spatial model, as a system of two seemingly unrelated equations, are computed. Diagnostic tests for the presence of spatial effects are performed in the conditional convergence model (system 1). Test results suggest the presence of a significant level of spatial dependence among regions[14].

Both spatial error and spatial lag models are then estimated by assuming that spatial effects are identical across spatial regimes. The weight matrix is computed by means of the distance between the capital cities, where the critical cut-off value is given by the first quartile (such results are robust to some other definitions of the limit value, e.g. median). Results relative to the spatial error model are summarized in table 3. In table 4, analogous results are reported for

[11] A Moran's I test and two Lagrange multipliers tests (Lagrange multiplier, and robust Lagrange multiplier) are performed. The Moran’s I test is very powerful against both forms of spatial dependence. We find a value the Moran statistic of 2.133 (p-value 0.033). A clear evidence of spatial dependence comes from the robust Lagrange multiplier test (LM test=0.397/p-value=0.529 for error autocorrelation; LM test=8.494/p-value=0.004 for spatial lag).

[12] Tests for heteroskedasticity of errors (Breusch-Pagan and robust White test) are not significant, with reference to the whole sample (1960-1999) and for sub-periods (‘60s, ‘70s, ‘80s, and ‘90s).

[13] Detailed results for the whole sample (1960-1999) and for sub-periods (‘60s, ‘70s, ‘80s, and ‘90s) are available upon request.

[14] A Moran's I test and two Lagrange multipliers tests (Lagrange multiplier, and robust Lagrange multiplier) are performed. The Moran’s I test is very powerful against both forms of spatial dependence. We find a value the Moran statistic of 1.556 (p-value 0.12). A clear evidence of spatial dependence comes from the robust Lagrange multiplier test (LM test=3.341/p-value=0.068 for error autocorrelation; LM test=4.846/p-value=0.028 for spatial lag).

the spatial lag model. For the period 1970-99, some differences emerge by comparing estimates of error and lag models. In both specifications, we obtain different coefficients of the lagged per capita income for regime A and B, which yield convergence only for regime A (1.1%, for SEM model; 1.2% for SAR model)[15].

Moreover, the convergence across regime A regions in the 1970-99 period is concentrated in the last decade, given that the 70s and ‘80s exhibit lack of convergence (table 5). For regime B, the lack of convergence during the period 1970-99, if analyzed in its evolution over time, seems to indicate that Italian regions included in that regime tend to diverge (table 5).

With reference to other explanatory variables, for the period 1970-99 we observe that the effect of population growth rate (*lndx*) is negative and significant only in regime A.

However, the other regressors, namely the investment in physical capital (*lsk*) and in human capital (*lsh*), have not significant effects on growth[16]. We also report the results relative to the spatial coefficients ($\hat{\lambda}, \hat{\rho}$) in tables 3 and 4 that, by assumption, are equal for both regimes. Estimates of λ and ρ show positive values for the whole period 1970-99. Only for the spatial lag model we find a significant coefficient. Spatial effects are also checked in sub-periods analyses (table 5). Estimates of the spatial coefficients λ and ρ in all cases are not significant.

6. Remarks and conclusions

In this work a two step procedure has been developed with the aims of (i) identifying potential multiple regimes and economies whose growth behavior obeys a common statistical model, and (ii) estimating a spatial convergence club models that incorporates also spatial dependence among regions. Regime identification has been endogenously performed, by means of a mapping analysis. More specifically, by introducing a set of control variables in a conditional convergence growth model, TFP differentials across regions have been identified and used to determine multiple regimes. In this first phase of the analysis, an entropy-based estimation procedure has also been proposed in order to overcome problems of endogeneity and collinearity. In the second step of the procedure, a theoretically more satisfactory approach that directly incorporates spatial effects or externalities connected to relative location into the multiple regime model has been suggested.

With respect to the estimation procedure proposed in step-I, several advantages can be pointed out. The maximum entropy-based estimator is more efficient than traditional estimators, in particular when data constraints are included in the maximum entropy-based problem formulations. This procedure is able to produce estimates in models where the number of parameters exceeds the number of data points and in models characterized by a non-scalar identity covariance matrix. Prior information can be introduced by adding suitable constraints in the formulation without imposing strong distributional assumptions.

With respect to the mapping analysis which has been proposed as a suitable method to identify regimes, it is important to emphasize some points. First, it is possible to identify groupings of regional economies that are converging at different speed. Second, the number

[15] Analogous results are obtained without controlling for spatial autocorrelation. The rate of convergence is 0.0122 for Regime A, and 0.007 for Regime B and the hypothesis of a null rate cannot be rejected only for the latter one.

[16] The result related to human capital is standard in the literature on Italian regional growth, with the exception of Mauro (2002) who finds a positive value when controlling for unemployment. The impact of physical investment is consistent with previous empirical contributions (Mauro and Podrecca, 1994; Paci and Pigliaru, 1995; Cellini and Scorcu, 1997; Carmeci and Mauro, 2002). Carmeci and Mauro (2004) show that this finding has to be imputed to an untested constraint of homogeneity of private and public output-capital elasticity. Admitting heterogeneity, private investment has a positive effect, and public investment has not.

of clubs and the composition of groups of regions in each regime are endogenously recovered by means of map' dimensions, which depend on observed and unobserved effects relative to initial conditions, respectively.

The two-step approach has been employed to assess the existence of conditional convergence across Italian regions over 1960-1999 period. Remarkable differences in TFP levels have been detected, even when differences in human capital investment rates and in the intensity of economic activities have been considered. In synthesis, our results strongly support the presence of TFP heterogeneity across Italian regions. The key role of both technology spillovers through human capital accumulation and agglomeration economies within industrial districts as the relevant determinants of TFP differences has been confirmed by our results. More specifically, results relative to the first step of the analysis have suggested some kind of heterogeneity across Italian regions: the convergence process if it exists, could be different across regimes and these clubs are also spatially concentrated. With reference to the second step procedure, both the two-club spatial error model and the two-club spatial autoregressive model have been implemented as suggested by the appropriate diagnostics, which have shown the presence of spatial dependence. Our analysis, while confirming the convergence club hypothesis across Italian regions over 1970-1999 period, has shown that global externalities are not associated with random shocks, but neighbors' growth rates tend to positively influence the economic performance of a region.

One important extension of our work is to investigate the potential for differentiated spatial effects in modeling club convergence by assuming that spatial effects are not identical across spatial regimes.

References

Abramovitz M. 1986. Catching-up, forging ahead and falling behind. *Journal of Economic History* 46: 385-406

Abreu M, de Groot HLF, Florax RJGM. 2004. Space and growth: a survey of empirical evidence and methods. *Région et Développement* 21: 12-43

Anselin L, Bera A. 1998. Spatial dependence in linear regression models with an introduction to spatial econometrics. In *Handbook of Applied Economic Statistics*, Ullah A, Giles D (eds). Springer: Berlin.

Arbia G, Basile R, Salvatore M. 2003. Measuring spatial effects in parametric and nonparametric modelling of regional growth and convergence, *mimeo*.

Barro RJ, Sala-i-Martin X. 1997. Technological diffusion, convergence, and growth. *Journal of Economic Growth* 2: 1-26

Barro RJ, Sala-i-Martin X. 2004. *Economic Growth.* MIT Press: London.

Basile R, de Nardis S, Mantuano M. 2003. Multiple regimes in cross-region growth regressions with spatial dependence: a parametric and a semi-parametric approach. Proceedings of the ECRSA 2003.

Bernardini Papalia R. 2002. Analyzing partial-incomplete economic data generation processes using maximum entropy. In *Proceedings of the International Conference on Improving Surveys*. Copenhagen.

Canova F. 2004. Testing for convergence clubs in income per capita: a predictive density approach. *International Economic Review* 45(1): 49-77.

Carmeci G. and Mauro L. 2002. The convergence of the Italian regions and unemployment: theory and evidence. *Journal of Regional Science* 42(3): 509-532.

Carmeci G. and Mauro L. 2004. A positive effect of investment on Italian regional growth. *RISEC* 51(3): 423-445.

Caselli F, Esquivel G, Lefort F. 1996. Reopening the convergence debate: a new look at cross-country growth empirics. *Journal of Economic Growth* 1(3): 363-390.

Cellini R, Scorcu A. 1995. How many Italies? Working paper n. 215, Dipartimento di Scienze Economiche, Università degli Studi di Bologna.

Corrado L, Martin R, Weeks M. 2005. Identifying and Interpreting Convergence Clusters Across Europe. *Economic Journal* 115(502): C133-C160

Desdoigts A. 1999. Patterns of economic development and the formation of clubs. *Journal of Economic Growth* 4(3): 305–330

Durlauf S, Johnson P. 1995. Multiple regimes and cross country growth behavior. *Journal of Applied Econometrics* 10(4): 365-384

Durlauf S, Kourtellos A, Minkin A. 2001. The local Solow growth model. *European Economic Review* 45(4-6): 928-940

Ertur C, Le Gallo J, Baumont C. 2006. The European regional convergence process, 1980-1995: do spatial regimes and spatial dependence matter? *International Regional Science Review* 29(1): 3-34

Fischer MM, Stirboeck C. 2004. Regional income convergence in the enlarged Europe, 1995-2000: a spatial econometric perspective. *Annals of Regional Science* 40(3): 1-29

Galor O. 1996. Convergence? Inferences from theoretical models. *Economic Journal* 106: 1056-1069

Galor O. 2005. From stagnation to growth: unified growth theory. In *Handbook of Economic growth* Aghion P, Durlauf S (eds). Elsevier: New-York.

Galor O, Tsiddon D. 1997. The distribution of human capital and economic growth. *Journal of Economic Growth* 2(1): 93-124

Golan A, Judge G, Miller D. 1996. *Maximum entropy econometrics: robust estimation with limited data.* Wiley: New York.

Golan, A, Judge G, Miller D. 1997. The maximum entropy approach to estimation and inference: an overview. In *Applying Maximum Entropy to Econometric Problems,* Fomby TB, Hill RC (eds): 3-24. Jai Press Ltd. England: London.

Islam N. 1995. Growth empirics: a panel data approach. *Quarterly Journal of Economics* 110: 1127-1170

Judge G, Giffiths WE, Lutkephol H, Lee TS. 1988. *Introduction to the theory and practice of econometrics*. Wiley: New York.

Lee K, Pesaran MH, Smith R. 1995. Growth and convergence in a multi-country empirical stochastic Solow model. *Journal of Applied Econometrics* 12(4): 357-392

Le Gallo J, Dall'Erba S. 2006. Evaluating the temporal and the spatial heterogeneity of the European convergence process, 1980-1999. *Journal of Regional Science* 46(2): 269-288.

Lucas RE. 1988. On the mechanics of economic development. *Journal of Monetary Economics* 22: 3-42

Mankiw NG, Romer D, Weil DN. 1992. A contribution to the empirics of growth. *Quarterly Journal of Economics* 107: 407-437

Mauro L. 2002. Human capital and the regional Italian growth: why does unemployment matter? *Rivista di Politica Economica* 62: 127-154

Mauro L, Podrecca E. 1994. The Case of Italian Regions: Convergence or Dualism? *Economic Notes* 24(3): 447-472

Pesaran MH, Smith R. 1995. Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics* 68: 79-113

Quah D. 1996. Regional convergence clusters across Europe. *European Economic Review* 40: 951-958

Paci R, Pigliaru F. 1995. Differenziali di crescita tra le regioni italiane: un'analisi cross-section. *Rivista di Politica Economica* 85(10): 3-34

Rey SJ, Montouri BD. 1999. U.S. regional income convergence: a spatial econometric perspective. *Regional Studies* 33: 143-156
Solow R. 1956. A contribution to the theory of economic growth. *Quarterly Journal of Economics* 70: 65-94
Tsionas EG 2000. Regional Convergence and Common, Stochastic Long-run Trends: A Re-examination of the US Regional Data. *Regional Studies* 35(8): 689-696
Zellner A. 1997. A Bayesian method of moments (BMOM): theory and applications. *Advances in Econometrics*, Vol. 12. *Applying Maximum Entropy to Econometric Problems*, Formby TB, Hill RC (eds): 85-105. JAI Press: Grenwich

APPENDIX: Description of data

Table A: Description of CRENOS 1960-2000 data set
(monetary values at 1995 constant prices)

Description of variables	
Gross Domestic Product at market prices	Monetary values in millions of Euro
Gross fixed investment	Monetary values in millions of Euro
Population	Demographic variables in thousand of units
Enrollment in secondary school	Demographic variables in thousand of units
Population of age 14-19	Demographic variables in thousand of units

Table B: Time intervals – 5-year averages

Time	**Interval**
1975	1970-1974
1980	1975-1979
1985	1980-1984
1990	1985-1989
1995	1990-1994
2000	1995-1999
2001	2000-2001

Table C: Description of regressors
(variables are in logs)

ly	lagged per capita GDP
lsk	lagged investment in physical capital
lsh	lagged investment in human capital
lndx	lagged population growth rate + 0.05
district	ratio of the number of districts in a region over the number of districts in Italy

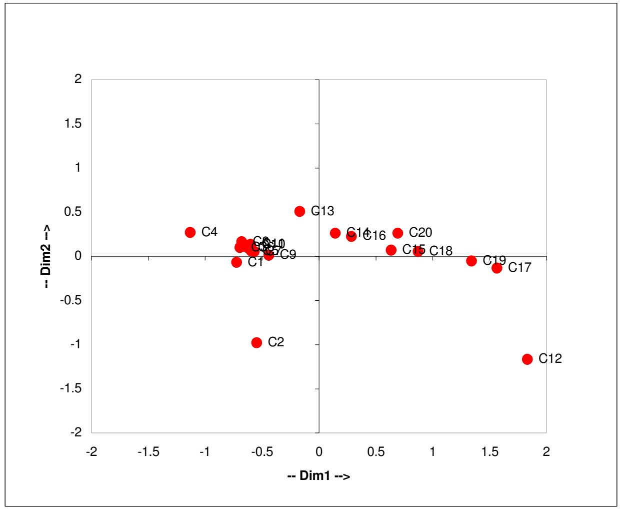
Tables and Figures

Table 1. Results of Step I - Procedure: Max Entropy estimates
Dependent variable: (log of) per capita GDP level at time t

Region	ly	lsk	lsh	lndx	district	Rate of conv.
C1	0.62	-0.0004	0.004	-0.002	-0.0003	0.0951
C2	0.53	-0.0003	0.008	-0.002	-0.0005	0.1264
C3	0.63	-0.0007	0.005	-0.002	-0.0002	0.0925
C4	0.68	-0.0002	0.006	-0.001	-0.0003	0.0760
C5	0.62	-0.0005	0.005	-0.001	-0.0002	0.0944
C6	0.63	-0.0004	0.004	-0.001	-0.0004	0.0921
C7	0.62	-0.0009	0.003	-0.002	-0.0004	0.0955
C8	0.64	-0.0004	0.003	-0.001	-0.0002	0.0882
C9	0.61	-0.0005	0.0002	-0.001	-0.0002	0.0991
C10	0.63	-0.0007	0.003	-0.0005	0.003	0.0919
C11	0.63	-0.0004	0.003	-0.001	-0.0003	0.0916
C12	0.12	-0.001	0.007	-0.005	-0.001	0.4193
C13	0.66	-0.0005	0.003	-0.0003	-0.0002	0.0829
C14	0.62	0.0001	0.003	0.0001	-0.0003	0.0949
C15	0.58	-0.0006	0.004	-0.001	-0.0002	0.1087
C16	0.62	-0.0005	0.003	-0.001	-0.0005	0.0956
C17	0.48	-0.001	0.009	-0.0002	-0.0005	0.1459
C18	0.56	-0.0002	-0.014	-0.001	-0.0002	0.1151
C19	0.52	-0.0005	0.005	-0.001	-0.0004	0.1293
C20	0.61	-0.0006	0.004	-0.001	-0.0004	0.0972
Average	**0.58**	**-0.0005**	**0.003**	**-0.001**	**-0.0002**	**0.1081**

Explanatory variables: *ly*, *lsk*, *lsh*, *lndx*, and *district* are lagged per capita GDP level, lagged investment rates in physical and human capital, lagged sum of population growth rate and 0.05, and district intensity, respectively.
Regions: C1: Piemonte, C2 : Val d'Aosta, C3: Lombardia, C4: Trentino Alto Adige, C5: Veneto, C6: Friuli Venezia Giulia, C7: Liguria, C8: Emilia Romagna, C9: Toscana, C10: Umbria, C11: Marche, C12: Lazio, C13: Abruzzo, C14: Molise, C15: Campania, C16: Puglia, C17 Basilicata, C18: Calabria, C19: Sicilia, C20: Sardegna

Figure 1. Two-dimensional MDS solution (GME estimates)



Regions: C1: Piemonte, C2 : Val d'Aosta, C3: Lombardia, C4: Trentino Alto Adige, C5: Veneto, C6: Friuli Venezia Giulia, C7: Liguria, C8: Emilia Romagna, C9: Toscana, C10: Umbria, C11: Marche, C12: Lazio, C13: Abruzzo, C14: Molise, C15: Campania, C16: Puglia, C17 Basilicata, C18: Calabria, C19: Sicilia, C20: Sardegna

Table 2. Description of Italian regions (regional code in brackets)

Regimes	Regions
REGIME A	PIEMONTE (C1) VAL D'AOSTA (C2) LOMBARDIA (C3) TRENTINO ALTO ADIGE (C4) VENETO (C5) FRIULI VENEZIA GIULIA (C6) LIGURIA (C7) EMILIA ROMAGNA (C8) TOSCANA (C9) UMBRIA (C10) MARCHE (C11) ABRUZZO (C13)
REGIME B	LAZIO (C12) MOLISE (C14) CAMPANIA (C15) PUGLIA (C16) BASILICATA (C17) CALABRIA (C18) SICILIA (C19) SARDEGNA (C20)

Table 3: Results of Step II – Procedure:
SEM model – ML estimates, 1970-1999

	Regime A		
	Coefficient	**Std. Err.**	**t**
ly	-0.0518	0.0262	-1.98
lsk	-0.0027	0.0234	-0.12
lsh	-0.0272	0.0340	-0.8
lndx	-4.5853	2.2157	-2.07
constant	0.225		
Rate of conv.*	0.011		
	Regime B		
	Coefficient	**Std. Err.**	**t**
ly	-0.0345	0.0577	-0.6
lsk	0.0013	0.0268	0.05
lsh	0.0061	0.0696	0.09
lndx	-0.9948	2.7989	-0.36
constant	0.1777	0.1510	1.18
Rate of conv.*	0.007		
λ	0.3118	0.4111	0.76

*Wald test on H_0 : Rate of conv. = 0.
For regime A, χ^2=3.72 (p-value=0.05);
for regime B, χ^2=0.35 (p-value=0.56).

Table 4: Results of Step II – Procedure:
SAR model – ML estimates, 1970-1999

	Regime A		
	Coefficient	**Std. Err.**	**t**
ly	-0.0602	0.0203	-2.96
lsk	-0.0048	0.0232	-0.21
lsh	-0.0187	0.0267	-0.7
lndx	-4.4432	2.030	-2.19
constant	0.196		
Rate of conv.**	0.012		
	Regime B		
	Coefficient	**Std. Err.**	**t**
ly	-0.0416	0.0551	-0.76
lsk	0.0034	0.0219	0.16
lsh	0.0114	0.0680	0.17
lndx	-0.9317	2.6063	-0.36
constant	0.1557	0.1506	1.03
Rate of conv.**	0.009		
ρ	0.4689	0.2618	1.79

**Wald test on H_0 : Rate of conv. = 0.
For regime A, χ^2=8.25 (p-value=0.004);
for regime B, χ^2=0.55 (p-value=0.46).

Table 5: Results of Step II – Procedure
Conditional convergence rates and spatial effects coefficients
ML estimates – sub-periods

NO SPATIAL EFFECTS	*Spatial effect*	*Rate of convergence*	
		Regime A	*Regime B*
60s		0.012	0.056
70s		0.006	0.034
80s		0.016	-0.005
90s		0.030	-0.008
SPATIAL ERROR MODEL	λ	*Rate of convergence*	
		Regime A	*Regime B*
60s	-0.108	0.011	0.059
70s	0.045	0.005	0.033
80s	-0.394	0.016	0.002
90s	-0.107	0.032	-0.007
SPATIAL LAG MODEL	ρ	*Rate of convergence*	
		Regime A	*Regime B*
60s	0.0429	0.011	0.054
70s	0.2109	0.004	0.030
80s	-0.2627	0.015	-0.006
90s	0.1454	0.029	-0.007