Spatial Econometric Analysis of the Evolution of the European Regional Convergence Process, 1980-1999

Abstract:

In this paper, we assess the evolution of the convergence process between 145 European regions over 1980-1999. In that purpose, we use the formal tools of spatial econometrics to identify and include the relevant spatial effects in the estimation of the appropriate β-convergence model for two sub-periods (1980-1989 and 1989-1999). While a spatial error model is the best specification for both periods, we detect spatial heterogeneity in the form of structural instability and groupwise heteroskedasticity only in the second period. These results highlight the formation of a convergence club between the peripheral regions of the European Union and a differentiation between the convergence process of the core regions and the one of the peripheral regions. Therefore, all the regions do not converge to the same steady-state anymore and this process is dependent upon each region's geographic location.

Keywords: β-convergence, convergence clubs, European regions, spatial econometrics

JEL Classification: C21, O52, R11, R15

INTRODUCTION

In Europe, following the successive enlargements during the 80's to the Southern and less developed countries (Greece in 1981, Spain and Portugal in 1986), the regional inequalities became so obvious and unacceptable, both on equity and policy grounds, that the European Commission decided to devote as much as one-third of its budget to foster cohesion. The process of accelerating deeper integration also required greater cohesion efforts among members. Indeed, the 1986 Single Act was the basis of the Single Market with the aim of ensuring free circulation of goods and people among member countries. A necessary condition for this policy stood in the creation of transportation infrastructures, able to link to the core even the most remote regions. Convergence efforts were also necessary before the implementation of the single currency. Indeed, according to the theory of optimal currency areas, initiated by Mundell (1961), cohesion ensures that the member countries will be equally affected by external shocks and will not be destabilized by the imposition of a common monetary policy.

However, if the process of integration and the massive amount of regional funds allocated by the European Commission since 1989 have succeeded in decreasing income differences among member States over the past two decades, regional inequalities have increased within numerous countries and peripheral regions stay less developed than those located in the core (Neven and Gouyette, 1995; Quah, 1996; Martin, 1999). Therefore, it seems that deeper integration and regional development funds devoted to transportation infrastructures have both contributed to dismantling trade barriers and reducing transportation costs between regions. In the presence of increasing returns and spatially limited externalities, it has led to an agglomeration of productive activities in the richest and centrally located areas (Krugman, 1991a, 1991b; Vickerman, 1991; Martin, 1999).

Economic integration and cohesion efforts devoted to the less developed regions have had an effect on the convergence process between the European regions since the eighties, but the question as to whether they have fostered the convergence process remains open. In the absence of data allowing for a direct estimation of their impact, this paper focuses on the convergence process between 145 European regions over 1980-1999. More precisely, we evaluate whether some form of temporal heterogeneity is present by decomposing this total period into two subperiods: 1980-1989 and 1989-1999. The choice of this temporal decomposition is firstly due to data availability. Indeed, given the size of our sample, the REGIO database is not able to provide more ancient data and we prefer avoiding lack of homogeneity due to the combination of different databases. Moreover, the year 1989 has the advantage of separating our total period in two equivalent sub-periods and it also corresponds to the considerable development of regional policies and the reform of structural funds.

From a methodological point of view, this paper is not based on the same methods and assumptions than those used for cross-countries convergence analysis, following the well-known studies performed by Barro and Sala-I-Martin (1991, 1995). On the contrary, we follow the regional science literature (see, for instance, Fingleton, 1999; Rey and Montouri, 1999) and avoid considering the regions as "isolated islands" (Quah, 1996). In that purpose, we use the tools of spatial econometrics to formally take account of the spatial environment of each region and their potential interregional links. Specifically, we aim at avoiding bias in statistical inference due to omitted spatial effects in order to obtain more reliable estimates of the convergence rate. These spatial effects are spatial autocorrelation and spatial heterogeneity. Using spatial econometrics methods also allows estimating the magnitude of geographical spillover effects in regional growth processes and detecting spatial convergence clubs. We therefore suggest in this paper an empirical evaluation of the convergence process between European regions focusing both on its spatial dimension and on its temporal evolution.

The paper proceeds as follows: section 1 provides some insights into the β-convergence model and spatial effects upon which the empirical estimations described in the following sections rely. Section 2 presents the data and weights matrix. In Section 3, exploratory spatial data analysis (ESDA) is used to detect spatial autocorrelation and spatial heterogeneity among European regional GDP. These two spatial effects are then included in the estimation of the appropriate β-convergence model, first over the 1980-1989 period, second over the 1989-1999 period. The last section provides some concluding remarks.

I. β-CONVERGENCE MODELS AND SPATIAL EFFECTS

1. β-convergence models

Since the publication of the seminal articles of Barro and Sala-i-Martin (1991, 1992, 1995), a very large number of studies have examined β–convergence between different countries and regions for different time periods [1]. This concept is linked to the neoclassical growth model, which predicts that the growth rate of a region is positively related to the distance that separates it from its own steady-state. Empirical evidence for β-convergence is investigated by regressing growth rates of GDP on its initial levels. Two cases are usually considered in the literature.

If all economies are structurally identical and have access to the same technology, they are characterized by the same steady state and differ only by their initial conditions. This is the hypothesis of *absolute* β–convergence, which is usually tested on the following cross-sectional model, in matrix form:

$$g_T = \alpha e_N + \beta y_0 + \varepsilon \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I) \qquad (1)$$

where g_T is the (N×1) vector of average growth rates of per capita GDP between date 0 and T; e_N is the (N×1) vector composed of unit elements; y_0 is the vector of log per capita GDP levels at date 0; α and β are the unknown parameters to be estimated. There is absolute β–convergence when the estimate of β is significantly negative. This hypothesis is typically supported when applied to data from relatively homogenous groups of economic units, such as US states, OECD countries or European regions.

The concept of *conditional* β–convergence is used when the assumption of similar steady-states is relaxed. Note that if economies have very different steady states, this concept is compatible with a persistent high degree of inequality among economies. In this case, a matrix of variables maintaining constant the steady-state is added in equation (1) [2]. It is usually tested on the following cross-sectional model:

$$g_T = \alpha e_N + \beta y_0 + X\phi + \varepsilon \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I) \qquad (2)$$

with the same notations as above and X is a matrix of variables, maintaining constant the steady state of each economy. There is conditional β–convergence if the estimate of β is significantly negative once X is held constant.

Both β-convergence concepts have been heavily criticized on theoretical and methodological grounds. From a theoretical point of view, Friedman (1992) and

Quah (1993) show that the interpretation of the β-convergence tests may be plagued by Galton's fallacy of regression toward the mean. However, the study by Le Gallo (2004), based on a Markov chains approach, indicates that the mobility of European regions in the distribution of per capita GDP over the 1980-1995 period is very limited, so that this problem is not relevant for our case study. Furthermore, these tests face several methodological problems such as robustness with respect to choice of control variables, multicolinearity, heterogeneity, endogeneity, and measurement problems (Durlauf and Quah 1999; Temple 1999; Durlauf *et al*., 2005). Therefore, other estimation methods and convergence concepts have been suggested: panel data techniques (Islam, 1995; Lee *et al*., 1998; McCoskey, 2002), time-series techniques (Bernard and Durlauf, 1995; Linden, 2002; Nahar and Inder, 2002; Maeso-Fernandez F., 2003) or distribution analysis (Quah, 1996; Fingleton, 1999; Le Gallo, 2004).

In this paper, we point out that the spatial dimension of the data used in these studies raises particular identification, estimation and interpretation issues. The first study highlighting these potential problems is the one of De Long and Summers (1991) who explain that the assumption of independence across residuals is untenable. Mankiw (1995) and Temple (1999) also draw attention on error correlation and geographic spillovers between economic units. As pointed out by Abreu *et al.* (2005), the spatial dimension of data is usually modelled in two different ways: models of absolute location and models of relative location. Absolute location refers to the impact of being located at a particular point in space (continent, climate zone) and is usually captured through dummy variables (Barro, 1991; Ades and Chua, 1997). Relative location refers to the effect of being located closer or further away from other specific countries or regions and its effects should be analyzed through the methods of spatial econometrics (Anselin, 1988, 2001). Abreu *et al.* (2005) add that the distinction between models of absolute and relative location can be related to a similar classification used in spatial econometrics, i.e. the distinction between spatial heterogeneity and spatial dependence. We now present these two effects in detail in the convergence context.

2. Spatial autocorrelation

Spatial autocorrelation refers to the coincidence of attribute similarity and locational similarity (Anselin, 1988, 2001). Therefore, there is positive spatial autocorrelation when high or low values of a random variable tend to cluster in space and there is negative spatial autocorrelation when geographical areas tend to be surrounded by neighbors with very dissimilar values. In the context of European regions, positive spatial autocorrelation means that rich regions tend to be geographically clustered as well as poor regions. It may come from the fact that the data are affected by processes touching different locations. Indeed, at the regional scale, several factors, such as trade between regions, labor and capital mobility, technology and knowledge diffusion, etc. may lead to spatially interdependent regions. Note that the inclusion of spatial autocorrelation in convergence models can even be motivated theoretically. Indeed, Koch (2004), Lopez-Bazo *et al.* (2004) and Vaya *et al.* (2004) have recently derived neoclassical models with spatial externalities yielding to convergence models including spatial autocorrelation. Spatial autocorrelation can also arise from model misspecifications (omitted variables, measurement errors) or from a variety of measurement problems, such as boundary mismatching between the administrative boundaries used to organize the data and the actual boundaries of the economic processes believed to generate regional convergence (Cheshire and Carbonaro, 1995).

Spatial concentration of economic activities in European regions has already been documented in Lopez-Bazo *et al.* (1999), Le Gallo and Ertur (2003), Dall'erba (2005) with the formal tools of spatial statistics. It is therefore important to incorporate explicitly spatial autocorrelation into β-convergence models (Armstrong, 1995; Moreno and Trehan, 1997; Fingleton, 1999, 2001; Rey and Montouri, 1999). Formally, several econometric models can be used to deal with spatially dependent observations (Anselin, 1988, 2001; Anselin and Bera, 1998). Here, we present the spatial lag and the spatial error models. In the spatial lag model, an endogenous variable of the form Wg_T is introduced in model (1) as follows:

$$g_T = \rho W g_T + \alpha e_N + \beta y_0 + \varepsilon \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I) \tag{3}$$

where W is an $(N \times N)$ spatial weights matrix where each element (i,j) exogenously defines the way regions i and j are spatially connected to each other. When W is row-standardized, the spatial lag variable Wg_T contains the spatially weighted average of the growth rates of the neighboring regions. The parameter ρ indicates the level of spatial interaction between regions. This specification allows measuring how the growth rate in a region may relate to the one in its surrounding regions after conditioning on the starting levels of per capita GDP. Since the spatial lag is a stochastic regressor, which is always correlated with ε, estimation of this model by OLS produces inconsistent estimators; it must therefore be estimated by Maximum Likelihood (ML) or Instrumental Variables (IV).

Alternatively, spatial autocorrelation can be introduced by means of the error term:

$$g = \alpha e_N + \beta y_0 + \varepsilon \qquad \varepsilon = \lambda W \varepsilon + u \qquad u \sim N(0, \sigma_u^2 I) \tag{4}$$

where λ indicates the level of spatial autocorrelation between error terms of neighboring regions. Spatial autocorrelation in the error terms may arise because of omitted variables or measurement problems. Since the errors are non-spherical, estimation of this model by OLS yields inefficient estimators; it must therefore be estimated by ML or Generalized Method of Moments (GMM). This model can be rewritten in another form, which can be interpreted as a minimal model of conditional β–convergence integrating two spatial environment variables (Le Gallo *et al.*, 2003). Indeed, pre-multiplying equation (4) by $(I-\lambda W)$ yields:

$$(I-\lambda W)g_T = \alpha(I-\lambda W)e_N + \beta(I-\lambda W)y_0 + (I-\lambda W)\varepsilon \qquad (5)$$

Since $\left(I-\lambda W\right)\varepsilon = u$, then model (5) can be rewritten as :

$$g_T = \alpha(I-\lambda W)e_N + \beta y_0 + \lambda W g_T + \gamma W y_0 + u \qquad (6)$$

with the restriction $\gamma = -\lambda\beta$. The model (6) is called the *spatial Durbin model*. It can be estimated by ML and highlights two forms of geographic spillover effects: the average growth rate of a region *i* is influenced by the average growth rates (through Wg_T) and the initial per capita GDP (through Wy_0) of its neighboring regions. The restriction $\gamma + \lambda\beta = 0$ can be tested by means of the common factor test (Burridge, 1981). If it cannot be rejected then model (6) reduces to model (4).

As can be seen from this technical presentation, integrating spatial autocorrelation into β-convergence models is useful for several reasons. First, it provides more reliable estimation and inference of the rate of convergence through the β parameter when the assumption of independence of error terms in OLS estimation is not met. Second, it allows capturing geographic spillover effects between European regions through the spatial lag variables.

3. Spatial heterogeneity

Spatial heterogeneity means that economic behaviors are not stable over space. In a regression model, spatial heterogeneity can be reflected by varying coefficients (structural instability) and/or by varying error variances across observations (groupwise heteroskedasticity) or both. These variations follow for example specific geographical patterns such as East and West, or North and South.

Spatial heterogeneity can be linked to the concept of convergence clubs, characterized by the possibility of multiple, locally stable, steady state equilibria (Durlauf and Johnson 1995). A convergence club is a group of economies whose initial conditions are near enough to converge toward the same long-term equilibrium. From a theoretical point of view, convergence clubs may be based on endogenous growth models characterized by multiple steady state equilibria (Azariadis and Drazen, 1990) or standard neoclassical growth models where heterogeneity across individuals is permitted (Galor, 1996).

When convergence clubs exist, standard convergence tests can have some difficulties to discriminate between these multiple steady state models and the standard Solow model (Durlauf and Johnson, 1995). In this case, one convergence equation should be estimated per club. To determine those clubs, some authors select *a priori* criteria, as the belonging to a geographic zone (Baumol, 1986) or some GDP per capita cut-offs (Durlauf and Johnson, 1995). Others prefer to use endogenous methods, as for example, polynomial functions (Chatterji 1992), cluster analysis (Pugno, 1996; Hobijn and Franses, 2001) or regression trees (Durlauf and Johnson, 1995; Berthélemy and Varoudakis, 1996). In the context of regional economies characterized by strong geographic patterns, like the core-periphery pattern, we will detect convergence clubs using exploratory spatial data analysis which relies on geographic criteria.

Formally, spatial heterogeneity can be modelled in two ways. First, let us consider the possibility of structural instability. For matter of representation, suppose that we have two clubs only, the core (indicated by *C*) and the periphery (indicated by *P*). Then, a different set of coefficients must be estimated for each club. A model of unconditional β-convergence for the two convergence clubs can then be specified as follows:

$$g_T = \alpha_C D_C + \alpha_P D_P + \beta_C D_C y_0 + \beta_P D_P y_0 + \varepsilon \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I) \tag{7}$$

where D_C and D_P are dummy variables qualifying the two regimes core and periphery. This specification allows the convergence process to be different across regimes. This model can also be formulated in matrix form as follows:

$$\begin{bmatrix} g_{T,C} \\ g_{T,P} \end{bmatrix} = \begin{bmatrix} S_C & y_{0,C} & 0 & 0 \\ 0 & 0 & S_P & y_{0,P} \end{bmatrix} \begin{bmatrix} \alpha_C \\ \beta_C \\ \alpha_P \\ \beta_P \end{bmatrix} + \begin{bmatrix} \varepsilon_C \\ \varepsilon_P \end{bmatrix} \tag{8}$$

with $\varepsilon' = \begin{bmatrix} \varepsilon_c' & \varepsilon_P' \end{bmatrix}$ and $\varepsilon \sim N(0, \sigma_\varepsilon^2 I)$.

This latter assumption of normally and independently distributed error terms may be overly restrictive. Assuming an error variance that is different in each club results in the second form of spatial heterogeneity, represented here as groupwise heteroskedasticity. Formally:

$$\varepsilon \sim N\left(0, \begin{bmatrix} \sigma_{\varepsilon,C}^2 I_C & 0 \\ 0 & \sigma_{\varepsilon,P}^2 I_P \end{bmatrix}\right) \tag{9}$$

where σ_C^2 and σ_P^2 denote the club-specific constant error variances; I_C and I_P are identity matrices of dimensions equal respectively to the number of observations in the core and in the periphery regime. Estimation can be carried out using FGLS or ML and the equality of variances can be tested for with likelihood ratio (LR) tests. The last two effects can be present at the same time. Finally, note that spatial autocorrelation may occur in conjunction with spatial heterogeneity.

At the cross-country level, studies explicitly incorporating spatial effects are relatively rare (Moreno and Trehan, 1997). They are more numerous for regional studies since spatial effects are more relevant and sample sizes are greater at a smaller scale, thus yielding more degrees of freedom. For example, Rey and Montouri (1999) and Lall and Shalizi (2003) integrate spatial autocorrelation in the estimation of β-convergence models between respectively US states and Brazilian *municipios*. Similarly, some articles dealing with European regions highlight the importance of spatial spillovers effects (Fingleton, 2000, 2003; Maurseth, 2001; Arbia and Paelinck, 2003a, b; Le Gallo *et al*., 2003; Carrington, 2003; Vaya *et al*., 2004) and/or the presence of strong spatial heterogeneity (Ertur *et al*., 2005) in the convergence process[3]. This article analyzes simultaneously spatial autocorrelation and spatial heterogeneity. In addition, we follow the approach of Barro and Sala-I-Martin (1995) and Neven and Gouyette (1995) and take into account the presence of temporal heterogeneity by subdividing our study period into two sub-periods.

II. DATA AND SPATIAL WEIGHTS MATRIX

The regional per capita GDP series are drawn out the most recent version of the NewCronos Regio database by Eurostat. This is the official database used by the

European Commission for its evaluation of regional convergence. We use the logarithms of the per capita GDP of each region over the 1980-1999 period. Our sample is composed of 145 regions at NUTS II level (Nomenclature of Territorial Units for Statistics) over 12 EU countries: Belgium (11 regions), Denmark (1 region), Germany (30 regions, Berlin and the nine former East German regions are excluded due to historical reasons), Greece (13 regions), Spain (16 regions, as we exclude the remote islands: Las Palmas, Santa Cruz de Tenerife Canary Islands and Ceuta y Mellila), France (22 regions), Ireland (2 regions), Italy (20 regions), Netherlands (12 regions), Portugal (5 regions, the Azores and Madeira are excluded because of their geographical distance), Luxembourg (1 region), United Kingdom (12 regions, we use regions at the NUTS I level, because NUTS II regions are not used as governmental units, they are merely statistical inventions of the EU Commission and the UK government) [4]. We are aware that our empirical results could be affected by missing regions and/or by the choice of our level of spatial aggregation. Indeed, the NUTS II level implies that regions have heterogeneous area and population sizes and this choice influences the magnitude of various measures of association. In fact, our decision is driven by the European Commission reports where the NUTS II level is used for the estimations of the convergence process. In addition, regional development objectives are mainly defined at this spatial level.

We now present the spatial weights matrix, on which all the following analyses rely. In the European context, the existence of islands doesn't allow considering simple contiguity matrices (two regions are considered to be connected if they share common borders); otherwise the weights matrix would include rows and columns with only zeros for the islands. Since unconnected observations are eliminated from the results of spatial autocorrelation statistics, this would change the sample size and the interpretation of the statistical inference. Following the recommendations of Anselin and Bera (1998), we choose to base them on pure geographical distance, as exogeneity of geographical distance is unambiguous. More precisely, we use the great circle distance between regional centroids. Formally, distance-based weights matrices are defined as:

$$\begin{cases} w_{ij}^*(k) = 0 \text{ if } i = j, \forall k \\ w_{ij}^*(k) = 1/d_{ij}^2 \text{ if } d_{ij} \leq D(k) \\ w_{ij}^*(k) = 0 \text{ if } d_{ij} > D(k) \end{cases} \quad \text{and} \quad w_{ij} = w_{ij}^* / \sum_j w_{ij}^* \quad \text{for } k = 1,\ldots 3 \qquad (10)$$

where w_{ij}^* is an element of the unstandardized weights matrix; w_{ij} is an element of the standardized weights matrix; d_{ij} is the great circle distance between centroids of region i and j; $D(1) = Q1$, $D(2) = Me$ and $D(3) = Q3$, $Q1$, Me and $Q3$ are respectively the lower quartile, the median and the upper quartile of the great circle distance distribution. $D(k)$ is the cutoff parameter for $k = 1,...3$ above which interactions are assumed negligible. We use the inverse of the squared distance, in order to reflect a gravity function. Each matrix is row standardized so that it is relative and not absolute distance which matters [5].

III. EVOLUTION OF THE CONVERGENCE PROCESS BETWEEN EUROPEAN REGIONS OVER 1980-1999

1. Detection of spatial regimes and methodology

Using the spatial weights matrices previously described, the first step of our analysis is to detect the existence of spatial heterogeneity in the distribution of regional per capita GDPs. In that purpose, we use the G-I* statistics developed by

Ord and Getis (1995) [6] on the regional per capita GDP values in 1980 [7]. These statistics are defined as following:

$$G_i^*(d) = \frac{\sum_j w_{ij} x_j - W_i^* \overline{x}}{s\left\{[(nS_{1i}^*) - W_i^{*2}]/(n-1)\right\}^{1/2}} \tag{11}$$

where w_{ij} is an element of the weights matrix W; $W_i^* = \sum_{j \neq i} w_{ij} + w_{ii}$; n is the size of the sample ; $S_{1i}^* = \sum_j w_{ij}^2$, $\overline{x}$ and s^2 are respectively the mean and variance of the sample. These statistics are computed for each region and they allow detecting the presence of local spatial autocorrelation: a positive value of this statistic for region i indicates a spatial cluster of regions with a high per capita GDP, whereas a negative value indicates a spatial clustering of regions with a low per capita GDP around region i. Based on these statistics, we determine our spatial regimes, which can be interpreted as spatial convergence clubs, using the following rule: if the statistic for region i is positive, then this region belongs to the group of "rich" regions and if the statistic for region i is negative, then this region belongs to the group of "poor" regions.

For all weights matrices described above, two spatial regimes, representative of the well-known core-periphery framework (Krugman 1991a, 1991b; Fujita *et al.*, 1999), are persistent over the period. They are represented in figure 1 and highlight some form of spatial heterogeneity:

- 96 regions belong to the spatial regime "rich" which is located in the core and thus will be called "Core" from now on:

Belgium, Germany, Denmark, France, Italy (but Umbria, Marche, Lazio, Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna), Luxembourg, the Netherlands, the United-Kingdom (but Northern-Ireland and Scotland).

- 49 regions belong to the spatial regime “poor” located in “Periphery”:

Spain, Greece, Ireland, Southern Italy (Umbria, Marche, Lazio, Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna), Portugal, the North of the United-Kingdom (Northern-Ireland and Scotland).

[Figure 1 around here]

Next, based on these two spatial regimes, we assess the evolution of the convergence process during 1980-1999 by estimating two β-convergence equations for both sub-periods 1980-1989 and 1989-1999. In order to detect the appropriate form of spatial autocorrelation and spatial heterogeneity, we use and adapt the classical “specific to general” specification search approach outlined in Anselin and Rey (1991) or Anselin and Florax (1995) using tests described in Anselin *et al.* (1996). Indeed, in the absence of a formal theory, this strategy provides ways to discriminate between a spatial lag and a spatial error model.

More specifically, they suggest Lagrange Multiplier (LM) tests (resp. LMERR and LMLAG) and their robust versions (resp. R-LMERR and R-LMLAG). The decision rule suggested by Anselin and Florax (1995) is then used to decide the most appropriate specification as follows: if LMLAG (resp. LMERR) is more significant than LMERR (resp. LMLAG) and R-LMLAG (resp. R-LMERR) is significant whereas R-LMERR (resp. R-LMLAG) is not, then the most appropriate model is the spatial autoregressive model (resp. the spatial error model). This choice can then be confirmed by performing additional LM tests: the common factor test and the test for an additional spatial lag in the presence of spatial error autocorrelation. Florax *et al.* (2003) show by means of Monte Carlo simulation that this classical approach outperforms Hendry’s “general to specific” approach.

There is no such formal strategy that has been suggested to detect the form of spatial heterogeneity. Therefore, we will complement the preceding strategy by computing the following tests: the Breusch-Pagan test and its spatially adjusted version (Anselin, 1988) to test for heteroskedasticity, an LR test for groupwise heteroskedasticity in addition to the Wald tests and their spatially adjusted versions (Anselin, 1990) to test for individual and global structural instability of the coefficients.

2. Convergence Process over 1980-1989

The OLS estimation results of the absolute β-convergence model (1) over 1980-1989 are displayed in table 1, using the squared inverse distance weights matrix $D(1)$ with cut-off equal to the first quartile of the distance distribution between the regions' centroids. This matrix has been chosen since it maximizes the value of Moran's I statistics adapted to regression residuals (Cliff and Ord, 1981). However, we will present some robustness analysis at the end of the section.

The results show that $\hat{\beta}$ has the expected sign ($\hat{\beta}$ = -0.015) and is significant (p-value = 0.000), highlighting the presence of significant absolute β-convergence among the European regions. It implies a convergence speed of 1.61% and a half-life of 45 years [8]. Looking at the diagnostic tests, it appears that the Jarque-Bera test does not reject the assumption of normality of the residuals (p-value = 0.518). We also note that the White test clearly rejects homoskedasticity (p-value = 0.004) as does the Breusch-Pagan test (p-value = 0.025) *versus* D_C, the dummy variable for the core regime. As a consequence, inference based on OLS may be biased. Moreover, as noted by Anselin (1988), the links between heteroskedasticity and spatial autocorrelation are strong and complex. In particular, the presence of the former can be due to the omission of the latter.

Figure 2 is the standard map of the residuals of model (1) estimated by OLS. As can clearly be seen from the map, they are not randomly distributed over the EU but spatial concentrations of similar values can be observed. Specifically, clusters of high residuals are to be found in Italy, South of Germany and Spain while clusters of low residuals are located in Greece, France, North Germany and Benelux. Spatial autocorrelation in the residuals is therefore highly probable. In order to detect the form taken by spatial autocorrelation, we apply the decision rule presented above. It appears that the spatial error model is the best specification: LMERR (227.009) is greater than LMLAG (208.042) and R-LMERR is significant whereas R-LMLAG is not.

[Table 1 and figure 2 around here]

Our next step is therefore the estimation of a spatial error model (model 4). The ML estimation results are also displayed in table 1. The level of convergence ($\hat{\beta}$=0.010) has decreased compared to the OLS-estimation, but is still significant. Compared to the OLS specification, the convergence speed has decreased (1.05%) and the half-life increased (67 years). The information criteria (AIC and SC) indicate that this model specification is better than the OLS-specification. We also note a positive and significant spatial autocorrelation of the errors ($\hat{\lambda}$=0.836). Other specification diagnostics to test the assumptions on which the maximum likelihood estimation in the spatial error model is based are also provided. The two tests for heteroskedasticity *versus* the regime variable (the unadjusted and spatially adjusted Breusch-Pagan statistics) are not significant anymore (*p*-value = 0.991) indicating absence of residual heteroskedasticity. Further consideration of spatial heterogeneity is therefore not necessary in the first sub-period since it has adequately been dealt with by taking spatial autocorrelation into account. Furthermore, the LR-test on common factor hypothesis and the LM-test on residual spatial lag dependence are not significant, indicating that the spatial error model is the appropriate specification. In other words, following the discussion in section 2, since the spatial error model can be rewritten under the form of a constrained spatial Durbin model interpreted as a minimal conditional convergence model, it is not an absolute but a conditional convergence process that is relevant for that period.

All these results indicate that the spatial error model is the most appropriate model for the 1980-1989 sub-period. This specification implies a rather low convergence between the European regions below the 2% usually found in the literature (see, for instance, Barro and Sala-I-Martin, 1995). The presence of spatial autocorrelation is synonymous of positive geographic spillovers between regions. As a conclusion, they cannot be considered independent from each other.

3. Convergence Process over 1989-1999

Column 1 of table 2 presents the estimation results of model (1) over 1989-1999. The results of the Lagrange Multiplier tests and their robust versions show that the spatial error model is more appropriate than the spatial lag model (93.4 for LMERR is greater than 92.5 for LMLAG and R-LMERR is significant, whereas R-LMLAG is less significant). The Koenker-Basset test for heteroskedasticity also rejects the null hypothesis of homoskedasticity. The results of the estimation by ML of the spatial error model (4) are presented in column 2 of table 2. As pointed out by the Breusch-Pagan heteroskedasticity tests against D_C, there is still some groupwise heteroskedasticity. Contrary to 1980-1989, further consideration of spatial heterogeneity is therefore needed in this subperiod.

[Table 2 around here]

First, we test the presence of spatial heterogeneity by assessing whether there is significant presence of structural instability across the two regimes previously defined. We therefore estimated model (7) with dummy variables combined with spatial error autocorrelation. We therefore assume that the same spatial autoregressive process affects all the errors. In other words, spatial autocorrelation is supposed to be identical in core and in peripheral regions and all the regions are still interacting spatially through the spatial weights matrix. The estimation results by ML estimation are displayed in column 3 of table 2 and show that only $\hat{\beta}_P$ has the expected sign and is significant ($\hat{\beta}_P$ = -0.027). This is confirmed by the Chow-Wald test for overall structural instability that rejects the null hypothesis of equality of coefficients. Similarly, the individual coefficient stability tests cannot reject the corresponding null hypotheses. In other words, if there is a convergence process for the 1989-1999 period, it only concerns the regions located in the periphery of the European Union. Finally, note that a positive and significant spatial autocorrelation of the errors is found and that the Breusch-Pagan test *versus* the core-periphery dummy variable rejects homoskedasticity. Groupwise heteroskedasticity is therefore still present in the model and should be taken into account.

The last column of table 2 shows the estimation results for the model with structural instability, groupwise heteroskedasticity and spatial error autocorrelation:

$$g_T = \alpha_C D_C + \beta_C D_C y_0 + \alpha_P D_P + \beta_P D_P y_0 + \varepsilon$$

$$\text{with } \varepsilon = \lambda W \varepsilon + u \text{ and } u \sim N\left(0, \begin{bmatrix} \sigma^2_{\varepsilon,C} I_{96} & 0 \\ 0 & \sigma^2_{\varepsilon,P} I_{49} \end{bmatrix}\right) \qquad (12)$$

The estimation results by ML estimation display significant convergence in periphery only ($\hat{\beta}_P$=-0.027) since $\hat{\beta}_C$ is positive and non-significant. In the peripheral regime, the convergence speed is 3.15% corresponding to a half-life of 25 years. The convergence process for peripheral regions seems therefore to be stronger than the one in the initial model without spatial heterogeneity. A positive and significant spatial autocorrelation of the errors is found ($\hat{\lambda}$ = 0.748). The Chow-Wald test for overall structural instability rejects the null hypothesis on the equality of coefficients and is significant (*p*-value = 0.001). This is confirmed by the individual coefficient stability tests, which reject the corresponding null hypotheses as well. Moreover, the LR-test on groupwise heteroskedasticity is significant (*p*-value = 0.000). The convergence process is therefore quite different across regime. In the core regime, the absence of convergence may be due to some form of residual intra-regime heterogeneity that deserves to be taken into account. Indeed, the standard deviation of initial per capita GDP is much greater in this regime than in the peripheral one (1689.4 versus 1122.5). This is left for future research. In the peripheral regime, significant convergence means that the poorest regions tend to catch-up the most developed regions of this club. This is not a trivial result since the per capita GDP of Scotland (UK) represents as much as 3.7 times the one of Norte (Portugal) in 1980.

Compared to the results found for the 1980-1989 period, these results indicate a differentiation of the convergence process between the European regions and the formation of a convergence club between the peripheral regions during the nineties. In other words, the poorest regions of the periphery have experienced a certain process of catching-up towards the richest regions in the periphery. However, our results do not allow us to compare the evolution of the differences between the two regimes. We also show that the nature of the spatial effects evolves: the steady-state to which the regions converge depends on the absolute (convergence clubs) and relative (spatial autocorrelation) geographic location of each region in the second period, whereas only the relative location matters in the first period.

Tables 3 and 4 provide some robustness analysis when 1988 and 1990 are used as cut-offs and when a 10-nearest neighbor and a binary weights matrix are used. In each case, spatial error autocorrelation is found in both sub-periods and spatial heterogeneity in the form of structural instability and groupwise heteroskedasticity are found only in the second subperiod. Moreover, all the results are qualitatively similar to those previously obtained.

[Tables 3 and 4 around here]

IV. CONCLUSION

The aim of this paper has been to highlight the evolution of the convergence process of 145 European regions over the 1980-1999 period. Over these two decades, the European Commission has made significant efforts to foster the integration process. In this context, we assess how the regional convergence process has evolved over that period that we decompose into two subperiods, 1980-1989 and 1989-1999. In addition, we pay special attention to the presence of spatial effects in the determination of the appropriate β-convergence model. In that purpose, we start by using the Getis-Ord statistics to detect the presence of significant local spatial autocorrelation in the form of two regimes representative of the well-known core-periphery pattern (Krugman 1991a, 1991b; Fujita *et al.* 1999). Then, various tests aiming at including the presence of significant spatial effects in our model lead to a spatial error model for both periods. Spatial heterogeneity in the form of spatial regimes and groupwise heteroskedasticity is detected as well, but only in the second period. Estimation results display significant convergence among all the regions over 1980-1989 and significant convergence only among the peripheral regions over 1989-1999.

These results highlight the formation of a convergence club between the peripheral regions of the European Union and a differentiation between the convergence process of the regions located in the core and the one of the regions located in periphery after 1989. This indicates that the steady-state to which the regions converge is dependent on relative location over both periods but has become dependent on the absolute location only over the second period. This does not necessarily mean that the periphery will always be poorer than the core since no significant convergence is detected between the core regions. In addition, if the objective of European integration and cohesion policy is to reduce "disparities between the levels of development of the various regions" (Article 158 of the Treaty establishing the European Community) then it may have been a relative success for the poorest peripheral regions, since they significantly converge to the richest peripheral ones. However, if these efforts were meant to reduce regional differences in steady-state growth rates, then our results do not allow us to raise conclusions concerning the reduction of inequalities for the whole sample. Of course, it can always be claimed that the situation of the peripheral regions could have been worsened without cohesion efforts at all. This dilemma as well as the question of the robustness of our outcomes to other convergence models, samples and methods of club convergence detection is left for future research.

Notes

[1] See Durlauf and Quah (1999), Islam (2003) Magrini (2005) and Durlauf *et al*. (2005) for recent reviews of this extensive literature.
[2] These variables can be state variables – as the stock of physical or human capital – or control variables – as the fertility rate, the degree of political instability, urbanization rate, etc. More than 90 of these variables have been used in the literature (Durlauf et Quah, 1999).
[3] Rey and Janikas (2005) and Abreu *et al*. (2005) provide extensive literature reviews of the way space is integrated into convergence models.
[4] The European Commission uses as administrative regional units the spatial classification established by Eurostat on the basis of national administrative units. Europe can then be divided into 77 NUTS I regions, or 211 NUTS II regions, 1031 NUTS III regions, 1074 NUTS IV regions and 98433 NUTS V regions. .
[5] The robustness of the results is also tested by using other weight matrices based on the *k*-nearest neighbors, with $k = 10$, 15, 20, 25 neighbors. In the European context, the minimum number of nearest neighbors that guarantees international connections between regions is $k = 7$, otherwise the Greek regions would not be linked to Italy. With $k = 10$, Ireland is also connected to the UK, which in turn is connected to the whole continent; and the islands of Sicilia, Sardegna, Corsica are connected to the continental French regions. Finally, three distance contiguity matrices are built according to the critical cut-off previously defined.
[6] All computations in this section are carried out using the SpaceStat 1.91 software (Anselin, 1999).
[7] The use of initial values of per capita GDP is necessary to avoid the selection bias problem raised by De Long (1988).
[8] Estimations by GMM lead to similar results. Complete results are available from the authors upon request. The convergence speed is defined as: $b = -\ln(1 + T\beta)/T$. The half-life is the time necessary for the economies to fill half of the variation, which separates them from their steady state. It is defined by: $\tau = -\ln(2)/\ln(1+\beta)$.

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TABLE 1. ESTIMATION RESULTS OF THE β-CONVERGENCE MODEL OVER 1980-1989 WITH WEIGHTS MATRIX $D(1)$

ESTIMATION RESULTS			TESTS		
	Model (1)	**Model (4)**		**Model (1)**	**Model (4)**
	OLS-White	ML-ERR		OLS-White	ML-ERR
$\hat{\alpha}$	0.206 (0.000)	0.167 (0.000)	**Moran's *I***	16.238 (0.000)	-
$\hat{\beta}$	-0.015 (0.000)	-0.010 (0.011)	**LMERR**	227.009 (0.000)	-
$\hat{\lambda}$	-	0.836 (0.000)	**R-LMERR**	19.106 (0.000)	-
$\hat{\sigma}^2$	0.0149	0.0094	**LMLAG**	208.042 (0.000)	-
Convergence Speed	1.61%	1.05%	**R-LMLAG**	0.139 (0.709)	-
Half-life	45	67	**Jarque-Bera**	1.316 (0.518)	-
Sq. Corr.	-	0.165	**White test**	10.946 (0.004)	-
LIK	405.122	460.859	**BP-test for heteroskedasticity**	4.981 (0.025)	0.0001 (0.991)
AIC	-806.243	-917.717	**Spatial BP-test**	-	0.0001 (0.991)
SC	-800.290	-911.764	**LR-test common factor hypothesis**	-	1.480 (0.224)
			LM-test on spatial lag dependence	-	0.723 (0.395)

Notes: *p*-values are in brackets. *OLS-White* indicates the use of heteroskedasticity consistent covariance matrix estimator. *ML-ERR* indicates maximum likelihood estimation of the spatial error model. *Sq. Corr.* is the squared correlation between predicted values and actual values. *LIK* is the value of the maximum likelihood function. *AIC* is the Akaike information criterion. *SC* is the Schwarz information criterion. *MORAN* is Moran's *I* test for spatial autocorrelation adapted to regression residuals (CLIFF AND ORD, 1981). *LMERR* stands for the Lagrange Multiplier test for residual spatial autocorrelation and *R-LMERR* for its robust version. *LMLAG* stands for the Lagrange Multiplier test for spatially lagged endogenous variable and *R-LMLAG* for its robust version (ANSELIN *et al*., 1996). *BP* is the Breusch-Pagan test for groupwise heteroskedasticity and spatial BP-test is its spatially adjusted version.

TABLE 2. ESTIMATION RESULTS OF THE β-CONVERGENCE MODEL OVER 1989-1999 WITH WEIGHTS MATRIX $D(1)$

ESTIMATION RESULTS						
	Model (1)	**Model (4)**	**Model (5)**		**Model (6)**	
	OLS-White	ML-ERR	ML – ERR		ML – HET/ERR	
			Core	*Periph.*	*Core*	*Periph.*
$\hat{\alpha}_r$	0.210 (0.000)	0.116 (0.000)	0.024 (0.565)	0.295 (0.000)	0.025 (0.475)	0.293 (0.000)
$\hat{\beta}_r$	-0.018 (0.000)	-0.008 (0.026)	0.001 (0.696)	-0.027 (0.000)	0.001 (0.666)	-0.027 (0.044)
$\hat{\lambda}$	-	0.801 (0.000)	0.757 (0.000)		0.748 (0.000)	
$\hat{\sigma}_{\varepsilon}^{2}$	0.0109	0.0083	0.0079		$9.942.10^{-5}$ (0.000)	$4.552.10^{-6}$ (0.000)
Convergence Speed	1.98%	0.83%	-	3.14%	-	3.15%
Half-life	39	86	-	26	-	25
Sq. Corr.	-	0.294	0.357		0.352	
LIK	450.965	480.509	487.583		499.952	
AIC	-897.930	-957.018	-967.167		-991.904	
SC	-891.976	-951.065	-955.260		-979.997	
TESTS						
Moran's *I*	10.531 (0.000)	-	-		-	
LMERR	93.414 (0.000)	-	-		-	
R-LMERR	6.470 (0.011)	-	-		-	
LMLAG	92.587 (0.000)	-	-		-	
R-LMLAG	5.642 (0.017)	-	-		-	
White test	2.431 (0.296)	-	-		-	
Koenker-Basset test for heteroskedasticity	9.899 (0.001)	-	-		-	
BP-test for heteroskedasticity	-	12.767 (0.000)	11.617 (0.000)		-	
Spatial BP-test	-	12.875 (0.000)	-		-	
LR-test common factor hypothesis	-	5.532 (0.018)	3.832 (0.147)		-	
LM-test on spatial lag dependence	-	0.834 (0.361)	0.048 (0.826)		-	
Chow-Wald	-	-	15.259 (0.000)		12.873 (0.001)	
Ind. stab. test on $\hat{\alpha}_r$	-	-	15.016 (0.000)		11.743 (0.000)	
Ind. stab. on $\hat{\beta}_r$	-	-	14.553 (0.000)		11.044 (0.000)	
LR – group. het.	-	-	-		24.687 (0.000)	

Notes: *see notes table 1. ML-HET/ERR* indicates maximum likelihood estimation of the spatial error model with groupwise heteroskedasticity. The individual coefficient stability tests are based on a spatially adjusted asymptotic Wald statistics, distributed as χ^2 with 1 degree of freedom. The Chow – Wald test of overall stability is also based on a spatially adjusted asymptotic Wald statistic, distributed as χ^2 with 2 degrees of freedom (Anselin, 1988). *LR* is the likelihood ratio test for groupwise heteroskedasticity.

TABLE 3. ESTIMATION RESULTS FOR DIFFERENT CUT-OFFS

	Cut-off in 1988			**Cut-off in 1990**		
	1980-1988	1988-1999		1980-1990	1990-1999	
		Core	*Periph*		*Core*	*Periph.*
$\hat{\alpha}_r$	0.207	0.044	0.245	0.205	0.028	0.249
	(0.000)	(0.186)	(0.000)	(0.000)	(0.460)	(0.000)
$\hat{\beta}_r$	-0.015	-0.000	-0.021	-0.015	0.001	-0.023
	(0.000)	(0.976)	(0.002)	(0.000)	(0.824)	(0.004)
$\hat{\lambda}$	0.764	0.699		0.819	0.818	
	(0.000)	(0.000)		(0.000)	(0.000)	
$\hat{\sigma}_\varepsilon^2$	0.0118	$8.116.10^{-5}$	$4.208.10^{-5}$	0.0100	$9.658.10^{-5}$	$5.443.10^{-5}$
		(0.000)	(0.000)		(0.000)	(0.000)
Convergence Speed	1.61%	-	2.35%	1.60%	-	2.61%
Half-life	45	-	32	47	-	30
Sq. Corr.	0.110	0.408		0.189	0.293	
LIK	431.165	508.666		453.164	492.049	
AIC	-858.330	-1009.33		-901.328	-976.099	
SC	-852.377	-997.424		-896.375	-964.192	

TABLE 4. ESTIMATION RESULTS FOR DIFFERENT WEIGHTS MATRICES

	10 nearest neighbors			**Binary *D*(1) matrix**		
	1980-1989	1989-1999		1980-1989	1989-1999	
		Core	*Periph*		*Core*	*Periph.*
$\hat{\alpha}_r$	0.203	0.006	0.378	0.196	0.066	0.374
	(0.000)	(0.891)	(0.000)	(0.000)	(0.142)	(0.000)
$\hat{\beta}_r$	-0.014	0.004	-0.036	-0.013	-0.003	-0.035
	(0.000)	(0.332)	(0.000)	(0.000)	(0.550)	(0.004)
$\hat{\lambda}$	0.823	0.827		0.922	0.872	
	(0.000)	(0.000)		(0.000)	(0.000)	
$\hat{\sigma}_\varepsilon^2$	0.010	$9.145.10^{-5}$	$4.688.10^{-5}$	0.0102	$9.358.10^{-5}$	$4.991.10^{-5}$
		(0.000)	(0.000)		(0.000)	(0.000)
Convergence Speed	1.48%	-	4.46%	1.38%	-	4.30%
Half-life	47	-	19	52	-	19
Sq. Corr.	0.165	0.310		0.165	0.325	
LIK	466.355	491.957		458.440	484.499	
AIC	-928.711	-975.914		-912.879	-960.998	
SC	-922.757	-964.007		-906.926	-949.092	

Figure 1: Spatial regimes detected with the Getis-Ord statistics

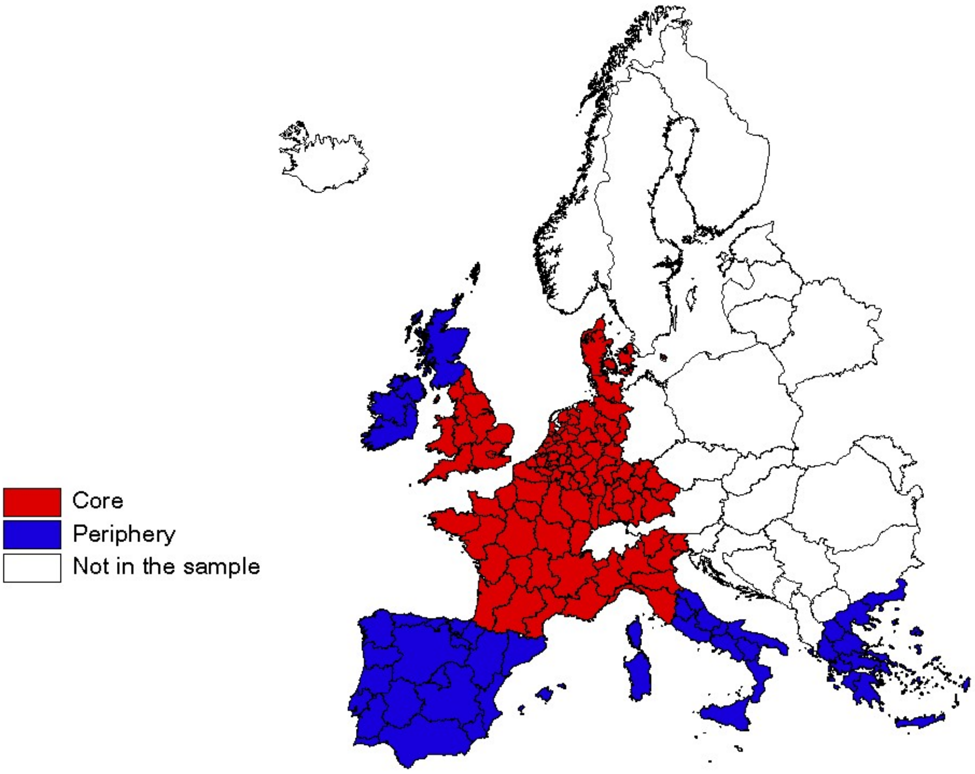

Figure 2: Residuals of model (1)