A SPATIAL ECONOMETRIC APPROACH TO EU REGIONAL DISPARITIES BETWEEN ECONOMIC AND GEOGRAPHICAL PERIPHERY

C. Brasili, F. Bruno, A. Saguatti

1. INTRODUCTION

The process of European integration, which aims at creating economic and social cohesion between territories and reducing regional disparities, has been rising great questions. The political and financial sustainability of EU regional policies and the possible trade-off between social cohesion and competitiveness (Fitoussi, 2006) are often debated, especially given that an increasing quantity of funds are devoted to the poorest regions. These were granted 70% of the Structural Funds in the period 1989-1993 and have been given 81% for 2007-2013 (European Commission, 1996; Regulation EC 1083/06).

The idea of a progressive reduction of disparities in social and economic indicators of well-being in a group of economies is at the basis of the concept of "convergence" (Leonardi, 1995), which therefore constitutes an important goal for EU policies. The measurement of convergence can reveal the real chances of achieving greater cohesion in different territories, and this is the main reason why measuring economic convergence is so popular, particularly in the field of European Regional policy studies (e.g. Rodriguez-Pose and Fratesi, 2004; Dall'Erba and Le Gallo, 2008; Piras and Arbia, 2007; Ramajo *et al.*, 2008).

Since Baumol's (1986) pioneering work, convergence studies have been developed which used several different analysis techniques. Each of these was able to highlight different dimensions of this phenomenon. The "classical" method of analysis of absolute and conditional convergence (Sala-i-Martin, 1996) – notably the estimation of β-convergence in a cross-section of economies – is a parametric technique which originates directly from Solow's neoclassical model of economic growth and it was mainly elaborated by Barro (1991) together with Sala-i-Martin (1991, 1992, 1995). It suggests that there is a tendency for the per capita income of the poorer economies to grow faster than the richer ones, given a negative relationship between the growth rate of per capita income and its initial level, and this generates convergence (Sala-i-Martin, 1996). There is however no empirical proof of the absolute convergence hypothesis, particularly when studying the economies of different States or the regional economies of different States. Barro and Sala-i-Martin (1991) themselves admit that some other factors – called conditioning variables – need to be taken into account, as they prevent convergence to a unique steady-state from taking place. Economic theory can help by suggesting which the best conditioning variables to include are.

A wide literature covers the topic of regional convergence by using the techniques of spatial econometrics (Fingleton, 1999; López-Bazo *et al.*, 1999; Baumont *et al.*, 2001; Battisti and Di Vaio, 2008; Arbia *et al.*, 2010, among others), since, as it is widely known, it can help dealing with some of the main weaknesses of convergence analysis, particularly the spatial dependence of residuals (Arbia, 2006).

This paper presents the results of the estimation of a conditional β-convergence model with spatial effects. It contributes to previous literature by identifying two clubs of convergence according to an exogenous criterion, where endogenous procedures are usually followed (e.g. Ertur *et al.*, 2006; Le Gallo and Dall'Erba, 2006). The final model specification is based on the main assumption of substantial conformity in the geographical and economic periphery in EU-15: the spatial pattern is taken into account by considering the Objective 1 and non-Objective 1 regions distinction made in the context of European regional policies. The results confirm the importance of explicitly considering spatial effects and support our a-priori criterion for determining convergence clubs.

The structure of this paper is as follows. Section 2 drafts an introduction to spatial econometric models by focusing also on β-convergence. Then the data and the results of the exploratory spatial analysis are described (Section 3). Section 4 presents the model specification and the results. Finally in section 5, the main conclusions are discussed.

2. INTRODUCTION TO SPATIAL ECONOMETRIC MODELS

The New Economic Geography has shown that the spatial location of economies plays an important role in explaining their growth path, inasmuch as it originates a circular mechanism that, once established, perpetuates the unequal development of territories[1]. A recent approach to economic convergence enriches Barro's neoclassical measure of convergence by including the concepts of New Economic Geography, in order to fill the gap between theoretical advances and empirical analysis.

Let $g_{it} = [\ln(y_{it}) - \ln(y_{it_0})]/\tau$ be the average growth rate of per capita GDP in region *i* over the period t_0 and t in a cross-section of *N* economies and for a τ number of years; then the classical model to test convergence is:

[1] Myrdal and Hirschman's theory of "circular cumulative causation", proposed in the '50s, and then developed by Marshall's advantages of localisation and by the "New Economic Geography" (Ottaviano and Puga, 1998; Krugman, 1995).

$$g_{it} = a + b \cdot \ln(y_{it_0}) + \varepsilon_{it} \tag{1}$$

where i= 1, ..., N, y_i is the level of per capita GDP in economy i, $\varepsilon \sim N(0, \sigma^2)$ is the error term, a and b are parameters which are assumed to be stable across the economies. A negative estimate of the parameter b in model (1) indicates *absolute* convergence, following the neoclassical theory (Barro and Sala-i-Martin, 1992, 1995). Once a vector of conditioning variables X_{t_0} and one of parameters ψ is added, a negative estimate of b in model (2) indicates that there is *conditional* convergence:

$$g_{it} = a + b \cdot \ln(y_{it_0}) + \psi X_{it_0} + \varepsilon_{it} \tag{2}$$

This classic methodology has been enriched by the contribution of spatial econometrics, a branch of econometric theory that deals with the major problems generated by the spatial dimension of data (Anselin, 1988). These are spatial dependence and heterogeneity, and, if not properly modelled, they can affect the reliability of cross-country estimations.

Spatial dependence is "the existence of a functional relationship between what happens at one point in space and what happens elsewhere" (Anselin, 1988). The spatial location of a region compared to that of other regions is thus highly relevant in explaining the value of a given variable in that region. Spatial dependence can occur either as a form of spatial interdependence between the observations of a variable (in this case, "attribute similarity" corresponds to "similarity of location") or as spatial autocorrelation of errors (which can compromise the predictive ability of the model). Spatial heterogeneity can appear in two possible ways in a regression model (Dall'Erba and Le Gallo, 2008): either in the form of spatial instability of observations, which is closely related to the presence of multiple spatial regimes and convergence clubs, or in the form of group-wise heteroskedasticity of errors.

The links between spatial autocorrelation and heterogeneity are quite complex. In cross-section analysis these two effects often appear at the same time and in the same manner. The omission of proper formalisation of spatial heterogeneity can also cause autocorrelation of the regression residuals. In other words, the autocorrelation of residuals may simply indicate misspecification of the model (Ertur at al., 2006). Since the traditional Ordinary Least Squares (OLS) method of estimation may be inappropriate in the case of spatially correlated observations, it is crucially important to identify whether or not spatial dependence is present, and, if it is, take it into account. The spatial autocorrelation of the OLS residuals can be due either to an autoregressive process of the errors or to the omission of the spatial lag of the dependent variable in the specification of the model. In the first case only the efficiency of the estimate will be affected, but in the second case the OLS estimate will be inconsistent (Anselin *et al.*, 1996).

3. A SPATIAL MODEL FOR ECONOMIC CONVERGENCE APPLIED TO EUROPEAN REGIONS

3.1. *Description of the data*

The database used in this analysis is taken from the Cambridge Econometrics Regional Database and covers the period 1980-2006 for 196 NUTS-2 regions summarised in table 1. For a complete list of regions see tables A.1 and A.2 and figure A.1 in the Appendix.

TABLE 1

NUTS-2 (Nomenclature of Territorial Units for Statistics, Eurostat) belonging to 15 European countries included in the analysis

Country	Number of NUTS-2	Country	Number of NUTS-2
Austria	9	Ireland	2
Belgium	11	Italy	21
Denmark	3	Luxembourg	1
Finland	5	Portugal	5
France	22	Spain	18
Germany	30	Sweden	8
Great Britain	37	The Netherlands	11
Greece	13	*Total*	*196*

The growth rate of the logarithm of per capita GDP (in Euros at 2000 prices), being the dependent variable of the model, is expressed in deviations with respect to the EU-15 mean. As a result the dependent variable of the model is: $\Gamma_{it} = g_{it} - g_{UE,t}$, where $g_{UE,t} = [\ln(\overline{y}_{UE,t}) - \ln(\overline{y}_{UE,t_0})]/\tau$. Thus the analysis appears to be coherent with the criterion of eligibility for Objective 1 funds, which uses the relative per capita GDP to measure the general well-being of European regions. Working with scaled per capita GDP also helps to eliminate the effects of European economy-wide cycles and of common trends, and to reduce the effects of the outliers (Ramajo *et al.*, 2008).

In accordance with the data available at regional level, the regional employment rate and the percentage of agricultural employment as a share of total employment are chosen as conditioning variables to this model. The inclusion of the regional employment rate (expressed as the ratio of employment to population) as a conditioning variable is coherent with the growing importance given to employment in EU structural policies. Employment is, together with growth, the main aim of the Lisbon Strategy for cohesion and competitiveness and it is a fundamental factor affecting economic growth in these two areas. Moreover, the employment rate is used by some authors to quantify the effects of labour market disparities (Ramajo at al., 2008), since differences in employment rates can be due either to different rates of unemployment or to the different demographic structures of the population. An additional reason for including this variable in this model is that a higher employment rate can significantly contribute to an increase in per capita GDP, given the differences between this variable and productivity (GDP per worker).

Disparities between the productive systems of the regions are captured by the share of agricultural employment, which reflects not only the different composition of economic activities (Ramajo *et al.*, 2008), but also the potential amount of funding obtained from the Common Agricultural Policy (CAP) (Button and Pentecost, 1999). Other authors prefer to use the share of manufacturing employment to reflect the regional economic structure (Fingleton, 1999).

3.2. *Exploratory Spatial Data Analysis*

Creating maps which showed the spatial distribution of the considered variables was a useful way of highlighting the potential spatial pattern of the observations (figure 1). The spatial distribution of the regional per capita GDP in 1980 suggests that there was spatial heterogeneity, with two clusters of richer and poorer regions. The hypothesis that the geographical and economic peripheries substantially coincide is thus supported by this result. Spatial heterogeneity is also evident with regards to the other variables considered in the model: growth of per capita GDP between 1980 and 2006, regional employment rate and regional share of agricultural employment. Maps shown in figure 1 (panels *a* and *b*) also support the classical convergence hypothesis which associates a higher growth rate of per capita GDP to lower initial levels of per capita GDP.

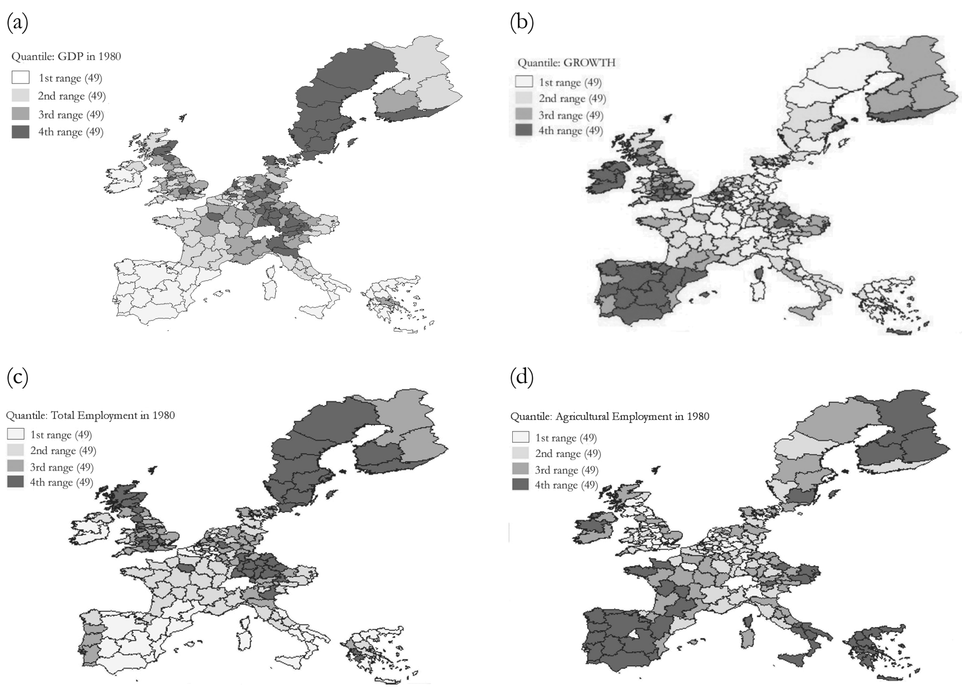

Figure 1 – Spatial percentile distribution for the log of per capita GDP in 1980 with deviations with respect to the EU-15 mean (a), the growth of per capita GDP between 1980 and 2006 (b), the total employment in 1980 (c), the share of agricultural employment in 1980 (d).

The spatial interaction between the regions is modelled, as usual in spatial analysis of lattice data, using the spatial weight matrix (**W**): a square, non-stochastic and symmetric matrix, whose elements (w_{ij}) measure the intensity of the spatial connection between regions i and j and take on a finite and non-negative value. The appropriate **W** used in most of the literature on spatial econometrics in a European regional context is a distance-based matrix (Fingleton, 1999; Baumont *et al.*, 2001; Ertur *et al.*, 2006; Le Gallo and Dall'Erba, 2006; Dall'Erba and Le Gallo, 2008; Ramajo *et al.*, 2008), where each w_{ij} is defined as $w_{ij} = w^*_{ij} / \sum_j w^*_{ij}$ and

$$\begin{cases} w^*_{ij} = 0 & if \quad i = j \\ w^*_{ij} = 1/d^2_{ij} & if \quad d_{ij} \le D \\ w^*_{ij} = 0 & if \quad d_{ij} > D \end{cases}$$

where w^*_{ij} is an element of the non-standardised spatial weights matrix; w_{ij} is an element of the standardised matrix (**W**); d_{ij} is the great circle distance between regions i and j; and D is the *cut-off parameter* above which any interaction between the regions is considered to be negligible; in this case it is defined as a quartile of the great circle distance distribution[2]. Standardising the spatial weight matrix does not influence the relative dependence between neighbours, but it makes it easier to interpret and compare the results of the calculations in which the matrix is used and also the results of different analyses.

Relative to the variable per capita GDP in 1980, the Moran's I index (Moran, 1950) is 0.5107, which is well above the expected value under the null hypothesis of no spatial correlation, $E(I)$=-0.0051. Initial per capita GDP is therefore spatially correlated and a positive spatial dependence is revealed in the distribution of this variable. A similar result was obtained for the GDP per capita growth rate between 1980 and 2006, leading to I= 0.2131. Another explorative analysis index of spatial autocorrelation (APLE; Li *et al.*, 2007) confirms the existence of a positive spatial autocorrelation. All these results are coherent to the choice of the weighting matrix.

Another explorative tool is the "Moran" scatterplot: each quadrant corresponds to a particular kind of spatial association between a region and its neighbours. The first and third quadrant display the situations of positive dependence between, respectively, the high/low values of the variable in one region and those in its neighbours. The second and fourth quadrant, on the other hand, show negative dependence. Thus from the Moran scatterplot one can identify

[2] Here we present the results obtained by fixing the upper quartile of the distribution as the cut-off parameter. We also used binary matrices (queen contiguity matrices and k-nearest neighbours spatial weights matrices for k=5 and k=10). The results generated by these other matrices are very similar to those presented in this paper.

whether or not there is spatial heterogeneity in the sample. The Moran scatterplot for per capita GDP in 1980 (figure 2) show two distinct clusters, one made up of rich regions surrounded by other rich regions (first quadrant) and the other of poor regions surrounded by poor regions (third quadrant).

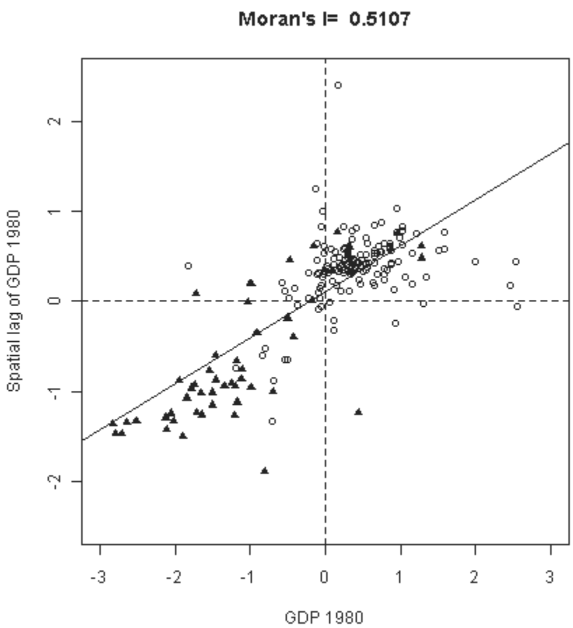

Figure 2 – Moran scatterplot for the logarithm of per-capita GDP in 1980. Objective 1 regions are identified by triangles, non-Objective 1 regions otherwise.

As a conclusion to the exploratory spatial analysis, a model is proposed that identifies two convergence clubs following the assumption of conformity between geographical and economic periphery in the European Union. The criterion for the detection of the spatial regimes is therefore the economically-defined eligibility of each region to Objective 1 of the European regional policy: the first regime includes 50 NUTS-2, which were part of Objectives 1 and 6 during the programming period 1994-1999[3] (which are also identified by triangles in figure 2), the second regime includes the other 146 regions in the sample. All the regions that were granted the Funds for Objectives 1 and 6 during the programming period 1994-1999 are considered to be part of the Objective 1 cluster in the

[3] We chose these dates so as to include Austrian, Swedish and Finnish regions in our analysis. These countries joined the EU in 1995 and took part to the assignment of Structural Funds only from that programming period on. For a detailed list of the regions which were eligible to Objectives 1 and 6 during the programming period 1994-1999, see Council Regulation (EEC) No 2081/93 and Council Decision of 1 January 1995 in respect to adjusting the instruments concerning the accession of new member states to the European Union.

present analysis, although they might have been phased out in the following years. In accordance with the findings in literature (Ramajo *et al.* 2008), this distinction is expected to be suitable for modelling the possible spatial heterogeneity in the sample. Indeed it is well-known that in Europe economic disadvantages are usually accompanied by geographical disadvantages (the term "European periphery" commonly indicates the poorest European regions). During the programming period 2000-2006, Objective 1 covered the former Objective 6 regions and the most remote regions, as well as those where development was lagging behind (Reg. 1260/99 EC). This reflects the EU's awareness of the relationship between the geographical and the economic periphery. This hypothesis is also confirmed by the results of the exploratory spatial analysis. Any parameter instability between the two groups of regions that were exogenously defined will be considered to be proof of the existence of two convergence clubs with both a spatial and an economic dimension.

4. A CONVERGENCE MODEL AND SPATIAL EFFECTS AMONG EU REGIONS

4.1. *The model of conditional β-convergence and spatial effects*

The choice of the best model specification, in accordance with the results of the exploratory spatial analysis, follows the usual steps for model construction in spatial econometrics (Anselin, 2005).

Firstly, a model of conditional β-convergence without spatial effects (3) is estimated via OLS:

$$\mathbf{\Gamma}_y = \mathbf{y}b + \mathbf{X\theta} + \boldsymbol{\varepsilon} \tag{3}$$

where $\mathbf{\Gamma}_y$ is a column vector with 196 observations for the rate of growth of per capita GDP in EU regions for the period 1980-2006, expressed in logarithms and in deviations with respect to the EU-15 mean; $\mathbf{y}$ is a column vector with 196 observations for the level of per capita GDP in 1980, expressed in logarithms and in deviations with respect to the EU-15 mean; $\mathbf{X} = [\mathbf{1} \quad \mathbf{c}_1 \quad \mathbf{c}_2]$ is a *196*x*3* matrix where the first column permits to include the intercept, $\mathbf{c}_1$ is a column vector referred to the total employment rate in each region in 1980, $\mathbf{c}_2$ is the column containing data for agricultural employment in each region in 1980; $\mathbf{\theta} = [a \quad \psi_1 \quad \psi_2]$ and b are the regression coefficients; $\boldsymbol{\varepsilon}$ is the column vector of errors with the usual properties. For the sake of coherence with the definition of β-convergence models, the vector $\mathbf{y}$ was not included in the matrix $\mathbf{X}$, which contains the vectors of the intercept and the covariates. The results of the OLS estimation of model (3), here not reported, show that each of the explanatory variables included is statistically significant and that they support the neoclassic assumption of conditional convergence. Moreover, since the the Breusch-Pagan test on the residuals does not rejected the hypothesis of homoskedasticity (*p*-value=0.374), parameters instability was thought to be the most suitable tool to account for the spatial heterogeneity found through the exploratory spatial analysis.

Second step consists in testing for spatial autocorrelation in the regression residuals (Anselin, 1988; Anselin *et al.*, 1996). The Moran's I test statistic adapted to regression residuals rejects the hypothesis of no spatial autocorrelation for all cut-off distances, without providing any additional information on the best specification to choose (table 2).

TABLE 2

Moran's I test for global spatial autocorrelation

	Q1 (554 km)	(p-value)	Median (1044 km)	(p-value)	Q3 (1597 km)	(p-value)
Moran's I test	0.1142	(0.017)	0.0996	(0.001)	0.0903	(0.000)

In order to choose the more appropriate spatial model, four Lagrange Multiplier (LM) tests (Anselin, 1988, Anselin *et al.*, 1996) are performed and the results are collected in table 3.

TABLE 3

Lagrange Multiplier tests for global spatial autocorrelation

Test	Q1 (554 km)	(p-value)	Median (1044 km)	(p-value)	Q3 (1597 km)	(p-value)
LMlag test	6.3514	(0.012)	10.352	(0.001)	12.1379	(0.000)
LMerr test	3.4991	(0.061)	7.3779	(0.007)	8.026	(0.005)
RLMlag test	3.9643	(0.046)	2.9777	(0.084)	4.1439	(0.042)
RLMerr test	1.112	(0.292)	0.0036	(0.953)	0.032	(0.858)

The results of the LM tests led to choose the spatial weights matrix based on third quartile, following Anselin's suggestion (Ertur *et al.*, 2006) to choose the cut-off distance which maximises the absolute value of the significant Lagrange multiplier statistic for spatial autocorrelation. The LMlag test is more statistically significant than the LMerr (p-value=0.000 for the LMlag test and p-value=0.005 for the LMerr test), the RLMerr test is not significant (p-value=0.858) and the RLMlag is statistically significant at the 5% level (p-value=0.042). For the reasons above, a *spatial lag model,* or *spatial auto-regressive model* (SAR) is best for modelling the identified spatial dependence.

The spatial heterogeneity identified in subsection 3.2 is modelled by using two convergence clubs, defined according to both geographical and economic criteria. Using the estimates of a β-convergence model with two convergence clubs permits to have two spatial regimes with two distinct convergence processes, and also means that, thanks to the inclusion of conditioning variables, each regional economy inside each group of regions converges towards its own steady state. Following Ramajo *et al.* (2008), the spatial lags of the explanatory variables were included in the model specification as in a *cross-regressive* spatial model, but only the spatial lag of initial GDP was found to be significant. The final model is chosen by referring to the usual AIC and the log-likelihood value.

Let define the 196x196 diagonal matrix $\mathbf{D}^{OB1} = diag(\mathbf{I}_{(region_i \in OB1)}; i = 1,...,196)$ that permits to select the regions belonging to Objective 1 (OB1), and analogously $\mathbf{d}^{OB1} = \mathbf{D}^{OB1}\mathbf{1}_{196}$ is the column vector used to select regions belonging to OB1. In the model proposed, **y** is a 196-dimensional column vector containing the per capita GDP in 1980, expressed in logarithms and in deviations with respect to the EU-15 mean. The 196x4-dimensional matrix of covariates $\mathbf{X} = [\mathbf{1} \quad \mathbf{c}_1 \quad \mathbf{c}_2 \quad \mathbf{c}_3]$ contains respectively: in the first column unit values in order to include an intercept, in $\mathbf{c}_1$ the total employment rate in each region in 1980, in $\mathbf{c}_2$ the share of agricultural employment in of each region in 1980 and finally in $\mathbf{c}_3$ the spatial lag of **y**. By using $\mathbf{D}^{OB1}$ we obtain $\mathbf{X}^{OB1} = \mathbf{D}^{OB1}\mathbf{X}$, and $\mathbf{X}^{NN1} = (\mathbf{1}_{196}\mathbf{1}_{196}^{'} - \mathbf{D}^{OB1})\mathbf{X}$. By considering vector $\mathbf{d}^{OB1}$, $\mathbf{y}^{OB1} = \mathbf{d}^{OB1}\mathbf{y}$ and $\mathbf{y}^{NN1} = (\mathbf{1}_{196} - \mathbf{d}^{OB1})\mathbf{y}$ are analogously obtained.

Then the chosen model, for $\mathbf{\Gamma}_y$ i.e. the rate of growth of per capita GDP in EU regions for the period 1980-2006, expressed in logarithms and in deviations with respect to the EU-15 mean; is:

$$\mathbf{\Gamma}_y = \mathbf{y}^{OB1}b^{OB1} + \mathbf{y}^{NN1}b^{NN1} + \mathbf{X}^{OB1}\boldsymbol{\theta}^{OB1} + \mathbf{X}^{NN1}\boldsymbol{\theta}^{NN1} + \rho\mathbf{W}\mathbf{g}_y + \boldsymbol{\varepsilon} \tag{4}$$

where $\boldsymbol{\theta}^{OB1}$, $\boldsymbol{\theta}^{NN1}$ are the 4-dimensional vectors parameters, $\boldsymbol{\theta}^i = [a^i \quad \psi_1^i \quad \psi_2^i \quad \varphi^i]^{'}$ respectively for regions belonging to Objective 1 (i=OB1) and the others (i=NN1). Parameters b^{OB1}, b^{NN1} are coefficients of the per capita GDP in 1980; ρ is the spatial regression coefficient; **W** is the spatial weight matrix; $\boldsymbol{\varepsilon}$ is the column vector of errors with the usual properties.

The estimation results for model (4) are shown in the right-hand section of table 4, together with the results of the ML estimation of a model with no spatial regimes (left-hand section) which is included for comparison purposes.

TABLE 4

ML estimation results

Variable/parameter	*No convergence clubs*	*(p-value)*	*Objective 1*	*(p-value)*	*non-Objective 1*	*(p-value)*
Constant (a)	-0.00758	(0.011)	-0.00312	(0.460)	-0.01505	(0.000)
GDP (b)	-0.01735	(0.000)	-0.02824	(0.000)	-0.01569	(0.000)
Total Employment (ψ_1)	0.00026	(0.000)	-0.00002	(0.846)	0.00043	(0.000)
Share of Agricultural Employment (ψ_2)	-0.00030	(0.000)	-0.00029	(0.000)	-0.00019	(0.037)
W_GDP (φ)	0.00304	(0.245)	0.02282	(0.000)	-0.00521	(0.089)
Spatial Parameter (ρ)	0.40931 (0.000)		0.35186 (0.001)			
Convergence rate (β) %	2.3		5.3		2.0	
Half life (years)	40		24.5		44	
Breusch-Pagan test	4.432	(0.351)	13.5457 (0.139)			
LMerr test	0.781	(0.377)	2.8226 (0.093)			
Log likelihood	740.58		746.04			
Chow test			47.01 (0.000)			
AIC	-1467		-1504			

4.2. *Conditional β-convergence and spatial effects among EU-15 regions*

The results of the ML estimation of model (4) support the assumption that there are two spatial convergence clubs, since the value of the Chow test rejects the null hypothesis of parameter stability between the two groups of regions. The choice of the model with spatial regimes is also supported by the usual AIC and log-likelihood values.

The model with no convergence clubs, which does not allow for parameter instability across space, appears to cause a loss of information if compared to the results of model (4). The estimated convergence rate is quite low (2.3%) and very close to that estimated for non-Objective 1 regions via model (4). The estimates of b obtained via model (4) are statistically significant and have the expected negative sign. The implied convergence rate (β) of Objective 1 regions (5.3%) is much higher than that of the other group (2%) and the half-life of the first group (24.5 years) is much lower than that of the second (44 years). As a result it seems to be advisable to estimate a SAR model with two spatial regimes. The choice of policy-defined exogenous clusters is supported by these results.

The assessment of two groups of regions converging at different rates towards different steady states is confirmed by the estimation of an unconditioned spatial error model (here not shown). Objective 1 regions appear to converge at a significantly higher rate than non-Objective 1 regions, irrespective of whether or not the spatial lag of GDP is included in the unconditioned model specification.

Although the existence of a convergence process across European regions is confirmed by some results in the literature, their comparison should be made with great caution, because some elements such as the time span considered, the estimation procedures and model specification may influence the estimates[4], as it was made clear by Piras *et al.* (2006).

The estimate of the spatial parameter (ϱ) confirms the crucial role of geography in explaining the economic growth. A β-convergence model with spatial effects reveals that there are significant spillover effects between European regions, and that these affect the economic performance of each of them. This result agrees with those of other studies (López-Bazo *et al.*, 2004; Baumont *et al.*, 2001; Ramajo *et al.*, 2008). The more dynamic and fast growing the economies of the surrounding regions are, then the higher the growth rate of a region will be.

There is evidence that a high total employment rate has, on average, a significant positive influence on the growth of non-Objective 1 regions. The estimates of the share of those employed in agriculture reveal that there is an inverse relationship between the importance of the agricultural sector and economic growth. In fact in both groups of regions the estimates of ψ_2 are negative and significant at 5% level. In general, the initial self-employment rate is more important in richer regions, while the economic growth of Objective 1 regions is affected more by the initial share of self-employment in agriculture. Finally, the GDP of

[4] See, for example, López-Bazo *et al.* (2004) for a spatial cross-sectional model; Esposti and Bussoletti (2010) for a non-spatial dynamic panel data model; Piras and Arbia (2007) for a spatial panel data model.

neighbouring regions has a positive effect on the growth of Objective 1 regions (0.023). The poorest regions, whose per capita GDP is less than 75% of the Community average, are the ones that are most affected by the economic situations of their neighbours.

4.3. *Policy implications*

The main findings of this analysis are that development is polarised into two convergence clubs (Objective 1 and non-Objective 1 regions), and that these converge at different rates (respectively 5.3% and 2%) towards different steady states. As a result it is important to recognise that there will be permanent per capita income disparities between the two groups of regions. The significance of the conditioning variables, which affect the steady state of each region, reinforces this conclusion. The identification of two distinct spatial regimes also allowed to assess the different impact of the conditioning variables on growth in the two groups of regions. The spatial lag of per capita GDP is found to be highly relevant in explaining the rate of growth in those regions that are lagging behind. Objective 1 regions are evidently more affected by the surrounding economic environment than richer regions are. The inclusion of this variable also gave the best improvements in the goodness of fit of the model and the biggest differences in the estimates of *b*. The greater negative effects of a high initial share of agricultural self-employment in Objective 1 regions should also be borne in mind, while a high initial self-employment rate has a positive effect mainly in non-Objective 1 regions. The different contribution of the composition of the productive system and of the employment rate to the regional economic growth should also be taken into great consideration when planning regional cohesion Policy.

A model of this kind cannot explicitly demonstrate the causal relationship between a higher convergence rate among poorer regions and regional policy funding. However one cannot fail to notice that Objective 1 regions receive a much higher share of the total amount of funding for regional policy than is their share of total EU-15 GDP. Indeed during the programming period 1989-1993 the regions where development lagged behind received 69.6% of Structural Funds, while they only contributed 11% of EU GDP. In 1994-1999 they were granted 68.5% of the Funds and produced 13% of total EU-15 GDP. Finally, during the period 2000-2006, Objective 1 regions were given 69.9% of Structural Funds and produced 10% of EU-15 GDP[5]. It can reasonably assumed that such a distribution of aid contributed to the higher convergence rate among the poorest regions, and this supports the hypothesis that the regions with a lower level of initial per capita income will grow at a higher rate, thus generating convergence. The evidence from the literature concerning the use of Structural Funds expenditure data within a convergence approach for policy evaluation purposes is still controver-

[5] The data on the amount of funding are taken from European Commission (1996; 2001) and do not include the funding of the Cohesion Fund. The data on the GDP of Objective 1 regions are taken from the Cambridge Econometrics Regional Database.

sial (Rodrìguez-Pose and Fratesi, 2004; Esposti and Bussoletti, 2008; Dall'Erba and Le Gallo, 2008; Muccigrosso, 2010) and closely related with the model specification (cross-sectional or panel data models, spatial or non-spatial approach). Moreover, the availability of data on the actual expenditure of the Structural Funds allocated to each NUTS-2 is still seriously limited.

The parameters estimated for the spatial autoregressive term and for the spatially lagged GDP also reveal that there are geographical spillover effects which are of primary importance in explaining the economic growth of European regions. The relative geographical location of each region plays a key role in explaining the structure of economic growth in the EU-15. These findings have profound implications for policy and suggest that specific investments aimed at exploiting the spillover effects are important, as close coordination between neighbouring regions is. The funding granted to Objective 1 regions will be more effective in terms of economic convergence as the cohesion policies assume an "area", and not just a regional, dimension. It is important to avoid replicating the National Strategic Reference Frameworks on a regional scale, pasting them into the Regional Operational Programmes without adapting them to the real specific territorial needs. Greater coordination between regions which have similar structural characteristics or are geographically adjacent would allow more accurate detection of the strengths of each region. The concentration of resources on these different strengths (at a regional level) would also stimulate stronger spillover effects towards neighbours. Consequently, the policy-makers should take the crucial role of geographical spillover effects into account when planning economic policies.

5. CONCLUSIONS

The aim of this paper is to assess the economic convergence among EU-15 regions by estimating a conditional β-convergence model which takes into account the effects of spatial dependence and spatial heterogeneity. Per capita GDP follows a spatial pattern: the highest values are found in the European geographical core, as the traditional "centre-periphery" models usually predict. This confirms the hypothesis that the economic and geographical periphery in Europe generally coincide. This analysis then employed a model which discriminates regions (Objective 1 vs. non-Objective 1 regions) in order to study the economic growth in these two policy-defined groups. This work can be considered as a starting point for constructing a model able to evaluate the effects of cohesion policy.

Differently from the majority of previous studies (Dall'Erba and Le Gallo, 2006, 2008; Ertur *et al.*, 2006; Rodríguez-Pose and Fratesi, 2004) that accounted for spatial heterogeneity through the identification of different convergence clubs, in this paper we chose to adopt an exogenous criterion for the definitions of the clubs. The spatial autocorrelation was also modelled. This added greatly to the value of the analysis, because the results highlighted some factors which are not usually revealed by those studies which do not explicitly take spatial effects into account: Objective 1 regions are affected more by geographical spillovers and also converge faster to their steady state than do non-Objective 1 regions and per capita income disparities between the two groups of regions seem to be persistent.

The results of our analysis can be also considered from a policy-making point of view: the spatial spillovers and the different contributions of both the economic structure and the labour market to the growth of Objective 1 and non-Objective 1 regions should be taken into consideration when planning an effective EU cohesion Policy.

Further possible developments of this analysis include the estimation of a spatial panel data model for considering the temporal dynamic of economic convergence together with the spatial one and the inclusion of data on Structural Funds expenditure among the conditioning variables, in order to better assess the effects of European Cohesion Policy on economic growth.

APPENDIX

TABLE A.1

List of NUTS-2 non-Objective 1 regions included in the sample

Code	Region	Code	Region
AT12	Niederösterreich	FR53	Poitou-Charentes
AT13	Wien	FR61	Aquitaine
AT21	Kärnten	FR62	Midi-Pyrénées
AT22	Steiermark	FR63	Limousin
AT31	Oberösterreich	FR71	Rhône-Alpes
AT32	Salzburg	FR72	Auvergne
AT33	Tirol	FR81	Languedoc-Roussillon
AT34	Vorarlberg	FR82	Provence-Alpes-Côte d'Azur
BE10	Région de Bruxelles-Capitale	ITC1	Piemonte
BE21	Antwerpen	ITC2	Valle d'Aosta/Vallée d'Aoste
BE22	Limburg (B)	ITC3	Liguria
BE23	Oost-Vlaanderen	ITC4	Lombardia
BE24	Vlaams Brabant	ITD1	Provincia Autonoma Bolzano-Bozen
BE25	West-Vlaanderen	ITD2	Provincia Autonoma Trento
BE31	Brabant Wallon	ITD3	Veneto
BE33	Liège	ITD4	Friuli-Venezia Giulia
BE34	Luxembourg (B)	ITD5	Emilia-Romagna
BE35	Namur	ITE1	Toscana
DE11	Stuttgart	ITE2	Umbria
DE12	Karlsruhe	ITE3	Marche
DE13	Freiburg	ITE4	Lazio
DE14	Tübingen	LU00	Luxembourg
DE21	Oberbayern	NL11	Groningen
DE22	Niederbayern	NL12	Friesland
DE23	Oberpfalz	NL13	Drenthe
DE24	Oberfranken	NL21	Overijssel
DE25	Mittelfranken	NL22	Gelderland
DE26	Unterfranken	NL31	Utrecht
DE27	Schwaben	NL32	Noord-Holland
DE50	Bremen	NL33	Zuid-Holland
DE60	Hamburg	NL34	Zeeland
DE71	Darmstadt	NL41	Noord-Brabant
DE72	Gießen	NL42	Limburg (NL)
DE73	Kassel	SE11	Stockholm
DE91	Braunschweig	SE12	Östra Mellansverige
DE92	Hannover	SE21	Småland med öarna
DE93	Lüneburg	SE22	Sydsverige
DE94	Weser-Ems	SE23	Västsverige
DEA1	Düsseldorf	UKC1	Tees Valley and Durham
DEA2	Köln	UKC2	Northumberland, Tyne and Wear
DEA3	Münster	UKD1	Cumbria
DEA4	Detmold	UKD2	Cheshire
DEA5	Arnsberg	UKD3	Greater Manchester
DEB1	Koblenz	UKD4	Lancashire
DEB2	Trier	UKD5	Merseyside
DEB3	Rheinhessen-Pfalz	UKE1	East Riding and North Lincolnshire
DEC0	Saarland	UKE2	North Yorkshire
DEF0	Schleswig-Holstein	UKE3	South Yorkshire
DK01	Hovedstadsreg	UKE4	West Yorkshire
DK02	Øst for Storebælt	UKF1	Derbyshire and Nottinghamshire
DK03	Vest for Storebælt	UKF2	Leicestershire, Rutland and Northants
ES21	Pais Vasco	UKF3	Lincolnshire
ES22	Comunidad Foral de Navarra	UKG1	Herefordshire, Worcestershire and Warks
ES23	La Rioja	UKG2	Shropshire and Staffordshire
ES24	Aragón	UKG3	West Midlands
ES30	Comunidad de Madrid	UKH1	East Anglia

TABLE A.2

List of NUTS-2 Objective 1 regions included in the sample

Code	Region	Code	Region
AT11	Burgenland	GR25	Peloponnisos
BE32	Prov. Hainaut	GR30	Attiki
ES11	Galicia	GR41	Voreio Aigaio
ES12	Principado de Asturias	GR42	Notio Aigaio
ES13	Cantabria	GR43	Kriti
ES41	Castilla y León	IE01	Border, Midlands and Western
ES42	Castilla-la Mancha	IE02	Southern and Eastern
ES43	Extremadura	ITF1	Abruzzo
ES52	Comunidad Valenciana	ITF2	Molise
ES61	Andalucia	ITF3	Campania
ES62	Región de Murcia	ITF4	Puglia
ES63	Ciudad Autónoma de Ceuta (ES)	ITF5	Basilicata
ES64	Ciudad Autónoma de Melilla (ES)	ITF6	Calabria
FI13	Itä-Suomi	ITG1	Sicilia
FI19	Länsi-Suomi	ITG2	Sardegna
FI1A	Pohjois-Suomi	PT11	Norte
FR83	Corse	PT15	Algarve
GR11	Anatoliki Makedonia, Thraki	PT16	Centro (PT)
GR12	Kentriki Makedonia	PT17	Lisboa
GR13	Dytiki Makedonia	PT18	Alentejo
GR14	Thessalia	SE31	Norra Mellansverige
GR21	Ipeiros	SE32	Mellersta Norrland
GR22	Ionia Nisia	SE33	Övre Norrland
GR23	Dytiki Ellada	UKM6	Highlands and Islands
GR24	Sterea Ellada	UKN0	Northern Ireland

Figure A.1 – Maps of NUTS-2 non-Objective 1 regions included in the sample (left-hand panel) and Objective 1 regions included in the sample (right-hand panel).

Dipartimento di Scienze Statistiche
Università di Bologna

CRISTINA BRASILI
FRANCESCA BRUNO
ANNACHIARA SAGUATTI

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SUMMARY

A spatial econometric approach to EU regional disparities between economic and geographical periphery

A conditional β-convergence model and a distance-based weight matrix are used to analyse the economic convergence among European NUTS-2 regions over the period 1980-2006. A Spatial Autoregressive Model which identifies two spatial regimes and spatial dependence finds that the convergence process among EU regions is affected by polarization into two clusters defined both on a geographical and economic criterion, which converge at different rates towards different steady states.

This result confirms the hypothesis that a methodology which uses spatial econometric techniques is needed to model spatial effects, and that otherwise the estimates are likely to be inefficient or even biased.