

A spatial econometric model for evaluating conditional β -convergence across EU regions.

Cristina Brasili¹, Francesca Bruno¹, Annachiara Saguatti²

¹Department of Statistics “P.Fortunati”, ² Faculty of Political Science, University of Bologna
Email: cristina.brasili@unibo.it; francesca.bruno@unibo.it

The aim of this paper is to assess European Union Cohesion Policy by estimating a conditional β -convergence model for a sample of 196 EU regions over the period 1980-2006, using a spatial econometric perspective and a distance-based weight matrix. Under the assumption of substantial coincidence of geographical and economic periphery in EU-15, the final model combines the identification of two regimes and spatial dependence. In particular, we consider Objective 1 and non Objective 1 regions, relatively to 1994-1999 period. A spatial auto-regressive model (Anselin, 1988) with two spatial regimes, including cross-regressive terms to further investigate the role of geographical spillover effects on regional convergence, was estimated. Moreover, the conditioning variables, the regional employment rate and the agricultural share on total employment, allow for further heterogeneity within each regime. The results of this work support the importance of an explicit consideration of spatial effects in convergence analysis (as highlighted in Piras and Arbia, 2007 and Ramajo et al, 2008). The main finding is that the convergence process among EU regions is affected by a polarization into two different clusters converging separately to different steady states, thus implying relative income differences to be persistent. Furthermore, Objective 1 regions are more affected by geographical spillover effects and converge faster to their steady state than non Objective 1 regions. These findings suggest a positive role of EU Regional Policy on convergence among Objective 1 regions and, at the same time, call for a better consideration of spatial spillover effects in planning Regional Policy.

Keywords: β -convergence; Geographic Spillovers; Spatial Heterogeneity; EU Regional Policy.

JEL Codes: C21; C51; O52; R11; R15.

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1 Introduction

The process of European integration ventured along the path of enlargement as far as to the accession of 12 new member States (2004-2007) and to the Monetary and Economic Union. This process is rooted in the objective of economic and social cohesion, explicitly formulated since the Single European Act (1986), but already mentioned in the Treaty of Rome of 1957 as a need to reduce regional disparities. The evolution of European Cohesion policies acknowledges that both the deepening of European integration and the territorial enlargement of the Union are not sustainable without a proper redistribution of resources between the member States and their regions as well, thus recognizing the regional dimension of development as the major framework of Structural policies.

These great ambitions of deeper integration give birth to great questions. The political and financial sustainability of EU Regional policies, the possible trade-off between social cohesion and competitiveness (Fitoussi, 2006) are often debated, especially in light of the increasing funds devoted to the poorest regions, which have been granted 70% of the Structural Funds in the period 1989-1993 and 81% of them in 2007-2013 (European Commission, 1996; Regulation EC 1083/06). Therefore, criticisms towards Regional policies, perceived just as solidarity measures which damage European competitiveness, are not missing (Fadda, 2006).

This paper aims to assess the effects of Cohesion policies on economic convergence among European regions by estimating a conditional β -convergence model with spatial effects, thus taking the contribution of New Economic Geography to a substantially neoclassical-born methodology into the due consideration. The debates about the parametric analysis of economic convergence are not ignored and we are aware of the irreducible multidimensional nature of economic growth, which cannot reasonably be synthesised in one single parameter. However, we believe that the rather recent techniques of spatial econometrics that are used in this analysis can lead to interesting findings.

The structure of this paper is as follows. Section 2 presents the definition of β -convergence and discusses the advantages and disadvantages of this measure of economic convergence. The spatial econometrics techniques that were used for the present analysis are presented in Section 3 and their added value is highlighted. Section 4 describes the data and the results of the exploratory spatial analysis. Model specification and results are presented in Section 5. Finally, the main conclusions and some possible strategies of economic policies are discussed in Section 6.

2 Economic Convergence

Convergence is defined as a socio-economic process that is revealed by the progressive reduction of disparities in social and economic indicators of well-being relative to a group of economies (Leonardi, 1995). The existence of a convergence process can therefore reveal the real chances of reaching the aim of better cohesion among different territories and this is the main reason why the measures of economic convergence are so popular, particularly in the field of European Regional policies studies (Button and Pentecost, 1999; Leonardi, 1995; López-Bazo et al., 2004; Rodríguez-Pose and Fratesi, 2004; Ertur et al., 2006; Dall’Erba and Le Gallo, 2007; Piras and Arbia, 2007; Ramajo et al., 2008).

Since Baumol’s (1986) pioneering work, convergence studies have been developed through several different techniques of analysis, each of them being able to highlight different dimensions of this phenomenon. The “classical” (Sala-i-Martin, 1996) method of analysis of absolute and conditional convergence –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 whose elaboration is mainly due to the contribution of Robert Barro (1991) and Sala-i-Martin (1991, 1992, 1995). The concept of β -convergence suggests the tendency of per capita income of the poorest economies to grow faster than the richest ones’, given a negative correlation between the growth rate of per capita income and its initial level, thus generating a process of convergence (Sala-i-Martin, 1996).

If we define $\gamma_{it} = [\ln(y_{it}) - \ln(y_{it_0})] / \tau$ as 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 that is proposed to test the existence of a convergence process is:

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

where $i = 1, \dots, N$, 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 estimation of the parameter b in model (1) indicates *absolute* convergence, following the neoclassical theory.

Barro and Sala-i-Martin (1992) show how model (1) can be derived through a log-linear approximation from the equation that expresses the dynamic of transition in a

neoclassical model of growth with technological progress. The speed of convergence (β) can be estimated through the linear regression (1) ¹, following the relation $b = (1 - e^{-\beta\tau}) / \tau$:

$$\hat{\beta} = -\ln(1 - \hat{b}\tau) / \tau \quad (2)$$

By calculating the *half life* (T) of convergence (Barro and Sala-i-Martin, 1995), it is possible to calculate the number of years that it would take for half of the initial gap between economies to be eliminated. Following $e^{-\beta T} = 1/2$,

$$T = \ln(2) / \beta = 0,69 / \beta \quad (3)$$

The *absolute* convergence hypothesis is not supported by any empirical proof, though, particularly when studying the economies of different States or regional economies of different States. Barro and Sala-i-Martin (1991) themselves admit the need to take some other factors –called *conditioning variables*– into account, as they prevent the convergence to a unique steady-state to take place. The subsequent model is a model of *conditional* convergence, in which structural differences modify the steady-states of the economies; empirically, the steady-states of the economies (\tilde{y}_i^*) need to be kept constant in order to estimate β . The most common way to do this is to add one or more conditioning variables to model (1):

$$\gamma_{it} = a + b \cdot \ln(y_{it_0}) + \psi X_{it_0} + \varepsilon_{it} \quad (4)$$

where X_{t_0} is the vector of conditioning variables and ψ is its parameter.

Once added the conditioning variables are included, a negative estimate of b indicates that a process of *conditional* convergence is taking place. The economic theory can guide the search of the best conditioning variables to include: the Solow model suggests the saving rate, the level of technology and the growth rate of the technological progress, the population growth rate and the rate of depreciation of capital. Other theories may rather suggest the

¹ The estimation of β following the linear regression (1) leaves the standard error unknown. $\hat{\sigma}_\beta = \hat{\sigma}_b / \tau(1 - \hat{\beta})$ can be calculated as an approximation for the unknown standard error. Alternatively it is possible to estimate β as the coefficient of a non linear model through the *non linear least squares* (NLS) method, thus obtaining the estimation of the *standard error* (Sala-i-Martin, 1996).

inclusion of the expenditure in R&D, the level of human capital, the economic structure, the labour market structure, the political stability, etc...².

One of the main criticisms that have been raised against the β -convergence approach is that the estimates of β persistently tend to equal a value around 0.02 (Quah, 1995). This empirical regularity cannot be considered the product of an economic mechanism: in fact, if this value expressed a general regularity of convergence processes, it would predict a catching up of poorest economies towards the richest ones within 70 years. However, the literature demonstrates that this recurrence is explained by purely statistical reasons (Quah, 1995; Canova and Marcet, 1995).

Not surprisingly, the assumptions which the concept of β -convergence is based on have been criticised too. Quah (1993) highlights the lack of empirical evidence of a stable long-term trend in the growth of economies. The growth process is rather continuously influenced by shocks that make any assumption of stable growth paths unreal. According to Quah, it is impossible to describe the dynamics of changes that take place in time through a parametric analysis, because what is actually observed is just the situation at the beginning and at the end of the period, under the assumption that a regular trend ruled the changes in between.

Finally, the cross-country parametric approach has been criticised because it hardly reveals the presence of multiple regimes in a convergence process, because this concept contrasts with the idea that a unique linear specification exists, which is common to all the observed economies. Possible alternative approaches either identify multiple locally stable steady-states (Durlauf and Johnson, 1995) or analyse effects of polarisation or stratification (Quah, 1997) in search of *convergence clubs* (Canova, 2004).

3 Spatial effects

Intuitions derived from the New Economic Geography show the importance of the spatial location of economies in explaining their growth path, inasmuch as it originates a

² On the choice of possible conditioning variables, see Barro e Sala-i-Martin (1995).

circular mechanism that would perpetuate the unequal development of territories, once it is established³.

A recent approach to economic convergence enriches Barro's neoclassical measure of convergence with the acknowledgements of New Economic Geography, in order to fill the gap between theoretical advances and empirical analysis. Through the techniques of spatial econometrics (Anselin, 1988) it is possible to deal with the major problems generated by the spatial dimension of data –spatial dependence and heterogeneity-, which might affect the reliability of cross-country estimations if not properly modelled.

Spatial dependence refers to “the existence of a functional relationship between what happens at one point in space and what happens elsewhere” (Anselin, 1988, p. 11). What is highly relevant in explaining the value of a given variable in a region is therefore the spatial location of that region compared to that of the other regions. Spatial dependence can occur either as a form of spatial interdependence between the observations of a variable (in this case, it is a matter of coincidence of attribute similarity and 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, 2007), either in the form of spatial instability of observations, which is strictly related to the presence of multiple spatial regimes and convergence clubs, or/and in the form of groupwise 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. Moreover, the omission of a proper formalisation of spatial heterogeneity can originate an autocorrelation of the regression residuals. In other words, the autocorrelation of residuals can simply be a clue for model misspecification (Ertur et al., 2006). Since the traditional Ordinary Least Squares (OLS) method of estimation can be inappropriate in case of spatially correlated observations, it is crucial to identify the presence of spatial dependence and 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 estimation will be affected, but in the second case the OLS estimation will be inconsistent (Anselin et al., 1996).

³ 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).

4 European regions and spatial effects

4.1 The data

The database employed in this analysis is taken from the Cambridge Econometrics Regional Database and covers the period 1980-2006. Our sample includes 196 NUTS-2 regions (Nomenclature of Territorial Units for Statistics, Eurostat) of 15 European countries: Austria, 9; Belgium, 11; Germany, 30; Denmark, 3; Spain, 18; Finland, 5; France, 22; Greece, 13; Ireland, 2; Italy, 21; Luxembourg, 1; The Netherlands, 11; Portugal, 5; Sweden, 8; Great Britain, 37⁴.

The variable that is used to measure the income of regions is per capita GDP in Euros at 2000 prices, expressed in logarithms and in deviations with respect to the EU-15 mean. Thus, the analysis appears coherent with the criterion of eligibility to Objective 1 funds, which refers to the relative level of per capita GDP as a measure of general well-being of European regions. Moreover, working with scaled per capita GDP helps to control the effects of European economy-wide cycles and of common trends, and to reduce the effects of the outliers (Ramajo et al., 2008). Therefore the dependent variable of our model is:

$$\Gamma_{it} = \gamma_{it} - \gamma_{UE,t}$$

where $\gamma_{it} = [\ln(y_{it}) - \ln(y_{it_0})] / \tau$ e $\gamma_{UE,t} = [\ln(\bar{y}_{UE,t}) - \ln(\bar{y}_{UE,t_0})] / \tau$.

In accordance with data availability at a regional level, we choose to include the regional employment rate and the share of agricultural to total employment as conditioning variables to our 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 the context of 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 directions. In addition, the employment rate is used by some authors as a means to quantify the effects of labour market disparities (Ramajo et al., 2008), since differences in employment rates can be due either to different rates of unemployment or to different demographic structures of the population. An additional reason

⁴ See Appendix 1 for a detailed list of the regions included in the sample.

for including this variable in our model is that a higher employment rate can highly 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 different compositions of economic activities (Ramajo et al., 2008), but also the potential amount of financing obtained through 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).

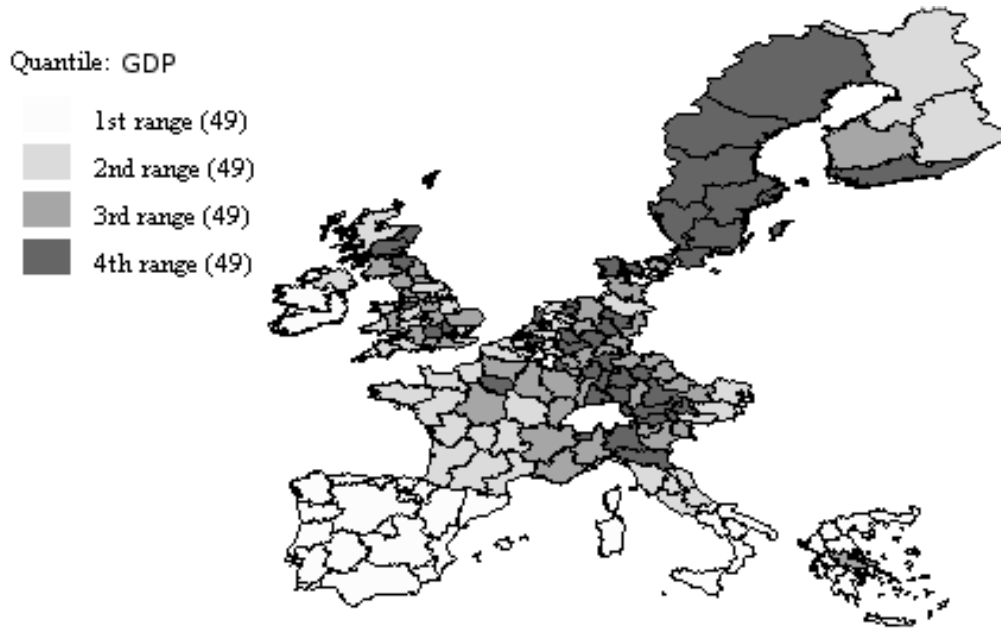
The eligibility of regions to Objective 1 of European Structural Policies (during the programming period 1994-1999) is taken into consideration through a dummy variable and, in accordance to the findings presented in literature (Ramajo et al. 2008), this distinction is expected to be suitable to model the potential spatial heterogeneity in our sample. In fact, it is known that in Europe the economic disadvantage is usually accompanied by a geographical disadvantage (we commonly talk about “European periphery” to indicate European poorest regions). During the programming period 2000-2006, Objective 1 covered the former Objective 6 regions and the most remote regions as well as those regions whose development was lagging behind (Reg. 1260/99 EC): this reflects the institutional awareness of the relationship between geographic and economic periphery. This assumption has been verified through the exploratory spatial analysis.

4.2 Exploratory Spatial Data Analysis

In order to highlight the potential spatial pattern of our observations it is useful to create a map which shows the spatial distribution of the considered variable. The spatial distribution of the regional per capita GDP in 1980 suggests the existence of spatial heterogeneity in the form of two spatial clusters of richer and poorer regions. The assumption of substantial coincidence between geographic and economic periphery is therefore supported by this result⁵ (Figure 1).

⁵ Figure 1 can cast doubts about the inclusion of some Scandinavian regions in the “Objective 1” cluster. However, when these areas are included in the sample of “non Objective 1” regions, the results do not differ significantly.

Figure 1. Spatial percentile distribution for the log of per capita GDP in 1980, in deviation with respect to the EU-15 mean.



The spatial interaction between the regions is modelled through the spatial weight matrix (W):

$$W = \begin{bmatrix} 0 & w_{12} & \dots & w_{1N} \\ w_{12} & 0 & \dots & w_{2N} \\ \dots & \dots & \dots & \dots \\ w_{N1} & w_{N2} & \dots & 0 \end{bmatrix}$$

W is a square, non-stochastic and symmetric matrix, whose externally defined 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 choice of the spatial weights matrix is a delicate operation which can heavily impact on the final results of the analysis and which is widely treated in literature. The majority of the researches about European regions use distance-based matrices (Fingleton, 1999; Baumont et al., 2001; Ertur et al., 2006; Le Gallo and Dall’Erba, 2006; Dall’Erba and Le Gallo, 2007; Ramajo et al., 2008).

A synthetic measure of spatial association is the “Moran’s I ” statistics, which tests for spatial dependence:

$$I = \frac{n}{S} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

where $S = \sum_i \sum_j w_{ij}$; y is the considered variable; \bar{y} is the mean of the sample; n is the size of the sample and w_{ij} are defined as:

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

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 ; $D(1)=Q(1)$, $D(2)=\text{Mdn}$ e $D(3)=Q(3)$; $Q(1)$ is the lower quartile (25%), Mdn is the median value (50%) and $Q(3)$ is the upper quartile (75%) of the great circle distance distribution; $D(k)$ is the *cut-off parameter* for $k=1, \dots, 3$, above which any interaction between the regions is considered to be negligible⁶. The standardisation of the spatial weight matrix does not have any influence on the relative dependence between neighbours, but it attributes a value of either 0 or 1 to each element of the matrix, thus making the results of the calculations in which the matrix is involved and the results of different analysis more easily interpretable and better comparable.

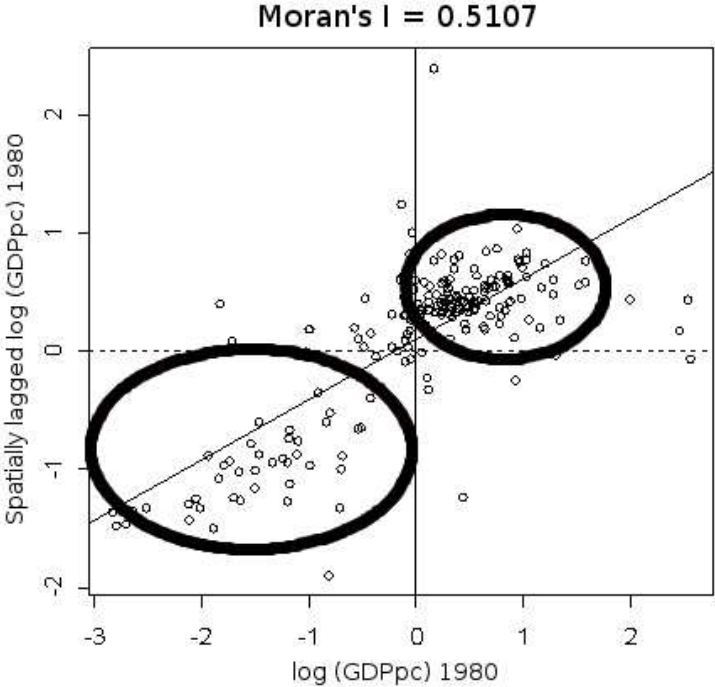
Relatively to the variable per capita GDP in 1980, the Moran's I value is 0.5107 (p -value=0.000), well above the expected value under the null hypothesis of no spatial correlation, $E(I)=-0.0051$: initial per capita GDP is therefore spatially correlated and a positive spatial dependence is revealed in the distribution of this variable. A similar result was obtained for the growth rate of per capita GDP between 1980 and 2006: $I= 0.2131$ (p -value=0.000).

The "Moran" scatterplot provides a clearer view of the spatial dimension of the data. Each quadrant in the scatterplot 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, high/low values of y in one region and in its neighbours; on the contrary, the second and fourth quadrants display a negative dependence. Therefore, through the observation of the Moran scatterplot it is possible to identify the existence of spatial heterogeneity in the sample. Two distinct clusters are displayed, one made

⁶ 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.

up of rich regions surrounded by other rich regions (first quadrant) and another one made up of poor regions surrounded by poor regions (third quadrant) (Figure 2).

Figure 2. Moran scatterplot for the logarithm of per- capita GDP in 1980.



As a conclusion to the exploratory spatial analysis, we choose to estimate a model with two spatial regimes. The first one includes 50 NUTS-2 regions which were part of Objective 1 and 6 during the programming period 1994-1999⁷, whereas the second one includes the other 146 regions of our sample. Any parameter instability between these two groups of regions will be considered as a proof of the existence of two convergence clubs with both a spatial and an economic dimension.

5 A convergence model and spatial effects among EU regions

5.1 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 OLS estimation of a model of conditional β -convergence without

⁷ This choice aims at including the Austrian, Swedish and Finnish regions, that joined the EU in 1995, in this analysis.

spatial effects (5) and the testing for spatial autocorrelation on the regression residuals (Anselin, 1988; Anselin et al., 1996) (Table 1).

$$\Gamma_{it} = a + bGDP_{it_0} + \psi_1TOT_EMP_{it_0} + \psi_2AGR_EMP_{it_0} + \varepsilon_{it} \quad (5)$$

where Γ_{it} is the rate of growth of per capita GDP in region i for the period 1980-2006, expressed in logarithms and in deviations with respect to the EU-15 mean; GDP_{it_0} is the level of per capita GDP in region i in 1980, expressed in logarithms and in deviations with respect to the EU-15 mean; $TOT_EMP_{it_0}$ is the total employment rate in region i in 1980 and $AGR_EMP_{it_0}$ is the share of agricultural employment in region i in 1980.

Table 1. Tests of global spatial autocorrelation.

Test	Q(1)=554 km		Mdn=1044 km		Q(3)=1597 km	
		(p-value)		(p-value)		(p-value)
Moran's I test (residuals)	0.1142	(0.017)	0.0996	(0.001)	0.0903	(0.000)
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	1.1120	(0.292)	0.0036	(0.953)	0.032	(0.858)

The Moran's I test statistic adapted to regression residuals shows the existence of residual spatial autocorrelation, without providing any additional information on the best specification to choose. The results of the Lagrange Multiplier (LM) tests lead us to choose the spatial weights matrix based on Q(3), according to Anselin's suggestion (in Ertur et al., 2006) to choose the cut-off distance which maximises the absolute value of significant Lagrange multiplier statistic for spatial autocorrelation. Moreover, the same tests suggest a *spatial lag model*, or *spatial auto-regressive model (SAR)* as the best specification to model the identified spatial dependence: in fact, 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).

As already explained, the identified spatial heterogeneity is modelled through two convergence clubs, based on a criterion of geographic periphery and economic backwardness at the same time.

On the one hand, the estimation of a model of conditional β -convergence with two convergence clubs reflects the existence of two distinct spatial regimes, each characterised by its own convergence process and, on the other hand, the inclusion of the conditioning variables allows for each region in the two groups to converge towards its own steady-state. Following Ramajo et al. (2008), we included the spatial lags of the explanatory variables in the model specification such as in a *cross-regressive spatial model*. Then, the Akaike criterion and the log-likelihood value guided our choice of the model in light of the trade-off between goodness of fit and number of parameters estimated; between the various possible specifications of the model, we chose the one that associates the major number of significant parameter estimations with the best goodness of fit statistics (6):

$$\begin{aligned} \Gamma_{it} = & a^{OB1} D_i^{OB1} + a^{NN1} D_i^{NN1} + (b^{OB1} D_i^{OB1} + b^{NN1} D_i^{NN1}) GDP_{i0} + \\ & + (\psi_1^{OB1} D_i^{OB1} + \psi_1^{NN1} D_i^{NN1}) TOT_EMP_{i0} + \\ & + (\psi_2^{OB1} D_i^{OB1} + \psi_2^{NN1} D_i^{NN1}) AGR_EMP_{i0} + \\ & + (\phi^{OB1} D_i^{OB1} + \phi^{NN1} D_i^{NN1}) WGDP_{i0} + \rho W\Gamma_{it} + \varepsilon_{it} \end{aligned} \quad (6)$$

where D_i^g is a dummy variable which takes on the value of 1 for Objective 1 regions ($g=OB1$) and 0 for non-Objective 1 regions ($g=NN1$). The estimation results for model (6) are shown in Table 2.

Table 2. OLS and ML estimations results.

Variable/parameter	OLS	ML	
		Objective 1	Non Objective 1
Constant (a)	-0.00904 (0.003)	-0.00312 (0.460)	-0.01505 (0.000)
GDP (b)	-0.01917 (0.000)	-0.02824 (0.000)	-0.01569 (0.000)
Total Employment (TOT_EMP) (ψ_1)	0.00032 (0.000)	-0.00002 (0.846)	0.00043 (0.000)
Share of Agricultural Employment (AGR_EMP) (ψ_2)	-0.00039 (0.000)	-0.00029 (0.000)	-0.00019 (0.037)
W_GDP (ϕ)		0.02282 (0.000)	-0.00521 (0.089)
Spatial Parameter (ρ)		0.35186 (0.001)	
Convergence rate (β) %	2.7	5.3	1.6
Half life (years)	36	24.5	44
R ²	0.2995		
Adjusted R ²	0.2886		
Jarque-Bera test	248.75 (0.000)		
Breusch-Pagan test	3.1162 (0.374)	13.5457 (0.139)	
LMerr test		2.8226 (0.093)	
Log likelihood		746.04	
Chow test		47.01 (0.000)	
AIC		-1504.1	

5.2 Conditional β -convergence and spatial effects among EU-15 regions

The results of the OLS estimation of model (5) show that each of the included explanatory variables is statistically significant and that they support the neoclassic assumption of conditional convergence. The rate of convergence (2,7%) and the half-life (36 years) are consistent with the values found in literature (Barro and Sala-i-Martin, 1992; Sala-i-Martin, 1996) for models which do not include spatial effects.

The tests for spatial autocorrelation, however, highlight the need for taking spatial effects into account. The results of the ML estimation of model (6) support the existence of two spatial convergence clubs, as the value of the Chow test rejects the null hypothesis of parameter stability between the two groups of regions. The estimates of b 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 (1.6%); consequently the half-life for the first group (24.5 years) is much lower than that of the second one (44 years). Therefore, the estimation of a SAR model with two spatial regimes seems to be advisable. The inclusion of the spatial lag of per capita GDP among the explanatory variables, which allows a deeper analysis of spatial interactions and is supported by better AIC and log-likelihood statistics, contributes to better explain spatial correlation: in fact, a pure SAR model estimates $\hat{b}^{OB1} = -0.0158$ (p-value=0.000) and $\hat{b}^{NM1} = -0.01629$, thus implying the same rate of convergence (2.1%) for both groups of regions.

The estimation of the spatial parameter (ρ) supports the crucial role of the geographic-territorial dimension of economic growth: a β -convergence model with spatial effects reveals the existence of spillover effects between European regions that affect the economic performance of each of them. This result is in accordance with those of other studies (López-Bazo et al., 2004; Baumont et al., 2001; Ramajo et al., 2008) and with the theories of New Economic Geography: the more a region is surrounded by dynamic and fast growing economies, the higher its growth rate will be.

The estimate regarding the self initial total employment rate is negative for Objective 1 regions, without being statistically significant, though. On the contrary, it suggests that a high total employment rate has, on average, a significant positive influence on the convergence process of Non-objective 1 regions towards their steady state. The estimates concerning the share of agricultural employment reveal an inverse relationship between the importance of the agricultural sector and the economic growth: in both groups of regions, in

fact, the estimates of AGR_EMP are negative and significant at the 5% level. In general, the self-initial employment rate is more important in regard to richer regions, whereas the economic growth of Objective 1 regions is more affected by the self-initial share of agricultural employment.

Finally, the GDP of neighbouring regions has a positive effect on the growth of Objective 1 regions (0.023). These being the results, we conclude that a generally advanced and dynamic economic environment favours growth, especially concerning the poorest regions.

Some further considerations are required to confront these results with those presented in the previous literature on convergence among EU regions and spatial effects. Ramajo et al. (2008) find similar convergence rates relatively to the period 1981-1995, by estimating a model with two spatial regimes (Cohesion and non-Cohesion countries) which includes the same two self-initial conditioning variables, the auto-regressive and cross-regressive spatial lags: the estimates regarding the b coefficients reveal a higher convergence rate among the poorest regions. Dall'Erba and Le Gallo (2006; 2007) find evidence of two “centre-periphery”-like clubs of convergence, particularly at the end of the 80s and with a higher rate of convergence among peripheral regions. Ertur et al. (2006) find two spatial regimes; however, no evidence of an on-going convergence process is detected among the northern regions and only weak convergence concerns the southern ones. The authors suggest that this result may be due to the conditioning of the model. Rodríguez-Pose and Fratesi (2004) find higher convergence rates when only Objective 1 regions are taken into account, although they do not explicitly model spatial effects.

The construction of the clusters according to the criterion of the eligibility of a region to Objective 1 funding proves to be significant, thus supporting the assumption –already made by the European Institutions themselves in the context of Regional policies- that economic backwardness and geographical periphery often coincide. Moreover, it allows us to make more coherent remarks about the EU Cohesion policy than those that a generic “centre-periphery” disaggregation would suggest. This result reveals the existence of two groups of regions that converge towards two distinct steady states, in which the disparities in per capita income are likely to be lasting and persistent.

In regards to the analysis of spatial effects, the estimates highlight significant spillover effects which influence the economic growth of European regions and cause, in models that do not explicitly model them, econometric problems due to error spatial autocorrelation. Overall, it should be concluded that, in accordance with the remarks of New

Economic Geography, the economic growth of a region depends on initial per capita GDP in neighbouring regions; this is more evident in relation to Objective 1 regions. Therefore, the poorest regions -those whose per capita GDP is lower than 75% of the Community average- are the ones that are more affected by the economic situation of their neighbours.

6 Conclusions

The aim of this paper is to indirectly assess the effects of EU Cohesion policy, by analysing the process of economic convergence among EU-15 regions through the estimation of a conditional β -convergence model which takes the effects of spatial dependence and spatial heterogeneity into account.

The exploratory spatial data analysis revealed the existence of an evident spatial pattern in the distribution of per capita GDP: the highest values are concentrated in the European geographic core as the traditional “centre-periphery” development models predict. This finding confirms the assumption of substantial coincidence between economic and geographic periphery in the European context. Therefore our analysis was conducted through a model which took this spatial pattern into account through a dummy variable (Objective 1 vs. non-Objective 1 regions) and by modelling OLS residual spatial autocorrelation. This constituted an important added value of this analysis, as our results highlighted some factors which are not usually revealed by those studies which do not explicitly take spatial effects into account.

The main findings show a polarization of development into two convergence clubs (Objective 1 and non-Objective 1 regions) that converge at different rates towards different steady states: therefore, it is important to acknowledge the existence of 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. On the other hand, the higher convergence rate that was found for Objective 1 regions suggests a positive evaluation of EU Cohesion policy, which appears to affect the growth rates of the poorest regions positively.

The quantification of the speed of convergence through the estimation of a single parameter is the major strength of parametric methods for convergence analysis; the estimated half-life is 24.5 years for Objective 1 regions and 44 years for non-Objective 1 regions. Moreover, the specification of two spatial regimes allows assessing the different impact of the

conditioning variables on growth in the two groups of regions. Firstly, the spatial lag of per capita GDP is more relevant in explaining 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 determines the best improvements in the goodness of fit of the model and the biggest differences in the estimates of b . It is also worth considering that, relatively to total and agricultural employment, the negative effect of a high self-initial share of agricultural employment is bigger on Objective 1 regions, whereas a high self-initial employment rate has a prevailing positive effect on non-Objective 1 regions.

It is not possible, through a model of this kind, to explicitly demonstrate the causal relation between a higher convergence rate among poorest regions and the Structural policies funding: however, we cannot fail to notice that Objective 1 regions receive a share over the total amount of funding for Regional policy, that is much higher than the share of their GDP over the total GDP of EU-15. In fact, during the programming period 1989-1993 the regions whose development is lagging behind received 69.6% of Structural Funds compared to 11% of 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 compared to their 10% contribution to EU-15 GDP⁸. Consequently, we can reasonably assume that such a distribution of aids contributes to the higher convergence rate among poorest regions, thus supporting the thesis of those who think that the regions with a lower level of initial per capita income will grow at higher rate, thus generating convergence.

The estimates of the spatial autoregressive parameter and of the spatially lagged GDP also reveal the existence of geographical spillover effects which are of primary importance in explaining the economic growth of European regions. Therefore, the relative geographical location of each region has a key role in explaining the structure of economic growth in the context of EU-15. From a methodological point of view, this result confirms the need to recur to spatial econometrics techniques in order to model those spatial effects that otherwise would lead to inefficient or even biased estimates.

We acknowledge several deep policy implications which suggest the importance of specific investments aimed at exploiting the spillover effects and call for strong coordination between neighbouring regions. The funding granted to Objective 1 regions will be more effective in terms of economic convergence as the Cohesion policies assume an “area” and

⁸ The data relative to the amount of funding are taken from European Commission (1997; 2001) and do not include the funding of the Cohesion Fund. The data relative to the GDP of Objective 1 regions are taken from the Cambridge Econometrics Regional Database.

not just a regional dimension. It would be important to avoid replicating National Strategic Reference Frameworks on a regional scale, pasting them into the Regional Operational Programmes without adapting them to the real specific territorial needs. A stronger coordination between regions which have similar structural characteristics or are geographically adjacent would allow a more accurate detection of the strengths of each region. Moreover, the concentration of resources on these different strengths (on a regional level) would stimulate stronger spillover effects towards neighbours. The findings of this analysis suggest that the policy-makers should take the crucial role of geographical spillover effects into account when planning economic policies.

APPENDIX 1

Our sample includes 196 NUTS-2 regions, divided into two groups: the first group is composed by those regions that were eligible to Objective 1 funding during the programming period 1994-1999, whereas the second one is formed by the rest of the regions. The Canary Islands (ES) are excluded from the sample because, being much more distant than the other regions, they would have influenced the distance-based spatial weights matrix by requiring a too high cut-off distance. Other 17 regions (of the Cambridge Econometrics Regional Database) were excluded from the sample: Germany's eastern Landers, because of a lack of data previous to 1991, the French Overseas Departments, the Azores Islands and Madeira (PT), whose data are totally lacking.

Table A1.1. 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
	Région de Bruxelles-Capitale/ Région de Bruxelles-Capitale/	ITC1	Piemonte
BE10	Brussels Hoofdstedelijk Gewest	ITC2	Valle d'Aosta/Vallée d'Aoste
BE21	Antwerpen	ITC3	Liguria
BE22	Limburg (B)	ITC4	Lombardia
BE23	Oost-Vlaanderen	ITD1	Provincia Autonoma Bolzano-Bozen
BE24	Vlaams Brabant	ITD2	Provincia Autonoma Trento
BE25	West-Vlaanderen	ITD3	Veneto
BE31	Brabant Wallon	ITD4	Friuli-Venezia Giulia
BE33	Liège	ITD5	Emilia-Romagna
BE34	Luxembourg (B)	ITE1	Toscana
BE35	Namur	ITE2	Umbria
DE11	Stuttgart	ITE3	Marche
DE12	Karlsruhe	ITE4	Lazio
DE13	Freiburg	LU00	Luxembourg
DE14	Tübingen	NL11	Groningen
DE21	Oberbayern	NL12	Friesland
DE22	Niederbayern	NL13	Drenthe
DE23	Oberpfalz	NL21	Overijssel
DE24	Oberfranken	NL22	Gelderland
DE25	Mittelfranken	NL31	Utrecht
DE26	Unterfranken	NL32	Noord-Holland
DE27	Schwaben	NL33	Zuid-Holland
DE50	Bremen	NL34	Zeeland
DE60	Hamburg		

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	Västsvrige
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 A1.2. 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	Stereia Ellada	UKN0	Northern Ireland

Figure A1.1. NUTS 2 non-Objective 1 regions included in the sample.



Figure A1.2. NUTS 2 Objective 1 regions included in the sample.



Figures A1.1 e A1.2 show the maps of non Objective 1 and Objective 1 regions included in our analysis. The assumption of coincidence of economic and geographic marginality among EU-15 regions is strongly confirmed by these images.

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