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# A spatial approach to EU regional economic convergence: a comparison between parametric and non-parametric analysis.

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# **A spatial approach to EU regional economic convergence: a comparison between parametric and non-parametric analysis.**

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ABSTRACT. The economic convergence among European regions over the period 1980-2006 is analysed in the first place by using a conditional  $\beta$ -convergence model and a distance-based weight matrix and secondarily by a spatially-conditioned stochastic kernel approach.

A Spatial Autoregressive model which identifies two spatial regimes and spatial dependence finds that the convergence process is affected by polarization into two clusters defined both on a geographical and economic criterion, which converge at different rates towards different steady states. A similar result is then reached through a non-parametric analysis of the income distribution dynamics.

These results confirm the hypothesis that a methodology which uses spatial econometric techniques is needed. They also suggest some implications for EU Regional Policy that should be taken into account.

Keywords:  $\beta$ -convergence; Geographic Spillovers; Spatial Heterogeneity; EU Regional Policy, Stochastic Kernel Analysis.

This paper is a joint-production of the authors. However Professor Cristina Brasili wrote sub-section 4.1 and section 5; Professor Francesca Bruno wrote section 2 and sub-section 3.2; Doctor Annachiara Saguatti wrote sub-sections 3.1, 4.2 and 4.3. The introduction and the conclusions were a joint production of the authors.

## 1. INTRODUCTION

The process of European integration expanded along the path of enlargement as far as to the adhesion of 12 new member States (between 2004 and 2007) and to the Monetary and Economic Union, with the aim of creating economic and social cohesion and reducing regional disparities. The aim of greater integration gives rise to deep questions about the political and financial sustainability of EU Regional policies and the possible trade-off between social cohesion and competitiveness (Fitoussi, 2006), 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). As a result regional policies have been criticised as being merely expressions of solidarity which damage European competitiveness (Fadda, 2006).

Convergence is defined as a socio-economic process that results in the progressive reduction of disparities in social and economic indicators of well-being in a group of economies (Leonardi, 1995). Convergence can thus 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 (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 which used several different analysis techniques. Each of these was 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  $\beta$ -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 Robert Barro (1991) and Sala-i-Martin (1991, 1992, 1995).  $\beta$ -convergence 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 correlation 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. The resulting model is a model of *conditional* convergence, in which structural differences modify the steady-states of the economies. Economic theory can help by suggesting which the best conditioning variables to include are.

This paper acknowledges the results of the estimation of a conditional  $\beta$ -convergence model with spatial effects presented by Brasili et al. (2011), thus taking into consideration the contribution of New Economic Geography to a substantially neoclassical methodology (Arbia, 2006). However, the debates about the parametric analysis of economic convergence are not ignored, together with the irreducible multidimensional nature of economic growth, which cannot reasonably be synthesised in one single parameter (Quah, 1993, 1995; Canova and Marcet, 1995). For this reasons, the results of the parametric analysis are followed by a non-parametric study of the entire distribution dynamics of per capita income of European regions, so that the conclusions in terms of convergence can be compared.

Both the approaches followed in this work confirm the importance of explicitly considering spatial effects when doing convergence analysis.

The structure of this paper is as follows. Section 2 describes the data used for both the parametric and non-parametric analysis. Section 3 presents the conditional  $\beta$ -convergence model specification and the results in terms of both statistical and policy interpretation. Section 4 presents the results of the non-parametric analysis. Section 5 compares the results of the two approaches to convergence analysis and draws some implications of economic policy. Finally in Section 6 the main conclusions are discussed.

2. DESCRIPTION OF THE DATA

The database used in this analysis is taken from the Cambridge Econometrics Regional Database and covers the period 1980-2006. It refers to 196 NUTS-2 regions (Nomenclature of Territorial Units for Statistics, Eurostat) from 15 European countries:

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	Tot.	196

The main object of this analysis is per capita GDP (in Euros at 2000 prices) expressed in logarithms and in deviations with respect to the EU-15 mean. The distribution of this variable is mainly investigated through a stochastic kernel approach.

As for the parametric analysis, the growth rate of the logarithm of per capita GDP (in Euros at 2000 prices) ( $g_{it}$ ), expressed in deviations with respect to the EU-15 mean, is taken to be the dependent variable of the model. 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 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 policy-defined Objective 1 and non-Objective 1 regions distinction, through a dummy a variable.

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

#### 3.1. *Exploratory Spatial Data Analysis*

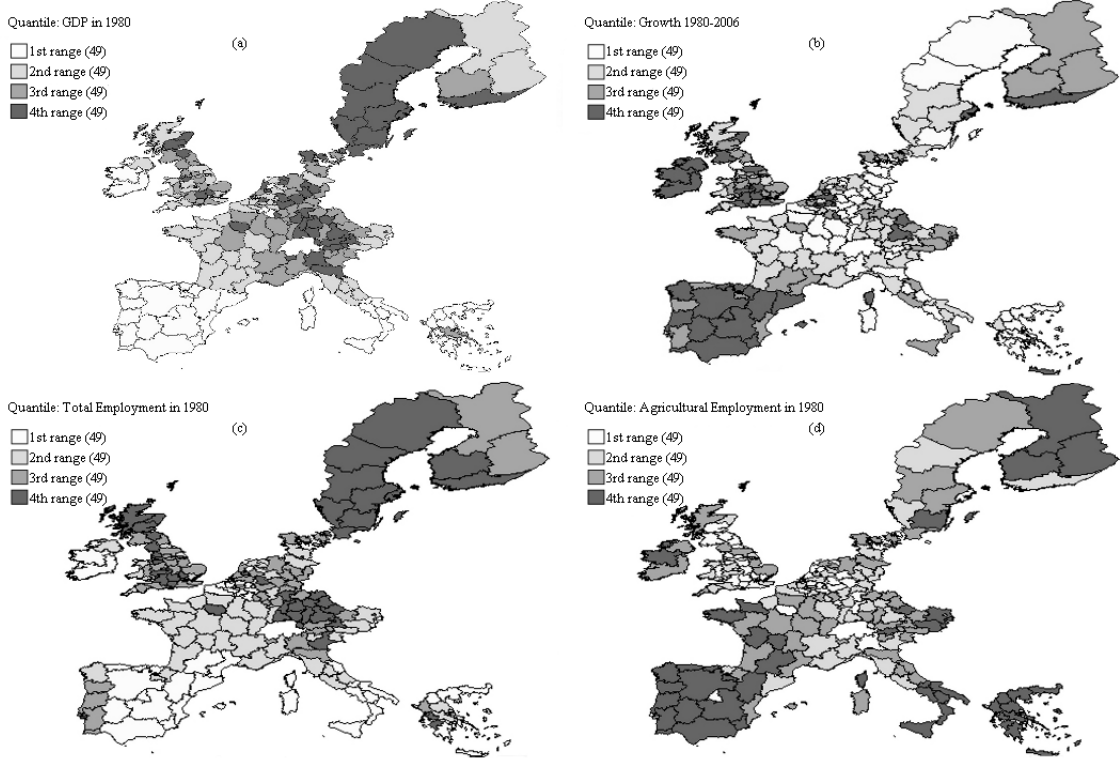
The specification of spatial econometric model of conditional  $\beta$ -convergence follows an accurate Exploratory Spatial Data Analysis (ESDA) whose main results can be summarised as follows<sup>1</sup>.

Figure 1 highlights the presence of heterogeneity in the spatial distribution of the regional per capita GDP in 1980 and of 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 *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.

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<sup>1</sup> For a more detailed description of the ESDA and the instruments that were used, see Brasili et al. (2011).

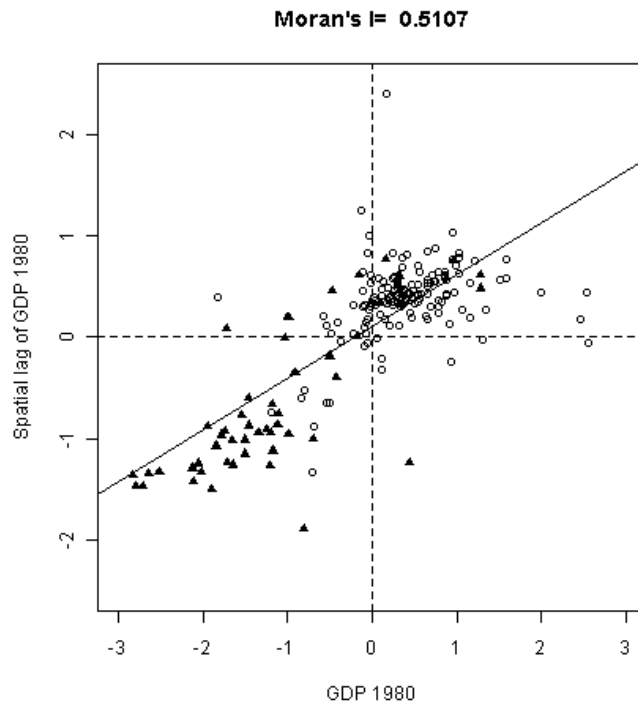
Figure 1. Spatial percentile distribution for the log of per capita GDP in 1980 with deviations with respect to the EU-15 mean (a), the growth of per capita GDP between 1980 and 2006 (b), the total employment in 1980 (c), the share of agricultural employment in 1980 (d).



The presence of positive spatial dependence relatively to per capita GDP in 1980 is revealed by the Moran's I index, whose value 0.5107 (p-value=0.000) is well above the expected value under the null hypothesis of no spatial correlation,  $E(I) = -0.0051$ . A similar result was obtained for the GDP per capita growth rate between 1980 and 2006:  $I = 0.2131$  (p-value=0.000).

The same considerations are raised by the Moran scatterplot, which show the existence of 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).

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 data analysis, a model with two spatial regimes is proposed. The first regime includes 50 NUTS-2 regions, which were part of Objectives 1 and 6 during the programming period 1994-1999<sup>2</sup>, the second regime includes the other 146 regions in the sample. Any parameter instability between these two groups of regions will be considered to be proof of the existence of two convergence clubs with both a spatial and an economic dimension.

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<sup>2</sup> We chose these dates so as to include Austrian, Swedish and Finnish regions in our analysis. These countries joined the EU in 1995. 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.

### 3.2. A model of conditional $\beta$ -convergence with spatial effects

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

A *spatial lag model*, or *spatial auto-regressive model* (SAR) was found to be best for modelling the identified spatial dependence, while the spatial heterogeneity identified in subsection 3.1 was modelled by using two convergence clubs, defined according to both geographical and economic criteria. Using the estimates of a  $\beta$ -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.

Let define the 196x196 diagonal matrix  $\mathbf{D}^{OB1} = \text{diag}(\mathbf{I}_{(\text{region } i \in OB1)}; i = 1, \dots, 196)$  that permits to select the regions belonging to 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,  $\mathbf{y}$  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  $\mathbf{y}$ . By using  $\mathbf{D}^{OB1}$  we obtain easily  $\mathbf{X}^{OB1} = \mathbf{D}^{OB1} \mathbf{X}$ , and  $\mathbf{X}^{NN1} = (\mathbf{I}_{196} - \mathbf{D}^{OB1}) \mathbf{X}$ . 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  $\mathbf{g}_y$  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:

$$\mathbf{g}_y = \mathbf{y}^{OB1} b^{OB1} + \mathbf{y}^{NN1} b^{NN1} + \mathbf{X}^{OB1} \boldsymbol{\theta}^{OB1} + \mathbf{X}^{NN1} \boldsymbol{\theta}^{NN1} + \rho \mathbf{W} \mathbf{g}_y + \boldsymbol{\varepsilon} \quad (1)$$

where  $\boldsymbol{\theta}^{OB1}$ ,  $\boldsymbol{\theta}^{NN1}$  are the 4-dimensional vectors parameters,  $\boldsymbol{\theta}^i = [a^i \quad \psi_1^i \quad \psi_2^i \quad \phi^i]'$  respectively for regions belonging to Objective 1 ( $i=OB1$ ) and the others ( $i=NN1$ );  $b^{OB1}$ ,  $b^{NN1}$  are coefficients of the per capita GDP in 1980;  $\rho$  is the spatial regression coefficient;  $\mathbf{W}$  is the distance-based spatial weight matrix<sup>3</sup>;  $\boldsymbol{\varepsilon}$  is the column vector of errors with the usual properties.

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<sup>3</sup> Each element of  $\mathbf{W}$ ,  $w_{ij}$ , is defined as:



The estimation results for model (1) are shown in Table 1:

TABLE 1.  
*ML estimation results.*

Variable/parameter	ML	
	<i>Objective 1</i>	<i>non-Objective 1</i>
Constant (a)	-0.00312 (0.460)	-0.01505 (0.000)
GDP (b)	-0.02824 (0.000)	-0.01569 (0.000)
Total Employment ( $\psi_1$ )	-0.00002 (0.846)	0.00043 (0.000)
Share of Agricultural Employment ( $\psi_2$ )	-0.00029 (0.000)	-0.00019 (0.037)
W_GDP ( $\varphi$ )	0.02282 (0.000)	-0.00521 (0.089)
Spatial Parameter ( $\rho$ )	0.35186 (0.001)	
Convergence rate ( $\beta$ ) %	5.3	2.0
Half life (years)	24.5	44

The results of the ML estimation of model (1) support the hypothesis that there are two spatial convergence clubs. The estimates of  $b$  are statistically significant and have the expected negative sign. The implied convergence rate ( $\beta$ ) 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).

The estimation of the spatial parameter ( $\rho$ ) provides support for the hypothesis of the crucial role of the geographic-territorial dimension in economic growth. A  $\beta$ -convergence model with spatial effects reveals that there are 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) and with the theories of New Economic Geography (Krugman, 1991). The more dynamic and fast growing the economies of the neighbouring regions are, then the higher the growth rate of per capita GDP in a region will be. There is evidence that, 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.

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$$\begin{cases} w_{ij}^* = 0 & \text{if } i = j, \forall k \\ w_{ij}^* = 1/d_{ij}^2 & \text{if } d_{ij} \leq Q3 \text{ and } w_{ij} = w_{ij}^* / \sum_j w_{ij}^* \\ w_{ij}^* = 0 & \text{if } d_{ij} > Q3 \end{cases}$$

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  $j$ ;  $Q3$  is the third quartile of the distance distribution.

Finally, the GDP of neighbouring regions has a positive effect on the growth of Objective 1 regions (0.023). The analysis of the estimates of the spatial parameters highlights significant spillover effects that influence the economic growth of European regions and cause econometric problems in models that do not explicitly model them, due to spatial error autocorrelation. Overall it can be concluded that, as has been stated by the New Economic Geography theory, the economic growth of a region is influenced by the economic well-being and dynamism in neighbouring regions. This is even more evident in Objective 1 regions.

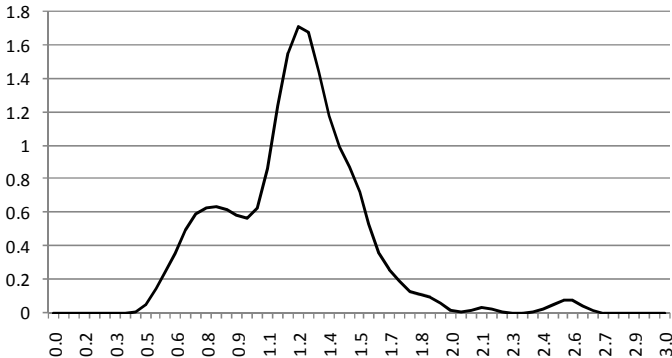
4. A NON-PARAMETRIC ANALYSIS

4.1. Analysis of the marginal density functions

The analysis of the dynamics of the distribution of log relative per capita GDP of the 196 considered regions starts from the study of the marginal density functions. These were estimated for the years 1980, 1995 and 2006, in order to detect the changes in shape that might occur throughout the period, showing alternatively convergence or polarization.

The values of log relative per capita GDP are graphed on the x-axis and the estimates of the density function are plotted along the y-axis. Each peak of the plotted curve represents a concentration of economies around the same level of relative per capita GDP, the peak being more or less evident according to the number of units that belong to that group. The greater the concentration, the higher the convergence to that specific level of the variable. Particular attention needs to be paid to the modes of the distribution: unimodality indicates cohesion, while a multimodal distribution detects emerging polarization among the economies.

Figure 3. Densities of log relative per capita GDP (1980) ( $h=0.185^4$ )



<sup>4</sup> The *smoothing* parameter (or bandwidth)  $h$  has been computed as a average between the  $h$  suggested by *Silverman*  $h = 0.9An^{-1/5}$ , where  $A$  is the minimum value obtained between the standard deviation and the first quartile divided for 1.34, and the “rule-of-thumb” bandwidth in case of Gaussian kernels,  $h = \left(\frac{4\hat{\sigma}^5}{3n}\right)^{1/5}$ .

The marginal density function relative to year 1980 (Figure 3) shows two major peaks, which indicate the presence of a first group of regions whose level of per capita GDP is around 80% with respect to the EU mean, and a second group of regions whose incomes are about 20-30% higher than the average. Two lower peaks can be noticed at the right-hand side of the distribution, that reveal the concentration of some economies around more than twice the level of European average per capita GDP.

Figure 4. Densities of log relative per capita GDP (1995) ( $h=0.336$ )

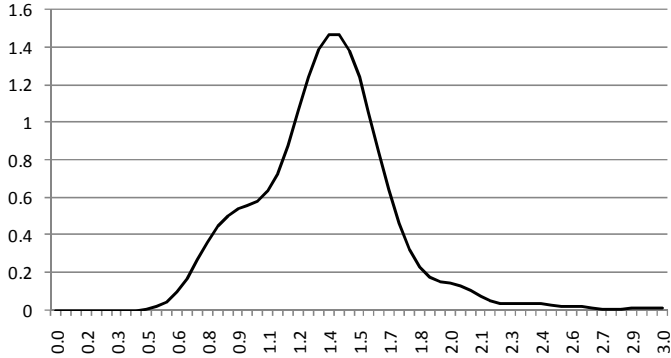
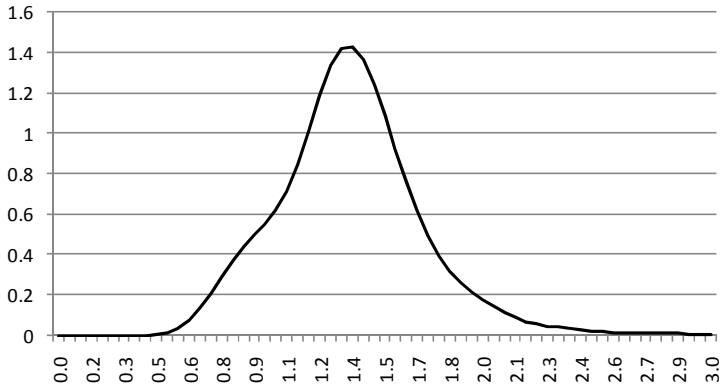


Figure 5. Densities of log relative per capita GDP (2006) ( $h=0.354$ )



The marginal density function relative to year 1995 (Figure 4) still shows the presence of two peaks, but they appear to be closer together. Finally, Figure 5 plots a smoother density relatively to year 2006, even if one can still notice a small bump in correspondence of a level of per capita GDP which is about 80% of the European mean. Another feature that should be noticed is the shift of the greater peak towards higher levels of relative per capita GDP (from 1.2 in 1980 to 1.4 in 2006), thus revealing a possible process of non convergence.

A better understanding of the distribution dynamics of relative per capita GDP requires further analysis, which is presented in the following sub-sections.

#### 4.2. The Stochastic Kernel

The intra-distribution dynamics can be described by using a stochastic kernel, which is a suitable technique for revealing the presence of the effects of persistence and/or polarization (Quah, 1997) in the income distribution dynamics.

The stochastic kernel proposed by Quah (1993) plots the evolution of the distribution of relative per capita GDP over time. It is a sort of transition probability matrix (Markov chain transition matrix) where no discretization occurs and the original set of continuous variables is retained, and it evaluates the long time perspectives of the distribution. The final output of stochastic kernel is the ergodic income distribution (for  $time \rightarrow \infty$ ), estimated on the basis of the transitions occurred in the considered time span.

Following Quah (1993), let  $F_t$  be the distribution of incomes across countries at time  $t$ . Then the evolution of  $\{F_t : \text{integer } t\}$  can be described by the law of motion:

$$F_{t+1} = M \cdot F_t \quad (2)$$

where  $M$  (the stochastic kernel) maps the evolution of the distribution from time  $t$  to time  $t+1$ . Iteration let us obtain a predictor for future distributions, from time  $t$  to time  $t+s$ , under the assumption of  $M$  being invariant over time:

$$\begin{aligned} F_{t+2} &= M \cdot F_{t+1} = M(M \cdot F_t) = M^2 F_t \\ &\vdots \\ F_{t+s} &= M^s F_t \end{aligned} \quad (3)$$

By taking this to the limit  $s \rightarrow \infty$ , one obtains an estimate of the limit distribution of incomes, which eventually reveals the presence of a convergence process or the prevalence of a bi/multi-modal ergodic distribution.

A graphic representation favours an easier understanding of the dynamics of the distribution over time. One can plot the values of relative income at time  $t$  ( $t1$  in the following figures) on the y-axis and the values of the same variable over a specified time horizon on the x-axis ( $t2$ ). The third axis plots the estimates of the kernel function. The graph then shows how the cross-sectional distribution at time  $t$  evolves periodically over a fixed number of year horizons. The interpretation of the graph is as follows: if most of the plotted surface were concentrated along the main diagonal of the x-y plane, one should interpret it as persistence of the elements of the distribution around the same values; on the contrary, if the surface rotated 90 degrees counter-clockwise from that diagonal –which is along the opposite diagonal-, then substantial reversal periodically occurs, which means that the rich become poor and vice-

versa. Finally, the concentration of the surface around the 1-value of the x-axis (extending parallel to the y-axis) suggests convergence of the distribution towards equality; similarly, the concentration of the mass around any other mode at time  $t_2$  means convergence of the distribution towards that value of relative income.

Figure 6. Log relative per capita GDP dynamics over a 15-year horizon

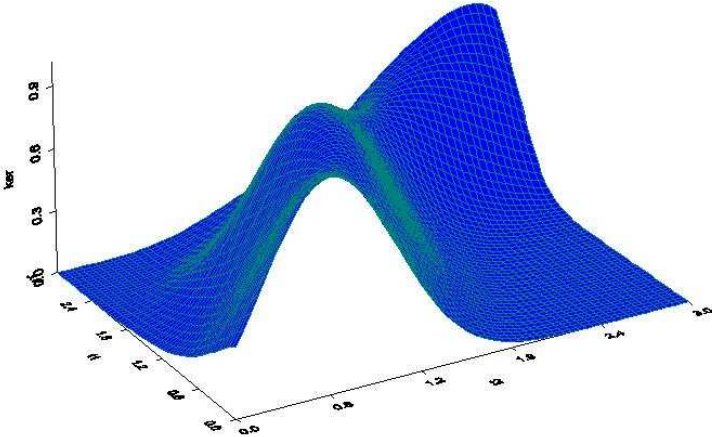


Figure 7. Contour plot of log relative per capita GDP dynamics over a 15-year horizon

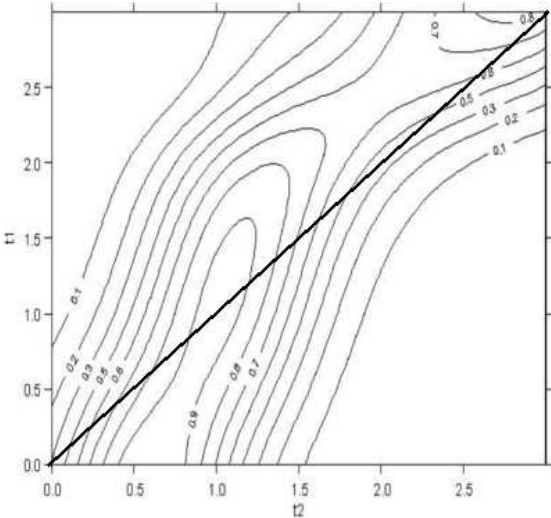


Figure 6 and Figure 7<sup>5</sup> show the evolution of the distribution of log relative per capita GDP of the regions included in our analysis over a 15-year horizon, revealing a substantial polarization of the regions into two groups. The first one includes lower income regions (below EU average), while the second one -in the upper right side of the contour plot- is made up of regions which are characterized by almost 3 times the average EU per capita GDP. The

<sup>5</sup> The analysis was implemented thanks to the Gauss routines by Professor Luciano Gutierrez which are available on request on his website (<http://www.gutierrezluciano.net/>).

group of poorer regions appears to face a weak process of convergence. While middle-income regions are vanishing towards the 1-value at time  $t_2$ , a strong persistence is experienced by the rich regions: in correspondence of the higher levels of income, the probability mass forms a peak that is located along the main diagonal.

#### 4.3. *The spatially conditioned distribution dynamics*

So far an *unconditional* distribution's dynamic analysis has been proposed. Analogously to the parametric analysis of convergence, one can be interested in observing the distribution dynamics all other conditions being equal: the *conditional* convergence can be studied, following the non-parametric approach, by describing how a set of conditioning factors alters the original distribution. In order to understand if a set of factors explains emerging twin-peaks features or growing cohesion, we can investigate if the stochastic kernel that transforms the original distribution into a conditional one removes those same features.

In general, one can be interested in investigating the difference between the original and the conditioned distribution. Quah (1997) describes not only the evolution from one distribution to the other through a stochastic kernel that models this process, but also makes a dynamic analysis providing representations on 15-year transitions in the conditioned distributions.

The major interest of this paper is about the effects of a spatial conditioning in a non-parametric framework of analysis. Future developments will regard the conditioning to the same variables which were used in the parametric analysis of convergence presented in previous sections, in order to reach better comparable results.

The spatial conditioning scheme presented by Quah (1997) was used in order to calculate the spatially conditioned distribution of the log relative per capita GDP of the considered regions. Then the stochastic kernel that maps the original distribution into the spatially conditioned one was plotted (Figures 8 and Figure 9), followed by the representation of the spatial-conditioned distribution dynamics over a 15-year time horizon (Figures 10 and Figure 11).

Figure 8. Log relative per capita GDP, original and spatially conditioned distributions

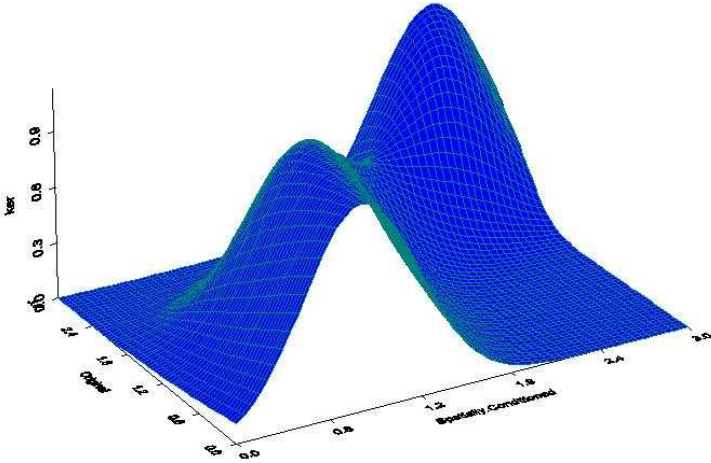
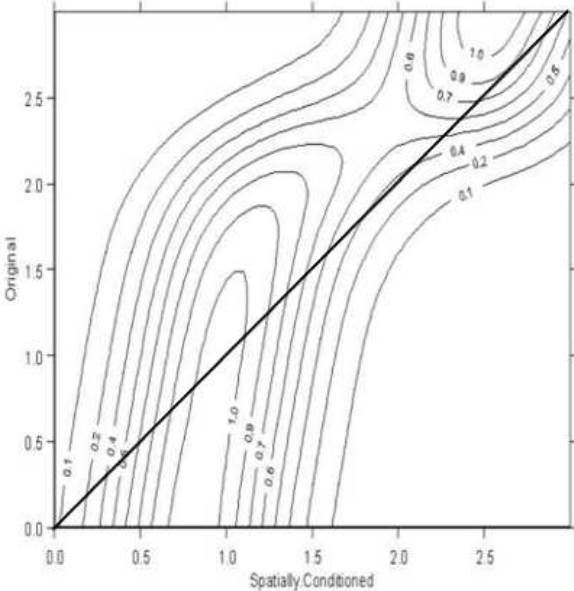


Figure 9. Contour plot of log relative per capita GDP, original and spatially conditioned distributions



The spatial conditioning proves again to be highly significant in explaining the distribution dynamics of per capita GDP, as a non-influent conditioning factor would cause the probability mass to lay on the 45 degrees diagonal of x-y axis, that report respectively the conditioned and original distribution. Any deviation from this situation indicates that relative positions of unites are altered by the conditioning factor. Figure 8 and more clearly Figure 9 show that there is a substantial alignment of the probability mass parallel to the “Original” axis, for both the groups of regions that the unconditional analysis revealed. Then one shall conclude that similar levels of relative per capita GDP are spatially contiguous in the European regions.

Figure 10. Spatially-conditioned log relative per capita GDP dynamics over a 15-year horizon

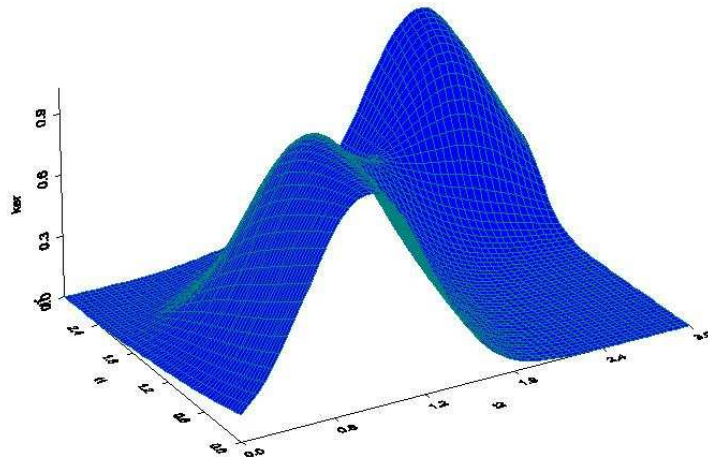
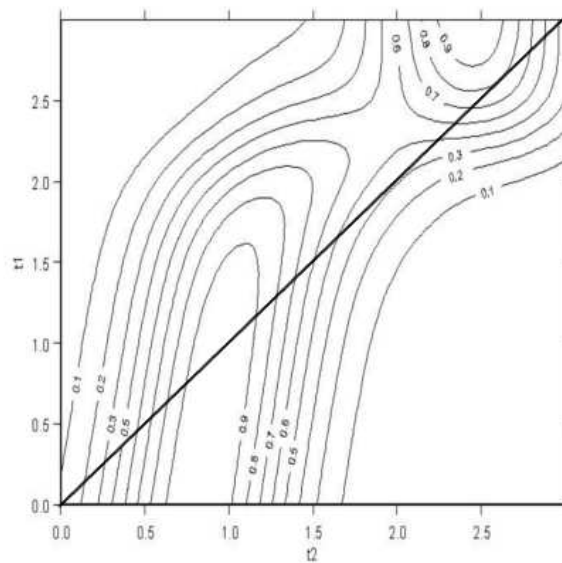


Figure 11. Contour plot of spatially-conditioned log relative per capita GDP dynamics over a 15-year horizon



The dynamic analysis of the spatially conditioned distribution (represented graphically in Figure 10 and Figure 11) reveals a more evident convergence process among both groups of regions: the surface shows a great counter-clockwise rotation in correspondence of the peak of lower income regions than it showed in the unconditional case; moreover, the peak of richer regions is perfectly parallel to the y-axis, thus revealing a strong process of convergence that was not shown by the non-conditional analysis. However, the persistence of the twin-peaks feature –which resulted from the parametric analysis as well- is clear.



## 5. A COMPARISON OF THE RESULTS AND POLICY IMPLICATIONS

The main findings of the parametric analysis that was presented in section 3 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. Quantification of the speed of convergence by estimating 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.

Similar conclusions can be drawn after the non-parametric analysis conducted in section 4: the unconditional distribution dynamics of per capita GDP reveals an emerging “twin-peaks” feature that can be related to the concept of convergence clubs as we referred to in the parametric section. Even if it does not quantify the convergence speed, the stochastic kernel approach shows the polarization process as the result of the analysis of the distribution of the considered variable and not as an hypothesis to be confirmed, which is predominant in the  $\beta$ -convergence analysis. To this extent, the conclusions of the non-parametric analysis reinforce the hypothesis at the basis of the parametric model that was estimated.

The  $\beta$ -convergence approach also allows to draw some implications of economic policy. Although a model of this kind cannot explicitly demonstrate the causal relationship between a higher convergence rate among poorer regions and Structural Policy funding, 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<sup>6</sup>. Therefore it can reasonably be assumed that such a distribution of aid contributed to the higher convergence rate among the poorest regions, and this supports the hypothesis that the

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<sup>6</sup> 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.

regions with a lower level of initial per capita income will grow at a higher rate, thus generating convergence.

The spatial effects are proven to be of great relevance in both approaches to convergence analysis. The estimates of the spatial autoregressive parameter and of the spatially lagged GDP in the  $\beta$ -convergence model revealed that there are geographical spillover effects which are of primary importance in explaining the economic growth of European regions. The same conclusion followed from the stochastic kernel analysis. Thus the relative geographical location of each region plays a key role in explaining the structure of economic growth and the per capita income dynamics in the EU-15. This result confirms the hypothesis that a methodology which uses spatial econometric techniques is needed in order to model spatial effects.

These findings have profound implications for policy and suggest that specific investments aimed at exploiting the spillover effects are important, as is close 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 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.

## 6. CONCLUSIONS

The aim of this paper is to assess the economic convergence among European regions over the period 1980-2006 by estimating in the first place a conditional  $\beta$ -convergence model which takes into account the effects of spatial dependence and spatial heterogeneity and subsequently by a spatially-conditioned stochastic kernel approach.

The main finding of the parametric analysis, namely that development is polarised into two convergence clubs, is supported and confirmed by the non-parametric approach. The  $\beta$ -convergence model also finds that the two different groups of regions converge at different rates towards their different steady states.

The importance of explicitly taking into consideration the spatial effects is confirmed by both kinds of approaches: it adds greatly to the value of the analysis and the results highlight some factors which are not usually revealed by those studies which do not explicitly take spatial effects into account. As for the parametric analysis, these are the fact that Objective 1 regions are affected more by geographical spillovers and also converge faster to their steady state than non-Objective 1 regions do and the fact that per capita income disparities between the two groups of regions seem to be persistent. The spatially-conditioned distribution dynamics studied through the non-parametric approach also confirms that spatial neighbourhood is a relevant factor that explains the dynamic of per capita GDP distribution.

The results of our analysis are also relevant from a policy point of view. The crucial role of spatial spillovers to the economic growth European regions should be taken into great consideration when planning an effective EU Cohesion Policy.

In conclusion, it is useful to compare the contributions of these two different approaches to the study of regional economic convergence, because each of them has peculiar characteristics that lead to results that should be integrated for a more exhaustive analysis. In the future, we plan to condition the per capita GDP distribution not only to spatial neighbourhood but also to those conditioning variables that were used for the parametric analysis, so that the results can be compared even more coherently.

## REFERENCES

- Anselin L (1988) *Spatial Econometrics: Methods and Models*. Dordrecht, Boston, London: Kluwer Academic Publishers
- Anselin L, Bera AK, Florax R, Yoon MJ (1996) Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics* 26: 77-104
- Anselin L (2005) Exploring Spatial Data with GeoDa<sup>TM</sup>: A Workbook. *Centre for Spatially Integrated Social Sciences*
- Arbia G (2006) *Spatial Econometrics*. Berlin Heidelberg, Springer-Verlag
- Barro RJ (1991) Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics* 106(2): 407-443
- Barro R, Sala-i-Martin X (1991) Convergence across states and regions. *Brookings Papers on Economic Activity* 22: 107-182
- Barro R, Sala-i-Martin X (1992) Convergence, *Journal of Political Economy* 100: 223-251
- Barro R, Sala-i-Martin X (1995) *Economic Growth*. McGraw-Hill, Inc
- Baumol WJ (1986) Productivity Growth, Convergence, and Welfare: What the Long-Run Data Show. *The American Economic Review* 75(5): 1072-1085
- Baumont C, Ertur C, Le Gallo J (2001) A Spatial Econometric Analysis of Geographic Spillovers and Growth for European Regions, 1980-1995. Working Paper n.2001-04, LATEC UMR-CNRS 5118, Université de Bourgogne
- Brasili C, Bruno F, Saguatti A (2011) A spatial econometric approach to EU Regional Policy between Economic and Geographical Periphery. *Submitted*
- Canova F, Marcet A (1995) The Poor stay Poor: Non-Convergence Across Countries and Regions. CEPR Working Paper 1265
- Council Regulation (EC) 2081/93
- Council Regulation (EC) 1260/99
- Council Regulation (EC) 1083/06
- Dall'Erba S, Le Gallo J (2007) Regional Convergence and the Impact of European Structural Funds over 1989-1999: A Spatial Econometric Analysis. Discussion Paper 01-07, Regional Economics Applications Laboratory, University of Illinois
- Ertur C, Le Gallo J, Baumont C (2006) The European Regional Convergence Process, 1980-1995: Do Spatial Regimes and Spatial Dependence Matter?. *International Regional Science Review* 29: 3-34
- European Commission (1996) *First report on economic and social cohesion*.

Luxembourg, Office for Official Publications of the European Communities

- European Commission (2001) *Second report on economic and social cohesion..*  
Luxembourg, Office for Official Publications of the European Communities
- Fadda S (2006) Competitività e coesione nella nuova programmazione comunitaria.  
*Argomenti* 17: 13-36
- Fitoussi JP (2006) Democrazia e Mercato. *Argomenti* 17: 5-11
- Krugman P (1991) *Geography and Trade*. Cambridge, MIT Press
- Leonardi R (1995) *Convergence, cohesion and integration in the European Union*. New York, St. Martin's Press
- López-Bazo E, Vayà E, Artis M (2004) Regional Externalities and Growth: Evidence from European Regions. *Journal of Regional Science* 44: 43-73
- Piras G, Arbia G (2007) Convergence in per capita GDP across EU-NUTS2 regions using panel data models extended to spatial autocorrelation effects. *Statistica* 67(2): 157-172.
- Quah D (1993) Empirical cross-section dynamics in economic growth. *European Economic Review* 37: 426-434
- Quah D (1995) Empirics for Economic Growth and Convergence. Discussion Paper n. 253, Centre for Economic Performance, LSE
- Quah D (1997) Empirics for Growth and Distribution: Stratification, Polarization and Convergence Clubs. *Journal of Economic Growth* 2: 27-59
- Ramajo J, Marquez MA, Hewings GJD, Salinas MM (2008) Spatial Heterogeneity and Regional Spillovers in the European Union: Do cohesion policies encourage convergence across regions?. *European Economic Review* 52: 551-567
- Rodríguez-Pose A, Fratesi U (2004) Between Development and Social Policies: The impact of European Structural Funds in Objective 1 Regions. *Regional Studies* 38(1): 97-113
- Sala-i-Martin X (1996) The Classical Approach to Convergence Analysis. *The Economic Journal* 106(437): 1019-1036