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Half Life or Half Convergence? Endogenous Identification of Regional Clubs Across Europe. 1980-2002

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Half Life or Half Convergence? Endogenous Identification of Regional Clubs Across Europe. 1980-2002[♦]

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Abstract

Assessing regional growth and convergence across Europe is a matter of primary importance, either in light of the effectiveness of cohesion policies, or in terms of the expectations of New Entrants. Empirical models that not account for structural heterogeneities and spatial effects could fail to detect club convergence phenomena. In this paper, we adopt a spatially filtered mixture regression approach that endogenously identifies regional clubs of beta-convergence, in order to avoid a*d hoc* predeterminations, as North-South or centre-periphery divisions. Results indicate that spatial effects matter, and *absolute* or *conditional* convergence might be too much restrictive assumptions, not supported by the data. Excluding a small number of regions that behave as outliers, only few regions show fast convergence. The majority of the sample, in fact, exhibits slow convergence, with the remaining part showing no convergence at all. In addition, a dualistic phenomenon seems to be present inside some States, reinforcing the "diverging-convergence" paradox.

JEL Classifications: C21, O40, R11.

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1. Introduction

Assessing regional convergence across Europe, in terms of per capita income or product, is a matter of primary importance not only to empirically verify the growth theories predictions, but also to evaluate the effectiveness of the Cohesion Policies. The expectations of New Entrants, indeed, require feasible answers from the policy makers. After the recent enlargement, economic disparities underwent a dramatic increase. The ten richest Union's regions have a GDP per head equal to 189% of the EU-25 average, whilst the ten poorest ones have a GDP per head equal only to 36%. In the New Member States, 90% of total population live in regions with a level of per capita income below 75% of the Community average, that is the admissibility threshold in order to receive the Objective 1 Structural Funds (Commission of the European Communities, 2005).

During the last few years, however, an intense debate had occurred on the topics of European economic integration, regional convergence, and cohesion policies (see, for a review, Funck and Pizzati, 2003). From one side, the EC stresses the integration's gains, and positively judges the role of regional policies sustaining the economic growth of lagging behind regions (European Commission, 2001, 2004). From the other, some scepticism has been shed (Boldrin and Canova, 2001). Consequently, some questions have been raised. Will EU citizens see their welfare being equalised to Community's averages? On the contrary, will their standard of living worse off, being subjected to growing inequalities? Will cohesion policies have a positive impact on growth and convergence? Will those policies, instead, be ineffective, serving mainly as redistributive instruments?

In this work we try to assess the above mentioned questions, looking at the past EU-15 experience. The remainder of the paper is structured as follows: section 2 reviews the standard approach to the empirics of regional convergence. Section 3 highlights the existence of structural heterogeneity and spatial effects among the European regions. Section 4 introduces a methodology that tries to go beyond such problems. Section 5 shows the results and, in section 6, some conclusions follow.

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2. Empirics of regional convergence: a brief review and some open issues

Convergence hypotheses across countries or regions have been subjected to several, and often alternative, theoretical interpretations. Starting from the taxonomy originally proposed by Galor (1996), three different definitions can be distinguished:

a) the *unconditional* or *absolute* convergence, meaning that per capita incomes converge to a common level in the long-run, if structural homogeneities are present across the economies and their initial conditions do not matter[1];

b) the *conditional* convergence, meaning that per capita incomes converge to different levels in the long-run, if structural heterogeneities are partially present across the economies and their initial conditions do not matter;

c) the *clubs* convergence, meaning that per capita incomes converge to different levels in the long-run, if structural heterogeneities are present across the economies and their initial conditions do matter.

Much of the empirical analysis, aimed to test the validity of these hypotheses, is based on the measure of beta-convergence, derived from the neoclassical growth model developed by, among others, Solow (1956), Cass (1965), and Koopmans (1965). As is well known, the measure refers to the tendency for the poor economies to grow faster than the rich ones[2], and it is related to intra-distributional dynamics. In the standard cross-sectional analysis, in fact, beta-convergence gives an average measure of the ranking mobility of the distribution (Sala-i-Martin, 1996a). Other measures are often employed, that look at the reduction of the distributional dispersion over time, as the sigma-convergence[3] (Barro and Sala-i-Martin, 1992), or the evolution of the entire distribution, as the ergodic convergence[4] (Quah, 1993a,

[1] This hypothesis seems to be the one that the EC is interested in, as Quah (1996b, p. 1048, footnote 4) already pointed out.

[2] In the neoclassical model, the growth rate of per capita income is positively related with the distance from the steady-state, being the economy below it, because of Inada (1963) conditions and diminishing returns to capital. Thereby, the less advanced economies tend to exhibit faster economic growth, giving rise to an inverse relationship between initial levels of income and subsequent growth rates. In the technological adoption literature, a similar concept is the tendency for follower economies to "catch-up" with the leaders (Abramovitz, 1986, Baumol, 1986, and, for a regional perspective, Paci and Pigliaru, 2002).

[3] Typical measures of sigma-convergence are the sample standard deviation or the coefficient of variation, that constitutes aggregate statistics of the distributional dispersion. As random shocks may produce crisscrossing or overshooting effects, beta-convergence is a necessary but not sufficient condition for sigma-convergence (for an analytical exposition, see Barro and Sala-i-Martin, 2004).

[4] The distributional evolution is usually obtained calculating a Markov chain transition matrix. Some researchers prefer this approach, because it provides a more complete set of information. Beta-convergence, in fact, suffers from the so-called "Galton's fallacy", so it may be consistent with a stationary distribution over time (Quah, 1993b, Hart, 1995).

1996a). Those concepts, however, are less suited to the questions we try to assess and to the methodology we adopt here, so we prefer to focus here on beta-convergence.

Empirical beta-convergence models usually take the form of a cross-country/cross-region growth regression

$$g_i = a - bx_i + \sum_{j=1}^{m} c_j z_{ij} + u_i, \quad i = 1,...,n, \quad j = 1,...,m, \tag{1}$$

where $g_i = [\ln(y_{i,T}) - \ln(y_{i,0})]/T$ is the average growth rate of the economy i's per capita income between time 0 and T, a is a constant, $b = (1 - e^{-\beta T})/T$ is a convergence coefficient, $x_i = \ln(y_{i,0})$ is the log of the economy i's initial level of per capita income, c_j is a slope parameter, z_{ij} is a control variable, and $u_i \sim \mathrm{N}(0, \sigma^2)$ is an error term with usual properties (for a broad review, see Durlauf *et al.*, 2004). A positive value of the parameter β[5] is supportive of convergence, and provides the rate at which the economy approaches the steady-state[6].

Early empirical studies (Barro and Sala-i-Martin, 1991, Sala-i-Martin, 1996b), usually estimated equation (1) without control variables, on the base of two strong homogeneity assumption. First, the constant term was thought as inclusive of technological progress (γ_i), steady-state value of effective per capita output $(\tilde{y}_i^*)$, and initial efficiency $(A_{i,0})$, namely

i) $$a = a_i = \gamma_i + (1 - e^{-\beta_i T})/T \cdot \ln(A_{i,0} \cdot \tilde{y}_i^*), \quad \forall i.$$

Second, the convergence coefficient was considered constant across the economies, that is

[5] In the "textbook" Solow model, with a Cobb-Douglas production function and a labour-augmenting technological progress, $\beta = (1-\alpha)(\gamma + n + \delta)$, where α is the elasticity of income with respect to capital, γ is the technological progress, n is the population growth, and δ is the depreciation rate. A positive $\hat{\beta}$, implying $0 \prec \alpha \prec 1$, is usually seen as empirical evidence of diminishing returns to capital, against endogenous growth theories, that commonly predicts increasing returns (see Durlauf, 2003, for a discussion).

[6] Estimates are usually obtained calculating $\hat{b}$ by ordinary least squares (OLS), and re-parameterizing $\hat{\beta} = -\ln(1 - \hat{b}T)/T$. Standard errors are approximated by the formula $\hat{\sigma}_\beta = \hat{\sigma}_b / T(1 - \hat{\beta})$. This procedure works until $\hat{b}T \prec 1$, because the log of a negative number is not defined. On the contrary, estimation may be run with non linear least squares (NLS), and standard errors can be directly applied. Looking at the existing literature, however, the use of OLS, instead of NLS, does not lead to any appreciable statistical differences (see Abreu *et al.*, 2005a).

ii) $$b = b_i = (1 - e^{-\beta_i T}) / T, \quad \forall i.$$

Basically, equation (1) with assumptions i) and ii), considering the parameters underlying the economies as structurally homogeneous, and not depending on the initial income level, can be seen as a test for type a) convergence. A positive $\hat{\beta}$, indeed, implies that poor regions *unconditionally* grow faster than rich ones toward a unique steady-state, independently from the initial conditions.

Barro and Sala-i-Martin (1991, p. 154), for instance, found in a sample of 73 Western European regions, over the period 1950-1985, an "empirical regularity that the rate of β convergence is roughly 2 percent a year in a variety of circumstances […] the half-life of this convergence process is 35 years"[7]. In the last edition of their book, they conclude that "absolute β convergence is the norm for these regional economies" (Barro and Sala-i-Martin, 2004, p. 496).

Convergence tests of type a) are plausible when the matter of study is convergence *within*-country, where x_i is measured in terms of deviations from the country mean. Regions in the same countries, in fact, may share common steady-states, being affected by similar saving rates, preferences, governmental policies, property rights, infrastructures, and so on. For the case of convergence *between*-country[8], instead, *absolute* convergence results quite unrealistic, because regions belonging to different countries may not exhibit a common steady-state. As Solow (1999, p. 640) argued, "there is nothing in growth theory to require that the steady-state configuration be given once and for all […] the steady-state will shift from time to time [and, we say, from space to space] whenever there are major technological revolutions, demographic changes, or variations in the willingness to save and invest". So, if $\tilde{y}_i^*$ is not constant, it follows that $a_i \neq a$, $\forall i$, leading assumption i) to fail[9].

Mankiw *et al.* (1992), in their famous paper, tried to overcome this problem relaxing the assumption i) in two ways. First, in presence of heterogeneity, steady-state determinants can

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[7] The so-called half-life condition is given by $e^{-\beta T} = 1/2 \Rightarrow T = \ln(2)/\beta$. If the speed of convergence is equal to 2% per year, it follows that $T \cong 0.69/0.02 \cong 35$, so the economy fills half the gap in about 35 years.

[8] If the reduction of economic disparities across Europe is the matter of interest, this perspective appears more appropriate. Convergence *within*-countries does not necessarily produce convergence *between*-country.

[9] Steady-state variables might be comprised in the error term, $u_i = (1 - e^{-\beta_i T}) / T \cdot \ln(\tilde{y}_i^*) + \varepsilon_i$, where ε_i is a random component. However, if steady-state determinants were related with initial income levels, and they had an impact on growth, $\tilde{y}_i^*$ would be an omitted variable and the coefficient $\hat{b}$ would be biased (Bernard and Durlauf, 1996; Sala-i-Martin, 2002).

be included among the control variables. In the canonical regression, $\left[z_{ij}\right]' = \left[\ln(sk_i)\ \ln(sh_i)\ \ln(n_i + \gamma + \delta)\right]'$, where sk_i and sh_i are respectively the saving rates of physical and human capital, n_i and γ are respectively the growth rates of population and technology, and δ is the depreciation rate[10]. Second, if $A_{i,0}$ reflects not only the initial technology, but also resource endowment, climate, institution, and other country-specific factors affecting growth, it may be constituted by a common and a random component, $\ln(A_{i,0}) = \ln(A_0) + e_i$, where A_0 is the common factor and e_i is the country or region-specific effect. The error term is now equal to $u_i = (1 - e^{-\beta T})/T \cdot e_i + \varepsilon_i$, and the variables $\left[z_{ij}\right]'$ are considered independent of specific factors that shift the production function.

Assumption i) is so replaced by

iii) $$a = a_i = \gamma_i + (1 - e^{-\beta_i T})/T \cdot \ln(A_0), \quad \forall i .$$

Equation (1), with the assumptions ii) and iii), and the inclusion of $\left[z_{ij}\right]'$, implies homogeneity in the convergence parameter[11], the initial efficiency, and the technological progress. Steady-states determinants, on the contrary, are heterogeneous. So equation (1) can be considered as a test for type b) convergence, with a positive $\hat{\beta}$ meaning that the poor regions grow *conditionally* faster than the rich ones, at the same rate, toward their specific steady-state.

Armstrong (1995), testing for *absolute* and *conditional* convergence on a sample, and sub-samples, of 85 EU-12 regions over the period 1950-1990, either *within* or *between-country*, found the convergence rates being sensibly variable. The rate of *between*-country *absolute* convergence was about 1% per annum, much slower than the 2% found by previous studies. A 2% rate, in fact, was only found, for the *within*-country *conditional* convergence[12], during

[10] The advancement of knowledge and the depreciation could be thought as not country-specific, so they are treated as constant, i.e. $x_i = x$ and $\delta_i = \delta$.

[11] In the "augmented" Solow model with human capital $\beta = (1 - \alpha - \eta)(\gamma + n + \delta)$. The parameters are the same of the "textbook" model, except for η , the elasticity of income with respect to human capital. Interestingly, a theoretical contradiction derives from assuming, on one hand, $n_i \neq n$ when it is included among the control variables, and, on the other, $n_i = n$ when it is in the convergence coefficient.

[12] Country-specific dummies are used to control for heterogeneities in steady-states. The common practice to employ dummy variables is due to lack of data at regional level.

the Post-war period. The years following the oil crises, instead, saw a decrease of the annual rate ranging from 0.8% or annual rate ranging from 0.8% to 1%

Convergence tests of type a) and b), however, have been criticized under many respects. From a general cross-country perspective, parameters heterogeneity, outliers, and measurement errors, have been highlighted (Temple, 1998, 2000). Looking at specific cross-regional aspects, instead, problems related to spatial dependence and spatial heterogeneity need to be taken into account (see, among others, Anselin, 1988, Rey and Montouri, 1999, Arbia, 2006).

Some researchers (Martin, 1998, Petrakos *et al.*, 2005), verifying the existence of different degrees of convergence, *within* or *between*-countries[13], address that the European convergence process does not obey to an homogeneous pattern of growth, and it may be well characterized by a situation similar to the one depicted below. Figure 1 plots the growth rate vs. the initial per capita income, for six hypothetical regions. Testing for convergence of type a) or b), illustrated by the bold line, would be misleading. We might erroneously conclude that all the regions were converging at the same rate either toward a common level or toward different income levels. The "true" convergence process, instead, represented by the dotted lines, indicates that the regions are converging at different rates toward different income levels. In such a case, a test of type c) convergence should result as more appropriate.

Structural heterogeneity in growth patterns, as shown in Figure 1 (see Appendix A), is well compatible with the multiple regimes in cross-country growth behaviour identified by Durlauf and Johnson (1995), or with the convergence clubs – the "twin-peaks" – in the world income distribution detected by Quah (1997). On one hand, country-specific constraints to the adoption of technologies may affect the efficiency of regional economies (see Parente and Prescott, 2000), producing structural heterogeneities world-wide, as verified by Durlauf *et al.* (2001). In this case, assumption iii) does not hold, because

iv) $$a \neq a_i = \gamma_i + (1 - e^{-\beta_i T}) / T \cdot \ln(A_0), \quad \forall i .$$

On the other one, growth models similar to the one developed by Azariadis and Drazen (1990) assume that thresholds effects, stemming from spillovers due to physical or human capital accumulation, may produce shifts in the aggregate production function, leading to multiple, locally stable, steady-state equilibria – i.e. to different convergence "clubs" (see

Durlauf and Quah, 1999). For instance, a threshold value in income level, $\bar{y}$, may cause $\beta_i = \beta_1$, if $y_{i,0} \prec \bar{y}$, and $\beta_i = \beta_2$, otherwise. It follows that assumption ii) needs to be replaced by

v) $$b \neq b_i = (1 - e^{-\beta_i T})/T, \quad \forall i .$$

If initially poorer regions converge toward a lower income level, defined as a "poverty trap", estimates of equation (1) with assumptions iv) and v) can be seen as tests of type c) convergence. So, a positive $\hat{\beta}$ indicates that poor regions grow faster than rich ones, at different rates, toward different steady states, depending on their initial condition.

The existence of clubs convergence across European regions has been recognized by several authors. First studies imposed exogenous assumptions on the number of clubs, to emphasize geographical and distributional factors, as North-South, centre-periphery, or rich-poor divisions. Neven and Gouyette (1995) split a sample of 142 European regions, over the period 1980-1989, in two clubs of Northern and Southern regions. They found a very low rate of 0.53% *absolute* convergence for the whole sample, and no statistically significant convergence each of the two clubs. Only if country-specific effects are controlled for, the rate of convergence assumes statistically significant values, comprised between 1.78% and 1.13%.

Endogenous criteria to detect the presence of clubs, however, should be better considered. Exogenous choices equals to assign in arbitrary ways the structural heterogeneities to different clubs in the sample. Canova (2004), in a recent study, adopted a predictive density approach to find the existence of convergence clubs across a sample of 144 EU regions, over the period 1980-1992. Avoiding a priori assumptions on the grouping procedure, he found four homogeneous clubs, with different convergence rates and steady-states values, that emphasize North-South or poor-rich dimensions, with the initial conditions influencing the probability of belonging to a club.

Turning to regional specific problems, instead, some authors have argued that, due to geographical spillovers, the distribution of regional per capita income across Europe tends to be influenced by their physical location (Quah, 1996c, López-Bazo *et al.*, 1999). As we will see in the next section, the existence of spatial effects leads OLS estimates to be biased or not

[13] Convergence *between* States – towards the outside – but not *within* – towards the inside – has been defined as the "diverging-convergence" phenomenon (Labour Asociados, 2003).

efficient. Ertur *et al.* (2006) treat spatial problems in the context of club convergence. On a sample of 138 EU regions, over the period 1980-1995, they found per capita income levels to be highly spatially correlated. Particularly, an exploratory spatial analysis (ESDA) revealed a division between Northern-rich regions and Southern-poor ones. So, assuming the existence of heterogeneity across two different spatial regimes, and taking the spatial autocorrelation into account, no convergence is found in the Northern club, whilst an annual rate equal to about 2.9% is present only in the Southern one.

The procedure followed by Ertur *et al*. (2006) is based on an exogenous assumption that parameters are heterogeneous across regions, deriving from their geographical locations. An endogenous criterion, however, as Durlauf and Johnson (1995) points out, seems to be more appropriate. To our knowledge, a procedure that merge together an endogenous identification of clubs and the spatial effects, appears to be not yet available in the empirical literature. In the following sections, we try to implement a strategy that goes in such direction.

3. Structural heterogeneity and spatial effects across Europe

In this section, we perform some descriptive statistics, to detect the existence of possible structural heterogeneities and spatial effects, in the form of spatial dependence, among the European regions. Figure 2 a) and b) (see Appendix A) represents some histograms of variables usually considered as determinants of steady-sates, for a sample of regions of EU-15. Figure 2 a) shows the ratio of total investment over total Gross Value Added (GVA), as a proxy for saving rates of physical capital. On the left of the histogram, there only are the British regions, with very low saving rates, and few regions from Greece. In the middle, there mainly are regions from rich States, i.e. the "core" of Europe, along with some poor "peripherical" Greek regions. The right side, with high saving rates, includes regions from the Cohesion Countries and Objective 1 areas, as the Southern Italy, and some "rich" regions from Austria, Luxembourg, and Nederland[14].

Figure 2 b) illustrates the ratio of the number of students with an upper-secondary education over the total of the economically active population. This measure proxies for

[14] The British regions seem to face very low investment rate, following their path of first movers to industrialization. The high saving rates of Cohesion Countries are not uncommon for less advanced areas, undertaking a take-off process. Greek regions show low saving rates, typical of agricultural economies, or economies experiencing an unbalanced growth.

investments in human capital[15]. The left part of the histogram includes, above all, less advanced regions with low education levels, as regions from the Cohesion Countries. The right part, instead, with high levels of education, comprise regions from rich areas of Europe, with the exception of the Objective 1 regions located in the Mezzogiorno of Italy[16].

As Figure 2 points out, high structural heterogeneity is present among the European regions. Looking at the spatial effects, in the form of spatial correlation, a simple inspection can be done with a scatterplot based on Moran's I statistic[17]. As is well known, the statistic can be expressed as

$$I = \frac{n}{q} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} x_i x_j}{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j}$$

where w_{ij} is an element of a binary spatial weights matrix $\mathbf{W}$[18], x_i is a specific variable for observation i, n is the observations number, q is a scaling factor equalling the sum of all the elements of the matrix $\mathbf{W}$. We use a row-standardized distance-based matrix, whose element is

$$\begin{cases} w_{ij} = 0 \text{ for } i = j \\ w_{ij} = 1 \text{ for } i \neq j \text{ if } d_{ij} \prec \bar{d} \\ w_{ij} = 0 \text{ for } i \neq j \text{ if } d_{ij} \succ \bar{d} \end{cases}$$

where d_{ij} is the distance from centroids of the regions, and $\bar{d}$ is a minimum distance cut-off, able to guarantee that the most remote location has at least one neighbour.

Figures 3 and 4 (see Appendix A) show Moran scatterplots of the log of per capita GDP at 1980, and of the average growth rate over the period 1980-2002, for a sample of 191 NUTS-2 regions from EU-15. The data, expressed at 1995 constant prices, are taken from Cambridge Econometrics, *European Regional Database*, 2004 (for the list of regions see Appendix B).

[15] Unfortunately, such kind of regional data, as well as data on technological innovation, are available only for recent years. They are able to depict only a rough image of the long-run. However, if large differences persisted nowadays, we would not expect that they were less pronounced in previous years.
[16] The distribution of investment in human capital is more heterogeneous than the investment in physical capital's one, either *between* or *within*-country.
[17] Calculations were done using the software GeoDa (see Anselin, 2005).
[18] Abreu *et al.* (2005b) show as contiguity matrices are the most popular in empirical literature.

As it can be seen, an highly positive spatial correlation, stronger for the case of per capita income levels, is present among European regions. Rich (poor) regions, indeed, were surrounded by rich (poor) ones, as well as regions with high (low) growth rates were surrounded by regions with high (low) ones[19].

From the above descriptive analysis, we would not expect that *absolute* beta-convergence, tested by standard OLS, could be the best hypothesis to explain regional growth across Europe, at least over the period considered. We estimate equation (1), without control variables, for the period 1980-2002, and for the sub-periods 1980-1990 and 1990-2002. During the Nineties, in fact, the implementation of the Cohesion policies, as well as the Maastricht Treaty and the adhesion to EMU, produced main economical, political and institutional changes. In light of those factors, the breakdown is useful to evaluate possible differences in the convergence process between the two sub-periods.

As it can be seen from Table 1, in the upper part, over the whole period 1980-2002, *absolute* beta convergence is very slow. The annual rate is equal to 0.6%, giving rise to an half-life of 116 years[20]. Looking at the two sub-periods, during the Eighties the convergence coefficient is not statistically significant, pointing out the absence of convergence. During the Nineties, instead, the convergence rate is equal to 0.8% per annum, producing an half-life of 87 years.

In the middle part of the Table there are the regression diagnostics. The Jarque-Bera statistics is highly significant over all the periods considered, stressing the non normality of the errors. This seems to suggest a different specification of the model, pointing towards a conditional or club convergence hypothesis. The Breusch-Pagan test, furthermore, signals errors heteroskedasticity over the period 1980-1990.

Finally, the bottom part of the Table shows the spatial dependence diagnostics. The Moran's I z-value highlights high spatial autocorrelation, so the regression needs to take into account specific spatial components. The robust versions of the Lagrange Multiplier (LM) statistics seems to indicate that, for the period 1980-2002, the spatial error model should be preferred. For the period 1980-1990 the statistics does not chose one of the two models model, while for the 1990-2002 period the spatial lag model should be considered.

[19] Similar results are obtained for the sub-periods 1980-1990 and 1990-2002. The spatial correlation in the growth rates, however, slightly increases during the Nineties.

[20] In such a case, poor regions will catch up with the richest ones in about 232 years. Comprehensibly, the result might be not very interesting in terms of policy implications.

So a preliminary regression analysis confirms that the *absolute* beta convergence, tested by standard OLS with no spatial specification, suffers many shortcomings to be a hypothesis able to explain the growth process of the European regional economies.

4. A spatially filtered mixture regression approach

Our interest lies here in an endogenous determination of heterogeneity in regional convergence patterns, with possible formation of clubs. We avoid a priori geographical (as North-South or centre-periphery divisions), or exploratory (based upon Moran indices) restrictions. To this aim, we use a spatially filtered mixture regression approach (see, for mixture distributions, Titterington *et al.*, 1985, Wedel and Kamakura, 1998, MacLachlan and Peel, 2000). Previous attempts to apply mixture models to convergence analysis are in Paap and Van Djik (1998), and in Tsionas (2000). Those studies, however, do not explicitly consider spatial related questions, and they also differ in many aspects from the our.

Let us begin considering spatial dependence. As is well known, if spatial dependence is present across a sample, OLS estimates are biased or not efficient (Anselin, 2001). If spatial effects influence errors in equation (1), statistical inference based on OLS is not reliable, because assumption of errors independence from neighbouring regions may be violated (Anselin, 1988). To overcome such problem, a spatial error model can be used (see Anselin and Bera, 1998), whose error structure is , in matrix notation,

$$\mathbf{u} = \lambda \mathbf{W}\mathbf{u} + \boldsymbol{\xi}\,, \tag{2}$$

where $\mathbf{W}$ is a weight matrix, λ is the spatial autoregressive parameter, and $\boldsymbol{\xi} \sim N(0, \sigma^2 \mathbf{I})$ is a random component. If we substitute (2) in equation (1) we obtain

$$\mathbf{g} = \mathbf{a} - \mathbf{b}\mathbf{x} + \boldsymbol{\xi}(\mathbf{I} - \lambda \mathbf{W})^{-1}\,. \tag{3}$$

We use equation (1) without control variables, because in the following procedure we admit heterogeneity in steady-states, allowing for different intercepts across clubs. In order to properly apply the OLS estimator we need to filter out the spatial dependence in the dependent and independent variables, through the term between brackets in the left hand side of the equation (3)

$$\mathbf{g}(\mathbf{I} - \lambda \mathbf{W}) = \mathbf{a}(\mathbf{I} - \lambda \mathbf{W}) - \mathbf{b}\mathbf{x}(\mathbf{I} - \lambda \mathbf{W}) + \boldsymbol{\xi}\,. \tag{4}$$

Then we obtain an equation with spatially filtered variables (where F stands for filtered)

$$\mathbf{g}^F = \mathbf{a}^F - \mathbf{b}\mathbf{x}^F + \boldsymbol{\xi}. \tag{5}$$

In this way we implement a two step procedure (see, for example Badinger *et al.*, 2004). In the first step we "clean up" the spatial dependence, by filtering out the variables through the λ obtained from a maximum likelihood estimation for the whole sample[21]. In a similar manner we might filter out the spatial dependence adopting a spatial lag model. The choice of the models will follow the results of the spatial dependence tests. In the second step we use the mixture regression model to detect the existence of regional convergence clubs.

Suppose now that the "true" density function of a population is a mixture of more functions, one for each club with different parameters, weighted by the probability to belong to a club. If the population is divided in k clubs, the number of them being unknown, and the probabilities sum to one, then, according to the total probability theorem, the conditional distribution function is

$$f(g_i \mid \boldsymbol{\theta}) = \sum_{s=1}^{k} \psi_s f_s(g_i \mid \boldsymbol{\theta}_s), \tag{6}$$

where g_i is the dependent variable, ψ_s is the probability to belong (a priori) to a club s, $s = 1,...,k$, and $\boldsymbol{\theta}$ is a vector of parameters. Once ψ_s has been estimated, the posterior probability that observation i comes from s has to be computed by Bayes theorem.

Consider that the function of the filtered variable g_i^F is normal. The density function conditional to belong to the club k is

$$f(g_i^F \mid \mathrm{s} = \mathrm{k}, \boldsymbol{\theta}) = (2\pi\sigma_k^2)^{1/2} e^{-\left[g_i^F - (a_k^F - b_k x_i^F)\right]^2 / 2\sigma_k^2} \tag{7}$$

In this way, the component represented by $(a_k^F - b_k x_i^F)$ gives us a linear predictor that replace the population mean of the club. From Bayes rule, it is straightforward to extract the probability of g_i^F for $s = k$ as a joint probability, that is the product of conditional probability and the probability of staying in a club. With the latter equal to ψ_k, the joint probability is $\psi_k f(g_i^F \mid \mathrm{s} = \mathrm{k}, \boldsymbol{\theta})$.

Summing all the values of s gives the unconditional density of g_i^F

$$f(g_i^F,\boldsymbol{\theta}) = \sum_{s=1}^{k} \psi_s (2\pi\sigma_s^2)^{1/2} e^{-\left[g_i^F-(a_s^F-b_s x_i^F)\right]^2/2\sigma_s^2} \qquad (8)$$

The vector of parameters $\boldsymbol{\theta}$, that also contains the weights ψ_s, is unknown. A simple way to solve this problem of missing data is the Expectation-Maximization (EM) algorithm. The solution is to find an initial value of the parameters, then compute the density for these parameters, and re-compute the final $\boldsymbol{\theta}$, by maximization of the log-likelihood. So the algorithm has two alternated steps: in the fist one (expectation) it computes the density function for the chosen parameters, while in the second one (maximization) it derives the estimation of the parameters a_s^F, b_s^F, and σ_s^2. In the case of a linear mixture regression, De Sarbo and Cron (1988) show as the second step is equivalent to perform k weighted least squares regressions, where the weights are the roots of the probabilities to belong to a club.

We begin with random starting probabilities, and then we update the probabilities step by step. This strategy could have two types of shortcoming. First, the results might depend on the initial probabilities. Second, the maximization of the log-likelihood could converge in a local optimum. To avoid these problems we run a high number of p regressions, increasing the number of clubs, and we choose the highest value of log-likelihood $(L_{highest})$

$$L_{highest} = \max\{L_p \mid rsp_p\}, \qquad p = 1,\ldots,m, \qquad (9)$$

where rsp_p is the random starting probability, and $m = 500$. Once $L_{highest}$ is found, whose value also determines the number of the component in the mixture, each region is attributed to a club if the probability to belong to that club is higher than the probability to belong to the other ones[22].

Since equation (8) allows heterogeneity in steady-states and convergence coefficients, that is $a_i \neq a \;\; \forall i$, and $b_i \neq b \;\; \forall i$, respectively, if regions with similar initial conditions belong to the same club, the procedure we employ tests for type c) convergence.

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[21] Other filtering procedures, that allow to distinguish between local spatial and non spatial components for each location are discussed for example in Getis and Griffith (2002).

[22] Obviously, in some cases the attribution might be more or less precise (i.e. there are regions with a 100% probability to stay in a club, and regions with only 51% probability to belong to a club). Generally, we found about 90% of regions that are attributed with a difference threshold more than 10% with respect to the alternatives.

5. Results

Previous section stressed the relevance to consider spatial effects. We tested both spatial models (lag and error), with the main result that they tend to reduce the magnitude of the convergence coefficient. The significance of the robust LM-error statistics, indicates that the spatial error model should be preferred for the whole sample. The statistic is not very clear for the sub-period 1980-1990, while a preference for the lag model is shown for the sub-period 1990-2002. As a first step, we proceed to filter out the spatial dependence from the variables, following the procedure based on the spatial error model described in the previous section. Then we compare the results with a spatial lag filtering procedure.

After this preliminary step, we run the mixture regression model. We chose the number of clubs looking at two criteria: the increments of the log-likelihood and a meaningful interpretation of the data. The latter criterion regards either the coefficients of the clubs (two segments[23] with the same coefficient are not considered properly different), or a more certain attribution of the regions (looking at the probabilities to stay in a club given the alternatives). According to the log-likelihood based tests reported in Figure 6 a), b), and c), the choice of four clubs seems to be the better one, except for the period 1980-1990 where a specification with five clubs could be preferred, given the scarce interpretability of the two clubs choice[24]. The logic of the tests (see Hawkins et *al.*, 2001) is to apply a different penalty (2, 3 or the natural log of the observation number) multiplied by the parameters, in order to avoid an excessive – and not useful – number of parameters, due to the increased components of the mixture. The AIC penalization is less restrictive, so it generally selects less parsimonious specifications, while the MDL is the most restrictive.

Table 2 reports the results obtained by the mixture regression (see the raw labelled mixture), applied to the spatially filtered variables[25]. Generally, there is an "outlier bin", consisting of regions following particular growth experiences, a small club of faster convergence, a major club of slower convergence, and a remaining group showing no convergence at all. During the Eighties, however, the faster convergence club is not present, while there is a group of very slow convergence[26].

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[23] We use here the terms clubs, segments, or groups, as interchangeable.

[24] In the case of two clubs, for all the periods, we obtain an "outlier bin", and a large club with smaller convergence with respect to the whole sample. The results, however, are in all the cases better than the simple OLS regression, so type a) convergence seems not to be confirmed by the data.

[25] We also tested a cross-regressive mixture model, but the cross-regressive term is never significant.

[26] Applying the lag (SAR) model, that in matrix notation is $\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\beta + \boldsymbol{\varepsilon}$, the only series to be filtered is the dependent variable, through the component $\mathbf{y}(\mathbf{I} - \rho\mathbf{W})$. The results of the mixture are very close to those we

Once the regions have been attributed by the mixture model, we also run OLS regressions for each club[27]. The general difference between the two estimates is a greater spread among the coefficients of the clubs. Such difference, however, is very small, and the fit of the regressions are really appreciable, since the R^2 are higher than the usual cross-section results. Most interestingly, the segmentation process solved normality problems seen in Tab. 1. A simple "outliers cut" is not sufficient to ensure normality to the rest of the sample, so it is a further evidence of the probable existence of more densities in the full sample.

As a final step, we proceed with a geographical inspection of the groups defined by the mixture model (see the maps and the legend in Appendix A). Generally, groups in black are outliers. The light grey group, that is a good description for the large number of regions, is the slow convergence club. In the dark grey group fall regions exhibiting fast convergence, and in the white group are the regions that not converge, or that converge at a very slow pace. Over the whole period, the majority of the regions converge slowly, while only few regions converge at a fast rate. The remaining regions do not converge at all. Looking at the sub-periods, during the Eighties the convergence process is less diffuse across Europe. At the same time, dualistic phenomena are present in many States, as UK, Germany, Spain, Italy, etc., where large areas do not converge[28]. Greece seems to not converge as well. During the Nineties, convergence is more diffuse, the diverging area is reduced, and a group of few regions converge at a very fast rate.

Finally, probability to belong to the clubs seems to be not influenced by the starting income levels, i.e. initial conditions do not matter. So type c) convergence might be not the right hypothesis, replaced by a scenario of completely different regimes.

6. Conclusions

The results of this work show as *absolute* and *conditional* convergence are not the best candidate to explain regional growth across Europe, over the period 1980-2002. Spatial effects matter, and log-likelihood based tests show as a common specification for the whole sample is a too much restrictive assumption. Separate regressions for sub-samples of regions,

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obtained for the error (SEM) filtered series, but the convergence rate is a bit slower. For the period 1990-2002 we selected three clubs, with more than 70% of the sample exhibiting slow convergence (0.6% per year). For the period 1980-1990 the situation is similar to the one depicted in Table 2, with a convergence rate of 0.4%.

[27] As we have already seen, the weight and the number of regions for each club do not coincide, since regions are attributed to the different clubs with the highest probability. OLS estimation is equivalent to the mixture regression, for the same segment, with probabilities rounded to 1.

endogenously identified by the mixture, are much more consistent with the data, and they avoid problems posed by outliers and non normality of the errors. Structural heterogeneity of parameters could indicate the hypothesis of club convergence. Since initial conditions do not matter, however, a multiple regimes scenario is much more plausible.

A four clubs specification renders one club that behaves as an "outlier bin", one club with a slow convergence speed, on club with fast convergence, and another one with no convergence at all. The analysis of sub-periods highlights less diffuse convergence during the Eighties, and more diffuse convergence, even if at different speeds, for the following decade. Many richest regions, either inside "poor" or "rich" States, fall in the non convergence club, where agglomeration factors, and increasing returns, might play a role. Such mechanism reinforces the paradox of the "diverging-convergence", that is convergence between States, but not within. A North-South division does not emerge, but for the Italian case, while a core-periphery dynamic seems to take place.

For the majority of the sample, to conclude, convergence is reduced much more then the empirical "norm" of 2% per year. So we wonder if could be appropriate to talk about a "half-convergence", instead of a "half-life".

References

Abramovitz M. 1986. Catching Up, Forging Ahead, and Falling Behind. *Journal of Economic History* **46**: 385-406.

Abreu M, De Groot HLF, Florax RJGM. 2005a. A Meta-Analysis of β-Convergence: the Legendary 2%. *Journal of Economic Surveys* **19**: 389-420.

–––. 2005b. Space and Growth: A survey of Empirical Evidence and Methods. *Région et Développement* **21**: 13-44.

Anselin L. 1988. *Spatial Econometrics: Methods and Models*. Kluwer: Dordrecht.

–––. 2001. Spatial Econometrics. In *A companion to Theoretical Econometrics*, Baltagi BH (ed). Blackwell: Oxford.

–––. 2005. *Exploring Spatial Data with GeoDa: A Workbook*. Center for Spatial Integrated Social Science.

[28] We consider the group that converge at the rate of 0.3% as a club of no convergence, since the half-life is about 260 years.

Anselin L, Bera AK. 1998. Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. In *Handbook of Applied Economic Statistics*, Ullah A, Giles DEA (eds). Marcel Dekker: New York.

Arbia G. 2006. *Spatial Econometrics. Statistical Foundations and Applications to Regional Convergence*. Springer: Berlin. Forthcoming.

Armstrong HW. 1995. Convergence among regions of the European Union, 1950-1990. *Papers in Regional Science* **74**: 143-152.

Azariadis C, Drazen A. 1990. Threshold Externalities in Economic Development. *Quarterly Journal of Economics* **105**: 501-526.

Badinger H, Müller WG, Tondl G. 2004. Regional Convergence in the European Union, 1985-1999: A Spatial Dynamic Panel Analysis. *Regional Studies* **38**: 241-253.

Barro RJ, Sala-i-Martin X. 1991. Convergence across States and Regions. *Brookings Papers on Economic Activity* **1**: 107-182.

——. 1992. Convergence. *Journal of Political Economy* **100**: 223-251.

——. 2004. *Economic Growth* (2nd ed). MIT: Cambridge, MA.

Baumol WJ. 1986. Productivity Growth, Convergence, and Welfare: What the Long-Run Data Show. *American Economic Review* **76**: 1072-1085.

Bernard AB, Durlauf SN. 1996. Interpreting tests of the convergence hypothesis. *Journal of Econometrics* **71**: 161-173.

Boldrin M, Canova F. 2001. Inequality and convergence in Europe's regions: reconsidering European regional policies. *Economic policy* **16**: 207-253.

Canova F. 2004. Testing for Convergence Clubs in Income per Capita: a Predictive Density Approach. *International Economic Review* **45**: 49-77.

Cass D. 1965. Optimum Growth in an Aggregative Model of Capital Accumulation. *Review of Economic Studies* **32**: 233-240.

Commission of the European Communities. 2005. *Communication from the Commission. Third progress report on cohesion: Towards a new partnership for growth, jobs and cohesion*. 17.5.2005. COM(2005) 192 final. Brussels.

De Sarbo WS, Cron WL. 1988. A Maximum Likelihood Methodology for Clusterwise Linear Regression, *Journal of Classification* **5**: 249-282.

Durlauf SN. 2003. *The Convergence Hypothesis After 10 Years*. SSRI Working Paper 6. Department of Economics. University of Wisconsin-Madison.

Durlauf SN, Johnson PA. 1995. Multiple Regimes and Cross-country Growth Behaviour. *Journal of Applied Econometrics* **10**: 365-384.

Duraluf SN, Quah DT. 1999. The New Empirics of Economic Growth. In *Handbook of Macroeconomics*, Vol. 1, Taylor JB, Woodford M (eds). North Holland: Amsterdam.

Durlauf SN, Kourtellos A, Minkin A. 2001. The Local Solow Growth Model. *European Economic Review* **45**: 928-940.

Durlauf SN, Johnson PA, Temple JRW. 2004. *Growth Econometrics*. SSRI Working Paper 18. Department of Economics: University of Wisconsin – Madison. Forthcoming in *Handbook of Economic Growth*, Durlauf SN, Aghion P. (eds). North Holland: Amsterdam.

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**: 3-24.

European Commission. 2001. *Unity, solidarity, diversity for Europe, its people and its territory. Second report on economic and social cohesion*. Office for Official Publications of the European Communities: Luxembourg.

——. 2004. *A new partnership for cohesion. Convergence competitiveness cooperation. Third report on economic and social cohesion*. Office for Official Publications of the European Communities: Luxembourg.

Funck B, Pizzati L (eds). 2003. *European Integration, Regional Policy, and Growth*, World Bank: Washington D.C.

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

Getis A, Griffith DA. 2002. Comparative Spatial Filtering in Regression Analysis. *Geographical Analysis* **34**: 130-140.

Hart PE. 1995. Galtonian Regression Across Countries and the Convergence of Productivity. *Oxford Bulletin of Economics and Statistics* **57**: 287-293.

Hawkins DS, Allen DM, Stromberg AJ. 2001. Determining the number of components in mixture of linear models. *Computational Statistics and Data Analysis* **38**: 15-48.

Inada K. 1963. On a Two-Sector Model of Economic Growth: Comments and a Generalization. *Review of Economic Studies* **30**: 502-526.

Koopmans TC. 1965. On the Concept of Optimal Economic Growth. *Pontificae Academiae Scientiarum Scripta Varia* **28**: 225-300. Reprinted as Cowles Foundation Paper 238.

Labour Asociados. 2003. *Analysis of the impact of Community Policies on Regional Cohesion*. Contract number: 2002 CE 16 0 AT 171. European Commission. DG Regional Policy.

López-Bazo E, Vayá E, Mora AJ, Suriñach J. 1999. Regional Economic Dynamics and Convergence in the European Union. *Annals of Regional Science* **33**: 343-370.

MacLachlan G, Peel D. 2000. *Finite Mixture Models*. John Wiley and Sons: New York.

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

Martin P. 1998. Can Regional Policies Affect Growth and Geography in Europe?. *World Economy* **21**: 757-774.

Neven D, Gouyette C. 1995. Regional Convergence in the European Community. *Journal of Common Market Studies* **33**: 47-65.

Paap R, van Dijk HK. 1998. Distribution and Mobility of Wealth of Nations. *European Economic Review* **42**: 1269-1293.

Paci R, Pigliaru F. 2002. Technological diffusion, spatial spillovers and regional convergence in Europe. In *Regional convergence in the European Union: Facts, prospects and policies*, Cuadrado-Roura JR, Parellada M (eds). Springer: Berlin.

Parente SL, Prescott EC. 2000. *Barriers to Riches*. MIT: Cambridge, MA.

Petrakos G, Rodríguez-Pose A, Rovolis A. 2005. Growth, Integration, and Regional Disparities in the European Union. *Environment and Planning A* **37**: 1837-1855.

Quah DT. 1993a. Empirical cross-section dynamics in economic growth. *European Economic Review* **37**: 426-434.

–––. 1993b. Galton's Fallacy and Tests of the Convergence Hypothesis. *Scandinavian Journal of Economics* **95**: 427-443.

–––. 1996a. Empirics for economic growth and convergence. *European Economic Review* **40**: 1353-1375.

–––. 1996b. Twin Peaks: Growth and Convergence in Models of Distribution Dynamics. *Economic Journal* **106**: 1045-1055.

–––. 1996c. Regional Convergence Clusters across Europe. *European Economic Review* **40**: 951-958.

–––. 1997. Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs. *Journal of Economic Growth* **2**: 27-59.

Rey SJ, Montouri BD. 1999. US Regional Income Convergence: A Spatial Econometric Perspective. *Regional Studies* **33**: 143-156.

Sala-i-Martin X. 1996a. The Classical Approach to Convergence Analysis. *Economic Journal* **106**: 1019-1036.

——. 1996b. Regional Cohesion: Evidence and Theories of Regional Growth and Convergence. *European Economic Review* **40**: 1325-1352.

——. 2002. *15 Years of New Growth Economics: What Have We Learnt?*. Discussion Paper Series 0102-47. Department of Economics: Columbia University.

Solow RM. 1956. A Contribution to the Theory of Economic Growth. *Quarterly Journal of Economics* **70**: 65-94.

Temple JRW. 1998. Robustness Tests of the Augmented Solow Model. *Journal of Applied Econometrics* **13**: 361-375.

——. 2000. Growth Regressions and What the Textbooks Don't Tell You. *Bulletin of Economic Research* **52**: 181-205.

Titterington DM, Smith AFM, Makov UE. 1985. *Statistical Analysis of Finite Mixture Distributions*. Wiley: Chichester.

Tsionas EG. 2000. Regional Growth and Convergence: Evidence from the United States. *Regional Studies* **34**: 231-238.

Wedel M, Kamakura WA. 1998. *Market Segmentation: Conceptual and Methodological Foundations*. Kluwer: Dordrecht.

Appendix A

Fig. 1. Club convergence.

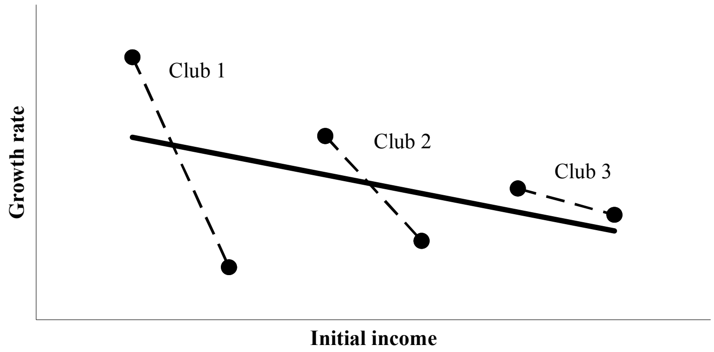
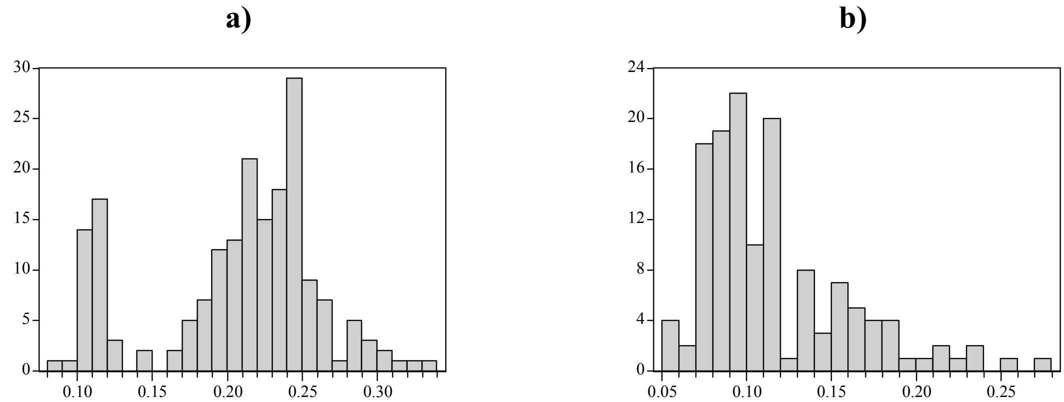
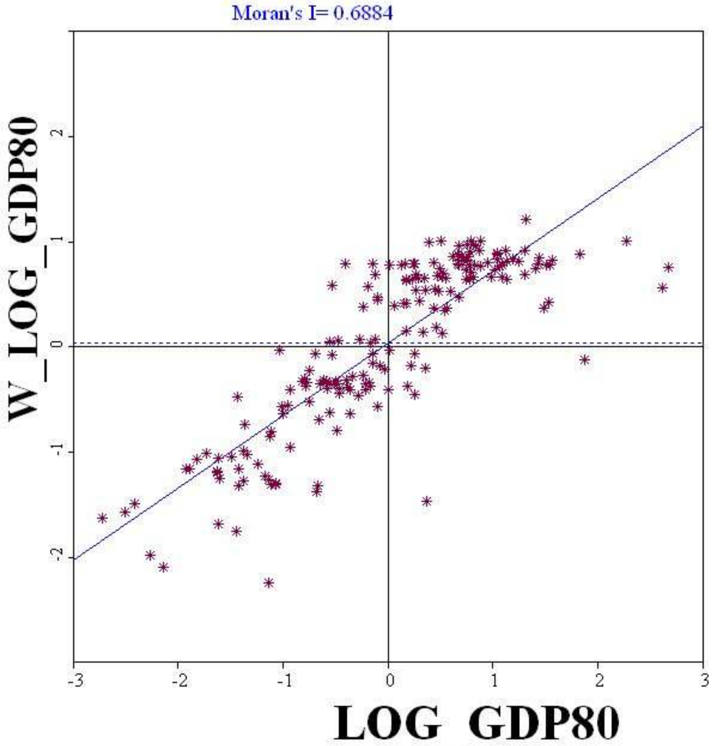


Fig. 2 a) Total investment/Total GVA (190 NUTS-2 regions, average 1980-2002) b) Number of students by upper secondary education level*/Economically active population (136 NUTS-1 and 2 regions, average 1999-2001***)**



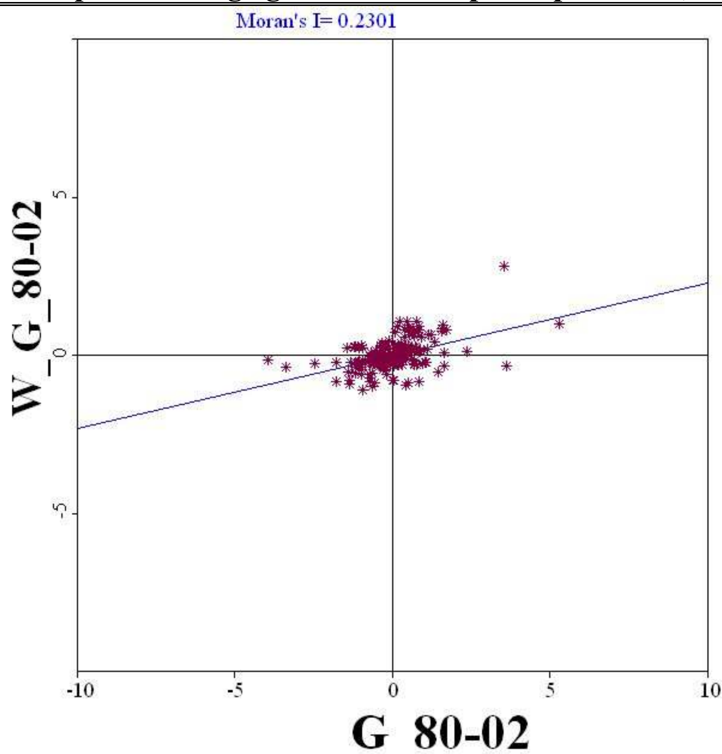
*Level 3, ISCED 1997. **15 years and over. *** Data for Portugal are available at country level, and for Austria, Denmark, Ireland, Greece, Luxembourg, and UK, for shorter periods.
Source: Personal elaboration on **a)** Cambridge Econometrics, *European Regional Database*, 2004 **b)** Eurostat, *Regio database* (Date of extraction: Sun, 5 Mar 06 10:59:14)**.**

Fig. 3. Moran scatterplot. Per capita GDP, 1980.



Source: Personal elaboration on Cambridge Econometrics, *European Regional Database*, 2004.

Fig. 4. Moran scatterplot. Average growth rate of per capita GDP, 1980-2002.



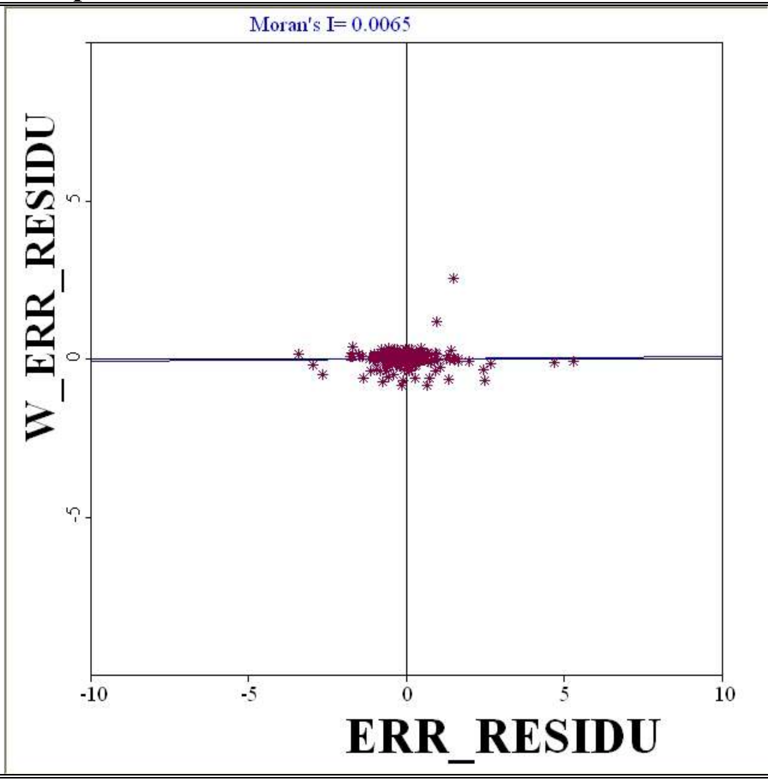
Source: Personal elaboration on Cambridge Econometrics, *European Regional Database*, 2004.

Tab. 1. *Absolute* convergence. OLS estimates, regression diagnostics, and diagnostics for spatial dependence*.

	1980-2002	1980-1990	1990-2002
	OLS		
$\hat{a}$	.075**	.039*	.095**
$\hat{b}$	.006**	.002	.008**
$\hat{\beta}$	0.6%	-	0.8%
Half-life	116 years	-	87 years
R^2	.12	.01	.16
Log likelihood	690	614	662
	Regression diagnostics		
Jarque-Bera	287**	739**	652**
Breusch-Pagan	.09	10.5**	.17
	Diagnostics for spatial dependence		
Moran's I (error)	8.6**	9.7**	7.0**
LM (lag)	42.9**	69.9**	42.4**
LM (error)	57.7**	75.3**	37.5**
Robust LM (lag)	1.2	9.13**	5.4*
Robust LM (error)	16.0**	14.5**	.460

** Statistically significant at 1% * Statistically significant at 5%.
Source: Personal elaboration on Cambridge Econometrics, *European Regional Database*, 2004.

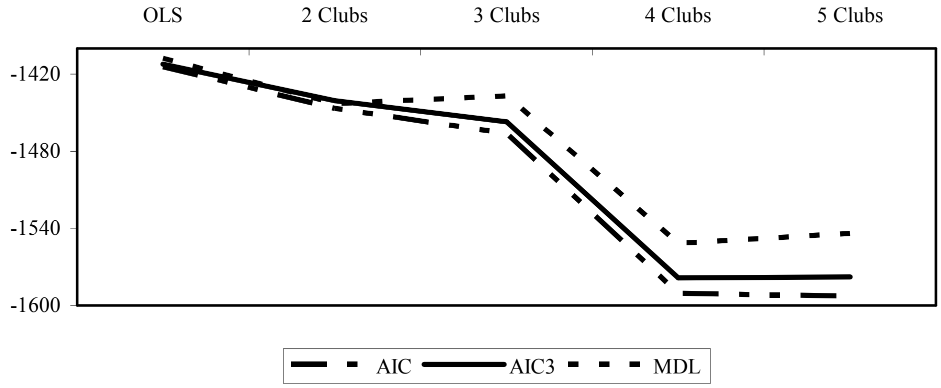
Fig. 5. Moran scatterplot of the residuals from SEM model. 1980-2002.



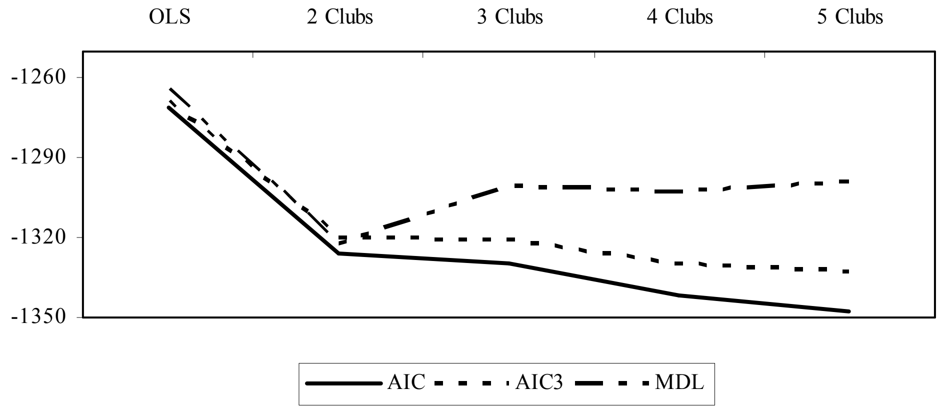
Source: Personal elaboration on Cambridge Econometrics, *European Regional Database*, 2004.

Fig. 6. Log-likelihood based tests.

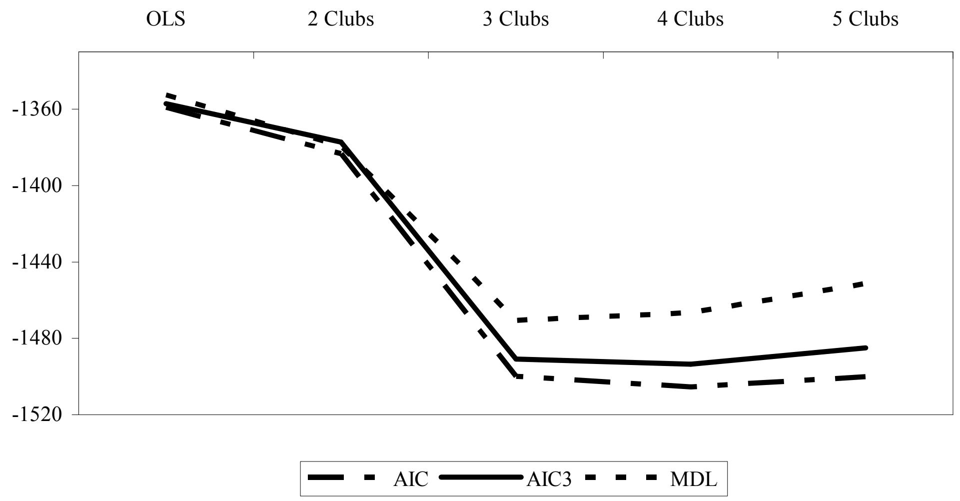
a) 1980-2002



b) 1980-1990



c) 1990-2002



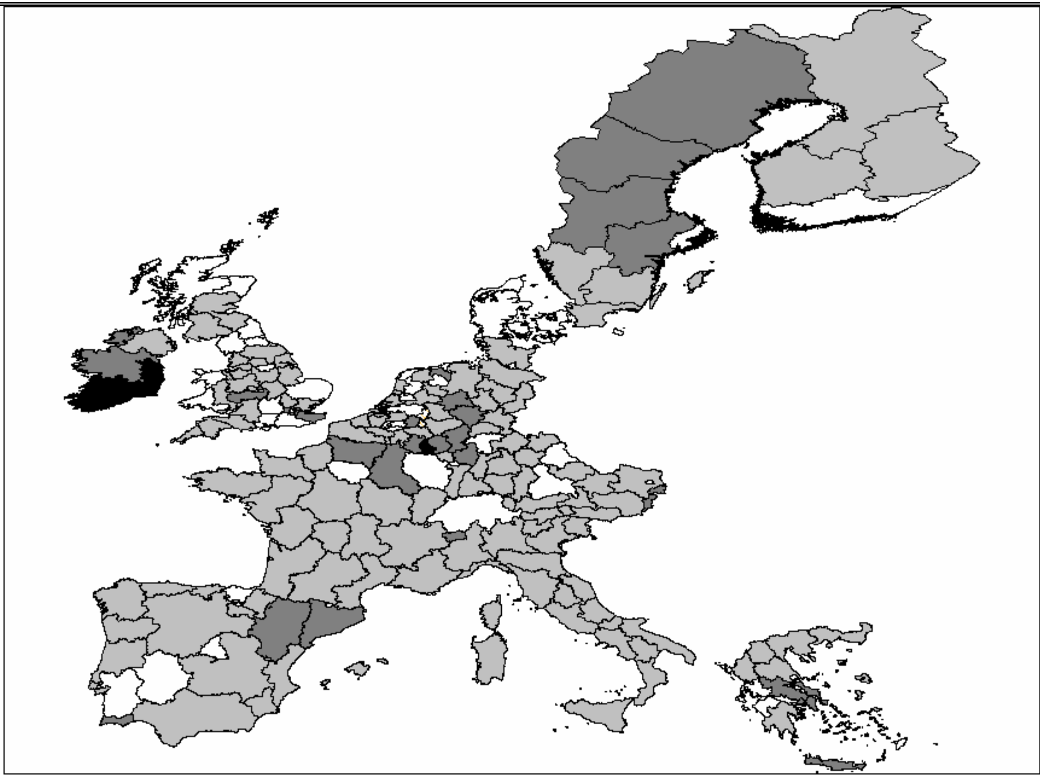
Source: Personal elaboration on Cambridge Econometrics, *European Regional Database*, 2004.

Tab. 2. Mixture and OLS estimates on spatially filtered series*.

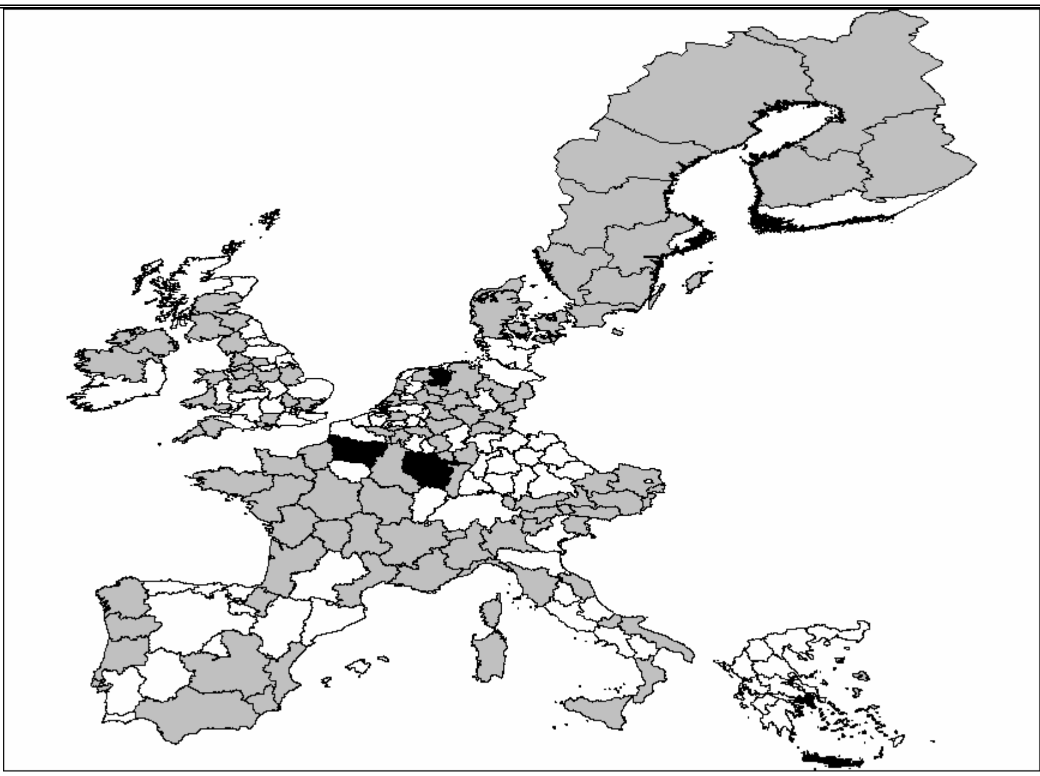
		Club 1	Club 2	Club 3	Club 4	Club 5
		1980-2002				
Mixture	$\hat{a}$	.305	.288	.023	.065	-
	$\hat{b}$	.021	.029	.000	.005	-
	Weight	1%	18%	36%	45%	-
OLS	$\hat{a}$	-	.301**	-.010	.065**	-
	$\hat{b}$	-	.031**	-.004	.005**	-
	$\hat{\beta}$	-	5%	-	.6%	-
	Half-life	-	13 years	-	126 years	-
	R^2	-	.95	.02	.20	-
	Jarque-Bera	-	1.4	2.0	4.7	-
	Regions	2	26	36	127	-
		1980-1990				
Mixture	$\hat{a}$	.597	.126	-.149	.051	.071
	$\hat{b}$	.065	.010	-.015	.001	.006
	Weight	4.4%	17%	9%	24%	45%
OLS	$\hat{a}$	-	.211	-.149**	.064**	.073**
	$\hat{b}$	-	.017	-.015**	.003*	.006**
	$\hat{\beta}$	-	-	-	.3%	.7%
	Half-life	-	-	-	257 years	104 years
	R^2	-	.05	.93	.08	.25
	Jarque-Bera	-	.9	.6	3.8	3.6
	Regions	6	14	17	52	102
		1990-2002				
Mixture	$\hat{a}$	-1.100	-.042	.261	.062	-
	$\hat{b}$	-.127	-.006	.027	.005	-
	Weight	1%	34%	27%	38%	-
OLS	$\hat{a}$	-	-.172**	.315**	.060**	-
	$\hat{b}$	-	-.020**	.033**	.004**	-
	$\hat{\beta}$	-	-	6%	.5%	-
	Half-life	-	-	12 years	147 years	-
	R^2	-	.31	.76	.11	-
	Jarque-Bera	-	1.4	1.0	5.7	-
	Regions	2	32	37	120	-

** Statistically significant at 1% * Statistically significant at 5%.
Source: Personal elaboration on Cambridge Econometrics, *European Regional Database*, 2004.

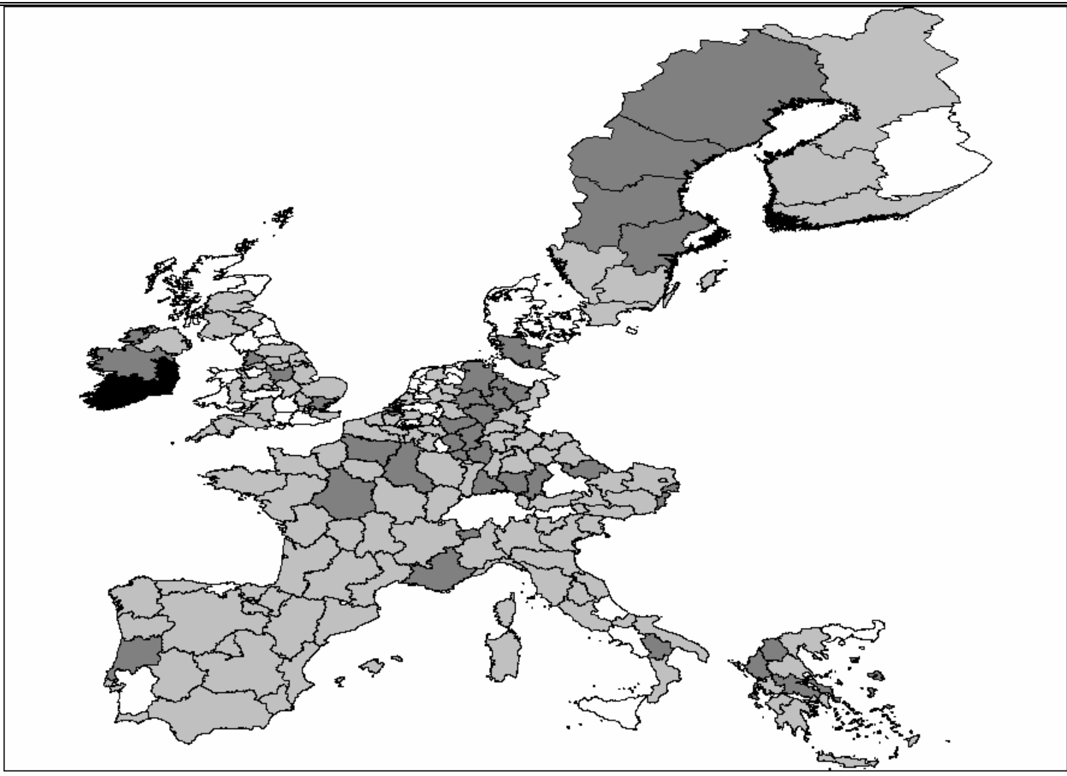
Map 1. Clubs 1980-2002.



Map 2. Clubs 1980-1990.



Map 3. Clubs 1990-2002.



Legend

Black: outliers.

Dark grey: fast convergence.

Light grey: slow convergence.

White: no convergence or very slow convergence.

Appendix B[29]

AT (9) 1. Burgenland 2. Niederosterreich 3. Wien 4. Karnten 5. Steiermark 6. Oberosterreich 7. Salzburg 8. Tirol 9. Vorarlberg **BE (11)** 10. Bruxelles-Brussel 11. Antwerpen 12. Limburg 13. Oost-Vlaanderen 14. Vlaams-Brabant 15. West-Vlaanderen 16. Brabant Wallon 17. Hainaut 18. Liège 19. Luxembourg 20. Namur **DE (30)** 21. Stuttgart 22. Karlsruhe 23. Freiburg 24. Tübingen 25. Oberbayern 26. Niederbayern 27. Oberpfalz 28. Oberfranken 29. Mittelfranken 30. Unterfranken 31. Schwaben 32. Bremen 33. Hamburg 34. Darmstadt 35. Gießen 36. Kassel 37. Braunschweig 38. Hannover 39. Lüneburg 40. Weser-Ems 41. Düsseldorf 42. Köln 43. Münster 44. Detmold 45. Arnsberg 46. Koblenz 47. Trier 48. Rheinhessen-Pfalz 49. Saarland 50. Schleswig-Holstein **DK (1)** 51. Denmark **ES (16)** 52. Galicia 53. Asturias 54. Cantabria 55. País Vasco 56. Navarra 57. Rioja 58. Aragón 59. Madrid 60. Castilla-León 61. Castilla-la-Mancha 62. Extremadura 63. Cataluña 64. Com. Valenciana 65. Baleares 66. Andalucía 67. Murcia **FI (4)** 68. Itä-Suomi 69. Etelä-Suomi 70. Länsi-Suomi 71. Pohjois-Suomi **FR (22)** 72. Île-de-France 73. Champagne-Ardenne 74. Picardie 75. Haute-Normandie 76. Centre 77. Basse-Normandie 78. Bourgogne 79. Nord-Pas de Calais 80. Lorraine 81. Alsace 82. Franche-Comté 83. Pays de la Loire 84. Bretagne 85. Poitou-Charentes 86. Aquitaine 87. Midi-Pyrénées 88. Limousin 89. Rhône-Alpes 90. Auvergne 91. Languedoc-Roussillon 92. Provence-Alpes-Côte d'Azur 93. Corse **GR (13)** 94. Anatoliki Makedonia 95. Kentriki Makedonia 96. Dytiki Makedonia 97. Thessalia 98. Ipeiros 99. Ionia Nisia 100. Dytiki Ellada 101. Sterea Ellada 102. Peloponnisos 103. Attiki 104. Voreio Aigaio 105. Notio Aigaio 106. Kriti. **IE (2)** 107. Border, Midland and Western 108. Southern and Eastern. **IT (21)** 109. Piemonte 110. Valle d'Aosta 111. Liguria 112. Lombardia 113. Provincia Autonoma Bolzano 114. Provincia Autonoma Trento 115. Veneto 116. Friuli-Venezia Giulia 117. Emilia-Romagna 118. Toscana 119. Umbria 120. Marche 121. Lazio 122. Abruzzo 123. Molise 124. Campania 125. Puglia 126. Basilicata 127. Calabria 128. Sicilia 129. Sardegna **LU (1)** 130. Luxembourg **NL (11)** 131. Groningen 132. Friesland 133. Drenthe 134. Overijssel 135. Gelderland 136. Utrecht 137. Noord-Holland 138. Zuid-Holland 139.

[29] The original dataset has been modified to make it compatible with Eurostat's NUTS-2 classification. Denmark has been considered at national level, and the Italian region Trentino-Alto Adige has been split in two different regions, using weights calculated from Eurostat Regio Database. Regions excluded for lack of data, low population or extremely remote location are ex-Länder (DE), Departements d'Outre-Mer (FR), Flevoland (NL), Aland (FI), Canarias and Ceuta y Melilla (ES), Acores and Madeira (PT).

Zeeland 140. Noord-Brabant 141. Limburg **PT (5)** 142. Norte 143. Algarve 144. Centro 145 Lisboa e V.do Tejo 146. Alentejo **SE (8)** 147. Stockholm 148. Östra Mellansverige 149. Sydsverige 150. Norra Mellansverige 151. Mellersta Norrland 152. Övre Norrland 153. Småland med öarna 154. Vastsverige **UK (37)** 155. Tees Valley and Durham 156. Northumb. *et al.* 157. Cumbria 158. Cheshire 159. Greater Manchester 160. Lancashire 161. Merseyside 162. East Riding 163. North Yorkshire 164. South Yorkshire 165. West Yorkshire 166. Derbyshire 167. Leicestershire 168. Lincolnshire 169. Herefordshire *et al.* 170. Shropshire 171. West Midlands (co.) 172. East Anglia 173. Bedfordshire 174. Essex 175. Inner London 176. Outer London 177. Berkshire *et al.* 178. Surrey 179. Hants. 180. Kent 181. Gloucestershire *et al.* 182. Dorset 183. Cornwall 184. Devon 185. West Wales 186. East Wales 187. North Eastern Scotland 188. Eastern Scotland 189. South Western Scotland 190. Highlands and Islands 191. Northern Ireland.