The Regional Economics Applications Laboratory (REAL) is a cooperative venture between the University of Illinois and the Federal Reserve Bank of Chicago focusing on the development and use of analytical models for urban and regional economic development. The purpose of the **Discussion Papers** is to circulate intermediate and final results of this research among readers within and outside REAL. The opinions and conclusions expressed in the papers are those of the authors and do not necessarily represent those of the Federal Reserve Bank of Chicago, Federal Reserve Board of Governors or the University of Illinois. All requests and comments should be directed to Geoffrey J. D. Hewings, Director, Regional Economics Applications Laboratory, 607 South Matthews, Urbana, IL, 61801-3671, phone (217) 333-4740, FAX (217) 244-9339.
Web page: www.uiuc.edu/unit/real

DISTRIBUTION OF REGIONAL INCOME AND REGIONAL FUNDS IN EUROPE 1989-1999: AN EXPLORATORY SPATIAL DATA ANALYSIS

by

Sandy Dall'erba

REAL 03-T-1 January, 2003

Distribution of Regional Income and Regional Funds in Europe 1989-1999: an Exploratory Spatial Data Analysis

Sandy Dall'erba[1]

Department of Economics, University of Pau (France)
sandy.dallerba@etud.univ-pau.fr

Abstract: The purpose of this paper is to explore the spatial distribution of regional income and regional development funds (Community structural funds and region's own additional funds) among 145 European regions over 1989-1999. Using a set of tools of spatial statistics, we first detect the presence of global and local spatial autocorrelation in the distribution of regional per capita incomes. In other words rich (poor) regions tend to be clustered close to other rich (poor) regions. Global and local spatial autocorrelations also characterize the regional growth rate and regional funds. Second, the results of LISA statistics reveal the presence of spatial heterogeneity in the form of two spatial clusters of rich and poor regions over the decade as well, highlighting the persistence of a significant core-periphery pattern among European regions. However, the negative correlation between growth and initial income tends to confirm the hypothesis of β-convergence. In its efforts to favor cohesion, the European Commission allocates the majority of structural funds to peripheral regions where per capita GDP levels are low. A positive relationship between regional growth and structural funds is also identified among the significant results. Only Andalucia, Galicia and Sterea Ellada show atypical linkages. These results suggest further research including spatial effects, regional initial conditions and the spatial distribution of regional funds in the spatial econometric estimation of regional convergence in Europe.

[1] This paper has been written while I was a Fulbright Visiting-Researcher at the Regional Economics Applications Laboratory, University of Illinois at Urbana-Champaign (USA). I have benefited from useful comments of the participants of the 49th Annual North American Meetings of the RSAI. I would like to thank most especially Julie Le Gallo and Phil Rees for their valuable suggestions. Financial support from the Region Aquitaine is gratefully acknowledged.

Section 1- Introduction

The phenomenon of persistent income disparities among European regions has been widely studied in the literature, using β-convergence models most of the time based on neo-classical specifications (Esteban, 1994; Neven and Gouyette, 1995). Together with σ-convergence, these concepts have been criticized for several econometric problems they bring about, like the Galton's fallacy problem, and their inadequacy to explain economic polarization, persistent poverty and clustering (Quah, 1993). In contrast, the concepts of convergence club (Durlauf and Johnson, 1995; Chatterji, 1992; Quah, 1996) and core-periphery (Krugman, 1991a, 1991b; Fujita *et al.*, 1999) are compatible with the existence of multiple, locally stable steady state equilibria that are more relevant in the European regional case.

Another often-raised criticism is the majority of these empirical tests of regional income convergence are based on the same hypotheses as the ones underlying international income convergence: regions are considered as isolated entities, as if their geographical location and potential interregional linkages did not matter. Only recently, with the development of the appropriate tools of spatial statistics and spatial econometrics (Anselin, 1988, 2001; Anselin and Berra, 1998), the role of spatial effects has been considered in empirical works. These tools have been applied to regional convergence in the United-States (Rey and Montouri, 1999; Rey, 2001), in Europe (Fingleton, 1999 and 2001; Baumont *et al.*, 2002; Bivand and Brunstad, 2002), in China (Ying, 2000), in Brazil (Magalhães *et al.*, 2000), in Chile (Aroca *et al.*, 2000) and Turkey (Gezici and Hewings, 2002). The underlying idea, based on economic geographic theories and growth theories, is that forces driving to relocation/agglomeration process and hence to even/uneven regional development such as productivity (Hirschman, 1958), transportation infrastructures (Krugman and Venables, 1995, 1996), technology and knowledge spillovers (Martin and Ottaviano, 1999), factor mobility (Krugman, 1991a, b; Puga, 1999), have explicit geographic components. Since geographic spillover effects generate regional development, this last should exhibit a non-random distinctive geographic pattern. Applied to the spatial distribution of income, it means that the rich (poor) regions have a propensity to be clustered close to other rich (poor) regions.

However, the European Commission considers regional imbalances unacceptable on distributional and political grounds. The successive enlargements of the European Community to less developed countries have made regional disparities so obvious that 68%

of structural funds are devoted to the least developed regions (objective 1). Structural funds are the most important instruments of the European regional development policy with Ecu 154.5 billion (at 1994 prices) over 1994-1999. Their impact on regional development is not clear yet: most of structural funds finance public infrastructures which are supposed to enhance cohesion among European regions (Aschauer, 1989). But when such investments finance transportation infrastructures that come to a decrease in transportation costs, it may affect the process of industry location. As a result, they do not systematically benefit the region where they are implemented (Martin P., 2000; Vickerman, 1996).

The purpose of this survey is to apply the newly developed techniques of spatial statistics on the distribution of per capita GDP and regional funds among 145 European regions over 1989-1999. The period under study corresponds to the first two programming periods that implemented and developed the European regional development policy to reduce the lack of cohesion among regions. The paper proceeds as follows: section 2 describes the linkages between regional funds and even/uneven regional development. Section 3 presents the data. In section 4, we perform the exploratory spatial data analysis of the distribution of regional per capita GDP, of structural funds and of additional funds. The article concludes with a summary and some closing remarks.

Section 2- Impact of structural funds on the spatial distribution of income

European regional assistance over 1989-1999 period dealt with six different objectives, the most important of which, with 68% of total structural funds devoted to this objective, was the objective 1. It was dedicated to the economic adaptation of the least developed regions. NUTS II level regions[2] were eligible under this objective when their per capita GDP (in PPP, Purchasing Power Parity) is below 75% of the Community average. This group included about 50 NUTS II level regions, from which the Italian regions Mezzogiorno, the whole regions of Greece, Ireland and Portugal, and about two third of the Spanish regions. With regards to the type of projects financed, one third of structural funds (Ecu 77 billion at 1999 prices) were devoted to transportation infrastructures. Transportation infrastructures have also been strongly supported through one half of the cohesion funds (Ecu 8 billion at 1999

[2] NUTS: Nomenclature of Territorial Units for Statistics. The Commission uses as regional statistical concept the spatial classification established by Eurostat on the basis of national administrative units. Europe can therefore be shared either in 77 NUTS I level regions, or 211 NUTS II, 1031 NUTS III, 1074 NUTS IV or 98433 NUTS V. Regional objectives are however mostly designated at either NUTS II or NUTS III level regions.

prices), the second main instrument of regional policies, allocated since 1994 to Spain, Portugal, Greece and Ireland. They will not be formally included in the rest of the analysis since they are allocated at the national but not regional level, and since no data display their regional distribution. For the European Commission, transportation infrastructures play a key role in the efforts to reduce the lack of cohesion among members.

However, from a theoretical as well as empirical point of view, their impact on regional development is not clear. On the one hand the endogenous growth models *à la* Aschauer (1989) and Barro (1990) predict that if public infrastructures are an input in the production function, then policies financing new public infrastructures increase the marginal product of private capital, fostering thus capital accumulation and growth. On the other hand, the economic geography theoretical works developed by Martin and Rogers (1995) and Martin P. (2000) demonstrate when transportation infrastructures are financed, they affect the process of industry location and lead to involuntary effects: financing intra-regional transport infrastructures in the poorest regions increases the probability of firms locating there, but reduces the country's aggregate growth rate and increases regional income inequalities, whereas interregional transport infrastructures foster the aggregate growth, but lead to greater concentration in the core. Moreover, an increasing part of the new transport infrastructures planed for the development of the trans-European network tend to be built within and between core regions, where transport demand is the highest (Vickerman, 1991, 1996). Only the regions that belong to the main network will gain in accessibility, whereas the regions that do not belong to it or are located at the edge of it will not.

The relationship between gain in accessibility and economic development in peripheral regions is not clear and requires further research, since it depends on the specific requirement in transport cost of each singular sector. It is stated however that gains in accessibility due to interregional transport infrastructures will always be relatively higher in the core region than in the peripheral one (Vickerman *et al.*, 1999; Venables and Gasiorek, 1999). Peripheral regions have generally lower unit costs than core regions which may attract activities to locate there. However, this also depends on the level of transport infrastructure, the lack of which impedes the development of growth potential in periphery, but the improvement of which does not necessarily promote its growth.

Three other points confirm that the allocation of regional funds does not guarantee regional development. First, a firm located in the targeted region does not necessarily undertake the construction of new infrastructures. As a result, a part of the value added of a project in one region may first benefit another location. Second, beyond this apparent desire to reduce interregional income inequalities, the Community aid is not necessarily correlated to the development gap. As pointed out by Fayolle and Lecuyer (2000), only objective 1 was devoted to the poorest regions. Objectives 2 and 3 (respectively for regions affected by industrial crisis and regions with long-term unemployment), even if they handle lower amounts, concern aids to reconverting and to industry restructuring that affect mostly regions which were formerly prosperous. Finally, a particular project is never implemented without additional regional or national financing. This is the principle of additionality that impedes regions to present unviable projects[3]. There is a bias introduced through this principle which comes from the fact that poor regions have problems to accompany the European aid in poor regions, whereas they can be tripled or quadrupled in regions with medium or high income levels, as they are more able to complement structural funds (Martin R., 1998).

Section 3- Data

The regional per capita GDP series in Ecu current prices come from the database NewCronos Regio by Eurostat. This is the official database used by the European Commission for its evaluation of regional convergence. We use the logarithms of the per capita GDP of each region over the 1989-1999 period in constant prices. Our sample is composed of 145 regions at NUTS II level (Nomenclature of Territorial Units for Statistics) over 12 EU countries:

- Belgium: 11 regions
- Denmark: 1 region
- Germany: 30 regions. Berlin and the nine former East German regions are excluded due to historical reasons
- Greece: 13 regions
- Spain: 16 regions, as we exclude the remote islands: Las Palmas, Santa Cruz de Tenerife Canary Islands and Ceuta y Mellila.
- France: 22 regions
- Ireland: 2 regions
- Italy: 20 regions
- Netherlands: 12 regions

[3] Community funds support up to 75% of total public expenditure in NUTS regions, the rest depends on national or regional additionality in order to avoid regions present unviable projects. The ceilings vary according to the objective concerned: objective 1 finances a maximum 75% of the total cost, but 80% in cohesion countries (Spain, Portugal, Greece and Ireland) and 85% in the most remote regions and the outlying Greek islands. The other objectives financed a maximum 50% of the total cost.

- Portugal: 5 regions. The Azores and Madeira are excluded because of their geographical distance
- United Kingdom: 12 regions. In the case of the UK, we use regions at the NUTS I level, because NUTS II regions are not used as governmental units, they are merely statistical inventions of the EU Commission and the UK government.
- Luxembourg: 1 region

We do not include Austria, Finland and Sweden since they joined the EU only in 1995. The choice of studying European regions at the NUTS II level is purely based on regional development policies consideration. The data on structural funds come from the publications of the Commission. The period under study covers the two first programming periods: the data over 1989-1993 are from "*Community structural interventions*", *Statistical report n°3 and 4,*(July and Dec., 1992)[4] and for 1994-1999, from *The 11th annual report on the structural funds*. The data represent the total payments plus the total engagements of the European Commission at the data of publication of the 11th report. Some of the funds were allocated to 6 German NUTS I regions and 2 Belgian NUTS I regions. We therefore disaggregate these funds at the NUTS II level with respect to their objective and their redistribution pattern[5]. With regard to total cost of Community projects, we apply the same methodology and take also into account the fact that the richer NUTS 2 regions within the NUTS 1 region have more facility to accompany Community funds. This allows to respect the bias introduced by additional funds. Since these data are not annually available and we want to consider funds relatively to the local population, data are divided by the number of inhabitant (average over 1989-1999) for each region and expressed in constant prices. As we have seen in the previous section, structural funds are just a part of the financing of public infrastructures in lagging regions. Since national and regional co-financings also support Community investments, we will also consider the total cost of Community projects over the same period.

We are aware that our empirical results could be affected by missing regions and by the use of different levels of spatial aggregation. The choice of the spatial aggregation influences the magnitude of various measures of association. In the literature, this problem is referred to the modifiable areal unit problem (MAUP) well known to geographers (see Openshaw and

[4] The authors would like to thank Jacky Fayolle and Anne Lecuyer for providing this dataset.

[5] The disaggregating methodology is available upon request.

Taylor, 1979), also called problem of ecological fallacy (Anselin and Cho, 2000). Messner and Anselin (2001) add that scale is important as well. If the scale and spatial extent of units of observations for the data do not match up the scale and spatial extent of the studied process, then it may result in a statistical problem wherein spatially correlated and/or heteroskedastic error structures occur. For instance, the area of Castilla-y-Leon (in Spain) is 585 times greater than the one of Brussels (Belgium), but both are official NUTS II regions (Casellas and Galley, 1999). Moreover, per capita growth in open formal NUTS 2 regions may reflect characteristics of neighboring regions. Boldrin and Canova (2001) show the problem linked to measuring a variable on a territorial unit artificially defined in which people are free to move. They give the example of the city of Hamburg which is a NUTS II level region with high per capita income, but half the population of the whole Hamburg metropolitan area lives in the nearby NUTS II level regions of Schleswig-Holstein and Lower Saxony, commuting to Hamburg for work. As a result, the value added in Hamburg is overstated by 20% relative to its effective population, while those of Schleswig-Holstein (value added equals 102% of EU average) and Lower Saxony (104%) are understated. This is similar for Ile de France (160%) and Bassin Parisien (92.7%), Communidad de Madrid (101%) and its two neighboring Castillas (66 and 76%).

Section 4- Exploratory spatial data analysis (ESDA)

ESDA is a set of techniques used to describe and visualize spatial distributions, identify atypical locations or spatial outliers, discover patterns of spatial association, clusters or hot spots, and suggest spatial regimes or other forms of spatial heterogeneity (Anselin, 1988, 1999; Messner and Anselin, 2001; Haining, 1990)

4.1- Choropleth map

We start the analysis with the figure 1[6]. It is a choropleth map displaying the distribution of regional per capita GDP level in 1989 relative to the European average. A clear core-periphery pattern appears in this map, with the core (the darker color) composed of the richest regions, whereas the peripheral regions are also the poorest ones. Four different categories are presented. The first one includes the regions of Ireland, Portugal, Greece, the majority of the Spanish regions and six southern Italian since their per capita GDP was below 75% of the

[6] All figures have been realized using ArcView GIS 3.2 (Esri).

European average in 1989 (objective 1). The other categories show the distribution of regional income below the average but superior to 75% (75%-100%), higher than the average (100%-150%) and strongly greater than the average (>150%). Three regions had an exceptionally greater level of income than the overall distribution (greater than 1.5 interquartile ranges), thus are considered as outliers. These are the regions of Hamburg and Darmstadt in Germany, Ile-de-France in France. These results are partly due to the great commuting from their neighboring regions, as mentioned earlier.

<<insert figure 1 here>>

We do not need to display a map for the final year 1999. The core-periphery pattern is still apparent. Only the situation of the two Irish regions has clearly improved in comparison with the initial year. Actually the Irish per capita GDP is greater than the EU average since 1997.

Figure 2 displays the distribution (in quartile) of the sum of structural funds on the average regional GDP over 1989-1999. As expected, the poor and peripheral regions are the one that benefited the most from Community support. Note that two core regions (Hainaut in Belgium and Flevoland in Netherlands) belong to the most assisted regions as well. They even received more structural assistance than Attiki (Greece) or some Portuguese or Spanish regions. It may be explained by the fact that these two regions received high structural funds, but under objective 2 (for regions in industrial decline), whereas the poor Portuguese and Spanish regions received assistance under objective 1. As explained in section 2, structural assistance is not only based on the objective of reducing income gaps. We do not perform an analysis of detecting outliers since the map makes clear that the poor and peripheral regions received exceptionally high levels of structural funds compared to the sample mean.

<<insert figure 2 here>>

Figure 3 presents the ratio total project cost on structural funds (in quartile). The greater is this ratio, the greater is the regional or national co-financing in the total investment. In the poorest regions (first quartile), the total cost is until 2.2 times higher than the level of structural funds. It means that the region itself has to pay an amount equal to 1.2 times the level of structural funds. As pointed out in section 2, peripheral regions are just able to double the Community support (first quartile), whereas the wealthiest north Spanish regions and numerous core regions succeed in providing from 2.5 to 6.4 times the amount committed by structural funds (last quartile).

<< insert figure 3 here>>

Choropleth maps are a useful tool to describe the general characteristics of the distribution of per capita GDP throughout European regions. However, the range of each category defined in the previous choropleth maps is pretty big, and choropleth maps do not allow to say whether the spatial distribution of this variable is significantly persistent over the period. Moreover, they are also limited in the ability to identify any significant spatial effects we defined in section 2.1.

4.2- Determination of the spatial weight matrix

Before going further in the spatial analysis of regional income distribution, we need to say some words on the construction of the spatial weight matrix, since all the following analysis relies on the definition of space throughout the weight matrix. In the European context, the existence of islands such as the United-Kingdom, Ireland or Corse impedes to consider simple contiguity matrices, otherwise the weight matrix includes rows and columns with only zeros. Since unconnected observations are eliminated from the results of the global statistics, this would change the sample size and the interpretation of the statistical inference. Following the recommendations of Anselin (1996) and Anselin and Bera (1998), we choose to base them on pure geographical distance, as exogeneity of geographical distance is unambiguous[7]. More precisely, we use the great circle distance between regional centroids. The great distance circle allows to consider that the relevant direction of the dependence can take place in every direction. As in Le Gallo and Ertur (2002), we base our weight matrices on the k = 10, 15, 20 nearest neighbors.

[7] In the case of European regions, it could be attractive to base these weights on the channels of communication between regions, such as roads and railways (see Bodson and Peeters, 1975). However, as pointed out by Anselin and Bera (1998), "indicators for the socioeconomic weights should be chosen with great care to ensure their exogeneity, unless their endogeneity is considered explicitly in the model specification".

The form of the spatial weight matrix is the following:

$$\begin{cases} w_{ij}(k) = 0 \;\; if \;\; i = j \\ w_{ij}(k) = 1 \;\; if \;\; d_{ij} \le D_i(k) \; and \; \overset{*}{w}_{ij}(k) = w_{ij}(k) \Big/ \sum_j w_{ij}(k) \qquad\qquad for \; k = 10,15,20 \\ w_{ij}(k) = 0 \;\; if \;\; d_{ij} > D_i(k) \end{cases} \tag{1}$$

where d_{ij} is the great circle distance between centroids of region *i* and *j*. $D_i(k)$ is the critical cut-off distance defined for each region *i*, above which interactions are assumed negligible. In other words, $D_i(k)$ is the k^{th} order smallest distance between regions *i* and *j* such that each region *i* has exactly *k* neighbors. Each matrix is row standardized so that it is relative and not absolute distance which matters, yielding the matrix $\overset{*}{w}$. It is worth mentioning that in the European context, the minimum number of nearest neighbors that guarantees international connections between regions is *k*=7, otherwise the Greek regions would not be linked to Italy at all. With is *k*=10, Ireland is connected to the UK, which in turn is connected to the whole continent; and the islands of Sicilia, Sardegna, Corsica are connected to the continental French regions. When the number of *k*-nearest neighbors increases, the share of international interconnections increases as well.

4.3- Moran' *I*

We start further analysis of the spatial distribution of regional income and regional funds with the use of Moran's *I* statistics. It allows to capture the global spatial autocorrelation of the variables of interest. In other words, it gives for each variable the degree of linear association between its value at one location and the spatially weighted average of neighboring values. We use a permutation approach with 10000 permutations (Anselin, 1995)[8]. Formally, for each variable of interest, the Moran's *I* is given by:

$$I_t = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \overset{*}{w}_{ij}(k) x_{it} x_{jt}}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{it} x_{jt}} \tag{2}$$

[8] We use the SpaceStat 1.91 software to realize all the computations (Anselin, 1999a).

where $\overset{*}{w}_{ij}$ is the (row-standardized) degree of connection between the spatial units i and j and x_{it} is the variable of interest in region i at year t (measured as a deviation from the mean value for that year). Values of I larger (respectively smaller) than the expected value $E(I) = -1/(n-1)$ indicate positive (resp. negative) spatial autocorrelation. In our case, $E(I) = -0.00694$.

<<insert table 1 here>>

The results in table 1[9] report the value of Moran's I and of the standard deviation for all the variables. Moran's I statistics are positive and significant (p-value = 0.0001) for all variables. For the regional per capita income, it means that the rich (poor) regions have a propensity to be clustered close to other rich (poor) regions. We note that the values of the statistics seem stable over the period, but they are higher over 1993-1995, period which corresponds to greater integration after the 1992 Maastricht Treaty. The distribution of the regional per capita GDP in Europe is therefore certainly not random. With the same idea, objective (non-objective) regions, i.e. regions with high (low) structural funds, have a propensity to be close to other objective (non-objective) regions. The extent of Moran's I statistics shows a higher clustering of regions with similar structural funds than with similar Community projects, for every weight matrices. Differences among values of Community projects seem smaller than among structural funds according to the standard deviation as well. One explanation is that the last ones have structural purposes, therefore their amount and location are targeted. On the contrary, the first ones depend more on national/regional contributions that easily complete Community support in the rich regions. Results also display a clustering of regions with high (slow) growth rates. The Moran's I is useful to detect global spatial autocorrelation, but it is not able to identify local patterns of spatial association, such as local spatial clusters or local spatial outliers of high (low) values that are statistically significant. Identifying the groups of regions belonging to clustering of high (low) values of per capita income is based on the results of a Moran scatterplot.

[9] The results are similar to those found with the Geary's c statistics. Complete results are available upon request.

4.4- Moran's scatterplot

The idea of the Moran scatterplot, suggested by Anselin (1996), is to display the per capita income for each region (on the horizontal axis) against the standardized spatial weighted average (average of the neighbors' per capita income, also called spatial lag) on the vertical axis. As pointed out by Anselin (1999), expressing the variables in standardized form (i.e. with mean zero and standard deviation equal to one) allows to assess both global spatial association, since the slope of the line is the Moran's *I* coefficient, and local spatial association (the quadrant in the scatterplot). The Moran scatterplot is therefore divided into four different quadrants corresponding to the four types of local spatial association between a region and its neighbors:

- quadrant I (on the top right corner) displays the regions with a high per capita income (above the average) surrounded by regions with high per capita income (above the average). This quadrant is usually noted HH.
- quadrant II (on the top left corner) shows the regions with low value surrounded by regions with high values. This quadrant is usually noted LH.
- quadrant III (on the bottom left) displays the regions with low value surrounded by regions with low values, and is noted LL.
- quadrant IV (on the bottom right) shows the regions with high value surrounded by regions with low values. It is noted HL.

Regions located in quadrants I and III refer to positive spatial autocorrelation indicating the spatial clustering of similar values, whereas quadrants II and IV represent negative spatial autocorrelation indicating spatial clustering of dissimilar values.

<<insert figure 4 >>

Figure 4 displays the Moran scatterplots of regional per capita GDP for 1989, with *k*= 10 nearest neighbors. Positive spatial autocorrelation which was detected by the value of Moran's I is reflected by the fact that most of the regions are located in quadrant I and III. Compared to the situation at the final period[10], most of the regions that belong to quadrant I (III) in 1989 also belong to quadrant I (III) in 1999. However, there are some exceptions such as the two Irish regions that were LL at the initial year and are HH (Dublin) or LH

[10] Complete results available upon request.

(Border) at the final year. This represents the fast development of Ireland over the decade. Other signs of development concern three Belgian regions (Luxembourg, Brabant-Wallon, Antwerpen) and Yorkshire and the Humber (UK) which go from LH-type to HH-type.

On the contrary, signs of decline concern one Italian region (Abruzzo) that moves from HH-type to LL-type, Picardie (France), Trier and Lüneburg (Germany) and Drenthe (Netherlands) that move from HH- to LH-type. Moran scatterplot also allows to identify regions with higher spatial instability for both years (HL-type and LH–type): Aquitaine in France (HL), whereas Corse, Languedoc-Roussillon, Limousin (France), Wales, North-East (UK), Namur, Hainaut (Belgium), Flevoland and Friesland (Netherlands) are LH-type. This implies that the spatial distribution of regional income is more complicated that the simple core-periphery framework previously noticed in the choropleth maps. Le Gallo and Ertur (2002) reach the same results for 138 European regions over 1980-1995.

The same method is applied to structural funds and Community projects total costs as well. The results for structural funds are presented in figure 5. Here again, most of the regions are located in quadrants I and III. Regions in I (III) are basically the regions that were in III (I) in figure 4, traducing the effort of cohesion of the Commission. However, the regions Madrid (Spain), Norte and Lisboa e Vale do Tejo (Portugal) were LL-type for their income in 1989 and 1999, but are LH for both structural funds and Community funds because they are among the richest of the Iberian Peninsula. The region of Dublin in Ireland is by far the first beneficiary of the allocation of structural funds and Community projects (it is not displayed in the figure). Then come with a lesser extent the Greek region Voreio Aigaio and the Spanish Extremadura.

<<insert figure 5>>

The last three columns of table 2 give the scatterplot quadrants for total structural funds over the average income 89-99, Community projects total costs over the average income 89-99 and additional funds. The results for additional funds confirm that the rich regions are more able to accompany structural funds whereas the poor ones cannot. In Spain for instance the regions of Navarra, La Rioja and Cataluña have much accompanied Community funds, which may be a reason for increasing disparities among Spanish regions (Fayolle and Lecuyer, 2000).

<<insert table 2>>

4.5- LISA (Local Indicator of Spatial Association)

The previous scatterplots display a slight modification of the overall structure of spatial autocorrelation between the initial and the final year. For instance, some regions that were HH in the initial year belong to another quadrant in the final year. We therefore calculate LISA statistics for each observation to obtain more insight into the significant spatial clustering of similar values around that observation. Since we use a row-standardized matrix, the average of local Moran statistics is equal to the global Moran's *I* statistics. LISA statistics is used for the detection of significant local spatial clusters (also called "hot spots") as well as for the diagnostics of local instability, significant outliers and spatial regimes. Anselin (1995) formalize the local Moran's statistics for each region *i* and year *t* in this way:

$$I_{it} = \left(\frac{x_{it}}{m_0}\right)\sum_j \overset{*}{w}_{ij}\, x_{jt} \quad \text{with } m_0 = \sum_i x_{it}^2 / n \qquad (3)$$

with x_{it} (x_{jt}) is the observation in region *i* (*j*) at year *t* (measured as a deviation from the mean value for that year). The results from the application of LISA with *k*= 10[11] nearest neighbors are summarized in columns three to seven of table 2. The significance level is based on a conditional permutation approach with 10000 random permutations of the neighboring regions for each observations (Anselin, 1995). The pseudo-significance level is 5%. However, due to a problem of multiple statistical comparison, since the neighborhood sets of two regions may contain common regions (Ord and Getis 1995; Anselin, 1995), we follow the methodology of Le Gallo and Ertur (2002)[12] and present also in column 8 the number of years for which the results are significant at a 5% Bonferroni pseudo-significance level (= 5% over 10 since we use the 10 nearest-neighbors).

In column three to seven of table 2, each cell displays the number of years the significant local Moran statistics is located in a particular Moran scatterplot quadrant. The regions revealing significant and great spatial association of per capita GDP (HH or LL) are basically those previously detected as core (HH cluster) and peripheral (LL cluster) regions. Over the period, 97% of the local statistics that are significant are either HH- or LL-type, reflecting the

[11] The robustness of these results is further tested in table 3 and 4 with *k*=15 and 20 neighbors respectively.

[12] See their paper for further details.

global trend of positive spatial association. However, not all core/peripheral regions cluster significantly over the period. Local Moran statistics are not significant over the period for various regions in different countries (column 3 in table 2). Denmark, Greece and Portugal are the only country without any non-significant statistics throughout the period (in Germany, Düsseldorf is the only region displaying non-significant statistics). Regions displaying positive local spatial association throughout the 11 years are composed like this:

- two different HH-type clusters can be identified because they are distant from each other:

  - all the German regions (but Düsseldorf), Denmark, four northern French regions (Nord-Pas-de-Calais, Lorraine, Alsace, Franche-Comté), four southern Belgian regions (Antwerpen, Luxembourg, Limburg and Vlaams-Brabant), and four southern Dutch regions (Zuid-Holland, Zeeland, Noord-Brabant and Limburg).

  - six Italian regions (Piemonte, Valle d'Aosta, Lombardia, Trentino-Alto Adige, Veneto and Friuli-Venezia Giulia).

- two different LL-type clusters can also be identified for the same reason :

  - all the Portuguese regions and eleven Spanish regions (Galicia, Asturias, Cantabria, Madrid, Castilla-y-Léon, Castilla-la-Mancha, Extremadura, Communidad Valenciana, Baléares, Andalucia and Murcia)

  - all the Greek regions and four southern Italian regions (Puglia, Basilicata, Calabria, Sicilia).

All of them show positive spatial autocorrelation with a significance level $p < 0.05$ for more than 5 years. The persistence of different clusters of high and low income is a sign of spatial heterogeneity among European regions traducing that income disparities last. These results are robust when we use k=15 or 20 neighbors, as shows the robustness analysis for LISA (suggested by Le Gallo and Ertur, 2002) displayed in tables for 3 and 4. Significant negative spatial autocorrelation occurs 10 years for the French region Corse (LH-type), but no more than three years elsewhere. Two facts can be noted from these tables. First, when we increase the number of neighbors, a region with a significant LISA remains in the same quadrant. Second, respectively 21.9% and 31.6% of the regions with non significant LISA for k=10 become HH-type when k= 15 and k=20. These regions are mostly French, North-Italian Belgian, Dutch and British, whereas the regions becoming LL-type (4.6% when k= 15 and 4.5% when k=20) are mostly Spanish and Southern Italian[13].

[13] Complete results are available upon request.

<<insert tables 3 and 4 here>>

If we focus now on the column giving the significant Moran scatterplot quadrants for growth over 1989-1999, the significant HH-type correlation concerns all the Portuguese and Irish regions, the Greek regions (except Ipeiros and Sterea Ellada), only Extremadura in Spain and five British regions. Only three regions have a significant Moran statistics in Spain, which can be explained by the fact that Spain is the country where regional inequities have increased at most over this period. The LL-growth-type regions are Italian (except Calabria and Puglia), ten French regions, mostly in the South, six German regions (Tübingen, Freiburg, Karlsruhe, Rheinhessen-Pflaz, Darmstadt and Arnsberg) and Baleares in Spain. Six regions show significant negative spatial autocorrelation: Andalucia and Galicia in Spain; Sterea Ellada in Greece are LH-type, which indicates that they failed to develop in spite of the dynamism of their neighboring regions. On the other hand, three HL-type regions (Corse in France, Gießen and Kassel in Germany) show a significantly higher dynamism than their neighbors.

<<insert table 5 here>>

Table 5 is a correlation table between the initial per capita income and the growth rate over the period. Only 27% of the results are significant for both initial per capita income and growth rate. However, it is interesting to note that 82% of these results show an inverse relationship between initial conditions and growth rates. The five Portuguese regions, nine out of thirteen Greek regions (the others do not have significant results) and Extremadura in Spain were LL-type for their initial income, but were HH-type for their growth rate over 1989-1999. Among the significant results, the hypothesis of β-convergence seems consistent since the poorest regions also have the higher growth rates. The Irish and Spanish regions do not appear in these results since the results for initial income are not significant in Ireland, and most of the results for growth are not significant in Spain. On the contrary, the regions displaying significant HH-type for the initial income and significant LL-type for growth are six German regions (Karlsruhe, Freiburg, Tübingen, Darmstadt, Arnsberg, Rheinhessen-Pflaz), three French regions (Alsace, Franche-Comté, Provence-Alpes-Cote-d'Azur), nine northern Italian regions (Piemonte, Valle d'Aosta, Liguria, Lombardia, Trentino-Alto Adige, Veneto, Friuli-Venezia Giula, Emilio-Romagna). Three regions, Gießen and Kassel in Germany and Corse in France (but only in 1989) were HH-type for the initial income and HL-type for growth. The two German regions have therefore succeeded in growing faster than their neighbors, in spite of a high initial level of income, like their neighbors. Three regions (Galicia and Andalucia in Spain and Sterea Ellada in Greece) are significantly LL-type for their initial income but LH-type for their growth. It means that even if these regions started with the same initial conditions as their neighbors, their neighbors performed better in terms of development.

Instead of describing the significant results for LISA statistics on regional funds[14], the last step of our analysis will focus directly on the correlation between structural funds (then additional funds) and regional growth presented in table 6.

<<insert table 6 here>>

Only 28% of the results are significant for both structural funds and growth. However, 78% of these results show a positive relationship between growth and structural funds. Fourteen regions characterized by significant HH-type structural funds show significant HH-type growth. These regions are nine Greek regions (see table 2), Dublin in Ireland, three Portuguese regions (Centro, Alentejo and Algarve) and Northern Ireland (UK). On the contrary, the regions with LL-type growth and LL-type structural funds are six German regions (Karlsruhe, Freiburg, Tübingen, Damrstadt, Arnsberg, Rheinhessen-Pflaz), five French regions (Alsace, Franche-Comté, Poitou-Chatentes, Limousin, Auvergne), six Italian regions (Piemonte, Valle d'Aosta, Lombardia, Trentino-Alo Adige, Veneto, Fruili Veneza Giulia) and Luxembourg (country).

The atypical patterns of growth-structural funds relations display regions with a different development behavior than their neighbors, in spite of the fact that they all are "similarly"[15] assisted. For instance, Gießen and Kassel (Germany) are LL-type for structural funds, but HL-type for growth. They performed better than their neighbors, in spite of a similar low level of structural funds. Norte and Liboa e Vale do Tejo in Portugal and Scotland (UK) are also insightful since they are HH-type growth but LH-type structural funds. On the contrary,

---

[14] These results are presented in the last three columns of table 2.

[15] We put this word in quotation marks because the per capita levels of regional assistance may be very different, even if they belong to the same quadrant in the Moran scatterplot.

Galicia, Andalucia (Spain) and Sterea Ellada (Greece) do not grow as well as their neighbors, even if they received "similar" structural assistance (LH growth, HH funds).

Clearly structural funds are not the main variable driving to even/uneven regional development. A closer look at the economic structure, the accessibility, the institutional aspects of each region as well as the type of projects that structural funds finance in these regions and their neighboring regions could help to understand why these regions display greater/smaller development than their neighbors even if they receive similar amount of structural funds.

A last probable explanation is the bias toward uneven regional investment rate due to additional funds. Again, the correlation displays that regions with low additional funds (the poor ones since they cannot afford additional investment) have a HH-type growth and inversely[16]. An interesting case is the one of these three regions that display significant LH-type for growth and LL-type for additional funds: Sterea Ellada in Greece, Andalucia and Galicia in Spain. Remember that these regions are HH-type for structural funds. Therefore, if they do not perform as well as their neighbors in terms of development, the reason does not come from higher additional funds in neighboring regions. Once again, a closer look at the specific economic structure of these regions as well as the use of regional funds could help to clarify the presence of "atypical" linkages between growth and structural funds detected in table 6.

Section V- Conclusion

The aim of this paper has been to explore the spatial distribution of per capita GDP and of regional funds of 145 European regions over 1989-1999, using an exploratory spatial data analysis. This period corresponds to the two first programming periods wherein regional assistance to the poorest regions was implemented and developed. Among the spatial statistic tools, we first use Moran's *I* to detect the presence of positive global spatial autocorrelation in the distribution of per capita GDP. In other words, the rich (poor) regions have a propensity to be clustered close to other rich (poor) regions. Global spatial autocorrelation also characterizes the regional growth rate, structural funds and Community projects total costs. Further analysis using Moran's scatterplot reveals also the presence of positive local spatial autocorrelation for each of the previous variables.

[16] Complete results upon request.

When LISA is performed, the results confirm the significant presence and persistence over time of local spatial autocorrelation in the form of two distinct spatial clusters of high and low values of per capita income. This form of spatial heterogeneity reflects a core-periphery pattern since per capita GDP inequalities are persistent among European regions. LISA is also performed on the spatial distribution of the regional growth rate. A negative relationship between the spatial pattern of regional growth and initial income level is detected among the significant results, which seems consistent with the hypothesis of β-convergence. A positive relationship between regional growth and structural funds is also identified among the significant results. It reflects the distributional efforts of the European Commission which devotes the most important part of its funds to help the least developed regions and provides little assistance to the rich regions. However, the results also indicate that structural funds are clearly not the only variable to control for the various growth rates among European regions. This is confirmed by the presence of "atypical" linkages between both variables (for Andalucia, Galicia and Sterea Ellada). These results show that studies on European regional development should take into account the level of structural funds devoted to the objective region itself, but also to its neighboring regions. This paper calls for further research in a spatial econometric perspective where spatial effects, initial conditions and the spatial distribution of both structural funds and Community projects total costs would be included in the estimation of the convergence process among European regions.

References

Anselin L. (1988), *Spatial Econometrics: Methods and Models*. Dordrecht: Kluwer Academic Publishers.

Anselin, L. (1995), Local Indicator of Spatial Association-LISA, *Geographical Analysis*, 27, 93-115.

Anselin L. (1996), "The Moran Scatterplot as an ESDA Tool to Assess Local Instability in Spatial Association", in Fisher M., Scholten H.J., Unwin D. (Eds), *Spatial Analytical Perspectives on GIS in Environmental and Socio-Economic Sciences,* 111-125, London: Taylor and Francis.

Anselin L. (1999), "Interactive Techniques and Exploratory Spatial Data analysis", in *Geographic Information System: Principles, Techniques, Management and Applications*, Longley P.A., Goodchild M.F., Maguire D.J. and Rhind D.W. (Eds.), New York: John Wiley.

Anselin L. (2001), S*patial Data Analysis, Laboratory Exercises*. Prepared for the Worksop in Spatial Analysis, Wharton Schoold, University of Pennsylvania, August 29-31, 2001.

Anselin L. and Bera A. (1998), "Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics", in Ullah A. and Giles DEA (Eds.), *Handbook of Applied Economic Statistics*. Berlin, Springer-Verlag.

Anselin L. and Cho W.K.T. (2000), "Spatial Effects and Ecological Inference", *Political Analysis*, 10, 276-297.

Aroca P., Bosch M. and Hewings G.J.D. (2000), "Regional Growth and Convergence in Chile 1960-1998: the Role of Public and Foreign Direct Investment", Working Paper of IDEAR, Universidad Catolica del Norte.

Aschauer D. (1989), "Is public infrastructure productive?", *Journal of Monetary Economics*, 23, 177-200.

Barro R. J. (1990), "Government Spending in a Simple Model of Endogenous Growth", *Journal of Political Economy*, 98, 103-125.

Baumont C., Ertur C. and Le Gallo J. (2002), "The European Regional Convergence Process, 1980-1995: Do Spatial Regimes and Spatial Dependence Matter?", Discussion Paper 02-T-10, Regional Economics Applications Laboratory, University of Illinois, Urbana.

Bivand R.S. and Brunstad R.J. (2002), "Regional Growth in Western Europe: an Empirical Exploration of Interactions with Agriculture and Agricultural Policy", Discussion Paper 01/02, Norwegian School of Economics and Business Administration.

Boldrin M. and Canova F. (2001), "Europe's regions, Income Disparities and Regional Policies", *Economic Policy,* 32*,* 207-253.

Casellas A. and Galley C. (1999), "Regional Definitions in the European Union: A question of Disparities?", *Regional Studies*, 33, 551-558.

Chatterji M. (1992), "Convergence Clubs and Endogenous Growth", *Oxford Review of Economic Policy*, 8, 57-69.

Durlauf S.N. and Johnson P.A. (1995), "Multiple Regimes and Cross-Country Growth Behaviour", *Journal of Applied Econometrics,* 10, 365-384.

European Commission (1992), *Community Structural Interventions*", *Statistical report n°3*, July.

European Commission (1992), *Community Structural Interventions*", *Statistical report n°4*, December.

European Commission (1999), *11th Annual Report on the Structural Funds,* Commission Report.

Eurostat (2002), NewCronos Regio database.

Fayolle J. and Lecuyer A. (2000), "Croissance régionale, appartenance nationale et fonds structurels européens, un bilan d'étape", *Revue de l'OFCE*, 73, 165-196.

Fingleton B. (1999), "Estimates of Time to Economic Convergence: an Analysis of Regions of the European Union", *International Regional Science Review*, 22, 5-34.

Fingleton B. (2001), "Equilibrium and Economic Growth: Spatial Econometric Models and simulations", *Journal of Regional Science*, 41, 117-147.

Fujita M., Krugman P. and Venables A.J. (1999), *The Spatial Economy*, Cambridge, MIT Press.

Gezici F. and Hewings G.J.D. (2002), "Regional Convergence and the Economic Performances of Peripheral Areas in Turkey", Discussion Paper 01-T-13, Regional Economics Applications Laboratory, University of Illinois, Urbana.

Haining R. (1990), *Spatial Data Analysis in the Social and Environmental Sciences.* Cambridge: Cambridge University Press.

Hirschman A.O. (1958), *The Strategy of Development*, Yale University Press, New Haven (Conn).

Krugman P. (1991a), *Geography and Trade*, Cambridge MA, the MIT Press.

Krugman P. (1991b), "Increasing Returns and Economic Geography", *Journal of Political Economy*, 99, 483-499.

Krugman P., Venables A. (1995), “Globalization and the Inequality of nations”, *Quarterly Journal of Economics*, 110, 715-756.

Krugman P., Venables A. (1996), “Integration, Specialization, and Adjustment”, *European Economic Review*, 40, 959-967.

Le Gallo J. and Ertur C. (2002), “Exploratory Spatial Data Analysis of the distribution of regional per capita GDP in Europe, 1980-1995”, forthcoming, *Papers in Regional Science*.

Magalhães A., Hewings G.J.D., Azzoni C.R. (2000), “Spatial Dependence and Regional Convergence in Brazil”, Discussion Paper 00-T-11, Regional Economics Applications Laboratory, University of Illinois, Urbana.

Martin P. (2000), “The Role of Public Policy in the Process of Regional Convergence”, *EIB Papers*, 5 (2), 69-79.

Martin P. and Ottaviano G.I.P.(1999), “Growing Locations: Industry Location in a Model of Endogenous Growth”, *European Economic Review*, 43, 281-302.

Martin P. and Rogers C.A. (1995), “Industrial Location and Public Infrastructure”, *Journal of International Economics*, 39, 335-351.

Martin R. (1998), “Regional Incentive Spending for European Regions”, *Regional Studies*, 32, 527-536.

Messner S.F. and Anselin L. (2001), “Spatial Analyses of Homicide with Areal Data”, Unpublished document.

Openshaw S. and Taylor P. (1979), “A Million or so Correlation Coefficient: Three Experiments on the Modifiable Areal Unit Problem”, in Wrigley N. (Eds.), *Statistical Applications in the Spatial Science*, Pion: London.

Puga D. (1999), “The Rise and Fall of Regional Inequalities”, *European Economic Review*, 43, 303-334.

Quah D. (1993), “Galton’s Fallacy and Tests of the Convergence Hypothesis”, *Scandinavian Journal of Economics,* 95, 427-443.

Quah D. (1996), “Regional Convergence Clusters across Europe”, *European Economic Review*, 40, 1951-1958.

Rey S.J. and Montouri B.D. (1999), “US Regional Income Convergence: A Spatial Econometric Perspective”, *Regional Studies*, 33, 143-156.

Rey S. (2001), “Spatial Empirics for Economic Growth and Convergence”, *Geographical Analysis*, 33, 194-214.

Venables A. and Gasiorek M. (1999), “Evaluating Regional Infrastructure: a Computable Equilibrium Approach”, in *Study of the Socio-economic Impact of the Projects Financed by the Cohesion Fund – A Modelling Approach*, vol. 2. Luxembourg: Office for Official Publications of the European Communities.

Vickerman R.W. (1991), *Infrastructure and Regional Development*, Pion, London.

Vickerman R.W. (1996), “Location, Accessibility and Regional Development: the Appraisal of Trans-European Networks”, *Transport Policy*, 2, 225-234.

Vickerman R., Spiekermann K. and Wegner M. (1999), “Accessibility and Economic Development in Europe”, *Regional Studies,* 33, 1-15.

Ying L.G. (2000), “Measuring the Spillover Effects: Some Chinese Evidence”, *Papers in Regional Science,* 79, 75-89.

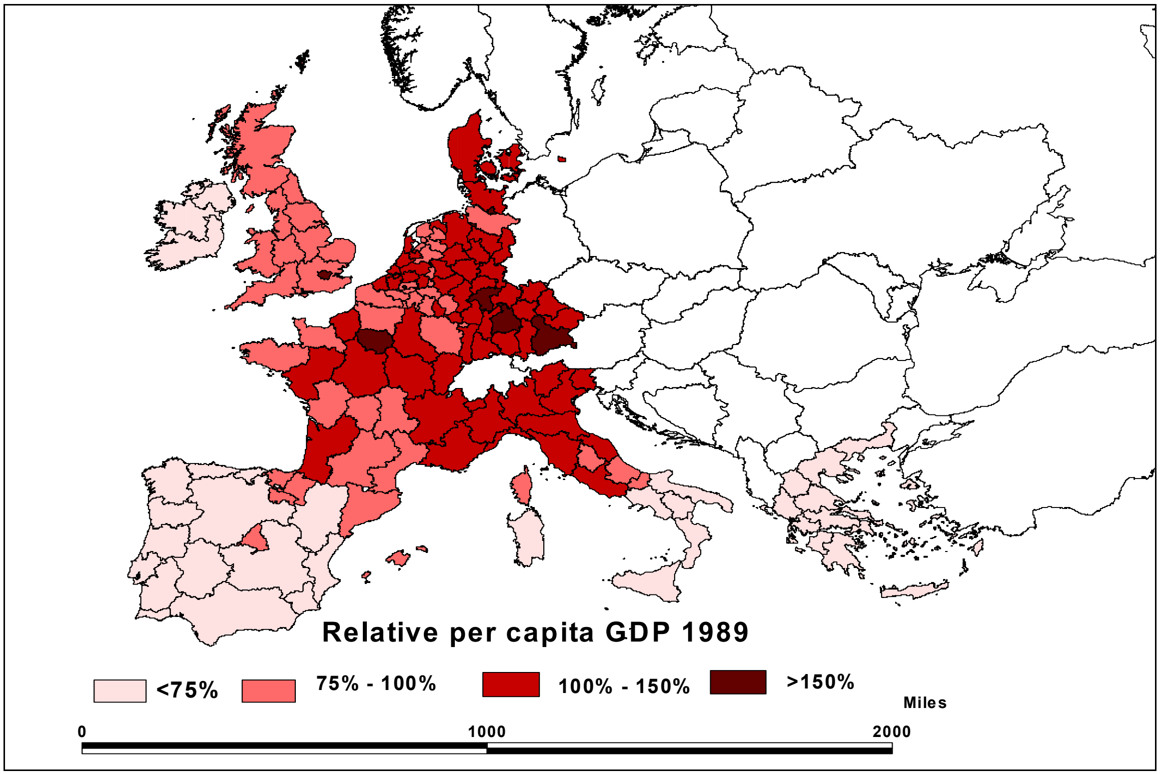

Figure 1: Spatial distribution of regional per capita GDP relative to the European average in 1989

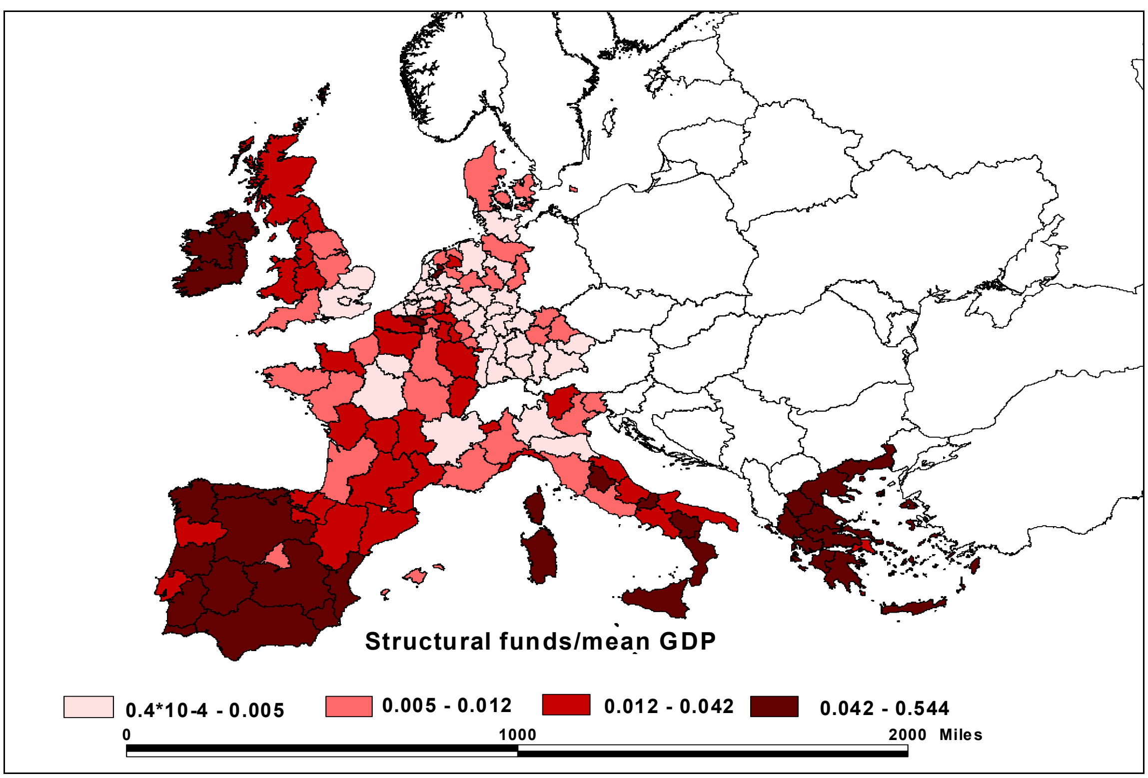

Figure 2: Structural funds divided by the mean regional GDP 1989-1999

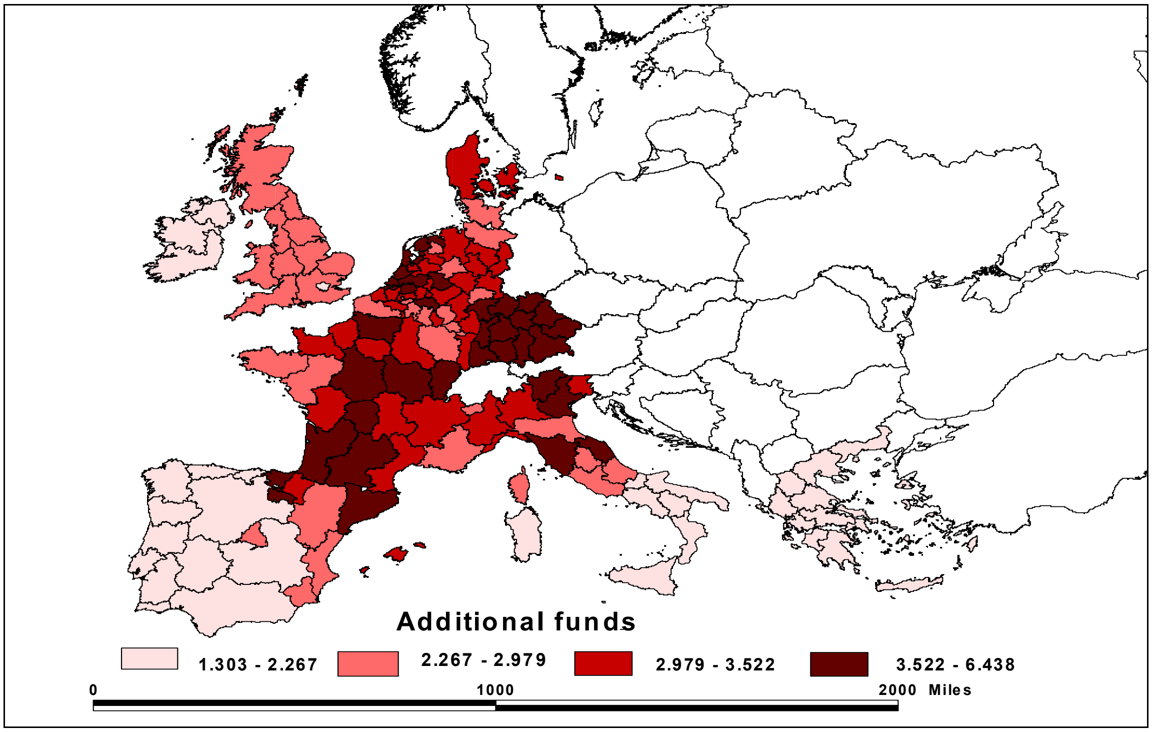

Figure 3: Additional funds: total costs/structural funds over 1989-1999

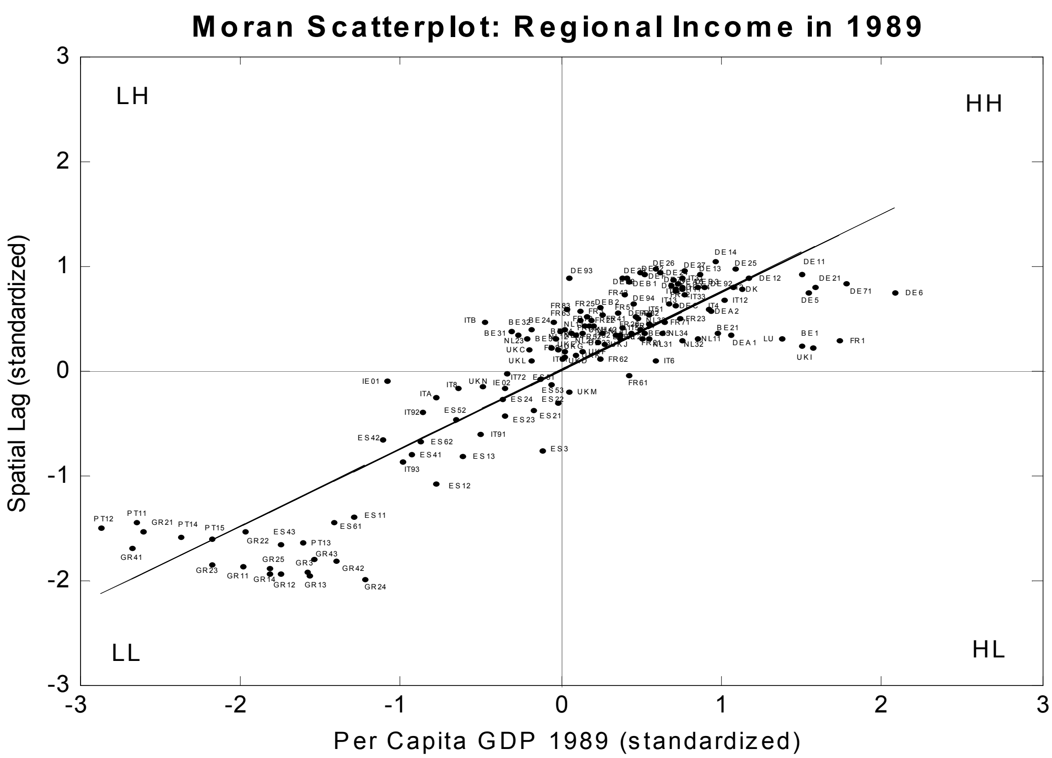

Figure 4: Moran scatterplot of regional per capita GDP in 1989
Note: See table 2 for the region's name corresponding to each code

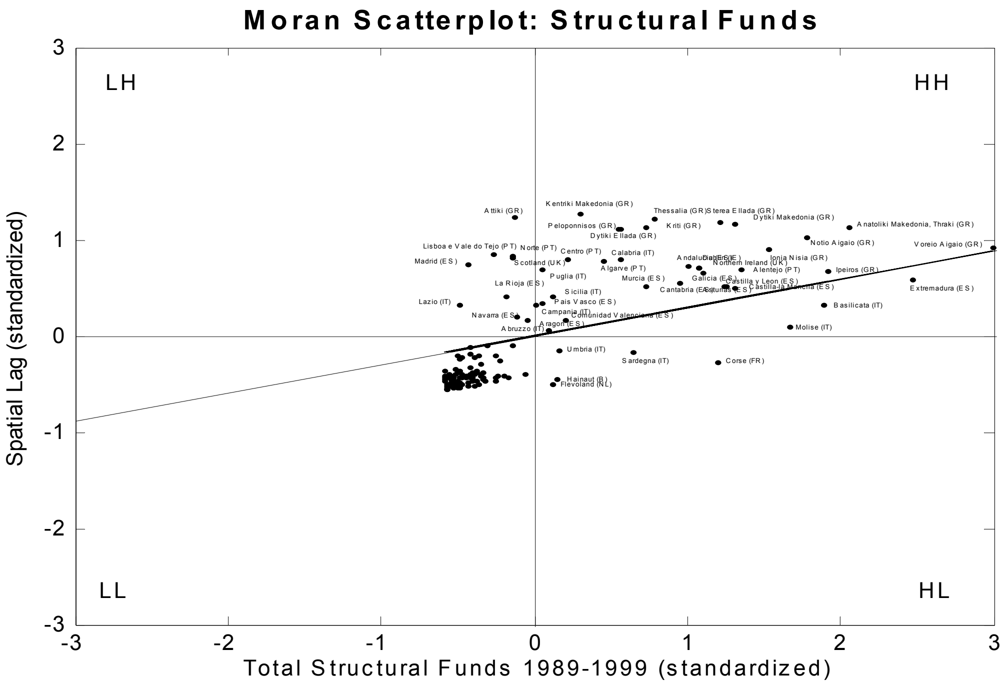

Figure 5: Moran scatterplot of total structural funds relative to region's average GDP

Note 1: Out of the figure is the Irish region Border (HL-type) of which coordinates are (8.252, -0.016)

Note 2: The codes of the regions located in the LL-quadrant are not displayed for facilitating the reading (complete results are available in table 2)

Table 1: Moran's *I* statistics and standard deviation

	10 neighbors		15 neighbors		20 neighbors	
GDP 1989	0.7453	(0.0337)	0.6787	(0.0265)	0.5921	(0.0223)
GDP 1990	0.7502	(0.0337)	0.6828	(0.0265)	0.5920	(0.0223)
GDP 1991	0.7378	(0.0337)	0.6706	(0.0265)	0.5795	(0.0223)
GDP 1992	0.7562	(0.0336)	0.6932	(0.0265)	0.6043	(0.0223)
GDP 1993	0.7776	(0.0336)	0.7308	(0.0265)	0.6600	(0.0223)
GDP 1994	0.7855	(0.0336)	0.7429	(0.0265)	0.6762	(0.0224)
GDP 1995	0.7864	(0.0336)	0.7502	(0.0266)	0.6904	(0.0224)
GDP 1996	0.7577	(0.0336)	0.7180	(0.0266)	0.6532	(0.0224)
GDP 1997	0.7209	(0.0337)	0.6868	(0.0265)	0.6251	(0.0224)
GDP 1998	0.7166	(0.0337)	0.6815	(0.0265)	0.6188	(0.0224)
GDP 1999	0.6984	(0.0336)	0.6654	(0.0265)	0.6054	(0.0224)
FS/M	0.2932	(0.0294)	0.2785	(0.0236)	0.2529	(0.0198)
CT/M	0.1995	(0.0271)	0.1836	(0.0217)	0.1722	(0.0182)
GROWTH	0.4411	(0.0335)	0.3454	(0.0267)	0.2387	(0.0225)

Note: Standard deviations are into brackets. All statistics are significant at $p = 0.0001$. Computations are based on 10000 random permutations. FS/M is total structural funds 89-99 over region's GDP average in 1989-1999; CT/M is Community projects total costs 89-99 over region's GDP average in 1989-1999.

Table 2: Local spatial autocorrelation

Code	Region	Not sign	HH	LL	HL	LH	Bonf. 5%	growth 89-99	Regions	fs/m	ct/m	ct/fs
	Belgium								**Belgium**			
BE1	Brussels	11	0	0	0	0	0	ns	Brussels	LL	LL	LH*
BE21	Antwerpen	4	7	0	0	0	0	ns	Antwerpen	LL	LL	HH*
BE22	Limburg	5	6	0	0	0	0	ns	Limburg	LL	LL	HH*
BE23	Oost-Vlaanderen	8	3	0	0	0	0	ns	Oost-Vlaanderen	LL	LL	HH*
BE24	Vlaams Brabant	5	6	0	0	0	0	ns	Vlaams Brabant	LL	LL	HH*
BE25	West-Vlaanderen	8	3	0	0	0	0	ns	West-Vlaanderen	LL	LL	HH*
BE31	Brabant Wallon	5	5	0	0	1	0	ns	Brabant Wallon	LL	LL	LH*
BE32	Hainaut	8	0	0	0	3	0	ns	Hainaut	HL	HL	HH*
BE33	Liège	7	4	0	0	0	0	ns	Liège	LL	LL	HH*
BE34	Luxembourg	4	7	0	0	0	0	ns	Luxembourg	LL	LL	LH*
BE35	Namur	8	1	0	0	2	0	ns	Namur	LL	LL*	LH*
	Germany								**Germany**			
DE11	Stuttgart	0	11	0	0	0	11	ns	Stuttgart	LL	LL	HH
DE12	Karlsruhe	0	11	0	0	0	11	LL	Karlsruhe	LL	LL	HH
DE13	Freiburg	0	11	0	0	0	11	LL	Freiburg	LL	LL	HH
DE14	Tübingen	0	11	0	0	0	11	LL	Tübingen	LL	LL	HH
DE21	Oberbayern	0	11	0	0	0	11	ns	Oberbayern	LL	LL	HH
DE22	Niederbayern	0	11	0	0	0	11	ns	Niederbayern	LL	LL	HH
DE23	Oberpfalz	0	11	0	0	0	11	ns	Oberpfalz	LL	LL	HH
DE24	Oberfranken	0	11	0	0	0	11	ns	Oberfranken	LL	LL	HH
DE25	Mittelfranken	0	11	0	0	0	11	ns	Mittelfranken	LL	LL	HH
DE26	Unterfranken	0	11	0	0	0	11	ns	Unterfranken	LL	LL	HH
DE27	Schwaben	0	11	0	0	0	11	ns	Schwaben	LL	LL	HH
DE5	Bremen	0	11	0	0	0	11	ns	Bremen	LL	LL	HH*
DE6	Hamburg	0	11	0	0	0	11	ns	Hamburg	LL	LL	LH*
DE71	Darmstadt	0	11	0	0	0	11	LL	Darmstadt	LL	LL	HH
DE72	Gießen	0	11	0	0	0	11	HL	Gießen	LL	LL	LH
DE73	Kassel	0	11	0	0	0	11	HL	Kassel	LL	LL	HH
DE91	Braunschweig	0	11	0	0	0	11	ns	Braunschweig	LL	LL	HH*
DE92	Hannover	0	11	0	0	0	11	ns	Hannover	LL	LL	HL*
DE93	Lüneburg	0	8	0	0	3	11	ns	Lüneburg	LL	LL	LL*
DE94	Weser-Ems	0	11	0	0	0	4	ns	Weser-Ems	LL	LL	HH*
DEA1	Düsseldorf	9	2	0	0	0	1	ns	Düsseldorf	LL	LL	HH*
DEA2	Köln	0	11	0	0	0	2	ns	Köln	LL	LL	HH*
DEA3	Münster	0	11	0	0	0	0	ns	Münster	LL	LL	LH*
DEA4	Detmold	0	11	0	0	0	11	ns	Detmold	LL	LL	HL*
DEA5	Arnsberg	0	11	0	0	0	11	LL	Arnsberg	LL	LL	HH*
DEB1	Koblenz	0	11	0	0	0	11	ns	Koblenz	LL	LL	HH*
DEB2	Trier	0	9	0	0	2	2	ns	Trier	LL	LL	LH*
DEB3	Rheinhessen-Pfalz	0	11	0	0	0	11	LL	Rheinhessen-Pfalz	LL	LL	HH
DEC	Saarland	0	11	0	0	0	3	ns	Saarland	LL	LL	LH
DEF	Schleswig-Holstein	0	11	0	0	0	11	ns	Schleswig-Holstein	LL	LL	LH*
DK	**Denmark**	0	11	0	0	0	11	ns	**Denmark**	LL	LL	HH*
	Spain								**Spain**			
ES11	Galicia	0	0	11	0	0	11	LH	Galicia	HH	HH*	LL
ES12	Asturias	0	0	11	0	0	11	ns	Asturias	HH*	HH*	LL
ES13	Cantabria	2	0	9	0	0	0	ns	Cantabria	HH*	HH*	LL*
ES21	Pais Vasco	7	0	4	0	0	0	ns	Pais Vasco	HH*	HH*	HL*
ES22	Navarra	10	0	1	0	0	0	ns	Navarra	LH*	HH*	HH*
ES23	La Rioja	11	0	0	0	0	0	ns	La Rioja	LH*	HH*	HL*

	Region	Not sign	HH	LL	HL	LH	Bonf. 5%	growth 89-99	Regions	fs/m	ct/m	ct/fs
ES24	Aragón	10	0	1	0	0	0	ns	Aragón	HH*	HH*	LH*
ES3	Comunidad de Madrid	0	0	9	2	0	6	ns	Comunidad de Madrid	LH	LH	LL*
ES41	Castilla y León	0	0	11	0	0	6	ns	Castilla y León	HH*	HH*	LL*
ES42	Castilla-la Mancha	0	0	11	0	0	5	ns	Castilla-la Mancha	HH*	HH*	LL*
ES43	Extremadura	0	0	11	0	0	11	HH	Extremadura	HH*	HH*	LL
ES51	Cataluña	11	0	0	0	0	0	ns	Cataluña	LL*	HH*	HH*
ES52	Comunidad Valenciana	4	0	7	0	0	0	ns	Comunidad Valenciana	HH*	HH*	LH*
ES53	Baleares	0	0	11	0	0	0	LL	Baleares	LL*	LH*	HH*
ES61	Andalucia	0	0	11	0	0	11	LH	Andalucia	HH	HH*	LL
ES62	Murcia	1	0	10	0	0	5	ns	Murcia	HH*	HH*	LL*
	France								**France**			
FR1	Ile de France	11	0	0	0	0	0	ns	Ile de France	LL*	LL*	HH*
FR21	Champagne-Ardenne	10	1	0	0	0	0	ns	Champagne-Ardenne	LL*	LL*	HH*
FR22	Picardie	3	5	0	0	3	0	ns	Picardie	LL	LL*	HH*
FR23	Haute-Normandie	8	3	0	0	0	0	ns	Haute-Normandie	LL	LL*	HH*
FR24	Centre	11	0	0	0	0	0	LL	Centre	LL*	LL*	HH*
FR25	Basse-Normandie	6	5	0	0	0	0	ns	Basse-Normandie	LL	LL	HL
FR26	Bourgogne	11	0	0	0	0	0	ns	Bourgogne	LL	LL	HH*
FR3	Nord - Pas- de-Calais	0	11	0	0	0	0	ns	Nord – Pas - de-Calais	LL	LL*	LH*
FR41	Lorraine	1	10	0	0	0	0	ns	Lorraine	LL	LL	LH*
FR42	Alsace	0	11	0	0	0	7	LL	Alsace	LL	LL	HH
FR43	Franche-Comté	0	11	0	0	0	3	LL	Franche-Comté	LL	LL	HH*
FR51	Pays de la Loire	6	5	0	0	0	0	ns	Pays de la Loire	LL	LL	LH*
FR52	Bretagne	11	0	0	0	0	0	ns	Bretagne	LL	LL	LL*
FR53	Poitou-Charentes	11	0	0	0	0	0	LL	Poitou-Charentes	LL	LL*	HH*
FR61	Aquitaine	11	0	0	0	0	0	ns	Aquitaine	LL*	LH*	HH
FR62	Midi-Pyrénées	11	0	0	0	0	0	LL	Midi-Pyrénées	LL*	LL*	HH
FR63	Limousin	11	0	0	0	0	0	LL	Limousin	LL	HL*	HH*
FR71	Rhône-Alpes	11	0	0	0	0	0	LL	Rhône-Alpes	LL*	LL*	HH*
FR72	Auvergne	11	0	0	0	0	0	LL	Auvergne	LL	LL*	HH*
FR81	Languedoc-Roussillon	11	0	0	0	0	0	LL	Languedoc-Roussillon	LL*	LL*	HH
FR82	Provence-Alpes-Côte d'Azur	10	1	0	0	0	0	LL	Provence-Alpes-Côte d'Azur	LL*	LL*	LH*
FR83	Corse	0	1	0	0	10	0	HL	Corse	HL*	HL*	LL*
	Greece								**Greece**			
GR11	Anatoliki Makedonia, Thraki	0	0	11	0	0	11	HH	Anatoliki Makedonia, Thraki	HH	HH*	LL
GR12	Kentriki Makedonia	0	0	11	0	0	11	HH	Kentriki Makedonia	HH	HH	LL
GR13	Dytiki Makedonia	0	0	11	0	0	11	HH	Dytiki Makedonia	HH	HH	LL
GR14	Thessalia	0	0	11	0	0	11	HH	Thessalia	HH	HH	LL
GR21	Ipeiros	0	0	11	0	0	11	ns	Ipeiros	HH	HH*	LL
GR22	Ionia Nisia	0	0	11	0	0	11	ns	Ionia Nisia	HH	HH*	LL
GR23	Dytiki Ellada	0	0	11	0	0	11	HH	Dytiki Ellada	HH	HH*	LL
GR24	Sterea Ellada	0	0	11	0	0	11	LH	Sterea Ellada	HH	HH*	LL
GR25	Peloponnisos	0	0	11	0	0	11	HH	Peloponnisos	HH	HH*	LL
GR3	Attiki	0	0	11	0	0	11	ns	Attiki	LH	LH	LL
GR41	Voreio Aigaio	0	0	11	0	0	11	HH	Voreio Aigaio	HH	HH*	LL

	Region	Not sign	HH	LL	HL	LH	Bonf. 5%	growth 89-99	Regions	fs/m	ct/m	ct/fs
GR42	Notio Aigaio	0	0	11	0	0	11	HH	Notio Aigaio	HH	HH*	LL
GR43	Kriti	0	0	11	0	0	11	HH	Kriti	HH	HH*	LL
	Ireland								**Ireland**			
IE01	Border	11	0	0	0	0	0	HH	Border	HH*	HH*	LL*
IE02	Dublin	11	0	0	0	0	0	HH	Dublin	HH	HH	LL*
	Italy								**Italy**			
IT11	Piemonte	0	11	0	0	0	4	LL	Piemonte	LL	LL	HH
IT12	Valle d'Aosta	1	10	0	0	0	0	LL	Valle d'Aosta	LL	LL	LH
IT13	Liguria	7	4	0	0	0	0	LL	Liguria	LL*	LH*	HH*
IT2	Lombardia	1	10	0	0	0	4	LL	Lombardia	LL	LL	HH
IT31	Trentino-Alto Adige	0	11	0	0	0	10	LL	Trentino-Alto Adige	LL	LL	HH
IT32	Veneto	1	10	0	0	0	4	LL	Veneto	LL	LL*	HH
IT33	Friuli-Venezia Giulia	0	11	0	0	0	4	LL	Friuli-Venezia Giulia	LL	LL*	HH
IT4	Emilia-Romagna	7	4	0	0	0	0	LL	Emilia-Romagna	LL*	LL*	LH*
IT51	Toscana	7	4	0	0	0	0	LL	Toscana	LL*	LH*	HH*
IT52	Umbria	11	0	0	0	0	0	LL	Umbria	HL*	HL*	LL*
IT53	Marche	11	0	0	0	0	0	LL	Marche	LL*	LH*	HL*
IT6	Lazio	11	0	0	0	0	0	LL	Lazio	LH*	LH*	LL*
IT71	Abruzzo	11	0	0	0	0	0	LL	Abruzzo	LH*	HH*	LL*
IT72	Molise	10	0	1	0	0	0	LL	Molise	HH*	HH*	LL*
IT8	Campania	6	0	5	0	0	0	LL	Campania	HH*	LH*	LL*
IT91	Puglia	0	0	11	0	0	6	ns	Puglia	HH	HH*	LL
IT92	Basilicata	4	0	7	0	0	1	LL	Basilicata	HH*	HH*	LL
IT93	Calabria	0	0	11	0	0	10	ns	Calabria	HH	HH*	LL
ITA	Sicilia	4	0	7	0	0	1	LL	Sicilia	HH*	HH*	LL
ITB	Sardegna	10	0	0	0	1	0	LL	Sardegna	HL*	HH*	LL*
LU	**Luxembourg**	10	1	0	0	0	0	LL	**Luxembourg**	LL	LL	HL*
	Netherlands								**Netherlands**			
NL11	Groningen	10	1	0	0	0	0	ns	Groningen	LL	LL*	HH
NL12	Friesland	10	1	0	0	0	0	ns	Friesland	LL	LL*	HH
NL13	Drenthe	7	4	0	0	0	0	ns	Drenthe	LL	LL*	LH
NL21	Overijssel	9	2	0	0	0	0	ns	Overijssel	LL	LL*	HH
NL22	Gelderland	10	1	0	0	0	0	ns	Gelderland	LL	LL*	HH
NL23	Flevoland	9	0	0	0	2	0	ns	Flevoland	HL	HL	HH
NL31	Utrecht	10	1	0	0	0	0	ns	Utrecht	LL	LL*	HH
NL32	Noord-Holland	11	0	0	0	0	0	ns	Noord-Holland	LL	LL*	HH
NL33	Zuid-Holland	4	7	0	0	0	0	ns	Zuid-Holland	LL	LL	HH
NL34	Zeeland	4	7	0	0	0	0	ns	Zeeland	LL	LL	HH*
NL41	Noord-Brabant	5	6	0	0	0	0	ns	Noord-Brabant	LL	LL*	HH
NL42	Limburg	4	7	0	0	0	0	ns	Limburg	LL	LL*	HH
	Portugal								**Portugal**			
PT11	Norte	0	0	11	0	0	11	HH	Norte	LH	LH*	LL
PT12	Centro	0	0	11	0	0	11	HH	Centro	HH	LH*	LL
PT13	Lisboa e Vale do Tejo	0	0	11	0	0	11	HH	Lisboa e Vale do Tejo	LH	LH*	LL
PT14	Alentejo	0	0	11	0	0	11	HH	Alentejo	HH	HH*	LL
PT15	Algarve	0	0	11	0	0	11	HH	Algarve	HH	HH*	LL
	United-Kingdom								**United-Kingdom**			
UKC	North East	11	0	0	0	0	0	HH	North East	LL	HL	LL*
UKK	South West	11	0	0	0	0	0	ns	South West	LL*	LL*	LL*
UKL	Wales	11	0	0	0	0	0	HH	Wales	LL*	LH*	LL
UKM	Scotland	11	0	0	0	0	0	HH	Scotland	LH	LH	LL
UKN	Northern Ireland	11	0	0	0	0	0	HH	Northern Ireland	HH	HH	LL*

	Region	Not sign	HH	LL	HL	LH	Bonf. 5%	growth 89-99	Regions	fs/m	ct/m	ct/fs
UKD	North West	11	0	0	0	0	0	HH	North West	LL*	LL*	HL
UKE	Yorkshire and the Humber	11	0	0	0	0	0	ns	Yorkshire and the Humber	LL*	LL	LL*
UKF	East Midlands	11	0	0	0	0	0	HH	East Midlands	LL*	LL*	LL*
UKG	West Midlands	11	0	0	0	0	0	ns	West Midlands	LL	LL	LL*
UKH	Eastern	9	2	0	0	0	0	ns	Eastern	LL	LL	LL*
UKI	London	11	0	0	0	0	0	ns	London	LL	LL	LL*
UKJ	South East	11	0	0	0	0	0	ns	South East	LL	LL	LL*

Note: Level of pseudo-significance $p<0.05$. **Not sign**. denotes the number of years local statistics is not significant at 0.05. Maximum number of years is 11. **HH**, number of years local statistics of significant and in quadrant HH of Moran's scatterplot; **LL**, number of years local statistics of significant and in quadrant LL of Moran's scatterplot; **HL**, number of years local statistics of significant and in quadrant HL of Moran's scatterplot; **LH**, number of years local statistics of significant and in quadrant LH of Moran's scatterplot. **Bonf. 5%** indicates the number of years the statistics is significant at 5% Bonferroni pseudo-significance level.
Growth 89-99 indicates if local statistics of growth rate over 1989-1999 is significant or not, if yes, then the quadrant in Moran's scatterplot it belongs to. ns means no significance at $p<0.05$. **fs/m is** total structural funds 89-99 divided by the region's mean per capita GDP over 1989-1999; **ct/m** is Community projects total costs 89-99 divided by the region's mean per capita GDP over 1989-1999; **ct/fs** is Community projects total costs divided by structural funds over 1989-1999, ***** indicates that the LISA statistics is not significant at the 5% pseudo-significance level.

Table 3: Robustness analysis for LISA from 10 to 15 neighbors

K=10 \ K=15	Not Sign.	HH	LL	HL	LH
Not Sign.	67.8%	21.9%	4.6%	0.1%	5.6%
HH	1.8%	98.0%	0%	0%	0.2%
LL	6.2%	0%	93.8%	0%	0%
HL	0%	0%	0%	100%	0%
LH	29.6%	0%	0%	0%	70.4%

Table 4: Robustness analysis for LISA from 10 to 20 neighbors

K=10 \ K=20	Not Sign.	HH	LL	HL	LH
Not Sign.	54.8%	31.6%	4.5%	0%	9.1%
HH	1.5%	98.3%	0%	0%	0.2%
LL	5.3%	0%	94.7%	0%	0%
HL	0%	0%	0%	100%	0%
LH	25.9%	0%	0%	0%	74.1%

Table 5: Correlation table of growth rate (1989-1999) by initial per capita GDP (1989)

	Per capita GDP 1989					
Growth rate	Not Sign.	HH	LL	HL	LH	Sum
Not Sign.	40	29	11	0	0	80
HH	8	0	Extremadura (ES), Anatoliki Makedonia (GR), Kentriki Makedonia (GR), Dytiki Makedonia (GR), Thessalia (GR), Dytiki Ellada (GR), Peloponnisos (GR), Voreio Aigaio (GR), Notio Aigaio (GR) Kriti (GR) PORTUGAL 15	0	0	23
LL	17	Karlsruhe (DE), Freiburg (DE), Tübingen (DE), Darmstadt (DE), Arnsberg (DE), Rheinhessen-Pfalz (DE), Alsace (FR), Franche-Comté (FR), Provence-Alpes-Côte d'Azur (FR), Piemonte (IT), Valle d'Aosta (IT), Liguria (IT), Lombardia (IT), Trentino-Alto Adige (IT), Veneto (IT), Friuli-Venezia Giulia (IT), Emilia-Romagna (IT), Toscana (IT) 18	Baleares (ES) 1	0	0	36
HL	0	Gießen (DE) Kassel (DE) Coarse (FR) 3	0	0	0	3
LH	0	0	Galicia (ES) Andalucia (ES) Sterea Ellada (GR) 3	0	0	3
Sum	65	50	30	0	0	145

Table 6: Correlation table of growth rate by structural funds 1989-1999

	Total structural funds 1989-1999					
Growth rate	Not Sign.	HH	LL	HL	LH	Sum
Not Sign.	16	4	56	2	2	80
HH	5	Anatoliki Makedonia (GR), Kriti (GR), Kentriki Makedonia (GR), Dytiki Makedonia (GR), Thessalia (GR), Dytiki Ellada (GR), Peloponnisos (GR), Voreio Aigaio (GR), Notio Aigaio (GR), Dublin (IE), Centro (PT), Alentejo (PT), Algarve (PT), Northern Ireland (UK) 14	North East (UK) 1	0	Norte (PT) Lisboa e Vale do Tejo (PT) Scotland (UK) (3)	23
LL	18	0	Karlsruhe (DE), Freiburg (DE), Tübingen (DE), Darmstadt (DE), Arnsberg (DE), Rheinhessen-Pfalz (DE), Alsace (FR), Franche-Comté (FR), Poitou-Charentes (FR), Limousin (FR), Auvergne (FR), Piemonte (IT), Veneto (IT), Valle d'Aosta (IT), Lombardia (IT), Trentino-Alto Adige (IT), Friuli-Venezia Giulia (IT) LUXEMBOURG 18	0	0	36
HL	1	0	Gießen (DE) Kassel (DE) 2	0	0	3
LH	0	Galicia (ES) Andalucia (ES) Sterea Ellada (GR) 3	0	0	0	3
Sum	40	21	77	2	5	145