Exploratory Spatial Data Analysis of the distribution of regional per capita GDP in Europe, 1980-1995

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Abstract. The aim of this paper is to study the dynamics of European regional per capita product over time and space. This purpose is achieved by using the recently developed methods of Exploratory Spatial Data Analysis. Using a sample of European regions over the 1980-1995 period, we find strong evidence of global and local spatial autocorrelation in per capita GDP throughout the period. The detection of clusters of high and low per capita products during the period is an indication of the persistence of spatial disparities between European regions. This analysis is finally refined by the investigation of the spatial pattern of regional growth.

JEL classification: C21, O18, O52, R11, R12

Key words: exploratory spatial data analysis, distribution of regional per capita GDP, European Union, spatial autocorrelation, regional inequalities

1 Introduction

The integration of the European market has stimulated the analysis of regional economic convergence within the European Union in the recent macroeconomic literature (Neven and Gouyette 1995; Abraham and Von Rompuy 1995; Armstrong 1995; Molle and Broeckhout 1995). Most of the time, the empirical methods that have been used are identical to the methods used in international studies. However, at the regional scale, spatial effects and particularly spatial autocorrelation are determining for the analysis of convergence processes. Several factors, like trade between regions, technology and knowledge diffusion and more generally regional externalities and spillovers, lead to geographically dependent regions: there are spatial interactions between regions and the geographical location plays an important role. Despite their importance, the role of spatial effects in convergence processes has been only recently examined using spatial statistics and spatial econometric methods (López-Bazo et al. 1999; Fingleton 1999; Rey and Montouri 1999).

Therefore, this paper aims at studying the dynamics of European regional per capita product over time and space. In this purpose, we use the recently developed methods of Exploratory Spatial Data Analysis to examine the spatial distribution of regional per capita products. The detection of global and local spatial autocorrelation enables to characterize the way the economic activities are located in the European Union and the way this pattern of location has changed over the period.

In the second section, we briefly present the principles and methods of Exploratory Spatial Data Analysis (ESDA). Using a sample of European regions over the 1980-1995 period, we compute in the third section a global spatial autocorrelation statistic, as well as local Moran autocorrelation statistics (Moran scatterplot and LISA; Anselin 1995, 1996) in order to detect clusters of high and low per capita products. Indeed, the existence of those clusters during the period would be an indication of the persistence of spatial disparities between European regions. The spatial pattern of regional growth is finally investigated.

2 Exploratory Spatial Data Analysis

Exploratory Spatial Data Analysis (ESDA) is a set of techniques aimed at describing and visualizing spatial distributions, at identifying atypical localizations or spatial outliers, at detecting patterns of spatial association, clusters or hot spots, and at suggesting spatial regimes or other forms of spatial heterogeneity (Haining 1990; Bailey and Gatrell 1995; Anselin 1998a, 1998b). These methods provide measures of global and local spatial autocorrelation.

2. 1 Global spatial autocorrelation

Spatial autocorrelation can be defined as the coincidence of value similarity with locational similarity (Anselin 2000). Therefore there is positive spatial autocorrelation when high or low values of a random variable tend to cluster in space and there is negative spatial autocorrelation when geographical areas tend to be surrounded by neighbors with very dissimilar values.

The measurement of global spatial autocorrelation is based on the Moran's I statistic, which is the most widely known measure of spatial clustering (Cliff and Ord 1973, 1981; Upton and Fingleton 1985; Haining 1990). For each year of the period 1980-1995, this statistic is written in the following way:

$$I_t = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij} \left(x_{i,t} - m_t\right)\left(x_{j,t} - m_t\right)}{\sum_i \left(x_{i,t} - m_t\right)^2} \qquad t = 1,...,16 \qquad (1)$$

where x_{it} is the observation in region i and year t, m_t is the mean of the observations across regions in year t. n is the number of regions. w_{ij} is the element of the spatial weight matrix W. This matrix contains the information about the relative spatial dependence between the n regions i. The elements w_{ii} on the diagonal are set to zero whereas the elements w_{ij} indicate the way region i is spatially connected to the region j. Finally, S_0 is a scaling factor equal to the sum of all the elements of W.

The spatial weight matrix we use in this study is based on the 10 nearest neighbors calculated from the great circle distance between region centroids. In Europe, regions have on average 5 to 6 contiguous neighbors, our choice of 10 yields a ring around each region of approximately the first and second order contiguous regions and moreover connects United-Kingdom as well as some islands such as Sicilia, Sardegna, and Baleares to continental Europe. Furthermore, it also connects Greece to Italy, so that the block-diagonal structure of the simple contiguity matrix is avoided. This feature is of particular interest when working on a sample of European regions, which are less compact than US states.

Noting z_t the vector of the n observations for year t in deviation from the mean m_t, (1) can be written in the following matrix form:

$$I_t = \frac{n}{S_0} . \frac{z_t' W z_t}{z_t' z_t} \qquad t = 1,...,16 \qquad (2)$$

In order to normalize the outside influence upon each region, the spatial weight matrix is row-standardized such that the elements in each row sum to 1. In this case, the expression (2) simplifies since for row-standardized weights $S_0 = n$.

Moran's I statistic gives a formal indication on the degree of linear association between the vector z_t of observed values and the vector Wz_t of spatially weighted averages of neighboring values, called the spatially lagged vector. Values of I larger than the expected value $E(I) = -1/(n-1)$ indicate positive spatial autocorrelation, while values smaller than the expected indicate negative spatial autocorrelation. Inference is based on the permutation approach with 10000 permutations. In this approach, it is assumed that, under the null hypothesis, each observed value could have occurred at all locations with equal likelihood. But instead of using the theoretical mean and standard deviation (given by Cliff and Ord 1981), a reference distribution is empirically generated for I, from which the mean and standard deviation are computed. In practice this is carried out by permuting the observed values over all locations and by re-computing I for each new sample. The mean and standard deviation for I are then the computed moments for the reference distribution for all permutations (Anselin 1995).

2.2 Local spatial autocorrelation

Moran's I statistic is a global statistic: it does not enable us to appreciate the regional structure of spatial autocorrelation. However, one can wonder which regions contribute more to the global spatial autocorrelation, if there are local spatial clusters of high or low values, and finally to what point the global evaluation of spatial autocorrelation masks atypical localizations or "pockets of local nonstationarity", i.e. respectively regions or groups of contiguous regions, which deviate from the global pattern of positive spatial autocorrelation.

The analysis of local spatial autocorrelation is carried out with two tools: first, the Moran scatterplot (Anselin 1996), which is used to visualize local spatial instability, and second, local indicators of spatial association "LISA" (Anselin 1995), which are used to test the hypothesis of random distribution by comparing the values of each specific localization with the values in the neighboring localizations.

Moran Scatterplot

Inspection of local spatial instability is carried out by the means of the Moran scatterplot (Anselin 1996), which plots the spatial lag Wz_t against the original values z_t. The four different quadrants of the scatterplot correspond to the four types of local spatial association between a region and its neighbors: (HH) a region with a high[1] value surrounded by regions with high values (Quadrant I in top on the right), (LH) a region a with low value surrounded by regions with high values (Quadrant II in top on the left), (LL) a region with a low value surrounded by regions with low values (Quadrant III in bottom on the left), (HL) a region with a high value surrounded by /regions with low values (Quadrant IV in bottom on the right). Quadrants I and III refer to positive spatial autocorrelation indicating spatial clustering of similar values whereas quadrants II and IV represent negative spatial autocorrelation indicating spatial clustering of dissimilar values. The Moran scatterplot may thus be used to visualize atypical localizations, i.e. regions in quadrant II or in the quadrant IV. Moreover, the use of standardized variables allows the Moran scatterplots to be comparable across time.

The global spatial autocorrelation may also be visualized in this graph since, from (2) Moran's *I* is formally equivalent to the slope coefficient of the linear regression of Wz_t on z_t using a row-standardized weight matrix. Therefore, this regression can be assessed with diagnostics for model fit. The detection of outliers and sites, which exert strong influence on Moran's *I*, is based on standard regression diagnostics: studentized residuals and leverage measures are used to detect outliers, and Cook's distance is an influence measure (Belsley et al. 1980; Haining 1994, 1995). The studentized residual is a measure of the extreme character of an observation along the dependent variable domain and is calculated as the studentized difference between the actual value and the predicted value. The leverage quantifies the extreme nature of an observation in the range of the independent variable and is assessed using the diagonal elements of the hat matrix[2] (Haoglin and Welsch 1978). Finally, the Cook's distance combines the two previous diagnostics and measures the extent to which regression coefficients are changed by the deletion of a particular observation (Cook 1977; Weisberg 1985).

[1] High (respectively low) means above (respectively below) the mean.

Let us note however that the Moran scatterplot does not give any indications of significant spatial clustering and therefore, it cannot be considered as a Local Indicator of Spatial Association in the sense defined by Anselin (1995).

Local indicators of spatial association (LISA)

Anselin (1995) defines a local indicator of spatial association as any statistics satisfying two criteria[3]. First, the LISA for each observation gives an indication of significant spatial clustering of similar values around that observation; second, the sum of the LISA for all observations is proportional to a global indicator of spatial association.

The local version of the Moran's *I* statistic for each region i and year t can then be written as following:

$$I_{i,t} = \frac{\left(x_{i,t} - m_t\right)}{m_0} \sum_j w_{ij} \left(x_{j,t} - m_t\right) \qquad \text{with } m_0 = \sum_i \left(x_{i,t} - m_t\right)^2 \Big/ n \tag{3}$$

where the summation over j is such that only neighboring values of j are included. It is straightforward to see that the sum of local Moran's statistics can be written:

$$\sum_i I_{i,t} = \frac{1}{m_0} \sum_i \left(x_{i,t} - m_t\right) \sum_j w_{ij} \left(x_{j,t} - m_t\right) = \frac{1}{m_0} \sum_i \sum_j w_{ij} \left(x_{i,t} - m_t\right)\left(x_{j,t} - m_t\right) \tag{4}$$

From (1), it follows that the global Moran's I statistic is proportional to the sum of local Moran's statistics:

$$I_t = \sum_i I_{i,t} \Big/ S_0 \tag{5}$$

For a row-standardized weight matrix, $S_0 = n$ so that $I_t = \frac{1}{n} \sum_i I_{i,t}$: the global Moran's *I* equals the mean of the local Moran's statistics. A positive value for $I_{i,t}$ indicates clustering of similar values (high or low) whereas a negative value indicates clustering of dissimilar values.

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[2] The hat matrix is defined as $H = X(X'X)^{-1}X'$ where *X* is the matrix of observations on the explanatory variables in a regression.

[3] Note that the Getis and Ord (1992) local statistics $G_i(d)$ and $G_i^*(d)$ are not LISAs in the sense defined by Anselin (1995) since they are not related to a global statistic of spatial association and will not be used in this study.

Due to the presence of global spatial autocorrelation, inference must be based on the conditional permutation approach: the value x_i at site *i* is held fixed, while the remaining values are randomly permuted over all locations (note that only the quantity $\sum_j w_{ij}\left(x_{i,t}-m_t\right)$ needs to be computed for each permutation since the term $\left(x_{i,t}-m_t\right)/m_0$ remains constant for a given region i). It should be stressed that *p*-values obtained for the local Moran's statistics are actually pseudo-significance levels. Inference is further complicated by the fact that local Moran's statistics will be correlated when the neighborhood sets of two regions contain common elements (Ord and Getis 1995; Anselin 1995). This is actually a problem of multiple statistical comparison and the significance levels must be approximated by the Bonferroni inequality or by the procedure elaborated by Sidák (1967)[4]. As noted by Anselin (1995, p.96): "This means that when the *overall* significance associated with the multiple comparisons (correlated tests) is set to a, and there are m comparisons, then the individual significance a_i should be set to a/m (Bonferroni) or $1-\left(1-a\right)^{1/m}$ (Sidák)". With $m=n$, the number of regions of the sample, these procedures can be overly conservative to assess the significance of local Moran's statistics. The second procedure requires that the variables are multivariate normal, which is unlikely to be the case with LISA. In this respect, we will present the results obtained with both the usual 5% pseudo-significance level, which may be too liberal, and the 10% Bonferroni pseudo-significance level (with $n=138$, we get $a_i=7.246.10^{-4}$), which may be too conservative in opposition to the preceeding one. These two significance level can therefore be considered as the two extreme bounds for the inference.

Anselin (1995) gives two interpretations for local Moran's statistics: they can be used, first, as indicators of local spatial clusters (or hot spots), which can be identified as locations or sets of neighboring locations for which the LISA are significant and second, as diagnostics for local instability, i.e. for significant outliers with respect to the measure of global spatial autocorrelation (atypical localizations or pockets of nonstationarity). The second interpretation of the LISA statistics is similar to the use of a Moran scatterplot to

[4] More about this problem can be found in Savin (1984).

identify outliers and leverage points for Moran's I: since there is a link between the local indicators and the global statistic, LISA outliers will be associated to the regions which are the most influential on Moran's I.

3 Empirical results

We apply ESDA techniques to European regional data on per capita GDP in logarithms. The data are extracted from the EUROSTAT-REGIO databank[5]. Our sample includes 138 regions for 11 countries (Denmark, Luxembourg and United Kingdom in NUTS1 level and Belgium, Spain, France, Germany, Greece, Italy, Netherlands and Portugal in NUTS2 level[6]) over the 1980-1995 period[7].

3.1 Global spatial autocorrelation

Table 1 displays the evolution of the spatial autocorrelation of per capita GDP over the 1980-1995 period for the 138 European regions of our sample. It appears that per capita regional GDPs are positively spatially autocorrelated since the statistics are significant with $p = 0.0001$ for every year[8]. This result suggests that the hypothesis of spatial randomness is rejected and that the distribution of per capita regional GDP is by nature clustered over the whole period. In other words, the regions with relatively high per capita GDP (respectively low) are localized close to other regions with relatively high per capita GDP (respectively low) more often than if this localization was purely random.

If we consider now the evolution of the Moran's I statistics over the period, we can see that the value of the statistic has slightly increased over the period. If this scheme keeps on in the future, the spatial distribution of per capita GDP will remain clustered and will not tend toward a spatially random distribution. Moran's I

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[5] Series E2GDP measured in Ecu_hab units.

[6] We use Eurostat 1995 nomenclature of statistical territorial units, which is referred to as NUTS: NUTS1 means European Community Regions while NUTS2 means Basic Administrative Units.

[7] We exclude Groningen in the Netherlands from the sample due to some anomalies related to North Sea Oil revenues, which increase notably its per capita GDP. We exclude also Canary Islands and Ceuta y Mellila, which are geographically isolated. Corse, Austria, Finland, Ireland and Sweeden are excluded due to data non-availability over the 1980-1995 period in the EUROSTAT-REGIO databank. Berlin and East Germany are also excluded due to well-known historical and political reasons.

[8] All computations are carried out by the means of the SpaceStat 1.90 software (Anselin 1999).

statistics thus indicates a global significant trend to the geographical clustering of similar regions in terms of log per capita GDP.

[Table 1 about here]

3.2 Moran scatterplots

Since Moran's *I* yields a single result for the entire data set, it cannot discriminate between a spatial clustering of high values and a spatial clustering of low values in the case of a global positive spatial autocorrelation. Furthermore, it may mask regions that deviate from this global pattern. These limitations are overcome by the Moran scatterplots.

Figures 1 and 2 display the Moran scatterplots for the initial and final years of our sample: 1980 and 1995. On the one hand, we can see that almost all of the European regions are characterized by positive spatial association (as indicated by the slope of the regression line). On the other hand, there are little "atypical" regions i.e. deviating from the global pattern of positive autocorrelation. More precisely, as can be seen in table 4, in 1980, 97.8% of the European regions show association of similar values (65.2% in quadrant I (HH) and 32.6% in quadrant III (LL)) and in 1995, 94.9% of the European regions show this positive association (56.5% in quadrant I (HH) and 38.4% in quadrant III (LL)). This may indicate the existence of two regimes of spatial autocorrelation, the first one corresponding to the HH scheme and the second one to the LL scheme, both of them representing positive spatial association. Not surprisingly, the Moran scatterplots reveal a clear north-south polarization of the regions: northern regions are to be found in the first quadrant (HH type) while southern regions are in the third quadrant (LL type). The major change between 1980 and 1995 concerns the British regions: they are in the third quadrant in 1995 (LL) whereas they were in the first quadrant in 1980 (HH).

In 1980, only 3 regions show association of dissimilar values (2 in quadrant II (LH) and 1 in quadrant IV (HL)). We can note however that Aquitaine (France) is located at the border between the French regions, which are HH regions, and the Spanish regions, which are LL regions. This geographical situation explains why Aquitaine is a HL region. The 2 LH regions are Wales and Northern Ireland (United-Kingdom). In 1995, there are 7 atypical regions (Hainaut and Namur (Belgium), Languedoc-Roussillon (France), East Anglia (United Kingdom)) in quadrant II (LH) and Aquitaine, Midi-Pyrénées (France) and Lazio (Italy) in quadrant IV (HL)).

[Figures 1 and 2 about here]

The Moran scatterplot can also be used to assess the presence of outliers, which are defined as the points further than 2 units away from the origin. In 1980, there are no regions that have a per capita GDP more than two standard deviations above the mean whereas Voreio Aigaio (Greece) and all Portuguese regions (except the capital region Lisboa) have per capita GDPs less than two standard deviations below the mean (horizontal axis in Figure 1). There is no outlier on the vertical axis (Figure 1). In 1995, Hamburg and Darmstadt (Germany) are outliers with per capita GDPs more than two standard deviations above the mean (Figure 2). The Portuguese regions cannot be considered as outliers anymore except Alentejo (Portugal) as well as Ipeiros and Voreio Aigaio (Greece).

The first 2 columns and first 2 rows of Table 2 display a summary of the most extreme observations according to the Moran regression diagnostics for 1980 and 1995. First, the largest studentized residuals represent large deviations from the model fit. In the table are reported the 7 studentized residuals larger than 2 in absolute value in 1980 and 1995. Second are reported the observations associated with leverages higher than $2p/n$ (where p is the number of explanatory variables in the regression, i.e. p= 2 and n = 138). There are 12 such observations in 1980 and 1995, most of them being located in Portugal, Greece and Germany. Finally, a region is considered to be influential if the associated Cook's distance is larger than $F(0.5; p; n-p) = 0.6967$ with $p = 2$ and n = 138. The results are not reported in the table since there was no occurrence of a region exceeding this level for all years (the highest value is 0.216 for Alentejo

(Portugal) in 1988). These results suggest that, although some regions have large leverages and studentized residuals, no region appears to be particularly influential in the sample.

[Table 2 about here]

More insight to the evolution of Moran's scatterplots over time is provided by a newly introduced measure of space-time transitions, which is based on the classification of the transitions over time of a region and its neighbors in four groups (Rey, 1999). The first includes the transitions with a relative move of only the region, for example a HH region in the first period that becomes a LH region in the following period. The other cases are HL-LL, LH-HH and LL-HL. The second group contains the transitions of the neighbors only: HH-HL, HL-HH, LH-LL and LL-LH while the transitions of both a region and its neighbors belong to the third group: HH-LL, HL-LH, LH-HL and LL-HH. Finally, the 4 cases in which the region and its neighbors remain at the same level are in the fourth group. High stability in the types of transitions is reflected by a high amount of type 4 transitions and low values of the flux (or instability) measure, which is defined as the frequency of the first and second type of transitions over all 15 years of transitions. For time intervals of 1, 5 and 10 years, the fourth type of transition is always the most common one (95.6%, 89.9% and 85.3%) and the flux measure is respectively equal to 4%, 7.9% and 8.8%. These results denote a high cohesion between European regions and a very low rate of mobility, increasing very slowly with the transition interval. This finding is refined by the study of local spatial autocorrelation statistics.

3.3 Local Spatial Autocorrelation Statistics

In order to examine further these results that are consistent with EU economic reports, it is worth computing the local indicators of spatial dependence since no indication of significant local spatial clustering is provided by the Moran scatterplots. With the aim of identifying the spatial movements that occurred during the whole 1980-1995 period, we will only retain the phenomena of local clusters and the atypical localizations for which the local Moran's statistics are significant. The results of this procedure are summarized in Table 3.

[Table 3 about here]

The number of years over the whole period with significant local statistics (using a pseudo-level of significance of 5% and a Bonferroni pseudo-level of significance of 10%) is displayed in the second column[9]. The number of years during which the region falls into a certain quadrant of the Moran scatterplot with a significant local statistics are displayed in the following columns (HH, HL LH or LL). The corresponding years are finally displayed in the two last columns. Several points can be highlighted.

First, the local pattern of spatial association reflects the global trend to positive spatial autocorrelation since 98.83% of the significant local indicators, using the 5% pseudo-significance level, fall either into quadrant I or in quadrant III of the scatterplot, i.e. representing HH and LL types of clustering. We note however that the distribution between associations of the HH and LL types is uneven since 62.23% of the regions fall into quadrant I: we thus mainly detect regions or sets of regions with high per capita GDP surrounded by other regions with high per capita GDP[10].

Second, deviations of the global trend are marginal and are dominated by a particular form of negative spatial association: the LH type, where a region with low per capita GDP is surrounded by regions with high per capita GDP (0.68% of the significant LISA). Only two HL regions, or "diamonds in the rough", are detected: Madrid (Spain) for 1991 and 1992. The "doughnuts" or LH clusters are Brabant Wallon for 3 years, Hainault for 2 years and Namur for 3 years (Belgium), Friesland for 6 years and Drenthe for only one year (Netherlands), these regions constitute therefore a little pocket of non-stationnarity for a limited period of time[11].

[9] We can note that 66.1% of these indicators are significant at the 5% pseudo-significance level (1459 versus a total of 2208) and only 28.4% at the 10% Bonferroni pseudo-significance level (628 versus a total of 2208).

[10] Using the Bonferroni 10% pseudo-significance level, the picture is quite different since 11.78% of significant LISA fall in quadrant I and 16.67% of significant LISA fall in quadrant III, the latter including the regions with low per capita GDP surrounded by other regions with low per capita GDP.

[11] No atypical localization is found when the Bonferroni 10% pseudo-significance level is used.

Third, four regional clusters persist in time. The first is a significant LL form of clustering between all the Portuguese regions and almost all the Spanish regions. We can note that these “poor” regions entered the EU in 1986, that they benefited since 1989 of the regional aid to the so-called Objective 1 regions but that over all the period, the per capita GDP of these regions remains lower than the average. The same comment apply for the two LL form of clustering between some Italian Objective 1 regions (Puglia, Basilicata, Calabria, Sicilia) and between all the Greek regions (the Greek and the Portuguese regions are even significant using the 10% Bonferroni pseudo-significance level). The last clustering, of the HH type, relates mainly to German regions but also to some Belgian, French, Dutch and north Italian regions. However, most of the French regions that were significant in 1980 do not belong to the cluster any more in 1995 (only 4 northern regions of the 16 regions remain significant). These results show a high persistence of spatial inequality between the European regions across time: the regions that were surrounded by rich neighbors still benefit from their environment whereas the regions with poor neighbors remain negatively affected.

[Figures 3 and 4 about here]

The spatial outliers identified by the 2 sigma rule are shown in the last set of rows in table 2. In 1980, all the Portuguese regions as well as the Spanish region Extremadura indicated clustering of very similar values. The situation in 1995 is very different since the Portuguese regions are replaced by the Greek regions (only Alentejo remains a spatial outlier).

3.4 Spatial patterns of growth rates

To refine this analysis, we apply the ESDA techniques to the growth rates of per capita GDP in order to study the geographical patterns in growth processes.

The computation of Moran’s I statistics on the growth rate of per capita GDP between 1980 and 1995 of the various regions reveals a positive spatial autocorrelation (0.422 with a p-value of 0.0001). It means that the regions with relatively high per capita GDP growth rate (respectively low) are localized close to other regions with relatively high per capita GDP growth rate (respectively low) more often than if this localization was purely random.

The Moran scatterplot for growth rates is displayed in figure 5. Compared to the scatterplots for per capita GDP in 1980 and 1995, there is much more instability: only 73.2% of the European regions show association of similar values (33.3% in quadrant I (HH) and 39.9% in quadrant III (LL)) while 26.8% of the regions are negatively associated (11.6% in quadrant II (LH) and 15.2% in quadrant IV (HL)). All the Portuguese regions have growth rates more than two standard deviations above the mean. Let's recall that they were outliers in the opposite quadrant in 1980. We will come back to this inverse relationship between the per capita GDP in 1980 and growth rates at the end of this paragraph. Finally, the most extreme observations according to the Moran regression diagnostics are shown in the last column of table 2. As for per capita GDP in 1980 and 1995, there was no influential region according to the Cook's distance criterion.

[Figure 5 about here]

The procedure of evaluation of local spatial autocorrelation applied to the growth rates (table 4, 3rd column) shows that the patterns of spatial association remain dominated by clustering of LL or HH types[12]. Galicia and Asturias in Spain are the 2 regions with low growth rates surrounded by regions with high growth rates. The regions with high growth rates surrounded by regions with low growth rates are to be found in Greece : Anatoliki Makedonia, Ionia Nisia and Kriti. The significant LISA at the 5% level are shown in figure 6.

[Figure 6 about here]

To study the possible geographical characteristics implied by b -convergence processes, we compared the pattern of spatial association of growth rate with the pattern of spatial association of initial per capita GDP

[12] 42.7% (15.2%) of the LISA computed are significant at the 5% pseudo-level (resp. 10% Bonferroni pseudo-level).

(table 4, first and 3rd columns) in order to look for a possible inverse relationship. Several results can be underlined.

It appears that, in only 43% of the cases, the regions that were in a certain quadrant for per capita GDP level in 1980 are in the opposite quadrant for their growth rate. But this global feature masks different behaviors. Thus, the regions of Portugal and some Spanish regions had in 1980 a low per capita GDP and were surrounded by regions with low per capita GDP (clustering of the LL type) but their growth rate is, as for their neighbors, higher than the average (clustering of the HH type). The spatial autocorrelation indicators highlight the dynamic character of these regions, whose economic performances within the group of the Southern regions of Europe were often underlined. On the contrary, the majority of the French regions, the British regions, some regions in Belgium and in the Netherlands, are characterized by a configuration of the initial per capita GDP of HH type and a configuration of the growth rates of the LL type.

Other characteristics between the patterns of spatial association can be highlighted. On the one hand, within the group of the Southern regions, certain poor regions of Spain, Italy and Greece do not manage to take off, just like their neighbors (configurations of the LL type for the initial per capita GDP and the growth rates) or in spite of the dynamism of their neighbors (configuration of the LL type for the initial per capita GDP and of LH type for the growth rates). These regions thus show strong signs of delay of development. On the other hand, almost all the German regions are very dynamic since they started with high levels, as well as their neighbors and still had a HH type form of clustering for their growth rates.

[Table 4 about here]

4 Conclusion

The study of the spatial distribution of regional per capita GDP in Europe over 1980-1995 using Exploratory Spatial Data Analysis (ESDA) highlights the importance of spatial interactions and geographical locations in regional growth and convergence issues. ESDA appears therefore as a powerful tool to finely reveal the characteristics of economic development of each region in relation to those of its geographical environment.

First, ESDA reveals significant positive global spatial autocorrelation, which is persistent over the whole period: regions with relatively high (resp. low) per capita GDP are and remain localized close to other regions with relatively high (low) per capita GDP and that the spatial distribution of regional per capita GDP is not random. From the applied econometrics perspective, this result has a major implication for the suitable estimation of b-convergence models: spatial autocorrelation should systematically be tested for in cross section specifications and if detected, an appropriate spatial specification (spatial autoregressive model, spatial error model or spatial cross regressive model) should be estimated using the proper econometric tools to achieve reliable statistical inference.

Second, the Moran scatterplot and LISA show the persistence of the high-high and low-low clustering types for regional per capita GDP, confirming the north-south polarization of European regions. This reveals some kind of spatial heterogeneity hidden in the global positive spatial autocorrelation pattern and may indicate the co-existence of two distinct spatial regimes. Spatial effects could then perform differently in Northern Europe than in Southern Europe. Moreover the convergence process, if it exists, may be different across regimes. Once again from the applied econometrics perspective, this result suggest that the potential for distinct spatial regimes should also be considered carefully in the estimation of b-convergence models, which should be tested for structural instability. All these aspects will be studied in further research.

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Table 1. Moran's *I* statistics for log per capita GDP over 1980-1995

Year	Moran's I	Standard deviation	Standardized value
1980	0.774	0.033940	23.024
1981	0.760	0.033971	22.574
1982	0.746	0.033956	22.161
1983	0.779	0.034083	23.060
1984	0.757	0.034019	22.446
1985	0.766	0.034077	22.692
1986	0.785	0.034126	23.213
1987	0.789	0.034164	23.289
1988	0.773	0.034196	22.802
1989	0.750	0.034221	22,113
1990	0.762	0.034242	22.461
1991	0.754	0.034311	22.174
1992	0.770	0.034323	22.651
1993	0.790	0.034272	23.259
1994	0.799	0.034267	23.514
1995	0.802	0.034222	23.653

Note: The expected value for Moran's I statistic is constant for each year: $E(I) = -0.007$. All statistics are significant at $p = 0.0001$.

Table 2. Outliers : initial and terminal years and growth rates for log per capita GDP

	1980		1995		Growth	
Studentized residuals exceeding 2 in absolute value	**Region**	**Studentized Residual**	**Region**	**Studentized Residual**	**Region**	**Studentized Residual**
	Sterea Ellada	-3.445158	Ile de France	-3.139385	Andalucia	3.497511
	Bruxelles	-2.893242	Hamburg	-2.886250	Extremadura	2.822284
	Hamburg	-2.500151	Bruxelles	-2.654439	Galicia	2.745314
	Attiki	-2.298205	Luxembourg (Lux)	-2.612451	Luxembourg (Lux)	-2.666020
	Ile de France	-2.225954	Attiki	-2.337432	Asturias	2.591420
	Asturias	-2.099516	Darmstadt	-2.130149	Kriti	-2.436728
	Lüneburg	2.073019	Madrid	-2.005542	Ionia Nisia	-2.195220
					Notio Aigaio	-2.142425
leverage exceeding 4/N	**Region**	**Leverage**	**Region**	**Leverage**	**Region**	**Leverage**
	Centro	0.072428	Ipeiros	0.052553	Algarve	0.105763
	Norte	0.065610	Hamburg	0.046399	Centro	0.102492
	Alentejo	0.062048	Voreio Aigaio	0.040424	Norte	0.089878
	Algarve	0.058095	Alentejo	0.038027	Sterea Ellada	0.065942
	Voreio Aigaio	0.038353	Darmstadt	0.037616	Lisboa	0.064531
	Hamburg	0.036314	Centro	0.034994	Luxembourg (Lux)	0.055558
	Extremadura	0.035489	Norte	0.032597	Alentejo	0.054656
	Ipeiros	0.035076	Dyptiki Ellada	0.031850	Picardie	0.030390
	Bruxelles	0.032278	Oberbayern	0.031539		
	Lisboa	0.031164	Luxembourg (Lux)	0.030974		
	Ionia Nisia	0.029664	Peloponnissos	0.030740		
	Anatoliki Makedonia	0.029641	Bremen	0.029290		
LISA outliers (2-sigma rule)	**Region**	**LISA**	**Region**	**LISA**	**Region**	**LISA**
	Extremadura	3.668896	Anatoliki Makedonia	2.995502	Norte	3.708258
	Norte	4.323912	Kentriki Makedonia	2.587855	Centro	5.333233
	Centro	5.100167	Dyptiki Makedonia	2.769021	Lisboa	4.516306
	Lisboa	3.432059	Thessalia	2.891856	Alentejo	4.173558
	Alentejo	4.938435	Ipeiros	3.841003	Algarve	5.762157
	Algarve	4.744208	Ionia Nisia	2.69785		
			Dyptiki Ellada	3.108809		
			Sterea Ellada	2.663872		
			Peloponissos	3.045441		
			Voreio Aigaio	3.275564		

		Alentejo	2.801488	

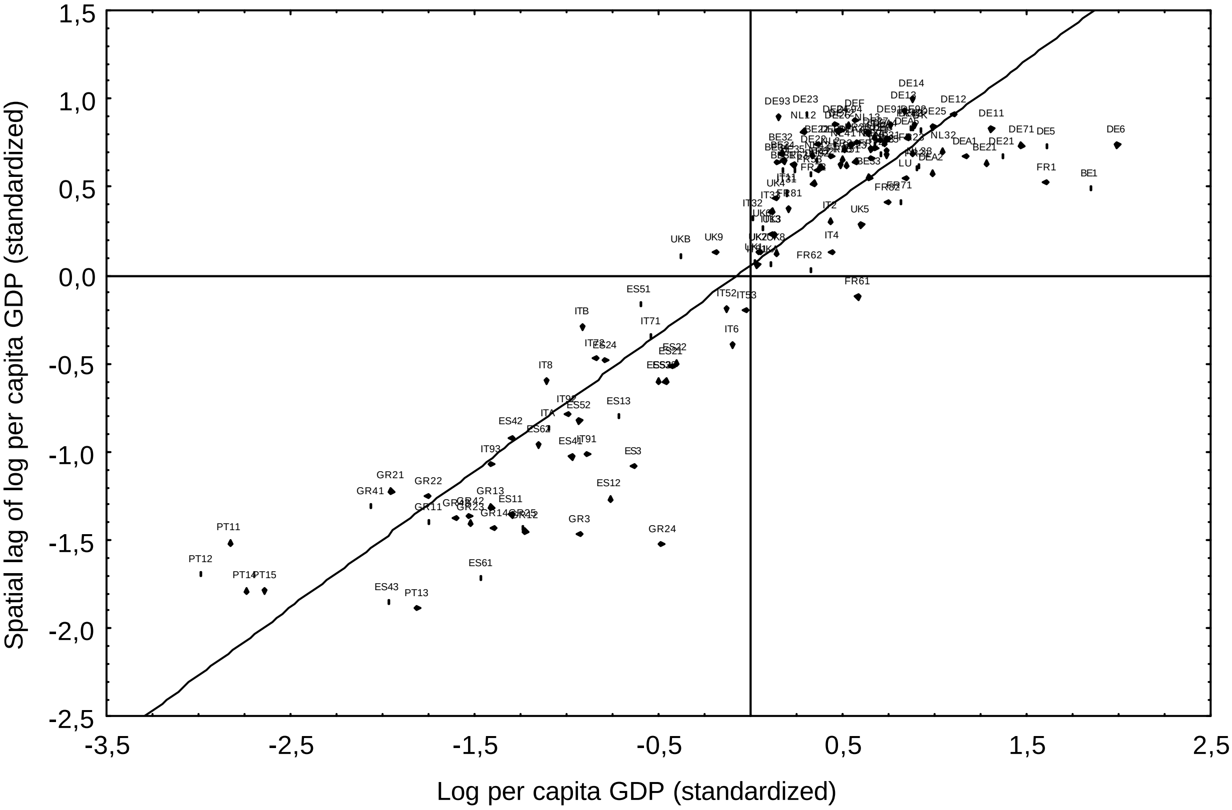

Fig. 1. Moran scatterplot for log per capita GDP 1980

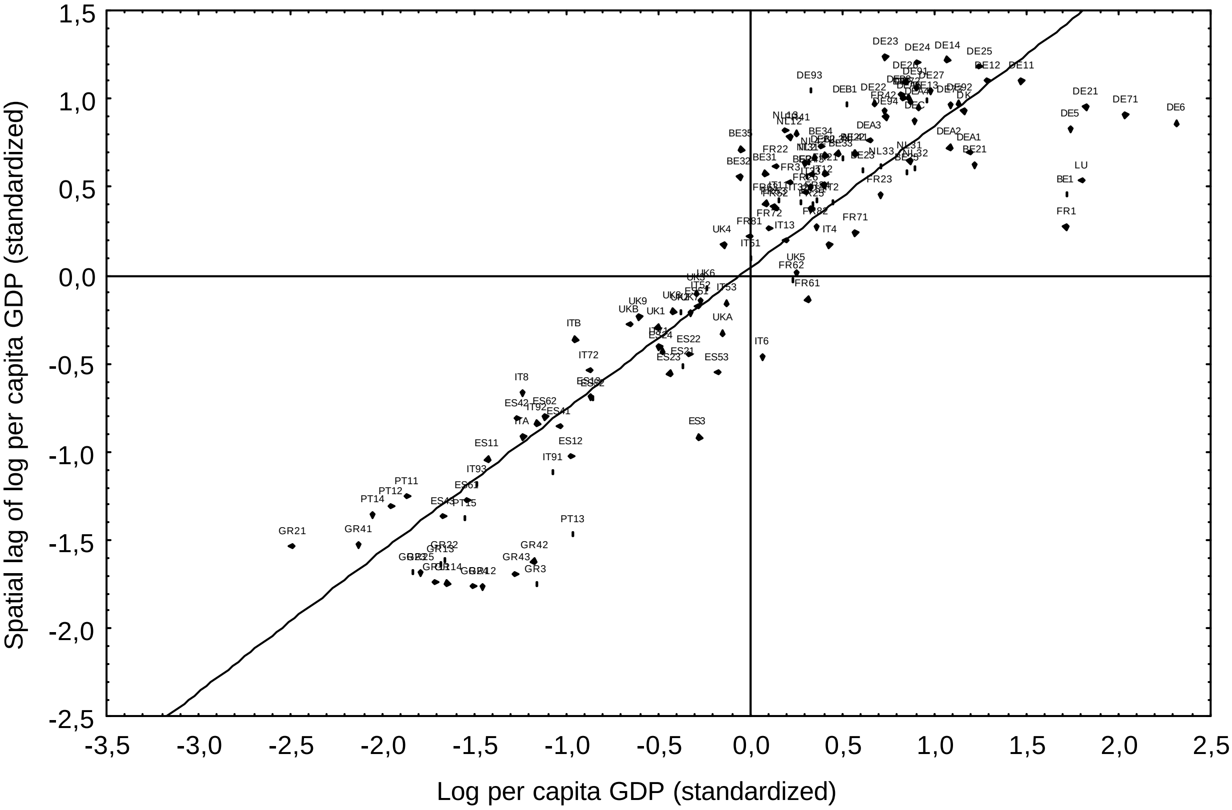

Fig. 2. Moran scatterplot log per capita GDP 1995

Table 3. Local Indicators of Spatial Association (LISA): Log per capita GDP (1980-1995)

Code	Region	Signif	HH	LH	LL	HL	Years 5%	Years 10% Bonf.
	BELGIUM							
Be1	Bruxelles	1 (0)	1				80	
Be21	Anvers	6 (0)	6				80-81;87; 93-95	
Be22	Limburg (B)	12 (0)	12				80-83;85-88;92-95	
Be23	Oost Vlaanderen	4 (0)	4				80-81;94-95	
Be24	Vlaams Brabant	4 (0)	4				80-81;94-95	
Be25	West Vlaanderen	5 (0)	5				80-81;93-95	
Be31	Brabant Wallon	5 (0)	2	3			80;95 / 81;93-94	
Be32	Hainaut	4 (0)	2	2			80-81 / 94-95	
Be33	Liège	4 (0)	4				80;93-95	
Be34	Luxembourg (B)	9 (0)	9				80-81;86-88;92-95	
Be35	Namur	5 (0)	2	3			80-81 / 93-95	
	GERMANY							
De11	Stuttgart	16 (15)	16 (15)				80-95	80;82-95
De12	Karlsruhe	16 (16)	16 (16)				80-95	80-95
De13	Freiburg	16 (16)	16 (16)				80-95	80-95
De14	Tübingen	16 (16)	16 (16)				80-95	80-95
De21	Oberbayern	16 (9)	16 (9)				80-95	83-84;87-88;91-95
De22	Niederbayern	16 (9)	16 (9)				80-95	87-95
De23	Oberpfalz	16 (16)	16 (16)				80-95	80-95
De24	Oberfranken	16 (13)	16 (13)				80-95	83-95
De25	Mittelfranken	16 (15)	16 (15)				80-95	80;82-95
De26	Unterfranken	16 (13)	16 (13)				80-95	83-95
De27	Schwaben	16 (13)	16 (13)				80-95	83-95
De5	Bremen	16 (0)	16				80-95	
De6	Hamburg	16 (3)	16 (3)				80-95	93-95
De71	Darmstadt	16 (2)	16 (2)				80-95	93;95
De72	Giessen	16 (11)	16 (11)				80-95	80;83-84;86-88;91-95
De73	Kassel	16 (4)	16 (4)				80-95	92-95
De91	Braunschweig	16 (11)	16 (11)				80-95	80;82-84;87-88;91-95
De92	Hannover	16 (7)	16 (7)				80-95	80;82-84;93-95
De93	Lüneburg	16 (14)	16 (14)				80-95	80-88;91-95
De94	Weser-Ems	16 (5)	16 (5)				80-95	80-83;95
Dea1	Düsseldorf	14 (0)	14				80-90;93-95	
Dea2	Köln	14 (0)	14				80-81;83;85-95	
Dea3	Münster	16 (0)	16				80-95	
Dea4	Detmold	16 (2)	16 (2)				80-95	93;95
Dea5	Arnsberg	16 (3)	16 (3)				80-95	93-95
Deb1	Koblenz	16 (3)	16 (3)				80-95	93-95
Deb2	Trier	12 (0)	12				80-81;85-90;92-95	
Deb3	Rheinhessen-Pfalz	16 (16)	16 (16)				80-95	80-95
Dec	Saarland	16 (0)	16				80-95	
Def	Schleswig-Holstein	16 (10)	16 (10)				80-95	81-87;93-95
Dk	***DENMARK***	16 (7)	16 (7)				80-95	80;82-84;93-95
	SPAIN							
Es11	Galicia	16 (15)			16 (15)		80-95	80-91;93-95
Es12	Asturias	16 (10)			16 (10)		80-95	80-88;94
Es13	Cantabria	16 (0)			16		80-95	
Es21	Pais Vasco	9 (0)			9		81-87 ;94-95	
Es22	Navarra	7 (0)			7		81-87	
Es23	La Rioja	11(0)			11		80-88;94-95	
Es24	Aragon	4 (0)			4		82-85	
Es3	Madrid	16 (7)			14 (7)	2	80-90;93-95/91-92	81-87
Es41	Castilla-Leon	16 (5)			16 (5)		80-95	81-85
Es42	Castilla-la Mancha	16 (2)			16 (2)		80-95	82-83
Es43	Extremadura	16 (16)			16 (16)		80-95	80-95
Es51	Cataluna	0 (0)						
Es52	Valenciana	13 (0)			13		80-89;93-95	
Es53	Islas Baleares	9 (0)			9		80-86;94-95	
Es61	Andalucia	16 (16)			16 (16)		80-95	80-95
Es62	Murcia	16 (5)			16 (5)		80-95	81-85
	FRANCE							
Fr1	Ile de France	2 (0)	2				80-81	
Fr21	Champagne-Ardenne	9 (0)	9				80-82 ;85-87 ;93-95	
Fr22	Picardie	10 (0)	10				80-83;85-87;93-95	
Fr23	Haute-Normandie	10 (0)	10				80-89	
Fr24	Centre	8 (0)	8				80-87	
Fr25	Basse-Normandie	10 (0)	10				80-89	
Fr26	Bourgogne	11 (1)	11(1)				80-90	81

Fr3	Nord-Pas-De-Calais	3 (0)	3				80-81;95	
Fr41	Lorraine	16 (0)	16				80-95	
Fr42	Alsace	16 (2)	16 (2)				80-95	80;95
Fr43	Franche-Comté	16 (0)	16				80-95	
Fr51	Pays de la Loire	8 (0)	8				80-87	
Fr52	Bretagne	10 (0)	10				80-89	
Fr53	Poitou-Charentes	8 (0)	8				80-87	
Fr61	Aquitaine	0 (0)						
Fr62	Midi-Pyrénées	0 (0)						

Code	Region		HH	LH	LL	HL	Years 5%	Years 10% Bonf.
Fr63	Limousin	9 (0)	9				80-88	
Fr71	Rhône-Alpes	2 (0)	2				86-87	
Fr72	Auvergne	4 (0)	4				80-82 ;86	
Fr81	Languedoc-Roussillon	0 (0)						
Fr82	PACA	9 (0)	9				83-91	
	GREECE							
Gr11	Anatoliki Makedonia	16 (16)			16 (16)		80-95	80-95
Gr12	Kentriki Makedonia	16 (16)			16 (16)		80-95	80-95
Gr13	Dytiki Makedonia	16 (16)			16 (16)		80-95	80-95
Gr14	Thessalia	16 (16)			16 (16)		80-95	80-95
Gr21	Ipeiros	16 (16)			16 (16)		80-95	80-95
Gr22	Ionia Nisia	16 (16)			16 (16)		80-95	80-95
Gr23	Dytiki Ellada	16 (16)			16 (16)		80-95	80-95
Gr24	Sterea Ellada	16 (16)			16 (16)		80-95	80-95
Gr25	Peloponnisos	16 (16)			16 (16)		80-95	80-95
Gr3	Attiki	16 (16)			16 (16)		80-95	80-95
Gr41	Voreio Aigaio	16 (16)			16 (16)		80-95	80-95
Gr42	Notio Aigaio	16 (16)			16 (16)		80-95	80-95
Gr43	Kriti	16 (16)			16 (16)		80-95	80-95
	ITALY							
It11	Piemonte	14 (0)	14				81-94	
It12	Valle d'Aosta	16 (0)	16				80-95	
It13	Liguria	10 (0)	10				83-92	
It2	Lombardia	12 (3)	12 (3)				83-94	89-91
It31	Trentino – Alto Adige	15 (2)	15 (2)				81-95	90-91
It32	Veneto	12 (1)	12 (1)				83-94	91
It33	Friuli – Venezia Giulia	14 (1)	14 (1)				82-95	91
It4	Emilia – Romagna	9 (0)	9				84-92	
It51	Toscana	7 (0)	7				86-92	
It52	Umbria	0 (0)						
It53	Marche	0 (0)						
It6	Lazio	0 (0)						
It71	Abruzzo	0 (0)						
It72	Molise	1 (0)			1		95	
It8	Campania	4 (0)			4		80-82;95	
It91	Puglia	16 (2)			16 (2)		80-95	94-95
It92	Basilacata	6 (0)			6		80-82;93-95	
It93	Calabria	16 (2)			16 (2)		80-95	94-95
Ita	Sicilia	8 (0)			8		80-83;85;93-95	
Itb	Sardegna	0 (0)						
Lu	***LUXEMBOURG***	7 (0)	7				80-81;86-87;93-95	
	NEDERLAND							
Nl12	Friesland	16 (0)	10	6			80-87;93-95 / 85;88-92	
Nl13	Drenthe	16 (1)	15 (1)	1			80-91;93-95 / 92	80
Nl2	Oost Nederland	12 (0)	12				80-88;93-95	
Nl31	Utrecht	14 (0)	14				80-90;93-95	
Nl32	Noord-Holland	12 (0)	12				80-88;93-95	
Nl33	Zuid-Holland	5 (0)	5				80-81;93-95	
Nl34	Zeeland	5 (0)	5				80-81;93-95	
Nl41	Noord-Brabant	12 (0)	12				80-83;86-90;93-95	
Nl42	Limburg (NL)	6 (0)	6				80-81;87 ;93-95	
	PORTUGAL							
Pt11	Norte	16 (16)			16 (16)		80-95	80-95
Pt12	Centro	16 (16)			16 (16)		80-95	80-95
Pt13	Lisboa e vale do Tejo	16 (16)			16 (16)		80-95	80-95
Pt14	Alentejo	16 (16)			16 (16)		80-95	80-95
Pt15	Algarve	16 (16)			16 (16)		80-95	80-95
	UNITED-KINGDOM							
Uk1	North	0 (0)						
Uk2	Yorkshire and Humberside	0 (0)						

Uk3	East Midlands	0 (0)						
Uk4	East Anglia	1 (0)	1				81	
Uk5	South East	0 (0)						
Uk6	South West	0 (0)						
Uk7	West Midlands	0 (0)						
Uk8	North West	0 (0)						
Uk9	Wales	0 (0)						
Uka	Scotland	0 (0)						
Ukb	Northern Ireland	0 (0)						
	Signif. tot. 5%	1459	908	15	534	2		
	% versus total of 2208	66.08	41.12	0.68	24.18	0.09		
	% versus signif. tot. 5%		62.23	1.03	36.6	0.14		
	Signif. tot. 10% Bonf.	(628)	(260)	(0)	(368)	(0)		
	% versus total of 2208	28.44	11.78	0	16.67	0		
	% versus signif. tot. 10%		41.4	0	58.6	0		

Note: signif: number of years local statistics is significant at 5% pseudo-significance level (in brackets at 10% Bonferroni pseudo-significance level) based on 10000 permutations; HH, LH, LL and HL: number of years local statistics is respectively in quadrant I, II, III and IV of Moran's scatterplot.

TABLE 4. Spatial Association Patterns: initial and terminal years and growth rates for log per capita GDP (1980-1995)

Code	Region	1980	1995	growth
	BELGIUM			
Be1	Bruxelles	**HH**	HH	LL
Be21	Anvers	**HH**	**HH**	LL
Be22	Limburg (B)	**HH**	**HH**	HL
Be23	Oost Vlaanderen	**HH**	**HH**	LL
Be24	Vlaams Brabant	**HH**	**HH**	HL
Be25	West Vlaanderen	**HH**	**HH**	HL
Be31	Brabant wallon	**HH**	**HH**	LL
Be32	Hainaut	**HH**	**LH**	**LL**
Be33	Liège	**HH**	**HH**	LH
Be34	Luxembourg (B)	**HH**	**HH**	HH
Be35	Namur	**HH**	**LH**	LH
	GERMANY			
De11	Stuttgart	**HH***	**HH***	**HH**
De12	Karlsruhe	**HH***	**HH***	HH
De13	Freiburg	**HH***	**HH***	HL
De14	Tübingen	**HH***	**HH***	HH
De21	Oberbayern	**HH**	**HH***	**HH**
De22	Niederbayern	**HH**	**HH***	**HH**
De23	Oberpfalz	**HH***	**HH***	**HH**
De24	Oberfranken	**HH**	**HH***	**HH**
De25	Mittelfranken	**HH***	**HH***	**HH**
De26	Unterfranken	**HH**	**HH***	**HH**
De27	Schwaben	**HH**	**HH***	**HH**
De5	Bremen	**HH**	**HH**	HH
De6	Hamburg	**HH**	**HH***	HH
De71	Darmstadt	**HH**	**HH***	HH
De72	Giessen	**HH***	**HH***	HH
De73	Kassel	**HH**	**HH***	**HH**
De91	Braunschweig	**HH***	**HH***	HH
De92	Hannover	**HH***	**HH***	HH
De93	Lüneburg	**HH***	**HH***	HH
De94	Weser-Ems	**HH***	**HH***	HL
Dea1	Düsseldorf	**HH**	**HH**	LL
Dea2	Köln	**HH**	**HH**	HH
Dea3	Münster	**HH**	**HH**	HL
Dea4	Detmold	**HH**	**HH***	HH
Dea5	Arnsberg	**HH**	**HH***	LH
Deb1	Koblenz	**HH**	**HH***	HH
Deb2	Trier	**HH**	**HH**	HH
Deb3	Rheinhessen-Pfalz	**HH***	**HH***	LH
Dec	Saarland	**HH**	**HH**	HH
Def	Schleswig-Holstein	**HH**	**HH***	HH
Dk	***DENMARK***	**HH***	**HH***	HH
	SPAIN			
Es11	Galicia	**LL***	**LL***	**LH***
Es12	Asturias	**LL***	**LL**	**LH**
Es13	Cantabria	**LL**	**LL**	LH
Es21	Pais Vasco	LL	**LL**	HH
Es22	Navarra	LL	LL	HH
Es23	La Rioja	**LL**	**LL**	HH
Es24	Aragon	LL	LL	HH
Es3	Madrid	**LL**	**LL**	**HH**
Es41	Castilla-Leon	**LL**	**LL**	**HH**
Es42	Castilla-la Mancha	**LL**	**LL**	HH
Es43	Extremadura	**LL***	**LL***	**HH***
Es51	Cataluna	LL	LL	HL
Es52	Valenciana	**LL**	**LL**	**HH**
Es53	Islas Baleares	**LL**	**LL**	HH
Es61	Andalucia	**LL***	**LL***	**HH***
Es62	Murcia	**LL**	**LL**	**HH**
	FRANCE			
Fr1	Ile de France	**HH**	HH	**LL**
Fr21	Champagne-Ardenne	**HH**	**HH**	LL
Fr22	Picardie	**HH**	**HH**	**LL**
Fr23	Haute-Normandie	**HH**	HH	**LL**
Fr24	Centre	**HH**	HH	**LL***
Fr25	Basse-Normandie	**HH**	HH	**LL***
Fr51	Pays de la Loire	**HH**	HH	**LL**
Fr52	Bretagne	**HH**	HH	**LL**
Fr53	Poitou-Charentes	**HH**	HH	**LL**
Fr61	Aquitaine	HL	HL	LL
Fr62	Midi-Pyrénées	HH	HL	LL
Fr63	Limousin	**HH**	HH	**LL**
Fr71	Rhône-Alpes	HH	HH	**LL**
Fr72	Auvergne	**HH**	HH	**LL***
Fr81	Languedoc-Roussillon	HH	LH	**LL**
Fr82	PACA	HH	HH	**LL**
	GREECE			
Gr11	Anatoliki Makedonia	**LL***	**LL***	**HL**
Gr12	Kentriki Makedonia	**LL***	**LL***	**LL**
Gr13	Dytiki Makedonia	**LL***	**LL***	**LL**
Gr14	Thessalia	**LL***	**LL***	**LL**
Gr21	Ipeiros	**LL***	**LL***	**LL**
Gr22	Ionia Nisia	**LL***	**LL***	**HL**
Gr23	Dytiki Ellada	**LL***	**LL***	**LL**
Gr24	Sterea Ellada	**LL***	**LL***	LL
Gr25	Peloponnisos	**LL***	**LL***	LL
Gr3	Attiki	**LL***	**LL***	**LL**
Gr41	Voreio Aigaio	**LL***	**LL***	HL
Gr42	Notio Aigaio	**LL***	**LL***	HL
Gr43	Kriti	**LL***	**LL***	**HL**
	ITALY			
It11	Piemonte	HH	HH	LL
It12	Valle d'Aosta	**HH**	**HH**	LL
It13	Liguria	HH	HH	HL
It2	Lombardia	HH	HH	LH
It31	Trentino – Alto Adige	HH	**HH**	HH
It32	Veneto	HH	HH	HH
It33	Friuli – Venezia Giulia	HH	**HH**	HH
It4	Emilia – Romagna	HH	HH	LH
It51	Toscana	HH	HH	LH
It52	Umbria	LL	LL	LH
It53	Marche	LL	LL	LH
It6	Lazio	LL	HL	HL
It71	Abruzzo	LL	LL	HL
It72	Molise	LL	**LL**	HL
It8	Campania	**LL**	**LL**	LL
It91	Puglia	**LL**	**LL***	LL
It92	Basilacata	**LL**	**LL**	LH
It93	Calabria	**LL**	**LL***	HL
Ita	Sicilia	**LL**	**LL**	LH
Itb	Sardegna	LL	LL	HL
Lu	***LUXEMBOURG***	**HH**	**HH**	HL
	NEDERLAND			
Nl12	Friesland	**HH**	**HH**	LL
Nl13	Drenthe	**HH***	**HH**	LL
Nl2	Oost Nederland	**HH**	**HH**	LL
Nl31	Utrecht	**HH**	**HH**	HL
Nl32	Noord-Holland	**HH**	**HH**	LL
Nl33	Zuid-Holland	**HH**	**HH**	LL
Nl34	Zeeland	**HH**	**HH**	LL
Nl41	Noord-Brabant	**HH**	**HH**	HL
Nl42	Limburg (NL)	**HH**	**HH**	LL
	PORTUGAL			
Pt11	Norte	**LL***	**LL***	**HH***
Pt12	Centro	**LL***	**LL***	**HH***
Pt13	Lisboa e vale do Tejo	**LL***	**LL***	**HH***
Pt14	Alentejo	**LL***	**LL***	**HH***
Pt15	Algarve	**LL***	**LL***	**HH***
	UNITED-KINGDOM			
Uk1	North	HH	LL	**LL***
Uk2	Yorkshire and Humberside	HH	LL	**LL***
Uk3	East Midlands	HH	LL	**LL***
Uk4	East Anglia	HH	LH	**LL**
Uk5	South East	HH	HH	**LL**

Fr26	Bourgogne	**HH**	HH	**LL***
Fr3	Nord-Pas-De-Calais	**HH**	**HH**	**LL**
Fr41	Lorraine	**HH**	**HH**	LH
Fr42	Alsace	**HH***	**HH***	LH
Fr43	Franche-Comté	**HH**	**HH**	**LL**

Uk6	South West	HH	LL	**LL***
Uk7	West Midlands	HH	LL	**LL***
Uk8	North West	HH	LL	**LL***
Uk9	Wales	LH	LL	**LL***
Uka	Scotland	HH	LL	**LL***
Ukb	Northern Ireland	LH	LL	**LL***

Note: in bold significant at 5% (***** significant at 10% Bonferroni) pseudo-signifiance level based on 10000 Permutations.

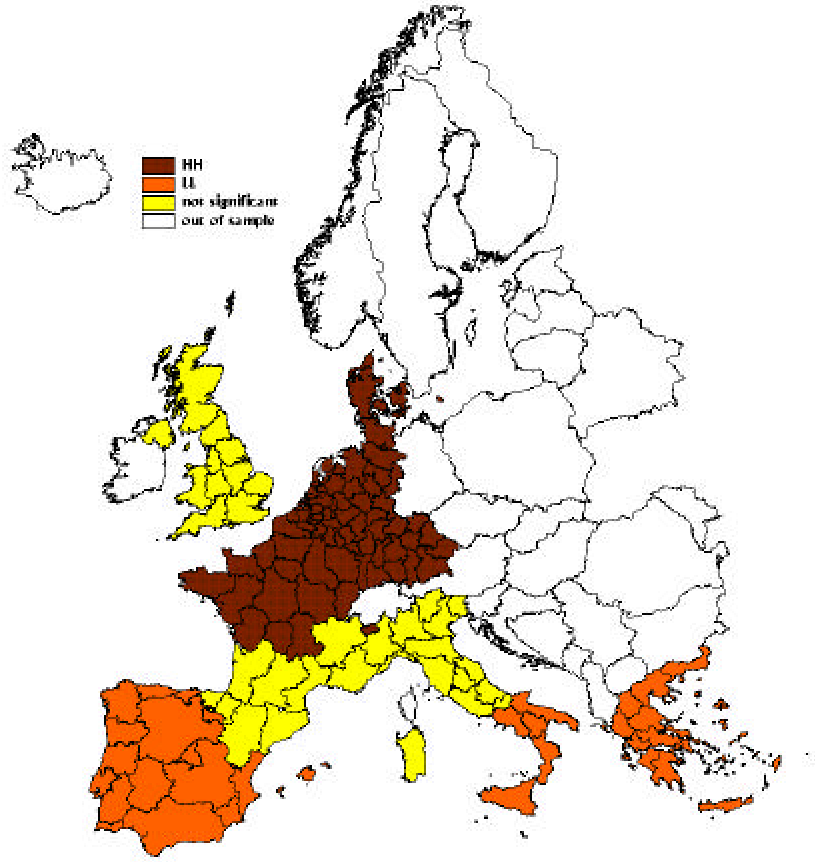

Fig. 3. Significant LISA Log per capita GDP 1980

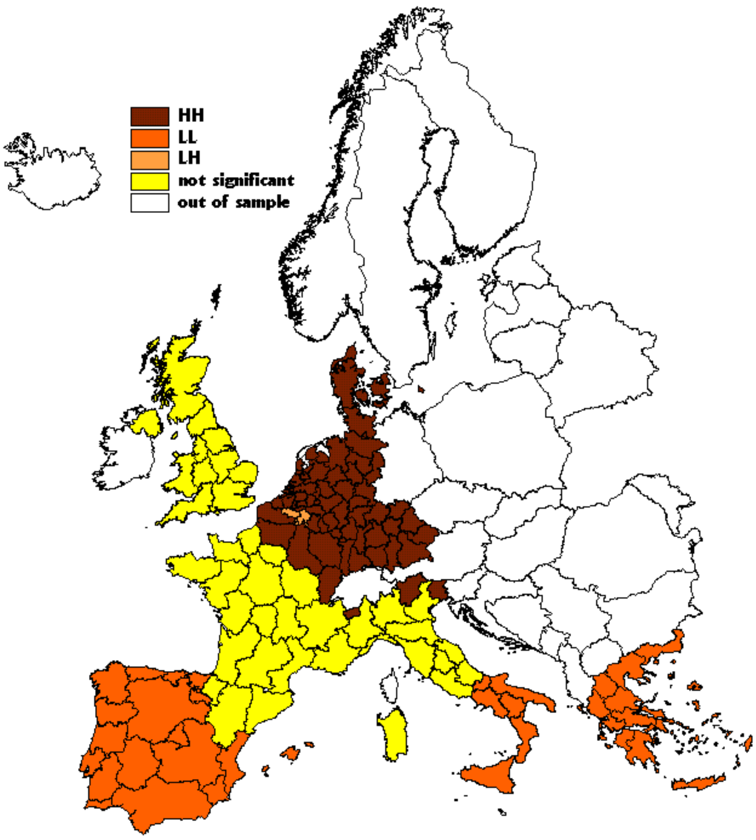

Fig. 4. Significant LISA Log per capita GDP 1995

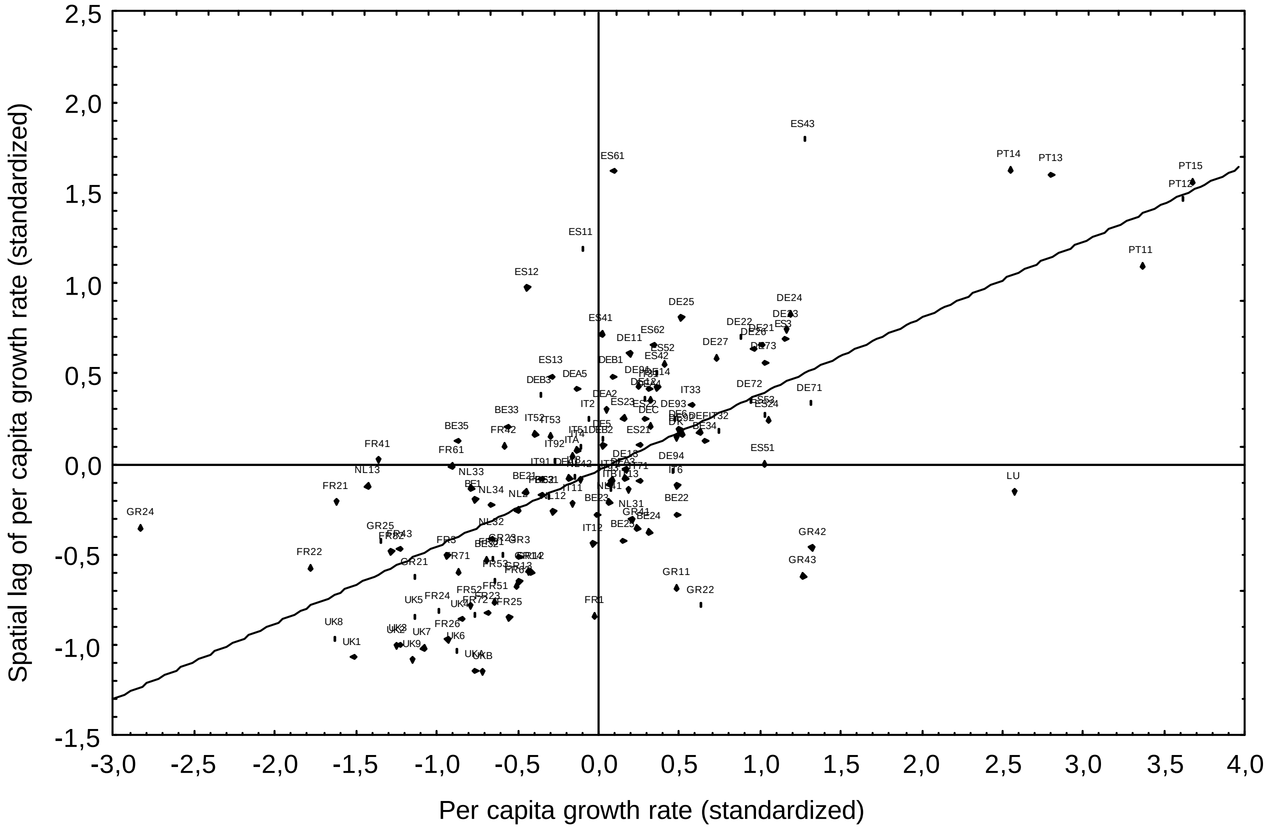

Fig. 5. Moran scatterplot growth rate of per capita GDP over 1980-1995

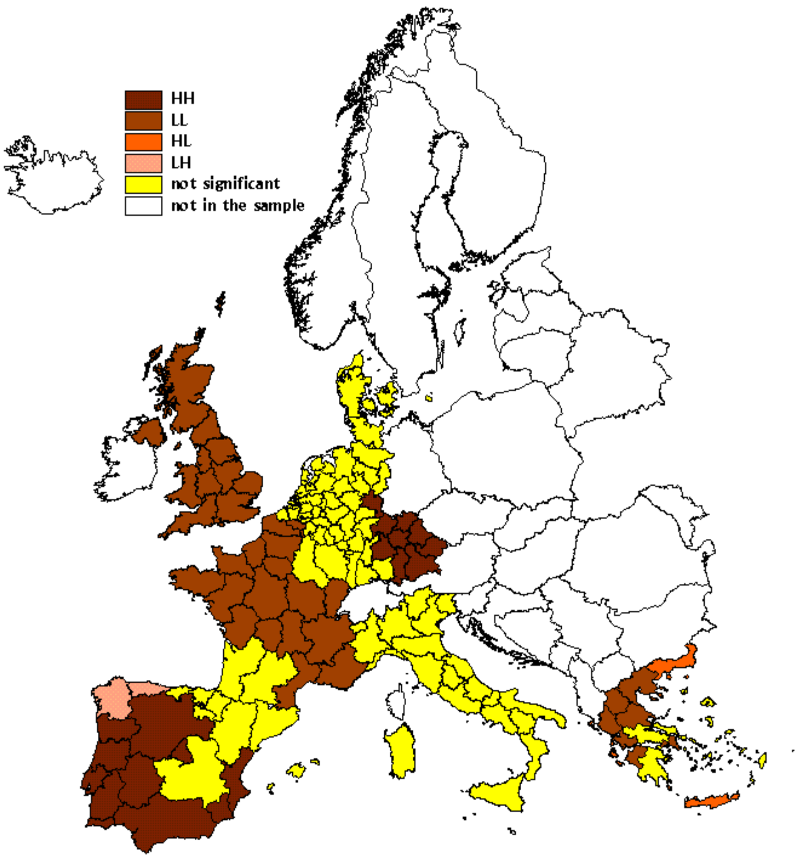

Fig. 6. Significant LISA growth rate of per capita GDP over 1980-1995