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SPATIAL HETEROGENEITY AND INTERREGIONAL SPILLOVERS IN EU: SOME EVIDENCE ABOUT THE EFFECTS OF COHESION POLICIES ON CONVERGENCE

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Spatial Heterogeneity and Interregional Spillovers in EU: Some Evidence about the Effects of Cohesion Policies on Convergence

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Abstract: In this work, using a spatial econometric perspective, the speed of convergence for a sample of 163 regions of the European Union over the period 1981-1996 is estimated. For this purpose, we use a specification strategy which allows an explicit modeling of both spatial heterogeneity and spatial autocorrelation found in the analyzed sample. The estimated final model combines groupwise-heterocedasticity, the identification of two regimes (Cohesion and non-Cohesion countries) and spatial dependence. Our results show how an appropriate treatment, simultaneously, of the problems derived from spatial structural instability and substantive spatial dependence can shed new insights into the European convergence process. One of the main findings of the paper is that the analysis opens a path to discern the ex-post general effects of European Union regional policies as a whole on the regional convergence process in terms of the Cohesion/Non Cohesion country dichotomy. Our estimations indicate that over the analyzed period there was a faster convergence in relative income levels of the regions belonging to Cohesion countries (5.3 per cent) than in the rest of the regions of the European Union (3.3 per cent). Therefore, our results contrast with other evidence that points to the fact that the convergence process in Europe stopped at the beginning of the 1980s.

JEL classification: C21, C51, O52, R11, R15
Keywords: regional growth, convergence, heterogeneity, spillovers, European Union

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Spatial Heterogeneity and Interregional Spillovers in EU: Some Evidence about the Effects of Cohesion Policies on Convergence

1. Introduction

In recent years, a growing interest in regional growth and convergence has been observed in the economic literature. At the European level, this interest is far more noticeable if one bears in mind that there exist significant regional disparities and that one of the main objectives of the EU, as recognized in the EU treaty, is the economic and social cohesion through the reduction of these disparities. During the last decade, there has been a wide literature discussing regional convergence, income distribution, labor productivity and economic disparities in EU regions.[1] Most of these studies point out that regional convergence in Europe is conditional upon a number of determinants. Furthermore, different approaches have explored the spatial dependence that characterizes regional growth in Europe. However, in most empirical work, spatial heterogeneity is not usually treated prior to the estimation of a spatial model to take into account spatial correlation [in spite of its recognition in spatial econometrics texts such as Anselin, 1988]. In the light of these findings, we propose a strategy based on the modeling of spatial heterogeneity, assessing later the issue of correction of the spatial correlation present in the sample.

Armstrong (2001) emphasizes that at the present time it is impossible to directly reconcile the evaluation evidence on regional policy with the evidence from the growth literature. This author distinguishes different ways to draw together evaluation and growth research, highlighting the lack of evidence to evaluate regional policy. This is due to serious problems like the variety of formal growth models and data limitations for explanatory and policy variables.

In the present paper, a simple empirical way is proposed to examine the effectiveness of regional policy in the European Union, to seek clear breaks in the analysis of per capita gross regional product placed within a formal growth theory approach. Thus, simply searching for different patterns of convergence within regions belonging to Cohesion (Greece, Ireland, Portugal and Spain) and Non-Cohesion countries in a neoclassical conditional model, it might be possible to explore the ex-post general effects of EU regional policies as a whole on the regional convergence process in terms of the Cohesion/Non Cohesion countries dichotomy.

[1] For an overview of recent studies of growth and convergence at the European regional level, see Armstrong (1995, 2001), Fingleton (2003) or Tondl (2001).

The structure of this paper is as follows. Section 2 presents a brief review of the empirical convergence model. Section 3 describes the data, presents an exploratory analysis of EU regional convergence and discusses the results of the estimations. Finally, the main conclusions drawn from this study are presented in Section 4.

2. Conceptual background in convergence analysis

Since Baumol's (1986) pioneering work, questions centered on regional convergence have gained interest in the economic literature (De la Fuente, 1997, Durlauf and Quah, 1999, Islam, 2003, Magrini, 2003, Sala-i-Martin, 1996a, or Temple, 1999, present outstanding surveys on this topic). Several types of convergence have been suggested in the literature (see Boyle and McCarthy, 1999): catching-up in per capita income levels (β-convergence), decline in the cross-sectional dispersion of per capita incomes (σ-convergence) or changes in the rankings of relative per capita income (γ-convergence). These indicators of convergence are referred to in the literature as cross-section tests. Also, alternative concepts of convergence based on time series, panel data or distribution methodologies have been used.

The convergence indicator used in this study is the so-called β-convergence. This type of convergence suggests that regional levels of per capita income do tend to converge since, on average, poor regions grow faster than the rich ones (less developed regions would be catching-up with more advanced regions). Consequently, β-convergence implies a negative correlation between growth rates of per capita income and the initial levels of this variable, that is, a positive correlation between growth rates and the distance of a region from its steady state. Using this type of approach to convergence, we are conscious of at least two limitations of our analysis. First, we do not address the issue outlined by Friedman (1992) or Quah (1993b) that regressions of the type carried out here are a form of Galton's fallacy of regression towards the mean.[2] Of course, we are by no means alone in carrying out this sort of cross-sectional regressions. Secondly, the β convergence concept (or any one of the other cross-section convergence approaches) does not provide evidence about the dynamics of the whole regional income distribution. However, other more qualified tools (associated with the work of Quah, 1993a) do

[2] If there is measurement error in output and if this measurement error is uncorrelated over time then, in a cross-sectional regression of the growth rate of output on the initial level, a significantly negative coefficient is likely to be estimated even if there is no such relationship or even if there is actually a tendency to divergence.

not provide an explicit quantification of the difference in the rates of convergence of the growth clusters detected here.

If we denote by y_{it} the level of real gross domestic product per capita (*GDPpc*) in region *i* at time *t*, it is well known that the linearization of the neoclassical growth model (Solow, 1956) yields the following cross-sectional specification (Mankiw *et al*., 1992):

$$g_{it} = \left(\log y_{it} - \log y_{i0}\right)/t = \alpha - \beta \log y_{i0} + \varepsilon_{it} \tag{1}$$

where g_{it} is the rate of growth of *GDPpc* in region *i* over the period [0, t], α and $\beta = \left(1 - e^{-\theta t}\right)/t$ are the parameters to be estimated, and θ is the average regional rate of convergence to the steady state.

As usual in the empirical growth literature, in order to control the differences in the initial conditions that could be potentially relevant for explaining a persistent degree of inequality among regions, we extend the above specification by introducing a set of variables X_0 conditioning the steady state of each region. If these variables are significant, the regions will converge to their own steady state, although there will exist permanent cross-region differences in per capita income levels. Therefore, the initial empirical model that is proposed for testing the conditional convergence hypothesis is:

$$g_{it} = \alpha - \beta \log y_{i0} + \gamma_1 x_{1,i0} + \gamma_2 x_{2,i0} + \ldots + \gamma_k x_{k,i0} + \varepsilon_{it} \tag{2}$$

In this expression, the α, β and γ_j parameters are assumed to be constant across regions. However, the convergence club hypothesis by Durlauf and Johnson (1995) allows (group) cross-region variation of the parameters in (2). Intuitively, convergence clubs refer to economies that are similar in structural characteristics and tend to converge within groups (see, for example, Armstrong, 1995, for an application to EU regions; Chatterji and Dewhurst, 1996, for a regional application at the county level in Great Britain; or Quah, 1996b, for an application to the US federal states). More formally, this concept is based on endogenous growth models that are characterized by (possible) multiple and locally stable steady states (see Krugman, 1991). The equilibrium reached by each region will depend on the range within which its initial conditions belong or other (spatial or a-spatial) attributes.

This hypothesis contrasts with that of conditional convergence, where each region approaches its own (unique and globally stable) steady state. Nevertheless, it is not clear whether the observed differences in regional per capita income levels reflect either conditional convergence or the membership of different convergence clubs due to initial condition disparities (Durlauf and Johnson, 1995; Johnson and Takeyama, 2001). This is one of the challenges that remains for the current convergence literature (Islam, 2003).

3. Data and results

This section starts by describing the data used and by offering an Exploratory Spatial Data Analysis (ESDA) in order to test whether spatial heterogeneity and spatial dependence are present in the sample. Next, the conditional convergence model presented above is estimated and the estimation results are discussed.

3.1. Data

The database employed in the analysis was obtained from the REGIO database elaborated by the Statistical Office of the European Communities (Eurostat) and covers the period 1981-1996. Our sample includes 163 NUTS-2 regions[3] of 12 EU countries: Belgium (11), Denmark (1), France (22), Germany (30), Greece (13), Holland (10), Ireland (1), Italy (20), Luxembourg (1), Portugal (5), Spain (17), and United Kingdom (32).

To measure income for the 163 EU regions, we use data on per capita GDP in Euros at 1985 prices. We express this variable in logarithms and in deviations with respect to the EU12 mean since, working with scaled per capita GDP, the co-movements due to the European economy-wide business cycle and the effect of trends in the average of regional GDP are eliminated and also the effect of the outliers is reduced. In this manner, equation (2) becomes

$$\Gamma_{it} = \alpha - \beta\left(\log y_{i0} - \log y_{UE,0}\right) + \gamma_1 x_{1,i0} + \gamma_2 x_{2,i0} + \ldots + \gamma_k x_{k,i0} + \varepsilon_{it} \qquad \text{(Model 1)}$$

where $\Gamma_{it} = g_{it} - g_{UE,t}$ is the rate of growth of per capita GDP in region *i* for the period 1981-1996 relative to that in the EU12.

As for the economic and social indicators used to control the specific characteristics of each region at the beginning of the time period under study, the limitations of the Eurostat REGIO database prevented us from using complete information about initial interregional disparities. However, we have used two variables to maintain constant the steady state of each economy: the weight of the agricultural sector (measured by the share of agricultural to total employment) and

[3] NUTS is an acronym of the French for the Nomenclature of Territorial Units for Statistics.

the regional employment rate (measured by the ratio of employment to population).[4] The former allows us to partially capture interregional disparities of the productive systems and the influence of low-productivity agricultural sector-dependent regions, whereas the latter quantifies the effect of labor market disparities (in this sense, a low employment rate might be due either to a high rate of unemployment or to a specific demographic structure of the population). In spite of the consideration of only two variables, and according to the European Commission (1999), these variables represent two of the more important and underlying factors when one tries to explain the observed differences on competitiveness between European regions for the period 1980-1996.

3.2. Exploratory analysis

In this section we will explore the geographic dimension of the data used in this work. All computations in this and the next section were carried out by using SpaceStat 1.91 (Anselin, 2002a), DynESDA 2.0 (Anselin, 2002b) and ArcView GIS 3.2 (ESRI, 1999) software packages.

First, we test global spatial autocorrelation for the initial per capita income by using Moran's *I* statistic (Cliff and Ord, 1981), $I = \dfrac{z'Wz}{z'z}$, where z_{it} is the log of *GDPpc* in region *i* at time *t*=1981, W is a row-standardized spatial weights matrix defined as $w_{ij} = w^*_{ij} \big/ \sum_j w^*_{ij}$, where

$$\begin{cases} w^*_{ij} = 0 \quad if \quad i = j \\ w^*_{ij} = 1/d^2_{ij} \quad if \quad d_{ij} \le Me \\ w^*_{ij} = 0 \quad if \quad d_{ij} > Me \end{cases}$$

, d_{ij} is the great circle distance between centroids of regions *i* and *j*, and Me is the median of the great circle distance distribution.[5]

The value of *I* for the 1981 per capita GDP was 0.5038, well above the expected value for this statistic under the null hypothesis of no spatial correlation, E[*I*]=-0.0062. It appears that the initial per capita income is spatially correlated since the statistic is strongly significant with

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[4] Because log of per capita GDP is the sum of the logs of productivity (GDP/employment) and employment rate (employment/population), and we are using the regional employment rate as conditioning variable, the differences between per capita GDP and productivity are partially captured.

[5] Also, we used other alternative definitions for the spatial weights matrix. Specifically, we used different distance weights matrices (defining the elements w^*_{ij} as the inverse of the distances, and changing the median for the lower quartile, the upper quartile and the maximum distance) and other binary matrices (rook and queen contiguity matrices, and *k*-nearest neighbours spatial weight matrices for *k*=5,10,15,20). All these matrices generated results very similar to those presented in this paper, so we omit them for the sake of brevity. Complete results are available from the authors upon request.

Other weights based on socio-economic distance as in Doreian (1980), Case *et al.* (1993), Conley and Topa (2002) have been also suggested in the literature. In this study, however data limitations do not allow us to work with this possibility.

p=0.0010. This result reveals the existence of a strong positive and statistically significant degree of spatial dependence in the distribution of regional per capita GDP in 1981. Similar results were found for both log *GDPpc* in 1996 and the change of *GDPpc* from 1981 to 1996. In these cases, I=0.4879 with p=0.001 and I=0.1873 with p=0.001, respectively.

Figure 1 shows the spatial distribution of regional per capita GDP in 1981, figure 2 provides a clearer view of the spatial autocorrelation in this year through the Moran scatterplot,[6] and in figure 3 the local Moran statistics -LISA[7] (Anselin, 1995) are mapped for each region. All these figures show a strong core-periphery pattern and reveal the presence of spatial heterogeneity in the form of two spatial clusters of rich and poor regions, with the poorest economies cluster including the regions of Ireland, Greece, Portugal and Spain and several regions in the south of Italy. The same core-periphery pattern was displayed when either the 1996 per capita incomes or the 1981-1996 regional growth rates were used. [8]

Observing the differences between the two groups of regions, it is clear that there is a sharp distinction between Objective 1 areas (*GDPpc*<75 per cent of EU average) and the others. The geographical cluster of regions in which the product per capita and its growth is well below the EU average is constrained by the boundaries of a few countries and mostly associated with a specific Cohesion-country profile (*GDPpc*<90 per cent of EU average). Consequently, from now on, the focus of attention will be directed to regions in Cohesion Countries as a group and placing all other regions in another group, though this choice does lead to grouping the Objective 1 areas in Italy with the core. Anyway, since our core/periphery structure is identified by making use of national factors, our choice would be justified, because Italy as a whole is a rich country. In addition, this choice let us to contrast the effects of European Union regional policy as a whole on the regional convergence process in terms of this Cohesion/Non Cohesion dichotomy. [9]

[6] The Moran scatterplot displays the spatial lag *Wz* against *z*, both standardized. The four quadrants of the scatterplot identify the four different types of local spatial association between a region and its neighbours (Anselin, 1996): quadrants I (*High* income-*High* spatial lag) and III (*Low* income -*Low* spatial lag) correspond to positive spatial autocorrelation while quadrants II (*Low* income -*High* spatial lag) and IV (*High* income -*Low* spatial lag) refer to negative spatial dependence.

[7] The local Moran statistic for region *i* takes the form $I_i = (z_i W_i' z) / z'z$. An extensive discussion of the properties of local spatial autocorrelation statistics can be found in Getis and Ord (1996).

[8] Canova (2004), using a procedure that employs the predictive density of the data, identify four poles of attraction in a sample of 144 European NUTS 2 regions for the period 1980-1992. The two first of these four convergence clubs are composed, except for the Italian region of Calabria, for Greek, Portuguese and Spanish regions.

[9] Anyway, when the Objective 1 areas in Italy are included in the sample of Cohesion regions, results do not differ significantly from those that are reported there. The authors will provide these results upon request.

Using the above results in the following subsection, we test the conditional convergence hypothesis in Model 1 after controlling for regional heterogeneity by allowing cross-region parameter variation in the form of two spatial regimes, the first one grouping the regions of the four Cohesion Countries (Ireland, Greece, Portugal and Spain) and the second one comprising all other regions (Non-Cohesion countries). We can interpret the parameter instability between the regimes (spatial heterogeneity) as a sign of regions belonging to two *spatial convergence clubs*, and consequently the convergence process, if it exists, could differ across the two considered regimes.

Furthermore, if different patterns of convergence are found within regions belonging to Cohesion and Non-Cohesion countries, this would allow us to assess the role of EU cohesion policies on the process of European regional convergence. In its efforts to favor integration and equality in the European Union, the European Commission allocates more than two thirds of structural funds to Objective 1 regions (most of regions located in cohesion countries are of this type) and these are, together with the cohesion funds, the most important instruments of the European regional development policy.

3.3. Econometric analysis

This paper follows a specification search based on a forward stepwise (specific-to-general) strategy aimed at remedying simultaneously the geographic heterogeneity and spatial dependence problems uncovered in the last section. As Florax *et al.* (2002) have demonstrated through experimental simulations, this classical approach outperforms the Hendry general-to-specific strategy in terms of finding the true data generation process as well as in the observed accuracy of the estimators for spatial and non-spatial parameters.

Following this specific-to-general strategy, the second column of table 1 shows the baseline estimates, White-corrected Ordinary Least Squares (OLS-White)[10] estimation of Model 1. These results show that each of the explanatory variables is highly significant and the coefficient estimates present the appropriate signs. Moreover, these results are consistent with the conditional convergence hypothesis since $\hat{\beta}$ is positive and significantly different from zero, leading us to conclude that the speed of convergence over the entire study period is 2.2%, which is in agreement with the usual values found in the convergence literature (see, for example, Badinger *et al.*, 2002, for a recent review of the estimates for the speed of income convergence).

However, there is evidence favorable to the presence of spatial effects in the residuals. Both Moran's I test and the two robust Lagrange multiplier tests show strong evidence of spatial misspecification. Furthermore, the Breusch-Pagan test rejects the null hypothesis of homoscedasticity, so we must model the spatial heterogeneity prior to correcting the spatial error autocorrelation found in the basic model.[11]

After a series of steps that are presented in some detail in the appendix, we add the spatial lags of the explanatory variables and the dependent variable to construct a model that combines spatial heterogeneity, groupwise-heteroscedasticity and spatial dependence:

$$\Gamma_{it} = \alpha^{NC} D_i^{NC} + \alpha^{C} D_i^{NC} - \left(\beta_1^{NC} D_i^{NC} + \beta_1^{C} D_i^{C}\right)\left(\ln y_{i0} - \ln y_{UE,0}\right) + \left(\gamma_{1,1}^{NC} D_i^{NC} + \gamma_{1,1}^{C} D_i^{C}\right) x_{1,i0} +$$
$$+\left(\gamma_{2,1}^{NC} D_i^{NC} + \gamma_{2,1}^{C} D_i^{C}\right) x_{2,i0} + \ldots + \left(\gamma_{k,1}^{NC} D_i^{NC} + \gamma_{k,1}^{C} D_i^{C}\right) x_{k,i0} + \rho W \Gamma_{it} + \left(\beta_2^{NC} D_i^{NC} + \beta_2^{C} D_i^{C}\right) W\left(\ln y_{i0} - \ln y_{UE,0}\right) +$$
$$+\left(\gamma_{1,2}^{NC} D_i^{NC} + \gamma_{1,2}^{C} D_i^{C}\right) W x_{1,i0} + \left(\gamma_{2,2}^{NC} D_i^{NC} + \gamma_{2,2}^{C} D_i^{C}\right) W x_{2,i0} + \ldots + \left(\gamma_{k,2}^{NC} D_i^{NC} + \gamma_{k,2}^{C} D_i^{C}\right) W x_{k,i0} + \varepsilon_{it}$$

$$\varepsilon \sim N\left(0, \begin{bmatrix} \sigma_{NC}^2 I_{NC} & 0 \\ 0 & \sigma_C^2 I_C \end{bmatrix}\right) \qquad \text{(Model 2)}$$

where $D_i^g = 1$ if region i belongs to one country of group g, for g=Non-Cohesion (NC) or Cohesion (C) countries-group, and zero otherwise.

In the last column of table 1, the results of the ML estimation for Model 2 are presented. In this model, there is no problem with residual spatial dependence and the spatially adjusted Breusch-Pagan test for heteroscedasticity is not significant. Consequently, this is the appropriate specification and, in the remainder of this paper, attention will be paid only to results from Model 2.

3.4. Results and discussion

According to these results, we find strong support for the existence of two different spatial regimes. Moreover, we observe that both Cohesion and Non-Cohesion β-parameters are highly significant and have the expected sign. Regarding the implied annual rates of convergence, it seems that convergence of regions belonging to the cohesion club is stronger than that of the non-cohesion convergence club; over the analyzed period, the speed of convergence for these last regions (3.3%) is about two thirds of the convergence rate estimated for the regions of the

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[10] OLS-White indicates the use of the White (1980) heteroscedasticity consistent covariance matrix estimator.

[11] The links between spatial autocorrelation and spatial heterogeneity are very complex (Anselin, 2001a) and can be observationally equivalent in cross-section analysis. Because statistical inference when heterogeneity is present is less reliable than when there exists spatial autocorrelation of errors (Anselin and Griffith, 1988), we decide first to model structural instability.

cohesion countries (5.3%). With respect to the implied half-life for regions of the cohesion countries, that is, the time necessary to fill half of the distance of this group of economies from their steady state, is about 19 years while for the rest of regions the half-life increases to 27 years. This evidence is surprising, and some comments need to be made about the comparison of these results with others. Several studies indicate that the speed at which regional per capita income levels converge is about 2% (for example, in Sala-i-Martin, 1996a, b, one of the first major empirical studies for US and European regions). With respect to the specific literature about the European case, several studies have estimated the rate of convergence within the European Union by using data from the early 1980s [e.g. Fagerberg and Vespagen (1996), Lopez-Bazo *et al*. (1999), Cuadrado-Roura *et al*. (2000, 2002)]. The general impression is that β-convergence had come to a halt at the beginning of the 1980s (Boldrin and Canova, 2001) and at most a very slow convergence was observed since the 1980s and early 1990s (Canova and Marcet, 1995).

In any case, few signs of rapid convergence were found in those studies while this is not our case (similar conclusions as ours are reached, for example, in Brasili and Gutierrez, 2004, who used the non-parametric method proposed by Quah, 1993a, 1996a, and the panel unit roots approach proposed by Evans, 1998; they found evidence of convergence among the EU regions during the period 1980-1999).

Our results distinguish different patterns of convergence within regions belonging to Cohesion and Non-Cohesion countries, showing high rates of convergence in each regime. The significant increase in the rates of convergence obtained in this paper with respect to the aforementioned studies could be explained by two factors: specification and spatial interaction. For the former, our paper provides a standard beta regression of regional per capita GDP in the EU modified by introduction of variables to reflect differences in initial conditions, spatial lags and cross region variation in parameters. It helps separate out the impacts of convergence club membership (cross-region parameter variation between Cohesion and non-Cohesion countries), disparities in initial conditions and proximity effects on the speed of growth in income per capita. The recognition of spatial spillovers (through spatial econometric techniques) allows us to consider regional interactions in order to take into account the initial misallocation of resources. This fact could support evidence of a faster convergence among EU regions; convergence tends to be faster once the effects of geographic distance are considered.

These results support the idea of a positive effect of the EU cohesion policies in fostering economic growth and convergence in the poorest European Union members.[12] The political implications of such finding for the European regional policy cannot be underestimated, especially in the view of the recent EU enlargement to include new central and eastern European countries as well as Malta and Cyprus. Since there has been a significant increase in income disparities (and possibly a new scheme of polarization), the EU government will have to face an unprecedented challenge regarding internal cohesion.[13] Thus, the EU regional development and cohesion policies could represent a major instrument to encourage economic and social cohesion and the processes of growth and convergence in the EU.

A second remark should be made about the relevance of externalities across regions in the process of growth, derived from the significance and magnitude of the estimated spatial autoregressive parameter ($\hat{\rho} = 0.793$). This coefficient measures the strength of the interregional spillover effects (such as technological spillovers or factor mobility) and indicates that the growth rate of a region is related to those of its neighbor regions after conditioning for the starting levels of income, the share of agriculture, the employment rate and the corresponding spatial lags of these variables. From another perspective, this result means that a non-zero realization of a shock in a particular region will impact not only on that region but, through the spatial transformation, on all other regions (Anselin, 2001b). In this sense, because all our calculations are made using the median (*Me*) as the cut-off distance parameter, and this corresponds to approximately 1000 km, externalities across regions are restricted to a moderate distance and have mainly a national profile.

With respect to the two variables introduced to maintain the steady state constant for each economy, the estimates regarding self-initial conditions reveal that a high dependence on agriculture has on average negative effects in both cases (Cohesion and Non-Cohesion countries), mainly due to low technological and market opportunities. This finding indicates negative influences of low-productivity agricultural sector-dependent regions on the process of

[12] The results in Dall'erba and Hewings (2003) complement ours, showing that the convergence pattern of Cohesion countries is characterized by a catching-up of their income on the EU average, but also increasing regional disparities within each country. Then, the regional policies, reducing disparities at the EU aggregate level, have not been effective enough to impede the process of increasing within-Cohesion country regional income inequalities.

[13] Following the analysis of the situation and trends done by the Commission of the European Communities (European Commission, 2003), the main factors that will have an undoubted impact on future cohesion policy are the widening of economic disparities within the Union, a geographical shift in the pattern of these disparities and a less advantageous employment situation.

convergence. The coefficient for the other variable (the ratio of employment to population) shows positive effects in both cases (Cohesion and Non-Cohesion countries): a high (low) employment rate implies a positive (negative) influence on the convergence of the region towards their own stationary state.

Finally, the significance of spatial cross-regressive variables in each group should be noted, namely, the spatial lag of initial per capita GDP, spatial lag of initial agricultural rate, and spatial lag of initial occupation rate. Except one (spatial lag of initial agricultural rate in Cohesion Countries), the spatially lagged exogenous variables $W\left(\ln y_{i0} - \ln y_{UE,0}\right)$ and $Wx_{j,i0}$ are significant (at least at the 9% level) in each regime.

From the signs of the estimated coefficients of the spatially lagged exogenous variables, it is also worth emphasizing that a region with a high (low) initial level of GDP per capita in its neighbors receives positive (negative) influences on the convergence process of the region. Thus, the process of convergence of a region also depends on the initial values of GDP per capita in the set of its neighboring regions.

In addition, the positive estimate for the coefficient of the spatial lag of the initial agricultural rate of Non-cohesion countries indicates that, on average, EU Non-Cohesion regions benefit from neighbors (regions) with high shares of agricultural employment over total employment. Nevertheless, the estimate for the coefficient of the spatial lag of the initial agricultural rate of Cohesion countries is not significant. Therefore, as expected, this result could be explained by the fact that EU Cohesion regions do not receive significant influences from neighbors (regions) with high (low) shares of employment in agriculture.

With respect to the estimation of the coefficients for the spatial lag of the initial employment rate, different signs are obtained for the two regimes. Thus, in the case of the spatial lag of the initial employment rate for the Non-Cohesion countries, the sign is negative, indicating that, on average, EU Non-Cohesion regions receive negative (positive) effects from neighbors (regions) with high (low) initial employment rate. For that reason, it would be possible to affirm that regions in Non-Cohesion countries were in competition with their neighbors for labor. This result is important, since Cohesion regions close to Non-Cohesion regions would be in competition in the labor market. On the contrary, the sign is positive for the Cohesion countries, indicating that a region with a high (low) initial level of the occupation rate of its area's neighbors has high (low) positive influence on the growth trajectory of the region.

Therefore, from a spatial externalities perspective, it seems that, whatever the regime, the growth rate of a region is influenced by both its own initial values and the neighbors' initial conditions. In this sense, our results are similar to those obtained in Chua (1993) and Carrington (2002), pointing out that the growth in each region depends not only on its own initial characteristics but also on those of the neighboring regions. Also, our results imply that the more an area's initial GDP differs from those of its neighbors, the faster its per capita income will grow, and vice-versa, therefore detecting local polarization effects which is one of the results of more descriptive approaches to European regional dynamics.

4. Summary and conclusions

This paper has assessed the importance of spatial heterogeneity and dependence problems in the analysis of the β-convergence process among the European regions. Following a specific-to-general strategy, a final model that combines groupwise-heteroscedasticity, varying coefficients across regimes and spatial dependence was constructed. The results confirm some well known results. First, the variables conditioning the steady state of each region are significant. This implies that each region approaches its own steady state; there will exist permanent cross-region differences in per capita income levels. Secondly, geographic localization and proximity *per se* play a key role in explaining the pattern of economic growth observed in the European Union.

On the other hand, evidence favorable to the existence of two spatial convergence clubs among European regions was found; the presence of two significantly different spatial clusters formed by regions belonging to Cohesion and Non-Cohesion countries. Under this empirical approach, it would be valuable to search for different patterns of convergence within regions belonging to Cohesion and Non-Cohesion countries in the specified neoclassical conditional model, exploring the ex-post general effects of European Union regional policy as a whole on the regional convergence process in terms of the Cohesion/Non Cohesion countries dichotomy. As result, exploring this path to evaluate the effects of Cohesion policies on regional growth in EU, the paper suggests that there is faster convergence of Cohesion country group regions (5.3 per cent) than non-Cohesion country group regions (3.3 per cent). Another finding of the paper is that, with respect to the research that considers the existence of convergence clubs, our work provides a joint and explicit quantification of the difference in the rates of convergence of the two detected clusters.

Finally, significant geographic spillovers are observed in the EU regional growth process. These effects appear not only through the endogenous spatial lag variable but also through the spatial cross-regressive lags of exogenous variables. Together, these externalities across regions are shown to be important factors in explaining the spatial correlation of EU regional growth rates. Thus, we can note that the process of convergence of a region also depends on the initial values of GDP per capita in the set of its neighboring regions; a region with a high (low) initial level of GDP per capita of its area's neighbors receives high (low) positive influences on the convergence process of the region. Secondly, EU Non-Cohesion regions benefits from neighbors (regions) with high shares of agricultural employment over total employment. Thirdly, EU Non-Cohesion regions receive negative (positive) effects from neighbors (regions) with high (low) initial employment rate, while an EU Cohesion region with a high (low) initial level of occupation rate of its area's neighbors has positive (negative) influence on the growth trajectory of the region. Hence, one of the more important findings of the paper is that the analysis emphasizes a role for spatial effects to estimate the speed at which European regions converge.

From a policy analysis point of view, the estimates obtained support policies explicitly that were designed to promote regional growth in the less-developed regions located in Cohesion countries (Ireland, Greece, Portugal and Spain) and, due to the existence of positive regional externalities, show the importance of the coordination of regional development policies between the member states and the different EU agencies.

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APPENDIX

In this appendix, the steps followed to reach our final specification (Model 2 in the main text) are detailed. Starting from the initial conditional convergence equation, and following a specific-to-general strategy, the second column of table 2 shows the results of the OLS-White estimation of the initial equation (Model 1 in main text):

$$\Gamma_{it} = \alpha - \beta\left(\log y_{i0} - \log y_{UE,0}\right) + \gamma_1 x_{1,i0} + \gamma_2 x_{2,i0} + \ldots + \gamma_k x_{k,i0} + \varepsilon_{it} \qquad \text{(A1)}$$

Through the regression diagnostics, there is evidence favorable to the presence of spatial effects in the residuals, because both Moran's *I* test and the two robust Lagrange multiplier tests show a strong evidence of spatial misspecification. Following the decision rule suggested by Florax *et al.* (2002), the robust tests point basically to the presence of spatial error autocorrelation (figure 4 shows the residuals of this starting model). Furthermore, the Breusch-Pagan test rejects the null hypothesis of homoscedasticity, so the spatial heterogeneity is modeled prior to correcting the spatial error autocorrelation found in the basic model.

The results derived from modeling the spatial heterogeneity through the analysis of the national effects can be seen in figure 3. Countries are grouping regions which may present similar social and economic conditions, for example, age composition of the population, sectoral composition of the production, human, physical and social capital stocks, technological level or even climate, political, cultural and legal traditions. Then, under the hypothesis that specific socio-economic factors affecting higher-spatial units of observation (the countries) could cause spatial autocorrelation between growth rates in neighboring regions, the possibility of a significant national component in the observed regional growth rates is considered through the following fixed (national) effects model: [14]

$$\Gamma_{it} = \alpha^1 D_i^1 + \alpha^2 D_i^2 + \ldots + \alpha^{12} D_i^{12} - \beta\left(\log y_{i0} - \log y_{UE,0}\right) + \gamma_1 x_{1,i0} + \gamma_2 x_{2,i0} + \ldots + \gamma_k x_{k,i0} + \varepsilon_{it} \qquad \text{(A2)}$$

where $D_i^n = 1$ if region *i* belongs to country *n* (for *n*=1,2,…,12) and zero otherwise. These incorporated national dummy variables have been used in a number of studies (e.g. Armstrong, 1995, Rodríguez-Pose, 1999) in order to exhibit a wide array of steady state values.

Estimating this second model, the Lagrange multiplier statistic for the null hypothesis H_0: $\{\alpha^1 = \alpha^2 = \ldots = \alpha^{12} = 0\}$ is clearly rejected by the data (see first note in table 2). In addition,

[14] More general models (allowing, for example, the slopes of Eq. (A2) to vary across the countries) were not used due to problems with degrees of freedom.

when introducing fixed effects, it is important to consider to what extent a random effects specification should be adopted (this hypothesis was also tested in Case, 1991). The random effects formulation of such model would imply $\alpha^{j} \sim (\overline{\alpha}, \sigma_{\alpha}^{2})$. Hausman's test result (see note 2, table 2) does not let us reject this hypothesis; consequently, the random effects model has been estimated by Generalized Least Squares (GLS).

The third column of table 2 reports the GLS estimation results for the random effects version of (A2). The coefficient estimates are very different from the previous estimation; specifically, the convergence rate implied by $\hat{\beta}$ is 4%, roughly double the value obtained from the baseline model. Also, the highly significant coefficients estimated for the agricultural and employment rates are larger than those reported in previous results. The two robust tests do not reject the null hypothesis of no spatial dependence[15] and, based on the value of Akaike and Schwarz Information Criterion statistics, the fit of the GLS version of (A2) is superior to that of the OLS conditional convergence model (A1). However, the evidence against the normality of errors is very strong and the Koenker-Bassett test clearly rejects the homoscedasticity hypothesis. Further consideration of spatial heterogeneity is therefore needed.

In order to capture the Cohesion/Non-Cohesion polarization pattern observed in the distribution (and growth) of income per capita among the European regions, we shall focus on the issue of structural instability in the form of two spatial clusters. Let us consider the possibility of a significant two spatial regimes model of conditional convergence which could be specified as following:

$$\Gamma_{it} = \alpha^{NC} D_i^{NC} + \alpha^{C} D_i^{NC} - \left(\beta^{NC} D_i^{NC} + \beta^{C} D_i^{C}\right)\left(\log y_{i0} - \log y_{UE,0}\right) +$$
$$\left(\gamma_1^{NC} D_i^{NC} + \gamma_1^{C} D_i^{C}\right)x_{1,i0} + \left(\gamma_2^{NC} D_i^{NC} + \gamma_2^{C} D_i^{C}\right)x_{2,i0} + \ldots + \left(\gamma_k^{NC} D_i^{NC} + \gamma_k^{C} D_i^{C}\right)x_{k,i0} + \varepsilon_{it} \qquad \text{(A3)}$$

where $D_i^g = 1$ if region i belongs to one country of group g, for g=Non-Cohesion (NC) or Cohesion (C) countries-group, and zero otherwise. This specification takes into account the possibility that the convergence process, if significant, may differ across regimes. If this

[15] This result is similar to that obtained in Attfield *et al.* (2000). These authors test the proximity hypothesis comparing the importance of distance versus national zero/one dummy variables. Their conclusion is that physical distance has almost no explanatory power when national dummies are introduced.

To some extent, our result is also similar to that obtained in Conley and Topa (2002). In our case, it seems that most of the spatial clustering observed, once we condition on covariates, may be driven by sorting the heterogeneous regions across countries. That's to say, socio-economic conditions within each country contribute the most to explain the spatial correlation of regional growth rates.

hypothesis is true, it means that the corresponding regions belong to two different spatial convergence clubs.

The estimation results by OLS-White of (A3) are displayed in the fourth column of the table 2. We have tested instability in the parameters through the hypothesis H0: $\{\alpha^{NC} = \alpha^{C}, \beta^{NC} = \beta^{C}, \gamma_1^{NC} = \gamma_1^{C}, \ldots, \gamma_k^{NC} = \gamma_k^{C}\}$. The Chow test of overall stability clearly rejects the above hypothesis and, therefore, we can interpret this result as evidence consistent with the spatial convergence clubs hypothesis. However, there are problems of heteroscedasticity and spatial dependence in the above specification.[16] As with the case for (A1), the diagnostic tests for spatial dependence indicate a preference for the spatial error model over the spatial lag model.
In order to take into account the two aforementioned problems simultaneously, the specification (A3) is extended and estimated. Thus, the existence of groupwise-heteroscedasticity is assumed across the two Cohesion/Non-Cohesion regimes and a SAR(1) process in the errors is introduced. That is, we estimate the following model:

$$\Gamma_{it} = \alpha^{NC} D_i^{NC} + \alpha^{C} D_i^{NC} - \left(\beta^{NC} D_i^{NC} + \beta^{C} D_i^{C}\right)\left(\log y_{i0} - \log y_{UE,0}\right) +$$
$$\left(\gamma_1^{NC} D_i^{NC} + \gamma_1^{C} D_i^{C}\right)x_{1,i0} + \left(\gamma_2^{NC} D_i^{NC} + \gamma_2^{C} D_i^{C}\right)x_{2,i0} + \ldots + \left(\gamma_k^{NC} D_i^{NC} + \gamma_k^{C} D_i^{C}\right)x_{k,i0} + \varepsilon_{it}$$
$$\varepsilon \sim N\left(0, \begin{bmatrix} \sigma_{NC}^2 I_{NC} & 0 \\ 0 & \sigma_C^2 I_C \end{bmatrix}\right), \ \varepsilon = \lambda W \varepsilon + u \quad \text{and} \quad u \sim N(0, \sigma^2) \qquad \text{(A4)}$$

The results of the estimation of (A4) by Maximum Likelihood (ML) are displayed in the fifth column of the table 2. As observed, the spatially adjusted Chow test strongly rejects the hypothesis of structural stability and the Likelihood Ratio (LR) test for differences in variances across regimes is highly significant. However, this specification has problems with the Common Factor hypothesis: the LR common factor test (Burridge, 1981) clearly indicates the rejection of this hypothesis. Therefore, we must extend the model (A4) by including spatial lags of the explanatory variables [$W\left(\log y_{i0} - \log y_{UE,0}\right)$ and $Wx_{j,i0}$ for $j = 1, 2, \ldots, k$] and, considering the spatial dependence, we must also include a spatial lag of the dependent variable ($W\Gamma_{it}$) instead of the error autoregressive component ($W\varepsilon_{it}$). These extensions lead us to our final specification

[16] It is noteworthy that the Jarque-Bera test does not reject the normality of errors, so the reliability of subsequent use of the Maximum Likelihood (ML) estimation method is warranted.

(A5) which incorporates spatial heterogeneity, groupwise-heteroscedasticity and spatial dependence: [17]

$$
\begin{aligned}
\Gamma_{it} &= \alpha^{NC} D_i^{NC} + \alpha^{C} D_i^{NC} - \left(\beta_1^{NC} D_i^{NC} + \beta_1^{C} D_i^{C}\right)\left(\log y_{i0} - \log y_{UE,0}\right) + \\
&\left(\gamma_{1,1}^{NC} D_i^{NC} + \gamma_{1,1}^{C} D_i^{C}\right)x_{1,i0} + \left(\gamma_{2,1}^{NC} D_i^{NC} + \gamma_{2,1}^{C} D_i^{C}\right)x_{2,i0} + \ldots + \left(\gamma_{k,1}^{NC} D_i^{NC} + \gamma_{k,1}^{C} D_i^{C}\right)x_{k,i0} + \\
&+ \rho W \Gamma_{it} + \left(\beta_2^{NC} D_i^{NC} + \beta_2^{C} D_i^{C}\right)W\left(\log y_{i0} - \log y_{UE,0}\right) + \\
&\left(\gamma_{1,2}^{NC} D_i^{NC} + \gamma_{1,2}^{C} D_i^{C}\right)Wx_{1,i0} + \left(\gamma_{2,2}^{NC} D_i^{NC} + \gamma_{2,2}^{C} D_i^{C}\right)Wx_{2,i0} + \ldots + \left(\gamma_{k,2}^{NC} D_i^{NC} + \gamma_{k,2}^{C} D_i^{C}\right)Wx_{k,i0} + \varepsilon_{it} \\
&\varepsilon \sim N\left(0, \begin{bmatrix} \sigma_{NC}^2 I_{NC} & 0 \\ 0 & \sigma_C^2 I_C \end{bmatrix}\right) \qquad \text{(A5)}
\end{aligned}
$$

In the last column of table 2 the results of the ML estimation for this model are presented. In this model there is no problem with residual spatial dependence and the spatially adjusted Breusch-Pagan test for heteroscedasticity is not significant. Consequently, this is the appropriate specification and this is the reason because in the empirical section of the paper attention has been paid only to results from equation (A5).

[17] It is interesting to note the similarity between the specification for each regime in (A5) and the empirical counterpart of the growth model with externalities across regional economies recently proposed by López-Bazo *et al.*, 2004. In both cases it is shown the relevance of interdependencies between regional economies, with externalities across regions positively influencing the process of economic growth (in income per capita in our case and in labour productivity in López-Bazo *et al.*'s case).

Table 1: Estimation results

Variable/parameter	Model 1 OLS-White/(p-value)	Model 2 ML-SAR(lag)-Group.Het./(p-value)	
	All EU countries	Non-cohesion countries	Cohesion countries
Constant (α)	-0.0136 (0.015)	-0.0032 (0.717)	-0.0237 (0.006)
Initial per capita *GDP* (β)	0.0185 (0.000)	0.0257 (0.000)	0.0356 (0.000)
Initial agricultural rate (γ_1)	-0.0002 (0.026)	-0.0003 (0.074)	-0.0003 (0.000)
Initial occupation rate (γ_2)	0.0004 (0.010)	0.0008 (0.000)	0.0006 (0.013)
Spatial lag of Initial per capita *GDP* (β)		0.0364 (0.000)	0.0388 (0.000)
Spatial lag of Initial agricultural rate (γ_1)		0.0007 (0.002)	0.0001 (0.413)
Spatial lag of Initial occupation rate (γ_2)		-0.0008 (0.001)	0.0003 (0.089)
Spatial parameter (λ / ρ)	-	0.793 (0.000)	
Implied convergence rate (θ)	*2.2%*	*3.3%*	*5.3%*
Coeff. of Determ. (R^2)	0.215	0.690	
Akaike Inform. Crit. (AIC)	-1054.48	-1201.15	
Schwarz Inform. Crit. (SC)	-1042.28	-1154.74	
Jarque-Bera Normality test	3.48 (0.17)	-	
Chow Struct. Instability test		35.08 (0.00)	
Heteroscedastic. Breusch-Pagan/ Koenker-Bassett test	6.79 (0.08)	0.63 (0.43) [3]	
Moran's I test (error)	19.70 (0.00)	-	
Spatial Dep. Robust LM (error) test	106.55 (0.00)	1.39 (0.24)	
Spatial Dep. Robust LM (lag) test	10.02 (0.00)	-	
Lik. Ratio test on Common Factor Hypothesis	-	-	

Notes: 1. The convergence rate θ is obtained using the formula $\theta = -\log(1 - t\beta)/t$

2. The spatial weights matrix used in the calculations is W defined as

$$\begin{cases} w_{ij}^* = 0 \quad if \quad i = j \\ w_{ij}^* = 1/d_{ij}^2 \quad if \quad d_{ij} \le Me \\ w_{ij}^* = 0 \quad if \quad d_{ij} > Me \end{cases}, \quad w_{ij} = w_{ij}^* \Big/ \sum_j w_{ij}^*$$

, d_{ij} is the great circle distance between centroids of regions *i* and *j*, and Me is the median of the great circle distance distribution.

3. Spatial Breusch-Pagan test

Table 2: Estimation results of different β-convergence models

Variable/parameter	**Equation A1** OLS-White/(p-value)	**Equation A2** GLS-Random effects[1,2]/ (p-value)	**Equation A3** OLS-White/(p-value)		**Equation A4** ML-SAR(error)- Group.Het./(p-value)		**Equation A5** ML-SAR(lag)- Group.Het./(p-value)	
	All EU countries	All EU countries	Non-cohesion countries	Cohesion countries	Non-cohesion countries	Cohesion countries	Non-cohesion countries	Cohesion countries
Constant (α)	-0.0136 (0.015)	-0.0274 (0.000)	-0.0197 (0.003)	-0.0114 (0.286)	-0.0290 (0.000)	-0.0104 (0.383)	-0.0032 (0.717)	-0.0237 (0.006)
Initial per capita *GDP* (β)	0.0185 (0.000)	0.0296 (0.000)	0.0047 (0.274)	0.0340 (0.000)	0.0242 (0.000)	0.0403 (0.000)	0.0257 (0.000)	0.0356 (0.000)
Initial agricultural rate (γ_1)	-0.0002 (0.026)	-0.0004 (0.000)	0.0004 (0.029)	-0.0006 (0.000)	-0.0002 (0.194)	-0.0003 (0.004)	-0.0003 (0.074)	-0.0003 (0.000)
Initial occupation rate (γ_2)	0.0004 (0.010)	0.0008 (0.000)	0.0004 (0.015)	0.0003 (0.371)	0.0007 (0.000)	0.0000 (0.717)	0.0008 (0.000)	0.0006 (0.013)
Spatial lag of Initial per capita *GDP* (β)							0.0364 (0.000)	0.0388 (0.000)
Spatial lag of Initial agricultural rate (γ_1)							0.0007 (0.002)	0.0001 (0.413)
Spatial lag of Initial occupation rate (γ_2)							-0.0008 (0.001)	0.0003 (0.089)
Spatial parameter (λ / ρ)			-		0.904 (0.000)		0.793 (0.000)	
Implied convergence rate (θ)	*2.2%*	*4.0%*	*0.5%*	*4.9%*	*3.1%*	*6.5%*	*3.3%*	*5.3%*
Regression diagnostics (p-values in parenthesis)								
Coeff. of Determ. (R^2)	0.215	0.824	0.332		0.695		0.690	
Akaike Inform. Crit. (AIC)	-1054.48	-1276.91	-1072.94		-1211.80		-1201.15	
Schwarz Inform. Crit. (SC)	-1042.28	-1230.51	-1048.19		-1187.05		-1154.74	
Jarque-Bera Normality test	3.48 (0.17)	23.50 (0.00)	2.79 (0.25)		-		-	
Chow Struct. Instability test			6.78 (0.00)		12.33 (0.01)		35.08 (0.00)	
Heteroscedastic. Breusch-Pagan/ Koenker-Bassett test	6.79 (0.08)	43.47 (0.00)	2.74 (0.09)		17.63 (0.00) [5]		0.63 (0.43) [6]	
Moran's I test (error)	19.70 (0.00)	2.14 (0.03)	16.61 (0.00)		-		-	
Spatial Dep. Robust LM (error) test	106.55 (0.00)	0.04 (0.84)	46.94 (0.00)		-		1.39 (0.24)	
Spatial Dep. Robust LM (lag) test	10.02 (0.00)	0.82 (0.36)	1.13 (0.29)		3.55 (0.06)		-	
Lik. Ratio test on Common Factor Hypothesis	6.79 (0.08)	43.47 (0.00)	-		20.35 (0.00)		-	

Notes: 1. Eq. A1 versus Eq. A2 Lagrange Multiplier test/(p-value): 1161.92 (0.00); 2. Fixed versus Random effects Hausman test/(p-value): 0.66 (0.88); 3. The convergence rate θ is obtained using the formula $\theta = -\log(1 - t\beta)/t$; 4. The spatial weights matrix used in the calculations is W defined as; $\begin{cases} w_{ij}^{*} = 0 & if \quad i = j \\ w_{ij}^{*} = 1/d_{ij}^{2} & if \quad d_{ij} \le Me \\ w_{ij}^{*} = 0 & if \quad d_{ij} > Me \end{cases}$, $w_{ij} = w_{ij}^{*} / \sum_j w_{ij}^{*}$, d_{ij} is the great circle distance between centroids of regions *i* and *j*, and Me is the median of the great circle distance distribution.; 5. Likelihood Ratio test on Groupwise Heteroscedasticity; 6. Spatial Breusch-Pagan test

Figure 1: Spatial percentile distribution for the log of per capita GDP in 1981

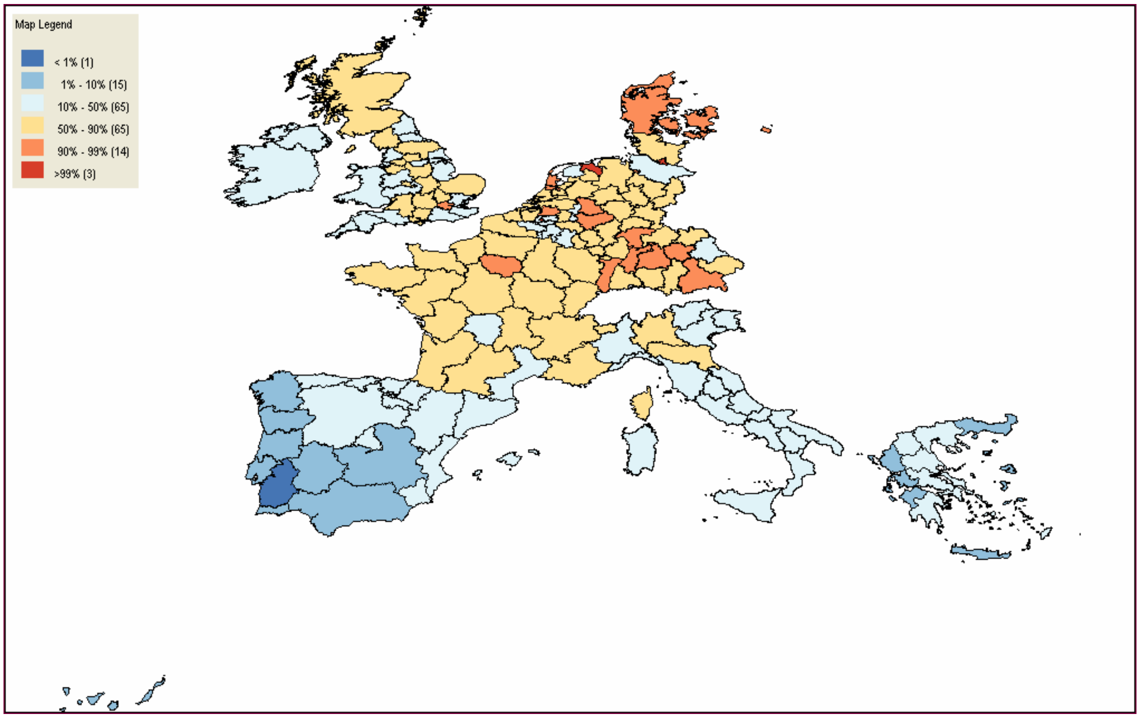

Figure 2: Moran scatterplot for the log of per capita GDP in 1981

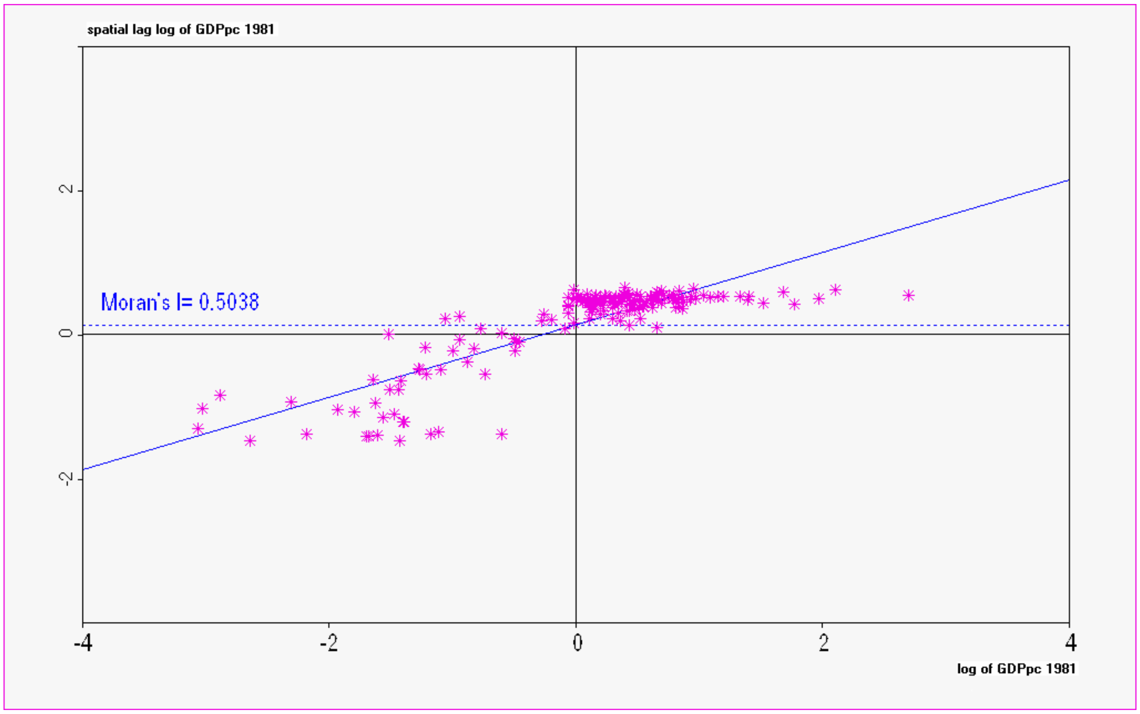

Figure 3: LISA and Moran Significance maps for the log of per capita GDP in 1981

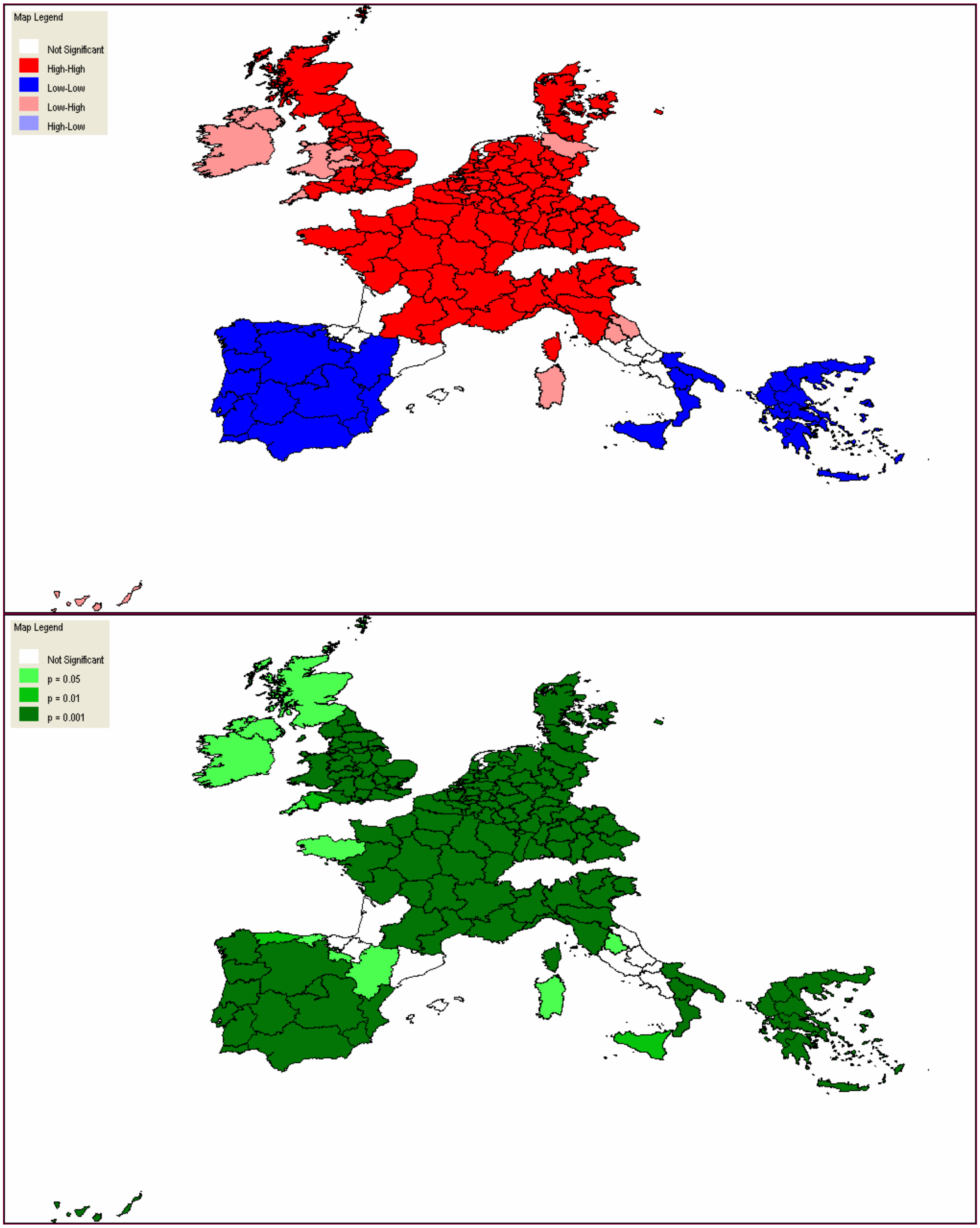

Figure 4: Residuals from the OLS estimation of Equation A1 in Appendix