REGIONAL CONVERGENCE AND THE IMPACT OF EUROPEAN STRUCTURAL FUNDS OVER 1989-1999: A SPATIAL ECONOMETRIC ANALYSIS

Sandy Dall'erba[1]

CATT, Université de Pau (France) and
REAL
University of Illinois at Urbana-Champaign
220 Davenport Hall, 607 S. Mathews Av.
Urbana, IL 61801-3671
USA
dallerba@uiuc.edu

and

Julie Le Gallo[1]

REAL
University of Illinois at Urbana-Champaign
220 Davenport Hall, 607 S. Mathews Av.
Urbana, IL 61801-3671
USA
jlegallo@uiuc.edu

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Abstract

The aim of this paper is to assess the impact of structural funds on the convergence process of 145 European regions over 1989-1999. With the aim of enhancing cohesion, these funds are primarily allocated to the least developed regions. The most important part of these funds is devoted to transportation infrastructures, which affect the process of industry location and induce strong spillover effects. As a result, they do not necessarily contribute to a more even regional development. Their impact has therefore to be seen in the light of growth rate variations of the targeted region and of the whole sample. Using the formal tools of spatial econometrics, we first detect strong evidence of spatial autocorrelation in the distribution of per capita GDP. Moreover, two clusters, representative of the core-periphery pattern, are persistent over the period and highlight spatial heterogeneity. Structural funds and spatial effects are then included in the estimation of the appropriate conditional β-convergence model. Estimation results display significant convergence in the peripheral regime only and a non-significant impact of the funds. We therefore assess their impact using another approach based on the spatial diffusion property due to correlation in the residuals. It allows us to control for spatial spillover effects among regions and to estimate, via simulation experiments, the impact of shocks, proportional to structural funds, first on the growth rate of the targeted region and second on the growth rate of all the regions of our sample. The results show that structural funds have positively benefited to the growth of the targeted regions, but that spillover effects are very small in peripheral regions.

Section 1 Introduction

The phenomenon of persistent income disparities among European regions has been widely studied in the literature, using convergence models most of the time based on neo-classical specifications. The results of empirical estimations reveal greater cohesion among European regions (Barro and Sala-I-Martin, 1991; Amstrong, 1995), but also increasing disparities among regions within countries (Esteban, 1994). Instead of a catching-up of all the poorest regions, European integration seems to have benefited mainly to the richest regions in the poorest countries.

In order to decrease disparities between European regions, structural funds are the most important instrument of the European regional development policy (which amounted for 247 billion Ecus over 1989-1999, i.e. one-third of the Community budget). However, the implementation of structural funds induces strong spatial externalities since they mainly finance public infrastructures. For instance, when they finance transportation infrastructures leading to a decrease in transportation costs, they may also affect the process of industry location. As a result, structural funds do not systematically benefit to the long-run growth of the region where they are implemented (Venables and Gasiorek, 1999; Vickerman *et al.*, 1999; Dall'erba, 2003a). The existence of these externalities makes the impact of regional funds harder to estimate. In the absence of details on the sectoral allocation of structural funds for each region, this paper considers structural funds as public capital acting directly on the regional growth rate and assesses their impact using two complementary methods.

First, we include these structural funds in the estimation of a standard conditional β-convergence model for 145 European regions over 1989-1999. Given the possible existence of geographic spillover effects, a particular attention is paid to the spatial dimension. Indeed,

the majority of empirical tests of regional income convergence are based on the same assumptions as the ones underlying for international income convergence: regions are considered as isolated entities, as if their geographical location and potential interregional linkages did not matter. Only recently, the role of spatial effects has been considered in empirical works using the formal tools of spatial statistics and econometrics[2]. The underlying idea is that forces driving to relocation/agglomeration process and hence to even/uneven regional development such as productivity (Lopez-Bazo *et al.*, 1999), transportation infrastructures (Krugman and Venables, 1995, 1996), technology and knowledge spillovers (Martin and Ottaviano, 1999), factor mobility (Krugman, 1991a, b; Puga, 1999), have explicit geographic components. We therefore include spatial effects in the estimation of the GDP convergence process using the formal tools of spatial statistics and spatial econometrics. In the absence of interregional input/output tables, this methodology is the only one that allows us modeling spatial effects among European regions in a proper way.

Second, we estimate the impact of a shock in a given region on its own development and on the development on its neighboring regions using the global diffusion properties of a spatial error model. Le Gallo *et al.* (2003) have already simulated the spatial diffusion of a shock on neighboring regions. They find that the strength of diffusion depends on the economic dynamism and on the spatial location of the targeted region. In this paper, we simulate these spillover effects as well, but we extend the analysis to 1999, and include the real values of structural funds over 1989-1999. To our knowledge, this paper is therefore the first one to analyze shocks proportional to the real value of structural funds and their impact not only on the targeted regions but also on all the European regions.

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[2] For the European regions, papers in this area include, among others, Fingleton (1999, 2001, 2003a and b), Maurseth (2001), Bivand and Brunstad (2003) or Le Gallo *et al.* (2003).

This paper proceeds as follows: section 2 gives an overview of recent theoretical and empirical studies on the impact of regional assistance on uneven development. Section 3 provides some insights into the β-convergence model and spatial effects upon which the empirical estimation described in the following sections relies. Section 4 presents the data and weight matrix. In Section 5, exploratory spatial data analysis (ESDA) is used to detect spatial autocorrelation and spatial heterogeneity among European regional GDP. These two spatial effects and the structural funds are then included in the estimation of the appropriate β-convergence model. Simulation experiments, relying on the property of spatial correlation in the residuals, are carried out in section 6 to estimate the impact of the funds, first on the targeted region itself and second on all the regions of the sample. The extent of spillover effects is measured and the regions are ranked according to the value of spillover effects they produce. Section 7 concludes and provides some comments on the allocation of the European structural funds.

Section 2 Impact of Regional Assistance on Uneven Development

The European Commission considers large regional imbalances unacceptable on distributional and political grounds. The successive enlargements of the European Community to the peripheral and less developed countries have made disparities in infrastructure endowments and per capita incomes so obvious (see figure 1[3]) that 68% of structural funds are devoted to the least developed regions[4]. Financed infrastructures mainly concern the transportation sector, in order to facilitate the development of the Single Market, and to a lower extent education, energy and telecommunication. Structural funds are the most important instruments of the European regional development policy with 247 billion Ecus

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[3] All figures have been realized using Arcview GIS 3.2 (Esri).
[4] Objective 1 regions having a per capita GDP below 75% of the European average.

over 1989-1999. In addition, the four least developed countries (Spain, Portugal, Ireland and Greece, which had a per capita GNP below 90% of the EU average) benefited from almost 17 billion Ecus allocated as cohesion funds over 1989-1999. Figure 2 displays the distribution of structural funds as a ratio of GDP during the 1989-1999 period. As expected, the poor and peripheral regions are the ones that benefited at most from Community support.

<< Insert figures 1 and 2 here>>

Four input-output models are used by the European Commission to assess the impact of structural funds on the four least developed countries (European Commission, 1999). Their results lead to the conclusion that structural funds have had a significant effect in reducing disparities in economic performance across the Union and succeeded in narrowing the gap in GDP per head between the four Cohesion countries and the rest of the Union. Several empirical studies confirm the catching-up of cohesion countries in terms of per capita GNP (Esteban, 1994; Neven and Gouyette, 1995; and more recently Martin, 1999; Dall'erba and Hewings, 2003). However, these last studies also reveal increasing regional disparities within these countries (but Greece). Therefore, a reconsideration of the impact of these funds on regional development is necessary.

From a theoretical perspective, two strands of literature provide insights into the effects of public assistance and infrastructures on regional growth and location of economic activity: growth models and economic geography models.

In a neoclassical Solow growth model, regional funds finance a greater level of physical capital, which corresponds to a higher steady state income. However, due to the decreasing marginal product of capital, the rate of investment declines towards the steady state income, where the stock of capital per person is constant. The investment rate is then

equal to effective capital depreciation. Therefore, a higher investment rate in poorer regions may increase the convergence speed to rich regions, but is only transitional and does not raise the steady state income in the long run. On the opposite, endogenous growth theory grants public policies an important role in the determination of growth rates in the long run. For instance, Aschauer (1989) and Barro (1990) predict that if public infrastructures are an input in the production function, then policies financing new public infrastructures increase the marginal product of private capital, hence fostering the capital accumulation and growth.

However, when such investments finance transportation infrastructures that yield to a decrease in transportation costs, it may affect the process of industry location. The economic geography literature shows that, as a result, they do not systematically benefit the region where they are implemented (Vickerman, 1996; Martin, 2000). In particular, with respectively 30% and 60% of structural and cohesion funds devoted to transportation infrastructures, their impact on regional development has to be seen in the light of characteristics of the transportation sector. The empirical study of Vickerman *et al.* (1999) points out that new transportation infrastructures tend to be built within or between core regions, where the demand in this sector is the highest. In other words, the European transportation network is more and more composed of hub-and-spoke interconnections. Puga and Venables (1997) show that this kind of network promotes agglomeration in the hub: firms located in the hub face lower transaction costs in trading with firms in spoke locations than a firm in any spoke location trading with a firm in another spoke.

For Venables and Gasiorek (1999), recent developments in the Iberian transportation network[5] have reinforced the place of Madrid as a central location through which traffic traveling from one edge of the peninsula to another has to pass. On the contrary, public infrastructures in peripheral regions, which do not necessarily increase the connection to the

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[5] The Madrid Ring road, which connects the most important Spanish highways to each other.

main network, like the bridge Tagus Crossing in Lisboã (Portugal), have very low spillover effects outside the region itself. The relationship between gain in accessibility and economic development in peripheral regions still requires considerable empirical investigation especially given the variations in transportation demands by sector. It is stated however that gains in accessibility due to interregional transport infrastructures will always be relatively higher in the core region than in the peripheral one (Vickerman *et al.*, 1999).

For Martin (2000), the impact of transportation infrastructures on regional development corresponds to a trade-off between efficiency and equity: intraregional transportation infrastructures in periphery do not necessarily promote the aggregate growth, even if they may favor local development. On the other hand, promoting the aggregate growth through interregional transportation infrastructures lead to industry relocation, which mainly benefits the core region. Transportation infrastructures thus cannot always be seen as an efficient instrument to reduce interregional disparities.

The next section introduces the β–convergence model and spatial effects upon which we will assess the impact of structural funds on the regional growth rate.

Section 3 β-convergence Models and Spatial Effects

Since the publication of the seminal articles of Barro and Sala-i-Martin (1991, 1992, 1995), numerous studies have examined β–convergence between different countries and regions[6]. This concept is linked to the neoclassical growth model, which predicts that the growth rate of a region is positively related to the distance that separates it from its steady-

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[6] See Durlauf and Quah (1999) for a review of this extensive literature.

state. Empirical evidence for β-convergence has usually been investigated by regressing growth rates of GDP on initial levels. Two cases are usually considered in the literature.

If all economies are structurally identical and have access to the same technology, they are characterized by the same steady state, and differ only by their initial conditions. This is the hypothesis of *absolute β–convergence*, which is usually tested on the following cross-sectional model, in matrix form:

$$g_T = \alpha S + \beta y_0 + \varepsilon \qquad\qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I) \qquad\qquad (1)$$

where g_T is the ($n\times1$) vector of average growth rates of per capita GDP between date 0 and T; S is the ($n\times1$) sum vector; y_0 is the vector of log per capita GDP levels at date 0. There is absolute β–convergence when the estimate of β is significantly negative.

The concept of *conditional β–convergence* is used when the assumption of similar steady-states is relaxed. Note that if economies have very different steady states, this concept is compatible with a persistent high degree of inequality among economies. It is usually tested on the following cross-sectional model:

$$g_T = \alpha S + \beta y_0 + X\phi + \varepsilon \qquad\qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I) \qquad\qquad (2)$$

with the same notations as above and X is a matrix of variables, maintaining constant the steady state of each economy. There is conditional β–convergence if the estimate of β is significantly negative once X is held constant.

Based on these two concepts, the convergence process can then be characterized by two additional parameters using the estimated β coefficient in equations (1) or (2). First, the convergence speed may be defined as: $b = -\ln(1+T\beta)/T$. Second, the half-life is the time necessary for the economies to fill half of the variation, which separates them from their steady state, and is defined by: $\tau = -\ln(2)/\ln(1+\beta)$.

Both β-convergence concepts have been heavily criticized both on theoretical and methodological grounds. For example, Friedman (1992) and Quah (1993) show that β-convergence tests may be plagued by Galton's fallacy of regression toward the mean. Furthermore, they face several methodological problems such as heterogeneity, endogeneity, and measurement problems (Durlauf and Quah, 1999; Temple, 1999). In this paper, we want to point out the fact that most empirical studies do not take into account the spatial dimension of data. In the absence of interregional input/output tables in Europe, our empirical estimations are based on the presence of spatial effects detected and modeled through the formal tools of spatial econometrics. These two different spatial effects are spatial autocorrelation and spatial heterogeneity.

Spatial autocorrelation refers to the coincidence of attribute similarity and locational similarity (Anselin, 1988, 2001). In our case, spatial autocorrelation means that rich regions tend to be geographically clustered as well as poor regions. Whereas spatial concentration of economic activities in European regions has already been documented (Lopez-Bazo *et al.*, 1999, Le Gallo and Ertur, 2003; Dall'erba, 2003b), few β-convergence studies take into account spatial interdependence between regions[7]. Indeed, β- and σ-convergence treat regions as if they were "isolated islands" (De Long, 1991; Mankiw, 1995; Quah, 1996). At the regional scale, though, spatial effects and particularly spatial autocorrelation cannot be neglected in the analysis of convergence processes: several factors, such as trade between regions, technology and knowledge diffusion, and more generally regional spillovers, may lead to spatially interdependent regions.

Integrating spatial autocorrelation into β-convergence models is useful for three reasons. First, from an econometric point of view, the underlying hypothesis in OLS

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[7] Exceptions include the following papers: Armstrong (1995), Moreno and Trehan (1997), Fingleton (1999, 2001), Rey and Montouri (1999), Baumont *et al.* (2003), Le Gallo *et al.* (2003).

estimations is based on the independence of the error, which may be very restrictive and should be tested since, if it is rejected, the statistical inference based on it is not reliable. Second, it allows capturing geographic spillover effects between European region using different spatial econometric models: the spatial lag model, the spatial error model or the spatial cross-regressive model (Rey and Montouri, 1999; Le Gallo *et al.*, 2003). Third, spatial autocorrelation allows accounting for variations in the dependent variable arising from latent or unobservable variables. Indeed, in the case of β-convergence models, the appropriate choice of these explanatory variables may be problematic because it is not possible to be sure conceptually that all the variables differentiating steady states are included[8]. Furthermore, data on some of these explanatory variables may not be easily accessible and/or reliable. Spatial autocorrelation may therefore act as a proxy to all these omitted variables and catch their effects. This is particularly useful in the case of European data, where explanatory variables are scarce (Fingleton 1999). For example, the impact of aid on convergence has been estimated on the European countries (Ederveen *et al.*, 2002) or on the developing countries benefiting from World Bank investments (Burnside and Dollar, 2000). Their conclusions point out that the aid is efficient only if it is conditioned by institution quality and good trade policies. Therefore, spatial autocorrelation allows us to consider smaller spatial units than the usual national level and furthermore may be able to capture the institutional quality and trade policy variables that are not available at the regional level. Note that nation-specific characteristics could have been captured by national dummy variables in our model specification as well. However, we reject this approach for the same reasons as those invoked in Fingleton (2003a): a) it may not entirely eliminate residual autocorrelation, and b) the significance of some variables (for example language, country of birth) could be null because of their quasi-perfect correlation with national dummy variables.

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[8] More than 90 of such variables have been included in cross-country regressions using international datasets (Durlauf and Quah, 1999).

Spatial heterogeneity means that economic behaviors are not stable over space. In a regression model, spatial heterogeneity can be reflected by varying coefficients, i.e. structural instability, or by varying error variances across observations, i.e. groupwise heteroskedasticity. These variations follow for example specific geographical patterns such as East and West, or North and South.

Spatial heterogeneity can be linked to the concept of convergence clubs, characterized by the possibility of multiple, locally stable, steady state equilibria (Durlauf and Johnson, 1995). A convergence club is a group of economies whose initial conditions are near enough to converge toward the same long-term equilibrium. When convergence clubs exist, one convergence equation should be estimated per club. To determine those clubs, some authors select *a priori* criteria, like the belonging to a geographic zone (Baumol, 1986) or some GDP per capita cut-offs (Durlauf and Johnson, 1995). Others prefer to use endogenous methods, as for example, polynomial functions (Chatterji, 1992) or regression trees (Durlauf and Johnson, 1995; Berthélemy and Varoudakis, 1996). In the context of regional economies characterized by strong geographic patterns, like the core-periphery pattern, convergence clubs can be detected using exploratory spatial data analysis which relies on geographic criteria (Baumont *et al.*, 2003).

Before going further in the spatial econometric estimation of European regional convergence, section 4 will introduce data and the spatial weight matrix since all the following analysis relies on the definition of space through the weight matrix.

Section 4 Data and Spatial Weight Matrix

The regional per capita GDP series are drawn out the most recent version of the NewCronos Regio database by Eurostat. This is the official database used by the European Commission for its evaluation of regional convergence[9]. We first use the logarithms of the per capita GDP of each region over the 1989-1999 period. Our sample is composed of 145 regions at NUTS II level (Nomenclature of Territorial Units for Statistics) over 12 EU countries: Belgium (11 regions), Denmark (1 region), Germany (30 regions, Berlin and the nine former East German regions are excluded due to historical reasons), Greece (13 regions), Spain (16 regions, as we exclude the remote islands: Las Palmas, Santa Cruz de Tenerife Canary Islands and Ceuta y Mellila), France (22 regions), Ireland (2 regions), Italy (20 regions), Netherlands (12 regions), Portugal (5 regions, the Azores and Madeira are excluded because of their geographical distance), Luxembourg (1 region), United Kingdom (12 regions, we use regions at the NUTS I level, because NUTS II regions are not used as governmental units, they are merely statistical inventions of the EU Commission and the UK government).

Austria, Finland and Sweden are not included in the study, as we want to focus on the impact of structural assistance over 1989-1999. These three countries joined the EU in 1995, meaning that they did not have access to any regional fund prior to membership. The data on structural funds come from the publications of the Commission[10]. The period under study covers the two first programming periods: the data over 1989-1993 are from "*Community structural interventions*", *Statistical report n°3 and 4,* (July and Dec. 1992)[11] and for 1994-1999, from *The 11th annual report on the structural funds*. These last data are the total

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[9] See the data appendix for further details.

[10] See the appendix for the methodology used for their calculation.

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

payments over the 1994-1999 period plus the commitments taken during this period, but that have not yet been paid.

We now present the spatial weight matrix, on which all the following analyses rely. In the European context, the existence of islands doesn't allow considering simple contiguity matrices; otherwise the weight matrix would include rows and columns with only zeros for the islands. Since unconnected observations are eliminated from the results of the global statistics, this would change the sample size and the interpretation of the statistical inference. Following the recommendations of Anselin (1996) and Anselin and Bera (1998), we choose to base them on pure geographical distance, as exogeneity of geographical distance is unambiguous. More precisely, we use the great circle distance between regional centroids. Distance-based weight matrices are defined as:

$$
\begin{cases}
w_{ij}^*(k) = 0 \text{ if } i = j, \forall k \\
w_{ij}^*(k) = 1/d_{ij}^2 \text{ if } d_{ij} \le D(k) \quad \text{and} \quad w_{ij} = w_{ij}^* / \sum_j w_{ij}^* \quad \text{for } k = 1,\ldots 3 \\
w_{ij}^*(k) = 0 \text{ if } d_{ij} > D(k)
\end{cases}
\tag{3}
$$

where w_{ij}^* is an element of the unstandardized weight matrix; w_{ij} is an element of the standardized weight matrix; d_{ij} is the great circle distance between centroids of region i and j; $D(1) = Q1$, $D(2) = Me$ and $D(3) = Q3$, $Q1$, Me and $Q3$ are respectively the lower quartile, the median and the upper quartile of the great circle distance distribution. $D(k)$ is the cutoff parameter for $k = 1,\ldots 3$ above which interactions are assumed negligible. We use the inverse of the squared distance, in order to reflect a gravity function. Each matrix is row standardized so that it is relative and not absolute distance which matters[12].

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[12] The robustness of the results is also tested by using other weight matrices based on the k-nearest neighbors, with k=10, 15, 20, 25 neighbors. In the European context, the minimum number of nearest neighbors that guarantees international connections between regions is k=7, otherwise the Greek regions would not be linked to Italy. With k=10, Ireland is connected to the UK, which in turn is connected to the whole continent; and the

Section 5 The Convergence Process Between European Regions Over 1989-1999

5. 1 Detection of spatial regimes

Using the spatial weight matrices previously described, the first step of our analysis is to detect the existence of spatial heterogeneity in the distribution of regional per capita GDPs. In that purpose, we use the G-I* statistics developed by Ord and Getis (1995)[13]. These statistics are computed for each region and they allow detecting the presence of local spatial autocorrelation: a positive value of this statistic for region i indicates a spatial cluster of high values, whereas a negative value indicates a spatial clustering of low values around region i. Based on these statistics, we determine our spatial regimes, which can be interpreted as spatial convergence clubs, using the following rule: if the statistic for region i is positive, then this region belongs to the group of "rich" regions and if the statistic for region i is negative, then this region belongs to the group of "poor" regions.

For all weight matrices described above two spatial regimes, representative of the well-known core-periphery framework (Krugman 1991a, 1991b; Fujita *et al.*, 1999), are persistent over the period and highlight some form of spatial heterogeneity:

- 100 regions belong to the spatial regime "Core":

Belgium, Germany, Denmark, France, Italy (but Molise, Campania, Puglia, Basilicata, Calabria, Sicilia), Luxembourg, the Netherlands, the United-Kingdom (but Northern-Ireland, Scotland and North West).

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islands of Sicilia, Sardegna, Corsica are connected to the continental French regions. Finally, three distance contiguity matrices are built according to the critical cut-off previously defined.
[13]   All computations in this section are carried out using the SpaceStat 1.91 software (Anselin, 1999).

- 45 regions belong to the spatial regime "Periphery":

Spain, Greece, Ireland, Southern Italy (Molise, Campania, Puglia, Basilicata, Calabria, Sicilia), Portugal, the North of the United –Kingdom (Northern-Ireland, Scotland and North West).

This methodology differs from the one in Baumont *et al*. (2003) that use Moran scatterplots (Anselin, 1996) to determine the spatial clubs: Moran scatterplots imply that the "atypical"[14] regions must be dropped out of the sample (in their case, three regions are eliminated). However, in our study, this methodology would imply eliminating 9 regions. We therefore feel that the use of Getis-Ord statistics is more appropriate in order to be able to work with the entire sample.

5. 2 Estimation results

The second step of our analysis consists in including both spatial effects in the estimation of the appropriate β-convergence model. Various tests aiming at detecting the presence of spatial effects have been described in Anselin (1988) and Anselin *et al.* (1996) and are applied here. Therefore, we shortly describe the various steps we followed to find the most appropriate model specifications in three cases: a) β-convergence model without structural funds, b) β-convergence model with structural funds (divided by GDP) and c) β-convergence model with structural funds and the lag of structural funds (both divided by GDP). In all cases, we start with the OLS estimation of the absolute β-conditional model (1). In order to identify the form of the spatial dependence (spatial error model or spatial lag), the Lagrange Multiplier tests (resp. LMERR and LMLAG) and their robust version are performed. The decision rule suggested by Anselin and Florax (1995) is then used to decide the most appropriate specification as follows: if LMLAG (resp. LMERR) is more significant

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[14] Atypical regions in this context are regions located in the "HL" ("High-Low") or in the "LH" ("Low-High") quadrants of the Moran scatterplot.

than LMERR (resp. LMLAG) and R-LMLAG (resp. R-LMERR) is significant whereas R-LMERR (resp. R-LMLAG) is not, then the most appropriate model is the spatial autoregressive model (resp. the spatial error model)[15].

β–convergence model without structural funds

In the case of the *β*-convergence model without structural funds, the application of the decision rule using the weight matrix $D(1)$[16] shows that the spatial error model is the best specification (table 1, column 1). In order to study whether spatial heterogeneity should also be included in the model, structural instability in the form of the two spatial regimes previously described is included in the spatial error model, which is estimated using Maximum Likelihood (ML). The estimation results are provided in column 2 of table 1. The individual and global stability tests on the coefficient always reject the null hypothesis, which confirms the existence of two spatial regimes. However, since the Breusch-Pagan test still reveals the presence of residual groupwise heteroskedasticity, the model is re-estimated including both structural instability and groupwise heteroskedasticity. This final model can then be described as follows:

$$g_T = \alpha_C D_C + \beta_C D_C y_0 + \alpha_P D_P + \beta_P D_P y_0 + \varepsilon$$
$$\text{with } \varepsilon = \lambda W \varepsilon + u \text{ and } u \ \square \ N\left(0, \begin{bmatrix} \sigma^2_{\varepsilon,C} I_{100} & 0 \\ 0 & \sigma^2_{\varepsilon,P} I_{45} \end{bmatrix}\right) \tag{4}$$

where g_T is the $(n \times 1)$ vector of average growth rates of per capita GDP between dates 0 and T; y_0 is the vector of log per capita GDP levels at date 0; D_C and D_P are dummy variables corresponding respectively to the core and periphery regimes previously defined; α_C, α_P,

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[15] Rey and Montouri (1999) and Le Gallo *et al.* (2003) provide a detailed description of spatial models in the context of *β*-convergence.
[16] $D(1)$ is the distance-based matrix with cut-off set to the first quartile of the distance distribution. All results are robust to the choice of the weight matrix and are available upon request from the authors.

β_C, β_P are unknown parameters to be estimated; λ is a coefficient indicating the extent of spatial correlation between the residuals. The estimation results by ML and Generalized Method of Moments (GMM) estimation are respectively displayed in columns 3 and 4 of table 1.

<<Insert table 1 here>>

The results show that there is significant convergence among the regions belonging to the periphery regime (*p*-value of 0.000) leading to a convergence speed of 3.42% for both ML and GMM and a half-life of 23.5 years. On the contrary, $\hat{\beta}_C$ does not have the expected sign and is not significant (*p*-value greater than 0.5). The Chow test of overall stability strongly rejects the joint null hypothesis and that the individual coefficient stability tests reject the corresponding null hypotheses.

The convergence process seems therefore to be quite different across regimes: if there is a convergence process among European regions, it mainly concerns the peripheral regions but does not concern the core regions. In other words, the core regions and the peripheral regions converge to two different steady-states, which is consistent with the persistence of inequalities among regions. These last results confirm those found by Beine and Jean-Pierre (2000) using a sample of 62 NUTS 1 regions over the 1980-1995 period with an endogenous determination of convergence clubs. It is also consistent with the results obtained by Baumont *et al.* (2002) for a sample of 138 NUTS 2 regions over the same period.

The presence of spatial autocorrelation is confirmed by a highly significant and positive λ coefficient ($\hat{\lambda} = 0.713$). This specification thus implies the existence of spatial spillover effects between the regions that will be further investigated in section 6.

β–convergence model with structural funds

Columns 1 and 2 of table 2 present the estimation results of model (1) to which we have added structural funds (as a ratio of GDP) as an explanatory variable. The results of the Lagrange Multiplier tests and their robust versions (column 1) show that the spatial lag model is more appropriate than the spatial error model (83.1 for LMLAG is greater than 77.4 for LMERR and R-LMLAG is significant, whereas R-LMERR is not). As in the preceding case, various tests aiming at detecting the presence of spatial heterogeneity have been performed and lead to the conclusion that the most appropriate model is the spatial lag model with structural instability defined by the two spatial regimes and groupwise heteroskedasticity:

$$g_T = \rho W g_T + \alpha_C D_C + \beta_C D_C y_0 + \delta_{1C} D_C F + \alpha_P D_P + \beta_P D_P y_0 + \delta_{1P} D_P F + \varepsilon$$

$$\text{with } \varepsilon \square N\left(0, \begin{bmatrix} \sigma_{\varepsilon,C}^2 I_{100} & 0 \\ 0 & \sigma_{\varepsilon,P}^2 I_{45} \end{bmatrix}\right) \tag{5}$$

with the same notations as above; F is the $(n \times 1)$ vector of structural funds divided by GDP; δ_{1C} and δ_{1P} are the corresponding unknown parameters to be estimated for the core and periphery regimes and ρ is a coefficient indicating the extent of spatial correlation in the dependent variable.

<<Insert table 2 here>>

The ML estimation results displayed in column 2 of table 2 show that there is significant convergence among the regions belonging to the periphery regime (*p*-value of 0.008) leading to a convergence speed of 1.51% for ML and a half-life of 49 years. The convergence is therefore a bit slower than in the model without structural funds. Again, the coefficient in the core regime does not give any evidence of convergence ($\hat{\beta}_C = 0.001$ and is not significant). The spatial lag ($\hat{\rho} = 0.735$) is strongly significant (*p*-value of 0.000)

indicating that in this model specification, the growth rate of a region is significantly influenced by the growth rate of its surrounding regions. On the contrary, the impact of the funds is not significant in any regime. The Chow test of overall stability does not reject the joint null hypothesis on the equality of the regimes' coefficients; whereas the individual coefficient stability tests reject the corresponding null hypotheses (except the coefficient on structural funds with a *p*-value of 0.804). The LR test confirms the presence of two significantly different variances across regimes. The convergence process seems therefore not to be significantly affected by the structural funds**.** In the model specification below, we measure if the regional growth rate is influenced by the amount of structural funds allocated to the region itself and also its neighbors.

β–convergence model with structural funds and the lag of structural funds

Columns 3 and 4 of table 2 present the estimation results of model (1) to which we have added structural funds and lagged structural funds, both as a ratio of GDP, as explanatory variables. Lagrange Multipliers tests on the OLS-estimation of model (1) with these explanatory variables lead to a spatial error model as the appropriate specification. However, when structural instability, which is significant, is added to this model (column 3), these tests reveal that the spatial lag model is the most appropriate specification. Column 4 displays the ML estimation results of this model where both structural instability and groupwise heteroskedasticity are significant:

$$g_T = \rho W g_T + \alpha_C D_C + \beta_C D_C y_0 + \delta_{1C} D_C F + \delta_{2C} D_C WF + \alpha_P D_P + \beta_P D_P y_0 + \delta_{1P} D_P F + \delta_{2P} D_P WF + \varepsilon$$

$$\text{with } \varepsilon \ \square \ N\left(0, \begin{bmatrix} \sigma_{\varepsilon,C}^2 I_{100} & 0 \\ 0 & \sigma_{\varepsilon,P}^2 I_{45} \end{bmatrix}\right) \tag{6}$$

with the same notations as above; *WF* is the lag of structural funds (i.e. the spatial cross-regressive variable, Florax and Folmer, 1992) and δ_{2C} and δ_{2P} are the corresponding unknown parameters to be estimated.

Both coefficients $\hat{\beta}$ have the expected sign, but it is not significant in the core (*p*-value = 0.875). As in the preceding model, the spatial lag coefficient is highly significant (*p*-value = 0.000). It is however lower than in the preceding model (0.670 versus 0.735). The coefficients on structural funds are not significant and the coefficient on the lag of structural funds is significant only in the periphery, but has a very small extent ($\hat{\delta}_2 = 4.91.10^{-3}$). The Chow test of overall stability rejects the joint null hypothesis. This is confirmed by the individual coefficient stability tests on the constant and the convergence parameter, which reject the corresponding null hypotheses. On the opposite, the individual coefficient stability tests on the fund and the lag coefficients do not reject the null hypotheses. The LR test confirms the presence of two significantly different variances across regimes. As a conclusion, the convergence process does not seem to be affected neither by the impact of structural funds nor by the impact of the lag of structural funds.

The results of the previous estimations do not conclude to a significant impact of structural funds on regional convergence. The next section will therefore assess the impact of structural funds using simulation experiments based on the diffusion properties of the spatial error model (4).

Section 6 Spatial Diffusion Effects in European Regions

Rather than introducing structural funds as explanatory variables in a conditional β-convergence equation, this section considers them as shocks affecting the regions through the

error process. Using the spatial diffusion properties of the spatial error specification estimated in section 5, it is then possible to consider the impact of shocks affecting a region on the region itself and on all the other regions of the sample.

Formally, since $\varepsilon = \lambda W \varepsilon + u \Rightarrow \varepsilon = (I - \lambda W)^{-1} u$, model (4) can be written in the following form:

$$g_T = \alpha_C D_C + \alpha_P D_P + \beta_C D_C y_0 + \beta_P D_P y_0 + (I - \lambda W)^{-1} u \tag{7}$$

In this specification, spatial spillovers are supposed to be global and a shock affecting one region propagates to all the other regions of the sample through the spatial transformation $(I - \lambda W)^{-1}$ (Anselin, 2003). We use this property to conduct a simulation experiment aimed at analyzing the way shocks in the regions of the sample propagate to all the other regions.

In that purpose, let a_i be the amount of the shock affecting region i and $\hat{u}^i$ be the $(n \times 1)$ vector containing the estimated error of model (7) after a shock on error i: $\hat{u}^i{}' = \left(\hat{u}_1 \quad \ldots \quad \hat{u}_i + a_i \quad \ldots \quad \hat{u}_n \right)'$. Therefore, the $(n \times 1)$ vector y^{i*} containing the observations on the simulated average growth rates of per capita GDP after a shock in region i can be computed in the following way:

$$y^{i*} = X \hat{\gamma} + (I - \hat{\lambda} W)^{-1} \hat{u}^i \tag{8}$$

where $X = \begin{bmatrix} D_C & D_P & D_C y_0 & D_P y_0 \end{bmatrix}$; $\hat{\gamma} = [\hat{\alpha}_C \quad \hat{\alpha}_P \quad \hat{\beta}_C \quad \hat{\beta}_P]'$; $\hat{\alpha}_C$, $\hat{\alpha}_P$, $\hat{\beta}_C$, $\hat{\beta}_P$ and $\hat{\lambda}$ are the ML estimations of α_C, α_P, β_C, β_P and λ in the spatial error model (4). Let Y^* be the matrix of dimension $(n \times n)$ containing the observations on the simulated average growth rates of per capita GDP after a shock in each region:

$$Y^* = \begin{bmatrix} y^{1*} & \ldots & y^{n*} \end{bmatrix} = \begin{bmatrix} X\hat{\gamma} & \ldots & X\hat{\gamma} \end{bmatrix} + A^{-1} \begin{bmatrix} \hat{u}^1 & \ldots & \hat{u}^n \end{bmatrix} \tag{9}$$

with $A = I - \hat{\lambda}W$. Equation (9) can also be rewritten in a more compact way:

$$Y^* = S' \otimes X\hat{\gamma} + A^{-1}\hat{U} \tag{10}$$

where $\otimes$ is the Kronecker product; $\hat{U}$ is the matrix of dimension $(n \times n)$ defined as: $\hat{U} = \begin{bmatrix} \hat{u}^1 & \ldots & \hat{u}^n \end{bmatrix}$. Given the definition of each element $\hat{u}^i$, this matrix $\hat{U}$ can also be written as:

$$\hat{U} = \begin{pmatrix} \hat{u}_1 + a_1 & \hat{u}_1 & \ldots & \hat{u}_1 \\ \hat{u}_2 & \hat{u}_2 + a_2 & \ldots & \hat{u}_2 \\ \vdots & \vdots & \ddots & \vdots \\ \hat{u}_n & \hat{u}_n & \ldots & \hat{u}_n + a_n \end{pmatrix} \Rightarrow \hat{U} = S' \otimes \hat{u} + \text{diag}(a_i) \tag{11}$$

Combining (10) and (11), we obtain:

$$Y^* = S' \otimes X\hat{\gamma} + A^{-1}(S' \otimes \hat{u} + \text{diag}(a_i)) \tag{12}$$

This expression yields a matrix of dimension $(n \times n)$ where the column i indicates the simulated average growth rates of per capita GDP for all regions in the sample after a shock in region i. The difference D between the matrix of simulated average growth rates Y^* (after the shock) and the matrix of actual average growth rates Y (without shock) is $D = Y^* - Y$. Since $Y = S' \otimes y$, with $y = X\hat{\gamma} + A^{-1}\hat{u}$, then:

$$D = A^{-1}diag(a_i) \qquad \text{with } A = I - \hat{\lambda}W \tag{13}$$

Finally, we consider the matrix V, containing the variation in percentage between the simulated and the actual average growth rates. V is obtained by dividing each term of the D matrix by each corresponding term of the Y matrix. On the one hand, the elements on the main diagonal represent the impact of a shock in a region on the region itself. On the other

hand, the other elements in each column i of the matrix V indicates how the region i affects the other regions of the sample when there is a shock in this region.

This methodology extends the one developed in Le Gallo *et al.* (2003), where all shocks are set equal to twice the residual standard error of the estimated spatial error model. Using a sample of 138 regions over the 1980-1995 regions, they show that the strength of diffusion both depends on the localization and the economic dynamism: rich regions located in the core diffuse more than the poor regions in the periphery. In this paper, rather than considering equal random shocks, we include the real values of average structural funds as a ratio of GDP over 1989-1999. Note that the simulation is carried out on the 1989-1999 growth rates that already include the effects of structural funds. Therefore, in that context, we do not directly analyze the impact of structural funds themselves but rather we study whether allowing for differentiated shocks offsets the effects of poor economic dynamism and unfavorable relative localization of peripheral regions.

We consider two different cases[17]. In the first one, each region experiences a similar shock proportional to average amount of structural funds distributed during the 1989-1999 period. In the second one, each region experiences a different shock proportional to the real amount of structural funds it has received during the period[18].

<<Insert figures 3 and 4 here>>

Figures 3 and 4 display the main diagonal of V that represents the impacts of the shocks on the region itself. In the case of an equal shock, the extent of the impact does not vary much from one region to another. In the case of differentiated shocks, the extent of the

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[17] The codes used to carry out the simulations in this section have been developed using Python 2.2 (http://www.python.org).
[18] The factor of proportionality is set to twice the average of residual standard errors of each regime in the estimated spatial error model (4).

impact on the targeted regions increases a lot, and more especially in the peripheral regions, since they receive the largest amounts of structural funds. We note however that the extent of the impact increases the least in Alentejo and Algarve (Portugal) and in Kentriki Makedonia, Kriti, Peloponnisos, Dytiki Ellada (Greece), considering that Community assistance was respectively 2.7 and 1.8 times greater than the average amount of structural funds for the Portuguese regions and respectively 1.6, 2.6, 1.8 and 1.7 times for the Greek regions. These results tend to demonstrate that the greater cohesion efforts allocated to these regions have not been sufficient enough to favor growth in these particular regions. This may be due to the peripherality of these regions or the lack of efficiency of financed infrastructures to favor cohesion, as depicted in section 2.

<<Insert figures 5 and 6 here>>

To capture the extent of spillover effects, we analyze the diffusion properties of a shock in each single region to all the other regions. It corresponds to the computed median for each column of V, excluding the main diagonal. As in Le Gallo *et al.* (2003) when the shocks are equal (figure 5), it appears that the most influential regions are rich northern European regions mainly belonging to Belgium, Germany, Netherlands, Luxembourg and the Northern and Eastern part of France. All these regions belong to the core of Europe. On the contrary, all the regions belonging to the periphery are the less influential. When the shocks are differentiated (figure 6), the overall picture is not really modified: the most influential regions are still located in the core even though they are less numerous than in the previous case. The diffusion properties of the peripheral regions have not increased, which can traduce the fact that the nature and the extent of diffusion properties does not depend on the amount of structural funds received, but rather on the characteristics of peripheral regions. They are relatively bigger than core regions and thus have fewer neighbors within the critical cut-off

we used for the weight matrix[19]. Because these regions are peripheral, and thus lined by the Mediterranean Sea, the spillover effect does not spread in every direction. On the contrary, core regions are centrally located and much smaller regions, which facilitates interregional dependences as well. They are also more connected with each other in terms of accessibility via transportation network. Finally, as the economic structure of core regions becomes more homogeneous and as trade among them becomes more concentrated, these regions tend to move in phase rather than according to different set of rhythms[20]. This result suggests also that the small extent of spillover effects in peripheral regions could be a relevant explanation of their backwardness, and that even greater targeted funds do not allow to favor spillovers in periphery.

Even though the extent of diffusion effects has not increased in peripheral regions when allowing for differentiated shocks, we propose in this section a more qualitative approach to identify the regions that win or loose when the shock is differentiated compared to the case of an equal shock. In that purpose, the regions are ranked according to their diffusion properties displayed in figures 5 and 6.

<<Insert figure 7 here>>

The standard deviation of the change in rankings between these two cases is about 32. As depicted in figure 7, it appears that 29 regions shifted by more than one standard deviation. Among these 29 regions, all the 16 regions that shifted downward belong to the core: greatest shifts occur in Zuid-Holland (rank 22 for an equal shock and 127 for a differentiated shock), Nord-Holland (resp. 30 and 135), Utrecht (15 and 117), Ile-de-France (51 and 138) and

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[19] However, all the results presented in this section are confirmed using a 10 nearest neighbors matrix, with which all regions has exactly the same number of neighbors.
[20] These results are confirmed by non-parametric tests on the equality of the medians between core regions and peripheral regions. In both cases of equal and differentiated shocks, the Kruskall-Wallis, U Mann-Whitney and Wald-Wolfowitz tests all reject the null hypothesis. Furthermore, these results are similar when considering the first or the third quartiles of each row of matrix *V*.

Stuttgart (41 and 119). Conversely, all the 13 regions that shifted upward are located in the periphery. The greatest changes concern Border (118 and 26), Molise (97 and 22), Corse (94 and 23), Basilicata (110 and 46), Cantabria (109 and 56) and then several other Italian and Spanish regions. On the other hand, the smallest changes among the peripheral regions (rank variation below 10) concern 11 of the 13 Greek regions, Puglia and Sicilia in Southern Italy, Centro and Algarve in Portugal. These last findings show that allowing for differentiated shocks increases the diffusion properties of the peripheral regions that are the closest from the core, whereas the most peripheral regions seem to never improve their diffusion properties, whatever the amount of structural funds allocated (for instance, the Greek region Anatoliki Makedonia receives 4.7 times more in the case of a differentiated shock than in the case of an equal shock or 2 times more than Cantabria in the case of a differentiated shock, but its ranking does not change anyway). This is consistent with section 2 which demonstrates the lack of success of regional policies in the most peripheral regions.

Section 7 Conclusion

The aim of this paper has been to highlight the impact of structural funds on the convergence process of 145 European regions over the 1989-1999 period. If these funds are mainly devoted to the least developed regions, the persistence of regional inequalities over the period leads to a real reconsideration of their efficiency. Since the majority of these funds finance transportation infrastructures which induce industry relocation effects, their impact on regional development is not clear yet but surely needs to be seen in the light of spillover effects their spatial allocation implies. In other words, estimating the impact of structural funds on regional growth without including the presence of significant spatial effects would lead to unreliable results.

In order to include spatial effects in the determination of the most appropriate β-convergence model, we start by using the Getis-Ord statistics. The results display the presence of significant local spatial autocorrelation in the form of two regimes representative of the well-known core-periphery pattern over the whole period (Krugman 1991a, 1991b; Fujita *et al.*, 1999). Various tests aiming at including the significant presence of spatial effects in our model lead to a spatial error model (in the case of no structural funds) or to a spatial lag model (in the case of structural funds) with groupwise heteroskedasticity and structural instability in the form of the two regimes detected using the Getis-Ord statistics. Estimation results display significant convergence in the peripheral regime only, a significant, positive and very small impact of the lag of the funds as well, but a non significant impact of the funds themselves. Therefore, we use another approach to estimate the impact of a shock proportional to structural funds on the growth rate of the targeted region first, and then on the growth rate of all the other regions of our sample. Based on the spatial diffusion properties of the spatial error model, simulation experiments are performed in two cases: first with shocks proportional to the mean structural funds for all the regions (equal shock), and second with shocks proportional to the real value of structural funds as a ratio of GDP for each region (differentiated shock). The results show that in the case of an equal shock, the extent of the impact on the targeted region's growth does not vary much from one region to another. In the case of differentiated shocks, the extent of the impact on most peripheral regions increases very much, traducing that they are the main beneficiaries of these funds. However the extent of the impact does not increase in some Greek and Portuguese regions, which implies that greater cohesion efforts are necessary for these regions. When it comes to measuring spillover effects through the impact of the shocks targeted in one region on the growth rate of all the other regions, the results detect the presence of a growth diffusion process only from the core regions, whatever the extent of the shock is (either equal or differentiated). This may

reflect that core regions are generally smaller and more connected with each other, through trade and transport network, than peripheral regions. This result also suggests that the small extent of spillover effects in peripheral regions could be an explanation of their backwardness. Finally, when the regions are ranked according to their diffusion properties, the results show that in the peripheral regions neighboring core regions the greater amount of targeted funds favors spillover effects, whereas these effects never increase in the most peripheral regions, whatever the amount allocated. It should be noted however that the empirical findings, while supporting the expectations advanced by the theory, may in part result from the particular nature of the modeling formulations we used. In this regards, further works examining the consistency of the nature and the extent of spillover effects would need to be undertaken.

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Data Appendix

The data are based on the most recent version of the NewCronos Regio database (2002) created by Eurostat. We use both datasets e2gdp79 and e2gdp95, which provide the per capita GDP at the NUTS 2 level in Ecus (Nomenclature of Territorial Units Statistics). This dataset is the official dataset used by the European Commission for evaluating regional income in Europe. Over 1989-1996, our data come from e2gdp79. We have added some modifications to this dataset since some data of our interest were missing. For instance, the data on the per capita income in Ireland are given only at the national level. We therefore used the dataset from Cambridge Econometrics (2001) which provides the Gross Value Added (GVA) at the NUTS 2 level for Ireland as well. Two NUTS 2 regions compose Ireland: Border and Dublin. The annual share of each region in the total GVA was calculated from this dataset and applied on e2gdp79 to estimate the annual per capita GDP of each region. For the United-Kingdom, the data are used at the NUTS 1 level, since NUTS 2 regions are not used as governmental units (they are merely statistical inventions of the EU Commission and the UK government). Luxembourg and Denmark are considered as NUTS 2 regions by Eurostat. The per capita GDP of Groningen (Netherlands) was exceptionally high in 1980 because all the North Sea oil revenues were attributed to this region until 1985. We therefore use the mean growth rate over 1980-1985 to calculate the data over 1980-1988, this last date being the first year were none oil income was systematically attributed to Groningen.

The data on commitments in structural funds for 1989-1993 come from "*Community structural interventions*", *Statistical report n°3 and 4* (July and Dec. 1992) and from *The 11th annual report on the structural funds* for 1994-1999. These funds are allocated either at the NUTS 1, NUTS 2 or NUTS 3 level. The last two levels are easy to implement in our database, but difficulty arises for the funds allocated at the NUTS 1 level. Since the NUTS 2 level is used for the data on regional GDP, we disaggregate regional funds to NUTS 2 level also. The disaggregating process described in the next paragraph has been used for objectives 2, 3, 4 and 5 in six German NUTS 1 regions that become 26 NUTS 2 regions:
- Baden Württenberg: Stuttgart, Karlsruhe, Freiburg, Tubingen
- Bayern: Oberbayern, Niederbayern, Oberpfalz, Oberfranken, Mittelfranken, Unterfranken, Schwaben
- Hessen: Darmstadt, Giessen, Kassel
- Niedersachsen: Braunschweig, Hannover, Lüneburg, Weser-Ems
- Nordhein Wetsfalen: Dusseldorf, Köln, Münster, Detmold, Arnsberg
- Rheinland-Pfalz: Koblenz, Trier, Rheinhessen-Pfalz

It also concerns two Belgian NUTS 1 regions (for objectives 2, 3, 4, 5 and the funds allocated as Community Initiatives):
- Vlaanderen: Oost Vlaanderen, Limburg, West-Vlaanderen, Antwerpen, Vlaams-Brabant.
- Wallonie: Brabant wallon, Namur, Luxembourg, Liege, Hainaut.

The methodology is also applied on two Dutch regions (Groningen and Drenthe for objectives 2 and 5), and on Dublin and Border (for the objective 1 and Community Initiatives). Note that the following disaggregating process concerns less than one third of the 145 regions of our sample. Moreover, except for the two Irish regions and for Hainaut (in Belgium) which received a great support respectively under objective 1 and 2, the extent of structural funds relative to GDP is negligible in these regions (less than 1% on average).

Since regional funds have different priority objectives, each of them is disaggregated to NUTS 2 regions according to the following process:

- For objective 1 funds (which concerns the least developed regions), we use the inverse of per capita GDP of NUTS 2 regions: the richer a NUTS 2 region within a NUTS 1 region is, the less it receives. In other words, inside each NUTS 1 region, if a NUTS 2 region has an income twice greater than another region, then it should receive twice as less structural funds than the other region. This respects the redistribution pattern of objective 1.
- For objective 2 funds (which concerns regions in industrial crisis), we use the share of energy and manufacturing GVA on total GVA: the higher it is, the less the region receives. Here we assume that in the targeted NUTS 1 region, the share of industry is high (otherwise it would not have been selected as objective 2), then within this region, more funds go to the NUTS 2 region having the smaller share.
- For objective 3 funds (for the regions with long-term unemployment), we use the employment rate: the higher it is, the less a region receives.
- For objective 4 funds (which concerns retraining to industry changes), we use the employment rate in energy and manufacturing: the smaller it is, the more a region receives.
- For objective 5 (financing the adaptation of agriculture, fishery, and rural structures), we use the share of agriculture in total GVA: the greater it is, the less a region receives. Here we assume again that the share of agriculture in region NUTS 1 is high (otherwise this region would not have been selected for this objective). Therefore, within this region, the region NUTS 2 having the smaller share receives the more.
- Community initiatives: since most of them have social issues (employment with EMPLOI, rural development with LEADER+, combating inequalities and discrimination in access to the labor market with Equal, sustainable development of cities and declining urban areas with Urban), we use the same reasoning as for objective 1: the richer the region is, the less it receives. We do not take into account the program INTERREG since it allocates funds to neighboring regions belonging to different countries.

We are aware that our empirical results could be affected by missing regions and by the use of different levels of spatial aggregation. The choice of the spatial aggregation and identification of the data influence the magnitude of various measures of association. In the literature, this problem is referred as the modifiable areal unit problem (MAUP) (Arbia, 1989; Anselin and Cho, 2000). Moreover, per capita growth in open formal NUTS 2 regions may reflect characteristics of neighboring regions. Boldrin and Canova (2001) illustrate this problem linked to measuring a variable on a territorial unit artificially defined in which people are free to move. They give the example of the city of Hamburg, which is a NUTS 2 level region with high per capita income, but half the population of the whole Hamburg metropolitan area lives in the nearby NUTS 2 level regions of Schleswig-Holstein and Lower Saxony, commuting to Hamburg for work. As a result, the value added in Hamburg is overstated by 20% relative to its effective population, while those of Schleswig-Holstein (value added equals 102% of EU average) and Lower Saxony (104%) are understated. This is similar for Ile-de-France (160%) and Bassin Parisien (92.7%), Communidad de Madrid (101%) and its neighboring Castillas (66 and 76%). The choice of studying European regions at the NUTS 2 level is purely based on regional development policy consideration. This scale level corresponds to the one used to allocate structural funds under objective 1 (around 70% of structural funds are objective 1).

Table 1: Estimation results of the β-convergence model without structural funds and weight matrix $D(1)$

	Model without structural funds						
	1	2		3		4	
	OLS-White	ML-ERR with regime		ML-ERR with regime and heteroskedasticity		GMM-ERR with regime and heteroskedasticity	
		Core	Periph.	Core	Periph.	Core	Periph.
$\hat{\alpha}_r$	0.211 (0.000)	0.019 (0.641)	0.309 (0.000)	0.020 (0.547)	0.308 (0.000)	0.023 (0.505)	0.313 (0.000)
$\hat{\beta}_r$	-0.018 (0.000)	0.002 (0.612)	-0.029 (0.000)	0.002 (0.566)	-0.029 (0.000)	0.002 (0.617)	-0.029 (0.000)
$\hat{\lambda}$	-	0.769 (0.000)		0.759 (0.000)		0.713 (0.000)	
$\sigma^2_{\varepsilon,P}$	-	-	-	-	$1.03 \cdot 10^{-4}$ (0.000)	-	$1.06 \cdot 10^{-4}$ (0.000)
$\sigma^2_{\varepsilon,C}$	-	-	-	$4.38 \cdot 10^{-5}$ (0.000)	-	$4.46 \cdot 10^{-5}$ (0.000)	-
Convergence speed	1.98%	-	3.42%	-	3.42%	-	3.42%
Half-life	38.16	-	23.55	-	23.55	-	23.55
Sq. Corr.	-	0.342		0.342		0.344	
LIK	450.965	488.598		502.467		-	
AIC	-897.930	-969.196		-996.933		-	
SC	-891.976	-957.289		-985.026		-	
Moran's I	10.531 (0.000)	-		-		-	
LMERR	93.415 (0.000)	-		-		-	
R-LMERR	6.470 (0.010)	-		-		-	
LMLAG	92.587 (0.000)	-		-		-	
R-LMLAG	5.643 (0.017)	-		-		-	
Chow-Wald	-	17.341 (0.000)		14.016 (0.000)		14.872 (0.001)	
Ind. stab. test on $\hat{\alpha}_r$	-	16.378 (0.000)		12.059 (0.000)		12.621 (0.000)	
Ind. stab. on $\hat{\beta}_r$	-	15.505 (0.000)		11.132 (0.000)		11.743 (0.000)	
BP-test on groupwise heteroskedasticity	-	13.900 (0.000)		-		-	
LR test on groupwise heteroskedasticity	-	-		27.737 (0.000)		-	

Notes: *p*-values are in brackets. *OLS-White* indicates the use of heteroskedasticity consistent covariance matrix estimator. *ML* indicates maximum likelihood estimation. *GMM* indicates iterated generalized moments estimation (Kelejian and Prucha 1999). *Sq. Corr.* is the squared correlation between predicted values and actual values. *LIK* is value of the maximum likelihood function. *AIC* is the Akaike information criterion. *SC* is the Schwarz information criterion. *LMERR* stands for the Lagrange Multiplier test for residual spatial autocorrelation and *R-LMERR* for its robust version. *LMLAG* stands for the Lagrange Multiplier test for spatially lagged endogenous variable and *R-LMLAG* for its robust version (Anselin *et al*., 1996). The individual coefficient stability tests are based on a spatially adjusted asymptotic Wald statistics, distributed as χ^2 with 1 degree of freedom. The Chow – Wald test of overall stability is also based on a spatially adjusted asymptotic Wald statistic, distributed as χ^2 with 2 degrees of freedom (Anselin 1988). *BP* is the Breusch-Pagan test for groupwise heteroskedasticity. *LR* is the likelihood ratio test for groupwise heteroskedasticity.

Table 2: Estimation results of the β-convergence model model with structural funds, with structural funds and their spatial lag and weight matrix $D(1)$

|	Model with structural funds			Model with structural funds and their lag			
	1	2		3		4	
	OLS-White	ML-LAG with structural instability and groupwise heteroskedasticity		OLS-White with structural instability		ML-LAG with structural instability and groupwise heteroskedasticity	
		Core	Periph.	Core	Periph.	Core	Periph.
$\hat{\alpha}_r$	0.178 (0.000)	0.001 (0.966)	0.142 (0.005)	0.136 (0.012)	0.277 (0.000)	0.020 (0.606)	0.146 (0.002)
$\hat{\beta}_r$	-0.014 (0.000)	0.001 (0.815)	-0.014 (0.008)	-0.01 (0.085)	-0.027 (0.000)	$-.6.1.10^{-4}$ (0.875)	-0.015 (0.004)
$\hat{\lambda}$	-	0.735 (0.000)		-		0.670 (0.000)	
$\hat{\delta}_{1r}$	0.003 (0.049)	0.002 (0.655)	0.001 (0.577)	-0.003 (0.680)	0.002 (0.164)	0.003 (0.574)	$4.4.10^{-4}$ (0.763)
$\hat{\delta}_{2r}$	-	-		-0.019 (0.083)	0.001 (0.000)	-0.008 (0.316)	$4.91.10^{-3}$ (0.019)
$\sigma^2_{\varepsilon,P}$		-	$1.07.10^{-4}$ (0.000)	-		-	$9.73.10^{-5}$ (0.000)
$\sigma^2_{\varepsilon,C}$		$4.46.10^{-6}$ (0.000)	-			$4.53.10^{-5}$ (0.000)	-
Convergence speed	1.51%	-	1.51%	-	3.15%	-	1.62%
Half-life	49.16	-	49.16	-	25.32	-	45.86
Sq. Corr.	-	0.615		-		0.629	
LIK	452.957	494.213		473.830		497.124	
AIC	-899.915	-974.426		-931.660		-976.247	
SC	-890.984	-953.589		-907.846		-949.457	
Moran's I	9.838 (0.000)	-		8.122 (0.000)		-	
LMERR	77.386 (0.000)	-		44.556 (0.000)		-	
R-LMERR	3.597 (0.057)	-		0.284 (0.593)		-	
LMLAG	83.180 (0.000)	-		53.693 (0.000)		-	
R-LMLAG	9.390 (0.002)	-		9.421 (0.002)		-	
Chow-Wald	-	5.687 (0.128)		8.095 (0.000)		10.078 (0.039)	
Ind. stab. test on $\hat{\alpha}_r$	-	5.075 (0.024)		4.331 (0.039)		4.322 (0.038)	
Ind. stab. test on $\hat{\beta}_r$	-	5.227 (0.022)		5.628 (0.019)		4.875 (0.027)	
Ind. stab. test on $\hat{\delta}_{1r}$	-	0.061 (0.804)		0.475 (0.492)		0.202 (0.653)	
Ind. Stab. test on $\hat{\delta}_{2r}$	-	-		6.935 (0.009)		2.514 (0.113)	
LR test on groupwise heteroskedasticity	-	13.129 (0.000)		-		9.604 (0.002)	

Notes: see table 1.
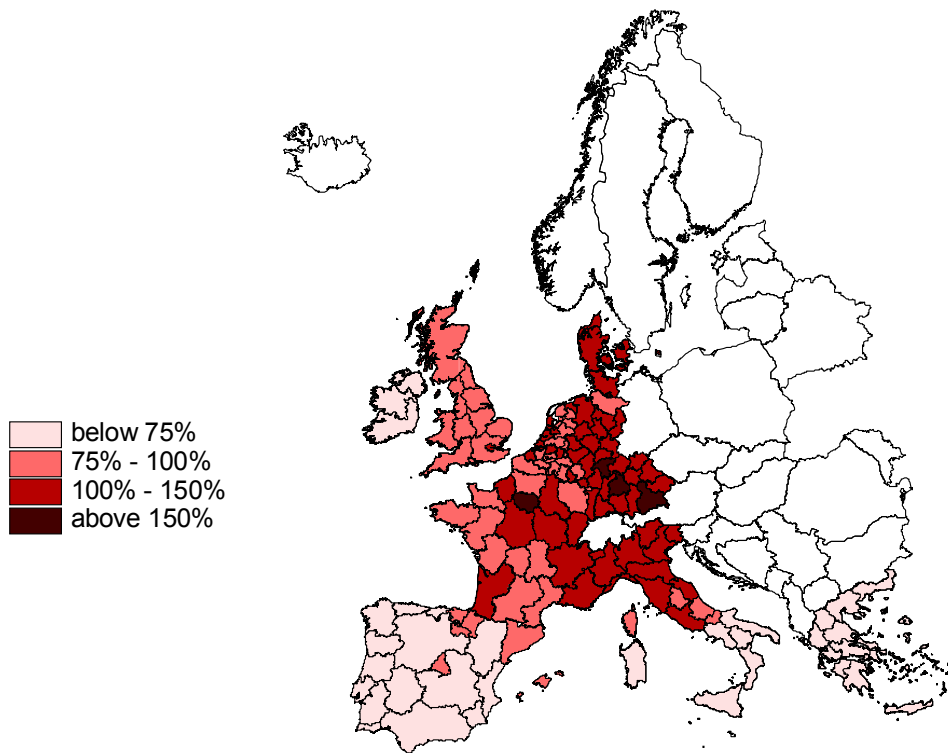
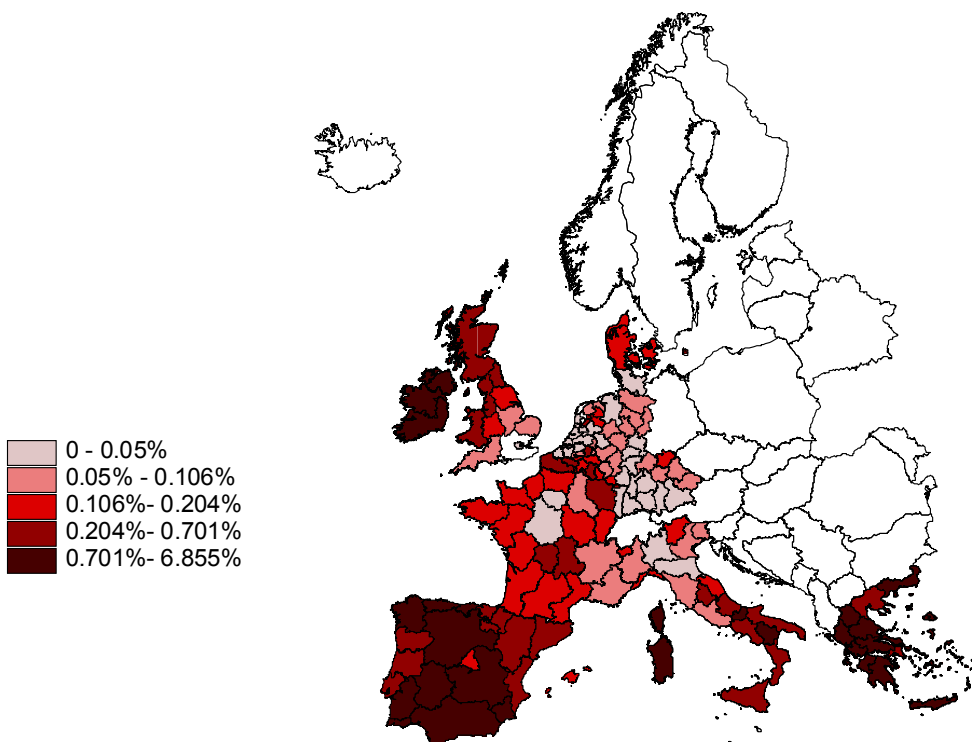**Figure 1: GDP per capita relative to the European average in 1989**

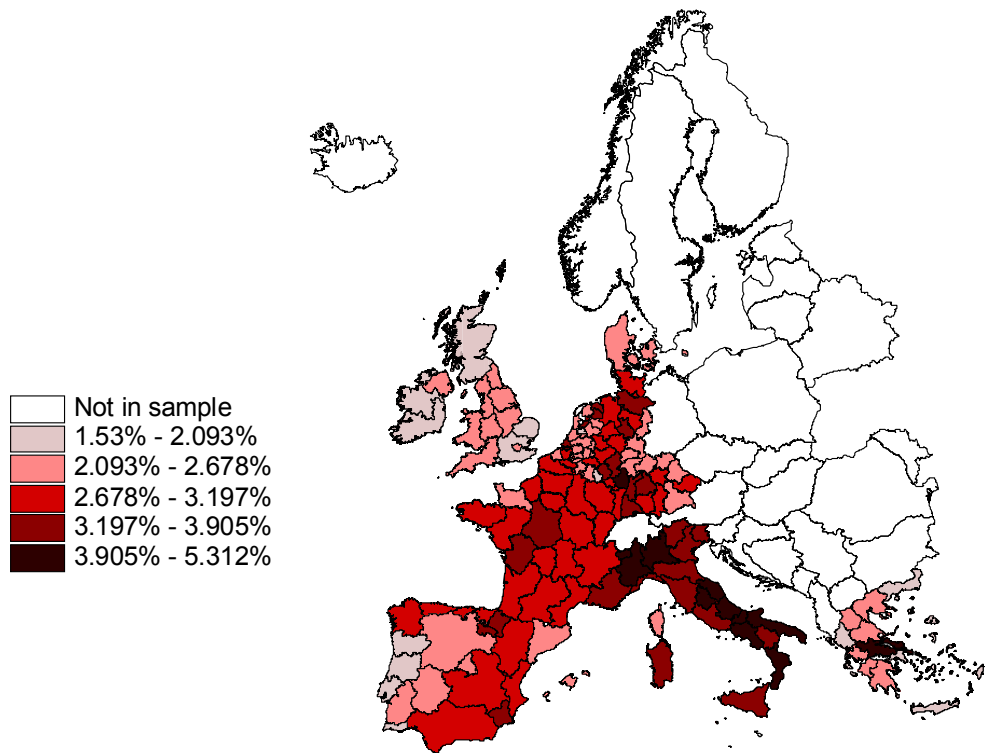**Figure 2: Spatial distribution of regional funds as a ratio of GDP during 1989-1999**

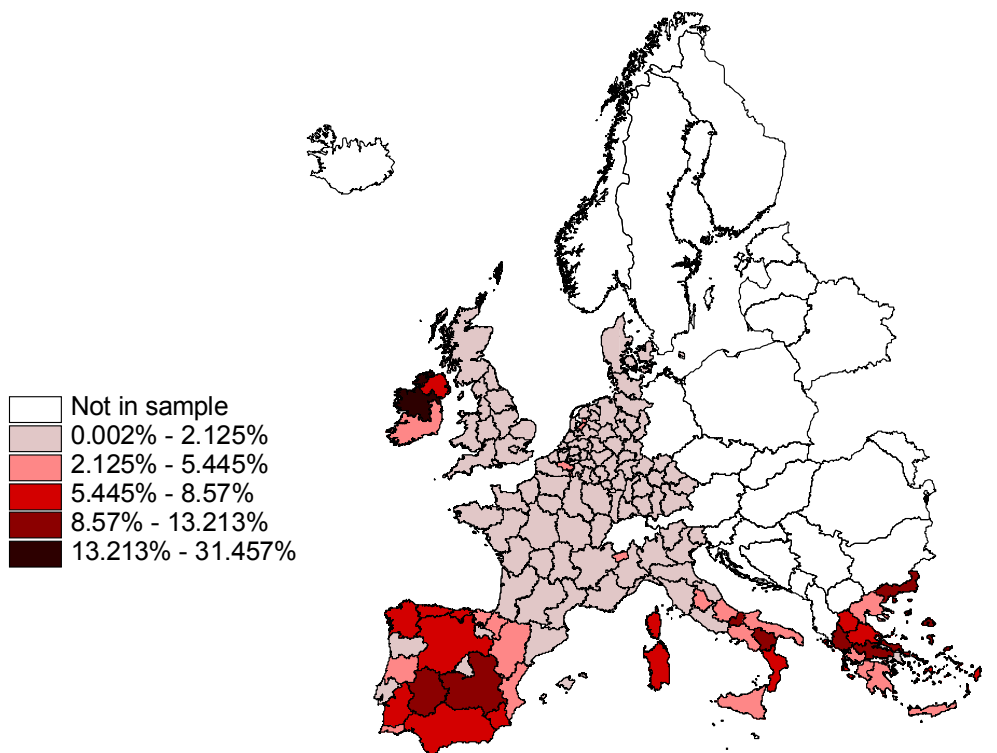**Figure 3: Impact of equal shocks on each region's growth**

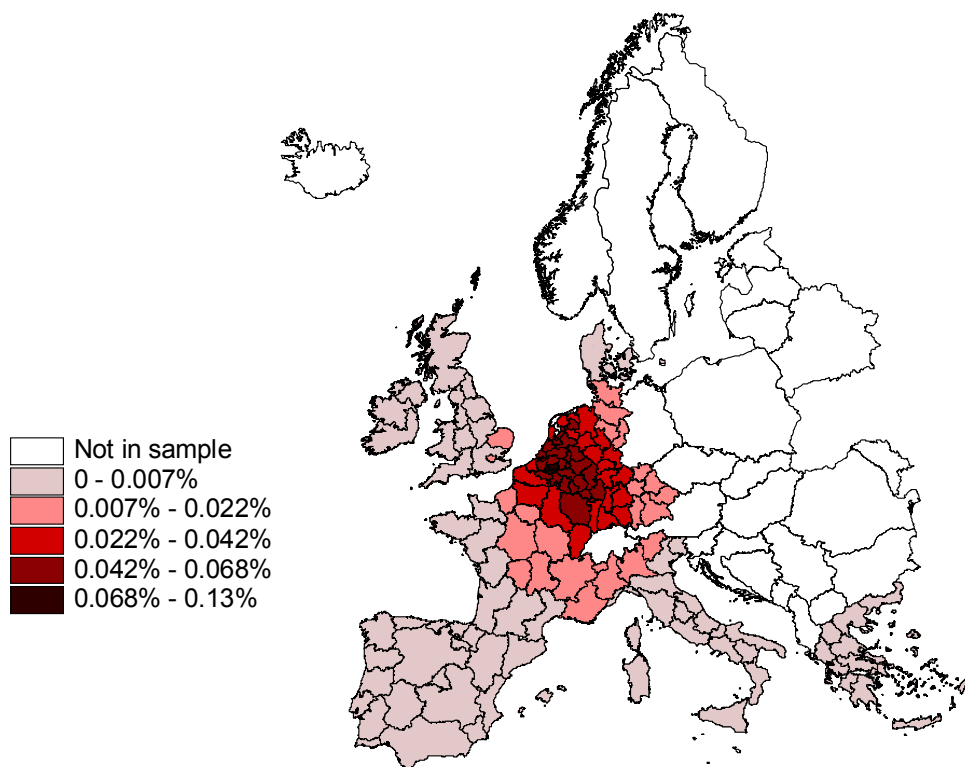**Figure 4: Impact of differentiated shocks on each region's growth**

Figure 5: Distribution of regions according to the extent of diffusion effects they produce with an equal shock
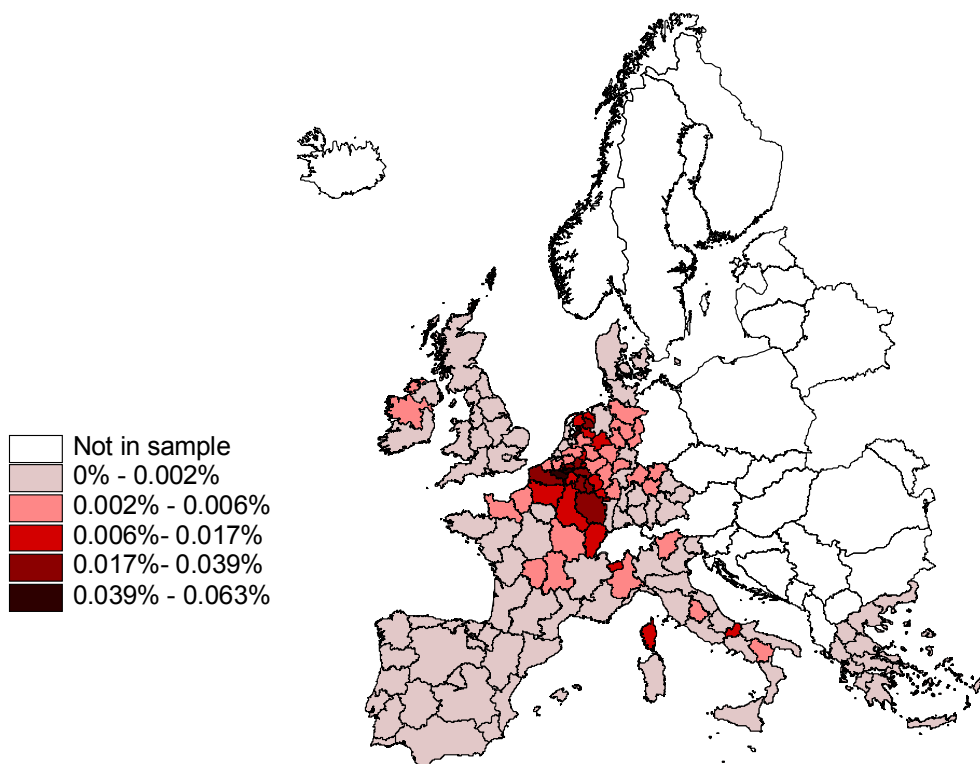

Figure 6: Distribution of regions according to the extent of diffusion effects they produce with differentiated shocks
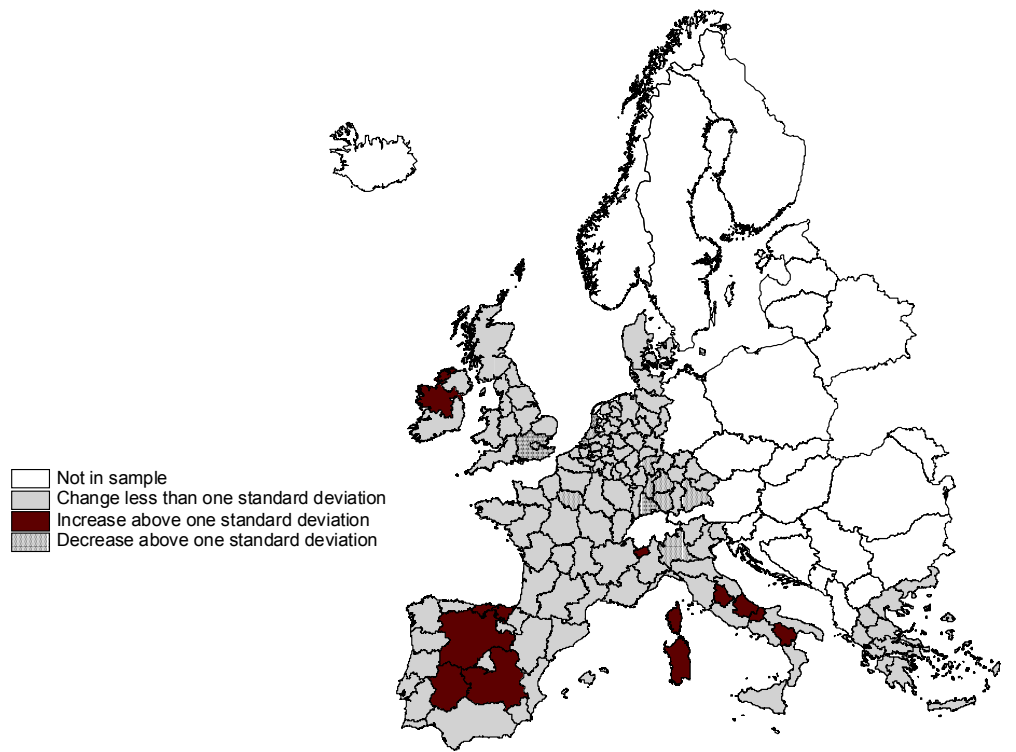
**Figure 7: Variations in regions' rankings between equal shocks
and differentiated shocks**