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

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Abstract

This paper estimates the impact of structural funds on the convergence process between 145 European regions over 1989-1999. We propose two novelties. First, we use spatial econometric methods to assess the impact of the funds not only on the targeted region, but also on its neighbors. Second, we control for endogeneity of the funds on regional growth. Estimation results indicate that significant convergence takes place, but that the funds have no impact on it. Simulation experiments show how investments targeted to the peripheral regions never spill over their neighbors, which calls for a reconsideration of current regional policy tools.

JEL Classification: C14, O52, R11, R15

Key words: European structural funds, β-convergence, spatial econometrics, geographic spillovers

1 Introduction

The phenomenon of persistent income and GDP disparities among European regions has been widely studied in literature, using mostly convergence models based on neoclassical specifications. The results of empirical estimations reveal greater cohesion among European regions (Barro and Sala-I-Martin 1991; Amstrong 1995), but at a slow rate (Martin, 2001) and also increasing disparities among regions within countries (Esteban, 1994). European integration seems to have benefited the richest regions in the poorest countries instead of the intended growth of all the poorest regions.

In order to decrease disparities, the European regional development policy (which amounted for 247 billion Ecus over 1989-1999, i.e. one-third of the Community budget) has implemented various instruments of which structural funds are the most important. These funds support agriculture and rural promotion, business and tourism, investment in education and various measures improving human capital, investments in infrastructure, transport and environment. An increasing number of studies focusing on the estimation of the impact of regional policies have appeared after the second half of the 90's. According to Ederveen et al. (2002a), those studies can be classified in three groups: simulation models, case studies and econometric models. Their results are not unanimous, mostly because the techniques and the period of time used differ from one study to another. However, even if one focuses on econometric estimations only, which rely on similar techniques as the ones used in our paper, we find that they lead to different results. Indeed, some studies do not find a significant impact of the funds (Garcia-Mila and McGuire 2001), or it is very modest (de la Fuente and Vives 1995; Rodriguez-Posé and Fratesi 2002, 2004). Some find that there is only a significant impact when it is delayed (Beugelsdijk and Eijffinger 2005) or conditional to country dummies (Fayolle and Lecuyer 2000). Ederveen et al. (2002b) find that the funds are effective for countries with "good" institutions. The lack of a common outcome is due, to some extent, to the differences in the sample (number of countries or regions), in the period under study and in the techniques used (panel, time series, cross-section, lag, country-effects…). The only common outcome is the evidence that investment in human capital tends to reduce regional inequalities more than investment in infrastructures (Barro and Sala-I-Martin 1991, 1995; De la Fuente and Vives 1995; Rodriguez-Posé and Fratesi 2002, 2004).

Opposite to these previous studies, this paper does not consider the EU regions as isolated entities, because several previous estimations have highlighted the presence of significant spatial spillovers among regions (Fingleton 1999, 2001; Arbia and Paelinck 2004; Dall'erba 2005a and b; Le Gallo and Dall'erba 2006). As a result, the point of this study is to measure whether the allocation of regional funds has a significant impact on the growth rate of the targeted regions and on the one of their neighbors. With that purpose, we use the formal tools of spatial econometrics to include the presence of spatial effects. Furthermore, endogeneity of some explanatory variables is explicitly accounted for. This is an aspect that is often overlooked in convergence studies, especially in those using spatial econometric methods.

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. Section 4 presents the data and the weight matrix upon which the formal definition of space relies. Indeed, in the absence of interregional input/output tables in Europe, our empirical estimations model the presence of spatial effects through the formal tools of spatial econometrics. 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 diffusion, are carried out in section 6 to analyze the impact of the funds, first on the targeted region itself and second on all the regions of the sample. Le Gallo et al. (2003) have already simulated the spatial diffusion of a shock on neighboring regions and 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. Section 7 concludes and provides some comments on the allocation of the European structural funds.

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[1]) that 68% of structural funds are devoted to the least developed regions[2]. Financed infrastructures mainly concern the transportation sector, in order to support 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 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 1994-1999. 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 most from Community support.

<< Insert figures 1 and 2 about here>>

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.

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

The neoclassical Solow growth model predicts convergence of welfare among regions with similar economies. Hence, when regional funds finance physical capital in capital-scarce regions, it temporarily stimulates growth above its usual steady state growth level. However, due to the decreasing marginal product of capital, it only allows the economy to converge faster towards its steady state, where the growth rate of per capita income is completely determined by technology. Still, not all economies converge to the same level of per capita income. A higher investment rate in poorer regions can therefore have effects on the per capita income steady state level, but it can only temporarily increase growth rates along the transition to the new steady state. Conversely, 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 capital accumulation and growth.

When such investments finance interregional transportation infrastructures yielding to a decrease in transportation costs, it may affect the process of industry location and favor agglomeration in rich regions. For example, Boarnet (1998) shows that highway projects in California counties benefit to the investing counties at the expense of the other counties within the state. Kelejian and Robinson (1997) make similar arguments concerning externalities at the state level. However, the economic geography literature shows that transportation infrastructures do not systematically benefit the region where they are implemented, especially when they are used as regional development instruments (Martin and Rogers 1995; Vickerman 1996; Martin 2000). 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 rich regions, where the demand in this sector is the highest.

Moreover, Puga and Venables (1997) show that in a transportation network based on hub-and-spoke interconnections, 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. Consequently, this type of network promotes gains in accessibility in the hub location first (Puga 2001; Venables and Gasiorek 1999). The relationship between gains in accessibility and economic development in peripheral regions still requires considerable empirical investigation especially given the variations in transportation demands by sector and differences in the productive structure of each region. The literature indicates however that gains in accessibility due to interregional transport infrastructures will always be relatively higher in the central location than in the peripheral one (Vickerman et al. 1999). Therefore, interregional transportation infrastructures cannot always be seen as an efficient instrument to reduce interregional disparities.

In addition, financing transportation infrastructures within a poor area does not guarantee it to catch-up towards the more developed areas either. As spillovers are usually locally limited (see the example of Lisbon's bridge, Portugal, in Venables and Gasiorek 1999), there is a threshold level in transaction costs below which agglomeration takes place and maintains itself. In this case, only a large improvement of southern attractiveness induces firms facing increasing returns to relocate. It is not obvious whether intra-regional transportation infrastructures in the South have a relocation impact on the very poor areas within the South for which the agglomeration process has already proved too strong, but may work for its richer areas, where firms are already located.

The role of the above discussion is to highlight the creation of spatial externalities when regional funds finance transportation infrastructures. In addition, regions are not isolated economies. Their spatial interactions with other regions include, among others, backward and forward linkages, technology spillovers (see, for instance, Coe and Helpman 1995; Keller 2002) and migration (Grant and Vanderkamp 1980; Van Dijk et al. 1989). As a result, these spatial effects need to be formally included in our convergence model. Note that we clearly do not claim that all the regions have financed transportation infrastructures through regional funds (actually the sectoral allocation of these funds for each region is unknown) nor that they are the only type of public investments financed. Regional policy instruments are also devoted to improve either the regional competitiveness as a whole or the incentives to locate at the level of each firm, as described in the introduction. However, Garcia-Mila and McGuire (2001) indicate that these policies do not lead to a crowding-in since they have neither been effective in stimulating private investment nor did they improve the overall economic performance of the poorer regions of Spain. Ederveen et al. (2002a) describe three more drawbacks of the current mechanisms upon which the distribution of the funds relies. First, nothing impedes regional governments of designing projects that meet the criteria of the EU, but which are not necessarily effective in stimulating growth (rent seeking). Second, they may use the EU funds for low-productive projects, so as to keep their region within the eligibility criterion for cohesion support (moral hazard). As a result, the authors propose to give up policies based on specific predefined projects at the EU level. Rather, they promote competition among regions for EU funds and thus for proposals with the highest rate of return. Third, they find that, on average, every euro of EU cohesion support withdraws seventeen cents of regional support from the State, as if regional development was primarily a European concern (crowding-out). They add that this phenomenon also occurs when EU funds finance projects that are close substitutes for private capital, or when they subsidy project in lagging regions and thus reduce labor mobility, which tends to promote greater cohesion. Two more points are highlighted in Dall'erba (2005a): first, it is not necessarily a firm from the targeted region which undertakes the construction of the project financed by the funds, so that a substantive part of the value added directly benefits another region. Second, a particular project is never implemented without additional regional or national financing. This is the principle of additionally that impedes regions to present unviable projects.

However, there is a bias introduced through this principle which comes from the fact that peripheral regions are just able to double the Community support, whereas the wealthiest north Spanish regions and numerous core regions succeed in providing between 2.5 and 6.4 times the amount committed by structural funds (Dall'erba, 2005a).

As a result, many recent empirical studies have investigated the impact of regional funds on development, but their conclusions are not necessarily optimistic. De la Fuente and Vives (1995) show that promoting education has significantly contributed to the reduction of per capita income inequalities among 17 regions of Spain between 1980 and 1991. Boldrin and Canova (2001) conclude that regional and structural policies mostly serve a redistributional purpose, but have little relationship with fostering economic growth. Rodriguez-Pose and Fratesi (2004) focus on different expenditure axes. They find no significant impact of the funds devoted to infrastructures or to business support. Only investment in education and human capital has medium-term positive effects, which is in tune with recent studies (Duranton and Monastiriotis, 2002), whilst support to agriculture has short-term positive effects on growth. Large agricultural sector and lack of R&D are the two major reasons that hamper growth and regional development efforts in the poor regions according to Cappelen et al. (2003). Finally, Midelfart-Knarvik and Overman (2002) find that European Structural Funds expenditure has an inconsistent effect on the location of industry, notably by encouraging the industries that are intensive in R&D to locate in countries and regions that have low endowments in skilled labor. As a result, these incentives have mostly been acting counter to states' comparative advantage and have not allowed poor regions to reach the EU average.

More studies could be cited but this is not the focus of this paper, which pays special attention to the presence of spatial externalities induced by the implementation of regional funds. As noted earlier, this is not the case of the papers cited above. The spatial effects we consider are described in the next section.

3 β-convergence models and spatial effects

Since the seminal articles of Barro and Sala-i-Martin (1991, 1995), numerous studies have examined β–convergence between different countries and regions[3]. 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 own steady-state[4]. Empirical evidence for β-convergence has usually been investigated by regressing growth rates of GDP on its initial levels. Two cases are usually considered in the literature: (i) 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, (ii) the concept of *conditional* β–convergence is used when the assumption of similar steady-states is relaxed. Formally, conditional β–convergence is investigated with the following cross-sectional model:

$$\mathbf{g_T} = \alpha \mathbf{e_N} + \beta \mathbf{y}_0 + \mathbf{X}\phi + \boldsymbol{\varepsilon} \qquad \boldsymbol{\varepsilon} \sim N(0, \sigma_\varepsilon^2 \mathbf{I}) \tag{1}$$

where $\mathbf{g_T}$ is the $(N\times 1)$ vector of average growth rates of per capita GDP between date 0 and T; $\mathbf{e_N}$ is the $(N\times 1)$ vector composed of unit elements; $\mathbf{y_0}$ is the vector of log per capita GDP levels at date 0; $\mathbf{X}$ is a matrix of variables, maintaining constant the steady state of each economy; α, β and ϕ are the unknown parameters to be estimated. There is conditional β–convergence if the estimate of β is significantly negative once $\mathbf{X}$ is held constant. Note that if economies have very different steady states, this concept is compatible with a persistent high degree of

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

[4] However, as pointed out by Islam (2003), β-convergence models should not be used as a basis for discriminating between neoclassical and endogenous growth models. Indeed, some endogenous growth models include a mechanism of conditional convergence and in the presence of spillovers, it is difficult to distinguish between the two family of models.

inequality among economies. Since we are interested in the effects of structural funds, they are also included as a conditioning variable:

$$\mathbf{g_T} = \alpha\mathbf{e_N} + \beta\mathbf{y}_0 + \mathbf{X}\phi + \mu\mathbf{SF} + \boldsymbol{\varepsilon} \qquad \boldsymbol{\varepsilon} \sim N(0, \sigma_\varepsilon^2\mathbf{I}) \tag{2}$$

If the estimate of μ is significant and positive, then structural funds positively affect the regions' steady-state, hence increasing the transitional growth rate of each region towards its own steady-state.

Both β-convergence concepts have been heavily criticized on methodological grounds: these tests face several problems such as robustness with respect to choice of control variables, multicolinearity, heterogeneity, endogeneity, and measurement problems (Durlauf and Quah 1999; Temple 1999; Durlauf et al. 2005). In this paper, we pay a particular attention to the problem of endogeneity of conditioning variables and to the spatial dimension of the data used in the convergence studies. As pointed out by Abreu et al. (2005), the spatial dimension of data is usually modeled in two different ways: models of absolute location and models of relative location. Absolute location refers to the impact of being located at a particular point in space (continent, climate zone) and is usually captured through dummy variables (Barro, 1991). Relative location refers to the effect of being located closer or further away from other specific countries or regions and its effects should be analyzed through the methods of spatial econometrics (Anselin 1988). Abreu et al. (2005) add that the distinction between models of absolute and relative location can be related to a similar classification used in spatial econometrics, i.e. the distinction between spatial heterogeneity and spatial dependence.

Spatial autocorrelation refers to the coincidence of attribute similarity and locational similarity (Anselin 1988). In the context of European regions, positive spatial autocorrelation indicates that wealthier regions tend to be geographically clustered as well as poorer regions.

It may come from the fact that the data are affected by processes touching different locations. Indeed, at the regional scale, several factors, such as trade between regions, labor and capital mobility, technology and knowledge diffusion, etc. may lead to spatially interdependent regions. Spatial autocorrelation can also arise from model misspecifications (omitted variables, measurement errors) or from a variety of measurement problems, as boundary mismatching between the administrative boundaries used to organize the data and the actual boundaries of the economic processes believed to generate regional convergence (Cheshire and Carbonaro 1995).

Spatial concentration of economic activities in European regions has already been documented in Lopez-Bazo et al. (1999), Le Gallo and Ertur (2003) and Dall'erba (2005a) with the formal tools of spatial statistics. It is therefore important to incorporate explicitly spatial autocorrelation into β-convergence models for three reasons[5]. First, from an econometric point of view, the underlying hypothesis in OLS estimations is based on the independence of the error terms, which may be very restrictive and should be tested since, if it is rejected, all statistical inference based on it is not reliable. Second, it allows capturing geographic spillover effects between European regions. 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[6]. 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).

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[5] See, for example, the following papers: Moreno and Trehan (1997), Fingleton (1999, 2001, 2003a, 2003b), Maurseth (2001), Rey and Montouri (1999). See also Abreu et al. (2005) for a recent literature review.

[6] 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 (structural instability) and/or by varying error variances across observations (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 similar enough to converge toward the same long-term equilibrium. From a theoretical point of view, convergence clubs may be based on endogenous growth models characterized by multiple steady state equilibria or standard neoclassical growth models where heterogeneity across individuals is permitted.

When convergence clubs exist, standard convergence tests can have some difficulties to discriminate between these multiple steady state models and the standard Solow model (Durlauf and Johnson 1995). In this case, one convergence equation should be estimated per club. To determine those clubs, some authors select *a priori* criteria, as 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), cluster analysis (Hobijn and Franses 2001) or regression trees (Durlauf and Johnson 1995). In the context of regional economies characterized by strong geographic patterns, like the core-periphery pattern, we will detect convergence clubs using exploratory spatial data analysis which relies on geographic criteria.

4 Data and spatial weight matrix

The data come from 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[7]. For the dependent variable, we use the average growth rate of per capita GDP of each region over the 1989-1999 period. The conditioning variables are: industrial structure (the shares of employment in agriculture and industry, respectively, in total employment); long-term unemployment as a share of the total labor force; physical infrastructure (kilometers of motorways per square kilometer); amount of structural funds received during 1989-1999; logarithm of GDP per capita in the initial year 1989. While the impacts of structural funds and transportation infrastructures on growth are not straightforward (see section 2), we expect that the share of employment in agriculture and long-term unemployment will have a negative impact on growth (Cappelen et al., 2005).

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: 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 period

[7] See the data appendix for further details.

under study covers the first two programming periods and the data on structural funds come from the publications of the Commission: the data over 1989-1993 are from "*Community structural interventions*", *Statistical report n°3 and 4,* (July and Dec. 1992)[8] and for 1994-1999, from *The 11th annual report on the structural funds*. These data are the total payments over 1994-1999 plus the commitments taken during this period, but that have not been paid yet. The lack of more recent data leads us to assume that structural funds commitments and expenditures are strongly correlated. We are aware that this may create some problems, as considerable lags between the commitments and actual expenditure often take place.

We now present the spatial weight matrix. In the European context, the existence of islands does not allow the use of simple contiguity matrices; otherwise the weight matrix would include rows and columns with only zeros for the islands. Following the recommendations of 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, defined as:

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

where w_{ij}^* is an element of the unstandardized weight matrix; w_{ij} is an element of the standardized weight matrix **W**; 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 $k = 1,...3$ 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. We also constructed

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

other weight matrices based on nearest-neighbors and binary distance matrices. All the results are robust to the choice of the weights[9].

5 Convergence 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 using exploratory spatial data analysis. Several tools have been used in the literature. For example, Ertur et al. (2003) use Moran scatterplots (Anselin, 1996) that imply a 4-way split of the sample to determine the spatial clubs: clusters of rich regions, clusters of poor regions and two types of “atypical”regions (rich regions surrounded by poor regions and vice-versa). Their methodology implies that those atypical regions must be dropped out of the sample (in their case, 3 regions are eliminated) while the clusters of rich and poor regions respectively constitute the core and peripheral regime. However, in our study, this methodology would imply eliminating 9 regions. We therefore use the G-I* statistics developed by Ord and Getis (1995)[10] on the regional per capita GDP values in 1980. Indeed, they imply a 2-way split of the sample without having to drop any region. The statistics are defined as following:

$$G_i^*(d) = \frac{\sum_j w_{ij} x_j - W_i^* \bar{x}}{s\left\{[(nS_{1i}^*) - W_i^{*2}]/(n-1)\right\}^{1/2}} \tag{4}$$

where w_{ij} is an element of the weight matrix $\mathbf{W}$; $W_i^* = \sum_{j \neq i} w_{ij} + w_{ii}$; N is the size of the sample ; $S_{1i}^* = \sum_j w_{ij}^2$, $\bar{x}$ and s^2 are respectively the mean and variance of the sample. These

[9] The other weight matrices are 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 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. All the results presented in sections 5 and 6 are robust to the choice of the weight matrix: complete results are available from the authors upon request.

[10] All computations in this section are carried out using the SpaceStat 1.91 software (Anselin, 1999).

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 regions with high per capita GDP, whereas a negative value indicates a spatial cluster of regions with low per capita GDP 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 1991; 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 (except Northern-Ireland, Scotland and North West).
- 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).

5.2 Econometric methodology

In order to evaluate consistently the impact of structural funds on the convergence process, we have to deal with 3 interrelated issues in our context of cross-sectional β-convergence models: spatial heterogeneity, spatial autocorrelation and endogeneity.

First, spatial heterogeneity can be modeled in two ways. To begin, let us consider the possibility of structural instability of the coefficients. As shown by the G-I* statistics, there are two potential convergence clubs: the core (indicated by *C*) and the periphery (indicated by

P). Then, a different set of coefficients must be estimated for each club. The model of conditional β-convergence for the two convergence clubs can then be specified as follows:

$$\begin{aligned}\mathbf{g_T} &= \alpha_{\mathrm{C}}\mathbf{D}_{\mathrm{C}} + \alpha_{\mathrm{P}}\mathbf{D}_{\mathrm{P}} + \beta_{\mathrm{C}}\mathbf{D}_{\mathrm{C}}\mathbf{y}_0 + \beta_{\mathrm{P}}\mathbf{D}_{\mathrm{P}}\mathbf{y}_0 \\ &\quad + \mathbf{D}_{\mathrm{C}}\mathbf{X}\phi_{\mathrm{C}} + \mathbf{D}_{\mathrm{P}}\mathbf{X}\phi_{\mathrm{P}} + \mu_{\mathrm{C}}\mathbf{D}_{\mathrm{C}}\mathbf{SF} + \mu_{\mathrm{P}}\mathbf{D}_{\mathrm{P}}\mathbf{SF} + \boldsymbol{\varepsilon} \qquad \boldsymbol{\varepsilon} \sim N(0, \sigma_{\varepsilon}^2\mathbf{I})\end{aligned} \tag{5}$$

where D_{C} and D_P are dummy variables qualifying the two regimes core and periphery. This specification allows the convergence process and the effects of the conditioning variables to be different across regimes. The assumption of normally and independently distributed error terms may be overly restrictive. Assuming an error variance that is different in each club results in the second form of spatial heterogeneity, represented here as groupwise heteroskedasticity. Formally:

$$\boldsymbol{\varepsilon} \sim N\left(0, \begin{bmatrix} \sigma_{\mathrm{C}}^2\mathbf{I}_{100} & 0 \\ 0 & \sigma_{\mathrm{P}}^2\mathbf{I}_{45} \end{bmatrix}\right) \tag{6}$$

where σ_{C}^2 and σ_{P}^2 denote the club-specific constant error variances; $\mathbf{I}_{100}$ and $\mathbf{I}_{45}$ are identity matrices of dimensions equal respectively to the number of observations in the core and in the periphery regime.

Second, in order to detect the appropriate form of spatial autocorrelation, we use the classical "specific to general" specification search approach outlined in Anselin and Florax (1995) using tests described in Anselin *et al.* (1996). Indeed, in the absence of a formal theory, this strategy provides ways to discriminate between a spatial lag and a spatial error model. More specifically, they suggest Lagrange Multiplier (LM) tests (resp. LMERR and LMLAG) and their robust versions (resp. R-LMERR and R-LMLAG). The decision rule used to choose the most appropriate specification is as follows: if LMLAG (resp. LMERR) is more significant 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).

We have therefore estimated models (2) and (5), with and without structural funds, with OLS and computed Moran's *I* and the LM test. The results are displayed in table 1. Following the decision rule described above, it appears that the spatial lag model is the most appropriate specification for all cases. Formally, an endogenous variable of the form $\mathbf{Wg_T}$ should be introduced in model (2) as follows:

$$\mathbf{g_T} = \rho\mathbf{Wg_T} + \alpha\mathbf{e_N} + \beta\mathbf{y}_0 + \mathbf{X}\phi + \mu\mathbf{SF} + \boldsymbol{\varepsilon} \qquad \boldsymbol{\varepsilon} \sim N(0, \sigma_\varepsilon^2\mathbf{I}) \tag{7}$$

where $\mathbf{W}$ is the (N×N) spatial weight matrix. Since $\mathbf{W}$ is row-standardized, the spatial lag variable $\mathbf{Wg_T}$ contains the spatially weighted average of the growth rates of the neighboring regions. The parameter ρ indicates the level of spatial interaction between regions. This specification allows measuring how the growth rate in a region may relate to the one in its surrounding regions after conditioning on the starting levels of per capita GDP and the other variables. A similar specification can be obtained when allowing for spatial regimes. Since the spatial lag is a stochastic regressor, which is always correlated with ε, estimation of this model by OLS produces inconsistent estimators; it must therefore be estimated by Maximum Likelihood (ML) or Two Stage Least Squares (2SLS).

<< Insert table 1 about here>>

Model (7) can be rewritten under the following form:

$$\mathbf{g_T} = (\mathbf{I} - \rho\mathbf{W})^{-1}(\alpha\mathbf{e_N} + \beta\mathbf{y}_0 + \mathbf{X}\phi + \gamma\mathbf{SF}) + (\mathbf{I} - \rho\mathbf{W})^{-1}\boldsymbol{\varepsilon} \tag{8}$$

Since $|\rho| < 1$ (in most case) and the elements of the standardized weight matrix $\mathbf{W}$ are less than one, a Leontief expansion of the matrix inverse $(\mathbf{I} - \rho\mathbf{W})^{-1}$ in (8) follows as: $(\mathbf{I} - \rho\mathbf{W})^{-1} = \mathbf{I} + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + \ldots$. Consequently, two types of global spillover effects are relevant in the spatial lag model (Anselin, 2003):

(i) *A multiplier effect* for the explanatory variables: the growth rate of region *i* is not only affected by a marginal change of the explanatory variables of region *i* but also is affected by marginal changes of the explanatory variables in the other regions, more importantly so for closer regions. As a consequence, the estimated coefficients in a spatial lag model include only the direct marginal effect of an increase in the explanatory variables, excluding all indirect induced effects, while in the standard model estimated by OLS, they represent the total marginal effect (Abreu et al., 2005). It is therefore not relevant to compare OLS and ML or 2SLS estimates for a spatial lag so that only the latter will be reported.

(ii) *A diffusion effect* for the error process: a shock in ε at any location will propagate to all the other regions of the sample. This diffusion effect also declines with distance and will be illustrated in section 6.

Third, conditioning variables account for the differences in steady-states in cross-sectional β-convergence models. Some authors (Islam, 1995) use panel data specifications with fixed effects instead, an approach that has the advantage of fully exploiting the temporal dimension but has also some drawbacks, such as biases due to high frequency or small samples (Islam, 2003). Our time period is not large enough for such an analysis and the inclusion of spatial autocorrelation in fixed panel data specification raises technical issues that are beyond the scope of this paper. In turn, using conditioning variables in a cross-sectional setting raises the problem of their possible endogeneity, for example, structural funds are not allocated randomly but are conditional on GDP. This problem has been overlooked in the papers dealing with the effects of structural funds on convergence. We have therefore estimated models (2) and (5), with and without structural funds, with 2SLS and computed Hausman tests for exogeneity. The results are displayed in table 2. The joint Hausman test leads to the rejection of the null hypothesis of exogeneity of all explanatory variables. The Hausman test of exogeneity of each single variable in the presence of other endogenous variables (Maddala, 2001) suggest that structural funds, share of agriculture and infrastructure are endogenous. Therefore, models (2) and (5) should be estimated by 2SLS:

(i) For the spatial lag of the endogenous variable, as advocated by Kelejian and Prucha (1999), we use as instrument the spatial lag of all explanatory variables

(ii) Finding instruments for the other endogenous variables that are highly correlated with these variables but uncorrelated with the error term is difficult (Temple, 1999). Therefore, we construct our instruments as defined by the 3-group method, advocated by Kennedy (1992) in the context of measurement errors and used in a spatial context by Fingleton (2003a). For structural funds, we construct a first variable that takes values 1,0 and -1 according to whether the structural funds are in the top, middle or bottom third of their ranking, ranging from 1 to 145. The spatial lag of this latter variable is also constructed leading to 2 instruments for structural funds. The instruments for the share of agriculture and infrastructure are constructed similarly and the necessary order condition for identification is satisfied.

<< Insert table 2 about here>>

5.3 Estimation results

Given the principles described above, we have estimated by 2SLS four different models: (i) spatial lag model without structural funds, (ii) spatial lag model with spatial regimes and groupwise heteroskedasticity without structural funds, (iii) spatial lag model with structural funds and (iv) spatial lag model with spatial regimes, groupwise heteroskedasticity and structural funds. The estimation results are displayed in table 3.

<< Insert table 3 about here>>

In the model without structural funds (column 1), the estimated coefficient associated with initial per capita GDP is highly significant and negative, leading to a convergence speed of 2.08% and a half-life of 37 years. The coefficients associated with the shares of manufacturing and infrastructure are not significant (p-values of 0.226 and 0.522) while those associated with the share of agriculture and unemployment are significant and have the expected negative sign. The presence of spatial autocorrelation is confirmed by a highly significant and positive ρ coefficient ($\hat{\rho} = 0.738$) indicating that the growth rate of a region is significantly influenced by the growth rate of its surrounding regions. The model is well specified since there is no residual spatial error autocorrelation: LMERR is not significant.

When allowing for spatial regimes and spatial heterogeneity, some of these results change drastically (column 2). First, β is significant both in the core (at 10%) and in the peripheral regime, leading respectively to convergence speeds of 0.97% and 5.91% and half-lives of 91 and 15 years. The convergence process seems therefore to be quite different across regimes: if there is a conditional convergence process among European regions, it mainly concerns the peripheral regions and it is very slow among the core regions. Second, concerning the coefficients associated with the other conditioning variables, it appears that infrastructure is never significant. However, the share of manufacturing and the long-term unemployment negatively affect the steady state of the regions in the core regime while the share of agriculture has a negative effect in both regimes. These interpretations are confirmed by considering the joint and the individual stability tests: the constant term and the coefficients associated with initial per capita GDP and unemployment are significantly different across regimes at 5% since the corresponding tests reject the null hypothesis of stability.

None of these conclusions are changed when structural funds as a ratio of GDP are included in the regressions (column 3 and 4): all coefficients are qualitatively similar with a convergence speed of 1.05% in the core and 5.45% in the periphery. Concerning the specific effect of structural funds, it appears that it is never significant, neither in the simple spatial lag model, nor in the model allowing for spatial regimes. Therefore, the steady states of the regions do not seem to be significantly affected by the amount of structural funds they have received. These results confirm those of the empirical studies listed in section 2. Structural funds may not be sufficient enough to counterbalance the ongoing agglomeration process in the rich regions. It can also be argued that regional policies fail to provide the appropriate strategies for higher economic growth. As stated in section 2, the allocation mechanisms encourage strategies which are not consistent with cohesion efforts and the nature of most of the projects financed by the funds are not necessarily benefiting the targeted region. Another possible explanation may be the delayed effect of structural funds on the convergence process, so that their impact does not appear in our short time period. However, Rodriguez-Posé and Fratesi (2004) include an annual lag of six years and do not find any significant impact either.

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 indirectly their impact using simulation experiments based on the diffusion properties of the spatial lag model.

6 Spatial diffusion effects in European regions

Rather than introducing structural funds as explanatory variables in a conditional β-convergence equation, this section considers as a point of departure the spatial lag β-convergence model with spatial regimes and groupwise heteroskedasticity without structural funds estimated in section 5 (column 2) and investigates in detail its spatial diffusion properties by considering the impact of shocks affecting growth in the targeted region itself and in all the other regions of the sample. The steady-state of each region is not assumed to be significantly affected by the shocks, which is consistent with the results found in the previous section.

Consider the spatial lag model without structural funds in the following reduced form:

$$\mathbf{g_T} = (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{Z}\gamma + (\mathbf{I} - \rho\mathbf{W})^{-1}\boldsymbol{\varepsilon} \tag{9}$$

where $\mathbf{Z}$ is a matrix containing all the explanatory variables and γ the unknown coefficients to be estimated. First, suppose that a shock with an amount of a_i affects region i and let $\hat{\boldsymbol{\varepsilon}}^{\mathbf{i}}$ be the vector containing the estimated error of model (9) with a shock in that region i:

$$\hat{\boldsymbol{\varepsilon}}^{\mathbf{i}}\,' = \begin{pmatrix} \hat{\varepsilon}_1 & \ldots & \hat{\varepsilon}_i + a_i & \ldots & \hat{\varepsilon}_N \end{pmatrix}' \tag{9}$$

Therefore, the $(n \times 1)$ vector $\mathbf{g}_{\mathbf{T}}^{\mathbf{i*}}$, containing the observations on the simulated average growth rate after a shock in region i can be computed in the following way, where $\hat{\rho}$ is the one found in estimation column 2 of table 3 (0.594) :

$$\mathbf{g}_{\mathbf{T}}^{\mathbf{i*}} = (\mathbf{I} - \hat{\rho}\mathbf{W})^{-1}\mathbf{Z}\hat{\gamma} + (\mathbf{I} - \hat{\rho}\mathbf{W})^{-1}\hat{\boldsymbol{\varepsilon}}^{\mathbf{i}} \tag{10}$$

As an illustration, we have represented the relative impact of a shock (set to two times the residual standard error) affecting Ile-de-France in figure 3. As expected, this shock has the largest relative impact on Ile-de-France but we can also observe a clear spatial diffusion pattern of this shock to all other regions of the sample.

<< Insert figure 3 about here>>

We now extend this analysis to study the relative impacts of shocks affecting all the regions of our sample[11]. Let $\mathbf{G}^*$ be the matrix of dimension $(N \times N)$ containing the observations on the simulated average growth rates after a shock in each region:

$$\mathbf{G}^* = \begin{bmatrix} \mathbf{g}_{\mathbf{T}}^{\mathbf{1*}} & \ldots & \mathbf{g}_{\mathbf{T}}^{\mathbf{N*}} \end{bmatrix} = \mathbf{A}^{\mathbf{-1}} \begin{bmatrix} \mathbf{Z}\hat{\boldsymbol{\gamma}} & \ldots & \mathbf{Z}\hat{\gamma} \end{bmatrix} + \mathbf{A}^{\mathbf{-1}} \begin{bmatrix} \hat{\boldsymbol{\varepsilon}}^{\mathbf{1}} & \ldots & \hat{\boldsymbol{\varepsilon}}^{\mathbf{N}} \end{bmatrix} \tag{11}$$

with $\mathbf{A} = \mathbf{I} - \hat{\rho}\mathbf{W}$. Equation (11) can also be rewritten in a more compact way:

$$\mathbf{G}^* = \mathbf{A}^{\mathbf{-1}}.(\mathbf{e}_{\mathbf{N}}' \otimes \mathbf{Z}\hat{\boldsymbol{\gamma}}) + \mathbf{A}^{\mathbf{-1}}.\hat{\mathbf{E}} \tag{12}$$

where $\otimes$ is the Kronecker product; $\mathbf{e}_{\mathbf{N}}$ is the $(N\times1)$ vector composed of unit elements ; $\hat{\mathbf{E}}$ is the matrix of dimension $(N \times N)$ defined as: $\hat{\mathbf{E}}^* = \begin{bmatrix} \hat{\boldsymbol{\varepsilon}}^{\mathbf{1}} & \ldots & \hat{\boldsymbol{\varepsilon}}^{\mathbf{N}} \end{bmatrix}$. Given the definition of each element $\hat{\boldsymbol{\varepsilon}}^{\mathbf{i}}$ (see equation (9)), this matrix $\hat{\mathbf{E}}$ can also be written as:

[11] Le Gallo et al. (2005) develop a similar analysis but based on the spatial error model.

$$\hat{\mathbf{E}} = \begin{pmatrix} \hat{\varepsilon}_1 + a_1 & \hat{\varepsilon}_1 & \dots & \hat{\varepsilon}_1 \\ \hat{\varepsilon}_2 & \hat{\varepsilon}_2 + a_2 & \dots & \hat{\varepsilon}_2 \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\varepsilon}_N & \hat{\varepsilon}_N & \dots & \hat{\varepsilon}_N + a_N \end{pmatrix} \Rightarrow \hat{\mathbf{E}} = \mathbf{e}_{\mathbf{N}}^{'} \otimes \hat{\boldsymbol{\varepsilon}} + \mathrm{diag}(a_i) \tag{13}$$

Combining (12) and (13), we obtain:

$$\mathbf{G}^{*} = \mathbf{A}^{\textbf{-1}}.(\mathbf{e}_{\mathbf{N}}^{'} \otimes \mathbf{Z}\hat{\boldsymbol{\gamma}}) + \mathbf{A}^{\textbf{-1}}.(\mathbf{e}_{\mathbf{N}}^{'} \otimes \hat{\boldsymbol{\varepsilon}} + \mathrm{diag}(a_i)) \tag{14}$$

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 $\mathbf{D}$ between the matrix of simulated average growth rates $\mathbf{G}^{*}$ (after the shock) and the matrix of actual average growth rates $\mathbf{G}$ (without shock) is $\mathbf{D} = \mathbf{G}^{*} - \mathbf{G}$. Since $\mathbf{G} = \mathbf{e}_{\mathbf{N}}^{'} \otimes \mathbf{g}_{\mathbf{T}}$, with $\mathbf{g}_{\mathbf{T}} = \mathbf{A}^{\textbf{-1}}.\mathbf{Z}\hat{\boldsymbol{\gamma}} + \mathbf{A}^{\textbf{-1}}.\hat{\boldsymbol{\varepsilon}}$, then:

$$\mathbf{D} = \mathbf{A}^{\textbf{-1}}\mathrm{diag}(a_i) \text{ with } \mathbf{A} = \mathbf{I} - \hat{\lambda}\mathbf{W} \tag{15}$$

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 **G** matrix in order to capture the percentage of change. 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 localization and 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. In that context, we analyze indirectly the impact of structural funds allocated to one region on the other regions and we study whether allowing for differentiated shocks can offset the effects of poor economic dynamism and unfavorable relative localization of peripheral regions.

We consider two different cases[12]. 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[13].

Figures 3 and 4 display the main diagonal of V representing the impacts of the shocks on the region itself. In the case of equal shocks, the extent of the impact is not necessarily greater in periphery, with the exception of some Italian regions. In the case of differentiated shocks, the extent of the impact on the peripheral regions increases a lot since they receive the largest amounts of structural funds. The three regions which are the most affected by the differentiated shock are Lisboa (Portugal), Dytiki (Greece) and Abruzzo (Italy).

<<Insert figures 4 and 5 about 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 6), 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 7), 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

[12] The codes used to carry out the simulations in this section have been developed using Python 2.2 (http://www.python.org).
[13] The factor of proportionality is set to twice the average of residual standard errors of each regime in the estimated spatial lag model with spatial regimes and groupwise heteroskedasticity.

case. The extent of the diffusion decreases in figure 7 because core regions received less assistance than the average amount of structural funds (used in figure 5). The diffusion properties of the peripheral regions have not increased. This result that can imply 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 (for instance, Castilla-y-Leon is 585 times greater than Brussels, but both are considered as NUTS 2 regions). 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 are much smaller regions, which facilitates interregional dependences as well. They are also more connected with each other in terms of accessibility via transportation network. Indeed, the empirical study of Vickerman et al. (1999) points out that transportation infrastructures are more developed between core regions, because the demand in this sector is the highest. 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. 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 would not favor spillovers in periphery. Note that the reverse may also be true: the lack of skilled labor and investments in human capital within poor regions hinders the diffusion of knowledge externalities from neighboring locations (Mankiw et al. 1992).

<<Insert figures 6 and 7 about here>>

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. Various tests aimed at including the significant presence of spatial effects in our model lead to a spatial lag model with groupwise heteroskedasticity and structural instability in the form of the two regimes detected using the Getis-Ord statistics. Structural funds and two other conditioning variables are found to be endogenous so that the simultaneity bias is corrected with 2SLS. Estimation results display much faster convergence in the peripheral regime but a non significant impact of the funds themselves on the regions' steady-states. Based on the spatial diffusion properties of the spatial lag model, we also evaluate 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. The simulation experiments are performed in two cases: first with shocks proportional to the average amount of structural funds distributed during the period 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 since they are the main beneficiaries of these funds. However, the extent of the impact does not increase much in some Greek and

Portuguese regions, which implies that greater regional development efforts are not necessarily useful within these regions, at least in its current form. This does not mean that regional support to Greece and Portugal should vanish. Indeed, it could also be argued that in the absence of these policies the regional divide could be worsened because of the circular and cumulative causation effects that lead to industry agglomeration in the core. Finally, 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 and an evidence of the need to reconsider regional policy strategies. We therefore recommend giving a deeper consideration to the role of interregional linkages or to the factors promoting externalities while defining regional development policies. It should be noted 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 regard, 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 of structural funds come from different reports of the European Commission: *Community structural interventions*, *Statistical report n°3 and 4,* (July and Dec. 1992) for the data over 1989-1993 and from *The 11th annual report on the structural funds* (1999) for the 1994-1999 period. These data are expressed in 1990 prices.

The data on per capita GDPs come from 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 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. We are aware that some of the previous corrections may appear arbitrary but we prefer to resort to them rather than excluding several regions from our sample.

Table 1. Spatial autocorrelation test results for models (2) and (5) estimated by OLS and weight matrix D(1)

	Model without structural funds		Model with structural funds	
	No spatial regimes	*Spatial regimes*	*No spatial regimes*	*Spatial regimes*
Moran's *I*	9.432 (0.000)	8.346 (0.000)	8.903 (0.000)	6.871 (0.000)
LMERR	63.295 (0.000)	39.965 (0.000)	54.525 (0.000)	24.596 (0.000)
R-LMERR	0.819 (0.366)	1.261 (0.261)	0.262 (0.609)	0.016 (0.899)
LMLAG	82.295 (0.000)	53.156 (0.000)	75.561 (0.000)	45.187 (0.000)
R-LMLAG	19.819 (0.017)	14.452 (0.017)	21.822 (0.017)	20.607 (0.017)

Notes: There are N = 145 observations. p-values are in brackets. Moran's I is Moran's I test adapted for regression residuals (Cliff and Ord 1981). *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).

Table 2. Hausman test results for models (2) and (5) estimated by 2SLS

	Model without structural funds	Model with structural funds
Joint test	4.946 (0.000)	6.843 (0.000)
Individual test for Structural Funds	-	9.334 (0.003)
Individual test for Manufacturing	0.135 (0.713)	0.380 (0.538)
Individual test for Agriculture	14.950 (0.000)	17.404 (0.000)
Individual test for Infrastructure	4.405 (0.038)	2.943 (0.088)
Individual test for Unemployment	0.316 (0.575)	0.273 (0.602)

Notes: There are N = 145 observations. p-values are in brackets. *2SLS* indicates the use of the instrumental variables method with instruments defined by the 3-group method for each variable (Kennedy 1992). The joint test is the joint Hausman test for exogeneity for all variables, distributed as a $F_{4,135}$ in the model without structural funds and as a $F_{5,133}$ in the model with structural funds. The individual tests are the Hausman test of exogeneity of each single variable in the presence of other endogenous variables (Maddala 2001). They are distributed as a χ^2 with 1 degree of freedom.

Table 3. IV Estimation results of the conditional β-convergence model with spatial lag and weight matrix $D(1)$

	Model without structural funds			**Model with structural funds**		
	1	2		3	4	
	2SLS-LAG	**2SLS -LAG with regimes and groupwise heteroskedasticity**		**2SLS -LAG**	**2SLS -LAG with regimes and groupwise heteroskedasticity**	
		Periph.	*Core*		*Periph.*	*Core*
Constant	0.202 (0.000)	0.446 (0.000)	0.106 (0.034)	0.211 (0.001)	0.404 (0.003)	0.134 (0.012)
Initial GDP per capita	-0.019 (0.000)	-0.046 (0.000)	-0.007 (0.097)	-0.020 (0.002)	-0.042 (0.003)	-0.010 (0.037)
Structural funds	-	-	-	-0.006 (0.366)	$5.2.10^{-4}$ (0.958)	-0.011 (0.143)
Manufacturing	-0.012 (0.226)	-0.024 (0.440)	-0.025 (0.007)	-0.013 (0.223)	-0.013 (0.648)	-0.032 (0.002)
Agriculture	-0.053 (0.000)	-0.126 (0.005)	-0.079 (0.009)	-0.026 (0.233)	-0.104 (0.009)	-0.060 (0.052)
Infrastructure	$3.4.10^{-6}$ (0.522)	$-4.8.10^{-5}$ (0.104)	$3.7.10^{-6}$ (0.448)	$3.3.10^{-6}$ (0.555)	$-3.5.10^{-5}$ (0.264)	$3.7.10^{-6}$ (0.438)
Unemployment	-0.001 (0.023)	$3.6.10^{-4}$ (0.164)	$-1.6.10^{-4}$ (0.006)	-0.001 (0.025)	$2.5.10^{-4}$ (0.290)	$-1.5.10^{-4}$ (0.006)
Spatial lag	0.738 (0.000)	0.594 (0.000)		0.804 (0.000)	0.590 (0.000)	
σ_ε^2	0.0081	$1.3.10^{-4}$	$3.7.10^{-5}$	0.0083	$1.1.10^{-4}$	$3.8.10^{-4}$
Convergence Speed	2.08%	5.91%	0.79%	2.23%	5.45%	1.05%
Half-life	36.60	15.18	91.23	34.35	16.15	68.97
Sq. Corr.	0.621	0.615		0.609	0.642	
LMERR	0.002 (0.961)	-		0.135 (0.713)	-	
Chow-Wald	-	19.140 (0.004)		-	19.421 (0.007)	
Ind. stab. test for constant	-	9.889 (0.002)		-	3.791 (0.051)	
Ind. stab. test for initial per cap. GDP	-	10.650 (0.001)		-	4.689 (0.030)	
Ind. stab. test for Structural funds	-	-		-	0.824 (0.364)	
Ind. stab. test for Manufacturing	-	0.001 (0.974)		-	0.344 (0.557)	
Ind. stab. test for Agriculture	-	0.756 (0.384)		-	0.761 (0.383)	
Ind. stab. test for Infrastructure	-	2.956 (0.085)		-	1.469 (0.225)	
Ind. stab. test for Unemployment	-	3.819 (0.051)		-	2.789 (0.095)	

Notes: There are $N = 145$ observations. p-values are in brackets. *2SLS-LAG* indicates the use of the instrumental variables method with instruments defined by the 3-group method for structural funds, share of agriculture and infrastructure and the spatial lag of all explanatory variables for the spatial lag of average growth rates. *Sq. Corr.* is the squared correlation between predicted values and actual values. *LMERR* stands for the Lagrange Multiplier test for residual spatial autocorrelation. 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).

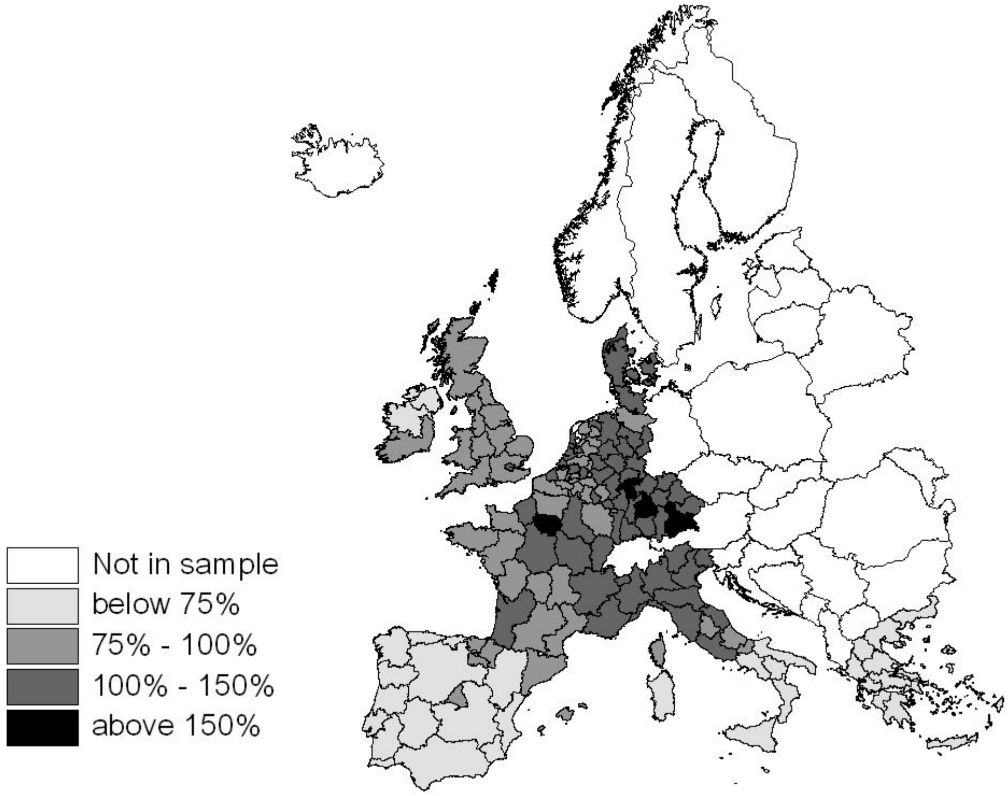

Fig. 1. GDP per capita relative to the European average in 1989

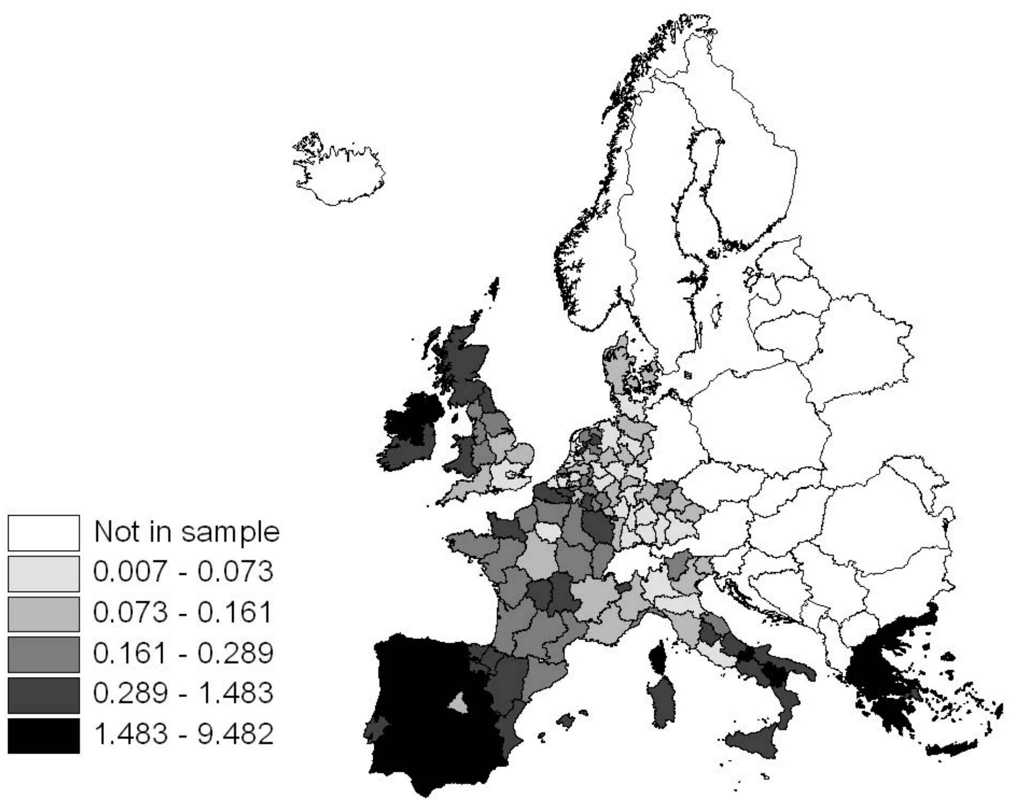

Fig. 2. Spatial distribution of regional funds as a ratio of GDP during 1989-1999

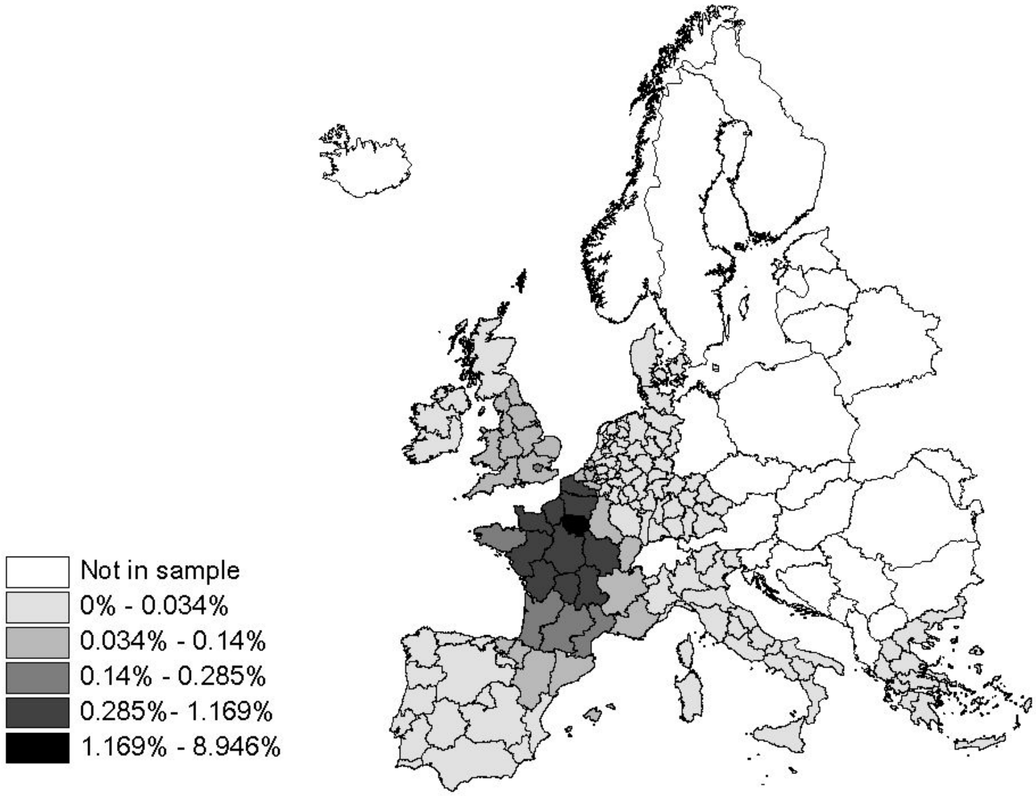

Fig. 3. Impact of a random shock in Ile-de-France

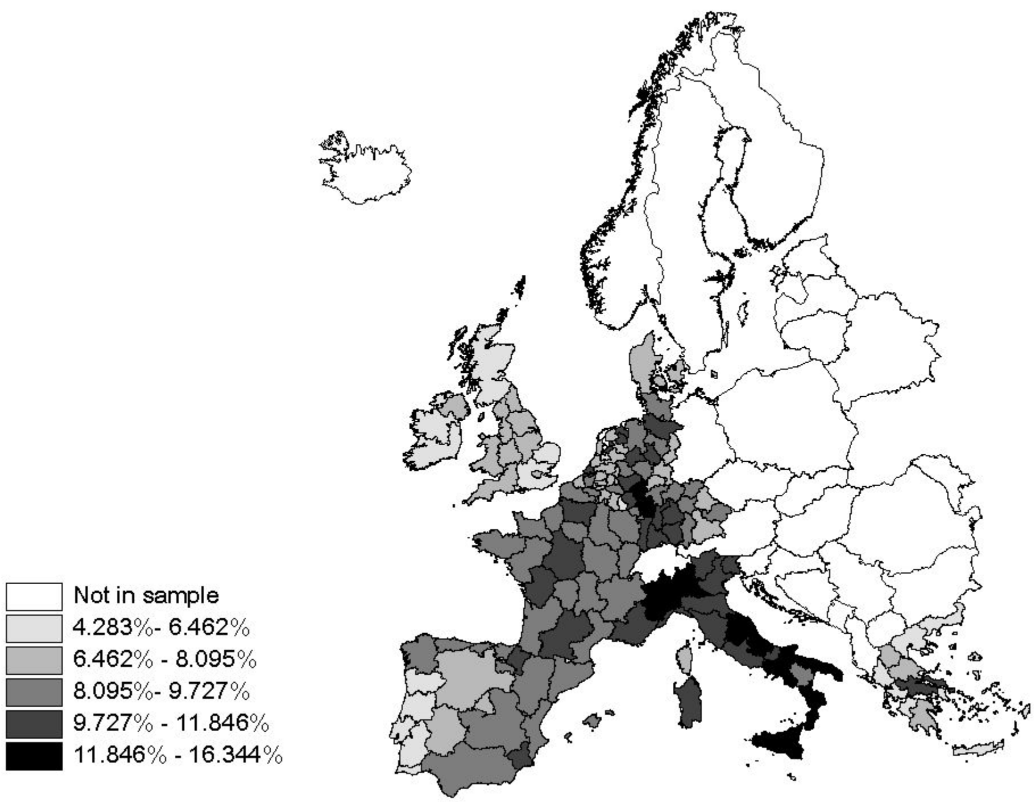

Fig. 4. Impact of equal shocks on each region’s growth

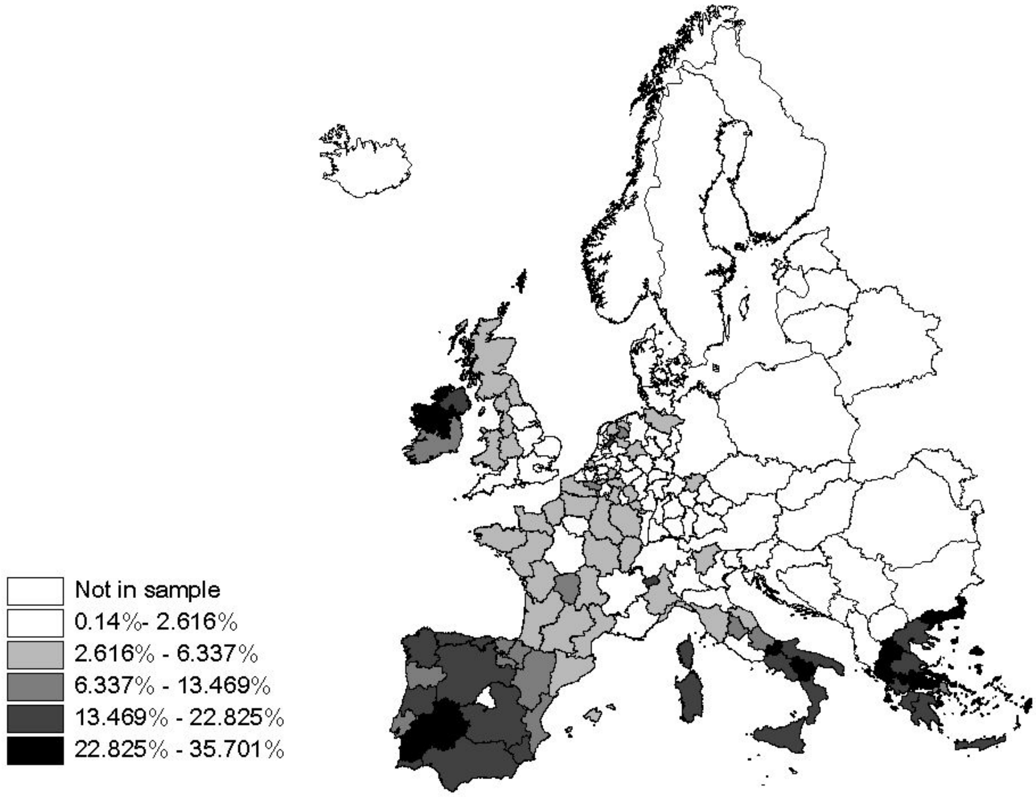

Fig. 5. Impact of differentiated shocks on each region’s growth

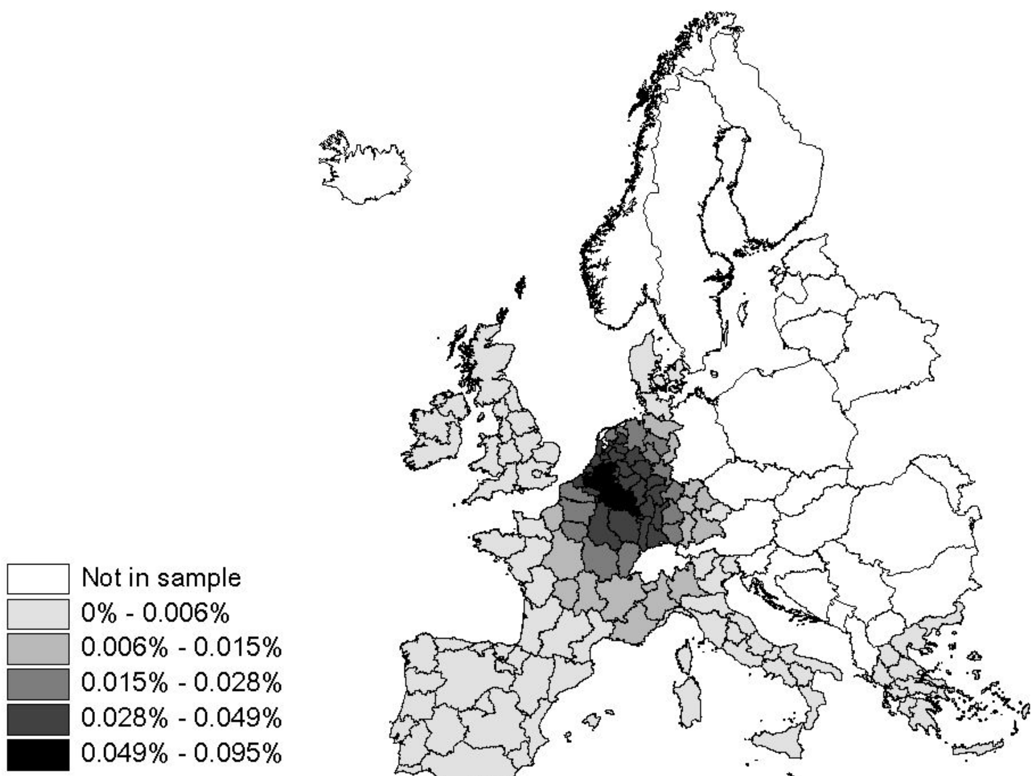

Fig. 6. Distribution of regions according to the extent of diffusion effects they produce with an equal shock

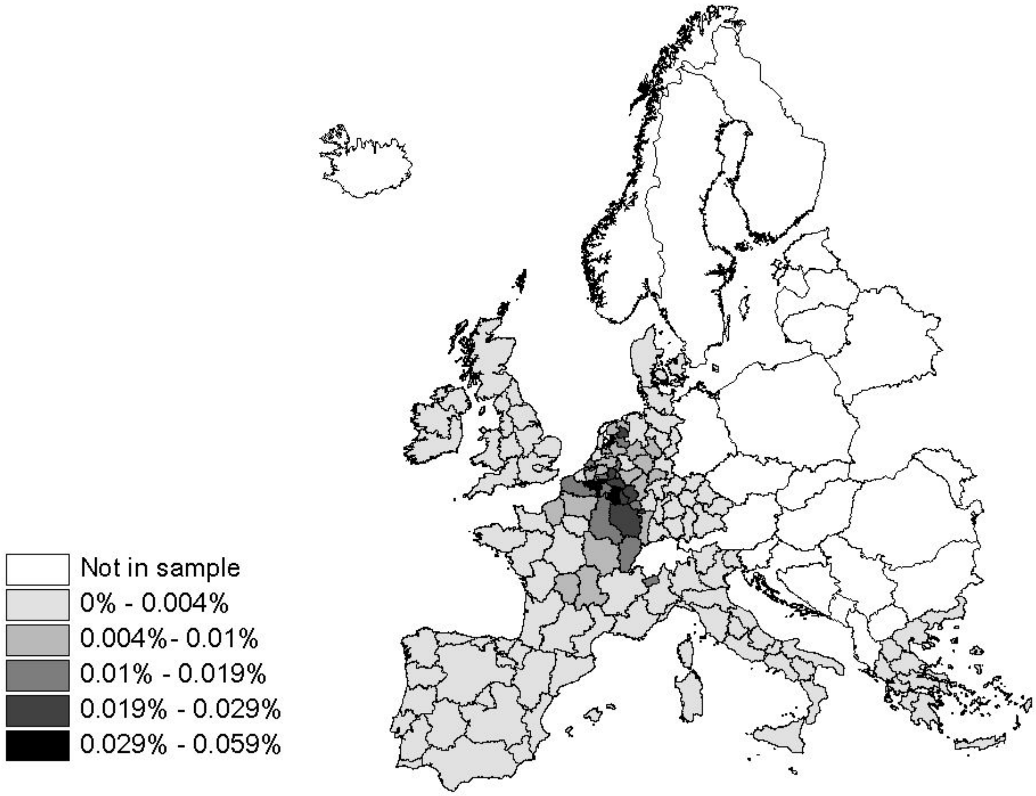

Fig. 7. Distribution of regions according to the extent of diffusion effects they produce with differentiated shocks