Geographic spillover and growth (a spatial econometric analysis for european regions)

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Abstract

The aim of this paper is to integrate the geographical dimension of data in the estimation of the convergence of European regions and emphasize the importance of spatial effects in regional economic growth phenomena. In a sample of 122 European regions over the 1980-1995 period, we find strong evidence of spatial autocorrelation in the unconditional β-convergence model using spatial econometric methods with different weight matrices: a simple contiguity matrix and 4 distance-based matrices. Therefore, this standard β-convergence model exhibit misspecification, its estimation by OLS leads to inefficient estimators and invalid statistical inference. We suggest then a "minimal" specification of β-convergence, which integrates and treats adequately the spatial autocorrelation detected.. Moreover, this model is interpreted as a conditional β-convergence model revealing a spatial spillover effect between European regions. Therefore the European regions are interdependent and we show by a simulation experiment that a random shock affecting a given region propagates to all the regions of the sample.

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Résumé

L'objectif de ce papier est d'intégrer la dimension géographique des données dans l'estimation du processus de convergence des régions européennes et de souligner le rôle des effets spatiaux dans l'analyse de la croissance régionale. Dans un échantillon de 122 régions européennes sur la période 1980-1995, nous mettons en évidence la présence d'autocorrélation spatiale dans le modèle de β-convergence absolue en utilisant les méthodes de l'économétrie spatiale et différentes matrices de poids : une matrice de contiguité et 4 matrices de distances. Par conséquent ce modèle de β-convergence est mal spécifié, son estimation par les MCO conduit à des estimateurs inefficients et à une inférence statistique peu fiable. Nous proposons alors une spécification « minimale » du modèle de β-convergence permettant le traitement approprié de l'autocorrélation spatiale détectée dont nous soulignons l'impact sur la croissance régionale. En outre, ce modèle peut être interprété comme un modèle de β-convergence conditionnelle révélant un effet de débordement spatial entre les régions européennes. Les régions européennes sont donc interdépendantes et nous montrons à l'aide d'une expérience de simulation qu'un choc aléatoire affectant une région donnée se propage à l'ensemble des régions de l'échantillon.

JEL Classification: C51, R11, R15

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Introduction

The problem of regional economic convergence has been widely studied in the recent macroeconomic literature. This hypothesis is based on neo-classical growth models (Solow, 1956; Swan, 1956), which assume constant returns to scale and decreasing marginal productivity. This implies a long run tendency towards the equalization of per capita product levels of different geographical areas. There is convergence when the growth rate of a « poor » region is bigger than the one of a « rich » region so that the « poor » region catches up in the long run the per capita income or product level of the « rich » region. This feature corresponds to the β-convergence concept (Barro and Sala-I-Martin, 1995).

Numerous empirical studies focus on the test of this hypothesis at the regional scale but they meet great econometric problems. Thus the interpretation of the results is subject to caution. Moreover, factors that explain economic convergence such as technology diffusions or factor mobility have a strong geographical dimension. Indeed, new economic geography theories and growth theories have been recently integrated in order to show the way interactions between agglomeration and growth processes could lead to new results and better explanations in regional growth studies (Baumont and Huriot, 1998). These theories stress on the role played by geographic spillovers in spatial and growth mechanisms. Most of the results highlight the dominating growth-geographical patterns of Core-Periphery equilibrium and uneven regional development. Therefore, these results mean that economic performances of neighboring regions are similar and not randomly spatially distributed on an economic integrated regional space.

This paper focuses on the theoretical and empirical problems, which arise when such a spatial order characterizes data used in empirical studies of regional growth.

From an econometric point of view, spatial dependence between observations leads to unbiased but inefficient estimators and unreliable statistical inference. It is then straightforward that models using geographical data should be systematically tested for spatial autocorrelation (Cliff et Ord, 1981) like time series models are systematically tested for serial correlation. However just a few empirical studies in the recent literature on growth theories using geographical data apply the appropriate spatial econometric tools (Klotz and Knoth, 1997; Fingleton and McCombie, 1998; Rey and Montouri, 1999; Fingleton, 1999).

Moreover, three important results can be obtained when spatial econometric tools are used in the estimation of regional growth process. First, they allow avoiding bias in statistical inference due to spatial autocorrelation and lead to more reliable estimates. Second, they allow estimating the magnitude of geographical spillover effects in regional growth processes. Third, they show that spatial dependence leads to a minimal but unavoidable specification of conditional β-convergence.

The empirical study of β-convergence for European regions we realize in this paper illustrates these three points. Using a sample of 122 European regions over the 1980-1995 period, we show that the unconditional β-convergence model is misspecified due to spatially autocorrelated errors. We then estimate different specifications integrating these spatial effects explicitly and compare the results obtained for various weight matrices: a contiguity weight matrix and 4 distance-based weight matrices. Our results indicate that the process of convergence is weak and are in conformity with other empirical studies on the convergence of the European regions (Barro and Sala-I-Martin, 1995; Jean-Pierre, 1999; Neven and Gouyette, 1994). But we also show that the mean growth rate of a region is positively influenced by those of neighboring regions stressing a spatial spillover effect. Moreover, the spatially autocorrelated error model implies a spatial diffusion process of random shocks that we evaluate by simulation. Our results are robust to the choice of the weight matrix.

In order to discuss theoretical and empirical results on interactions between agglomeration and regional growth processes we present some theoretical principles showing that economic phenomenon are spatially ordered and that geographic spillovers affect regional growth (Section 1). Then we explain how spatial econometric tools can be applied to the estimation of β-convergence models using European regional data (Section 2). Finally several estimations are realized and their results are discussed (Section 3).

1. Geography and Regional Growth

In this paper, we consider new economic geography theories[2], which have been developed following Krugman's formalization of inter-regional equilibrium with increasing returns (Krugman, 1991). These theories aim at explaining the location behaviors of firms and their agglomeration processes. They give several theoretical information and principles, which help us to understand the uneven spatial repartition of economic activities between regions.

Driven by dominating agglomeration forces, industrial and high tertiary activities tend to concentrate in a few numbers of places in developed nations.

The geographical distribution of areas characterized by high or low densities of economic activities is rarely random: the places where agglomerations take place are identified by first nature or second nature conditions (Krugman, 1993a). The former refers to natural conditions or to random location decisions taken by firms. The latter means that the attractiveness of a place for a firm is due to the presence of other firms, which have chosen to locate there before. In multi-regional models (Krugman, 1993b), it is shown that two agglomerations are separated by a minimum distance because a " shadow effect " prevents the formation of a distinct agglomeration in the neighborhood of another one. This minimum distance value increases with the size of the agglomeration.

Agglomeration processes are strongly cumulative because the agglomeration itself is a component of agglomeration forces. Even if the starting distribution of economic activities is spatially identical (i.e. there is no agglomeration), an exogenous shock, like the random decision of a firm to re-locate in another place, can lead to the formation of an agglomeration in that place.

The effects of the uneven spatial distribution of economic activities on regional economic growth have been pointed out in new economic geography by some theories constituting what we named " geography-growth synthesis " (Baumont, 1998b; Baumont and Huriot, 1999). The emergence of these theories is based on the fact that several similar economic mechanisms are involved both in spatial and dynamical accumulation processes of economic activities, which further and support economic growth. These common determinants affect the characteristics of production processes (like increasing returns, monopolistic competition, externalities, vertical linkage...) and focus on specific factors (like R&D, innovation, producer services, high tertiary activities, public infrastructures...). Then an

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[2] See Duranton (1997) and Fujita, Thisse (1997) for more details.

agglomeration as a whole can be considered as a factor of growth (Baumont, 1997). Several authors have formalized the links between agglomeration and growth processes (Englmann and Walz, 1995; Kubo, 1995; Martin and Ottaviano, 1996, 1999; Ottaviano, 1998; Pavilos and Wang, 1993; Walz, 1996)[3] and they have obtained important results for the analysis of regional growth mechanisms. On the one hand, it is shown that the spatial concentration of economic activities favors economic growth. As a result, uneven spatial distribution of economic activities is an efficient geographic equilibrium for economic growth. On the other hand, economic growth can be considered like another agglomeration force, that is to say that growth can reinforce polarization processes.

These theoretical approaches allow studying the way economic integration policies influence convergence processes between regional economies (Baumont, 1998a, 1998b). For example, the intensification of economic integration processes leads to lower costs of transaction, higher labor migrations and the widening of market size ; each of these factors contributing to agglomeration process and uneven regional development. We also know that the effects of vertical linkage and geographic spillovers on both firms location and productivity reinforce the strength of the interactions between agglomeration and growth processes. But few empirical studies on regional economic convergence consider the effects of explanatory spatial factors like labor migrations, interaction costs or geographic spillovers.

If we focus on geographic spillover effects, some theoretical results are especially important. Geographic spillovers refer to positive knowledge external effects produced by some located firms and affecting the production processes of firms located elsewhere. Local and global geographic spillovers must be distinguished. The former means that production processes of the firms located in one region only benefit from the knowledge accumulation in this region. In this case, uneven spatial distributions of economic activities and regional growth divergence are observed. The latter means that knowledge accumulation in one region improves productivity of all the firms whatever the region where they are located. A global geographic spillover effect doesn't reinforce agglomeration processes and contributes to growth convergence (Englmann and Walz, 1995). Intermediary spatial ranges can be considered if the concentration of firms in one region produces both local and global knowledge spillovers of different values (Kubo, 1995). Uneven or equilibrium patterns of regional growth appear according to the relative strengths of this geographic spillover in a region and between the regions.

[3] See Baumont and Huriot (1999) for more details.

All these theoretical results show that geographical patterns can be ordered by economic growth processes and that they can orient regional growth patterns. Applying them to the analysis of an integrated regional space would lead to the following observations. 1/ Since economic activities are unevenly distributed over space, cumulative processes of agglomeration take place and most of the economic activities tend to concentrate in a few numbers of regions. 2/ Since economic growth is stimulated by geographic concentration of economic activities, patterns of uneven development are observed. 3/ The shadow effect contained in the cumulative agglomeration process and the spatial ranges of geographic spillovers can now explain why rich and poor regions are or not regularly distributed[4]. Whereas all the regions could benefit from global geographic spillovers, cumulative processes of concentration in one region empties its surroundings of economic activities. As a result, rich regions can be close with each other if geographic spillovers are global and regularly distributed among them. On the contrary, the assumption of local spillovers would explain a more regular juxtaposition of rich and poor regions. 4/ Finally, since history matters through the initial conditions and the cumulative nature of both growth and agglomeration processes, the observed geographic distribution of rich and poor regions would be rather stable through time.

We could easily observe such spatial orders in European Union regional area. Rich and attractive regions[5] keep on being geographically concentrated in the south of England, in Benelux, in the east of France, in the west of Germany and in the north of Italy along the London-Munich-Turin axis. In Spain, Portugal and South-Italy, poor regions are numerous.

These persistent empirical observations lead to three types of issues. The first one refers to growth theories and investigates the convergence problem if poor regions don't catch up rich ones. The second one refers to economic geography theories and investigates the effect of geographic spillovers on growth processes to explain spatial development patterns. The third one refers to econometric methods we can use to estimate economic-geography phenomena since data are not spatially randomly distributed. The empirical research we present in this paper tries to answer these questions.

[4] like for example black and white cases on a chessboard.

[5] With per capita GDP above the mean of per capita GDP of European regions.

2. A spatial econometric approach of β-convergence

2.1. β-convergence concepts

The hypothesis of convergence based on the neo-classical growth theories implies that a "poor" economy tends to grow more quickly than a "rich" economy, so that the "poor" economy catches up in the long run the level of per capita income or production of the "rich" economy.

This property corresponds to the concept of β-convergence (Barro and Sala-I-Martin, 1991, 1992, 1995). β-convergence may be absolute (unconditional) or conditional. It is absolute when it is independent of the initial conditions. It is conditional when, moreover, the economies are supposed to be identical in terms of preferences, technologies and economic policies. The hypothesis of absolute β-convergence is usually tested on the following cross-sectional model:

$$\frac{1}{T}ln\left(\frac{y_{i,T}}{y_{i,0}}\right)=\alpha+\beta\, ln\left(y_{i,0}\right)+\varepsilon_i \qquad \varepsilon_i \sim i.i.d(0,\sigma_\varepsilon^2) \tag{1}$$

where $y_{i,t}$ is the per capita GDP of the region i $(i=1,...,N)$ at the date t, T is the length of the period, α and β are unknown parameters to be estimated and ε_i an error term. There is β–convergence when β is negative and statistically significant since in this case the average growth rate of per capita GDP between dates 0 and T is negatively correlated with the initial level of per capita GDP. The estimate of β makes it possible to calculate the speed of convergence: $\theta=-ln(1+T\beta)/T$. The time necessary for the economies to fill half of the variation, which separates them from their stationary state, is called the half-life: $\tau=-ln(2)/ln(1+\beta)$.

The test of the hypothesis of conditional β-convergence is based on the estimation of the following model where some variables, which differentiate the regions, are isolated:

$$\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right)=\alpha+\beta\ln\left(y_{i,0}\right)+\gamma X_i^{'}+\varepsilon_i \qquad \varepsilon_i \sim i.i.d(0,\sigma_\varepsilon^2) \tag{2}$$

X_i is a vector of variables, maintaining constant the stationary-state of economy i, including some state variables, like the stock of physical capital and the stock of human capital, and control or environment variables, like the ratio of public consumption to GDP, the ratio of domestic investment to GDP, the modification of terms of trade, the fertility rate, the degree of political instability etc. (Barro and Sala-I-Martin, 1995). Another way of testing the assumption of conditional convergence is still based on the equation (1) but it is estimated on subsamples of economies for which the assumption of similar stationary-states seems acceptable (construction of convergence clubs, see for example Baumol, 1986; Jean-Pierre, 1999).

We can observe that two effects on economic growth are estimated in the conditional β-convergence model. The first one is an expected negative effect of the initial per capita GDP through the estimated value of β in order to capture the convergence phenomenon. The second one corresponds to all other effects on growth of each explanatory variable introduced in X_i. As a result, estimating equation (2) provides information on a more general process of growth than in equation (1). We can deduce from the estimates, which variables contribute or weaken economic growth and the way the convergence process is constrained by some explanatory variables. Nevertheless, the appropriate choice of these explanatory variables is problematic because we can't be sure conceptually to include all the variables differentiating steady states. Even in this case data on some of these variables may not be easily accessible and reliable for international comparisons (Caselli, Esquivel and Lefort, 1996; Fingleton 1999). In addition some of these variables, including the initial per capita GDP, can be correlated with the error term invalidating estimation by Ordinary Least Squares and associated statistical inference (Quah, 1993; Evans, 1996).

Let us finally underline that in the convergence tests presented above, the analysis relates to regions observed in cross-sections by supposing implicitly that each one of them is a geographically independent entity and by neglecting the possibility of spatial interactions. Indeed the independence hypothesis on the error terms may be very restrictive and should be tested. If rejected, the estimation of these models by Ordinary Least Squares will be inefficient though unbiased and the statistical inference will not be reliable. The spatial dimension of the data should then be carefully integrated in the study and estimation of convergence processes.

2.2. Spatial dependence and econometric tools

Spatial dependence means that observations are geographically correlated due to some processes, which connect different areas: for example diffusion and dispersion processes or trade process, transfers or other social and economic interactions. Several economic factors, like labor force mobility, capital mobility, transportation costs or transaction costs are especially important because they directly affect trade between regions. Indeed, these various processes induce a particular organization of economic activity in space.

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

Three kinds of model can be used to deal with spatial dependence of observations: the spatial autoregressive model, the spatial cross-regressive model and the spatial error model (Anselin, 1988; Anselin and Bera, 1995; Cliff and Ord, 1981).

The spatial autoregressive model

In this model, spatial correlation of observations is handled by the endogenous spatial lag variable $W[(1/T)\ln(z)]$:

$$1/T \ln(z) = \alpha S + \beta \ln(y_0) + \rho W[(1/T)\ln(z)] + u \qquad u \sim \mathrm{N}(0, \sigma^2 I) \tag{3}$$

where z is the $(n \times 1)$ vector of the dependent variable in the unconditional β-convergence model, i.e. the vector of per capita GDP ratios for each region i between dates T and 0, $(1/T)\ln(z)$ is then the vector of average growth rates for each region i between dates T and 0; y_0 is the $(n \times 1)$ vector of per capita GDP level for each region i at date 0 and ε the $(n \times 1)$ vector of normal i.i.d. error terms; S is the sum vector; α, β and ρ are the unknown parameters to be estimated. ρ is the spatial autoregressive parameter indicating the extent of interaction between the observations according to the spatial pattern, which is exogenously introduced in the weight matrix W of dimension $(n \times n)$. This weight matrix is standardized such that the elements of a row sum up to one. The endogenous spatial lag variable $W[(1/T)\ln(z)]$ is then a vector containing the growth rates premultiplied by the weight matrix: for a region i of the vector, the corresponding line of the spatial lag vector contains the spatially weighted average of the growth rates of the neighboring regions. This weight matrix is of fundamental interest in spatial econometrics so we will specify its properties more deeply below.

Estimation of this model by Ordinary Least Squares (OLS) produces inconsistent estimators due to the presence of a stochastic regressor Wy, which is always correlated with ε, even if the residuals are identically and independently distributed (Anselin, 1988, chap 6).

Hence it is to be estimated by the Maximum Likelihood Method (ML) or the Instrumental Variables Method.

This specification can be interpreted in two ways. From the convergence perspective, it yields some information on the nature of convergence through the β parameter once spatial effects are controlled for and thus it can be interpreted like a minimal conditional β-convergence model allowing for spatially lagged endogenous effects. From the economic geography perspective, it indicates how the growth rate of per capita GDP in a region is affected by those of neighboring regions through the ρ parameter after conditioning on the initial per capita GDP levels. It may thus help to highlight a spatial spillover effect.

In addition, let us stress also that this model can be rewritten as following:

$$(I-\rho W)[(1/T)\ln(z)] = \alpha S + \beta \ln(y_0) + u$$

$$[(1/T)\ln(z)] = \alpha(I-\rho W)^{-1}S + \beta(I-\rho W)^{-1}\ln(y_0) + (I-\rho W)^{-1}u$$

Concerning the error process this expression means that a random shock in a specific region does not only affect the growth rate of this region, but also has an impact on the growth rates of all other regions through the inverse spatial transformation $(I-\rho W)^{-1}$. Moreover, it means as well that the growth rate of a given region is affected not only by its own per capita GDP initial level but also by those of all other regions through the same inverse spatial transformation. The second interpretation is rather disturbing when we consider this specification from the pure convergence perspective: it is hard to say if it is really consistent with the basic β-convergence concept. For the least, we think that this specification should be interpreted carefully in terms of convergence processes.

The spatial cross-regressive model

Another way to deal with spatial dependence is to introduce exogenous spatial lag variables:

$$1/T\ln(z) = \alpha S + \beta \ln(y_0) + WZ\gamma + u \qquad u \sim \mathrm{N}(0,\sigma^2 I) \qquad (4)$$

Here, the influence of h spatially lagged exogenous variables contained in the $(n \times h)$ matrix Z is reflected by the parameter vector γ. This general specification allows handling of spatial spillover effects explicitly and can be interpreted like a conditional convergence model integrating spatial environment variables possibly affecting growth rates.

The set of explanatory variables in Z can include or not $\ln(y_0)$. If it is the case, then the model gives estimates of both a direct and a spatially lagged effects of initial per capita

GDP levels on the growth rates, besides estimates of spatially lagged effects of other explanatory variables. If it is not the case then the model focuses only on the spatially lagged effects of other explanatory variables. The estimation of this model can be based on OLS.

An interesting special case appears when Z includes only $\ln(y_0)$, we have then:

$$1/T \ln(z) = \alpha S + \beta \ln(y_0) + \gamma W \ln(y_0) + u \qquad u \sim \mathrm{N}(0, \sigma^2 I) \tag{5}$$

in which only the spatially lagged initial per capita GDP levels affect growth rates. This model can be interpreted as the minimal specification allowing spatially lagged exogenous effects in a conditional β-convergence model.

The spatial error model

This specification is accurate when we think that spatial dependence works through omitted variables. It is then handled by the error process with errors from different regions displaying spatial covariance. When the errors follow a first order process, the model is:

$$1/T \ln(z) = \alpha S + \beta \ln(y_0) + \varepsilon \qquad \varepsilon = \lambda W \varepsilon + u \qquad u \sim \mathrm{N}(0, \sigma^2 I) \tag{6}$$

where λ is the scalar parameter expressing the intensity of spatial correlation between regression residuals. Use of OLS in the presence of non-spherical errors would yield unbiased but inefficient estimators. In addition inference based on OLS may be misleading due to biased estimate of the parameter's variance. Therefore this model should be estimated by ML or General Methods of Moments.

This model has two interesting properties. First, spatially correlated errors imply that a random shock in a specific region is propagated to all the regions of the sample (Rey and Montouri, 1999).

Indeed, since: $\varepsilon = \lambda W \varepsilon + u$, then $\varepsilon = (I - \lambda W)^{-1} u$ and the model (6) is:

$$(1/T)\ln(z) = \alpha S + \beta \ln(y_0) + (I - \lambda W)^{-1} u \tag{7}$$

This expression means that a random shock in a specific region does not only affect the growth rate of this region, but also has an impact on the growth rates of other regions through the inverse spatial transformation $(I - \lambda W)^{-1}$. Moreover, even if a given region has a limited number of neighbors, the inverse operator in the transformation defines an error covariance diffusing the shocks not only to his neighbors but also to all the system.

Second, this model can be rewritten in another form, which can be interpreted like a minimal model of conditional β-convergence integrating two spatial environment variables. Indeed, let us note that premultiplying equation (7) by $(I-\lambda W)$ we get:

$$(I-\lambda W)(1/T)\ln(z)=\alpha(I-\lambda W)S+\beta(I-\lambda W)\ln(y_0)+u \tag{9}$$

then:

$$(1/T)\ln(z)-\lambda W[(1/T)\ln(z)]=\alpha(I-\lambda W)S+\beta\ln(y_0)-\lambda\beta W\ln(y_0)+u \tag{11}$$

$$(1/T)\ln(z)=\alpha(I-\lambda W)S+\beta\ln(y_0)+\lambda W[(1/T)\ln(z)]+\gamma W\ln(y_0)+u \tag{12}$$

with the restriction $\gamma=-\lambda\beta$ (13)

This model can be estimated by ML and the restriction (13) can be tested by the common factor test (Burridge, 1981). If the restriction $\gamma+\lambda\beta=0$ cannot be rejected then model (12) reduces to model (6).

It should be stressed that model (11) encompasses model (3) and (5) in the sense that it incorporates either the spatially lagged endogenous and exogenous variables: $W[1/T\ln(z)]$ and $W\ln(y_0)$. It reveals two types of spatial spillover effects. Indeed, the growth rate of a region i may be influenced by the growth rate of neighboring regions, by the means of the endogenous spatial lag variable. It may be as well influenced by the initial per capita GDP of neighboring regions, by the means of the exogenous spatial lag variable. Spatial econometric models appear thus useful to highlight spatial spillover effects.

Tests of spatial autocorrelation

Three tests of spatial autocorrelation can be carried out on the absolute β-convergence model (3). The Moran's I test adapted to the regression residuals by Cliff and Ord (1981) is very powerful against all forms of spatial dependence but it does not allow discriminating between them (Anselin and Florax, 1995). In this purpose, we can use two Lagrange Multiplier tests (Anselin, 1988) as well as their robust counterparts (Anselin et al., 1996), which allow testing the presence of the two possible forms of autocorrelation: LMLAG for an autoregressive spatial lag variable and LMERR for a spatial autocorrelation of errors. The two robust tests have a good power against their specific alternative. The decision rule suggested by Anselin and Florax (1995) can then be used to decide which specification is the more appropriate.

The spatial weight matrix

Let us now detail the properties of the weight matrix W. This matrix contains the information about the relative spatial dependence between the n regions i. The elements w_{ii} on the diagonal are set to zero whereas the elements w_{ij} indicate the way the region i is spatially connected to the region j. In order to normalize the outside influence upon each region, the weight matrix is standardized such that the elements of a row sum up to one $w_{ij}^{*} = w_{ij} \Big/ \sum_{j} w_{ij}$. For a variable x, this transformation means that the expression Wx is simply the weighted average of the neighboring observations.

Two principal ways are used to evaluate geographical connections: a contiguity indicator or a distance indicator. In the first case, we assume that interactions can only exist if two regions share a common border: then $w_{ij} = 1$ if regions i and j have a common border and $w_{ij} = 0$ otherwise. This contiguity indicator can be refined by taking into account the length of this common border assuming that the intensity of interactions cannot be identical between regions sharing a border of 10 kilometers and those sharing a border of 100 kilometers. It is worth stressing that this later contiguity indicator is more relevant for European regions than for US States: the disparities in terms of length of common border are indeed more important for European regions than for US States.

In the second case, we assume that the intensity of interactions depends on the distance between the centroids of these regions or between the regional capitals. Various indicators can be used depending on the definition of the distance d_{ij} (great circle distance or distance by roads, including transportation cost or time considerations) and depending on the functional form (the inverse of the distance or the inverse of the squared distance...) we choose: $w_{ij} = 1/d_{ij}$ or $w_{ij} = 1/d_{ij}^2$. We can also define a cutoff above which $w_{ij} = 0$ assuming that above that distance the interactions are negligible.

Although W is exogenously defined by the researcher, the choice of a specific method to introduce spatial dependence means that specific assumptions are made. For example, if we calculate distance between regional centroids it means that economic activity is homogeneously distributed on the whole region whereas if we prefer evaluating distance between regional capitals it means that economic activity is concentrated in these regional capitals. Each functional form allows bringing out slight differences in the way spillovers affect pairs of regions. Finally, the kind of economic interactions we try to estimate may give information and help to choose a specific weight matrix.

Using a contiguity weight matrix, we have shown in a previous work (Baumont, Ertur and Le Gallo, 2000) that a strong positive spatial autocorrelation characterizes both per capita GDP levels and growth rates for a slightly different sample of European Union regions for the 1980-1995 period using Exploratory Spatial Data Analysis (ESDA) and Local Indicators of Spatial Association (LISA). We have also found strong positive spatial autocorrelation for the error process in the β-convergence model and estimated the various spatial specifications with a contiguity matrix. In this paper we want to compare the effects of geographic spillovers relative to the choice of a particular weight matrix and assess the robustness of our previous results using a more complete sample.

3. Estimation results stressing spatial spillover effects

We use spatial econometrics techniques briefly described above to detect and to treat spatial autocorrelation in the model of absolute β-convergence on the per capita GDP of the European regions over the 1980-1995 period. The data are extracted from the EUROSTAT-REGIO databank. Our sample includes 122 regions (Denmark, Luxembourg and United Kingdom in NUTS1 level and Belgium, Spain, France, Germany, Italy, Netherlands and Portugal in NUTS2 level)[6].

We first estimate the model of absolute β–convergence and carry out various tests aiming at detecting the presence of spatial dependence. We then consider the specifications integrating these spatial effects explicitly and compare the results obtained for various weight matrices: a contiguity weight matrix and 4 distance-based weight matrices.

Let us take as a starting point the following model of absolute β–convergence:

Model (I): $$(1/T)\ln(z) = S\alpha + \beta\ln(y_{1980}) + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2 I)$$

where $(1/T)\ln(z)$ is the vector of dimension N=122 of the average per capita GDP growth rates for each region i between 1995 and 1980, $T = 15$, y_{1980} is the vector containing the observations of per capita GDP for all the regions in 1980, α and β are the unknown

[6] This sample implies a block-diagonal pattern for the simple contiguity weight matrix due to the presence of United Kingdom, which doesn't share a common border with any other state of the sample.

parameters to be estimated, S is the unit vector and ε is the vector of errors with the usual properties.

The results of the estimation by OLS of this model are given in Table 1. The coefficient associated with the initial per capita GDP is significant and negative, which confirms the hypothesis of convergence for the European regions. The speed of convergence associated with this estimation is 1,37% and the half-life is 56 years. These results indicate that the process of convergence is weak and are in conformity with other empirical studies on the convergence of the European regions (Barro and Sala-I-Martin, 1995; Jean-Pierre, 1999; Neven and Gouyette, 1994). It is worth mentioning that the Jarque-Bera test doesn't reject Normality: the reliability of all subsequent testing procedures and the use of Maximum Likelihood estimation method are then strengthened. We note also that the Breusch-Pagan test of heteroskedasticity is not significant. Further consideration of spatial heterogeneity is therefore omitted and we only take into account spatial dependence in this empirical analysis[7].

Three tests of spatial autocorrelation are then carried out: the test of Moran's I adapted to the regression residuals indicates the presence of spatial dependence. To discriminate between the two forms of spatial dependence – endogenous spatial lag or spatial autocorrelation of errors - we perform two robust Lagrange Multiplier tests: respectively LMERR and LMLAG. Applying the decision rule suggested by Anselin and Florax (1995) these tests indicate the presence of spatial autocorrelation rather than a spatial lag variable[8].

Therefore model (I) is misspecified due to the omission of spatial autocorrelation of the errors. Actually, each region is not independent of the others, as it is frequently supposed in the former studies at the regional level. The model of absolute β–convergence must thus be modified to integrate this spatial dependence explicitly.

To handle the spatial dependence found, we first estimate the spatial autoregressive model including the endogenous lag variable:

$$\text{Model (II):} \quad (1/T)\ln(z) = S\alpha + \beta\ln(y_{1980}) + \rho W[(1/T)\ln(z)] + u \qquad u \sim N(0,\sigma^2 I)$$

The results of estimation by maximum likelihood using the contiguity weight matrix are given in Table 1. The coefficients are all significant. Concerning the convergence hypothesis, we note that the estimated value of the β parameter is indeed negative but much smaller than in the preceding model and leads to a convergence speed of 0.8% and a half-life of 91 years. The convergence process appears therefore to be even weaker. From the

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[7] It is not the case of Fingleton (1999) who rejects Normality and homoskedasticity for his sample.
[8] All estimations were carried out using SpaceStat 1.90.

economic geography perspective, the estimated spatial autoregressive parameter $\hat{\rho}$ is highly significant and positive $(\hat{\rho} = 0.631)$ and emphasizes a spatial spillover effect: the growth rate of per capita GDP in a given region is influenced by those of neighboring regions. The LMERR test does not reject the null hypothesis of no additional spatial error autocorrelation. The spatially adjusted Breusch-Pagan test is not significant indicating absence of spatial heterogeneity. This model performs better than the previous one in terms of information criteria (Akaike, 1974; Schwarz, 1978).

We estimate also the special case of the spatial cross-regressive model with only the spatially lagged initial per capita GDP level:

Model (III): $1/T \ln(z) = \alpha S + \beta \ln(y_{1980}) + \gamma W \ln(y_{1980}) + u \qquad u \sim N(0, \sigma^2 I)$

We saw that this specification can be interpreted as the minimal conditional β-convergence model allowing for spatially lagged exogenous effects. The estimation results by OLS using the contiguity weight matrix are presented in Table 1. $\hat{\beta}$ is highly significant and bigger than in the two preceding models leading to a convergence speed of 1.62% and a half-life of 48 years. The coefficient associated with the exogenous lag variable is not significant: the initial per capita GDP of neighboring regions doesn't influence the growth rate of a given region. There's no spatial spillover effect associated with the exogenous lag variable in this model. Moreover, there are some problems with spatial dependence tests, which indicate the presence of spatial error autocorrelation (Moran's I and LMERR) and presence of a lagged endogenous variable (LMLAG). The Breusch-Pagan test is also significant pointing to heteroskedasticity. The picture is worse than for model (I) and (II) according to information criteria. This model seems therefore to be strongly misspecified and is also the worst in terms of information criteria.

The tests carried out on model (I) suggested the presence of spatial error autocorrelation rather than an endogenous lag variable; we therefore estimate finally the spatial error model:

Model (IV): $(1/T)\ln(z) = S\alpha + \beta \ln(y_{1980}) + \varepsilon \qquad \varepsilon = \lambda W \varepsilon + u \qquad u \sim N(0, \sigma^2 I)$

Model (V): $(1/T)\ln(z) = \alpha(I - \lambda W)S + \beta \ln(y_{1980}) + \lambda W[(1/T)\ln(z)] + \gamma W \ln(y_{1980}) + u$

The estimation results by maximum likelihood are given in Table 1. The coefficients are all significant. The coefficient associated with the level of initial per capita GDP is higher than that of the model (I) and a positive spatial autocorrelation of the errors ($\hat{\lambda} = 0{,}694$) is found. The LMLAG test does not reject the null hypothesis of the absence of an additional autoregressive lag variable. The spatially adjusted Breusch-Pagan test is not significant indicating absence of spatial heterogeneity. The common factor test indicates that the restriction $\gamma + \lambda\beta = 0$ cannot be rejected then model (V) reduces to model (IV) with $\hat{\gamma} = -\hat{\lambda}\hat{\beta}$ but this coefficient is not significant at the 5% significance level. According to information criteria this model seems to perform better than all the preceding specifications. It thus appears that the model with spatial autocorrelation of the errors is the most appropriate specification.

This specification has two implications:

First, the speed of convergence in the model with spatial autocorrelation is 1,73% and is thus higher than that of all the preceding models; the half-life reduces to 45 years once the spatial effects are controlled for. This model reveals also a spatial spillover effect, when reformulated as model (V), in that the mean growth rate of a region i is positively influenced by the mean growth rate of contiguous regions, through the endogenous spatial lag variable $W[(1/T)\ln(z)]$. But it seems not to be influenced by the initial per capita GDP of contiguous regions, through the exogenous spatial lag variable $W\ln(y_{1980})$. This spillover effect indicates that the spatial association patterns are not neutral for the economic performances of European regions. The more a region is surrounded by dynamic regions with high growth rates, the more its growth rate will be high. In other words, the geographical environment has an influence on growth processes. This corroborates the theoretical results highlighted by the New Economic Geography. From the pure perspective of convergence processes, this first implication may seem qualitatively negligible, but we must underline that this is the only proper way of estimating a conditional model of β-convergence once spatially autocorrelated errors are detected and the only proper way of drawing reliable statistical inference.

The second implication is even more interesting. We saw that this specification has an interesting property concerning the diffusion of a random shock. We present some simulation results to illustrate this property with a random shock affecting Burgundy, which is close to the centroid of European regions included in our sample[9]. This shock has the largest relative impact on Burgundy where the estimated mean growth rate is 27,5% higher than the estimated mean growth rate without the shock. Nevertheless we observe a clear spatial diffusion pattern of this shock to all other regions of the sample excepted United-Kingdom (due to the block-

[9] This shock is set equal to two times the residual variance of the estimated spatial error model (IV).

diagonal structure of the contiguity weight matrix). The magnitude of the impact of this shock is between 1.8% and 5.5% for the regions neighboring Burgundy and gradually decreases when we move to peripheral regions (Figure 1). Therefore the spatially autocorrelated errors specification underlines that the geographical diffusion of shocks are at least as important as the dynamic diffusion of these shocks in the analysis of convergence processes. Integration of these two aspects may be studied in further research.

We reestimate then all these specifications with 4 distance-based matrices, which are defined as following $(k = 1,...,4)$:

$$\begin{cases} w_{ij} = 0 \text{ if } i = j \\ w_{ij} = 1/d_{ij}^2 \text{ if } d_{ij} \leq D(k) \\ w_{ij} = 0 \text{ if } d_{ij} > D(k) \end{cases}$$

$$w_{ij}^* = w_{ij} \Big/ \sum_j w_{ij}$$

where d_{ij} is the great circle distance between centroids of regions i and j; $D(1) = Q1$, $D(2) = Me$, $D(3) = Q3$ and $D(4) = Max$, where *Q1, Me, Q3* and Max are respectively the lower quartile (436 km), the median (767 km), the upper quartile (1218 km) and the maximum (2496 km) of the great circle distance distribution. $D(k)$ is a cutoff parameter for $k = 1,2,3$ above which interactions are assumed negligible. For $k = 4$, the distance matrix is full without cutoff. The choice of the cutoff can also be based on a residual correlogram with ranges defined by minimum, lower quartile, median, upper quartile and maximum great circle distances (see Table 2).

The determination of the cutoff that maximize the absolute value of significant Moran's I or robust Lagrange Multiplier test statistics for spatial autocorrelation of the errors lead to Q1 or Q3: we could only retain a cutoff of 436 km or 1218 km for the distance based weight matrix, but we prefer to maintain all 4 matrices for full robustness evaluation of estimation results.

The estimation results are presented in Tables 3 to 6. The overall picture is quite similar to those obtained with the contiguity matrix and indicates the robustness of our results to the choice of the weight matrix. More specifically, in the cross-regressive model, the coefficient of the exogenous lag variable is never significant and in the spatial autoregressive model, the half-life to convergence reaches always more than twice the value we find in other models. The spatial error model is the best one according to information criteria whatever the specification we adopt for the weight matrix and provides always a better fit than the absolute β-convergence model.

Conclusion

The aim of this paper is to analyze the consequences of spatial dependence on regional growth and convergence processes for European regions over the 1980-1995 period. Among all the specifications integrating spatial autocorrelation, the spatial error model is the best one according to test procedures and information criteria. This specification reveals spatial spillover effects in that the mean growth rate of per capita GDP of a region is affected by the mean growth rate of neighboring regions. Moreover, we stress the importance of the spatial diffusion process implied by this model. We interpret this specification as the minimal conditional β–convergence model in the sense that it captures the effects of all other variables that could explain differentiated steady states along the lines of Haining (1990) and Fingleton (1999). We could also suggest that standard conditional β–convergence models should be tested for spatial dependence and if it is detected they should include at least the endogenous lagged variable and be estimated by the appropriate econometric method.

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Model	β -convergence (I)	Spatial error (IV) and (V)	Spatial lag-dep (II)	Spatial lag-ex (III)
Estimation	**OLS**	**ML-cont**	**ML-cont**	**OLS-cont**
$\hat{\alpha}$	0.170 (0.000)	0.196 (0.000)	0.089 (0.000)	0.164 (0.000)
$\hat{\beta}$	-0.01239 (0.000)	-0.01523 (0.000)	-0.00761 (0.000)	-0.01439 (0.000)
conv. speed	1.37% (0.000)	1.73% (0.000)	0.8% (0.000)	1.62% (0.000)
half-life	56	45	91	48
$\hat{\lambda}$	-	0.694 (0.000)	-	-
$\hat{\rho}$	-	-	0.631 (0.000)	-
$\hat{\gamma}$	-	-	-	0.0026 (0.557)
Adj-R^2 or R^{2*}	0.253	0.39*	0.44*	0.249
LIK	406.72	436.70	431.89	406.90
AIC	-809.44	-869.40	-857.79	-807.80
BIC	-803.83	-863.79	-849.37	-799.38
$\hat{\sigma}^2$	$7.569.10^{-5}$	$3.931.10^{-5}$	$4.389.10^{-5}$	$7.610.10^{-5}$
Tests				
JB	2.429 (0.297)	-	-	3.348 (0.187)
BP or BP-S*	0.0156 (0.901)	1.084* (0.298)	0.286* (0.593)	11.904 (0.003)
Moran's I (error)	8.812 (0.000)	-	-	8.695 (0.000)
LMERR	69.255 (0.000)	-	1.686 (0.194)	68.199 (0.000)
R-LMERR	11.563 (0.000)	-	-	8.777 (0.003)
LMLAG	58.046 (0.000)	0.113 (0.737)	-	69.330 (0.000)
R-LMLAG	0.353 (0.552)	-	-	9.909 (0.001)
LR-com-fac	-	0.00060 (0.980)	-	-
$\hat{\gamma} = -\hat{\lambda}\hat{\beta}$	-	0.0106 (0.822)	-	-

Table 1 : Contiguity Matrix

Note: The data are extracted from the EUROSTAT-REGIO databank: 122 regions (Denmark, Luxembourg and United Kingdom in NUTS1 level and Belgium, Spain, France, Germany, Italy, Netherlands and Portugal in NUTS2 level). The contiguity matrix is block diagonal due to the presence of United-Kingdom, whose regions don't share any common border with any other region from another state in the sample.

P-values are in parentheses. LIK is value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). JB is the Jarque-Bera (1980) estimated residuals Normality test. MORAN is the Moran's I test adapted to estimated residuals (Cliff and Ord, 1981). LMLAG is the Lagrange multiplier test for spatially lagged endogenous variable, R-LMLAG is the robust version of this test and R-LMERR is the robust version of the Lagrange multiplier test for residual spatial autocorrelation (Anselin and Florax, 1995; Anselin et al., 1996). LR-com-fac is the likelihood ratio common factor test (Burridge, 1981). BP is the Breusch-Pagan (1979) test for heteroskedasticity and BP-S is the spatially adjusted version of this test.

Range (Km)	[Min;Q1[[15;436[	[Q1;Me[[436;767[	[Me;Q3[[767;1218[	[Q3;Max[[1218;2496[
Moran's I	12.690	-2.505	-10.210	-0.010
p-value	0.000	0.012	0.000	0.992
R-LMERR	39.61	7.97	56.21	1.17
p-value	0.000	0.005	0.000	0.278

Table 2: Residual Correlogram

Note: Q1, Me, Q3 and Max are respectively the lower quartile (436 km), the median (767 km), the upper quartile (1218 km) and the maximum (2496 km) of the great circle distance distribution between centroids of each region. For each range, we estimate the absolute β-convergence model and we perform Moran's I test adapted to estimated residuals and the robust Lagrange multiplier test for residual spatial autocorrelation based on a simple contiguity matrix.

Model	β -convergence (I)	Spatial error (IV) and (V)	Spatial lag-dep (II)	Spatial lag-ex (III)
Estimation	**OLS**	**ML-cont**	**ML-cont**	**OLS-cont**
$\hat{\alpha}$	0.170 (0.000)	0.175 (0.000)	0.069 (0.000)	0.163 (0.000)
$\hat{\beta}$	-0.01239 (0.000)	-0.01316 (0.000)	-0.00578 (0.002)	-0.01523 (0.000)
conv. speed	1.37% (0.000)	1.47% (0.000)	0.6% (0.000)	1.41% (0.000)
half life	56	53	120	55
$\hat{\lambda}$	-	0.747 (0.000)	-	-
$\hat{\rho}$	-	-	0.696 (0.000)	-
$\hat{\gamma}$	-	-	-	0.0035 (0.436)
Adj-R^2 or R^{2*}	0.253	0.29*	0.43*	0.250
LIK	406.72	434.28	430.41	407.03
AIC	-809.44	-864.57	-854.82	-808.07
BIC	-803.83	-858.96	-846.41	-799.65
$\hat{\sigma}^2$	$7.569.10^{-5}$	$4.235.10^{-5}$	$4.600.10^{-5}$	$7.593.10^{-5}$
Tests				
JB	2.429 (0.297)	-	-	3.887 (0.143)
BP or BP-S*	0.0156 (0.901)	3.268* (0.0706)	2.200* (0.138)	13.898 (0.000)
Moran's I (error)	10.157 (0.000)	-	-	9.970 (0.000)
LMERR	87.065 (0.000)	-	3.099 (0.078)	84.108 (0.000)
R-LMERR	21.170 (0.000)	-	-	2.601 (0.107)
LMLAG	66.520 (0.000)	0.0068 (0.935)	-	85.631 (0.000)
R-LMLAG	0.624 (0.429)	-	-	4.124 (0.042)
LR-com-fac	-	0.00015 (0.990)	-	-
$\hat{\gamma} = -\hat{\lambda}\hat{\beta}$	-	0.0098 (0.861)	-	-

Table 3 : Q1-distance weight matrix

Note: The data are extracted from the EUROSTAT-REGIO databank: 122 regions (Denmark, Luxembourg and United Kingdom in NUTS1 level and Belgium, Spain, France, Germany, Italy, Netherlands and Portugal in NUTS2 level).

P-values are in parentheses. LIK is value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). JB is the Jarque-Bera (1980) estimated residuals Normality test. MORAN is the Moran's I test adapted to estimated residuals (Cliff and Ord (1981). LMLAG is the Lagrange multiplier test for spatially lagged endogenous variable, R-LMLAG is the robust version of this test and R-LMERR is the robust version of the Lagrange multiplier test for residual spatial autocorrelation (Anselin and Florax, 1995; Anselin et al., 1996). LR-com-fac is the likelihood ratio common factor test (Burridge, 1981). BP is the Breusch-Pagan (1979) test for heteroskedasticity and BP-S is the spatially adjusted version of this test.

Model	β-convergence (I)	Spatial error (IV) and (V)	Spatial lag-dep (II)	Spatial lag-ex (III)
Estimation	OLS	ML-cont	ML-cont	OLS-cont
$\hat{\alpha}$	0.170 (0.000)	0.174 (0.000)	0.065 (0.001)	0.164 (0.000)
$\hat{\beta}$	-0.01239 (0.000)	-0.01307 (0.000)	-0.00577 (0.003)	-0.01421 (0.000)
conv. speed	1.37% (0.000)	1.45% (0.000)	0.6% (0.001)	1.6% (0.000)
half life	56	53	120	49
$\hat{\lambda}$	-	0.813 (0.000)	-	-
$\hat{\rho}$	-	-	0.761 (0.000)	-
$\hat{\gamma}$	-	-	-	0.00242 (0.616)
Adj-R^2 or R^{2*}	0.253	0.29*	0.41*	0.248
LIK	406.72	432.04	428.79	406.85
AIC	-809.44	-860.09	-851.58	-807.70
BIC	-803.83	-854.48	-843.16	-799.28
$\hat{\sigma}^2$	$7.569.10^{-5}$	$4.416.10^{-5}$	$4.741.10^{-5}$	$7.616.10^{-5}$
Tests				
JB	2.429 (0.297)	-	-	3.190 (0.203)
BP or BP-S*	0.0156 (0.901)	2.423* (0.119)	1.964* (0.161)	11.189 (0.004)
Moran's I (error)	9.944 (0.000)	-	-	9.869 (0.000)
LMERR	80.082 (0.000)	-	3.309 (0.069)	78.526 (0.000)
R- LMERR	19.469 (0.000)	-	-	0.675 (0.411)
LMLAG	60.871 (0.000)	0.154 (0.694)	-	79.127 (0.000)
R-LMLAG	0.259 (0.611)	-	-	1.276 (0.258)
LR-com-fac	-	0.08833 (0.766)	-	-
$\hat{\gamma} = -\hat{\lambda}\hat{\beta}$	-	0,0106 (0.859)	-	-

Table 4 : Q2-distance weight matrix

Note: The data are extracted from the EUROSTAT-REGIO databank: 122 regions (Denmark, Luxembourg and United Kingdom in NUTS1 level and Belgium, Spain, France, Germany, Italy, Netherlands and Portugal in NUTS2 level).

P-values are in parentheses. LIK is value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). JB is the Jarque-Bera (1980) estimated residuals Normality test. MORAN is the Moran's *I* test adapted to estimated residuals (Cliff and Ord (1981). LMLAG is the Lagrange multiplier test for spatially lagged endogenous variable, R-LMLAG is the robust version of this test and R-LMERR is the robust version of the Lagrange multiplier test for residual spatial autocorrelation (Anselin and Florax, 1995; Anselin et al., 1996). LR-com-fac is the likelihood ratio common factor test (Burridge, 1981). BP is the Breusch-Pagan (1979) test for heteroskedasticity and BP-S is the spatially adjusted version of this test.

Model	β -convergence (I)	Spatial error (IV) and (V)	Spatial lag-dep (II)	Spatial lag-ex (III)
Estimation	**OLS**	**ML-cont**	**ML-cont**	**OLS-cont**
$\hat{\alpha}$	0.170 (0.000)	0.169 (0.000)	0.063 (0.000)	0.166 (0.000)
$\hat{\beta}$	-0.01239 (0.000)	-0.01271 (0.000)	-0.00588 (0.002)	-0.01334 (0.001)
conv. speed	1.37% (0.000)	1.41% (0.000)	0.6% (0.000)	1.50% (0.000)
half life	56	55	118	52
$\hat{\lambda}$	-	0.857 (0.000)	-	-
$\hat{\rho}$	-	-	0.811 (0.000)	-
$\hat{\gamma}$	-	-	-	0.00135 (0.791)
Adj-R^2 or R^{2*}	0.253	0.27*	0.41*	0.247
LIK	406.72	431.25	428.64	406.757
AIC	-809.44	-858.50	-851.27	-807.514
BIC	-803.83	-852.89	-842.86	-799.10
$\hat{\sigma}^2$	$7.569.10^{-5}$	$4.461.10^{-5}$	$4.731.10^{-5}$	$7.628.10^{-5}$
Tests				
JB	2.429 (0.297)	-	-	2.815 (0.245)
BP or BP-S*	0.0156 (0.901)	2.072* (0.150)	2.321* (0.128)	11.617 (0.003)
Moran	9.579 (0.000)	-	-	9.557 (0.000)
LMERR	73.374 (0.000)	-	2.680 (0.102)	72.661 (0.000)
R-LMERR	16.124 (0.000)	-	-	0.437 (0.508)
LMLAG	57.322 (0.000)	0.312 (0.576)	-	72.895 (0.000)
R-LMLAG	0.072 (0.788)	-	-	0.671 (0.412)
LR-com-fac	-	0.2389 (0.625)	-	-
$\hat{\gamma} = -\hat{\lambda}\hat{\beta}$	-	0,0109 (0.846)	-	-

Table 5 : Q3-distance weight matrix

Note: The data are extracted from the EUROSTAT-REGIO databank: 122 regions (Denmark, Luxembourg and United Kingdom in NUTS1 level and Belgium, Spain, France, Germany, Italy, Netherlands and Portugal in NUTS2 level).

P-values are in parentheses. LIK is value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). JB is the Jarque-Bera (1980) estimated residuals Normality test. MORAN is the Moran's I test adapted to estimated residuals (Cliff and Ord (1981). LMLAG is the Lagrange multiplier test for spatially lagged endogenous variable, R-LMLAG is the robust version of this test and R-LMERR is the robust version of the Lagrange multiplier test for residual spatial autocorrelation (Anselin and Florax, 1995; Anselin et al., 1996). LR-com-fac is the likelihood ratio common factor test (Burridge, 1981). BP is the Breusch-Pagan (1979) test for heteroskedasticity and BP-S is the spatially adjusted version of this test.

Model	β-convergence (I)	Spatial error (IV) and (V)	Spatial lag-dep (II)	Spatial lag-ex (III)
Estimation	OLS	ML-cont	ML-cont	OLS-cont
$\hat{\alpha}$	0.170 (0.000)	0.173 (0.000)	0.068 (0.000)	0.156 (0.000)
$\hat{\beta}$	-0.01239 (0.000)	-0.01323 (0.000)	-0.00669 (0.000)	-0.01491 (0.000)
conv. speed	1.37% (0.000)	1.47% (0.000)	0.7% (0.000)	1.69 (0.000)
half life	56	52	104	47
$\hat{\lambda}$	-	0.868 (0.000)	-	-
$\hat{\rho}$	-	-	0.841 (0.000)	-
$\hat{\gamma}$	-	-	-	0.0041 (0.464)
Adj-R^2 or R^{2*}	0.253	0.29*	0.39*	0.249
LIK	406.72	430.43	428.03	407.00
AIC	-809.44	-856.87	-850.06	-807.99
BIC	-803.83	-851.26	-841.65	-799.58
$\hat{\sigma}^2$	$7.569.10^{-5}$	$4.542.10^{-5}$	$4.768.10^{-5}$	$7.600.10^{-5}$
Tests				
JB	2.429 (0.297)	-	-	3.603 (0.165)
BP or BP-S*	0.0156 (0.901)	1.498* (0.221)	1.695* (0.193)	11.170 (0.004)
Moran	9.408 (0.000)	-	-	9.175 (0.000)
LMERR	71.137 (0.000)	-	2.640 (0.104)	67.072 (0.000)
R- LMERR	17.636 (0.000)	-	-	3.545 (0.060)
LMLAG	54.050 (0.000)	0.446 (0.504)	-	68.913 (0.000)
R-LMLAG	0.549 (0.458)	-	-	5.386 (0.020)
LR-com-fac	-	0.2099 (0.650)	-	-
$\hat{\gamma} = -\hat{\lambda}\hat{\beta}$	-	0,0115 (0.849)	-	-

Table 6 : full-distance weight matrix

Note: The data are extracted from the EUROSTAT-REGIO databank: 122 regions (Denmark, Luxembourg and United Kingdom in NUTS1 level and Belgium, Spain, France, Germany, Italy, Netherlands and Portugal in NUTS2 level).

P-values are in parentheses. LIK is value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). JB is the Jarque-Bera (1980) estimated residuals Normality test. MORAN is the Moran's I test adapted to estimated residuals (Cliff and Ord (1981). LMLAG is the Lagrange multiplier test for spatially lagged endogenous variable, R-LMLAG is the robust version of this test and R-LMERR is the robust version of the Lagrange multiplier test for residual spatial autocorrelation (Anselin and Florax, 1995; Anselin et al., 1996). LR-com-fac is the likelihood ratio common factor test (Burridge, 1981). BP is the Breusch-Pagan (1979) test for heteroskedasticity and BP-S is the spatially adjusted version of this test.

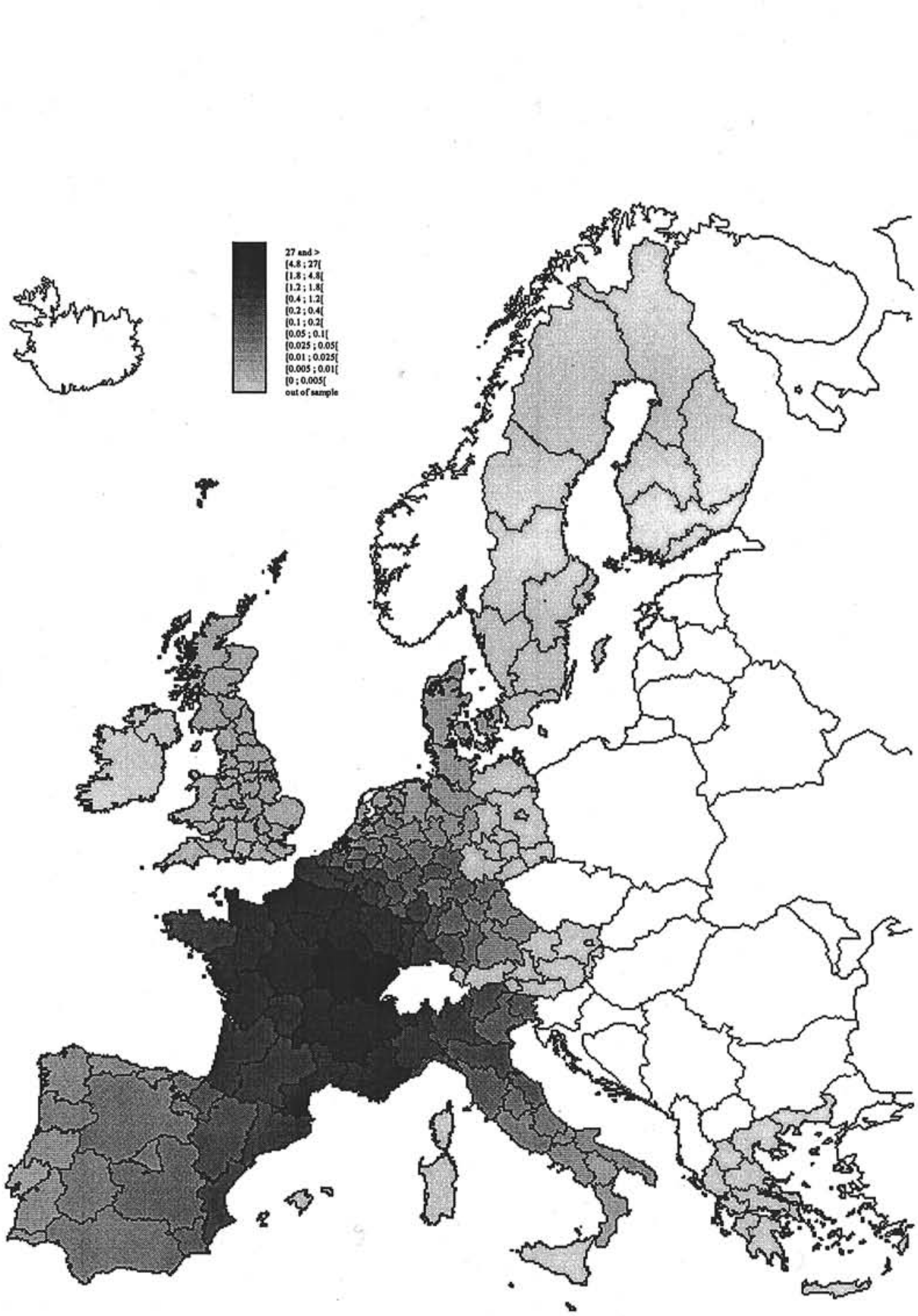

Figure 1

Percent variation of mean growth rates due to a shock in Burgundy 1980-1995
Diffusion in the spatial error model using a simple contiguity weight matrix
(median: 0.044%; mean: 0.66%)