

A Spatial Econometric Analysis of Geographic Spillovers and Growth for European Regions, 1980-1995

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January 2001

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* Previous versions of this paper were presented at the 6th RSAI World Congress 2000 “Regional Science in a Small World”, Lugano, Switzerland, May 16-20, 2000 and 40th ERSAs Congress “European Monetary Union and Regional Policy”, Barcelona, Spain, 29 August – 1 September, 2000. We would like to thank R. Florax for helpful comments. Any errors or omissions remain our responsibility.

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Abstract

The aim of this paper is to consider the geographical dimension of data in the estimation of the convergence of European regions and to emphasize geographic spillovers in regional economic growth phenomena. In a sample of 138 European regions over the 1980-1995 period, we show that the unconditional β -convergence model is misspecified due to spatially autocorrelated errors. Its estimation by Ordinary Least Squares leads to inefficient estimators and invalid statistical inference. Using spatial econometric methods and a distance based weight matrix we then estimate an alternative specification, which takes into account the spatial autocorrelation detected and leads to reliable statistical inference. Moreover this specification allows us to highlight a geographic spillover effect: the mean growth rate of a region is positively influenced by those of neighboring regions. We finally show by a simulation experiment that a random shock affecting a given region propagates to all the regions of the sample.

JEL Classification: C51, R11, R15

Introduction

New economic geography theories and growth theories have recently been integrated in order to show the way interactions between agglomeration and growth processes can lead to better explanations in regional growth studies (Baumont and Huriot, 1999). Two important results have to be highlighted. First these theories emphasize the role played by geographic spillovers in growth mechanisms. Second, most of the analysis point out the dominating growth-geographical patterns of Core-Periphery equilibrium and uneven development. Moreover, these results have two major implications for empirical studies on regional growth. On the one hand they mean that regional data can be spatially ordered since similar regions tend to cluster: econometric estimations based on geographical data (i.e. localized data) have to take into account the fact that economic phenomena may not be randomly spatially distributed on an economic integrated regional space, i.e. may be spatially autocorrelated. On the other hand, if we have good reasons to think that geographic spillovers could influence growth processes, it is worth estimating these impacts and the way the economic performance of each region interacts with each other.

The aim of this paper is to deal with these empirical issues in the analysis of **b**-convergence between European regions. More precisely, we want to show that new theoretical results about geographic spillovers and advances in spatial econometric methods can produce an alternative way of analyzing the **b**-convergence process.

From an econometric point of view, spatial dependence between observations leads to inefficient Ordinary Least Squares (OLS) estimators and unreliable statistical inference. It is then straightforward that models using geographical data should systematically be tested for spatial autocorrelation 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 (see for example Fingleton and McCombie, 1998; Rey and Montouri, 1999; Fingleton, 1999).

Moreover, we show that improved results can be obtained when spatial econometric tools are used in the estimation of regional growth process. First, we avoid bias in statistical inference due to spatial autocorrelation and obtain more reliable estimates of the convergence rate. Second, we estimate the magnitude of geographical spillover effects in regional growth processes and highlight the underlying spatial diffusion process. Third, we show that spatial dependence leads to a minimal but unavoidable specification of conditional **b**-convergence. What we mean here is that we won't try to

find the determinants of regional differentiation in steady states by including additional explanatory variables in a conditional \mathbf{b} -convergence model. We will consider instead that spatial dependence will absorb all these effects in the context of regional information scarcity and unreliability as suggested by Fingleton (1999).

The empirical study of \mathbf{b} -convergence for European regions we realize in this paper illustrates these three points. Using a sample of 138 European regions over the 1980-1995 period, we show that the unconditional \mathbf{b} -convergence model is misspecified due to spatially autocorrelated errors. We then estimate different specifications integrating these spatial effects explicitly using a distance-based weight matrix. Our results indicate that the most appropriate specification is the spatially autocorrelated error model and that the convergence process is somewhat stronger. 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, this specification implies a spatial diffusion process of random shocks that we evaluate by simulation.

In order to discuss theoretical and empirical results on interactions between agglomeration and regional growth processes we present some theoretical principles showing that economic phenomena 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 \mathbf{b} -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

New economic geography theories 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 (see Fujita, Thisse, 1997 and Fujita, Krugman and Venables, 1999 for more details). More precisely, three principles can be kept in mind.

First, driven by dominating agglomeration forces, industrial, high tertiary and R&D activities tend to concentrate in a few numbers of places in developed nations.

Second, 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.

Third, agglomeration processes are strongly cumulative because the agglomeration itself is a component of agglomeration forces. Even if the starting spatial distribution of economic activities is uniform (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 and Huriot, 1999). The emergence of these theories is based on the fact that several similar economic mechanisms are involved both in spatial and dynamic 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 agglomeration as a whole can be considered as a growth factor (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) 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, 1998). Since the regional integration

process is one of the most developed one in the European Union, these results are very important for our purpose. For example, the intensification of economic integration processes leads to lower transaction costs, higher labor migrations and the widening of market size; each of these factors contributes 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.

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 that 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; Martin and Ottaviano, 1996, 1999). 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.

All these theoretical results show that geographical patterns can be ordered by economic growth processes and that they can orient regional growth patterns. Geographic spillovers seem to play an important role in the interaction between geography and growth. 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 agglomeration processes 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 (Krugman, 1993) contained in the cumulative agglomeration process and the spatial ranges of geographic spillovers can now explain why rich and poor regions are or are not regularly distributed. The shadow effect means that 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 can easily observe such spatial orders in European Union regional area. Rich and attractive regions, i.e. with per capita GDP above the mean per capita GDP of European regions, 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.

2. A spatial econometric approach of **b**-convergence

The convergence hypothesis based on the neo-classical growth theories (Solow, 1956; Swan, 1956) implies that a "poor" region tends to grow more quickly than a "rich" region, so that the "poor" region catches up in the long run the level of per capita income or production of the "rich" region.

This hypothesis corresponds to the concept of **b**-convergence (Barro and Sala-I-Martin, 1991, 1992, 1995). **b**-convergence may be absolute (unconditional) or conditional. It is absolute when it is independent of the initial conditions. It is conditional when, moreover, the regions are supposed to be identical in terms of preferences, technologies and economic policies. If we assume spatial dependence between regions, then the relative location of a region can affect its economic performances. In that case, **b**-convergence is conditional to regions with similar geographical surroundings. Moreover, if we want to test the **b**-convergence hypothesis, we must first test for

spatial dependence between regions because OLS produces inefficient estimators and unreliable statistical inference when spatial autocorrelation is present.

2.1. **b**-convergence concepts

The hypothesis of unconditional β -convergence is usually tested on the following cross-sectional model:

$$\frac{1}{T} \ln \left(\frac{y_{i,T}}{y_{i,0}} \right) = \mathbf{a} + \mathbf{b} \ln(y_{i,0}) + \mathbf{e}_i \quad \mathbf{e}_i \sim i.i.d(0, \mathbf{S}_e^2) \quad (1)$$

where $y_{i,t}$ is the per capita GDP of the region i ($i = 1, \dots, N$) at the date t , T is the length of the period, \mathbf{a} and \mathbf{b} are unknown parameters to be estimated and \mathbf{e}_i an error term.

There is \mathbf{b} -convergence when \mathbf{b} 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 \mathbf{b} makes it possible to compute the speed of convergence: $\mathbf{q} = -\ln(1 + T\mathbf{b})/T$. The time necessary for the regions to fill half of the variation, which separates them from the stationary state, is called the half-life: $\mathbf{t} = -\ln(2)/\ln(1 + \mathbf{b})$.

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

$$\frac{1}{T} \ln \left(\frac{y_{i,T}}{y_{i,0}} \right) = \mathbf{a} + \mathbf{b} \ln(y_{i,0}) + \mathbf{g} X_i' + \mathbf{e}_i \quad \mathbf{e}_i \sim i.i.d(0, \mathbf{S}_e^2) \quad (2)$$

X_i is a vector of variables, maintaining constant the stationary-state of region i , including some state variables, like the stock of physical or 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). We can note that another way of testing the assumption of conditional convergence is still based on the equation (1), which is estimated on subsamples of regions for which the assumption of similar stationary-states seems acceptable and which leads to the construction of convergence clubs (see for example Baumol, 1986; Jean-Pierre, 1999).

Two effects on economic growth are estimated in the conditional \mathbf{b} -convergence model. The first one is an expected negative effect of the initial per capita GDP through the estimated value of \mathbf{b} 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 growth process than in equation (1). 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/or 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 OLS and associated statistical inference (Quah, 1993; Evans, 1996).

Let us finally underline that in the \mathbf{b} -convergence tests presented, 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 may be very restrictive and should be tested since if it is rejected the statistical inference provided by OLS 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 is defined as the coincidence of value similarity and locational similarity (Anselin, 2000). 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.

Spatial dependence means that observations are geographically correlated due to some processes, which connect different areas: for example diffusion or trade processes, transfers or other social and economic interactions. Several economic factors, like labor force mobility, capital mobility, technology and knowledge diffusion, transportation or transaction costs may be particularly important because they directly affect regional interactions. However, the problem we want to stress in this paper is that these various processes induce a particular organization of economic activity in space whatever the underlying explanatory variables. Hence, we focus on the spatial dependence induced by these processes given a purely spatial pattern exogenously introduced in the weight matrix defined below. Therefore we will not try to include these economic factors in this weight matrix nor as explanatory variables in the model. We will consider that spatial dependence will catch

these effects altogether in the context of regional information scarcity and unreliability as Fingleton (1999) suggested it.

The spatial weight matrix

The weight matrix W of dimension $(n \times n)$ contains the exogenous information about the relative spatial connections 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 $w_{ij}^* = w_{ij} / \sum_j w_{ij}$. For a variable x , this transformation means that the expression Wx , defined as a spatial lag variable, 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 miles and those sharing a border of 100 miles. However, the contiguity indicator can imply a block-diagonal pattern for the weight matrix if some regions don't share a common border with any other region in the sample considered (it is indeed the case of Great-Britain and Greece). Therefore it doesn't seem to be really appropriate for an exhaustive sample of European regions.

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, distance by roads etc.) and depending on the functional form we choose (the inverse of the distance: $w_{ij} = 1/d_{ij}$ or the inverse of the squared distance: $w_{ij} = 1/d_{ij}^2$...). We can also define a distance-cutoff above which $w_{ij} = 0$ assuming that above that distance-cutoff the interactions are negligible.

Defined this way, we exclude from this matrix all economic factors that could explain these spatial connections and we focus on the pure spatial pattern. Moreover, we think that this is the only way that we can consider this matrix as really exogenous.

Econometric models

Three kinds of econometric models can be used to deal with spatial dependence of observations (Anselin, 1988a; Anselin and Bera, 1995): the spatial autoregressive model, the spatial cross-regressive model and the spatial error model. Let us examine now the way they can be applied to the **b**-convergence model.

The spatial autoregressive model

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

$$(1/T)\ln(z) = \mathbf{a}S + \mathbf{b} \ln(y_0) + \mathbf{r}W[(1/T)\ln(z)] + u \quad u \sim N(0, \mathbf{S}^2 I) \quad (3)$$

where z is the $(n \times 1)$ vector of the dependent variable in the unconditional **b**-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 u the $(n \times 1)$ vector of normal i.i.d. error terms; S is the sum vector; \mathbf{a} , \mathbf{b} and \mathbf{r} are the unknown parameters to be estimated. \mathbf{r} is the spatial autoregressive parameter indicating the extent of interaction between the observations according to the spatial pattern exogenously introduced in the standardized weight matrix. 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 $(1/T)\ln(z)$, the corresponding line of the spatial lag vector contains the spatially weighted average of the growth rates of the neighboring regions.

Estimation of this model by OLS produces inconsistent estimators due to the presence of a stochastic regressor Wy , which is always correlated with u , even if the residuals are identically and independently distributed (Anselin, 1988a, chap 6). Hence it has to be estimated by the Maximum Likelihood Method (ML) or the Instrumental Variables Method (IV).

This specification can be interpreted in two ways. From the convergence perspective, it yields some information on the nature of convergence through the **b** parameter once spatial effects are controlled for. From the economic geography perspective, it may help to highlight a spatial spillover effect since it indicates how the growth rate of per capita GDP in a region is affected by

those of neighboring regions through the \mathbf{r} parameter after conditioning on the initial per capita GDP levels.

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

$$(I - \mathbf{r}W)[(1/T)\ln(z)] = \mathbf{a}S + \mathbf{b} \ln(y_0) + u \quad (4)$$

$$[(1/T)\ln(z)] = \mathbf{a}(I - \mathbf{r}W)^{-1}S + \mathbf{b}(I - \mathbf{r}W)^{-1} \ln(y_0) + (I - \mathbf{r}W)^{-1}u \quad (5)$$

This expression indicates that, on average, the growth rate of a given region is not only affected by its own per capita GDP initial level but also by those of all other regions through the inverse spatial transformation $(I - \mathbf{r}W)^{-1}$. However, this 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 \mathbf{b} -convergence concept. For the least, we think that this specification should be interpreted carefully in terms of convergence processes. 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 same inverse spatial transformation.

The spatial cross-regressive model

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

$$(1/T)\ln(z) = \mathbf{a}S + \mathbf{b} \ln(y_0) + WZ\mathbf{g} + u \quad u \sim N(0, \mathbf{s}^2 I) \quad (6)$$

Here, the influence of h spatially lagged exogenous variables contained in the $(n \times h)$ matrix Z is reflected by the parameter vector \mathbf{g} . 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 $\ln(y_0)$. This model can be estimated by OLS.

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

$$(1/T)\ln(z) = \mathbf{a}S + \mathbf{b} \ln(y_0) + \mathbf{g}W \ln(y_0) + u \quad u \sim N(0, \mathbf{s}^2 I) \quad (7)$$

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

conditional \mathbf{b} -convergence model. It gives estimates of both a direct effect and a spatially lagged effect of initial per capita GDP levels on the growth rates.

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:

$$(1/T)\ln(z) = \mathbf{a}S + \mathbf{b} \ln(y_0) + \mathbf{e} \quad \mathbf{e} = \mathbf{I}W\mathbf{e} + u \quad u \sim N(0, \mathbf{s}^2 I) \quad (8)$$

where \mathbf{I} is the scalar parameter expressing the intensity of spatial correlation between regression residuals. Use of OLS in the presence of non-spherical errors yields 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 (GMM).

This model has two interesting properties.

The first one refers to the spatial diffusion effect of random shocks we've highlighted in equation (5) as it appears here by noting that since: $\mathbf{e} = \mathbf{I}W\mathbf{e} + u$, then $\mathbf{e} = (\mathbf{I} - \mathbf{I}W)^{-1}u$ and the model (8) can be rewritten as following:

$$(1/T)\ln(z) = \mathbf{a}S + \mathbf{b} \ln(y_0) + (\mathbf{I} - \mathbf{I}W)^{-1}u \quad (9)$$

Second, this model can be rewritten in another form, which can be interpreted like a minimal model of conditional \mathbf{b} -convergence integrating two spatial environment variables. Indeed, let us note that premultiplying equation (8) by $(\mathbf{I} - \mathbf{I}W)$ we get:

$$(\mathbf{I} - \mathbf{I}W)(1/T)\ln(z) = \mathbf{a}(\mathbf{I} - \mathbf{I}W)S + \mathbf{b}(\mathbf{I} - \mathbf{I}W)\ln(y_0) + u \quad (10)$$

then:

$$(1/T)\ln(z) - \mathbf{I}W[(1/T)\ln(z)] = \mathbf{a}(\mathbf{I} - \mathbf{I}W)S + \mathbf{b} \ln(y_0) - \mathbf{I}W\mathbf{b} \ln(y_0) + u \quad (11)$$

$$(1/T)\ln(z) = \mathbf{a}(\mathbf{I} - \mathbf{I}W)S + \mathbf{b} \ln(y_0) + \mathbf{I}W[(1/T)\ln(z)] + \mathbf{g}W \ln(y_0) + u \quad (12)$$

$$\text{with the restriction } \mathbf{g} = -\mathbf{I}W\mathbf{b} \quad (13)$$

This model (12) is the so-called spatial Durbin model and can be estimated by ML. The restriction (13) can be tested by the common factor test (Burrige, 1981). If the restriction $\mathbf{g} + \mathbf{I}W\mathbf{b} = 0$ cannot be rejected then model (12) reduces to model (8).

It should be stressed that model (12) encompasses model (3) and (7) 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. The application of decision rules based on different spatial autocorrelation tests helps us to choose the best specification we have to estimate among all available spatial regressions.

Spatial autocorrelation tests

Three spatial autocorrelation tests can be carried out on the absolute \mathbf{b} -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, 1988b) 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 RLMLAG and RLMERR 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. If LMLAG is more significant than LMERR and RLMLAG is significant but RLMERR is not, then the appropriate model is the spatial autoregressive model. Conversely, if LMERR is more significant than LMLAG and RLMERR is significant but RLMLAG is not, then the appropriate specification is the spatial error model.

3. Estimation results stressing spatial spillover effects

Using Exploratory Spatial Data Analysis and Local Indicators of Spatial Association (Anselin, 1995), we have shown in previous work (Le Gallo and Ertur, 2000) that a strong positive

spatial autocorrelation characterizes both per capita GDP levels and growth rates for different samples of European Union regions for the 1980-1995 period.

We use spatial econometrics techniques briefly described above to detect and to treat spatial autocorrelation in the model of absolute **b**-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 138 regions (Denmark, Luxembourg and United Kingdom in NUTS1 level and Belgium, France, Germany, Greece, Italy, Netherlands Portugal and Spain in NUTS2 level).

We first estimate the model of absolute **b**-convergence by OLS and carry out various tests aiming at detecting the presence of spatial dependence using a spatial weight matrix specified below. We then consider the specifications integrating these spatial effects explicitly.

The spatial weight matrix

We choose the great circle distance between regional centroids to compute the spatial weight matrix and we define a cutoff using the residual correlogram. The general form of the distance weight matrix we use is defined as following:

$$\begin{cases} w_{ij} = 0 \text{ if } i = j \\ w_{ij} = 1/d_{ij}^2 \text{ if } d_{ij} \leq D(k) \\ w_{ij} = 0 \text{ if } d_{ij} > D(k) \end{cases} \quad k = 1, \dots, 4 \quad (14)$$

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

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 (321 miles), the median (592 miles), the upper quartile (933 miles) and the maximum (2093 miles) 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 be based on a residual correlogram with ranges defined by minimum, lower quartile, median, upper quartile and maximum great circle distances (see Table 1).

[Table 1 about here]

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 leads to Q1: we retain a cutoff of 321 miles for the distance based weight matrix.

Econometric results

Let us take as a starting point the following model of absolute \mathbf{b} -convergence:

$$(1/T)\ln(z) = S\mathbf{a} + \mathbf{b}\ln(y_{1980}) + \mathbf{e} \quad \mathbf{e} \sim N(0, \mathbf{S}_e^2 I) \quad (15)$$

where $(1/T)\ln(z)$ is the vector of dimension $n = 138$ 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, \mathbf{a} and \mathbf{b} are the unknown parameters to be estimated, S is the unit vector and \mathbf{e} is the vector of errors with the usual properties. All estimations were carried out using SpaceStat 1.90 software (Anselin, 1999).

The results of the estimation by OLS of this model are given in Table 2. The coefficient associated with the initial per capita GDP is significant and negative, $\hat{\mathbf{b}} = -0,0079$, which confirms the hypothesis of convergence for the European regions. The speed of convergence associated with this estimation is 0.84% and the half-life is 88 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). It is worth mentioning that the Jarque-Bera test (1987) doesn't reject Normality (p-value of 0.011): the reliability of all subsequent testing procedures and the use of Maximum Likelihood estimation method are then strengthened. We note however that the White test rejects homoskedasticity and that the Breusch-Pagan test (1979) rejects it vs. $\ln(y_{1980})$. Nevertheless further consideration of spatial heterogeneity per se is beyond the scope of this paper. We only take into account spatial dependence and consider, as a first approximation, that the heteroskedasticity found is implied by spatial autocorrelation (Anselin, 1988a, Anselin and Griffith, 1988).

Three tests of spatial autocorrelation are then carried out: Moran's I test adapted to 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 the Lagrange Multiplier tests: respectively LMERR and LMLAG and their robust versions. Applying the decision rule suggested by Anselin and Florax (1995) these tests indicate the presence of spatial autocorrelation rather than a spatial lag variable: the spatial error model appears to be the appropriate specification.

[Table 2 about here]

Therefore the absolute \mathbf{b} -convergence model 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 previous studies at the regional level. Statistical inference based on OLS estimators is not reliable. The model of absolute \mathbf{b} -convergence must thus be modified to integrate this form of spatial dependence explicitly.

The estimation results by ML for the spatial error model are given in Table 2. The coefficients are all strongly significant. $\hat{\mathbf{b}}$ is higher than in the absolute \mathbf{b} -convergence model estimated by OLS and a positive spatial autocorrelation of the errors $\hat{\mathbf{I}} = 0,783$ 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 no more significant at the 5% significance level, indicating absence of heteroskedasticity vs. $\ln(y_{1980})$. Therefore heteroskedasticity found in the absolute \mathbf{b} -convergence estimated by OLS can be interpreted as entirely due to spatial autocorrelation and is no more a problem. The common factor test indicates that the restriction $\mathbf{g} + \mathbf{I}\mathbf{b} = 0$ cannot be rejected so the spatial error model can be rewritten as the constrained spatial Durbin model:

$$(1/T)\ln(z) = \mathbf{a}(I - \mathbf{I}W)S + \mathbf{b} \ln(y_{1980}) + \mathbf{I}W[(1/T)\ln(z)] + \mathbf{g}W \ln(y_{1980}) + u \quad (16)$$

with $\mathbf{g} = -\mathbf{I}\mathbf{b}$, but this coefficient is not significant at the 5% significance level. According to information criteria this model seems to perform better than the preceding one (Akaike, 1974; Schwarz, 1978). Moreover estimation of this model by iterated GMM (Kelejian and Prucha, 1999) leads exactly to the same results on the convergence parameter \mathbf{b} . It is worth mentioning that all of our results are quite robust to the choice of the spatial weight matrix (results for Q2, Q3 and full distance based matrices are available from the authors).

To check for the decision rule applied, we also estimate the spatial autoregressive model including the endogenous lag variable and the special case of the spatial cross-regressive model with

only the spatially lagged initial per capita GDP level. The estimation results are given in Table 2. In the spatial autoregressive model, we note that the convergence process appears to be even weaker and that a spatial spillover effect is still found: the growth rate of per capita GDP in a given region is influenced by those of neighboring regions. However the spatially adjusted Breusch-Pagan test is significant indicating heteroskedasticity and this model does not perform better than the previous one in terms of information criteria. Finally, estimation of the spatial cross-regressive model shows that there's no spatial spillover effect associated with the exogenous lg variable. Moreover, there are some problems with normality, heteroskedasticity and spatial dependence tests, which still indicate the presence of spatial error autocorrelation. This latter model seems therefore to be strongly misspecified and is also the worst in terms of information criteria. Indeed, the spatial error model appears as the most appropriate specification as the decision rule suggested by Anselin and Florax (1995) showed us previously.

Economic implications of the spatial error model

This model has three economic implications:

First, from the convergence perspective, the speed of convergence in the model with spatial autocorrelation is 1.23 % and is thus bigger than that of the initial model; the half-life reduces to 62 years once the spatial effects are controlled for. The convergence process appears then to be a little stronger but it remains actually weak. This first implication may seem qualitatively negligible, but we must underline that this is the only proper way of estimating a **b**-convergence model once spatially autocorrelated errors are detected and the only proper way of drawing reliable statistical inference.

Second, from the New Economic Geography perspective, this model highlights a spatial spillover effect, when reformulated as the constrained spatial Durbin model, in that the mean growth rate of a region i is positively influenced by the mean growth rate of neighboring regions, through the endogenous spatial lag variable $W[(1/T)\ln(z)]$. But it doesn't seem to be influenced by the initial per capita GDP of neighboring 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 higher will be its growth rate. In other words, the geographical environment has an influence on growth processes. This corroborates the theoretical results highlighted by the New Economic Geography.

The third implication is even more attractive. 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, set equal to two times the residual standard-error of the estimated spatial error model, affecting Ile de France. This shock has the largest relative impact on Ile de France where the estimated mean growth rate is 22.2% 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. The magnitude of the impact of this shock is between 1.6% and 3.7% for the regions neighboring Ile de France 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.

[Figure 1 about here]

Conclusion

In this paper, we analyze the consequences of spatial dependence on regional growth and convergence processes. Indeed spatial error autocorrelation is detected in the unconditional \mathbf{b} -convergence model estimated for a sample of 138 European regions over the 1980-1995 period leading to inefficient OLS estimators and unreliable statistical inference. Therefore, we have to find the most appropriate specification taking into account the spatial autocorrelation detected and estimate it with the appropriate econometric method. Among all the specifications integrating spatial autocorrelation, the spatial error model is the best one according to the decision rule suggested by Anselin and Florax (1995) and to information criteria. We interpret this specification as the minimal conditional \mathbf{b} -convergence model in the sense that it captures the effects of all other variables that could explain differentiated steady states along the lines of Fingleton (1999). This specification reveals that the convergence process is somewhat stronger. Moreover, it 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. The spatial diffusion process implied by this model is also highlighted by a simulation experiment. Let us finally note that spatial heterogeneity, which may be present in the sample and that we discarded here to focus on spatial autocorrelation will be the object of further research.

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Data Appendix

The data are extracted from the EUROSTAT-REGIO databank:

series E2GDP measured in Ecu_hab units

Our sample includes 138 regions: Denmark, Luxembourg and United Kingdom in NUTS1 level and Belgium, France, Germany, Greece, Italy, Netherlands Portugal and Spain in NUTS2 level.

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

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

All computations are carried out using SpaceStat 1.90 software by Anselin (1999).

Range (Km)	[Min;Q1[[8; 321[[Q1;Me[[321;592[[Me;Q3[[592;933[[Q3;Max[[933;2093[
Moran's I	15.54	-3.07	-13.52	11.26
p-value	0.000	0.002	0.000	0.000
LMERR	157.50	8.94	108.58	33.05
p-value	0.000	0.002	0.000	0.000
R-LMERR	47.86	0.58	43.80	0.14
p-value	0.000	0.447	0.000	0.708

Table 1: Residual Correlogram

Note Table 1: Q1, Me, Q3 and Max are respectively the lower quartile (321 miles), the median (592 miles), the upper quartile (933 miles) and the maximum (2093 miles) of the great circle distance distribution between centroids of each region. For each range, we estimate the absolute *b*-convergence model and we perform the Moran's *I* test, the Lagrange multiplier test and its robust version for residual spatial autocorrelation based on the contiguity matrix computed for that range.

Model	b -convergence	Spatial error	Spatial lag-dep	Spatial lag-ex
	(I)	(II)	(III)	(IV)
Estimation	OLS-White	ML	ML	OLS-White
\hat{a}	0.129 (0.000)	0.158 (0.000)	0.053 (0.001)	0.123 (0.000)
\hat{b}	-0.0079 (0.000)	-0.0112 (0.000)	-0.0044 (0.005)	-0.0109 (0.006)
conv. speed	0.84% (0.000)	1.23% (0.000)	0.46% (0.002)	1.19% (0.021)
half-life	88	62	157	64
\hat{I}	-	0.783 (0.000)	-	-
\hat{r}	-	-	0.769 (0.000)	-
\hat{g}	-	-	-	-0.0037 (0.437)
R^2 or Sq.- Corr.*	0.13	0.13*	0.54*	0.14
LIK	456.14	494.32	491.78	456.44
AIC	-908.27	-984.65	-977.57	-906.90
BIC	-902.42	-978.80	-968.79	-898.11
\hat{S}^2	$7.996.10^{-5}$	$4.088.10^{-5}$	$4.263.10^{-5}$	$8.019.10^{-5}$
Tests				
JB	8.976 (0.011)	-	-	9.821 (0.007)
BP or BP-S* or KB** vs. $\ln(y_{1980})$	14.786 (0.000)	3.324* (0.068)	6.972* (0.008)	8.849** (0.003)
White	29.903 (0.000)	-	-	37.41 (0.000)
Moran's I (error)	13.425 (0.000)	-	-	13.310 (0.000)
LMERR	151.683 (0.000)	-	-	149.247 (0.000)
R-LMERR	18.102 (0.000)	-	-	1.448 (0.228)
LMERR*	-	-	2.198 (0.138)	-
LMLAG	134.199 (0.000)	-	-	150.828 (0.000)
R-LMLAG	0.618 (0.432)	-	-	3.029 (0.0818)
LMLAG*	-	0.705 (0.401)	-	-
LR-com-fac	-	0.151 (0.697)	-	-
$\hat{g} = -\hat{I}\hat{b}$	-	0.01 (0.869)	-	-

Table 2 : Q1 distance based weight matrix

Note Table 2: The data are extracted from the EUROSTAT-REGIO databank: 138 regions (Denmark, Luxembourg and United Kingdom in NUTS1 level and Belgium, France, Germany, Greece Italy, Netherlands, Portugal and Spain in NUTS2 level).

P-values are in parentheses. OLS-White indicates the use of the heteroskedasticity consistent covariance matrix estimator of White (1980) in the OLS estimation. 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). LMERR is the Lagrange multiplier test for residual spatial autocorrelation and R-LMERR is its robust version. LMLAG is the Lagrange multiplier test for spatially lagged endogenous variable and R-LMLAG is its robust version (Anselin and Florax, 1995; Anselin et al., 1996). LMERR* is the Lagrange multiplier test for an additional residual spatial autocorrelation in the spatial autoregressive model; LMLAG* is the Lagrange multiplier test for an additional spatially lagged endogenous variable in the spatial error model (Anselin 1988a). LR-com-fac is the likelihood ratio common factor test (Burrige, 1981). BP is the Breusch-Pagan (1979) test for heteroskedasticity, BP-S is the spatially adjusted version of this test (Anselin, 1988a, 1988b) and KB is the Koenker-Bassett (1982) test for heteroskedasticity in presence of non-normality.

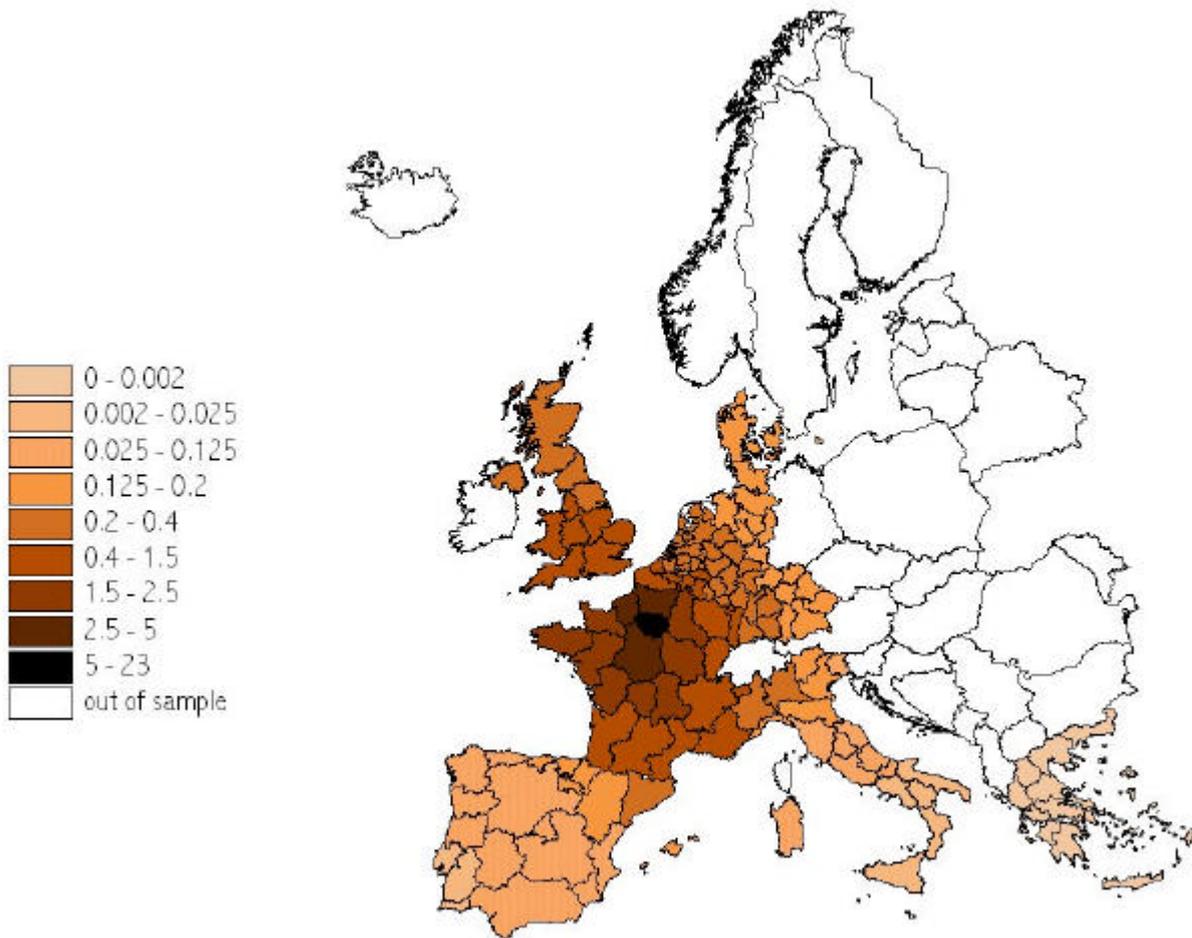


Figure 1
Diffusion in the spatial error model using the Q1-distance weight matrix
Percent variation of mean growth rates due to a shock in Ile de France 1980-1995
(median: 0.233%; mean: 0.572%)