INTERNATIONAL REGIONAL SCIENCE REVIEW 29, 1: 3–34 (January 2006)

THE EUROPEAN REGIONAL CONVERGENCE PROCESS, 1980-1995: DO SPATIAL REGIMES AND SPATIAL DEPENDENCE MATTER?

CEM ERTUR
University of Burgundy, Pôle d'Economie et de Gestion, Dijon, France, cem.ertur@u-bourgogne.fr

JULIE LE GALLO
IERSO (IFReDE-GRES), Université Montesquieu-Bordeaux IV, Pessac, France, legallo@u-bordeaux4.fr

CATHERINE BAUMONT
University of Burgundy, Pôle d'Economie et de Gestion, Dijon, France, catherine.baumont@u-bourgogne.fr

The authors show that spatial dependence and spatial heterogeneity matter in the estimation of the β-convergence process among 138 European regions over the 1980 to 1995 period. Using spatial econometrics tools, the authors detect both spatial dependence and spatial heterogeneity in the form of structural instability across spatial convergence clubs. The estimation of the appropriate spatial regimes spatial error model shows that the convergence process is different across regimes. The authors also estimate a strongly significant spatial spillover effect: the average growth rate of per capita GDP of a given region is positively affected by the average growth rate of neighboring regions.

Keywords: *β-convergence; spatial econometrics; spatial dependence; spatial regimes; geographic spillovers*

The convergence of European regions has been largely discussed in the macroeconomic and regional science literature during the past decade. Two observations are often emphasized. First, the convergence rate among European regions appears to be very slow in the extensive samples considered (Barro and Sala-i-Martin 1991,

---

Previous versions of this article were presented at the 40th European Regional Science Association Congress, Barcelona, August 29 to September 1, 2000; at the 56th Econometric Society European Meeting, Lausanne, August 25-29, 2001; at the 48th North American Meetings of the Regional Science Association International (RSAI), Charleston, South Carolina, November 15-17, 2001; at the Regional Science Seminar Series, Regional Science Applications Laboratory, University of Illinois at Urbana-

DOI: 10.1177/0160017605279453

1995; Sala-i-Martin 1996a, 1996b; Armstrong 1995b; Neven and Gouyette 1995). Moreover, regional income or GDP disparities seem to be persistent despite the European economic integration process and higher growth rates of some poorer regions as highlighted in the European Commission reports (1996, 1999). These observations may indicate the existence of different groupings of regions as found in cross-country studies using international data sets (Baumol 1986; Durlauf and Johnson 1995; Quah 1996a, 1997).

Second, the geographical distribution of European economic disparities, studied by López-Bazo et al. (1999) and Le Gallo and Ertur (2003), shows a permanent polarization pattern between rich regions in the North and poor regions in the South. This evidence can be linked to several results of new economic geography theories (Krugman 1991; Fujita, Krugman, and Venables 1999), which show that locations of economic activities are spatially structured by some agglomerative and cumulative processes. As a result, we can say that the geographical distribution of areas characterized by high or low economic activities is spatially dependent and tends to exhibit persistence. Moreover, the economic surrounding of a region seems to influence the economic development perspectives for this region: a poor (respectively rich) region surrounded by poor (respectively rich) regions will stay in this state of economic development, whereas a poor region surrounded by richer regions has more probability of reaching a higher state of economic development. These results are highlighted for European regions by Le Gallo (2004), who analyzed the transitional dynamics of per capita GDP over the period 1980 to 1995 by means of spatial Markov chains approach: the cluster of the poorest European regions in Southern Europe creates a great disadvantage for these regions and emphasizes a poverty trap.

All these observations lead us to analyze the convergence and growth processes among European regions over the 1980 to 1995 period in both a more disaggregated and comprehensive way. Indeed, both economic and geographic disparities embodied in the European regional polarization pattern should be taken into account. Actually, the purpose of this article is to integrate the spatial dimension of data in the estimation of the β-convergence model for European regions and to emphasize generally neglected spatial effects in regional growth phenomena in the context of European economic integration.

Following Anselin (1988b), spatial effects refer to both spatial autocorrelation and spatial heterogeneity. On one hand, we emphasize the link between the detec-

Champaign, November 14, 2001; at the Spatial Econometrics Workshop, Gremaq, Toulouse 1, June 14, 2002; and at the Spatial Inequality and Development Conference, Cornell/LSE/WIDER, London, June 28-30, 2002. We would like to thank L. Anselin, R. J. G. M. Florax, R. Haining, A. Heston, P. Krugman, J. LeSage, A. Venables, and Q. Xie for their valuable comments as well as all the participants/discussants at these meetings. We also thank two anonymous referees and the editor for their helpful suggestions. Finally, we would also like to thank Eurostat: G. Decand and A. Behrens from the regional statistics section (division E4) as well as J. Recktenwald and I. Dennis for the help they provided on the Eurostat-Regio database. The usual disclaimer applies.

tion of a positive spatial autocorrelation of regional GDPs and the regional polarization of the economies in Europe. Moreover, we show that modeling spatial autocorrelation in the β-convergence model allows estimating geographic spillover effects. On the other hand, spatial heterogeneity means that parameters are not stable over space. Such a spatial heterogeneity probably characterizes patterns of economic development under the form of spatial regimes and/or groupwise heteroskedasticity: a cluster of rich regions (the core) being distinguished from a cluster of poor regions (the periphery).

From an econometric point of view, it is well known that the presence of spatial dependence and/or spatial heterogeneity leads at best to unreliable statistical inference based on ordinary least squares (OLS) estimations. Concerning the spatial dependence issue, we use the appropriate spatial econometric tools to test for its presence in the standard unconditional β-convergence model and to estimate the appropriate spatial specification. Concerning the spatial heterogeneity problem, we determine spatial regimes, which are interpreted as spatial convergence clubs, using exploratory spatial data analysis (ESDA) to capture the North-South polarization pattern observed in European regions. Taking into account both of these effects, we show two results. First, the convergence process is different across regimes. Actually there is not such a convergence process for northern regions, whereas it is weak for southern regions. Second, a significant geographic spillover effect appears in the growth process in that the average growth rate for a given region is positively influenced by the average growth rates of neighboring regions.

In the following section, the convergence concepts used in this article are presented: β-convergence, club convergence, and spatial effects are defined more precisely. In the second section, the data and the weight matrix are presented. Finally, in the third section, we explain our empirical methodology and the econometric results are presented. In the first step, we define convergence clubs using ESDA. In the second step, we show that the global and aspatial unconditional β-convergence model is misspecified and that a spatial regimes model with spatially autocorrelated errors is more appropriate. In this model, a random shock affecting a given region propagates to all the region of the sample. Two simulation experiments, based on a southern region and on a northern region, illustrate this effect on the average growth rate of all the regions of our sample.

Convergence Concepts and Spatial Effects

Since the rather informal contribution of Baumol (1986) and the more formal contributions of Barro and Sala-i-Martin (1991, 1992, 1995) and Mankiw, Romer, and Weil (1992) among others, the controversial convergence issue has been extensively debated in the macroeconomic growth and regional science literature and heavily criticized on both theoretical and methodological grounds. The convergence hypothesis has been improved and made more precise and formal since Baumol's (1986) pioneering paper leading to β-convergence or σ-convergence concepts. Alternative concepts such as club convergence (Durlauf and Johnson 1995; Quah 1993a, 1993b, 1996a, 1996c), or stochastic convergence (Bernard and Durlauf 1995, 1996; Evans and Karras 1996) have also been developed. In relation to the convergence concepts used, econometric problems, such as heterogeneity, omitted variables, model uncertainty, outliers, endogeneity, and measurement errors are often raised; and alternative techniques like panel data (Islam 1995; Caselli, Esquivel, and Lefort 1996), time series (Bernard and Durlauf 1995, 1996; Carlino and Mills 1993, 1996a, 1996b; Evans and Karras 1996), and probability transition matrices (Quah, 1993a, 1996a, 1996c) are proposed. We will not attempt here to discuss this huge literature; Durlauf and Quah (1999), Mankiw (1995), and Temple (1999) present outstanding surveys of this debate.

Spatial effects have received less attention in the literature, although major econometric problems are likely to be encountered if they are present in the standard β-convergence framework, since statistical inference based on OLS will then be flawed. The first study we are aware of that takes up the issue of location and growth explicitly is DeLong and Summers (1991, 456 and appendix 1, 487-90). However, they were disappointed not to find evidence of spatial correlation in their sample.[1] Since then, the appropriate econometric treatment of these spatial effects is often neglected in the macroeconomic literature; at best it is handled by the straightforward use of regional dummies or border dummy variables (Chua 1993; Ades and Chua 1997; Barro and Sala-i-Martin 1995; Easterly and Levine 1998). Mankiw (1995, 304-5) also pointed out that multiple regression in the standard framework treats each country as if it were an independent observation. Temple (1999, 130-31), in his survey on the new growth evidence, also drew attention on the error correlation and regional spillovers, though he interpreted these effects as mainly reflecting an omitted variable problem.

It is therefore at least surprising that these effects, although acknowledged, are not studied more fully in the macroeconomic literature even though appropriate statistical techniques and econometric models used for analyzing such spatial processes have been developed in the regional science literature (Anselin 1988b, 2001b; Anselin and Bera 1998). Note that a reason for that may also be that the sample sizes usually used for international data sets are quite small. Spatial statistics and econometrics provide relevant tools to identify both “well-defined” spatial dependence and heterogeneity forms involved in the regional growth process. Nevertheless, just a few recent studies mainly focusing on spatial dependence apply the appropriate spatial econometric tools as Conley and Ligon (2002) and Moreno and Trehan (1997) using international data sets, Rey and Montouri (1999) using U.S. data, and Fingleton (1999) using European regional data.

β-*Convergence Models*

The prediction of the neoclassical growth model (Solow 1956) is that the growth rate of an economy is positively related to the distance that separates it from its own steady state if it is currently below its steady state. This is the concept known as *conditional* β-convergence. If economies have different steady states, this concept is compatible with a persistent high degree of inequality among economies.

The hypothesis of conditional β-convergence is usually tested on the following cross-sectional model, in matrix form:

$$g_T = \alpha e_N + \beta y_0 + X\phi + \varepsilon \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I), \tag{1}$$

where g_T is the $(n \times 1)$ vector of average growth rates of per capita GDP between dates 0 and T; y_0 is the vector of log per capita GDP levels at date 0; X is a matrix of variables, maintaining constant the steady state of each economy, e_N is the unit vector, and ε is the vector of errors with the usual properties. There is conditional β-convergence if the estimate of β is significantly negative once X is held constant. The speed of convergence and the half-life can then be recovered using this estimate.[2] This is the approach widely used in cross-country analysis, with more or less ad hoc specifications to control for the determinants of the steady state as discussed by Levine and Renelt (1992) or with specifications formally derived from structural growth models following Mankiw, Romer, and Weil (1992).

If we assume that all the economies are structurally similar, characterized by the same steady state, and differ only by their initial conditions, we define the concept known as *unconditional* β-convergence: all the economies converge to the same steady state. It is only in that case that the prediction of the neoclassical growth model that poor economies grow faster than rich ones and eventually catch them up in the long run holds true. Indeed, with common steady states, initially poorer economies are farther away from their steady state.

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

$$g_T = \alpha e_N + \beta y_0 + X\phi + \varepsilon \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I). \tag{2}$$

There is unconditional β-convergence when β is significantly negative. This approach is advocated, for example, by Sala-i-Martin (1996a, 1996b) for within-country cross-regional analysis together with an increasing emphasis on the test of the σ-convergence concept, which relates to cross-sectional dispersion. There is σ-convergence if the dispersion—measured, for example, by the standard deviation of log per capita real GDP across a group of economies—tends to decrease over time. These two concepts are designed to capture conceptually different phenomena: β-convergence relates to the mobility of per capita GDP within the same distribution and σ-convergence relates to the evolution over time of the distribution of per capita GDP. Although closely related these two concepts are far from being identical.[3]

Club Convergence

These convergence concepts and tests have been forcefully criticized in the recent literature, both on theoretical and methodological grounds, and several econometric problems are often raised. More precisely, in regard with the heterogeneity problem, the concept of club convergence used for example by Durlauf and Johnson (1995) is appealing. This concept is consistent with economic polarization, persistent poverty, and clustering. In case of unconditional convergence, there is only one equilibrium level to which all economies approach. In case of conditional convergence, equilibrium differs by economy, and each economy approaches its own but unique, globally stable, steady state equilibrium. In contrast, the concept of club convergence is based on endogenous growth models that are characterized by the possibility of multiple, locally stable, steady state equilibria as in Azariadis and Drazen (1990). Which of these different equilibria an economy will be reaching depends on the range to which its initial conditions belong. In other words, economies converge to one another if their initial conditions are in the "basin of attraction" of the same steady state equilibrium. When convergence clubs exist, one convergence equation should be estimated per club, corresponding to different regimes. In such a framework, as noted by Durlauf and Johnson (1995), standard convergence tests can have some difficulties to discriminate between these multiple steady state models and the Solow (1956) model. Moreover, Bernard and Durlauf (1996) showed that a linear regression applied to data generated by economies converging to multiple steady states can produce a negative initial per capita GDP coefficient. The standard global β-convergence result appears then to be an artifact.

Durlauf and Johnson (1995), using the Summers and Heston (1988) data set over the 1960 to 1985 period and the Mankiw, Romer, and Weil (1992) framework, showed that convergence is indeed stronger within groups of countries once they arbitrarily split the whole sample based on the initial per capita GDP level and the adult literacy rate at the beginning of the period. Moreover, estimated parameter values associated to conditioning variables differ significantly across the groups. They endogenized then the splitting using the regression tree method and noted the geographic homogeneity within each group. However, they failed to find evidence of convergence among the high-output economies, that is to say, North American and European countries. This nonconvergence result for economies with similar high initial outputs is furthermore qualitatively similar to that obtained by DeLong (1988). They interpreted the overall parameter instability as indicative of countries belonging to different regimes.

Galor (1996) showed that multiplicity of steady state equilibria and thus club convergence is even consistent with standard neoclassical growth models that exhibit diminishing marginal productivity of capital and constant return to scale if heterogeneity across individuals is permitted. The problem is then to distinguish evidence of club convergence from that of conditional convergence.

The standard β-convergence concept and test are also criticized by Friedman (1992) and Quah (1993b), who raised the Galton's fallacy problem. Moreover, Quah (1993a, 1996a, 1996c, 1997) argued that convergence should be studied by taking into account the shape of the entire distribution of per capita GDP and its intradistribution dynamics over time and not by estimating the cross section correlation between growth rates and per capita GDP levels or by computing first or higher moments. Using an alternative empirical methodology based on Markov chains and probability transition matrices, Quah (1993a, 1996a, 1996c, 1997) found evidence on the formation of convergence clubs, the international income distribution polarizing into "twin-peaks" of rich and poor countries. Quite surprisingly, Quah (1996b) did not find evidence supporting "twin-peakedness" in the European regional income distribution for a sample of 82 regions, indeed excluding southern poor Portuguese and Greek regions, over the 1980 to 1989 period. Yet Le Gallo (2004), using the same empirical approach, found such evidence for an extended sample of 138 European regions over the 1980 to 1995 period.

Finally, Quah (1996b) raised another criticism concerning the neglected spatial dimension of the convergence process: countries or regions are actually treated as "isolated islands" in standard approaches, while spatial interactions due to geographical spillovers should be taken into account. Quah (1996b, 954) found that "physical location and geographical spillover matter more than do national, macro factors" and noted that "the results highlight the importance of spatial and national spillovers in understanding regional income distribution dynamics."

Spatial Effects and Polarization Patterns

Following Anselin (1988b), spatial effects refer to both spatial dependence and spatial heterogeneity.

Spatial autocorrelation can be defined as the coincidence of value similarity with locational similarity (Anselin 2001b). Therefore, there is positive spatial autocorrelation when similar values of a random variable measured on various locations tend to cluster in space. Applied to the study of income disparities, this means for example that rich regions tend to be geographically clustered as well as poor regions.

Spatial heterogeneity means in turn that economic behaviors are not stable over space. In a regression model, spatial heterogeneity can be reflected by varying coefficients, that is, structural instability across space, or by varying error variances across observations, that is, heteroskedasticity.[4] These variations follow for example specific geographical patterns such as East and West, or North and South. Such a spatial heterogeneity probably characterizes patterns of economic development under the form of spatial regimes and/or groupwise heteroskedasticity: a cluster of rich regions (the core) being distinguished from a cluster of poor regions (the periphery).

The links between spatial autocorrelation and spatial heterogeneity are quite complex. First, as pointed out by Anselin (2001b), spatial heterogeneity often occurs jointly, with spatial autocorrelation in applied econometric studies. Moreover, in cross section, spatial autocorrelation and spatial heterogeneity may be observationally equivalent. For example, in polarization phenomena, a spatial cluster of extreme residuals in the center may be interpreted as heterogeneity between the center and the periphery or as spatial autocorrelation implied by a spatial stochastic process yielding clustered values in the center. Finally, spatial autocorrelation of the residuals may be implied by some spatial heterogeneity that is not correctly modeled in the regression (Brundson, Fotheringham, and Charlton [1999] provided such an example). In other words, in a regression, a spatial autocorrelation of errors may simply indicate that the regression is misspecified.

Three kinds of issues arise from these complex links between spatial dependence and spatial heterogeneity.

First, we must identify spatial clusters of regional wealth upon which a spatial regimes convergence model could be based. Each spatial cluster contains all regions connected by a spatial association criterion whereas the type of spatial association differs between clusters. Then, both spatial dependence and heterogeneity effects are associated in the construction of our spatial clubs.

Second, statistical inference based on OLS when heterogeneity or spatial dependence is present is not reliable. For example, if we try to estimate a model characterized by a specific form of structural instability, we cannot rely on standard tests of structural instability in presence of spatial autocorrelation and/or heteroskedasticity. It is therefore necessary to test if both effects are present. Furthermore, when spatial autocorrelation and spatial heterogeneity occur jointly in a regression, the properties of White (1980) and Breusch-Pagan (1979) tests for heteroskedasticity may be flawed (Anselin and Griffith 1988). Therefore, it is necessary to adjust structural instability and heteroskedasticity tests for spatial autocorrelation and to use appropriate econometric methods as proposed by Anselin (1988a, 1990a, 1990b).

Third, the role played by geographic spillovers in the convergence of European regions has to be considered. Le Gallo, Ertur, and Baumont (2003) showed that if spatial autocorrelation is detected in the unconditional β-convergence model, then it leads to specifications integrating potential geographic spillovers in the convergence process. However, since spatial heterogeneity is also integrated now in the estimation of the β-convergence model, appropriate specifications and tests should be used to obtain reliable estimates of geographic spillovers on regional growth in Europe.

Data and Spatial Weight Matrix

Data

Data limitations remain a serious problem in the European regional context, although much progress has been made recently by Eurostat. Harmonized and reliable data allowing consistent regional comparisons are scarce, in particular for the beginning of the time period under study. There is clearly a lack of appropriate or easily accessible data, to include control and environmental variables and estimate a conditional β-convergence model, compared to the range of such variables available for international studies as in Barro and Sala-i-Martin (1995) or Mankiw, Romer, and Weil (1992) (Summers and Heston [1988] data set, also called the Penn World Table).[5]

We use data on per capita GDP in logarithms expressed in Ecu.[6] The data are extracted from the Eurostat-Regio database. This database is widely used in empirical studies on European regions; see for example López-Bazo et al. (1999), Neven and Gouyette (1995), Quah (1996b), and Beine and Jean-Pierre (2000), among others. Our sample includes 138 regions in 11 European countries over the 1980 to 1995 period: Belgium (11), Denmark (1), France (21), Germany (30), Greece (13), Luxembourg (1), Italy (20), the Netherlands (9), Portugal (5), and Spain (16) in NUTS2 and the United Kingdom (11) in NUTS1 level[7] (see the appendix for more details).

It is worth mentioning that our sample is far more consistent and encompasses much more regions than the one initially used by Barro and Sala-i-Martin (1991, seventy-three regions; 1995, ninety-one regions) and Sala-i-Martin (1996b, seventy-three regions; 1996a, ninety regions). Indeed, these authors mix different sources and different regional breakdowns.[8] Moreover, the smaller seventy-three regions data set is largely confined to prosperous European regions belonging to Western Germany, France, United Kingdom, Belgium, Denmark, Netherlands, and Italy, excluding Spanish, Portuguese, and Greek regions, which are indeed less prosperous. This may result in a selection bias problem raised by DeLong (1988). Armstrong (1995a, 1995b) tried to overcome these problems by expanding the original Barro and Sala-i-Martin (1991) seventy-three regions data set to southern, less prosperous regions using a more consistent sample of eighty-five regions.

However, we are aware of all the shortcomings of the database we use, especially concerning the adequacy of the regional breakdown adopted, which can raise a form of the ecological fallacy problem (King 1997; Anselin and Cho 2002) or “modifiable areal unit problem” well known to geographers (Openshaw and Taylor 1979; Arbia 1989). The choice of the NUTS2 level as our spatial scale of analysis may appear to be quite arbitrary and may have some impact on our inference results. Regions in NUTS2 level may be too large in respect to the variable of interest and the unobserved heterogeneity may create an ecological fallacy, so that it might have been more relevant to use NUTS3 level. Conversely, they may be too small so that the spatial autocorrelation detected could be an artifact that comes out from slicing homogeneous zones in respect to the variable considered, so that it might have been more relevant to use NUTS1 level. Even if, ideally, the choice of the spatial scale should be based on theoretical considerations, we are constrained in empirical studies by data availability. Moreover, our preference for the NUTS2 level rather than the NUTS1 level, when data are available, is based on European regional development policy considerations: indeed, it is the level at which eligibility under Objective 1 of Structural Funds[9] is determined since their reform in 1989 (European Commission 1999). Our empirical results are indeed conditioned by this choice and could be affected by different levels of aggregation and even by missing regions. Therefore, they must be interpreted with caution.

The Spatial Weight Matrix

The spatial weight matrix is the fundamental tool used to model the spatial interdependence between regions. More precisely, each region is connected to a set of neighboring regions by means of a *purely spatial pattern* introduced *exogenously* in this spatial weight matrix W.[10] The elements w_{ii} on the diagonal are set to zero whereas the elements w_{ij} indicate the way the region is spatially connected to the region j. These elements are *nonstochastic*, nonnegative, and finite. To normalize the outside influence upon each region, the weight matrix is standardized such that the elements of a row sum up to one. For the variable y_0, this transformation means that the expression Wy_0, called the spatial lag variable, is simply the weighted average of the neighboring observations. Various matrices can be considered: a simple binary contiguity matrix, a binary spatial weight matrix with a distance-based critical cutoff, above which spatial interactions are assumed negligible, more sophisticated generalized distance-based spatial weight matrices with or without a critical cutoff. The notion of distance is quite general,[11] and different functional form based on distance decay can be used (for example, inverse distance, inverse squared distance, negative exponential, etc.). The critical cutoff can be the same for all regions or can be defined to be specific to each region leading in the latter case, for example, to k-nearest neighbors weight matrices when the critical cutoff for each region is determined so that each region has the same number of neighbors.

It is important to stress that the weights should be exogenous to the model to avoid the identification problems raised by Manski (1993) in social sciences. This is the reason why we consider pure geographical distance, more precisely great circle distance between regional centroids, which is indeed strictly exogenous; the functional form we use is simply the inverse of squared distance, which can be interpreted as reflecting a gravity function.

The general form of the distance weight matrix we use is defined as following:

$$\begin{cases} w_{ij}^*(k) = 0 \text{ if } i = j \\ w_{ij}^*(k) = 1/d_{ij}^2 \text{ if } d_{ij} \le D(k) \\ w_{ij}^*(k) = 0 \text{ if } d_{ij} > D(k), \end{cases} \quad \text{and} \quad w_{ij}(k) = w_{ij}^*(k) / \sum_j w_{ij}^*(k) \qquad k = 1, \ldots, 4 \tag{3}$$

where d_{ij} is the great circle distance between centroids of regions i and j; $D(1) = Q1$, $D(2) = Mdn$, $D(3) = Q3$, and $D(4) = \text{Max}$, where $Q1$, Mdn, $Q3$, and Max are respectively the lower quartile (321 miles), the median (592 miles), the upper quartile (933 miles), and the maximum (2,093 miles) of the great circle distance distribution. This matrix is row standardized so that it is relative and not absolute distance that matters. $D(k)$ is the cutoff parameter for $k = 1, 2, 3$, above which interactions are assumed negligible. For $k = 4$, the distance matrix is full without cutoff. We therefore consider four different spatial weight matrices. It is important to keep in mind that all subsequent analyses are conditional upon the choice of the spatial weight matrix. Indeed the results of statistical inference depend on spatial weights. Consequently, we use $k = 1, 2, 3, 4$ to check for robustness of our results. Let us finally note first that even when using $D(1) = Q1$, some islands such as Sicilia, Sardegna, and Baleares are connected to continental Europe so that rows and columns in with only zero values are avoided. Second, United Kingdom is also connected to continental Europe. Third, note that connections between southern European regions are assured so that eastern Spanish regions are connected to Baleares, which are connected to Sardegna, which is in turn connected to Italian regions, which are finally connected to western Greek regions. The block-diagonal structure of the simple contiguity matrix when ordered by country is thus avoided and the spatial connections between regions belonging to different countries are incorporated. In our opinion, these matrices have therefore more appealing features when working on a sample of European regions, which are less closely connected and less compact than U.S. states, than the simple but less appropriate contiguity matrix.

In the following section, we define more precisely and apply our empirical methodology,[12] which aims at explicitly taking into account the potential spatial effects previously defined, in the framework of the standard β-convergence process.

Econometric Methodology

In the first step of our analysis, we look for the potential presence of spatial autocorrelation and spatial structural instability in European regional per capita GDP in logarithms using ESDA. ESDA is a set of techniques aimed at describing and visualizing spatial distributions, at detecting patterns of global and local spatial association, and at suggesting spatial regimes or other forms of spatial heterogeneity (Haining 1990; Bailey and Gatrell 1995; Anselin 1988a, 1988b). Moran's *I* statistic is usually used to test for global spatial autocorrelation (Cliff and Ord 1981), while the Moran scatterplot is used to visualize patterns of local spatial association and spatial instability (Anselin 1996). In the second step, we estimate an unconditional β-convergence model by OLS and carry out various tests aiming at detecting the presence of spatial dependence and spatial heterogeneity. We then propose the most appropriate specification with respect to these two problems.

Exploratory Spatial Data Analysis: Detection of Spatial Clubs

We first test for global spatial autocorrelation in per capita GDP in logarithms using Moran's *I* statistic (Cliff and Ord 1981), which is written in the following matrix form, for each year of the period 1980 to 1995:

$$I_t(k) = \frac{n}{S_0} \cdot \frac{z_t' W(k) z_t}{z_t' z_t} \qquad t = 0,...,16 \qquad k = 1,...,4, \tag{4}$$

where z_t is the vector of the n observations for year t in deviation from the mean, and $W(k)$ is the spatial weight matrix. Values of I larger (resp. smaller) than the expected value $E[I_t(k)] = -1/(n-1)$ indicate positive (resp. negative) spatial autocorrelation. Inference is based on the permutation approach with ten thousand permutations (Anselin 1995).[13] It appears that with $W(1)$, per capita regional GDP is positively spatially autocorrelated since the statistics are significant with $p = .0001$ for every year. This result suggests that the null hypothesis of no spatial autocorrelation is rejected and that the distribution of per capita regional GDP is by nature clustered over the whole period under study. In other words, the regions with relatively high per capita GDP (resp. low) are localized close to other regions with relatively high per capita GDP (resp. low) more often than if their localizations were purely random. A similar result holds for the average growth rate of regional per capita GDP over the whole period. Moreover these results are extremely robust in respect to the choice of the spatial weight matrix $W(k)$, $k = 1, \ldots, 4$.[14]

Spatial instability in the form of spatial regimes is then investigated by means of a Moran scatterplot (Anselin 1996). Given our context of β-convergence analysis, we choose to define such local spatial association on the logarithm of the *initial* level of per capita GDP. As noted by Durlauf and Johnson (1995) the use of split variables, which are known at the beginning of the period, are necessary to avoid the sample selection bias problem raised by DeLong (1988).

The Moran scatterplot displays the spatial lag Wy_0 against y_0, both standardized. The four different quadrants of the scatterplot correspond to the four types of local spatial association between a region and its neighbors: (HH) a region with a high value surrounded by regions with high values, (LH) a region with a low value surrounded by regions with high values, (LL) a region with a low value surrounded by regions with low values, and (HL) a region with a high value surrounded by regions

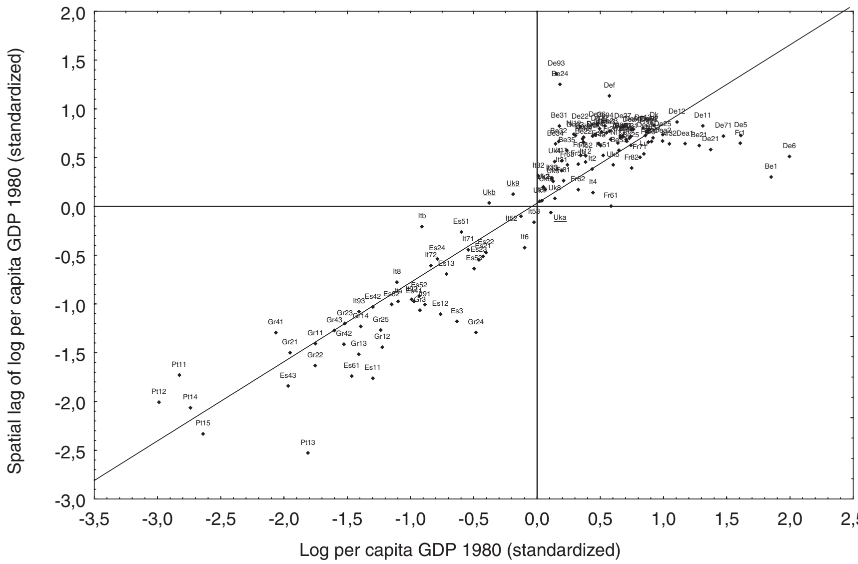

FIGURE 1. Moran Scatterplot for Log Per Capita GDP in 1980

with low values. Quadrants HH and LL refer to positive spatial autocorrelation indicating spatial clustering of similar values, whereas quadrants LH and HL represent negative spatial autocorrelation indicating spatial clustering of dissimilar values. The Moran scatterplot may thus be used to visualize atypical localizations in respect to the global pattern, that is, regions in quadrant LH or in the quadrant HL. A four-way split of the sample based on the two control variables, initial per capita GDP and initial spatially lagged per capita GDP, allowing for interactions between them, can therefore be based on this Moran scatterplot.

Figure 1 displays this Moran scatterplot computed with $W(1)$ for log per capita GDP in 1980. It reveals the predominance of HH and LL clustering types of regional per capita GDP: almost all the European regions are characterized by positive spatial association since ninety regions are of type HH and forty-five regions of type LL. The Moran scatterplot confirms the clear North-South polarization of the European regions: northern regions are located in the HH quadrant while southern regions are located in the LL quadrant. Only three regions show a spatial association of dissimilar values: Wales and Northern Ireland (United Kingdom) are located in the LH quadrant, which indicates poor regions, surrounded on average by rich regions; conversely, Scotland is located in the HL quadrant.

This suggests some kind of spatial heterogeneity in the European regional economies; the convergence process, if it exists, could be different across regimes. We consider therefore two spatial clubs constituted by HH and LL regions, which we call North and South. Since Wales, Scotland, and Northern Ireland are deleted,[15] our new sample contains 135 regions, which belong to North and South as following:

1/*North* = {France, Germany, Netherlands, Belgium, Denmark, Luxembourg, United Kingdom (excepted Wales, Scotland, and Northern Ireland) and northern Italy (Piemonte, Valle d'Aosta, Liguria, Lombardia, Trentino-Alto Adige, Veneto, Friuli-Venezia Guilia, Emilia-Romagna, and Toscana)}.

2/*South* = {Portugal, Spain, Greece, and southern Italy (Umbria, Marche, Lazio, Abruzzo, Molise, Campania, Puglia, Basilacata, Calabria, Sicilia, and Sardegna)}.

Not surprisingly, regions belonging to the South regime correspond to the Objective 1 regions and mainly belong to the "cohesion countries" defined by the European Commission.

The Moran scatterplots computed with the other spatial weight matrices $W(2)$, $W(3)$, and $W(4)$ lead to sensibly the same clubs: the only difference is the presence of Scotland in the North regime. This highlights again the robustness of our results in regard to the choice of the spatial weight matrix.[16] Moreover, the observed polarization seems to be persistent over the whole period since the composition of the clubs defined by the Moran scatterplots computed for each year remains globally unchanged.

The Moran scatterplot is illustrative of the complex interrelations between global spatial autocorrelation and spatial heterogeneity in the form of spatial regimes. Global spatial autocorrelation is reflected by the slope of the regression line of Wy_0 against y_0, which is formally equivalent to Moran's I statistic for a row-standardized weight matrix. It seems to be inherent to the layout of the spatial regimes corresponding to a clear North-South polarization pattern.

These exploratory results suggest that great care must be taken in the second step of our analysis concerning the estimation of the standard β-convergence model due to the presence of spatial autocorrelation and spatial heterogeneity. Standard estimation by OLS and statistical inference based on it are therefore likely to be misleading. Moreover, in respect to the simulation results presented by Anselin (1990b) on size and power of traditional tests of structural instability in presence of spatially autocorrelated errors, we are potentially in the worst case: positive global spatial autocorrelation and two regimes corresponding to closely connected or compact observations. These standard tests are also likely to be highly misleading. Concerning the methodological approach to be taken in empirical studies we will follow Anselin's suggestion: "it is prudent to always carry out a test for the presence of spatial error autocorrelation. . . . If there is a strong indication of spatial autocorrelation, and particularly when it is positive and/or the regimes correspond to compact contiguous observations, the standard techniques are likely to be unreliable and a maximum-likelihood approach should be taken" (p. 205). We are aware that this empirical approach raises the well-known pretest problem invalidating the use of the usual asymptotic distribution of the tests, but the simulation results presented by Anselin indicate that this problem may not be so harmful in this case.

Finally, the determination of the different regimes or clubs should, ideally, be endogenous as, for example Durlauf and Johnson (1995) in a nonspatial framework. However, to our knowledge, such an attempt has still not been made in a setting that also takes into account spatial dependence and remains beyond the scope of this article.[17]

Estimation Results

We first estimate the model of unconditional β-convergence by OLS and carry out various tests aimed at detecting the presence and the form of spatial dependence and spatial heterogeneity. Next, since the tests indicate both the presence of spatial error autocorrelation and spatial regimes, we estimate a spatial error model with structural instability where coefficients are allowed to vary across regimes. The implications of this model for the convergence process and spatial spillovers effects between the European regions are finally explored.

1. OLS Estimation of the Unconditional β-Convergence Model and Tests

Let us take as a starting point the following model of unconditional β-convergence:

$$g_T = \alpha e_N + \beta y_{1980} + \varepsilon \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I), \tag{5}$$

where g_T is the vector of dimension $n = 135$ 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 in logarithms for all the regions in 1980, α and β are the unknown parameters to be estimated, e_n is the unit vector, and ε is the vector of errors with the usual properties.

A suggested by Fingleton (1999), the choice of the cutoff for the spatial weight matrix can be based on the OLS residual correlogram. It uses binary weight matrices in which an element is equal to one when the distance between two regions is between predefined ranges. Here, the ranges are defined by minimum, lower quartile, median, upper quartile, and maximum great circle distances. With the sample of 135 regions we consider now, $Q1$, Mdn, $Q3$, and Max are modified as following: $Q1$ = 312 miles, Me = 582 miles, $Q3$ = 928 miles, and Max = 1,997 miles. The determination of the cutoff that maximizes the absolute value of significant Moran's I test statistic adapted to regression residuals (Cliff and Ord 1981) or Lagrange multiplier (LM) test statistic for spatial error autocorrelation (Anselin

TABLE 1. Residual Correlogram

	Range (Miles)			
	Min (8); Q*1 (312)*	*Q1 (312);* Mdn *(582)*	Mdn *(582);* Q*3 (928)*	Q*3 (928);* *Max (1,997)*
Moran's *I*	15.54	–3.35	–12.41	10.99
p value	.000	.001	.000	.000
LMERR	157.38	10.45	91.74	29.93
p value	.000	.001	.000	.000
R-LMERR	44.97	0.0097	34.92	0.0138
p value	.000	.922	.000	.907

Note: Min, *Q*1, *Mdn*, *Q*3, and Max are respectively the minimum allowable distance (230 miles), the lower quartile (312 miles), the median (582 miles), the upper quartile (928 miles), and the maximum (1,997 miles) of the great circle distance distribution between centroids of each region. For each range, we estimate the absolute β-convergence model and perform the Moran's *I* test, the Lagrange multiplier test and its robust version (respectively LMERR and R-LMERR) for residual spatial autocorrelation based on the contiguity matrix computed for that range.

1988a, 1988b) leads to *Q*1: we retain the distance based weight matrix with a cutoff of 312 miles, noted *W* (see Table 1).

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, $\hat{\beta} = -.00797$, which confirms the hypothesis of convergence for the European regions. The speed of convergence associated with this estimation is 0.85 percent (the half-life is eighty-seven years), far below the 2 percent usually found in the convergence literature but closer to about 1 percent as found by Armstrong (1995b). These results indicate that the process of convergence is indeed very weak.

Turning to the diagnostics, we note that the White (1980) test clearly rejects homoskedasticity as does the Breusch and Pagan (1979) test versus the explanatory variable y_{1980}. Versus D_1, which is the dummy variable for the northern regime, the rejection is slightly weaker with a *p* value of .015. Further consideration of spatial heterogeneity is therefore needed: we could think of some general form of heteroskedasticity, a more specific heteroskedasticity linked to the explanatory variable in the regression or groupwise heteroskedasticity possibly associated to structural instability across regimes.

To determine the form taken by spatial autocorrelation, spatial lag, or spatial error, five spatial autocorrelation tests are also carried out. Using the weight matrix *W*(1), Moran's *I* test adapted to regression residuals (Cliff and Ord 1981) indicates the presence of spatial dependence. To discriminate between the two forms of spatial dependence, we also perform the LM tests: respectively LMERR and LMLAG and their robust versions, which have a good power against their specific alternative (Anselin et al. 1996; Anselin 2001a, 2001b). A classical "specific to general" specification search approach[18] outlined in Anselin and Rey (1991) or Anselin and Florax (1995) in the context of spatial econometric modeling can then be applied to

TABLE 2. Estimation Results for the Unconditional β-Convergence Model

Estimation Result	*OLS-White*	*Tests*	
alpha	0.130 (0.000)	JB	8.50 (0.014)
beta	–0.00797 (0.002)	Moran	12.94 (0.000)
Conv. speed	0.85 % (0.000)	LMERR	140.68 (0.000)
Half-life	87	R-LMERR	16.61 (0.000)
R^2-adjusted	.14	LMLAG	124.58 (0.000)
LIK	446.35	R-LMLAG	0.509 (0.475)
AIC	–888.69	BP/ln(y_{1980})	14.57 (0.000)
BIC	–882.88	BP/D1	5.85 (0.015)
$\hat{\sigma}_\varepsilon^2$	$7.984.10^{-5}$	White test	28.39 (0.000)
JLM1	155.25 (0.000)	JLM2	46.53 (0.000)

Note: p values are in parentheses. OLS-White indicates the use of the White (1980) heteroskedasticity consistent covariance matrix estimator for statistical inference in the ordinary least squares (OLS) estimation. LIK is the value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). JB is the Jarque and Bera (1987) estimated residuals normality test. MORAN is the Moran's *I* test adapted to OLS 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). BP is the Breusch-Pagan (1979) test for heteroskedasticity. White is the White (1980) test of heteroskedasticity. JLM1 is the LM test of the joint null hypothesis of absence of heteroskedasticity linked to and residual spatial autocorrelation. JLM2 is the LM test of the joint null hypothesis of absence of heteroskedasticity linked to D1 and residual spatial autocorrelation (Anselin 1988a, 1988b).

decide which spatial specification is the more appropriate. If LMLAG is more significant than LMERR and R-LMLAG is significant but R-LMERR is not, then the appropriate model is the spatial autoregressive model. Conversely, if LMERR is more significant than LMLAG and R-LMERR is significant but R-LMLAG is not, then the appropriate specification is the spatial error model. The performance of such an approach is experimentally investigated in Florax and Folmer (1992). Furthermore, Florax, Folmer, and Rey (2003) showed by means of Monte Carlo simulation that this classical approach outperforms Hendry's (1979) "general to specific" approach.

Applying this decision rule, these tests indicate the presence of spatial error autocorrelation rather than a spatial lag variable: the spatial error model appears to be the appropriate specification. The LM test of the joint null hypothesis of absence of heteroskedasticity and residual spatial autocorrelation is highly significant whatever the form of the heteroskedasticity assumed (Anselin 1988a, 1988b).

Therefore, the unconditional-convergence model is strongly misspecified due to the spatial autocorrelation and heteroskedasticity of the errors. A direct implication of these results is that the OLS estimator is inefficient and all the statistical inference based on it is unreliable. In addition, as pointed out earlier, we must keep in mind that in presence of heteroskedasticity, results of the spatial autocorrelation tests may be misleading, and conversely, results of the heteroskedasticity tests may also be misleading in presence of spatial autocorrelation (Anselin 1988b, 1990a, 1990b; Anselin and Griffith 1988). Therefore, they must be interpreted with caution. More precisely, although the tests indicate heteroskedasticity, this may not be a problem because it can be due to the presence of spatial dependence (McMillen 1992).

2. Spatial Dependence and Spatial Heterogeneity

Previous results show the presence of spatial error autocorrelation and heteroskedasticity. The latter can be due to an unmodeled structural instability of the coefficients between the two regimes previously defined. Therefore, we estimate the following spatial regimes model, in which we assume that the same spatial autoregressive process affects all the errors:

$$g_T = \alpha_1 D_1 + \alpha_2 D_2 + \beta_1 D_1 y_{1980} + \beta_2 D_2 y_{1980} + \varepsilon, \tag{6}$$

with $\varepsilon = \lambda W \varepsilon + u$ and $u \sim N(0, \sigma_u^2 I)$. Or equivalently in matrix form,

$$\begin{bmatrix} g_{T,1} \\ g_{T,2} \end{bmatrix} = \begin{bmatrix} S_1 & y_{1980,1} & 0 & 0 \\ 0 & 0 & S_2 & y_{1980,2} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \beta_1 \\ \alpha_2 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \Rightarrow Z = X\delta + \varepsilon, \tag{7}$$

with $\varepsilon' = \begin{bmatrix} \varepsilon_1' & \varepsilon_2' \end{bmatrix}$; $\varepsilon = \lambda W \varepsilon + u$ and $u \sim N(0, \sigma_u^2 I)$.

The subscribe 1 stands for the North regime and the subscribe 2 for the South regime. This specification allows the convergence process to be different across regimes: it takes into account the fact that the convergence process, if it exists, could be different across regimes. Actually this approach can be interpreted as a spatial convergence clubs approach, where the clubs are identified using a spatial criterion with the Moran scatterplot as described above.

In the same time, this specification deals with spatially autocorrelated errors. However, spatial effects are assumed to be identical in northern regions and southern regions, but all the regions are still interacting spatially through the spatial weight matrix *W*. Indeed, it seems meaningless to estimate separately the two regressions allowing for different spatial effects possibly based on different spatial weight matrices across regimes. This would imply that northern and southern regions do not interact spatially and are independent. In addition, there is no obvious reason to consider different spatial weight matrices across regimes. Since the weight matrix contains the pure distance-based spatial pattern, which is completely exogenous, this assumption would appear to be even more unlikely.

The estimation results by maximum likelihood (ML) are presented in Table 3. First, we note that $\hat{\beta}_1$ and $\hat{\beta}_2$ both have the expected sign, but $\hat{\beta}_1$ is not significant for the North. For southern regions, $\hat{\beta}_2$ is strongly significant and negative. The convergence speed and the half-life are respectively 2.94 percent and twenty-nine years. The spatially adjusted Chow test (Anselin 1988b, 1990b) strongly rejects the joint null hypothesis of structural stability and the individual coefficient stability tests reject the corresponding null hypotheses.

Concerning the other diagnostics, it appears that the LMLAG* test does not reject the null hypothesis of the absence of an additional autoregressive lag variable in the spatial error model. The spatially adjusted Breusch and Pagan (1979) heteroskedasticity test versus D_1 is not significant at 5 percent. However, given the fact that the *p* value is quite close to 5 percent, (*p* value of .065), a model allowing for further groupwise heteroskedasticity has been estimated. However, since the estimation results are not affected, this model will not be presented. Finally, estimation of this model by general method of moments (GMM) (Kelejian and Prucha 1999) leads to almost the same results on the parameters of interest.

From an economic point of view, these results have two important interpretations. First, since the convergence parameters vary across the subsamples, it implies that the rate of convergence between northern regions and southern regions are different. More specifically, if there is a convergence process among European regions, it mainly concerns the southern regions and does not concern the northern regions, since the associated convergence parameter is not significant. Second, since the constants are also significantly different across the subsamples, the steady state level of income per capita in the North is different than the steady state level in the South. Taken together, these results imply that while the southern regions converge to a common steady state level per capita income, such a convergence does not exist between the regions of the North. This could reflect the existence of one convergence club in Europe existing between the southern regions and the lack of mobility of the northern regions in the GDP distribution.

3. Spatial Spillovers and Spatial Diffusion

The second aspect of the results we want to stress in this article refers to spatial spillover effects. We first note that a significant positive spatial autocorrelation is found under this assumption ($\hat{\lambda} = 0, 788$). As pointed out by Fingleton (1999) and Le Gallo, Ertur, and Baumont (2003), this evidence of spatial autocorrelation may reflect in part the effects of omitted variables. Indeed, since this data set does not allow controlling for the determinants of the steady state income, spatial autocorrelation may act as a proxy to all these omitted variables and catch their effects. As a result, the inclusion of spatial autocorrelation, rather than additional explanatory variables, yields to growth spillovers between the regions that are investigated below.

The spatial error model can also be expressed as the constrained spatial Durbin model, which can be formulated here as

TABLE 3. Estimation Results for the Spatial Regimes Spatial Error Model

	North 1		*South 2*		*Tests*	
ML	*ML*	*GMM*	*ML*	*GMM*		
alpha	0.0798 (0.014)	0.0837 (0.009)	0.263 (0.000)	0.280 (0.000)	Ind. stability test	12.88 (0.000)
beta	–0.0026 (0.438)	–0.0030 (0.405)	–0.0238 (0.000)	–0.0261 (0.000)	Ind. stability test	12.57 (0.000)
lambda	0.788 (ML) (0.000)	0.793 (GMM)			Chow-Wald test, overall stability	13.06 (0.001)
Conv. speed	—	2.94 percent (0.000)			LR-SED	63.68 (0.000)
Half-life	—	29			LMLAG*	0.032 (0.857)
Sq. corr.	0.22 (ML)	0.25 (GMM)			LR com. fac.	5.38 (0.068)
LIK			489.65			
AIC	–971.31 (k = 4)	–969.31 (k = 5)			S-BP/D1	3.396 (0.065)
BIC	–959.68 (k = 4)	–954.78 (k = 5)				
$\hat{\sigma}^2_\varepsilon$			$3.719.10^{-5}$			
gamma	0.002 (0.970)	0.0187 (0.729)				

Note: p values are in parentheses. ML indicates maximum likelihood estimation. Sq. Corr. is the squared correlation between predicted values and actual values. LIK is value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). The information criteria are computed both for four and five parameters, as lambda may be considered as nuisance parameters. The individual coefficient stability tests are based on spatially adjusted asymptotic Wald statistics, distributed as with 1 degree of freedom. The Chow-Wald test of overall stability is also based on a spatially adjusted asymptotic Wald statistic, distributed as with 2 degrees of freedom (Anselin 1988b). LR-SED is the likelihood ratio test for spatial error autocorrelation, LMLAG* is the Lagrange multiplier test for an additional spatially lagged endogenous variable in the spatial error model (Anselin 1988b, 1990b). LR-com-fac is the likelihood ratio common factor test; Wald-com-fac is the Wald common factor test (Burridge 1981). S-BP is the spatially adjusted Breusch-Pagan test for heteroskedasticity (Anselin 1988a, 1988b). The gamma coefficients are not estimated but computed using the accepted restrictions; their significance is assessed using the asymptotic delta method.

$$g_T = \alpha_1(I - \lambda W)D_1 + \alpha_2(I - \lambda W)D_2 + \beta_1 D_1 y_{1980} + \beta_2 D_2 y_{1980} + \lambda W g_T + \gamma_1 W D_1 y_{1980} + \gamma_2 W D_2 y_{1980} + u, \quad (8)$$

with $u \sim N(0, \sigma_u^2 I)$ and the two nonlinear restrictions: $\gamma_1 = -\lambda\beta_1$ and $\gamma_2 = -\lambda\beta_2$. The *LR* and Wald common factor tests (Burridge 1981) indicate that these restrictions cannot be rejected.

From the convergence perspective, this expression can be interpreted as a minimal *conditional* β-convergence model integrating two spatial environment variables (Le Gallo, Ertur, and Baumont 2003). From the spatial spillover perspective, this reformulation has an interesting interpretation: it appears that whatever the regime, the average growth rate of a region *i* is positively influenced by the average growth rate of neighboring regions, through the endogenous spatial lag variable Wg_T. However, it does not seem to be influenced by the initial log per capita GDP of neighboring regions, since the two coefficients γ_1 and γ_2 are not significant. 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.

Related to this spillover effects, the spatial regimes spatial error specification also has an interesting property concerning the diffusion of a random shock. Indeed, model 6 can be rewritten as follows:

$$g_T = \alpha_1 D_1 + \alpha_2 D_2 + \beta_1 D_1 y_{1980} + \beta_2 D_2 y_{1980} + (I - \lambda W)^{-1} u. \quad (9)$$

Concerning the error process, this expression means that a random shock in a specific region does not only affect the average growth rate of this region but also has an impact on the average growth rates of all other regions through the inverse spatial transformation $(I - \lambda W)^{-1}$.

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 regimes spatial error model, affecting Ile de France belonging to the North regime (Figure 2) and Madrid belonging to the South regime (Figure 3). This shock has the largest relative impact on Ile de France (resp. Madrid), where the simulated average growth rate is 21.22 percent higher than the actual average growth rate without the shock (resp. 20.90 percent). Moreover, in both cases, 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 1.57 and 3.74 percent for the regions neighboring Ile de France and gradually decreases when we move to peripheral regions (Figure 2). For Madrid, the magnitude of the impact of this shock is between 3.76 and 8.53 percent for the regions neighboring Madrid. As Madrid is not centrally

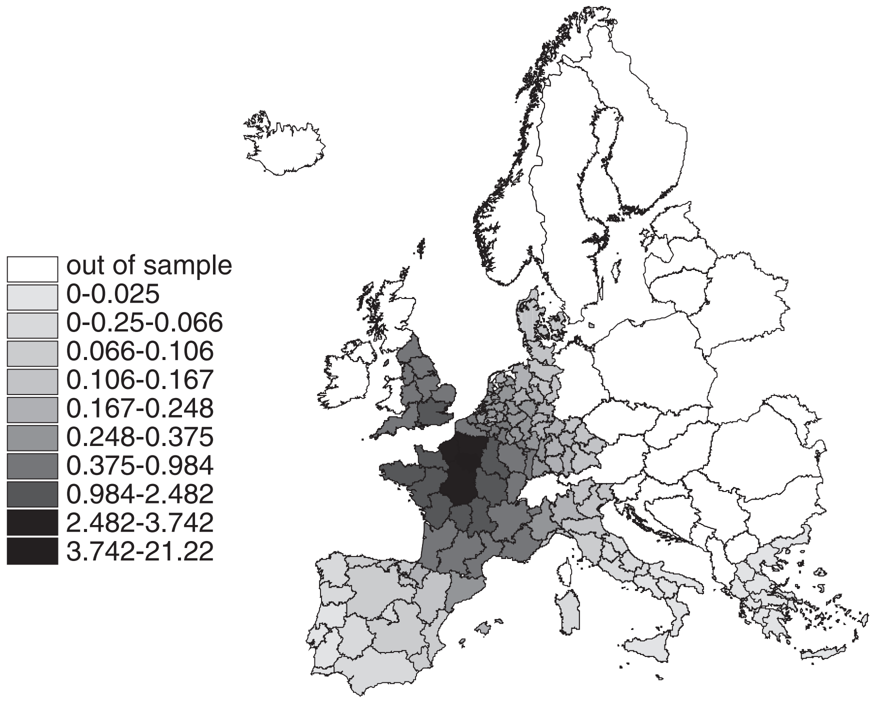

FIGURE 2. Diffusion in the Spatial Regimes Spatial Error Model Using the *Q*1-Distance Weight Matrix; Percentage Variation of Average Growth Rates Due to a Shock in Ile de France, 1980-1995 (North)

located in Europe, the magnitude of the shock strongly decreases when we move to northern peripheral regions (Figure 3). The impact of the shock appears stronger in the South regime than in the North regime due to nonsignificance of the convergence parameter in the North. 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.

4. Differentiated Spatial Effects

Finally, we investigate the potential for differentiated spatial effects in modeling club convergence, that is, a different λ coefficient for each regime and a North-South interaction coefficient, applying the methodology proposed by Rietveld and Wintershoven (1998) in a quite different context. The previous model assumed that spatial effects are identical across spatial clubs. This assumption should be tested. We also noted that running two separate regressions allowing for different spatial

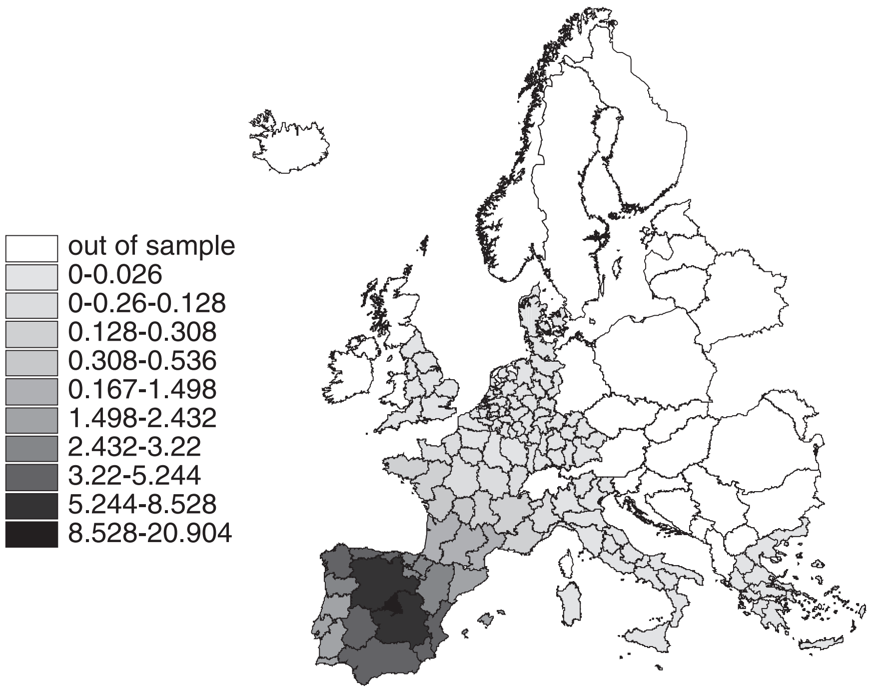

FIGURE 3. Diffusion in the Spatial Regimes Spatial Error Model Using the *Q*1-Distance Weight Matrix; Percentage Variation of Average Growth Rates Due to a Shock in Madrid, 1980-1995 (South)

effects seems unsatisfactory because it implies that northern regions do not interact with southern regions.

An interesting way to overcome these problems is to consider the following specification:

$$g_T = \alpha_1 D_1 + \alpha_2 D_2 + \beta_1 D_1 y_{1980} + \beta_1 D_1 y_{1980} + \varepsilon$$
$$\varepsilon = (\lambda_1 W_1 + \lambda_2 W_2 + \lambda_3 W_3)\varepsilon + u \qquad u \sim N(0, \sigma_u^2 I) \qquad (10)$$

where we take into account jointly structural instability and differentiated spatial effects within and between spatial clubs. The spatial weight matrix W is now split in three parts: W_1 includes only the spatial interconnections between regions belonging to the North regime, W_2 includes only the spatial interconnections between regions belonging to the South regime, and W_3 includes only the spatial intercon-

TABLE 4. Estimation Results for the Spatial Regimes Spatial Error Model with Differentiated Spatial Effects

ML	*North 1*	*South 2*		
alpha	0.0853 (0.007)	0.259 (0.000)	LIK	489.89
beta	–0.0032 (0.350)	–0.0234 (0.000)	AIC	–971.78 (k = 4)
				–965.78 (k = 7)
			BIC	–960.16 (k = 4)
				–945.44 (k = 7)
lambda1	0.871 (0.000)		$\hat{\sigma}^2_\varepsilon$	$3.653.10^{-5}$
lambda2	0.704 (0.000)		LR-regime	11.84 (0.003)
lambda3	–0.0914 (0.924)		LR-spatial effects	0.464 (0.793)
Conv. speed	—	2.89 percent (0.000)		
Half-life	—	29		

Note: p values are in parentheses. ML indicates maximum likelihood estimation. LIK is the value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). The information criteria are computed both for four and seven parameters, as lambdas may be considered as nuisance parameters.

nections between regions belonging to the North regime and regions belonging to the South regime. These matrices can be filled using two different approaches. The first one is based on the split of the previous standardized W matrix leading to nonstandardized W_j matrices (j = 1, 2, 3). The main advantage of this approach is that the homogeneity test of the spatial effects can be carried out in a straightforward manner since the model (model 6) is then the constrained model under the null hypothesis of equal λ_j coefficients. The drawback is the use of nonstandardized matrices in the ML estimation of model 10, which can be problematic since usual regularity conditions might not be met. In addition, the interpretation of the λ_j coefficients as spatial autocorrelation coefficients becomes ambiguous. The second approach is based on the split of the nonstandardized W matrix, the W_j matrices being then standardized. The major drawback is then that model 6 can no more be considered as the constrained model for the homogeneity test.

We will use the first approach and estimate model 10 by ML, the results are presented in Table 4.[19] The results are in line with those previously obtained concerning the convergence parameters with spatial clubs.

We can note that $\hat{\lambda}_1$ for the northern regions and $\hat{\lambda}_2$ for the southern regions are strongly significant and positive, while $\hat{\lambda}_3$ representing the North-South interactions is surprisingly not significant (p value = .924). However, this might be explained by the sparsity of the W_3 matrix, which contains too many zero values. We then carry out the LR test for the homogeneity of spatial effects under the maintained hypothesis of spatial clubs; it appears that the null hypothesis of equality of spatial effects cannot be rejected (p value = .793). We also carry out the LR test for

TABLE 5. Estimation Results for the Spatial Error Model with Differentiated Spatial Effects

Estimation Result	*ML*		
alpha	0.159 (0.000)	LIK	483.97
beta	–0.0114 (0.000)	AIC	–965.94 (k = 2)
			–957.93 (k = 5)
		BIC	–958.13 (k = 2)
			–943.41 (k = 5)
lambda1	0.871 (0.000)	$\hat{\sigma}_{\varepsilon}^{2}$	$4.007.10^{-5}$
lambda2	0.714 (0.000)		
lambda3	–0.488 (0.595)		
Conv. speed	1.25 percent (0.000)		
Half-life	61		

Note: p values are in parentheses. ML indicates maximum likelihood estimation. LIK is the value of the maximum likelihood function. AIC is the Akaike (1974) information criterion. BIC is the Schwarz information criterion (1978). The information criteria are computed both for two and five parameters, as lambdas may be considered as nuisance parameters.

spatial clubs under the maintained hypothesis of differentiated spatial effects. The ML estimation results of the constrained model are presented in Table 5. The null hypothesis of no spatial clubs is strongly rejected (*p* value = .003). These results confirm the fact that model 6 with spatial regimes but nondifferentiated spatial effects is indeed the most appropriate specification.

CONCLUSION

The aim of this article was to assess if spatial dependence and spatial heterogeneity really matter in the estimation of β-convergence processes. Based on a sample of 138 European regions over the period 1980 to 1995, we showed that they do matter. In front of the well-known theoretical inadequacy and econometric problems faced by the standard β-convergence model, we improved it on both aspects.

First, from the econometric point of view, the unreliability of statistical inference based on OLS estimation in presence of nonspherical errors is well known. Using the appropriate econometric tools, we detected spatial autocorrelation and overcame the problem by estimating the appropriate spatial error model that can be interpreted as a minimal conditional β-convergence model. Concerning spatial heterogeneity, it appeared that the problem was essentially due to structural instability in the form of spatial regimes. These spatial regimes, interpreted as spatial convergence clubs, were defined using ESDA, more precisely a Moran scatterplot. We therefore took into account spatial autocorrelation in conjunction with structural instability. The estimation of the appropriate spatial regimes spatial error model showed that indeed the convergence process is different across regimes. Furthermore, it appeared that actually there is no such a process for northern regions, but only a weak one for southern regions. This nonconvergence result is consistent with those obtained for rich countries by DeLong (1988) and Durlauf and Johnson (1995) using international data sets. It might be due to residual intraregime heterogeneity not taken into account. Inclusion of additional variables in a conditional β-convergence framework might lead to a convergence result for the North regime using the Mankiw, Romer, and Weil (1992) framework for example. Unfortunately, data for doing this are not available in the Eurostat-Regio database.

Second, from the economic point of view, we estimated a spatial spillover effect in the framework of spatial convergence clubs. This effect appeared to be strongly significant, indicating that the average growth rate of per capita GDP of a given region is positively affected by the average growth rate of neighboring regions. The geographic environment plays then an important role in the study of growth processes. The spatial diffusion process implied by this model is also highlighted by a simulation experiment.

Appendix

The data are extracted from the Eurostat-Regio database.

Eurostat is the Statistical Office of the European Communities. Its task is to provide the European Union with statistics at European level that enable comparisons between countries and regions. These statistics are used by the European Commission and other European institutions so that they can define, implement, and analyze European Community policies. The Regio database is the official source of harmonized annual data at the regional level throughout the 1980 to 1995 period for the European Union and per capita GDP is likely to be one of the most reliable series in this database.

We use the Eurostat 1995 nomenclature of statistical territorial units, which is referred to as NUTS (Nomenclature of Territorial Units for Statistics). The aim is to provide a single uniform breakdown of territorial units for the production of regional statistics for the European Union. In this nomenclature, NUTS1 means European Community Regions while NUTS2 means Basic Administrative Units. For practical reasons to do with data availability and the implementation of regional policies, this nomenclature is based primarily on the institutional divisions currently in force in the member states following “normative criteria.” Eurostat defines these criteria as follows: “normative regions are the expression of political will; their limits are fixed according to the tasks allocated to the territorial communities, according to the size of population necessary to carry out these tasks efficiently and economically, and according to historical and cultural factors” (Eurostat 1999, 7). It excludes territorial units specific to certain fields of activity or functional units (Cheshire and Carbonaro 1995) in favor of regional units of a general nature. The regional breakdown adopted by Eurostat appears therefore as one of the major shortcomings of the Regio database, which can have some impact on our spatial weight matrix and estimation results (scale problems).

We use the series E2GDP measured in Ecu per inhabitant over the 1980 to 1995 period for 138 regions in 11 European countries mentioned in the text. National GDPs according to the ESA 1979 (European System of Accounts) are broken down in accordance with the regional distribution of gross value added at factor cost or, in some case at market prices (Portugal). For the United Kingdom, the use of NUTS1 level is used because there is no official counterpart to NUTS2 units, which are drawn up only for the European Commission use as groups of counties. This explains data nonavailability at NUTS2 level throughout the period for this country. Luxembourg and Denmark may be considered as NUTS2 regions according to Eurostat. Our preference for NUTS2 level rather than NUTS1 level, when data are available, is based on European regional development policy considerations: indeed, it is the level at which eligibility under Objectives 1 and 6 of Structural Funds is determined (European Commission 1999). Our empirical results are indeed conditioned by this choice and could be affected by missing regions and different levels of aggregation. They must therefore be interpreted with caution.

We exclude Groningen in the Netherlands from the sample due to some anomalies related to North Sea Oil revenues, which substantially increase its per capita GDP (Neven and Gouyette 1995). We also exclude the Canary Islands and Ceuta y Mellila (Spain), which are geographically isolated. Corse (France), Austria, Finland, Ireland, and Sweden are excluded due to data nonavailability over the whole 1980 to 1995 period in the Eurostat-Regio databank. Berlin and East Germany are also excluded for well-known historical and political reasons.

NOTES

1. More specifically, their result is based on regressions of normalized products of fitted residuals for all country pairs obtained from a growth equation on different functional forms of the distance between country capitals: “We are quite surprised at the apparent absence of a significant degree of spatial correlation in our sample” (DeLong and Summers 1991, 489).

2. The *speed of convergence* is then $b = -\ln(1 + T\beta)/T$. The time necessary for the economies to fill half of the variation, which separates them from their steady state, is called the *half-life*: $\tau = -\ln(2)/\ln(1 + \beta)$.

3. However, we will not use this σ-convergence concept in this article because it is an aspatial concept. Note that Maurseth (2001) has recently proposed a conditional σ-convergence concept, which can be interpreted as a spatialized measure of dispersion.

4. Note that evidence of heteroskedasticity may also arise partly because of parameter heterogeneity, as pointed out by an anonymous referee.

5. Levine and Renelt (1992) discussed the wide range of variables (more than fifty) used in various studies.

6. Former European Currency Unit replaced by the Euro since 1999.

7. NUTS is the French acronym for Nomenclature of Territorial Units for Statistics used by Eurostat.

8. For example, for the sample of ninety-one regions used by Barro and Sala-i-Martin (1995): GDP data collected by Molle (1980) for the pre-1970 period, Eurostat data for the recent period, and personal income data from Banco de Bilbao for Spanish regions are mixed. Button and Pentecost (1995) also reported these problems.

9. For regions where development is lagging behind (in which per capita GDP is generally below 75 percent of the EU average). More than 60 percent of total EU resources used to implement structural policies are assigned to Objective 1.

10. As pointed out by Anselin (1999b, 6), "Also, to avoid identification problems, the weights should truly be exogenous to the model (Manski 1993). In spite of their lesser theoretical appeal, this explains the popularity of geographically derived weights, since exogeneity is unambiguous."

11. Weights based on "social distance" as in Doreian (1980) or "economic distance" as in Case, Rosen, and Hines (1993); Conley, Flyer and Tsiang (2003); and Conley (1999) have also been suggested in the literature. However in that case, as noted by Anselin and Bera (1998, 244), "Indicators for the socioeconomic weights should be chosen with great care to ensure their exogeneity, unless their endogeneity is considered explicitly in the model specification."

12. A similar empirical methodology is also used in the quite different context of criminology studies by Baller et al. (2001).

13. All computations were carried out using SpaceStat 1.90 software (Anselin 1999a).

14. In addition, the results are also robust to the use of a k-nearest neighbors spatial weight matrices, for $k = 10, 15, 20, 25$. Complete results are available from the authors upon request.

15. The spatial clubs (LH) and (HL) containing only two regions and one region, respectively, are omitted due to the small number of observations in each and lack of degrees of freedom for the second step of our analysis.

16. Using k-nearest neighbors spatial weight matrices, we obtained the same North-South polarization result. The complete results are available from the authors upon request.

17. This matter of fact is also noted by Anselin and Cho (2002). This issue is much more complex than in the standard nonspatial framework due to the spatial weight matrix and the spatial ordering of the observations.

18. Nevertheless, it must be stressed that this classical approach has three main drawbacks: the significance levels of the sequence of tests are unknown; every test is conditional on arbitrary assumptions; it does not always lead to the "best model." Some authors prefer to prewhiten or filter the variables to get rid of spatial autocorrelation (e.g., Getis and Griffith 2002, among others). Conley (1999) proposed an interesting alternative approach based on nonparametric estimation of covariance matrices yielding standard error estimates for coefficients that are robust versus spatial autocorrelation and heteroscedasticity. His approach is the spatial analog of that followed in time-series by, for example, Newey and West (1987) or Andrews (1991).

19. The Gauss code is available from the authors upon request.

References

Ades, A., and H. B. Chua. 1997. Thy neighbor's curse: Regional instability and economic growth. *Journal of Economic Growth* 2: 279-304.

Akaike, H. 1974. A new look at the statistical model identification. *IEEE Transactions on Automatic Control* AC-19: 716-23.

Andrews, D. W. K. 1991. Heteroskedasticity and autocorrelation consistent covariance matrix estimation. *Econometrica* 59: 817-59.

Anselin, L. 1988a. Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. *Geographical Analysis* 20: 1-17.

———. 1988b. *Spatial econometrics: Methods and models*. Dordrecht, the Netherlands: Kluwer Academic.

———. 1990a. Some robust approach to testing and estimating in spatial econometrics. *Regional Science and Urban Economics* 20: 141-63.

———. 1990b. Spatial dependence and spatial structural instability in applied regression analysis. *Journal of Regional Science* 30: 185-207.

———. 1995. Local indicators of spatial association-LISA. *Geographical Analysis* 27: 93-115.

———. 1996. The Moran Scatterplot as an ESDA tool to assess local instability in spatial association. In *Spatial analytical perspectives on GIS*, ed. M. Fisher, H. J. Scholten, and D. Unwin. London: Taylor & Francis.

———. 1999a. *SpaceStat, a software package for the analysis of spatial data*. Version 1.90. Ann Arbor, MI: BioMedware.

———. 1999b. Spatial econometrics. Working Paper, Bruton Center, School of Social Science, University of Texas, Dallas.

———. 2001a. Rao's score test in spatial econometrics. *Journal of Statistical Planning and Inference* 97: 113-39.

———. 2001b. Spatial econometrics. In *Companion to econometrics*, ed. B. Baltagi. Oxford, UK: Basil Blackwell.

Anselin, L., and A. Bera. 1998. Spatial dependence in linear regression models with an introduction to spatial econometrics. In *Handbook of applied economic statistics*, ed. A. Ullah and D. E. A Giles. Berlin: Springer-Verlag.

Anselin, L., A. K. Bera, R. Florax, and M. J. Yoon. 1996. Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics* 26: 77-104.

Anselin, L., and W. T. Cho. 2002. Spatial effects and ecological inference. *Political Analysis* 10: 276-97.

Anselin, L., and R. Florax. 1995. Small sample properties of tests for spatial dependence in regression models. In *New directions in spatial econometrics*, ed. L. Anselin and R. Florax. Berlin: Springer-Verlag.

Anselin, L., and D. Griffith. 1988. Do spatial effects really matter in regression analysis? *Papers in Regional Science* 65: 11-34.

Anselin, L., and S. Rey. 1991. Properties of tests for spatial dependence in linear regression models. *Geographical Analysis* 23: 110-31.

Arbia, G. 1989. *Spatial data configuration in statistical analysis of regional economic and related problems*. Boston: Kluwer Academic.

Armstrong, H. 1995a. An appraisal of the evidence from cross-sectional analysis of the regional growth process within the European Union. In *Convergence and divergence among European Regions*, ed. H. Armstrong and R. Vickerman. London: Pion.

———. 1995b. Convergence among the regions of the European Union. *Papers in Regional Science* 74: 143-52.

Azariadis, C., and A. Drazen. 1990. Threshold externalities in economic development. *Quarterly Journal of Economics* 105: 501-26.

Bailey, T., and A. C. Gatrell. 1995. *Interactive spatial data analysis*. Longman, UK: Harlow.

Baller, R. D., L. Anselin, S. F. Messner, G. Deane, and D. F. Hawkins. 2001. Structural covariates of U.S. county homicide rates: Incorporating spatial effects. *Criminology* 39: 561-90.

Barro, R. J., and X. Sala-i-Martin. 1991. Convergence across states and regions. *Brookings Papers on Economic Activity* 1991: 107-82.

———. 1992. Convergence. *Journal of Political Economy* 100: 223-51.

———. 1995. *Economic growth theory*. Boston: McGraw-Hill.

Baumol, W. J. 1986. Productivity growth, convergence and welfare: What the long run data show. *American Economic Review* 76: 1072-85.

Beine, M., and P. Jean-Pierre. 2000. L'apport des tests de racine unitaire en panel à l'identification des clubs de convergence. In *Croissance et convergence économiques des régions: Théorie, faits et déterminants*, ed. M. Beine and F. Docquier. Brussels, Belgium: De Boeck Université.

Bernard, A. B., and S. N. Durlauf. 1995. Convergence in international output. *Journal of Applied Econometrics* 10: 97-108.

———. 1996. Interpreting tests of the convergence hypothesis. *Journal of Econometrics* 71: 161-73.

Breusch, T., and A. Pagan. 1979. A simple test for heteroskedasticity and random coefficient variation, *Econometrica* 47: 1287-94.

Brundson, C., A. S. Fotheringham, and M. Charlton. 1999. Some notes on parametric significance tests for geographically weighted regression. *Journal of Regional Science* 39: 497-524.

Burridge, P. 1981. Testing for a common factor in a spatial autoregression model. *Environment and Planning Series A* 13: 795-800.

Button, K. J., and E. J. Pentecost. 1995. Testing for convergence of the EU regional economies. *Economic Inquiry* 33: 664-71.

Carlino, G., and L. Mills. 1993. Are US regional incomes converging? *Journal of Monetary Economics* 32: 335-46.

———. 1996a. Convergence and the US states: A time-series analysis. *Journal of Regional Science* 36: 597-616.

———. 1996b. Testing neoclassical convergence in regional incomes and earnings. *Regional Science and Urban Economics* 26: 565-90.

Case, A., H. S. Rosen, and J. R. Hines. 1993. Budget spillovers and fiscal policy interdependence: Evidence from the states. *Journal of Public Economics* 52: 285-307.

Caselli, F., G. Esquivel, and F. Lefort. 1996. Reopening the convergence debate: A new look at cross-country growth empirics. *Journal of Economic Growth* 1: 363-90.

Cheshire, P., and G. Carbonaro. 1995. Convergence-divergence in regional growth rates: An empty black box? In *Convergence and divergence among European regions*, ed. H. Armstrong and R. Vickerman. London: Pion.

Chua, H. B. 1993. On spillovers and convergence. Ph.D. diss., Harvard University, Cambridge, MA.

Cliff, A. D., and J. K. Ord . 1981. *Spatial processes: Models and applications.* London: Pion.

Conley, T. G. 1999. GMM estimation with cross sectional dependence. *Journal of Econometrics* 92: 1-45.

Conley, T. G., F. Flyer, and G. Tsiang. 2003. Local market human capital and the spatial distribution of productivity in Malaysia. *Advances in Economic Analysis & Policy* [online], 3: article 5.

Conley, T. G., and E. A. Ligon. 2002. Economic distance, spillovers, and cross-country comparisons. *Journal of Economic Growth* 7: 157-87.

DeLong, J. B. 1988. Productivity growth, convergence and welfare: Comment. *American Economic Review* 78: 1138-54.

DeLong J. B., and L. H. Summers. 1991. Equipment investment and economic growth. *Quarterly Journal of Economics* 106: 445-502.

Doreian, P. 1980. Linear models with spatially distributed data, spatial disturbances or spatial effects. *Sociological Methods & Research* 9: 29-60.

Durlauf, S. N., and P. A. Johnson. 1995. Multiple regimes and cross-country growth behaviour. *Journal of Applied Econometrics* 10: 365-84.

Durlauf, S. N., and D. Quah. 1999. The new empirics of economic growth. In *Handbook of macroeconomics*, ed. J. Taylor and M. Woodford. Amsterdam: North-Holland Elsevier Science.

Easterly, W., and R. Levine. 1998. Troubles with neighbors: Africa's problem, Africa's opportunity. *Journal of African Economies* 7: 120-42.

European Commission. 1996. *First report on economic and social cohesion*. Luxembourg: Official Publication Office.

———. 1999. *The European regions: Sixth periodic report on the socio-economic situation in the regions of the European Union.* Luxembourg: Official Publication Office.

Eurostat. 1999. *Regio database, user's guide, methods and nomenclatures*. Luxembourg: Official Publication Office.

Evans, P., and G. Karras. 1996. Convergence revisited. *Journal of Monetary Economics* 37: 249-65.

Fingleton, B. 1999. Estimates of time to economic convergence: An analysis of regions of the European Union. *International Regional Science Review* 22: 5-34.

Florax, R., and H. Folmer. 1992. Specification and estimation of spatial linear regression models: Monte-Carlo evaluation of pre-test estimator. *Regional Science and Urban Economics* 22: 405-32.

Florax, R., H. Folmer, and S. Rey. 2003. Specification searches in spatial econometrics: The relevance of Hendry's methodology. *Regional Science and Urban Economics* 33: 557-79.

Friedman, M. 1992. Do old fallacies ever die? *Journal of Economic Literature* 30: 2129-32.

Fujita, M., P. Krugman, and A. J. Venables. 1999. *The spatial economy*. Cambridge, MA: MIT Press.

Galor, O. 1996. Convergence? Inference from theoretical models. *Economic Journal* 106: 1056-69.

Getis, A., and D. A. Griffith. 2002. Comparative spatial filtering in regression analysis. *Geographical Analysis* 34: 130-40.

Haining, R. 1990. *Spatial data analysis in the social and environmental sciences*. Cambridge: Cambridge University Press.

Hendry, D. F. 1979. Predictive failure and econometric modelling in macroeconomics: The transactions demand for money. In *Economic modeling*, ed. P. Ormerod. London: Heinemann.

Islam, N. 1995. Growth empirics: A panel data approach. *Quarterly Journal of Economics* 110: 1127-70.

Jarque, C. M., and A. K. Bera. 1987. A test for normality of observations and regression residuals. *International Statistical Review* 55: 163-72.

Kelejian, H. H., and I. R. Prucha. 1999. A generalized moments estimator for the autoregressive parameter in a spatial model. *International Economic Review* 40: 509-34.

King, G. 1997. *A solution to the ecological inference problem: Reconstructing individual behavior from aggregate data*. Princeton, NJ: Princeton University Press.

Krugman, P. 1991. Increasing returns and economic geography. *Journal of Political Economy* 99: 483-99.

Le Gallo J. 2004. Space-time analysis of GDP disparities among European regions: A Markov chains approach. *International Regional Science Review* 27: 138-65.

Le Gallo, J., and C. Ertur C. 2003. Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980-1995. *Papers in Regional Science* 82: 175-201.

Le Gallo, J., C. Ertur, and C. Baumont. 2003. A spatial econometric analysis of convergence across European regions, 1980-1995. In *European regional growth*, ed. B. Fingleton. Berlin: Springer-Verlag.

Levine, R., and D. Renelt D. 1992. A sensitivity analysis of cross-country growth regressions. *American Economic Review* 82: 942-63.

López-Bazo, E., E. Vayá, A. Mora, and J. Suriñach. 1999. Regional economic dynamics and convergence in the European Union. *Annals of Regional Science* 33: 343-70.

Mankiw, N. G. 1995. The growth of nations. *Brooking Papers on Economic Activity* 1: 275-310.

Mankiw, N. G., D. Romer, and D. N. Weil. 1992. A contribution to the empirics of economic growth. *Quarterly Journal of Economics* 107: 407-37.

Manski, C. F. 1993. Identification of endogenous social effects: The reflection problem. *Review of Economic Studies* 60: 531-42.

Maurseth, B. 2001. Convergence, geography and technology. *Structural Change and Economic Dynamics* 12: 247-76.

McMillen, D. P. 1992. Probit with spatial autocorrelation. *Journal of Regional Science* 32: 335-48.

Molle, W. 1980. *Regional disparity and economic development in the European Community*. Farnborough, UK: Saxon House.

Moreno, R., and B. Trehan. 1997. Location and growth of nations. *Journal of Economic Growth* 2: 399-418.

Neven, D., and C. Gouyette. 1995. Regional convergence in the European Community. *Journal of Common Market Studies* 33: 47-65.

Newey, W. K., and J. D. West. 1987. A simple positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55: 703-8.

Openshaw, S., and P. Taylor. 1979. A million or so correlation coefficient: Three experiments on the modifiable areal unit problem. In *Statistical applications in the spatial science*, ed. N. Wrigley. London: Pion.

Quah, D. 1993a. Empirical cross-section dynamics in economic growth. *European Economic Review* 37: 426-34.

———. 1993b. Galton's fallacy and tests of the convergence hypothesis. *Scandinavian Journal of Economics* 95: 427-43.

———. 1996a. Empirics for economic growth and convergence. *European Economic Review* 40: 1353-75.

———. 1996b. Regional convergence clusters across Europe. *European Economic Review* 40: 951-58.

———. 1996c. Twin peaks: Growth and convergence in models of distribution dynamics. *Economic Journal* 106: 1045-55.

———. 1997. Empirics for growth and distribution: Stratification, polarization and convergence clubs. *Journal of Economic Growth* 2: 27-59.

Rey, S. J., and B. D. Montouri. 1999. U.S. regional income convergence: A spatial econometric perspective. *Regional Studies* 33: 145-56.

Rietveld P., and P. Wintershoven. 1998. Border effects and spatial autocorrelation in the supply of network infrastructure. *Papers in Regional Science* 77: 265-76.

Sala-i-Martin, X. 1996a. The classical approach to convergence analysis. *Economic Journal* 106: 1019-36.

———. 1996b. Regional cohesion: Evidence and theories of regional growth and convergence. *European Economic Review* 40: 1325-52.

Schwarz, G. 1978. Estimating the dimension of a model. *Annals of Statistics* 6: 461-64.

Solow, R. M. 1956. A contribution to the theory of economic growth. *Quarterly Journal of Economics* 70: 65-94.

Summers, R., and A. Heston. 1988. A new set of international comparisons of real product and price levels estimates for 130 countries, 1950-1985. *Revue of Income and Wealth* 34: 1-25.

Temple, J. 1999. The new growth evidence. *Journal of Economic Literature* 37: 112-56.

White, H. 1980. A heteroskedastic-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48: 817-38.