EVALUATING THE TEMPORAL AND THE SPATIAL HETEROGENEITY OF THE EUROPEAN CONVERGENCE PROCESS, 1980-1999*

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October 2003

* A previous version of this paper has been presented at the 50th North American Meetings of the Regional Science Association International (RSAI), Philadelphia, November 20-22, 2003. We would like to thank J.P. LeSage and J. Paelinck for their valuable comments as well as all the participants at this meeting. The usual disclaimer applies.

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Abstract

In this paper, we suggest a general framework that allows testing simultaneously for temporal heterogeneity, spatial heterogeneity and spatial autocorrelation in β*-convergence models. Based on a sample of 145 European regions over the 1980-1999 period, we estimate a Seemingly Unrelated Regression model with spatial regimes and spatial autocorrelation for two sub-periods: 1980-1989 and 1989-1999. The assumption of temporal independence between the two periods is rejected and the estimation results highlight the presence of spatial error autocorrelation in both sub-periods and spatial instability in the second sub-period, indicating the formation of a convergence club between the peripheral regions of the European Union.*

Keywords: β-convergence models, spatial autocorrelation, convergence clubs, temporal instability

JEL Classification: C14, O52, R11, R15

1. INTRODUCTION

The convergence of European regions has been widely studied in the macroeconomic and regional science literature, using β-convergence models based on neo-classical specifications. The results of empirical analyses first reveal that the speed of the convergence process between the European regions decreased after the 70s (Barro and Sala-I-Martin, 1992; Armstrong, 1995a; Neven and Gouyette, 1995). Second, GDP disparities are persistent despite the integration process and the massive amount of structural funds transferred to the poorer regions of the European Union (EU) since their reform in 1989. A core-periphery pattern is therefore still relevant to describe the spatial distribution of activities in the European Union (Lopez-Bazo et al., 1999; Le Gallo and Ertur, 2003; Dall'erba, 2003). Third, GDP per capita remains strongly spatially concentrated (Fingleton, 1999).

These results may reveal the presence of three phenomena, which so far have been investigated separately. First, the convergence process is *unstable over time*. Second, the core-periphery pattern occuring in the European regions is representative of *spatial heterogeneity* and may imply the presence of convergence clubs in Europe. Third, the distribution of per capita GDP is *spatially autocorrelated*.

On the one hand, capturing the temporal instability of the convergence process has usually been investigated by performing a series of cross-sections for several sub-periods (Barro and Sala-I-Martin, 1992; Armstrong, 1995a; Neven and Gouyette, 1995). However, these studies fail to capture the temporal interdependence that may exist between the different sub-periods. On the other hand, taking into account spatial heterogeneity and spatial autocorrelation necessitates the use of the tools of spatial statistics and econometrics (Anselin, 1988a, 2001). Our aim in this paper is to investigate all these issues and to suggest a general framework that allows testing simultaneously for temporal instability, spatial heterogeneity and spatial autocorrelation in β-convergence models. This aim is achieved by estimating a

SUR model for two-different subperiods, with spatial autocorrelation and spatial regimes in each subperiods.

The paper proceeds as follows: section 2 provides some insights into the β-convergence model and spatial effects upon which the empirical estimations described in the following sections relies. Section 3 presents the data and weight matrix. In Section 4, exploratory spatial data analysis (ESDA) is used to detect spatial autocorrelation and spatial heterogeneity among European regional GDP. These two spatial effects are then included in the estimation of a β-convergence model in a SUR specification over two sub-periods: 1980-1989 and 1989-1999. The last section concludes.

2. β-CONVERGENCE MODELS WITH TEMPORAL HETEROGENEITY, SPATIAL HETEROGENEITY AND SPATIAL AUTOCORRELATION

Absolute and conditional β*-convergence*

Since the seminal articles of Barro and Sala-i-Martin (1991, 1992, 1995), numerous studies have examined β–convergence between different countries and regions[i]. This concept is linked to the neoclassical growth model, which predicts that the growth rate of a region is positively related to the distance that separates it from its steady-state. Empirical evidence for β-convergence has usually been investigated by regressing growth rates of GDP on initial levels. Two cases are usually considered in the literature.

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

(1) $$\mathbf{g} = \alpha \mathbf{S} + \beta \mathbf{y_0} + \boldsymbol{\varepsilon} \qquad \boldsymbol{\varepsilon} \sim N(0, \sigma_\varepsilon^2 \mathbf{I})$$

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

The concept of *conditional* β–convergence is used when the assumption of similar steady-states is relaxed. In this case, a matrix of variables, maintaining constant the steady state of each economy is added to (1). Based on these two concepts, the convergence process can then be characterized by two additional parameters using the estimated β coefficient. First, the convergence speed may be defined as: $b = -\ln(1+T\beta)/T$. Second, the half-life is the time necessary for the economies to fill half of the variation, which separates them from their steady state, and is defined by: $\tau = -\ln(2)/\ln(1+\beta)$.

Both β-convergence concepts have been heavily criticized on theoretical and methodological grounds. For example, Friedman (1992) and Quah (1993) show that β-convergence tests may be plagued by Galton's fallacy of regression toward the mean. Furthermore, they face several methodological problems such as heterogeneity, endogeneity, and measurement problems (Durlauf and Quah, 1999; Temple, 1999). This paper points out three additional issues that need to be addressed: the temporal stability of the convergence process, the possibility of spatial regimes implying the presence of convergence clubs and the presence of spatial autocorrelation.

Temporal stability of the convergence process

Several studies estimate separate β-convergence models for sub-periods of their sample. For example, Barro and Sala-I-Martin (1992) and Armstrong (1995a) use sub-periods of 10 years each between 1950 and 1990. Neven and Gouyette (1995) consider two sub-periods: 1980-1985 and 1985-1989. This decomposition allows the authors to detect different patterns of the convergence process and its evolution over a longer time period. For example, Armstrong (1995a) shows that the speed of convergence between 85 European regions was about 2% for the periods 1950-1960 and then fell during the following periods 1960-1970 and 1970-1990.

However, all these papers perform a series of cross-sections assuming temporal independence of the errors between the different equations. This assumption should be tested and we suggest using instead Seemingly Unrelated Regressions (SUR) allowing for temporal interdependence between the different β-convergence regressions.

Spatial stability and convergence clubs

While absolute β-convergence is frequently rejected for large samples of countries and regions, it is usually accepted for more restricted samples of economies belonging to the same geographical area (Sala-I-Martin, 1996). This observation can be linked to the presence of convergence clubs. In other words, there isn't only one steady-state, to which all economies converge. Rather, there may be multiple, locally stable, steady state equilibria (Durlauf and Johnson, 1995). Therefore, a convergence club is a group of economies whose initial conditions are near enough to converge toward the same long-term equilibrium.

The main problem is to determine those clubs. While some authors select *a priori* criteria (as for example GDP per capita cut-offs, see Durlauf and Johnson, 1995), most prefer the use of endogenous methods, as polynomial functions (Chatterji, 1992) or regression trees (Durlauf and Johnson, 1995; Berthélemy and Varoudakis, 1996).

Regional economies are often characterized by strong geographic patterns, as the core-periphery pattern. The latter is representative of *spatial heterogeneity*. More generally, spatial heterogeneity means that economic behaviors are not stable over space. In a regression model, spatial heterogeneity can be reflected by varying coefficients, i.e. structural instability, or by varying error variances across observations, i.e. groupwise heteroskedasticity, or both. The presence of spatial heterogeneity in a sample could be representative of the presence of spatial convergence clubs. Therefore, as we will argue in section 4, they can be detected using exploratory spatial data analysis, which relies on geographic criteria.

Spatial autocorrelation

The last effect that should be tested when dealing with convergence processes is spatial autocorrelation. This effect is highly relevant in Europe since spatial concentration of economic activities in European regions has already been documented (Lopez-Bazo et al., 1999, Le Gallo and Ertur, 2003; Dall'erba, 2003). Some β-convergence studies take into account spatial interdependence between regions[ii].

Integrating spatial autocorrelation into β-convergence models is useful for three reasons. First, from an econometric point of view, the underlying hypothesis in OLS estimations is based on the independence of the error, which may be very restrictive and should be tested since, if it is rejected, the statistical inference based on it is not reliable. Second, it allows capturing geographic spillover effects between European regions using different spatial econometric models: the spatial lag model, the spatial error model or the spatial cross-regressive model (Rey and Montouri, 1999; Le Gallo et al., 2003). Third, spatial autocorrelation allows accounting for variations in the dependent variable arising from latent or unobservable variables. Indeed, in the case of β-convergence models, the appropriate choice of these explanatory variables may be problematic because it is not possible to be sure conceptually that all the variables differentiating steady states are included[iii]. Furthermore, data on some of these explanatory variables may not be easily accessible and/or reliable. Spatial autocorrelation may therefore act as a proxy to all these omitted variables and catch their effects. This is particularly useful in the case of European data, where explanatory variables are scarce (Fingleton, 1999).

3. DATA AND SPATIAL WEIGHT MATRIX

The regional per capita GDP series come from the most recent version of the NewCronos Regio database by Eurostat. This is the official database used by the European Commission for its evaluation of regional convergence. We use the logarithms of the per capita GDP of each region over the 1980-1999 period. Our sample is composed of 145 regions at NUTS II level (Nomenclature of Territorial Units for Statistics) over 12 EU countries: Belgium (11 regions), Denmark (1 region), Germany (30 regions, Berlin and the nine former East German regions are excluded due to historical reasons), Greece (13 regions), Spain (16 regions, as we exclude the remote islands: Las Palmas, Santa Cruz de Tenerife Canary Islands and Ceuta y Mellila), France (22 regions), Ireland (2 regions), Italy (20 regions), Netherlands (12 regions), Portugal (5 regions, the Azores and Madeira are excluded because of their geographical distance), Luxembourg (1 region), United Kingdom (12 regions, we use regions at the NUTS I level, because NUTS II regions are not used as governmental units, they are merely statistical inventions of the EU Commission and the UK government).

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

Distance-based weight matrices are defined as:

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

where w_{ij}^* is an element of the unstandardized weight matrix; w_{ij} is an element of the standardized weight matrix **W**; d_{ij} is the great circle distance between centroids of region *i* and *j*; $D(1) = Q1$, $D(2) = Me$ and $D(3) = Q3$, $Q1$, Me and $Q3$ are respectively the lower quartile, the median and the upper quartile of the great circle distance distribution. $D(k)$ is the cutoff parameter for $k = 1,...3$ above which interactions are assumed negligible. Each matrix is row standardized so that it is relative and not absolute distance that matters.

4. SPATIAL REGIMES AND CONVERGENCE CLUBS IN EUROPE

Few authors have tried to detect convergence clubs between the European regions. The methods that are applied are very diverse and lead to contrasted results. For exemple, Neven and Gouyette (1995) define *a priori* 2 regimes: Northern regions and Southern regions. They detect a convergence process between the southern regions on the period 1980-1985 and between the northern regions on the period 1985-1989. Armstrong (1995b) and Dewhurst and Mutis-Gaitan (1995) use polynomial functions to detect possible convergence clubs. Considering respectively the German region *Hamburg* and the French capital region *Ile-de-France* as the leader they conclude that no convergence club exists between the European regions. However, Armstrong (1995b) admits that these results could be modified with a higher degree of spatial desegregation and more observations (his sample only contains 85 observations). Finally, Fagerberg and Verspagen (1996), by using the regression tree method on 4 different variables, detect three convergence clubs. However, their sample is small (72 regions) and all the poor regions of Greece, Spain and Portugal are not taken into account.

Facing these results, it appears interesting to analyze the convergence clubs in Europe using a bigger sample. Moreover, we explicitly take into account the spatial dimension of the data that is neglected in all these studies. In that purpose, we use *Exploratory Spatial Data Analysis* (ESDA), in order to detect spatial regimes in our sample, which we will interpret as spatial convergence clubs. Note that another attempt to detect spatial regimes using ESDA already exists. Indeed, Baumont et al. (2003) use Moran scatterplots (Anselin, 1996) to determine the spatial clubs: Moran scatterplots imply that the "atypical"[iv] regions must be dropped out of the sample (in their case, three regions are eliminated). However, in our study, this methodology would imply eliminating 9 regions. Therefore, we use Getis-Ord statistics (Ord and Getis, 1995) in order to be able to work with the entire sample. The G_i^* statistics are computed on the regional per capita GDP values in 1980[v].

These statistics are defined as follows:

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

where w_{ij} is an element of the weight matrix **W**; $W_i^* = \sum_{j \neq i} w_{ij} + w_{ii}$; n is the size of the sample; $S_{1i}^* = \sum_j w_{ij}^2$, $\bar{x}$ and s^2 are the usual sample mean and variance. These statistics are computed for each region and they allow detecting the presence of local spatial autocorrelation: a positive value of this statistic for region *i* indicates a spatial cluster of high values, whereas a negative value indicates a spatial clustering of low values around region *i*. Based on these statistics, we determine our spatial regimes using the following rule: if the statistic for region *i* is positive, then this region belongs to the group of "rich" regions and if the statistic for region *i* is negative, then this region belongs to the group of "poor" regions.

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

- 96 regions belong to the spatial regime “Core”:

Belgium, Germany, Denmark, France, Italy (but Umbria, Marche, Lazio, Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna), Luxembourg, the Netherlands, the United-Kingdom (but Northern-Ireland and Scotland).

- 49 regions belong to the spatial regime “Periphery”:

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

The presence of spatial heterogeneity in our sample may reflect the presence of two convergence clubs. This should be confirmed with a confirmatory analysis with the framework of β-convergence models. The next section undertakes this task and considers in addition the other two methodological issues mentioned previously: temporal instability and spatial autocorrelation.

5. ESTIMATING THE EVOLUTION OF THE CONVERGENCE PROCESSS BETWEEN EUROPEAN REGIONS OVER 1980-1999

Estimation of β*-convergence using SUR models*

In our period of study, 1980-1999, several events may have affected the process of convergence at work between the European regions, as, for example, the entry of poor countries in the EU during the 80s (Greece in 1981, Portugal and Spain in 1986). Also, the reform of structural funds, decided in 1988 and implemented in 1989, induced massive transfers of regional aids, with the aim of helping the poor regions to converge to the European mean. All these reasons lead us to believe that the convergence process between the 145 European regions of our sample may be different at the beginning and at the end of our study period. In order to test this assumption and given the length of our study period, we estimate two β-convergence equations for both periods 1980-1989 and 1989-1999. Note that this choice of cut-off point does not imply that we are testing the impact of structural funds on the convergence process, since this would imply a more formal econometric test[vi]. Instead, our aim is to evaluate the temporal instability of the convergence process.

Formally, we use a spatial SUR model (Anselin, 1988a, 1988b) where one β-convergence equation is estimated for each time period and both equations are estimated simultaneously using Feasible Generalized Least Squares (FGLS) or maximum likelihood (ML). In a spatial SUR framework, the regression coefficients are assumed to be constant over space, but vary for each time period, here 1980-1989 and 1989-1999:

$$\mathbf{g}_t = \alpha_t \mathbf{S} + \beta_t \mathbf{y}_{\mathbf{0},t} + \boldsymbol{\varepsilon}_t \quad \text{with} \quad t = 1,2 \tag{4}$$

where $t=1$ corresponds to the period 1980-1989, $t=2$ corresponds to the period 1989-1999, $\mathbf{g}_t$ is the $(n\times1)$ vector of average growth rates of per capita GDP for period t; $\mathbf{S}$ is the $(n\times1)$ sum vector; $\mathbf{y}_{\mathbf{0},t}$ is the vector of log per capita GDP levels at the initial date (1980 for $t=1$ and 1989 for $t=2$); α_t and β_t with $t=1,2$ are the four unknown parameters to be estimated. There is absolute β–convergence in period t when the estimate of β_t is significantly negative. Moreover, as one equation is specified for each period, this technique allows testing the hypothesis of constant parameters between time periods, i.e. the *temporal* stability of the convergence process. This is performed using Wald statistics.

The error terms are allowed to be correlated between time periods, such as: $E\left[\varepsilon_{it}\varepsilon_{is}\right]=\sigma_{ts}$ with $i=1,...N$; $s,t=1,2$ and or in matrix form:

(5) $$E\left[\varepsilon_t\varepsilon_s^{'}\right]=\sigma_{ts}\mathbf{I_N} \quad \text{with} \quad s,t=1,2$$

This equation means that interdependence between each equation (β-convergence model) is allowed for via the error term. This assumption of dependence between equations can also be tested by means of a Lagrange Multiplier test or a likelihood ratio test of the diagonality of the error covariance matrix.

In equation (4), the coefficients are assumed to be constant in space in each equation. However, as stated in section 4, there may be some evidence for spatial convergence clubs that should be tested formally. In that purpose, a specification allowing for spatial regimes (Core and Periphery) in each equation should also be considered:

(6) $$\mathbf{g}_t=\alpha_{C,t}D_C+\alpha_{P,t}D_P+\beta_{C,t}D_C\mathbf{y}_{\mathbf{0},t}+\beta_{P,t}D_P\mathbf{y}_{\mathbf{0},t}+\boldsymbol{\varepsilon}_t \quad \text{with} \quad t=1,2$$

where the subscribe C stands for the core regime and the subscribe P stands for the peripheral regime; D_C and D_P are dummy variables corresponding respectively to the core and periphery regimes previously defined; $\alpha_{C,t}$, $\alpha_{P,t}$, $\beta_{C,t}$, $\beta_{P,t}$ with $t=1,2$, are the eight unknown parameters to be estimated. This specification allows the convergence process to be different across regimes for each time period.

Again, the hypothesis of temporal stability of the coefficients can be tested using this specification using a Wald statistics. In this case, the assumptions to be tested are the following:

(7) $$\begin{cases}\alpha_{C,1}=\alpha_{C,2}\\ \alpha_{P,1}=\alpha_{P,2}\\ \beta_{C,1}=\beta_{C,2}\\ \beta_{P,1}=\beta_{P,2}\end{cases}$$

Moreover, since the coefficients are differentiated by regime in each equation, a second test has to be performed, i.e. the test of *spatial* stability of the convergence process in each time period. In other words, we test the following assumptions:

(8)
$$\alpha_{C,t} = \alpha_{P,t} \quad \text{with} \quad t = 1,2$$
$$\beta_{C,t} = \beta_{P,t} \quad \text{with} \quad t = 1,2$$

All these tests can also be performed using Wald statistics.

Finally, spatial autocorrelation can be introduced in this framework, either in the form of a spatial lag or in the form of a spatial error. In the former case, a spatial lag of the form $\rho_t \mathbf{W}\mathbf{g}_t$ is introduced in each equation, ρ_t indicating the extent of spatial correlation in the dependent variable in each equation. In the latter case, the error terms are written for each equation in the system as follows:

(9)
$$\boldsymbol{\varepsilon}_t = \lambda_t \mathbf{W}\boldsymbol{\varepsilon}_t + \mathbf{u}_t \quad \text{with} \quad E\left[\mathbf{u}_t \mathbf{u}_s^{'}\right] = \sigma_{ts}\mathbf{I_N}$$

where λ_t is a coefficient indicating the extent of spatial correlation between the residuals. These two models are estimated by ML. Moreover, two Lagrange Multiplier tests, LMERR for spatial error and LMLAG for spatial lag, can be computed on the residuals of models (4) or (6) in order to discriminate between them (Anselin, 1988a, 1988b). Moreover, as in equations (4) or (6), the temporal stability of the coefficients (α_t and/or β_t) and of the spatial coefficients (ρ_t or λ_t) can be tested, as well as the spatial stability of the coefficients in each equation. However, due to the presence of spatial autocorrelation, the Wald tests used in this case must be adjusted for spatial autocorrelation (see Anselin, 1990, for details on the form of the statistics in this case).

Estimation results

Let us take as a starting point the ML estimation results of model (4)[vii]. They are displayed in the second and third columns of table (1). It appears that in both sub-periods, the coefficients associated to the initial per capita GDP are significant and negative: $\hat{\beta}_1 = -0.015$ for 1980-1989 and $\hat{\beta}_2 = -0.016$ for 1989-1999, which confirms the hypothesis of convergence between the European regions. The speed of convergence is 1.65% for the first sub-period and 1.78% for the second sub-period, they are quite close to the 2% usually found in the convergence literature (Barro and Sala-I-Martin, 1991, 1992).

As far as specification diagnostics are concerned, it appears that the SUR specification does not seem to be justified for our sample. Indeed, we cannot reject the hypothesis of temporal homogeneity of both the constant and the beta coefficients across the two equations since none of the associated temporal homogeneity tests is significant (resp. *p*-value= 0.817 and 0.794). Therefore, the convergence process does not seem to be different between the two sub-periods considered. Moreover, both the LM and LR tests of diagonality of the variance-covariance matrix are non significant, implying independence between the two β-convergence equations.

However, these tests should be considered with caution. Indeed, the two Lagrange multiplier tests for spatial error (LMERR) and spatial lag (LMLAG) reject their respective null hypothesis of absence of spatial autocorrelation. To determine the form taken by spatial autocorrelation, we compare the significance levels of the two tests, as in a cross-sectional setting (Anselin and Florax, 1995; Florax et al., 2003). Since LMERR is more significant than LMLAG, then the SUR model with spatial autocorrelation error terms in each equation as in (9) is the most appropriate specification. Therefore, the SUR model appears to be misspecified and all inference based on it is unreliable.

[Table 1 about here]

The ML estimation results of the SUR model with spatial error autocorrelation are displayed in the fourth and fifth columns of table 1. It appears that both coefficients associated to the initial per capita GDP are still negative and significant and that the convergence speeds have decreased. The Wald test on spatial dependence is strongly significant: there is positive and significant spatial error autocorrelation in each equation ($\hat{\lambda}_1 = 0.853$ and $\hat{\lambda}_2 = 0.793$). However, even if the LR test of diagonality rejects the null assumption of independence of the two equations, the SUR specification still doesn't appear to be the best specification: the hypothesis of temporal stability of the coefficients (including the spatial coefficients) cannot be rejected. Following the evidence depicted in section 4, all these results should nevertheless be reassessed by allowing spatial regimes in each equation.

The ML estimation results of equation (6) are displayed in columns 2 to 5 of table 2. Several results are worth mentioning. First, only the beta coefficient for the peripheral regime in the second sub-period is negative and significant (p-value = 0.000). The associated convergence speed in this case is 3.86%, which is much higher than in the previous model without spatial regimes. Concerning the specification diagnostics, it appears that the hypothesis of independence between the two equations cannot be rejected. Moreover, two kinds of stability tests can be performed in this model. First, the Wald tests on the temporal stability of the coefficients across equations are displayed in the second column of table 3. Only the constant and the beta coefficient in the peripheral regime can be considered as significantly different across periods. Second, the Wald tests on the spatial stability of the coefficients in each equation are displayed in the second column of table 4. It appears that in each equation, the constant and the beta coefficient are significantly different across regimes.

However, as in the SUR model without spatial regimes, all these results are not reliable since the LMERR test indicates the presence of omitted spatial autocorrelation.

[Tables 2, 3 and 4 about here]

The final model we estimate is therefore a SUR model with spatial regimes as in (6) and spatially correlated errors as in (9). The ML estimation results are displayed in columns 6 to 9 of table 2. Concerning the convergence process, the beta coefficients for the peripheral regime are negative and significant for both sub-periods (p-value = 0.042 for $\hat{\beta}_{P,1}$ and p-value = 0.000 for $\hat{\beta}_{P,2}$). Spatial error autocorrelation is strongly significant and positive (p-value = 0.000). As pointed in section 2, omitted variables may be at the origin of the presence of spatial autocorrelation: since the dataset we are using does not allow controlling for the determinants of the steady state per capita GDP, spatial autocorrelation may act as a proxy to all the omitted variables. Spatial autocorrelation in this case implies the presence of positive growth spillovers between European regions. Moreover, taking into account spatial autocorrelation has strongly modified some of the previous results. First, the hypothesis of independence between the two equations is now rejected at 5% (p-value = 0.039). Second, only the beta coefficient in the peripheral regime can be considered as significantly different at 10% across periods (p-value= 0.075, see table 3). Third, the constant and the beta coefficient are now significantly different across regimes only in the second sub-period (see table 4).

Finally, it appears that the best model is a SUR model with no spatial regime in the first sub-period and spatial regimes in the second sub-period. From an economic point of view, these results have two important interpretations. First, since there are no spatial regimes in the first sub-period, then it means that all regions converge to the same steady state over 1980-1989. Second, since spatial regimes cannot be rejected in the second sub-period then the convergence process is spatially differentiated over 1989-1999: while the peripheral regions converge to a common steady state level of per capita GDP, such a convergence process does not exist between the regions of the core. This could reflect the formation of a convergence club in Europe among peripheral regions at the end of the period and a polarization process across the whole European regions[viii].

5. CONCLUSION

The aim of this paper is to suggest a general framework that allows testing simultaneously for temporal heterogeneity, spatial heterogeneity and spatial autocorrelation in β-convergence models. An application is provided using a sample of 145 European regions over the 1980-1999 period.

In order to assess how the regional convergence process has evolved over that period, we decompose it into two subperiods, 1980-1989 and 1989-1999, and estimate a β-convergence model using a SUR specification allowing for temporal dependence between the two sub-periods. Moreover, we include spatial effects, spatial autocorrelation and spatial heterogeneity, in this SUR specification. In that purpose, Getis-Ord statistics are used to detect the presence of significant local spatial autocorrelation in the form of two regimes representative of the well-known core-periphery pattern (Krugman 1991a, 1991b; Fujita et al., 1999). Then, two Lagrange multiplier tests aimed at including the presence of significant spatial effects in our model lead to a SUR model with spatial error autocorrelation.

Three points are worth mentioning. First, several tests (diagonality test of variance-covariance matrix, spatial and temporal stability tests) point to different results whether or not spatial autocorrelation is taken into account. Therefore, a careful attention should be given to spatial autocorrelation in β-convergence models in order to have reliable results and inference. Second, we showed that the assumption of temporal independence between β-convergence models at different sub-periods is rejected. This assumption should therefore be considered carefully when performing a series of cross-sections. Third, the spatial stability tests indicate that the convergence process between European regions becomes spatially differentiated in the second sub-period while no spatial regimes can be detected in the first sub-period. This result may indicate the formation of a convergence club between the peripheral regions at the end of the period.

In conclusion, three aspects are important when considering the convergence process between European regions: temporal instability of the convergence process, spatial instability under the form of different convergence clubs and spatial autocorrelation implying positive growth spilloversbetween regions. All these results are of course dependent of the sample and period used in this study. They should be reassessed using a larger number of regions and a longer period of time. This is left for future research.

NOTES

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

[ii] See for example the following papers: Armstrong (1995a), Moreno and Trehan (1997), Fingleton (1999, 2001, 2003), Rey and Montouri (1999), Lall and Shalizi (2003), Le Gallo et al. (2003).

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

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

[v] Using the initial values of per capita GDP is necessary to avoid the selection bias problem that has been pointed out by De Long (1988).

[vi] This question is investigated in Cappelen et al. (2003) and Dall'erba and Le Gallo (2003).

[vii] All results were obtained using programs written in Python 2.2. They are available upon request from the authors.

[viii] All these results are robust when other cut-off points, 1988, 1990 and 1991 are chosen. They are available upon request from the authors.

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TABLE 1: Maximum likelihood estimation results of the SUR model of β-convergence for 1980-1989 and 1989-1999

ESTIMATION RESULTS				
	SUR model		**SUR model with spatial error**	
1	**2**	**3**	**4**	**5**
	1980-1989	***1989-1999***	***1980-1989***	***1989-1999***
$\hat{\alpha}$	0.206 (0.000)	0.198 (0.000)	0.166 (0.000)	0.152 (0.000)
$\hat{\beta}$	-0.015 (0.000)	-0.016 (0.000)	-0.010 (0.013)	-0.012 (0.000)
$\hat{\lambda}$	-	-	0.853 (0.000)	0.793 (0.000)
Convergence speed	1.65%	1.78%	1.07%	1.24%
Half-life	45 years	42 years	68 years	59 years
LIK	857.468		943.848	
TESTS				
LMERR	291.738 (0.000)		-	
LMLAG	274.820 (0.000)		-	
Wald test on spatial dependence	-		446.096 (0.000)	
Temporal homogeneity test on $\hat{\alpha}$	0.054 (0.817)		0.099 (0.752)	
Temporal homogeneity test on $\hat{\beta}$	0.068 (0.794)		0.086 (0.769)	
Temporal homogeneity test on $\hat{\lambda}$	-		0.568 (0.451)	
LM test of diagonality	2.425 (0.119)		-	
LR test of diagonality	2.764 (0.096)		4.960 (0.026)	

Notes: *p*-values are in brackets. *LIK* is value of the maximum likelihood function. *LMERR* and *LMLAG* stand for the Lagrange Multiplier test respectively for residual spatial autocorrelation and spatially lagged endogenous variable in a SUR model (Anselin, 1988b). The temporal coefficient stability tests are based on an asymptotic Wald statistics, distributed as χ^2 with 1 degree of freedom. In the SUR model with spatial error autocorrelation, the Wald statistics are spatially adjusted (Anselin, 1990). The LM and LR tests of diagonality stand respectively for the Lagrange Multiplier and the Likelihood Ratio test of diagonality of the error variance-covariance matrix.

TABLE 2: Maximum likelihood estimation results of the SUR model of β-convergence with spatial regimes for 1980-1989 and 1989-1999

ESTIMATION RESULTS								
	SUR model with spatial regimes				**SUR model with spatial error And spatial regimes**			
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
	1980-1989		***1989-1999***		***1980-1989***		***1989-1999***	
	Core	**Periph.**	**Core**	**Periph.**	**Core**	**Periph.**	**Core**	**Periph.**
$\hat{\alpha}$	0.231 (0.001)	0.040 (0.462)	0.102 (0.043)	0.337 (0.000)	0.114 (0.015)	0.205 (0.000)	0.050 (0.218)	0.315 (0.000)
$\hat{\beta}$	-0.182 (0.181)	0.005 (0.444)	-0.006 (0.232)	-0.032 (0.000)	-0.004 (0.360)	-0.014 (0.042)	-0.001 (0.789)	-0.029 (0.000)
$\hat{\lambda}$	-		-		0.844 (0.000)		0.772 (0.000)	
Convergence speed	-	-	-	3.86%	-	1.53%	-	3.48%
Half-life	-	-	-	21 years	-	48 years	-	23 years
LIK	870.739				952.678			
TESTS								
LMERR	271.681 (0.000)				-			
LMLAG	268.185 (0.000)				-			
Wald test on spatial dependence	-				387.743 (0.000)			
LM test of diagonality	0.242 (0.623)				-			
LR test of diagonality	0.339 (0.561)				4.278 (0.039)			

Notes: *p*-values are in brackets. *LIK* is value of the maximum likelihood function. *LMERR* and *LMLAG* stand for the Lagrange Multiplier test respectively for residual spatial autocorrelation and spatially lagged endogenous variable in a SUR model (Anselin, 1988b). The LM and LR tests of diagonality stand respectively for the Lagrange Multiplier and the Likelihood Ratio test of diagonality of the error variance-covariance matrix.

TABLE 3: Wald tests on the temporal stability of the coefficients in the SUR model with spatial regimes

	SUR model with spatial regimes	SUR model with spatial regimes and spatial error
$\hat{\alpha}_C$	2.181 (0.140)	1.236 (0.266)
$\hat{\alpha}_P$	19.238 (0.000)	2.194 (0.138)
$\hat{\beta}_C$	1.584 (0.208)	0.347 (0.555)
$\hat{\beta}_P$	12.398 (0.000)	3.158 (0.075)
$\hat{\lambda}$	-	0.724 (0.395)

Notes: *p*-values are in brackets. The temporal coefficient stability tests are based on an asymptotic Wald statistics, distributed as χ^2 with 1 degree of freedom. In the SUR model with spatial error autocorrelation, the Wald statistics are spatially adjusted (Anselin, 1990).

TABLE 4: Wald tests on the spatial stability of the coefficients in the SUR model with spatial regimes

		SUR model with spatial regimes	SUR model with spatial regimes and spatial error
1980-1989	$\hat{\alpha}$	4.659 (0.031)	1.418 (0.234)
	$\hat{\beta}$	5.242 (0.022)	1.143 (0.285)
1989-1999	$\hat{\alpha}$	14.173 (0.000)	15.127 (0.000)
	$\hat{\beta}$	14.872 (0.000)	15.034 (0.000)

Notes: *p*-values are in brackets. The spatial coefficient stability tests are based on an asymptotic Wald statistics, distributed as χ^2 with 1 degree of freedom. In the SUR model with spatial error autocorrelation, the Wald statistics are spatially adjusted (Anselin, 1990).