The European Enlargement process and regional convergence revisited: Spatial effects still matter

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Abstract
This paper has two main goals. First, it reconsiders regional growth and convergence processes in the context of the enlargement of the European Union to new member states. We show that spatial autocorrelation and heterogeneity still matter in a sample of 237 regions over the period 1993-2002. Spatial convergence clubs are defined using exploratory spatial data analysis and a spatial autoregressive model is estimated. We find strong evidence that the growth rate of per capita GDP for a given region is positively affected by the growth rate of neighbouring regions. The second objective is to test the robustness of the results with respect to non-normality, outliers and heteroskedasticity using two other methods: The quasi maximum Likelihood and the Bayesian estimation methods.

1. Introduction

For more than a decade, the study of the convergence process on the regional and international levels has been the centre of interest of regional science and macroeconomic literature. Areas extensively studied are US regions (Rey and Montoury, 1999; Miller and Genk, 2005) and European regions (EU-15) (López-Bazo *et al*, 1999; Carrington, 2003; Ramajo *et al*, 2005). The study of European region shows two important characteristics. First, it is widely accepted that the rate of convergence among these regions is quite low. The literature generally agrees on a 2% rate per year (Barro and Sala-I-Martin, 1991, 1995; Amstrong, 1995; Sala-I-Martin, 1996; Capron, 2000; Ertur *et al* (2006). Moreover, disparities among regions do not decline quickly in spite of the European regional policy. Some authors have thus suggested the existence of groups converging to different long term equilibriums (Durlauf and Johnson, 1995; Quah, 1993, 1996, 1997). This view could be reinforced with the adhesion of 10 new countries whose per capita GDP are much lower than Western members.

The second characteristic refers to the geographical distribution of economic activities. Several authors (López-Bazo *et al*, 1999; Carrington, 2003; Magrini, 2004; Le Gallo and Ertur, 2003) have shown that European regions were polarized in two groups: rich regions situated in the North and poor in the South. This observation can be linked to several results of the New Economic Geography (Krugman, 1991) which state that there exists agglomeration and cumulative processes which spatially determine locations of economic activities. For instance, we can easily think that a region surrounded by rich region has higher probability to record a high economic growth than another region surrounded by poor regions.

This second point, referring to spatial interactions is especially relevant at the regional level. One only needs to think about opening of borders, which made easier the mobility of commodities and technology, or to interregional trade to be convinced that the growth of a given region is partly determined by its neighboring performances. This statement, even though easily understandable, was largely ignored by scientists working on this topic. Two main reasons lie behind this fact. First omission of space must be linked with the partitioning of disciplines, space being mostly studied in regional and geographical sciences. The second point refers to the fact that capturing the spatial effect in a regression generates a lot of problems. However, this difficulty has been solved with the apparition of spatial econometrics, a methodology gathering all techniques and tools required to capture the spatial dimension in an econometric regression. Spatial econometrics allows taking problems presented hereafter into account.

Problems implied by taking space into account in the econometric regression are of two dimensions. More precisely, space interferes in two different ways on estimators. We thus speak of spatial effects. When one works on European regions, one can quite easily think of correlation among observation units. In other words, the observation of a variable in a location partly depends of the observation of the same variable in neighboring locations. This effect is called spatial autocorrelation and refers to the absence of independence between regions. Moreover, we can also imagine that economic behaviors and relationship differ across space. As an example, we can consider urban versus rural behavior. This point characterizes the second spatial effect, namely spatial heterogeneity.

Many studies on the European Union before the enlargement process were performed. However, the literature regarding the UE-25 regions needs still to be expanded. To our knowledge, only two studies were executed on the enlarged sample. The first one was made by Ertur and Koch (2006) which looked at the spatial distribution of the regions and the second one, performed by Fischer and Stirböck (2005), tests convergence processes among the enlarged EU-25 regions. This lack of literature can be explained by the recent nature of this event (May 2004) and by complex problems arising within this sample that requires careful analysis. For instance, one must deal with pronounced spatial heterogeneity.

This paper has thus two main objectives. Firstly, we analyze the convergence process among regions of the enlarged European Union using cross-sectional data and taking spatial interactions into account. More specifically, we will test the presence of absolute convergence and clubs convergence processes using the tools of spatial econometrics allowing us to capture spatial effects in the estimation. Results obtained here will be compared with two others works. The study of Ertur *et al.* (2006) focusing on convergence clubs among regions before the enlargement of Europe and the study carried out by Fischer and Stirböck (2005). The second objective, more technical, consists in testing the robustness of the estimates by using two alternatives methods: the quasi-maximum likelihood and the Bayesian estimation methods. The quasi-maximum likelihood method corrects for the mistake made when imposing normality on the error term. The Bayesian estimation allows capturing heteroskedasticity and outliers in the estimation.

The remainder of the article is organized as followed: section 2 introduces both concepts of convergence used in the paper and precisely defines spatial effects. Section 3 presents empirical estimation results as well as a robustness analysis. Section 4 concludes.

2. Methodology

2.1. Concepts of convergence.

Literature generally distinguishes nominal from real convergence. The former treats the adjustment of nominal variables to their long term equilibrium. Variables considered are the inflation, interest and exchange rates, but the government debt or deficit, in terms of GDP percentage also are included. Moreover, fiscal variables are often introduced. The concept of real convergence, used in this paper and in most of the macroeconomic literature, analyzes convergence of economic and development structures between regions. Variables mainly used are wealth creation, unemployment and productivity growth.

In this article, two different convergence notions are considered: absolute β-convergence, directly derived from the neoclassical theory, and convergence clubs, which allow capturing some spatial heterogeneity.

The concept of β-convergence directly comes from the neoclassical theory. In its simplest model, this theory stipulates that in the long term, per capita GDP growth only depends on exogenous technical progress. When one generalizes to several economies, different situations must be distinguished. If economies share the same structural characteristics (in terms of human capital, saving rate, production function …), a convergence in GDP per capita levels and in growth rate is present. However, if structural characteristics differ between economies, only a convergence in growth rate is observed. In the first case, we speak of absolute (unconditional) β-convergence because the long-run equilibrium is the same for all economies. In the second case, each economy tends to its own long-run equilibrium, which is unique and determined by the characteristics of the economy. The concept used is thus conditional β- convergence.

Barro and Sala-I-Martin (1992) have shown that for cross-sectional data, the equation which is used to test absolute convergence processes is as follows:

$$g_T = \alpha S + \beta y_0 + \varepsilon \text{ with } \varepsilon \sim i.i.d(0, \sigma_\varepsilon^2 I) \quad (1)$$

where g_T is the vector (N,1) of annual average growth rate (defined by the following expression : $\left[\log Y_T / \log Y_0\right] / T$), N is the number of observations, S is the unity vector and y_0

is the GDP per capita in logarithms on initial period. Convergence is observed if β is negative and significant. Indeed, the growth rate is then negatively correlated with the level of GDP per capita.

To test the conditional β-convergence hypothesis, conditioning variables are included in equation (1):

$$g_T = \alpha S + \beta y_0 + X\gamma + \varepsilon \text{ where } \varepsilon \sim iid(0, \sigma^2{}_\varepsilon I) \quad (2)$$

with same notations as before and X, a matrix of variables holding constant the steady state equilibrium of each economy. This matrix is constituted of state-variables, as the physical and human capital stock, environment variables, as the ratio of public spending on GDP, the fertility rate, the economic instability degree, etc. Conditional convergence is present if β is negative and significant once X is held constant.

These two first concepts assume that it is variation in basic growth parameter which explains the difference in long-run equilibrium reached. However, we could suggest that economies tend to different long run growth rate because they do not share the same initial conditions. Under such suggestion, we could find similar economies converging to the same long run equilibrium (convergence clubs) but little or no convergence between such clubs (Martin 2001). Formally, one can define a club as a group of economies with identical structural characteristics and initial conditions similar enough to tend to the same steady-state equilibrium. Economies will converge among them if they belong to the attraction field of the same equilibrium. The concept of convergence clubs appeared in order to capture specificities of economies. It thus allows taking some kind of spatial heterogeneity among economies into account, namely spatial instability of the parameters.

The concept of convergence clubs is quite different from the two first presented here. In absolute and conditional β-convergence, it is the idea of uniqueness of the steady state which is important. In absolute convergence, this uniqueness is straightforward to understand since all economies tend to the same long-un equilibrium. In conditional convergence, even though each economy tends to its own equilibrium (given its structural characteristics) this steady state is unique. In studies devoted to convergence clubs, the dominant idea is the multiplicity of equilibriums. Several steady states coexist and it is the initials attributes of the economy which will determine the equilibrium that will be reached. A group of countries, regions, can thus tend to the same equilibrium if they share initials conditions which lead to it. This difference between concepts has been empirically checked. In their study, Durlauf and Johnson (1995) could not confirm the existence of a global convergence process but found out several clubs.

Empirically, several approaches were proposed to determine convergence clubs. It is nevertheless possible to gather all the studies into two categories. On the one hand, those which select the clubs exogenously and, on the other hand, those in which clubs are determined endogenously.

In the first class, composition is made a priori (by one or several criteria) and the β–convergence hypothesis is afterwards tested for each group. Criteria used to create clubs are, for instance, the belonging to a geographical zone or an institutional system (Baumol, 1986). In their study, Durlauf and Johnson (1995) chose threshold levels of per capita GDP to define their clubs.

In the other approach, several methods are used to endogenize the determination of clubs. Baumol and Wolff (1988) employed a quadratic form of the equation (2) to experience the existence of clubs. Another technique, initiated by Durlauf and Johnson (1995) consists in using regression trees. Finally, Chatterij (1992) and Chatterij and Dewhurst (1996) have discriminated clubs in function of the gap of per capita GDP with respect to a leader economy.

As written above, we use cross-section spatial data for this study. One of their advantages is that we can apply spatial econometrics tools since each observation unit is geographically located. However, in their surveys, Durlauf and Quah (1999) and Temple (1999) have highlighted several problems linked to cross sectional analysis. In this paper, we will only present the most important.

The first limitation of cross sectional convergence is that even it is derived from the neo-classical theory, it does not allow to test the validity of this theory against other sometimes conflicting (Magrini, 2004). For instance, cross sectional regression does not allow discriminating the neoclassical theory from the endogenous growth.

A second limitation has to do with the information content. To analyse β–convergence, we only dispose of two reference marks, the initial and final periods. The annual average growth rate is then computed from those two values. The problem with such a definition is that it does not allow taking the real evolution of economies between this time interval into account.

A last drawback, raised by Quah (1996b) concerns the neglected spatial dimension of the β-convergence model. Indeed, until recently, countries and regions were treated as independent economies, without any interaction. However, on the regional level, spatial spillovers are of interest given that each region is likely to interact with neighboring regions. The aim of the next point is thus to explain how to capture spatial effects in an econometric regression.

2.2. Spatial Effects

In this section, we will define the two spatial effects, namely spatial autocorrelation and heterogeneity more accurately and introduce some specifications to take them into account.

Anselin and Bera (1998, p. 241) define spatial autocorrelation as follows: "*Spatial autocorrelation can be loosely defined as the coincidence of value similarity with locational similarity.*"

In other words, the observation of a random variable in a given localization is partly determined by the observation of this variable in neighboring localizations (the neighborhood being defined by the spatial weight matrix). One distinguishes positive and negative spatial autocorrelation. The former is characterized by similar values of a random variable in similar localizations whereas the latter refers to value dissimilarity in similar locations. Absence of spatial autocorrelation is defined by random spatial distribution of the variable of interest.

The presence of spatial autocorrelation gives additional information with respect to traditional statistics like mean or standard errors because it provides an idea about the geographical distribution of the values of the studied variable. Moreover, modeling spatial autocorrelation allows taking the existence, influence and size of geographic spillovers effects into account.

Spatial autocorrelation has two different sources. Firstly, it can be detected in a sample if data obey to an underlying spatial process. This process links spatial units by an exact function which captures interaction effects among studied localizations. Secondly, spatial autocorrelation can result from a misspecification of the model. The omission of some spatially correlated variables, measurement error or an incorrect functional form (Le Gallo, 2002) constitute some examples.

Before presenting specifications used in spatial econometrics, it is important to specify the modeling of interactions among regions. As we only dispose of N observations, it is necessary to impose a structure to spatial interactions,[1] which is given by the spatial weight matrix, *W*. The objective of this matrix is to set a neighborhood to each region. Criteria used to define such neighborhood are of different natures (contiguity, k-nearest neighbors and decreasing functions of distance) but the matrix must be exogenous to avoid problems with inference and computation of estimators (Anselin and Bera, 1998). In this paper, we use an accessibility weight matrix based on transport times between regions. So the concept of distance used is not kilometric-distance but time-distance. We therefore create a spatial weight matrix where the connection between two regions is defined as the time needed, using roads, to join the two regional capitals (which serve as reference points for regions). For regions without capital, mainly located in Eastern Europe, we chose the most populated city as reference. We then use the Viamichelin® website to compute distances between all pair of regions.[2] We assume that the time-distance separating two regions is identical, no matter the selected direction chosen. For instance, the time needed to join Paris from Berlin is the same as the one to join Berlin from Paris. Concretely, this means that distances are only computed for the inferior triangle of the matrix and then transposed in the upper triangle.

Formally, the following spatial weight matrix was used:

$$\begin{cases} w^*_{i,j} = (d_{i,j})^{-\beta}; \forall i \neq j \\ w^*_{i,i} = 0 \end{cases}$$

where $w^*_{i,j}$ is called the spatial weight and measures the interaction between regions i and j, $d_{i,j}$ is a measure of the distance separating both regions (in this case it is a concept of time-distance), β is a parameter fixed a priori (in our study, we have set β equal to 1). By convention, $w^*_{i,i}$ is set to 0. The last operation we performed on the weight matrix consists in row-standardizing it. The aim of this transformation is to facilitate comparison between spatial parameters and the interpretation of spatially lagged variables[3] (Anselin and Bera, 1998). Formally, we can express this row-standardization in the following way:

$$w_{i,j} = \frac{w^*_{i,j}}{\sum_j w_{i,j}}, \forall i$$

with all weights belonging to the interval [0,1]. Because of this standardization, spatial weights are no more interpreted in absolute terms but express relative measurements.

The concept of spatial weight matrix being introduced, we can now present specifications capturing spatial dependence. Spatial autocorrelation can have two different natures, sometimes jointly present in the same regression. These two types are the endogenous spatial lag and spatially autocorrelated errors. However, in this paper, due to space constraint, we will only focus on the model of interest, namely the endogenous spatial lag one (SAR).[4]

The initial model from which spatial specifications will be derived is the classical linear one:

$$y = X\beta + \varepsilon \qquad \varepsilon \sim iid(0, \sigma^2 I_N) \tag{3}$$

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[1] The structure is compulsory because one cannot estimate N(N-1)/2 parameters with only N observations.

[2] Specifically, we took as the benchmark route the recommended route of the ViaMichelin® website, which is a mix between the shortest and the quickest routes. All this work has been done between November, 2nd and 22nd 2004. As Viamichelin® takes deviations, road works, speed limits among others into account, it is important to note that the constructed matrix is subject to some variation.

[3] We get a spatially lagged variable by the multiplication of a variable with the weight matrix. Assuming that *y* is a random variable, *Wy* is the spatially lagged variable.

[4] SAR stands for Spatial Autoregressive model.

with y, the vector [N,1] of observations of the dependent variable, X, the matrix [N,K] of observations of the K explanatory variables, β, the vector [K,1] of the unknown parameters to be estimated and ε, the vector [N,1] of the errors. The errors are assumed to well-behave.

The SAR model consists in inserting the endogenous spatial lag, *Wy*, in the set of explanatory variables. Formally, the initial model (1) is transformed as follows:

$$y = \rho Wy + X\beta + \varepsilon \tag{4}$$

with *Wy,* the endogenous spatial lag, and ρ, the autoregressive spatial parameter expressing the interaction intensity between observations of the dependent variable. Let's remind that when W is row-standardized, $(Wy)_i$ is a weighted average of observations of regions in the neighborhood of region *i*.

The introduction of the endogenous spatial lag in the regression allows assessing the spatial dependence degree given the effect of others variables is controlled for. In order to see the two effects induced by this specification, it is worthwhile to write (4) in its reduced form:

$$y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1}\varepsilon \tag{5}$$

Note that to write the reduced form, the matrix $(\mathrm{I} - \rho W)^{-1}$ must be non-singular.[5] It follows from the reduced form (5) that the spatially lagged variable *Wy* is correlated with the error term. Therefore OLS estimators will be biased and inconsistent. The simultaneity embedded in the *Wy* term must be explicitly accounted for in a maximum likelihood estimation framework as first outlined by Ord (1975).[6] More recently, Lee (2004) presents a comprehensive investigation of the asymptotic properties of the maximum likelihood estimators of SAR models.

If we write the inverse spatial transformation under the geometric expansion form, we get:

$$y = (I + \rho W + \rho^2 W^2 + \rho^3 W^3 + ...)X\beta + (I + \rho W + \rho^2 W^2 + \rho^3 W^3 + ...)\varepsilon \tag{6}$$

The first term on the right hand side of (6) describes the spatial multiplier effect. This multiplier effect means that the expected value of *y* in the region *i* does not only depend on the value of explanatory variables in this region but also on the value of independent variables of all regions of the sample. This multiplier effect is decreasing with the distance.

The second effect, namely the spatial diffusion one, and expressed by the second term on the right hand side, indicates that a random shock hitting a given region will gradually affect all regions belonging to the sample. This effect is decreasing with the distance too.

The SAR specification captures spatial dependence when it is present as an endogenous spatial lag. However, spatial autocorrelation may be present under the form of spatially autocorrelated errors. As written down above, we will not detail this model but only provide some useful information about it.

A Spatially autocorrelated Error (SEM) model is generally preferred when autocorrelation is viewed more as a nuisance than a substantial parameter (Florax and Nijkamp, 2003). Several specifications assuming autocorrelated errors exist but the most used

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[5] This property is satisfied if $|\rho| \neq 0$ and when $1/\rho$ is not an eigenvalue of *W*.

[6] In addition to the maximum likelihood method, see for more details Anselin (1988), Anselin and Bera (1998) or Anselin (2001), the method of instrumental variables (Anselin 1988, Kelejian and Prucha 1998, Lee 2003) may also be applied to estimate SAR models.

is a spatial autoregressive process which stipulates that the error term, ε, is a function of $W\varepsilon$, the spatial lag associated with the errors.

Formally, this model is written as follows:

$$\left| \begin{array}{l} y = X\beta + \varepsilon \\ \varepsilon = \lambda W \varepsilon + u \end{array} \right. \tag{7}$$

with λ, the spatial autoregressive coefficient and u, the vector of errors with usual characteristics [(*i.i.d.* (0, σ^2 I)]. The λ parameter reflects the intensity of the interdependence between residuals. Due to non-spherical errors, OLS estimators are inefficient and the maximum likelihood method or the generalized method of moments should be used instead (see, for instance, Anselin and Bera, 1998 or Anselin, 2001).

Merging the two components of (7), we find the reduced form of the SEM model:

$$y = X\beta + (\mathrm{I} - \lambda W)^{-1} u \tag{8}$$

As for the SAR model, the matrix $(I - \lambda W)^{-1}$ must be non singular. Equation (8) shows that the SEM specification only includes a spatial diffusion effect. Indeed, the term $X\beta$ is not premultiplied by the inverse spatial transformation $(I - \lambda W)^{-1}$. Let us also note that premultiplying equation (8) by $(I - \lambda W)$ we get:

$$y = X\beta + \lambda Wy + WX\gamma + u \tag{9}$$

with the non linear restrictions : $\gamma + \lambda\beta = 0$. The model (9) is the so-called *spatial Durbin model* and can be estimated by ML. The restriction $\gamma + \lambda\beta = 0$ can be tested by the common factor test (Burridge 1981). If it cannot be rejected then model (9) reduces to model (8).

We will now turn to the second spatial effect, namely spatial heterogeneity. For the sake of space, we will not present all the details of this effect but only give useful material for this article. Spatial heterogeneity has two components that can be present jointly. The first one, spatial instability of the parameters, refers to the fact that comportments, or economic relationships, can vary over space. This spatial instability comes from the variation of the functional form and parameters according to the localization. From the econometric point of view, this is reflected by a differentiation of the parameters with respect to localization. Assuming two clubs, equation (1) can be rewritten in the following way (assuming homoscedasticity of the error term):

$$\begin{array}{l} g_T = \alpha_1 D_1 + \alpha_2 D_2 + \beta_1 D_1 \ln Y_0 + \beta_2 D_2 \ln Y_0 + \varepsilon \\ \varepsilon \sim N(0, \sigma_\varepsilon^2 I) \end{array} \tag{10}$$

with D_1 and D_2, dummy variables representing regions belonging to spatial regimes 1 and 2 respectively. More specifically, D_{1i} takes the value 1 if the region i belongs to regime 1 and 0 otherwise while $D_{2,i}$ equals 1 if region i belongs to the second spatial regime and 0 otherwise. Spatial instability of parameters is reflected by different values of β's according to the regime.

Heteroskedasticity is the second facet of spatial heterogeneity. However, given that it can be treated by traditional methods, it will not be discussed here.

The two spatial effects can be present jointly in a regression but he link between the two is not straightforward. Actually, three different categories of links can be distinguished between spatial autocorrelation and heterogeneity. Firstly, in cross-sectional data, the two effects may be observationally equivalent (Anselin et Bera, 1998, p. 240). For instance, the observation of a cluster of high values of a variable in urban areas may come from spatial heterogeneity (under the form of groupwize heteroskedasticity) or from spatial autocorrelation (concentration of high values for cities and low values for rural sphere. Secondly, spatial heterogeneity tests are not reliable in the presence of spatial autocorrelation and must be adjusted. Reciprocally, properties of spatial autocorrelation tests are altered in the presence of heteroskedasticity of unknown form. Finally, spatial dependence may be due to parameter instability not modeled.

3. Empirical Results

3.1 Absolute β-convergence

In this section, we will apply the tools of spatial econometrics (developed by Cliff and Ord (1973); Anselin (1988); Anselin and Florax (1995) among others) to absolute β-convergence and convergence clubs models. The exercise bears on regions of the enlarged European Union between 1993 and 2002. Databases used are the Cambridge Econometrics completed with the Eurostat REGIO database. The reason that leads us to work on unconditional β-convergence is the lack information on potential control variables at the regional scale for the sample we use. Indeed, the sole available for the extensive 237 NUTS 2 regions studied is the per capita Gross Value Added (GVA).

This empirical section has different objectives. Firstly, we want to show that spatial autocorrelation still matters in this new sample. Several studies have shown that it was the case for the EU-15 regions Fingleton (2002); Ertur *et al.* (2003b); Ertur *et al.* (2006); Lopez-Bazo *et al.* (2004) but only one on regions of the EU-25 (Fischer and Stirböck (2005). It is thus interesting to compare results. Secondly, we will introduce some heterogeneity by assuming spatial instability of parameters. Thirdly, we will test the robustness of our results by re-estimating our models with the quasi-maximum likelihood and the Bayesian estimation methods.

Our goal being to show the presence of spatial effect, the first step consists in estimating an a-spatial model, namely the classical linear one. The equation estimated is the following:

$$g_T = \alpha S + \beta Y_{1993} + \varepsilon \qquad \varepsilon \sim N\left(0, \sigma_\varepsilon^2 I\right) \tag{10}$$

with g_t, the vector (237,1) of the average annual per capita GVA growth rate for each region i between 1993 and 2002, T = 9, Y_{1993} is the vector containing the observations of the per capita GVA in logarithms in 1993, α and β are unknown parameters to be estimated and ε is the error term vector with usual properties. Table 1 summarizes estimation results.
Table 1 shows that the estimated β parameter is negative (-0.004761) and significant, which means that a weak convergence process is present in this sample. From this result, we can easily compute the convergence speed and the half-life, which are respectively 0.48% and 145 years. It is interesting to compare these results with the ones found in the study of Ertur *et al.* (2006) which was based on the EU-15 regions. In their paper, the authors found a β coefficient of -0.00797, which is twice as high as the estimate found here and it is strongly significant too.

Before comparing results with the ones of Fischer and Stirböck (2005), we will briefly present their work. The sample they use is quite similar to ours: 256 NUTS 2 European regions between 1995 and 2000 whereas we study the growth of 237 European regions between 1993 and 2002. However, spatial weight matrices used differ between studies. They define spatial weight by a threshold distance, w_{ij} equals 1 if region j is situated within a distance d of region i, whereas we use an inverse distance matrix based on time needed to join each pair of regional capitals. The difference between estimators found is quite important since they found a convergence speed of 1.9%. This result can partly be explained by the different period considered. Time studied by Fischer and Stirböck (2005) stops before the decrease of economic growth of 2001. So, their sample only looked at the convergence process for what may be considered as a high economic growth period.

Table 1: OLS results of the absolute convergence process

Dependent variable : g_T		Tests	
R^2 adjusted	0.0708	Moran's I	3.604 (0.000)
LIK	705.996	LM_{ERR}	2.898 (0.088)
σ^2	0.0002	LM_{LAG}	5.433 (0.019)
$\hat{\alpha}$	0.065468 (0.000)	RLM_{ERR}	5.095 (0.023)
$\hat{\beta}$	-0.004761 (0.005)	RLM_{LAG}	7.629 (0.005)
Convergence speed[7] Half-life[8]	0.48% 145 years	LM_{ERR}*	43.4235947 (0.000)

Note: numbers in brackets are the p-values, Moran's I is the Moran test for global spatial autocorrelation, LM_{ERR}, LM_{LAG} are the Lagrange multiplier statistics which test for the presence of spatial autocorrelation in the errors and a endogenous spatial lag respectively, RLM_{ERR} and RLM_{LAG} are their robust counterpart and finally, LM_{ERR}* is the conditional Lagrange Multiplier statistic for the presence of autocorrelated errors given a spatially lagged dependent variable. BP is the Breusch Pagan test for heteroskedasticity.

Given the economic intuition that regions are correlated by factors like international trade or knowledge spillovers, we have checked the presence of spatial autocorrelation. The most commonly applied statistic to test the presence of global spatial dependence is the Moran's *I*. If significant, the sample is not randomly distributed and spatial autocorrelation is present among observations. However, this test does not specify the nature of dependence. In the case where it is significant, one first has to try to include more exogenous variables, one source of spatial autocorrelation being the omission of independent variables. If not possible, as in this study, one must perform specification tests which will help us to determine the nature of spatial dependence.

Table 1 shows that the Moran's *I* statistic is positive and significant, confirming the presence of positive spatial autocorrelation. Five Lagrange Multipliers tests have been performed in order to discriminate between two forms of spatial dependence (spatial autocorrelation of the error term or an endogenous spatial lag). Results of both LM_{LAG} and RLM_{LAG} are more significant than their counterpart for the autocorrelated errors model. According to the decision rule elaborated by Anselin and Rey (1991) and modified by Anselin and Florax (1995), it thus seems that the presence of spatial dependence is better modeled by the endogenous spatial lag[9] than by spatial error autocorrelation (see also Florax et al., 2003).

[7] The convergence speed, θ, is computed as follows: $\theta = -\ln(1+T\beta)/T$.

[8] Half-life τ, comes from the following expression:. $\tau = -\ln(2)/\ln(1+\beta)$.

[9] The conditional test LM_{ERR}* shows that a more general specification should be used but as we estimate it, none spatial parameters are significant. A possible cause is that the conditional test is biased, because of the omission of independent variables.

This result is unusual for European regions but is really interesting. Until now, empirical literature always found spatial autocorrelation was better modeled by a SEM (Spatial Error Model) model which means that autocorrelation is more a nuisance parameter. This study shows that spatial autocorrelation can be viewed as a substantive phenomenon derived from a theoretical model, which is more appropriate from the economic point of view.

The model (10) is thus modified in the following way:

$$g_T = \rho W g_T + X\beta + \varepsilon \tag{11}$$

where W is the weight matrix defined in the previous section, Wg_T, the endogenous spatial lag, and ρ, the autoregressive spatial parameter. Under the hypothesis of normality of the error term, the model is estimated by maximum likelihood. Table 2 reports the estimation results and those of two other alternative methods used to test the robustness of the estimates. These methods are the quasi-maximum likelihood (QML) and Bayesian estimation (BE). The objective of estimating the model by QML is to provide standard errors robust to non-normality of the error term and thus to execute reliable statistical inference (Lee, 2004). Bayesian estimation has different purposes. This method was used to capture the effect of outliers and is robust with regard to heteroskedasticity (Le Sage, 1997).

Table 2: Results of the estimation of the SAR Model

Estimation Method Dependent variable : g_T	ML	QML	BE
σ^2	0.0001	0.0001	0.0002
LIK	790.19956	790.19956	
AIC	-1574.4	-1574.4	
BIC	-1560.7	-1560.7	
$\hat{\alpha}$	0.043376 (0.000)	0.043376 (0.000)	0.033595 (0.000)
$\hat{\beta}$	-0.003971 (0.000)	-0.003971 (0.000)	-0.003130 (0.000)
$\hat{\rho}$	0.720999 (0.000)	0.720999 (0.000)	0.769932 (0.000)
Convergence speed	0.4%	0.4%	0.32%
Half-life	174 years	174 years	221 years

Notes: ML stands for maximum likelihood, QML for quasi maximum likelihood and BE for Bayesian estimation. Numbers between brackets are the p-values, LIK is the value of the log-likelihood function, AIC is the Akaïke criterion and BIC the Schwartz criterion.

We will first analyze results from the ML estimation. Table 2 shows that the absolute convergence process is still present but weaker than in the OLS estimation. The reason is that we have removed the spatial interaction effect from the initial per capita GVA variable. Our results are thus lower than those found in the literature (a convergence speed of 2%). We also note that the spatial parameter is highly positive and significant, meaning that the intensity of spatial interactions is quite high. For a region *i*, an increase of 1% of the weighted average of the average annual growth rate of its neighboring regions (the neighborhood being defined by the weight matrix) will lead to an increase of the growth rate of region *i* of 0.72%, once the effect of other variables is controlled for. As Table 2 shows, ML results are robust to non-Normality. Indeed, *p*-values of the maximum and quasi-maximum likelihood estimation are similar.

Finally, in order to deal with potential outliers, which could exert a substantial impact on inference regarding convergence in the context of our sample together with heteroscedasticity, we estimate a Bayesian heteroscedasticity robust model using the method described in LeSage (1997, 2002). This model allows the disturbances to take the form $\varepsilon \sim N(0,\sigma^2 V)$, where $V = diag(v_1, v_2,..., v_n)$ and is estimated using MCMC methods (Gelfand and Smith, 1990). A prior distribution is assigned to the v_i terms taking the form of a set of n independent, identically distributed, $\chi^2(r)/r$ distributions, where r represents the single parameter of the χ^2 distribution. This allows us to estimate the additional n variance scaling parameters v_i by adding only a single parameter r to the model (see Geweke, 1993).

The χ^2 prior assigned to the v_i terms can be motivated by considering that the prior mean equals unity and the prior variance is $2/r$. This implies that as our prior assignment of a value for r becomes very large, the terms v_i will all approach unity, resulting in $V = I_n$, the traditional assumption of constant variance across space. On the other hand, assigning small prior values to r leads to a skewed distribution permitting large values of v_i that deviate greatly from the prior mean of unity. The role of these large v_i values is to accommodate outliers or observations containing large variances by down-weighting these observations. In the context of spatial modeling, outliers arise due to "enclave effects", where a particular observation exhibits divergent behavior from nearby observations. Geweke (1993) shows that this approach to modeling the disturbances is equivalent to a model that assumes a Student-*t* distribution for the errors. This type of distribution has frequently been used to deal with sample data containing outliers, (e.g., Lange *et al.* 1989). In practice, one can either assign an informative prior for the parameter r based on the exponential distribution centered on a small value, or treat this as a hyper-parameter in the model, set to a small value, say 4 to 7. Our estimates presented in the last columns of Table 2 are based on $r = 4$.[10]

Potential outliers are presented in Figure 1 as regions for which the posterior mean v_i estimate is higher than 4: the regions concerned are mainly Eastern European regions, which joined EU recently, belonging to Slovenia, Estonia, Poland and Hungary. Irish regions appear also to be outliers as well as Berlin and a Finnish region. It is also the case of Groningen in the Netherlands. This region appears as an outlier because of anomalies related to North Sea Oil revenues, which substantially increase its per capita GDP.

The Bayesian estimation shows also that when potential outliers are taken into account in the regression, the β estimator goes up (from -0.00397 to – 0.00313) decreasing the speed of convergence from 0.40% to 0.32%. We thus conclude that outliers biase the ML estimation upward. We also note that the spatial parameter is higher in this estimation expressing larger spatial interactions. A comparison between ML and Bayesian heteroscedastic β estimates is presented in Figure 2 where the simulated normal distribution for β from the ML estimation and the posterior distribution for β from the Bayesian estimation are plotted. The posterior distribution for β appears to be skewed to the right compared to the simulated normal distribution, most likely because of the outliers or non-constant variances, as an illustration of our point.

[10] All computations are carried on by means of the Matlab Spatial Econometrics Toolbox developed by James LeSage (http://www.spatial.econometrics.com).

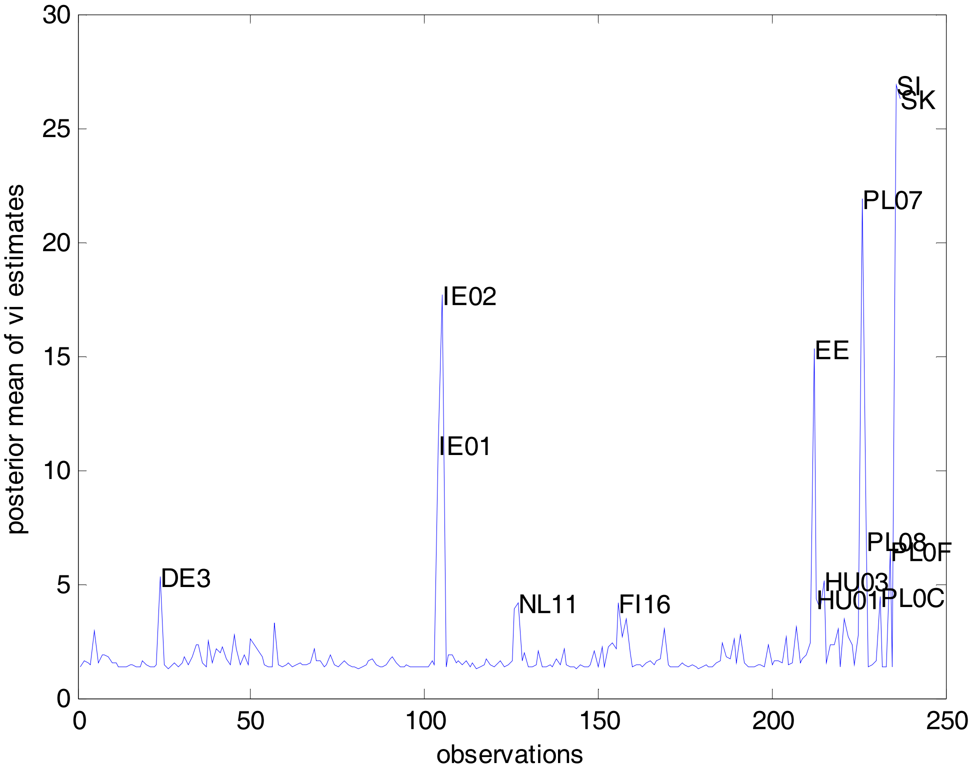

Figure 1: posterior v_i estimates

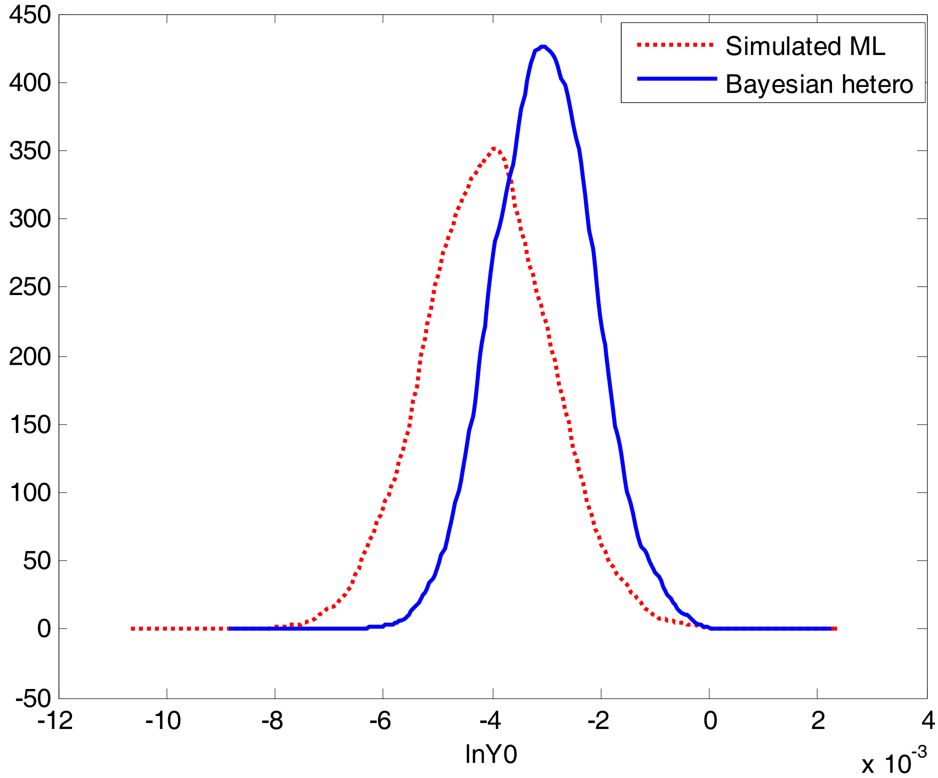

Figure 2: ML simulated normal distribution versus Bayesian heteroscedastic posterior distribution for β in the SAR model

3.2 Convergence clubs

Spatial regimes are used to model spatial instability of the parameters. So, before stating the econometric regression that will be estimated, it is worthwhile to give some details about the determination of the clubs.

We defined clubs by using tools of the Exploratory Spatial Data Analysis (ESDA). This analysis allows deciphering spatial distribution of the sample. In addition to capture spatial autocorrelation, these techniques detect spatial regimes and other forms of spatial heterogeneity (Haining, 1990; Bailey and Gatrell, 1995; Anselin, 1998a, 1998b). Moreover, atypical localizations, outliers and spatial association models can be identified.

ESDA techniques allow differentiating global from local spatial autocorrelation. The first one is tested by the Moran's I and bears on the whole sample. On the opposite, local spatial dependence does not assume the homogeneity of the sample because it captures atypical localizations as the "wealthy islet" (a rich region surrounded by poor ones) or "the black sheep" (a poor region surrounded by rich ones) and assess their significance. Several statistics exist to give an account of local spatial autocorrelation. The most used are the Moran scatter plot (Anselin, 1996), the Getis' statistics (Getis and Ord, 1992; Ord and Getis, 1995) and Local Indicator of Spatial Association (LISA) developed by Anselin (1995).

We specified our spatial regimes with the statistic developed by Getis and Ord, the $G_i(d)$. We will briefly present it to allow the reader to understand how it works.

The $G_i(d)$ was created by Getis and Ord (1992) in order to locate local clusters of spatial association which are not necessarily detected by global spatial dependence tests. For each region i and period t, this statistic is written as follows (Getis et Ord, 1992):

$$G_{i,t}(d) = \frac{\sum_{j \neq i} w_{ij}(d) x_{j,t}}{\sum_{j \neq i} x_{j,t}}$$

where $w_{ij}(d)$ are the elements of a symmetric binary spatial weight matrix. $w_{ij}(d)$ equals one for all links within a distance d of a given region i and equals zero for all other links. The variable x has a natural origin and is positive.

The numerator of the statistic is the sum of all x_j situated within a distance d of the region i (x_i being not included in the calculation) while the denominator is the sum of all x_j (excepted x_i) [11]. Once the Matrix is row-standardized, a positive value of $G_{i,t}(d)$ denotes a spatial cluster of high values whereas a negative one indicates clustering of low values around region i. This statistic has been extended by Ord and Getis (1995) to variables that do not have a natural origin and to non binary standardized weight matrices and is written in the following way:

$$G_i(d) = \frac{\sum_j w_{ij}(d) x_j - W_i \overline{x}(i)}{\sigma(i)\{[(N-1)S_{1i} - W_i^2]/(N-2)\}^{1/2}}, \quad j \neq i$$

[11] The statistic that takes the region i into account also was suggested by Getis and Ord (1992) and Ord and Getis (1995) and was labelled $G_i^*(d)$.

where $S_{1i} = \sum_j w_{ij}^2$ and $W_i = \sum_{j \neq i} w_{ij}(d)$. The sample mean and standard deviation for the sample of size N-1 (exclusion of the region *i*) are $\bar{x}(i)$ and $\sigma(i)$ respectively. The sign of this statistic must be interpreted in the same way than the preceding one.

We will now apply it to our sample. It is worthwhile noting that we only have considered the value of the statistic and not its significance. Concretely, we assigned regions whom statistic was positive to the regime labeled "West" and the other to the regime labeled "East". We applied Getis statistic on the per capita GVA expressed in logarithms in initial period. The spatial weight matrix held for the computation in an inverse distance one because it minimizes the number of atypical[12] regions that have to be excluded from the sample.[13] Those regions are the 5 Portuguese ones and our sample shrank from 237 to 232 regions.

The composition of the two clubs is the following: in the club labeled "West", we find regions mainly belonging to the Western Europe, namely Belgium; France; Germany; Spain; Ireland; Italy; Luxembourg; Netherlands; United Kingdom; Sweden; Slovenia; some regions in Austria (Karnten, Steiermark, Oberosterreich, Salzburg, Tirol, Vorarlberg), Finland (Aland), Poland (Zachodniopomorskie) and Czech Republic (Jihozapad). This club thus includes rich regions.

The other regime, labeled "East", is composed of Greece; Estonia; Slovakia; regions of Burgenland, Niederosterreich and Wien in Austria; all but one regions of Poland, of Czech Republic and of Finland.

Clubs founded out in this study show that polarization among European region is not more North-South (as in studies devoted to EU-15 regions) but West-East. It is relevant to note that heterogeneity is very pronounced within our regimes, and especially in the West one. The reason behind this lies in the composition of this club. We showed that it included nearly all regions of the previous EU-15. However, in studies devoted to convergence among EU-15 regions (Ertur *et al*, 2003b; Durlauf and Johnson, 1995; Armstrong, 1995), authors found out two spatial regimes within their sample, namely one for Northern regions (the rich ones) and one composed of Southern regions (the poor ones). In our study, we have merged those two clubs, and thus created heterogeneity into our regime. This is partly for this reason that we will perform a robustness study of our results.

Now that clubs are identified, we can proceed with estimation. The econometric regression is based on the absolute β-convergence model (1) and explicitly specifies the presence of clubs:

$$\begin{aligned} g_T &= \alpha_1 D_1 + \alpha_2 D_2 + \beta_1 D_1 y_{93} + \beta_2 D_2 y_{93} + \varepsilon \\ \varepsilon &\sim N(0, \sigma_\varepsilon^2 I) \end{aligned} \tag{12}$$

where D_1 and D_2 are dummy variables qualifying the two spatial regimes previously defined. Specifically, $D_{1,i}$ equals 1 if region *i* belongs to the "West" regime and 0 otherwise while $D_{2,i}$ equals 1 if region *i* belongs to the "East" regime and 0 otherwise.

As in the first case, we start with an OLS estimation of equation (12). Results are summarized in table 3.

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[12] An atypical region is either a rich region surrounded by poor ones, either a poor region surrounded by rich ones.

[13] Atypical regions have to be excluded because their number is too small to compose a club of their own.

Table 3 : Results of the convergence clubs model estimation using OLS

Dependent variable : g_T			
Adjusted R² σ²	0.1284 0.0001	Ind. stability test $\hat{\alpha}$	14.21034 (0.000)
Global stability test	7.98238 (0.000)	Ind. stability test $\hat{\beta}$	15.057107 (0.000)

	West (1)	East (2)
$\hat{\alpha}$	0.121664 (0.000)	0.014944 (0.388)
$\hat{\beta}$	-0.010640 (0.000)	0.001477 (0.477)
Convergence speed	1.12%	-
Half-life	65 years	-

Moran's I	1.873 (0.068)	RLM_{ERR}	3.587 (0.058)
LM_{ERR}	0.149 (0.699)	RLM_{LAG}	4.667 (0.031)
LM_{LAG}	1.229 (0.266	LM_{ERR}^{*}	0.824 (0.364)

Notes: p-values are in brackets, stability tests are performed using Likelihood ratio.

Table 3 shows quite different results of those obtained in absolute convergence. In this framework, we observe a convergence process among regions belonging to the spatial regime labeled "West" but the β estimator is neither of the expected sign or significant in the "East" regime.

This estimation allows us to see the impact on Eastern regions in the convergence speed computed under the absolute β-convergence model. The convergence speed is twice higher when only rich regions (belonging to regime "West") are taken into account whereas the convergence process disappears in the "East" regime (poor regions). We thus can think that rich regions draw the economic convergence.

Table 3 also shows that coefficients are significantly different between spatial regimes (the global stability test reveals that coefficients of clubs are significantly different). Consequently, the adjusted coefficient of determination goes from 7 to nearly 13%. Nevertheless, these results must be interpreted with caution because they do not take into account spatial effects which, let us point it out, produce unreliable estimators.

Fischer and Stirböck's results are here too, quite different from ours. They found a convergence coefficient significant and of the expected sign for both convergence clubs. Moreover, convergence speeds are much higher in their work, 4.8% for their "West" club and 2% for their "East" one. Again we can partly attribute this difference on the time period studied.

The second part of table 3 tests the presence of spatial autocorrelation. The Moran's I test is positive and significant (to the 10% threshold), meaning that the sample is characterized by spatial dependence.

When we look to the simple hypothesis Lagrange Multiplier tests, namely those which only test the presence of spatially autocorrelated errors or the spatially lagged endogenous variable, we see that neither is significant. Their robust version indicate that a SAR model seems to be more appropriate than a SEM one when we follows the decision rule of Anselin and Rey (1991) and Anselin and Florax (1995). Moreover, the LM_{ERR}^{*} test, which tests for the presence of a residual autocorrelation in the errors when a SAR model is already present, is not significant. The most appropriate model thus seems to be the endogenous spatial lag one.

The estimable equation for the convergence club model is thus transformed in the following way:

$$g_T = \alpha_1 D_1 + \alpha_2 D_2 + \rho W g_T + \beta_1 D_1 \ln Y_0 + \beta_2 D_2 \ln Y_0 + \varepsilon \qquad (13)$$

with the same notations as before, Wg_T, the endogenous spatial lag and ρ, the autoregressive spatial parameter expressing the intensity of interactions between observation of the dependent variable. Table 4 summarizes results of estimating equation (13) by the maximum likelihood method and by the two other methods designed to test the robustness of the results.

We will first analyze coefficients estimated by the maximum likelihood method. We see that the convergence process is significant only in the West regime and the convergence speed is quite low (1.03%). The spatial autoregressive parameter, ρ, is still positive but lower than in the absolute case and more importantly, only significant at 10.3%, which is quite low. In the Fischer and Stirböck's case, results are again different. Firstly, the preferred specification to model spatial dependence is a SEM model, whereas we chose an endogenous spatial lag. Secondly, convergence estimators are significant and of the expected sign for both clubs, and the convergence speed is rather high: 1.5% for their "West" regime and 2.4% for the "East" one.

The story is different in the study of Ertur *et al* (2006). These authors found a convergence process in the club composed of poor regions (they labeled this regime South) but no significant estimator for the regime made of rich regions and labeled North. Moreover, the convergence speed computed is quite high since it nearly equals 3 % (2.94%). As Fischer and Stirböck, they preferred the spatially autocorrelated errors specification to model spatial autocorrelation. Nevertheless, even though we use different specifications, both studies found highly positive and significant spatial parameter (0.72 for this study against 0.79 for their study).

We will now turn to columns 3 and 4 of table 4, which represent the robustness study. The quasi-maximum likelihood estimation shows that the maximum likelihood *p*-values are robust to non-normality of the residuals (*p*-values of both estimation methods are similar). More interesting are the results of the Bayesian estimation. Several points deserve some attention. First of all, we can see that when we perform Bayesian estimation, whose aim is to capture the effect of outliers and heteroskedasticity, all estimated coefficients except the constant term for the second spatial regime, are significant at the 5% level. Our result therefore confirms that the classical convergence clubs model is misspecified since the spatial parameter is indeed significant. Note that its estimated value (0.639) is higher than the one obtained in ML estimation (0.496). The second observation is that both β coefficients are significant, which was not the case under the ML estimation. A convergence process is still present in the West regime but weaker whereas in the east regime, we observe a significant divergence process (in the ML estimation, the β coefficient was already of the wrong sign but insignificant). This second observation shed light on the potential biais that could plague ML estimators when outliers present.

Figure 3 presents numerous outliers detected as regions exhibiting a posterior mean v_i estimate higher than 4: regions belonging to Poland and to the Czech Republic, a Finnish regions, Irish regions as well as Berlin and Luxembourg appear therefore as outliers. It is also the case of Groningen for the reason already given above (see Figure 1). Figures 2 and 3 display a comparison for the SAR model with two regimes between the simulated normal distribution for β from the ML estimation and the posterior distribution for β from the

Bayesian estimation are plotted. The posterior distribution for β appears to be skewed to the right compared to the simulated normal distribution, most likely because of the outliers or non-constant variances. These Figures show clear evidence on favor of the severe biases in ML β estimates for both regimes. Therefore this study shows that eastern regions, between 1993 and 2002, tend to diverge from each other, whereas regions belonging to the West regime, namely regions of EU15, tend to converge.

Table 4: Results of the estimation of the SAR Model

Estimation Method	ML	QML	BE
σ^2	0.0001	0.0001	0.0002
LIK	778.80293	778.80293	
AIC	-1547.61	-1547.61	
BIC	-1530.4	-1530.4	
α_{West}	0.10437	0.10437	0.07655
	(0.000)	(0.000)	(0.000)
α_{East}	0.00472	0.00472	-0.01996
	(0.794)	(0.794)	(0.109)
β_{West}	-0.00987	-0.00987	-0.00736
	(0.000)	(0.000)	(0.000)
β_{East}	0.00139	0.00139	0.00368
	(0.498)	(0.498)	(0.018)
ρ	0.49599	0.49599	0.63933
	(0.103)	(0.103)	(0.011)
Convergence speed			
West	1.03%	1.03%	0.76%
East	-	-	-
Half-Life			
West	70 years	70 years	94 years
East	-	-	-
Tests			
Individual stability test for α	12.0116	12.0116	
	(0.000)	(0.000)	
Individual stability test for β	12.5275	12.5275	
	(0.000)	(0.000)	
Global stability test	12.8896	12.8896	
	(0.002)	(0.002)	

Notes: ML stands for maximum likelihood, QML for quasi maximum likelihood and BE for Bayesian estimation. Numbers between brackets are the p-values, LIK is the value of the log-likelihood function, AIC is the Akaïke criterion and BIC the Schwartz criterion. The coefficient of determination, and its robust version, is not reported because in presence of spatial autocorrelation, they are not appropriated to assess the quality of a regression (Anselin and Bera, 1998, P.263). Stability tests have been performed using the Likelihood ratio test.

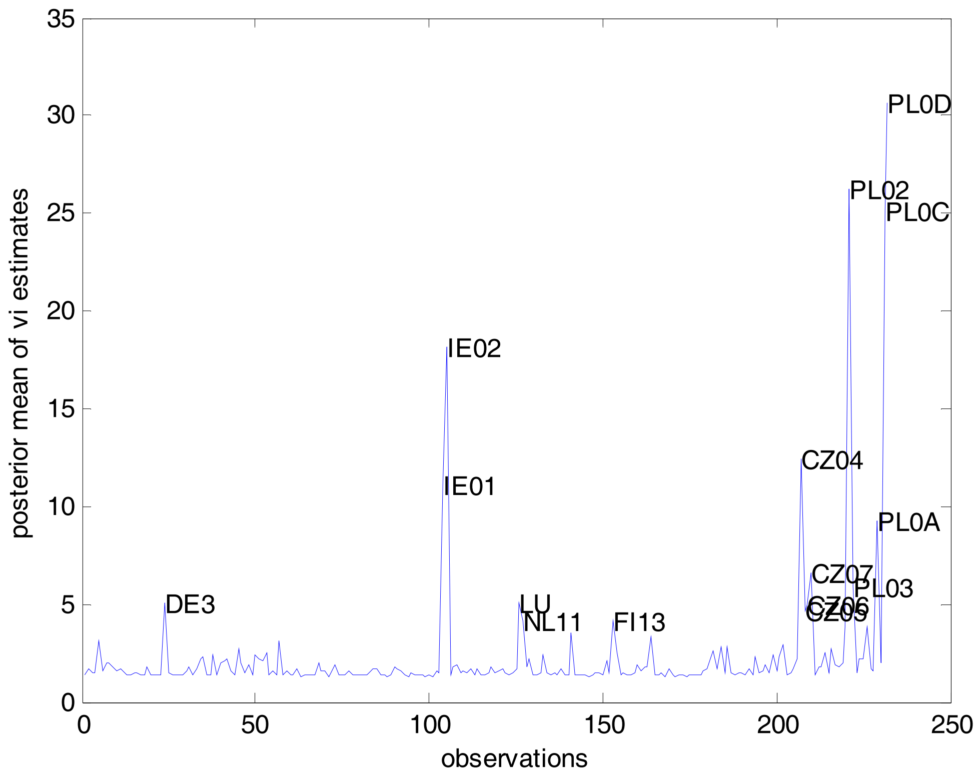

Figure 3: posterior mean of v_i estimates

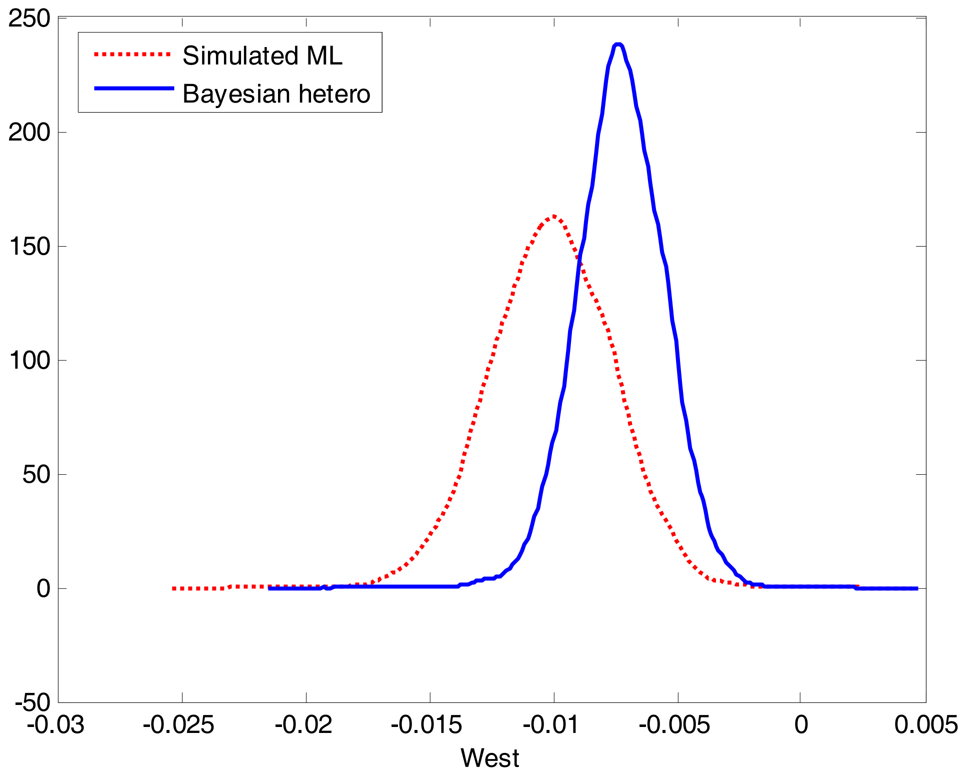

Figure 4: ML simulated normal distribution versus Bayesian heteroscedastic posterior distribution for β_{West} in the SAR model with two spatial regimes

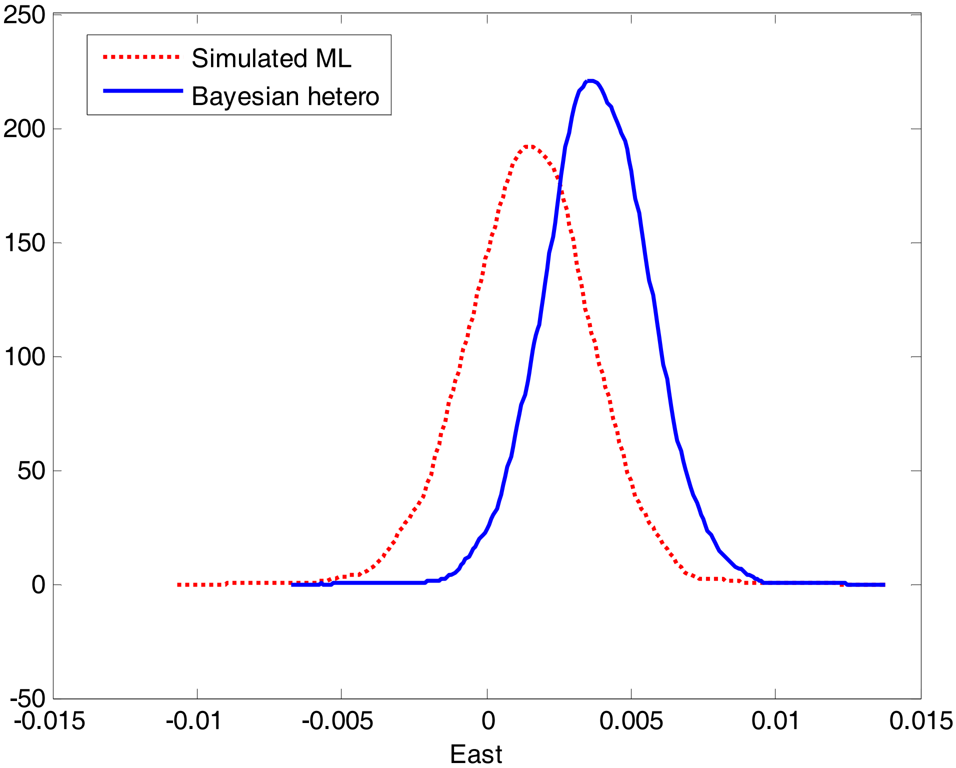

Figure 5: ML simulated normal distribution versus Bayesian heteroscedastic posterior distribution for β_{East} in the SAR model with two spatial regimes

4. Conclusion

This paper studied the convergence process among regions of the Enlarged Europe. We considered two different models, namely absolute β-convergence and convergence clubs. In the first model, when spatial autocorrelation is omitted, we found a weak but significant convergence process. Taking space into account lead us to conclude to the presence of a still weaker process but significant. However, the spatial parameter, representing the interaction intensity among regions, has a positive, high value, meaning positive spatial dependence and is significant. The direct interpretation of the significance of this parameter is that the classical linear model is misspecified.

Estimation of convergence clubs allowed us to discriminate steady state between groups of economies. We have seen that both OLS and maximum likelihood methods provide a negative and significant β estimator for the "West" regime whereas we did not find any convergence process in the "East" spatial regime.

The robustness study performed here nevertheless changes in some ways the results obtained. If we look at the QML estimation, results are similar, meaning that the correction for non-normality of the residuals is negligible. However, Bayesian estimation provides interesting results. On the absolute β-convergence process, we found that the β estimator had decreased, due to the effect of outliers, but remained significant and negative. However, in convergence clubs, results are more contrasting. If we look at the spatial parameter, and compare the maximum likelihood estimation with the Bayesian one, in the latter case, when the effect of outliers and heterosckedasticity is controlled for, we find that it is quite positive and highly significant whereas it was hardly significant at the 10% level in the former case. More importantly, Bayesian estimation provides significant convergence parameters for both clubs. These estimation results also show that Eastern regions are diverging while Western regions are weakly converging.

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A-1 Index of regions belonging to the sample

Code	Region	Code	Region
BE1	Bruxelles-Brussel	DED3	Leipzig
BE21	Antwerpen	DEE1	Dessau
BE22	Limburg	DEE2	Halle
BE23	Oost-Vlaanderen	DEE3	Magdeburg
BE24	Vlaams Brabant	DEF	Schleswig-Holstein
BE25	West-Vlaanderen	DEG	Thuringen
BE31	Brabant Wallon	GR11	Anatoliki Makedonia
BE32	Hainaut	GR12	Kentriki Makedonia
BE33	Liege	GR13	Dytiki Makedonia
BE34	Luxembourg	GR14	Thessalia
BE35	Namur	GR21	Ipeiros
DK	DENMARK	GR22	Ionia Nisia
DE11	Stuttgart	GR23	Dytiki Ellada
DE12	Karlsruhe	GR24	Sterea Ellada
DE13	Freiburg	GR25	Peloponnisos
DE14	Tubingen	GR3	Attiki
DE21	Oberbayern	GR41	Voreio Aigaio
DE22	Niederbayern	GR42	Notio Aigaio
DE23	Oberpfalz	GR43	Kriti
DE24	Oberfranken	ES11	Galicia
DE25	Mittelfranken	ES12	Asturias
DE26	Unterfranken	ES13	Cantabria
DE27	Schwaben	ES21	Pais Vasco
DE3	Berlin	ES22	Navarra
DE4	Brandenburg	ES23	Rioja
DE5	Bremen	ES24	Aragon
DE6	Hamburg	ES3	Madrid
DE71	Darmstadt	ES41	Castilla-Leon
DE72	Giessen	ES42	Castilla-la Mancha
DE73	Kassel	ES43	Extremadura
DE8	Mecklenburg-Vorpomm.	ES51	Cataluna
DE91	Braunschweig	ES52	Com. Valenciana
DE92	Hannover	ES53	Baleares
DE93	Luneburg	ES61	Andalucia
DE94	Weser-Ems	ES62	Murcia
DEA1	Dusseldorf	FR1	Ile de France
DEA2	Koln	FR21	Champagne-Ard.
DEA3	Munster	FR22	Picardie
DEA4	Detmold	FR23	Haute-Normandie
DEA5	Arnsberg	FR24	Centre
DEB1	Koblenz	FR25	Basse-Normandie
DEB2	Trier	FR26	Bourgogne
DEB3	Rheinhessen-Pfalz	FR3	Nord-Pas de Calais
DEC	Saarland	FR41	Lorraine
DED1	Chemnitz	FR42	Alsace
DED2	Dresden	FR43	Franche-Comte

Code	Region	Code	Region
FR51	Pays de la Loire	AT11	Burgenland
FR52	Bretagne	AT12	Niederosterreich
FR53	Poitou-Charentes	AT13	Wien
FR61	Aquitaine	AT21	Karnten
FR62	Midi-Pyrenees	AT22	Steiermark
FR63	Limousin	AT31	Oberosterreich
FR71	Rhone-Alpes	AT32	Salzburg
FR72	Auvergne	AT33	Tirol
FR81	Languedoc-Rouss.	AT34	Vorarlberg
FR82	Prov-Alpes-Cote d'Azur	PT11	Norte
FR83	Corse	PT12	Centro
IE01	Border	PT13	Lisboa e V.do Tejo
IE02	Southern and Eastern	PT14	Alentejo
IT11	Piemonte	PT15	Algarve
IT12	Valle d'Aosta	FI13	Ita-Suomi
IT13	Liguria	FI14	Vali-Suomi
IT2	Lombardia	FI15	Pohjois-Suomi
IT31	Trentino-Alto Adige	FI16	Uusimaa
IT32	Veneto	FI17	Etela-Suomi
IT33	Fr.-Venezia Giulia	FI2	Aland
IT4	Emilia-Romagna	SE01	Stockholm
IT51	Toscana	SE02	Ostra Mellansverige
IT52	Umbria	SE04	Sydsverige
IT53	Marche	SE06	Norra Mellansverige
IT6	Lazio	SE07	Mellersta Norrland
IT71	Abruzzo	SE08	Ovre Norrland
IT72	Molise	SE09	Smaland med oarna
IT8	Campania	SE0A	Vastsverige
IT91	Puglia	UKC1	Tees Valley and Durham
IT92	Basilicata	UKC2	Northumb. et al.
IT93	Calabria	UKD1	Cumbria
ITA	Sicilia	UKD2	Cheshire
ITB	Sardegna	UKD3	Greater Manchester
LU	LUXEMBOURG	UKD4	Lancashire
NL11	Groningen	UKD5	Merseyside
NL12	Friesland	UKE1	East Riding
NL13	Drenthe	UKE2	North Yorkshire
NL21	Overijssel	UKE3	South Yorkshire
NL22	Gelderland	UKE4	West Yorkshire
NL23	Flevoland	UKF1	Derbyshire
NL31	Utrecht	UKF2	Leics.
NL32	Noord-Holland	UKF3	Lincolnshire
NL33	Zuid-Holland	UKG1	Hereford et al.
NL34	Zeeland	UKG2	Shrops.
NL41	Noord-Brabant	UKG3	West Midlands (county)
NL42	Limburg	UKH1	East Anglia

Code	Region	Code	Region
UKH2	Bedfordshire	EE	Estonia
UKH3	Essex	HU01	Kozep-Magyarorszag
UKI1	Inner London	HU02	Kozep-Dunantul
UKI2	Outer London	HU03	Nyugat-Dunantul
UKJ1	Berkshire et al.	HU04	Del-Dunantul
UKJ2	Surrey	HU05	Eszak-Magyarorszag
UKJ3	Hants.	HU06	Eszak-Alfold
UKJ4	Kent	HU07	Del-Alfold
UKK1	Gloucester et al.	PL01	Dolnoslaskie
UKK2	Dorset	PL02	Kujawsko-Pomorskie
UKK3	Cornwall	PL03	Lubelskie
UKK4	Devon	PL04	Lubuskie
UKL1	West Wales	PL05	Lodzkie
UKL2	East Wales	PL06	Malopolskie
UKM1	North East Scot.	PL07	Mazowieckie
UKM2	Eastern Scotland	PL08	Opolskie
UKM3	South West Scot.	PL09	Podkarpackie
UKM4	Highlands and Islands	PL0A	Podlaskie
UKN	Northern Ireland	PL0B	Pomorskie
CZ01	Praha	PL0C	Slaskie
CZ02	Stredni Cechy	PL0D	Swietokrzyskie
CZ03	Jihozapad	PL0E	Warminsko-Mazurskie
CZ04	Severozapad	PL0F	Wielkopolskie
CZ05	Severovychod	PL0G	Zachodniopomorskie
CZ06	Jihovychod	SI	Slovenia
CZ07	Stredni Morava	SK	Bratislavsky
CZ08	Moravskoslezko		