THE Β & Σ-CONVERGENCE OF EUROPEAN REGIONS: AN APPROACH USING SPATIAL ECONOMETRICS

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Abstract
The goal of this paper is to explore spatial dependency in the phase of integration of European countries. On the one hand, the recently evolved techniques of an observational study of spatial data are used to improve the definition of the regional complexities of the development of Western countries. This helps us to shed more light on the standard β-convergence metric that hides specific geographical trends that fluctuate across period. On the other side, in Integration systems, they have the existence of spatial self-creation utilizing spatial econometric techniques. It helps us to evaluate the data gathered pre and post considering spatial correlation coefficients in order to highlight the importance of spilling over impacts on geographic development anomalies.

Keywords: An exploratory study of spatial details, spatial self-correlation, spatial econometrics, globalization, spillover results, Western territories

Introduction

Some of the prevailing topics dealing with in the macroeconomic research for decades is the integration of national and regional economies. The central problem that arises is whether economies continue to migrate toward the same level of wealth or output per person, in other terms, when there is a snag-up mechanism the economy to rise to the level of revenue by a centre of more advanced economy [3].

Various objective scientific research aiming to test the theory at the global or national level have come up towards econometric difficulties, making it hard to analyse the data. In fact, other explanation variables for economic globalization, such as the convergence of innovations and the flexibility effect, have a clear geographical component. Nevertheless, recent empiric experiments have not directly incorporated the space-effect rifle except for the Scandinavian communities [10]. One reason to take into consideration the function of space is to assume spatial autocorrelation [8] even though the geographical distribution of national development anomalies is seldom random: on the opposite, the economic performance of the neighboring regions is often identical.

The purpose of this report is to incorporate the geographical aspect of the data into the calculation of the integration of regional economies. In the first section, we describe the different concepts of convergence and stress the standing enchanting into explanation spatial things in the study of convergence procedures. In the second part, we introduce the newly developed techniques of experimental study of spatial data [2] in order to improve the definition of the regional complexities of the development of European territories. This helps us to shed light on the normal calculation of β-convergence, which covers specific spatial variations that fluctuate

Vol. 5, No.03; 2021

ISSN: 2456-7760

across period. In the third section, the role of spatial autocorrelation in Convergence models is evaluated using space econometric techniques [2]. This helps us to compare the findings obtained before and after taking into account spatial autocorrelation in order to highlight the importance of spillover effects on geographic development phenomena.

1. Concepts of convergence and spatial effects

The various concepts of convergence which have been developed in the literature and the importance of spatial effects in the analysis of convergence processes is discussed in the following sections.

Hypothesis:

The convergence theory is based on neoclassical growth models which suggests a tendency towards a long-term equalization of the income or output growth rate per head in different geographical areas [3]. The β-convergence may be complete (unconditional) or contingent. It is complete 1 if it is independently of the boundary conditions. It is ambiguous because, in fact, markets are expected to be the same in terms of interests, infrastructure and economic policies.

The total β-convergence theory is generally evaluated on the appropriate boundary-section system:

$$\frac{1}{T}\ln\left(\frac{y_{i,r}}{y_{i,o}}\right) = \alpha + \beta ln(y_{i,0}) + \varepsilon_i$$

$$\varepsilon_i \sim i.i.d(0, \sigma_\varepsilon^2) \;\ldots Eq\ (1)$$

where $y_{i,0}$is the GDP per head of region $i\ (i\ =\ 7,\ldots,N)$ at dater, T is the length of the study period, where $\alpha\beta$and—are unknown parameters to estimate andε_i, a random error term. It is said that there isβ—convergence whenβ is negative and statistically significant because, in this case, the actual GDP growth rate per head between dates *0 and T* is negatively correlated with the original GDP per head. The calculation of β makes it possible to measure the rate of convergence: $\theta\ =\ -\ ln\ (i\ +\ T\beta)\ /\ T$and the time necessary for economies to close half of the distance that divides them from their steady state, called half-life:$\tau =\ -\ ln\ (z)\ /ln\ (i\ +\ \beta)$

The evaluation of the conditional β convergence hypothesis is based on the calculation of the following section, where some of the variables that separate the regions must be separated and held constant:

$$\frac{1}{T}\ln\left(\frac{y_{i,T}}{y_{i,0}}\right) = \alpha + \beta ln(y_{i,0}) + \gamma \ln X_i + \varepsilon_i$$

$$\varepsilon_i \sim i.i.d(0, \sigma_\varepsilon^2) \;\ldots Eq\ (2)$$

ISSN: 2456-7760

Where X_i is a vector of variables enabling the steady state of the economy to be sustained and where state variables such as the stock of physical capital and the stock of human capital can be found, and regulation or environmental variables such as the ratio of public consumption to GDP, i.e. the ratio of domestic investment to GDP, ie Fertility rate, degree of political instability, etc. [3]. Another approach to check the conditional convergence hypothesis is still based on equation (1) but is calculated on sub-samples of economies for which the hypothesis of identical stationary states tends to be acceptable [18].

The second definition used in the literature is that of w-convergence, which withdraws at a decrease in dispersion, determined by the standard deviation of the logarithm of sales or output per head[3]. It is simply based on the estimation and analysis of the standard deviation of GDP per capita at the initial and final date of the duration under consideration. We say that there is w-convergence when this standard deviation decreases. It can be noted that β −convergence is a necessary but not sufficient condition for w-convergence. The comparative study of the two types of convergence thus makes it possible to update two mechanisms which contribute to the final result: on the one hand β −convergence implies the presence of a catch-up mechanism which reduces the gap between the GDP per capita of different regions, on the other hand, regions are subject to specific shocks which lead to an increase in the dispersion of GDP per capita. β-convergence is the overall result of these two mechanisms because it only exists when β −convergence dominates the effect of shocks that affect each of the regions [16].

The third definition of convergence, defined by Bernard and Durlauf [5], is based on the stationary properties of the time series, which is why we are thinking about stochastic convergence. It is said that there is stochastic equilibrium when long-term pro-capita GDP gaps across two or more economies appear to be small. As Bernard and Durlauf also pointed out [5], this concept is not accepted if the particular shocks experienced by each country have a permanent effect on their long-term trajectory. In an odd case, to check this convergence theory is to test the existence of a unit root in a sequence of variations in GDP per capita. Several root test procedures are described in the literature and the most commonly used are the Dickey and Fuller research procedures [9]. But we could also think of the test procedure recently developed by Ngs and Perron [19] which has much better threshold and power properties. It can be noted, however, that in this context the null hypothesis tested is that of non-stationarity and therefore of non-convergence. In the more interesting multivariate case, we test whether the GDP per capita of the N regions of the sample have a common trend using for example the methodology of Johansen and Juselius [20]. The convergence test therefore amounts, in this context, to testing the presence of N - 1 co-integration relationships.

The empirical results obtained in studies in cross-sections convergence and β-convergence) and those obtained in time series (stochastic convergence) seem to be contradictory. Indeed, the tests carried out in cross sections generally attest the presence of convergence [3] while the tests carried out in time series generally fail to reject the 'non-convergence hypothesis [5]. This apparent contradiction can in fact be explained by the difference in the concepts of convergence tested: convergence-catching up convergence) or convergence-stationarity (stochastic convergence). In addition, the reason that the theory of stochastic non-convergence can not be denied may also be due to the presence of large exogenous shocks such as the 2 world wars, the great crisis of 1929, the 2 oil shocks etc. Indeed, in this case, Perron (1989)[1] indicates that the unit root tests are biased in favor of the null hypothesis of the unit root, which is interpreted in our context as a bias in favor of the hypothesis of non-convergence. But β −convergence's tests aren't free from criticism either. We can for example quote those of Evans (1996) [13] which raise the problem of the correlation between the initial GDP per capita and the error term of the regression: this invalidates the application of Ordinary Least Squares in the estimation of the model (l) or (2) and the statistical inference based on this estimation. Caselli, Esquivel and Lefort [7] raise the problems of omitting variables intended to capture the differences between the economies in equation (2) and that of their a priori selection. To respond to these criticisms and escape the many limitations of previous testing procedures, a new avenue of research has turned to the use of panel data [13,17, 18].

1.2 Spatial effects

Empirical analyses of regional convergence require the use of spatial data, that is, observations of one or more variables measured for different locations distributed across national, European or global space.

However, *the use of spatial data* is neither neutral nor immediate: it often leads to the treatment of spatial autocorrelation [8, 14]. Indeed, not taking this phenomenon into account while it is present produces inefficient estimators [2]. In addition, spatial autocorrelation can serve as a substitute for the omitted variables. Modeling it improves estimates and predictions, and also captures the role of space in the formation of the phenomena studied.

Spatial autocorrelation refers to the absence of independence between observations and indicates the correlation of a quantity with itself coming from the geographic arrangement of the data. On a map, the grouping of similar or dissimilar observations translates a positive spatial autocorrelation in the first case, negative in the second. There are two types of spatial autocorrelation.

- The significant spatial autocorrelation is related to economic variables. This is due to the fact that data is influenced by processes that connect different locations, such as diffusion or interaction processes. Of example, the diffusion of a phenomenon, such as the attraction of a position or the technical diffusion, means that the frequency or strength of a phenomenon depends on the distance to the origin: places adjacent to each other and situated at equal distances from the origin will therefore have similar values for the phenomenon examined. More commonly, events or situations in a given place impact conditions in other areas where they intervene in one manner or another: through flows of commodities, individuals, resources, spatial externalities or all types of activity where the economic agent responds to the behaviors of other actors.

[1] For a discussion of the different sequential testing strategies, we can refer to Ertur (1998)[12]

1. **Spatial autocorrelation of nuisance relates to the residues of a regression**. It comes from a bad specification of the model due to omitted variables, an incorrect functional form, measurement errors on the variables or even aggregation problems.

These different elements are thus at the origin of particular geographic arrangements of the phenomena observed in space that the presence of spatial autocorrelation makes it possible to detect.

For their part, spatial economic theories make it possible to appreciate the forms taken by the spatial distribution of economic data because they provide the elements for understanding the location choices and the aggregation processes of economic activities. In particular, the theories of the New Geographic Economy, initiated by Krugman [1991][2], aim to explain the unequal distribution of economic activities in space: under the impetus of generally dominant forces of concentration in developed economies, activities industrial, and especially higher tertiary activities tend to be concentrated in a few places. The geographic distribution of dense spaces in economic activities and spaces poor in economic activities is rarely random since the places of agglomeration are identified either by natural or first nature conditions or according to so-called second nature conditions when the attractiveness of a place depends on the economic activities which are present there. Multi-regional models insist on the fact that the proximity of one agglomeration can prevent formation close to another agglomeration: there would be a "shadow effect" implying a minimum distance between two agglomerations. In addition, the agglomeration processes appear to be highly cumulative: the agglomeration favors the agglomeration. Thus, even if at the outset there is a homogeneous geographical distribution of economic activities, An evolutionary quirk, such as the tactical decision of a company to position itself in one location rather than another, will lead to the formation of an agglomeration in that place. The effect of the imbalance of economic activities in space on the economic development of the regions has also been shown in the new geography-growth synthesis. [4].

The construction of this current is based on the similarity of the economic mechanisms involved both in the processes of spatial concentration and in the processes of temporal accumulation of certain economic activities favorable to growth (the production of inputs or differentiated goods, R&D and innovation, public infrastructure, business services ...). We can thus consider aggregation as such as a growth factor [4]. Numerous scholars have formally established the dynamic connections between agglomeration and development processes[11]. The results provided by these so-called theories of the Geography-Growth Synthesis generally show the links between the agglomeration and growth processes. On the one hand, the agglomeration promotes growth, which means that the uneven spatial distribution of economic activities is an efficient geographic configuration for growth. On the other hand, growth can favor the geographic concentration of economic activities which contributes to strengthening the processes of economic polarization. The widening of markets, the decrease in transaction costs, the increase in labor mobility, the degree of development of economies, the “vertical linkage” relationships between firms or the existence of spillover effects are all of which can explain the

[2] For a presentation of these theories, one can refer to Duranton, 1997 and Fujita, Thesis [1997]

Vol. 5, No.03; 2021

ISSN: 2456-7760

strength of the interactions uniting the growth and aggregation processes. These approaches thus provide the theoretical basis for studying the implications of economic integration policies on the convergence of regional economies [4]. However, still few empirical studies on regional convergence incorporate the economic effects of spatial variables, such as interaction costs, mobility or regional spillover effects.

If we are more particularly interested in the spillover effects, an important theoretical result shows that we must distinguish between the local spillover effects and the global spillover effects. The former means that only the region in which economic activities are concentrated will benefit from the advantages of concentration. Under these conditions, the local overflow effects reinforce the phenomena of polarization and uneven growth of spaces. On the other hand, in the presence of global spillover effects, all regions can benefit from the advantages of concentration in a particular region. In this case, the spatial distribution of activities between regions may be less unequal, which favors the reduction of growth disparities between regions[11]. We can finally consider intermediate situations, in which the concentration in each of the regions produces both local spillover effects and global spillover effects. The emergence of uneven or balanced patterns of growth and concentration then depends on a more precise analysis of the power relationships between these two types of effects.

Faced with these different results, incorporating the geographic effects of spillover between regions appears to be an interesting avenue for better understanding the phenomena of growth and convergence. The empirical approach that we are going to carry out thanks to the study of the spatial dependence between the regions allows the investigation of this question.

2. Exploratory spatial analysis of the convergence of GDP per European head

Exploratory spatial data analysis (ESDA) is a set of techniques intended to detect patterns of spatial association, local concentrations and spatial regimes present in a dataset for which location characteristics are essential [2,15]. The ESDA thus endeavors to describe and visualize the spatial distributions of these data to identify the dominant spatial association diagrams and atypical locations. To highlight potential geographic patterns in the convergence process, we have applied these techniques to the study of per capita GDP of European regions over the period 2003-2018.

Among all of these regions, we have chosen those that are contiguous, that is to say those that share one or more common borders. Consequently, we have excluded the United Kingdom, Ireland, Greece and the islands and in total our sample includes 92 regions (at NUTS1 level: Germany, Denmark, Luxembourg; at NUTS-2 level: Belgium, Spain, France, Italy, Netherlands, Portugal). The data come from the Euro region database and the list of regions selected is found in Table 1. Spatial autocorrelation in GDP per head and in the growth rate of GDP per head is studied in section 2.1 while the identification of local concentrations and atypical locations is carried out in section 2.2.

Table 1: Summary of the various local spatial association measures GDP per head 2003-2018 & spatial association schemes: initial year and growth rate

	p < 0.5	H.H	B.H	B.B	H.B	Years	2003	Growth
PORTUGAL								
North	16	0	0	16	0	2003-2018	B.B*	H.H*
Center	16	0	0	16	0	2003-2018	B.B*	H.H*
Lisbon and the Tagus Valley	16	0	0	16	0	2003-2018	B.B*	H.H“
Alentejo	16	0	0	16	0	2003-2018	B.B*	H.H*
Algarve	16	0	0	16	0	2003-2018	B.B*	H.H
SPAIN								
Galicia	16	0	0	16	0	2003-2018	B.B*	B.H
Asturias	16	0	0	16	0	2003-2018	B.B*	B.B
Cantabria	15	0	0	15	0	2003 ; 2004 ; 2005-2018	B.B*	B.B
Pays Basque	8	0	0	8	0	2003 ; 2004 ; 2005-2018	B.B*	H.B
Navarre	0	0	0	0	0		B.B*	H.H
Rioja	12	0	0	12	0	2003 ; 2004 ; 2005-2018	B.B*	H.H
Aragon	16	0	0	16	0	2003-2018	B.B*	H.H
Madrid	16	0	0	16	0	2003-2018	B.B*	H.H
Castile and Leon	16	0	0	16	0	2003-2018	B.B*	B.H*
Castile-La Mancha	16	0	0	16	0	2003-2018	B.B*	H.H
Extremadura	16	0	0	16	0	2003-2018	B.B*	H.H*
Catalonia	0	0	0	0	0		B.B*	H.H
Valence	16	0	0	16	0	2003-2018	B.B*	H.H
Andalusia	16	0	0	16	0	2003-2018	B.B*	B.H*
Murcia	16	0	0	16	0	2003-2018	B.B*	H.H
FRANCE								
Isle of France	0	0	0	0	0		H.H	B.B*
Champagne-Ardenne	0	0	0	0	0		H.H	B.B“
Picardie	0	0	0	0	0		H.H	B.B“
Upper Normandy	0	0	0	0	0		H.H	B.B“
Center	0	0	0	0	0		H.H	B.B*
Lower Normandy	0	0	0	0	0		H.H	B.B*
Burgundy	3	3	0	0	0	2003-2005	H.H	B.B*
Nord Pas de Calais	0	0	0	0	0		H.H	B.B
Lorraine	2	0	2	0	0	2018; 2017	H.H	B.H

Alsace	0	0	0	0	0		B.H	B.B
Franche-Comté	0	0	0	0	0		H.H	B.B*
Pays de la Loire	0	0	0	0	0		H.H	B.B*
Britain	0	0	0	0	0		B.H	B.B
Poitou-Charentes	0	0	0	0	0		H.H	B.B*
Aquitaine	0	0	0	0	0		H.H	B.B
Midi-Pyrenees	0	0	0	0	0		B.H	B.B
Limousin	0	0	0	0	0		H.H	B.B*
Rhone-Alpes	0	0	0	0	0		H.H	B.B*
Auvergne	0	0	0	0	0		H.H	B.B*
Languedoc-Roussillon	0	0	0	0	0		H.H	B.B
PACA	0	0	0	0	0		H.H	B.B
Brussels	0	0	0	0	0		H.H	
Antwerp	0	0	0	0	0		H.H	B.H
Limburg	0	0	0	0	0		H.H	B.B
East Flanders	0	0	0	0	0		H.H	H.B
Flemish Brabant	1	0	1	0	0	2003	H.H	B.B
West Flanders	0	0	0	0	0		H.H	H.B
Walloon Brabant	0	0	0	0	0		B.H	H.B
Hainaut	0	0	0	0	0		B.H	B.B
Cork	0	0	0	0	0		H.H	B.B*
luxembourg	0	0	0	0	0		B.H	B.H
Namur	0	0	0	0	0		H.H	H.B
NETHERLANDS							H.H	B.B
Groningen	0	0	0	0	0			
Frieze	7	0	7	0	0	2003-2009	B.H*	B.B
Drenthe	6	6	0	0	0	2003-2008	H.H	B.B*
West holland	0	0	0	0	0		H.H	B.B*
Utrecht	0	0	0	0	0		H.H	B.B
North Holland	0	0	0	0	0		H.H	H.B
South Holland	0	0	0	0	0		H.H	B.B
Zealand	0	0	0	0	0		H.H	B.B
North Brabant	0	0	0	0	0		H.H*	B.B
Limburg	0	0	0	0	0		H.H *	B.B
GERMANY							H.H	B.B
Baden-Württemberg	10	10	0	0	0	2009-2018		
Bavaria	12	12	0	0	0	2003 ;2004; 2008-2018	H.H	H.H

Bream	0	0	0	0	0		H.H	H.H
Hamburg	0	0	0	0	0		H.H	B.H
Hesse	12	12	0	0	0	2003 ;2004; 2008-2018	H.H	H.H
Lower Saxony	16	16	0	0	0	2003-2018	H.H	H.H
North Rhine-Westphalia	0	0	0	0	0		H.H	H.B
Rhineland-Palatinate	16	16	0	0	0	2003-2018	H.H	B.H
Saarland	0	0	0	0	0		H.H	B.H
Schleswig-Holstein	16	16	0	0	0	2003-2018	H.H	H.H
LUXEMBOURG	0	0	0	0	0		H.H	H.H
DENMARK	0	0	0	0	0		H.H	H.B
ITALY							H.H	H.H
Piedmont	4	4	0	0	0	2008-2011	B.H	B.H
Aosta Valley	0	0	0	0	0		H.H	B.B
Liguria	0	0	0	0	0		H.H	B.B
Lombardy	0	0	0	0	0		H.H	H.B
Trentino - Haut Adige	0	0	0	0	0		H.H	B.H
Veneto	3	3	0	0	0	2008-2011	H.H	H.H
Friuli - Veneto Julian	0	0	0	0	0		H.H	H.H
Emilia - Romagna	0	0	0	0	0		H.H	H.H
tuscany	0	0	0	0	0		B.B*	B.B
Umbria	0	0	0	0	0		B.B*	B.B
Marches	0	0	0	0	0		B.B*	B.B
Lazio	2	0	0	2	0	2003 ; 2018	B.B*	B.B
Abruzzo	0	0	0	0	0		B.B*	H.B
Molise	3	0	0	3	0	2003; 2018	B.B*	H.H
Campania	6	0	0	6	0	2003-2005 ; 2011-2018	B.B*	B.H
Puglia	10	0	0	10	0	2003-2005 ; 2011-2018	B.B*	B.B
Basilacate	16	0	0	16	0	2003-2018	B.B*	B.B
Calabria	0	0	0	0	0		B.B*	B.B
Total	**420**	**98**	**10**	**312**	**0**			
%	**28.53**	**6.66**	**0.68**	**21.2**	**0**			

* means that the corresponding local statistic is significant

2.1 σ- convergence and global spatial autocorrelation

The measurement of σ-convergence relates to the dispersion of the distribution of GDP by regional head. However, considering only this aspect can mask particular geographic patterns, patterns that may otherwise vary over time. Consequently, the analysis of the dispersion of the GDP per head of the 92 regions over the period 2003-2018 will be coupled with an exploration of the geographic dimension of this dispersion thanks to the AEDS. Figure 1 provides a diagram of the dispersion of GDP per head in European regions, measured by the coefficient of variation of the natural logarithm of GDP per head. Overall, this dispersion tends to decrease over the period studied, but this reduction is not uniform: in particular, the first 6 years are marked by disturbances during which no clear trend emerges. Finally, after a sharp drop in the period 2006-2017, the dispersion has increased slightly again in the last few years.

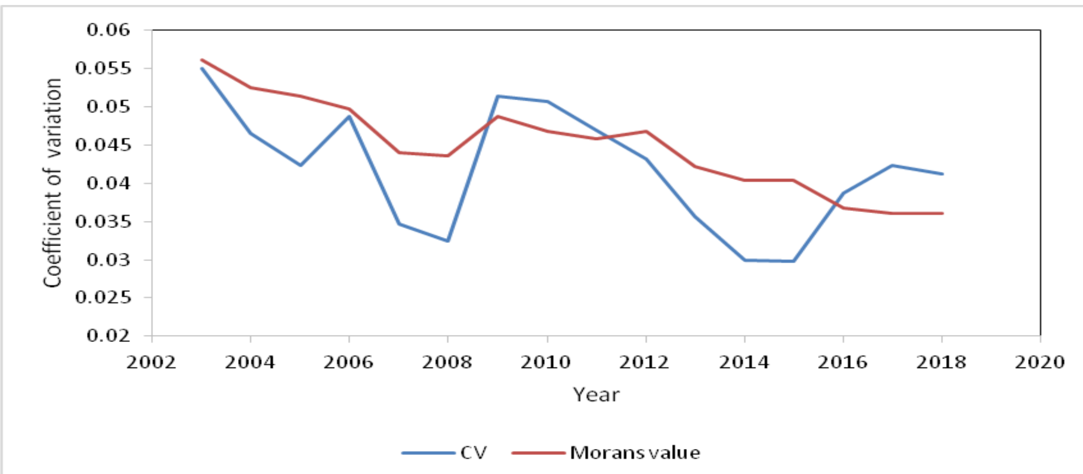

Figure 1: Sigma-convergence and spatial autocorrelation

Figure 1 also gives the evolution of the spatial autocorrelation of regional GDP per head for the same period of time. The measure of spatial self-organization is based on Moran's I statistics [8]. For each year, this statistic is written as follows:

$$I_t = \frac{n}{S_o} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} tx_{j,t}}{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i tx_{j,t}} \quad \dots Eq\ (3)$$

$$t = 1, \dots 16$$

Where w_{ij} is an element of a simple contiguity weight matrix, noted$W$, such that w_{ij}= l if the regions$i$ and j share a common border and 0 otherwise. $tx_{i,t}$, is the natural logarithm of GDP per head (deviating from the average) of region $i$at time$t$. n is the number of regions and S, is the standardization factor equal to the sum of all the elements of W. By notingx_t, ie vector of the n observations for each year$t$, (3) is written in matrix form:

ISSN: 2456-7760

$$I_t = \frac{n}{S_o} \cdot \frac{x_t' W x_t}{x_t' x_t} \quad \ldots Eq\ (4)$$

$$t = 1, \ldots 16$$

Moran's statistics give an indication of the degree of linear dependence that exists between the vector of GDP per head observed x_t, and the vector consists of weighted averages of GDP per head of neighboring regions Wx_t called spatial lag vector ("lag variable"). It is used as a basis for testing the presence of a spatial autocorrelation among the GDP per regional head. We based the significance of de Moran from an approach in terms of conditional probabilization with 10,000 permutations. It then appears that the regional GDP per head are very strongly spatially autocorrelated since the statistics are significant at p = 0.0001 for all years '. This autocorrelation is positive. This result suggests that the distribution of regional GDP by head, over the entire study period, is by nature concentrated. In other words, the regions with relatively high GDP per head (resp. Low) are located near other relatively high GDP per head regions (resp. Low) more often than if this location were purely random. Moran's statistic I thus makes it possible to detect a global and significant trend towards the geographic grouping of similar regions in terms of GDP per head.

Furthermore, the comparison of the autocorrelation measure with the coefficient of variation indicates that these two measures seem to evolve in the same way. Autocorrelation experienced disturbances between 2003 and 2009, decreased between 2009 and 2015 and went back up from 2015, which corresponds to the three periods already highlighted for the dispersion of GDP per capita. Furthermore, the simple correlation between the Moran statistic and the coefficient of variation of GDP per head is 0.819 for the period of 15 years.

This common movement is likely to reflect a dynamic characteristic of regional concentration and one may wonder what is the nature of this relationship between the two phenomena. What we observe here is that when the dispersion of regional GDP per head decreases (CV decreases) this is accompanied by a decrease in the tendency to the geographical regrouping of similar regions (I is positive but its value weakens). In other words, the random nature of the spatial distribution of regions according to their level of GDP per head is increasing. It should be noted, however, that the geographic link between neighbouring regions remains strong because the lowest value of the Moran coefficient recorded remains greater than 0.6.

This common movement nevertheless raises questions about the reasons which would explain a weakening of regional concentrations when the dispersion of GDP per head decreases? We can suggest the following hypothesis. If the dispersion of the levels of GDP per head decreases, this means that an improvement trend in GDP per head is more marked for the poor regions than for the rich regions and/or that a stronger degradation of the GDP per head is produced in rich regions than in poor regions. In any case, the decrease in spatial autocorrelation could be explained because certain poor regions (or certain rich regions) become less similar in terms of their wealth levels to other regions belonging to the same geographic group. Ultimately, the performance of regions belonging at the beginning of the period to the same geographic wealth

Vol. 5, No.03; 2021

ISSN: 2456-7760

group can become so different over the period studied that we can go so far as to observe disappearances of geographic concentrations during a period of decrease in dispersion. GDP per head.

To examine this question, it is useful to have a more disaggregated view of the spatial dependence structure in regional GDP per capita.

2.2 Analysis of local spatial autocorrelation of GDP per capita

Moran's statistical model: It fixes not require an understanding of the geographical system of self-coordination. In particular, one may wonder which regions contribute the most to global spatial autocorrelation, whether there are local clusters and to what degree the regional assessment of spatial self-correlation covers atypic locations, Only' Pockets of non-stationarity,' that is, of regions or groups of contiguous regions which deviate from the global scheme of positive spatial self-creation.

The study of local spatial autocorrelation is carried out using two tools: the Moran graph and the "Anselin" urban spatial interaction indicators [2], the latter is intended to test 1-hypothesis of random distribution by comparing the values of each specific location with those of the neighboring locations.

1. Moran's graph

The spatial association scheme is decomposed thanks to the construction of the MS graph "Moran Scatterplot" [2] where the abscissa is shown i.e., GDP per standardized head of a region and its ordinate spatial offset. The 4 parts of the graph refer to the four forms of local spatial interaction among an area and its neighbours: (H.H.) a region of high GDP per head6 surrounded by regions of lower GDP per head (Part I at the top right), (B.H.) a region of low GDP per head surrounded by regions of high GDP per head (Part II at the top left) (B.B) an area with low GDP per head, surrounded by regions with higher GDP per head (Part III below left), (H.B) a region with high GDP per head, surrounded by regions with medium GDP per head (Part IV below right).

Parts I and III refer to positive forms of spatial autocorrelation while Parts II and IV represent negative spatial autocorrelation. In the latter two cases, we speak of atypical locations.

Note that the global spatial autocorrelation is always visible in this graph since, starting from (4) and using a standardized matrix, I, is formally equivalent to the slope of the regression line ofWx_t, onx_t.

Constructed in this way, these graphs allow us to visualize both changes in the global spatial association (the slope) and the local spatial association (the point clouds in the Parts). We can thus detect on the one hand that most of the European regions belong to the positive spatial association and that on the other hand there are few "atypical" regions, that is to say deviating from the global scheme of self-creation. Positive. To confirm these results, it is necessary to calculate, in a second step, the local coefficients of spatial dependence.

2. Moran's local statistics

This local version of Moran's statistics takes the following form for each region i and for each year t [2]:

$$I_{i,t} = \frac{x_{i,t}}{m_0}\sum_j w_{ij}x_{j,t} \quad \dots Eq\ (5)$$

$$Where\ m_0 = \sum_j x^2{}_{j,t}$$

The observations$x_{j,t}x_{i,t}$, are centered and the sum j is such that only the values close to J are included. A positive value of it indicates a concentration of similar values (high or low) while a negative value indicates a concentration of dissimilar values. As with Moran's global statistics, the moments of $I_{i,t}$. under the valueless theory of non-appearance of spatial self-creation are derived from an empirical distribution generated by 10,000 permutations.

To order to identify spatial changes that happened during the time analyzed, we will only take into account the anomalies of local clusters and atypic positions for which local Moran figures are important. The findings of the test are summarized in Table 1The second column shows the number of years in which the local figures are relevant (with a pseudo-significant level of 5 per cent). In the following columns are the number of years during which the area falls within a certain portion of the MS, the associated local numbers being important. Periods or related years are listed in the last section. Different elements can be tinted.

Initially, the local pattern of spatial interaction represents the overall trend towards positive spatial autocorrelation, with 97.62 per cent of the relevant local variables falling either in Part I or Part III, i.e. Concentrations of the H.H and B.B. We remember, however, that the distribution between the H.H. and B.B. associations is extremely skewed since 74.28 per cent of the regions fell into the B.B. Part: we thus find, for the most part, areas or regions with low GDP per head, followed by other regions with low GDP per head.

Second, the differences from the global trend are small and governed by a particular form of negative spatial association: ie category B.H, a situation in which a region with a low GDP per head is surrounded by regions with a high GDP per head. No interaction of the H.B form or "capital uprising" has been observed. The "black sheep" (regions falling in Part II) are Lorraine for the last two years, ie Flemish Brabant for the first year and Friesland for the first seven years. There is therefore no "pocket of non-stationary", just a few atypical locations.

Third, 2 regional concentrations persist over time. The first sort, B.B., is the large concentration among all the Portuguese areas & Spanish areas. It can be remembered that these poor regions joined the EEC in 2009 and gained from them in 2012 as regions "lagging behind in development", from the economic measures of the Reform of the Structural Funds under Objective 1 but that over the entire period, the level of wealth in these regions remains below average. The second H.H-type concentration concerns certain German regions: Lower Saxony, Rhineland-Palatinate, Schleswig-Holstein for all years, Baden-Württemberg, Bavaria and Hesse not included in this concentration of regions richest Europeans since 2009. Finally, there is a small B.B-type concentration between several Italian regions, eligible for objective 1, but that this concentration has evolved over time: the Basilacate is accompanied by the Molise, Campania and Puglia at the beginning and at the end of the period, that is to say mainly during the periods of divergence.

These different results allow on the one hand, to better understand the evolution of the Moran coefficient over our study period and on the other hand, to specify the causes of the positive correlation between the global measure of Moran and the measure of the dispersion of GDP per head. Indeed, Figure 1 shows a rather disrupted evolution at the start of the period, then a decrease in the coefficient from 2009 to 2015 followed then by an increase until 2017. These evolutions are to be compared with periods or years for which certain regions belong significantly to a dial of the MS graph. We can then see, for example, that some regions "significantly" join the B.B or H.H dial at the start of the period, which for the corresponding years then translates into an increase in the Moran coefficient. This phenomenon is also observed at the end of the period. The intermediate period, characterized by the continuous decline in the Moran coefficient is explained on the contrary by the fact that certain regions "leave" over this period ie the dial to which they belonged (this is the case for example of certain Italian or Spanish regions). These results show at the same time that the positive correlation between the global measure of Moran and the measure of the dispersion of GDP per head seems to be due to the weakening of regional concentrations during periods of convergence rather than to the disappearance of previously formed concentrations. : Many regions do show stability in belonging to a B.B or H.H dial of the Moran graph over the entire period studied.

To complete these analyzes, it may therefore seem interesting to apply the ESDA techniques to GDP per capita growth rates in order to study the possible relationships between the geographical patterns and the β −convergence hypothesis.

2.3 Analysis of local spatial autocorrelation of per capita GDP growth rates

The calculation of Moran's statistics I on the growth rates of GDP per head between 2003 and 1995 of the different regions shows a strong positive spatial autocorrelation. This reflects a trend towards the geographic grouping of regions with high growth rates on the one hand and regions with low growth rates on the other. If we also apply the procedure of evaluation of local spatial autocorrelation to growth rates (table 1, 8column), we note that the spatial association schemes remain dominated by B.B or H.H type concentrations. Only significant atypical locations are of type B.H: the “black sheep” being the Spanish regions of Castile and Leon and Andalusia.

To look for possible geographic features involved in the convergence processes, we compared the spatial association scheme of the growth rate with the spatial association scheme of initial GDP per head (Table 1, 6 to 8 columns). Several results are worth highlighting.

It seems that, in just over 50% of cases, the areas that were in a particular part in 2003 are in the opposite section because of their growth rate. Therefore, in 2003, the provinces of Portugal and some Spanish areas had a higher GDP per head and were replaced by regions with a low GDP per head (B.B type concentration) but their growth rate was, as for their neighbours, higher than the mean (H.H type concentration). The regional self-organization coefficients have made it possible here to illustrate the dynamic nature of these regions, whose economic performance within the community of regions of southern Europe has often been highlighted. On the opposite, the bulk of French provinces, certain regions in Belgium and the Netherlands, are characterized by a configuration of initial H.H type GDP per head and a configuration of B.B type growth rates.

- Certain variations between spatial patterns can still be illustrated. Within the community of southern regions, some poor regions in Italy and Spain do not take off, as do their counterparts (B.B-type configurations for initial GDP per head and growth rates) or given the dynamism of their neighbors (B.B-type configuration for initial GDP per head and B.H-type configuration for growth rates). These regions thus show strong signs of developmental delay. On the other hand, in the group of northern regions, the relative dynamisms of the regions vis-à-vis their neighbors appear more fluctuating and no configuration of types B.H or H.B on the growth rates seems dominant.

Also, these different results demonstrate that the SDEA makes it possible to expose equally the patterns in the economic development of each country relative to those of its regional setting. We can thus not only find certain results highlighted in other studies by other methods (this is the case of the dynamism of certain Portuguese or Spanish regions and the existence of "underdevelopment trap" for some Spanish or Italian regions), but we can also give an account of the underlying geographic link. In particular, the SDEA also reveal here the presence of a positive spatial autocorrelation within these trends. It is therefore necessary to take this into account when testing the convergence hypothesis.

3. β- convergence and spatial econometric analysis

In this part, we implement methods of estimating spatial econometrics [2, 8] to detect and treat spatial autocorrelation in the absolute β −convergence model. We study the convergence process on the GDP per head of the European regions for the period 2003-1995. The first step consists in estimating the simple model of absolute convergence and in carrying out various tests to confirm the presence of the spatial effects that we detected in the previous section. These tests lead us to the choice of a specification explicitly and adequately integrating these spatial effects. In a second step, we then estimate the parameters of the convergence model taking into account the spatial autocorrelation. We finally show in a third step, how this specification allows to integrate the overflow effects in the β −convergence model. The impact of spatial association schemes on convergence is then analyzed.

3.1 Estimation and testing of the simple absolute convergence model

We take as starting point the following absolute convergence model:

ISSN: 2456-7760

$$\left(\frac{1}{T}\right)\ln(z) = S\alpha + \beta\ln(y2003) + \varepsilon \;\ldots Eq\ (6)$$

$$where\ \varepsilon \sim N(0, \sigma^2 I),$$

where z is the vector of dimension $N = 92$of the ratios of the GDP per head for each region$i$ in 1995 and in 2003, T= 15, y_{2003} is the vector containing the observations of the GDP per head for all the regions in 2003, α and β are the undefined parameters to be calculated are the Sum variable, and the Sum function is the vector of errors with the normal properties.

The results of the model estimate of this error are shown in Table 2. The factors are important and the coefficient of GDP per head is negative, supporting the theory of economic integration for European areas. The rate of convergence correlated with this calculation is 1.70 per cent and the half-life is 46 years. This consequence of β-convergence can be contrasted with the outcome of β -convergence previously obtained using the Henin and Le Pen diagram[16]. We are well below the convergence limit, in the β & σ -convergence region. Such results indicate that the overall convergence mechanism is slow and in line with other empirical studies on the integration of European regions [3, 6].

Table 2: Estimates and tests results

Model Estimation	(6)	(7)
constant	0.19 (0)	0.215 (0)
β	-0.015(0)	-0.017(0)
γ	-	-
ρ	-	-
λ	-	0.601(0)
R^2	0.14	
Likely	312.3	323.5
Akaike[1]	-621	-644
Schwarz	-616	-639
σ^2	$6.7\text{x}10^{-5}$	$4.7\text{x}10^{-5}$
Tests		
MOR	5.074 (0)	-
RTL	0.162(0.688)	0.052(0.819)
LMA	5.227(0.022)	-

Notes: The “p-values” are in brackets. Likely: value of the likelihood function at the optimum. Akaike: Akaike criterion[1]. Schwarz: Schwarz criterion. MOR is Moran's test. RTL and LMA are robust tests of the Lagrange multiplier aiming to test respectively the presence of an offset endogenous autoregressive variable or variable and of a spatial autocorrelation of errors.

In addition, three autocorrelation experiments were carried out, the Moran test tailored to the regression residues by Cliff[8] and two successful Lagrange multiplier tests[2]. In order to test the existence of the two possible forms of spatial autocorrelation, RTL for the shifted self-regressive or endogenous vector and LMA for the spatial autocorrelation of errors. The Moran test shows the existence of spatial dependency (Table 2). This check is very effective against the two modes of spatial dependency, but it does not make it possible to discriminate against them[2]. On the other hand, the two stable measures have good power against their particular alternative and indicate the presence of a spatial autocorrelation rather than a moving endogenous variable(Table 2). Therefore, the model (Eq.3) suffers from a poor specification due to the lack of a spatial autocorrelation of errors. In fact, each area is not independent of the others, as has often been believed in previous studies carried out at regional level. Therefore, the absolute β-convergence model must be updated in order to directly accommodate this spatial dependency.

3.2 Errors obey the autoregressive cycle of the first order.

When the error occurs in the first order of the self-regressive spatial cycle, the formula is written:

$$\left(\frac{1}{T}\right)\ln(z) = S\alpha + \beta\ln(y_{2003}) + \varepsilon \;\ldots Eq\ (7)$$

$$where\ \varepsilon = \lambda W\varepsilon + u$$

$$u \sim N(0, \sigma^2 I),$$

λ is the scalar parameter representing the strength of the spatial autocorrelation between the regression residues. As the errors are not distinct, the use of LMA in this situation creates core but unreliable estimators. The results of the estimate of maximum likelihood are shown in Table 2. All the coefficients are important. The ratio of GDP per initial head is smaller than that of the simple model and the calculation shows a strong positive spatial autocorrelation of the errors (d= 0.601). The RTL test does not dismiss the null hypothesis of the lack of an extra auto-regressive predictor. This model is equivalent to the previous model in terms of information criteria[1]. Consequently, the configuration of spatial autocorrelation of errors tends to be the most suitable specification. The definition has two consequences for the convergence statement. On the one hand, the convergence speed of the model of spatial autocorrelation is 1.96 per cent and is therefore greater than that of the original model, with a half-life of only 40 years. On the other hand, the geographic autocorrelation of errors means that the spontaneous shock in a specific region extends to all regions of the country.

Indeed, since: $\varepsilon = \lambda W\varepsilon + u, then\ \varepsilon = (I - \lambda W)^{-1}\ u$ and the model (7) is written:

$$\left(\frac{1}{T}\right)\ln(z) = S\alpha + \beta\ln(y_{2003}) + (I - \lambda W)^{-1}\ u \;\ldots Eq\ (7.1)$$

From this expression, we deduce that a spontaneous shock in a specific region does not only affect the growth rate of that region, but also has an effect on growth rates in other regions by means of spatial transformation$(I - \lambda W)^{-1}$. In fact, even if any area has a limited number of neighbors, the inverse transformation operator determines the covariance of errors that propagate different shocks not only to its neighbors but also to the entire system. Spatial econometric models also tend to be useful for predicting spill over impacts.

3.3 Modeling Spill over effects

It is interesting to note that the Eq (7) can still be rewritten in a different form and can be viewed as a conditional convergence model integrating spatial context variables. In addition, the Eq (7) can be reformulated as follows:

$$\varepsilon = \left(\frac{1}{T}\right)\ln(z) - S\alpha + \beta\ln(y_{2003}) \ldots . Eq\ (8)$$

by pre-multiplying byλW, we get:

$$\lambda W\varepsilon = \lambda W[\left(\frac{1}{T}\right)\ln(z)] - \lambda\alpha WS + \lambda\beta W\ln(y_{2003}) \ldots . Eq\ (9)$$

$$\text{As } \varepsilon = \lambda W\varepsilon = u \ldots . Eq\ (10)$$

So,

$$\left(\frac{1}{T}\right)\ln(z) = (\alpha S + \lambda\alpha WS) + \beta\ln(y_{2003}) + \lambda W\left[\left(\frac{1}{T}\right)\ln(z)\right] - \lambda\beta Wln(y_{2003}) + u \ldots . Eq\ (11)$$

$$\left(\frac{1}{T}\right)\ln(z) = C_{ste} + \beta ln(y_{2003}) + \rho W\left[\left(\frac{1}{T}\right)ln(z)\right] + (\alpha S + \lambda\alpha WS) + \gamma Wln(y_{2003}) + u \ldots . Eq\ (12)$$

$$\text{With } \rho = \lambda, \gamma = -\lambda\beta \ and\ u \sim N(0, \sigma^2 I)$$

This model has two forms of overflow impacts. On the one hand, the growth rate of the area i is determined by the growth rate of the regions adjacent to the region through the transferred endogenous vector $Wln(z)$.. On the other hand, the growth rate of the area$i$ is determined by the original per capita GDP of the contiguous regions by the offset exogenous vector$Wln(y_{2003})$.

The estimation of the Equation (4) makes it possible to quantify this double overflow effect: the growth rate in a region is positively influenced by the growth rate of in the growth processes. Two primary forms of interdependence between geographic proximity and initial GDP per head on the one hand, and geographic proximity to growth rates on the other have been revealed. But the theories of the geography-growth synthesis also emphasize the rifle of other initial conditions like the level of human capital or the stock of knowledge, like the level of equipment in infrastructures or the potential of innovation, like still the degree of urbanization ... These growth factors are all elements that can be integrated into the conditional convergence equations, the techniques of spatial econometrics making it possible to directly assess the existence and the strength of the spillover effects attributable to them. We can still wonder about the interdependence between the phenomena of growth and urbanization. Finally, structural elements linked to the construction of the European Union (such as the analysis of the impact of enlargement or the implementation of structural fund reform or cohesion policy) can also to be taken into account. All these themes constitute avenues for future research.

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Vol. 5, No.03; 2021

ISSN: 2456-7760

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