International Journal of Business and Social Science Research
Vol: 2, Issue: 1
January/2021
https://ijbssrnet.com/index.php/ijbssr
DOI: 10.47742/ijbssr.v2n1p2

Regional Convergence in North Africa Regions: Parametric and Non Parametric Approaches

HAZEM MOHAMED
University of Manouba
U.R.QUARG, ESCT, Tunisia
Email: hazem_mdm@yahoo.fr
Tunisia

ARTICLE INFO

Article history: Article
Received : 21 December 2020
Revised : 5 January 2021
Accepted: 12 January 2021
DOI: 10.47742/ijbssr.v2n1p2

ABSTRACT

Attention to issues of inequality and convergence has become a topic of considerable interest in both developing and developed economies. The purpose of this paper is to study empirically the evolution of the disparities between more than 360 Maghreb regions considering spatial dependence and to explore a non-parametric approach for characterizing convergence of GDP per capita. This study utilizes growth theory as the theoretical foundation to explore the convergence hypothesis. The methodology consists of identifying the shape of the long-run spatial associations through the use of Markov chains which make it possible to derive a unique stationary distribution related to the transition matrix. The results of the analysis indicate the persistence of regional disparities and the importance of geography to explain the global convergence process with positive spatial spillover effects. The proportion of high-income regions surrounded by similar regions has significantly increased detrimentally to the other spatial associations. This non-parametric approach complements the standard parametric method (absolute and conditional beta-convergence) which shows that the slow convergence process can be accelerated by beneficial spatial interaction effects. These results have strong policy implications with regard to national and territorial policies in these countries.

Keywords: North Africa, growth, convergence, spatial econometrics, Markov chain.
JEL classification codes: O55, R11, Q54

1. Introduction

Income growth and convergence are also known as the catch-up effect has been studied extensively in the literature with most studies citing the works of Solow (1956). The benefits associated with the catch-up effect have been well documented in the literature when viewed through the lens of income convergence (Zachary & Harper, 2013). Recent research on economic growth and regional convergence has incorporated the analysis of spatial spillovers, acknowledging that traditional determinants of regional growth are subtly altered when the spatial effect is taken into account (Abreu et al., 2005). In this sense, many studies have shown that geographic location does matter in terms of regional growth performance. Therefore, it is necessary to include the location in growth models, because otherwise the results obtained could be biased and any conclusions misleading (Ferrer, 2017). The spatial econometric approach has been employed in several studies alongside convergence models, both unconditional (Rey & Montouri, 1999) and conditional (López-Bazo et al., 1999; Fingleton & López-Bazo, 2006; Ezcurra & Rios, 2015). On the other hand, Econometric analysis of convergence processes across countries or regions usually refers to a transition period between an arbitrarily chosen starting year and a fictitious steady-state (Kosfeld & Lauridsen, 2004).

Over the past two decades, the issue of regional convergence has been the subject of a wide range of empirical research and the most widely used model for testing convergence hypotheses is beta-convergence analysis. In this sense, the new empirical literature has been dedicated to measuring the convergence process and identifying the main driving forces that explain the growth in North African and Middle-East countries (MENA). Most of these studies conclude that not all MENA countries show a clear convergence pattern of GDP and GDP per capita. When a clear convergence pattern does exist, this process can be explained by many variables, especially human capital, trade, and regional integration, transports, and infrastructures (Hammouda et al., 2009; Guétat & Serranito, 2010). Other factors commonly included in the econometric modeling of convergence are demographic variables, labor market conditions, industrial structure, institutional factors, and overall government policy (Davor & Andrea, 2013).

One limitation of these studies is the use of national data, which does not allow the exploration of spatial spillover effects and inequalities across regions. In this regard, the recent development of spatial econometrics and the increasing availability of regional data give new opportunities to describe and characterize the convergence process at a detailed geographical level (Alexiadis, 2013; Soundararajan, 2013). The present study focuses on growth and convergence in 366 regions located in Maghreb countries (Algeria, Morocco, and Tunisia). It goes further than the existing literature by proposing a non-parametric analysis based on Markov chains that provide a much more detailed exploration of long-term spatial associations of the regional units that we consider. In this regard, both global and local spatial interactions are investigated as well as the changes over time of these interactions.

The paper is organized as follows. After abrief review of the theoretical framework applied, in the second section of this paper we explore the global convergence process of the regional units of the Maghreb countries over the period 1990-2005, through the estimation of absolute and conditional spatial convergence models. Section 3 investigates the dynamics of the GDP per capital's spatial interactions over the same period through the identification of a stationary form of the Moran diagram based on a Markovian approach. Section 4 concludes and discusses the contributions and the complementarity of the non-parametric approach developed in Section 3 about the convergence model derived in Section

2. Regional convergence of per capita GDP in Maghreb countries: an application of a beta-convergence model (1990, 2005)

While the literature on regional growth reflects broad consensus on the need to incorporate elements from both supply and demand-based models, empirical analysis of growth in neoclassical models has shown that, in the main, supply factors determine the characteristics of the production function (Ayuso, 2007; Ferrer, 2017).

In recent years, renewed attention has been paid to these models, sparked by the interest aroused by the analysis of economic convergence and its determinants, which has produced empirical evidence on the catch-up process in income per capita. Thus, studies by Barro and Sala-i-Martin (1990; 1992) and Sala-i-Martín (1996) defined concepts of convergence (sigma and beta) and posited the existence of a steady-state solution towards which income per capita will tend as the consequence of diminishing marginal returns and the exogenous nature of technology (ferror, 2017). This process is known as absolute (or unconditional) beta convergence. Beta convergence simply means that poorer regions will grow faster than richer regions holding all things equal, while sigma convergence is related to a reduction in the disparity of incomes across economies.

Using a spatial Barro regression, the first insight into regional convergence in a Maghreb country can be provided by testing both absolute and conditional convergence. The model can be written as follows:

$$\Delta lnGDPC = \alpha S + \beta lnGDPC_{1990} + \delta lnX + \varepsilon \qquad (1)$$

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

where $\Delta logGDPC$ is the growth of GDP per capita, $GDPC_{1990}$ is the initial GDP per capita and X is the vector of additional explanatory variables that take into account initial conditions. S is the sum, and vectors α and β are the parameters to be estimated. If β is negative and significant, this means that the lower the initial GDP per capita, the greater its growth. This suggests an absolute convergence that is independent from the initial conditions when the parameter δ is equal to zero.

The model is tested for 366 regional areas in Maghreb countries, including Morocco, Algeria, and Tunisia. It is based on the dataset developed in the framework of the G-Econ research project (Yale University) that proposes a measure of Gross Cell Product (GCP). It corresponds to the economic activity (GDP) calculated for each regional area corresponding to a 1-degree longitude by 1-degree latitude resolution (approximately 100 km by 100 km). It covers a large number of regional areas in the world (about 27500) for the years 1990, 1995, 2000, and 2005 (for further details, refer to http://gecon.yale.edu/). Figure 1 shows the GCP per capita for the selected geographical areas.

Testing first the absolute convergence model, it is assumed that d=0. Tables 1a and 1b show the estimation results with the a-spatial OLS estimator as well as spatial model specifications. These are based on an alternative spatial weight matrix, including the inverse distance W(dist) and the 5 and 10 nearest neighbors, respectively W(5) and W(10).

Results show first that the convergence hypothesis is accepted for the Maghreb geographical areas. However, the convergence process is very slow as its speed is equal to 3.05% and the half-time necessary to reach the steady-state is equal to almost 28 years.[1] However, the spatial tests show that the Moran statistic (IM-Err) is significant no matter what spatial weight matrix is considered. This denotes the existence of spatial autocorrelation of the error terms that renders the standard OLS estimation inappropriate. Figure 1 illustrates the spatial interactions of GCPs across regional areas. Indeed, it is striking to observe that the regional units that are characterized by a high GCP level are generally surrounded by regions that also show high GCP levels. This remark applies particularly to the areas close to big cities.

To take into account these spatial interactions, the two main spatial models are the SAR (Spatial autoregressive model) and the SEM (spatial error model).[2] The choice between these two types of spatial models is based on the robust Lagrange Multiplier test applied to spatial error and lag models (RLM-Err and RLM-Lag respectively). The spatial lag model (SAR) seems to be more adequate. This model takes the following reduced-form specification:

$$\Delta lnGDPC = \alpha S + \rho W \Delta GDPC + \beta lnGDPC_{1990} + \delta logX + \varepsilon$$

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

where r measures the intensity of the spatial interactions between the regional units and W is the spatial weight matrix.

[1] We recall that the convergence speed is equal to: -ln(1+Tb)/T; the half time is equal to: -ln(2)/ln(1+b).

[2] Several other spatial models have also been tested. The first corresponds to the SARAR specification that combines SEM and SAR models. In addition, we have also tested the Spatial Durbin Model (SDM) specification. However, the likelihood statistic that tests the common factor concludes that the SDM is not the most appropriate specification, as the errors remain spatially correlated. In order to save space, the results for SARAR and SDM are not presented but are available upon request.

International Journal of Business and Social Science Research

Vol: 2, Issue: 1
January/2021
https://ijbssrnet.com/index.php/ijbssr
DOI: 10.47742/ijbssr.v2n1p2

Table 2 shows the estimation of the SAR model based on the inverse distance matrix.

Results for the absolute convergence model (Column 1) show that the convergence hypothesis is clearly accepted with a convergence speed and a half-time equal to 4.2% and 22.7 years respectively. Interestingly, the convergence speed is accelerated as compared with the results provided by the a-spatial model (Table 1a). Neighborhood effects that boost the convergence process of regional units can explain this. The high r and LRT values (0.70 and 15.1 respectively) suggest significant and positive spatial interactions concerning regional GDP per capita. Thus, it seems that the growth of GDP per capita is influenced by positive spatial spillover effects.

The conditional convergence model is estimated in Table 2 (Column 2). The control variables that are usually considered in the Solow model or the Barro regression are related to saving, technology, or any other variables that explain growth, such as institutions, infrastructure, openness, regional integration, or climate (Sala-i-Martin, 2004). However, data availability is a problem and is the major constraint for estimating this kind of model at the regional level. This problem is particularly acute when the dataset includes regions that belong to different countries, e.g., in this paper, Morocco, Algeria, and Tunisia. Still, climate variables are available at the same detailed geographical level as GDP. These data include temperature and precipitation. A new theoretical and empirical literature on the relationship between climate and income shows that the rise in temperature and the decrease in precipitation have a negative impact on growth (Dell et al.,2009). The climate dataset used here is based on "Terrestrial Air Temperature and Precipitation: 1900-2008 Gridded Monthly Time Series," version 2.01 (Matsuura & Willmott 2009).

The conditional model can thus be written as:

$$\Delta lnGDPC = \alpha S + \rho W\Delta GDPC + \beta lnGDPC_{1990} + \delta_1 lnTEMP + \delta_2 lnPREC + \varepsilon$$

$$\varepsilon \sim N(0,\sigma^2) \qquad (3)$$

The estimation results show that both climate variables are significant and have the expected sign. As a matter of fact, a decrease in temperature and an increase in precipitation lead to a rise in GDP per capita growth. In addition, the convergence hypothesis is still accepted (β is negative and significant). As compared to the absolute model, taking into account the climate variables slightly accelerate the convergence process as the convergence speed increases to 4.2% and the half-time decreases to 21.8 years. The other tests indicate that spatial interactions are still highly significant (r=0.64). In addition, the error heteroscedasticity problem disappears in this specification, as the Breush-Pagan test becomes insignificant at the 5% level.

Concluding this section, we show that regional areas in Maghreb countries experience a convergence process and that there are positive spatial spillover effects that slightly accelerate the convergence speed.

3.Exploring the dynamics of spatial associations in Maghreb countries through a Markov Chains approach

Exploratory Spatial Data Analysis brings together a body of techniques that enable the visualization of spatial distributions, that identify atypical localizations, detect extreme observations and configurations of spatial association (Haining, 1990; Bailey and Gatrell, 1995; Anselin, 1998; Boumont & al, 2000; Le Gallo, 2002). Clustering methods are based upon the detection of similarities between the localized units according to their metric distances. However, in regional sciences, the application of these methods is oriented more towards the detection of interdependences between the classes than on the formation of classes. the Moran diagram is one of those methods The previous section provides a first insight into convergence and spatial interactions of GDPs in the Maghreb regional areas. Spatial autocorrelation is usually measured by Moran's index (1950), which reflects the linear dependence between a variable at a specific location and the mean value of the same variable for its neighbors. Its value can be positive or negative depending on whether the scatter of points reflects a straight line sloping from the lower left-hand to the upper right-hand corner or from the upper left-hand to the lower right-hand corner, respectively.

The previous section provides a first insight into convergence and spatial interactions of GCPs in the Maghreb regional areas. However, it does not say anything either about local spatial associations or about the dynamics of these interactions. This section proposes a non-parametric analysis that is dedicated to further characterizing these spatial associations and their dynamics. This approach is complementary to the estimation of parametric convergence models.

Spatial autocorrelation is usually measured by Moran's index, which reflects the linear dependence between a variable at a specific location and the mean value of the same variable for its neighbors. Its value can be positive or negative depending on whether the scatter of points reflects a straight line sloping from the lower left-hand to the upper right-hand corner or from the upper left-hand to the lower right-hand corner, respectively (Ferrer, 2017). This statistic is equal to 0.452 in 1990 and 0.561 in 2005. It is significant at the 1% confidence level. This confirms the importance of spatial interactions with regard to GCPs in the Maghreb regional units. The Moran scatterplot allows us to go further by calculating local spatial associations. This scatterplot (Figure 2) is a graphic representation that enables a description of the schema of local spatial associations, identifies the atypical points, and detects the extreme observations. The horizontal axis shows the regional standardized GDP per capita (Z) and the vertical axis shows the standardized spatial lag of this GDP per capita (WZ). This makes it possible to split the diagram into four quadrants, each characterizing the local spatial associations, i.e., High-High (HH), High-Low (HL), Low-High (LH), and Low-Low (LL).

Table 3 displays the corresponding values for the years 1990 and 2005. Interestingly, most spatial associations correspond to similar values (positive spatial autocorrelation). As a matter of fact, summing the HH and LL values suggests that

International Journal of Business and Social Science Research

Vol: 2, Issue: 1
January/2021
https://ijbssrnet.com/index.php/ijbssr
DOI: 10.47742/ijbssr.v2n1p2

more than 70% of the regional units in 2005 were surrounded by regions with similar GDP per capita (either high or low). In addition, there has been a strong rise in the proportion of high-income regions surrounded by other high-income regions (from 29% to 37%) while the proportion of low-income regions surrounded by other low-income regions has tended to decrease (from 37% to 33%). This provides a first insight into the dynamics of the spatial associations. Calculating the transition matrix that analyses the moves toward each quadrant can further specify these dynamics. The transition can take several shapes. It can be *horizontal* when only the considered region moves toward a different quadrant (LH-HH, HH-LH, LL-HL, HL-LL) or *vertical* where only the neighboring regions move toward other quadrants (LL-LH, LH-HH, HL-HH, HH-HL). It can also be *diagonal*, when a parallel change of a regional unit and its neighbors is observed (LL-HH, HH-LL, LH-HL, HL-LH) or *homogenous* if the regional unit considered and its neighbors remain in the same quadrant during the entire period (HH-HH, HL-HL, LH-LH, LL-LL). We provide an application to Maghreb regional units between 1990 and 2005 in Figure 3.

This matrix suggests first that the great bulk (91%) of the high-income regional units surrounded by other rich regions remain in the same quadrant during the period considered. Conversely, only 68% of low-income regional units surrounded by similar regions remain in the same quadrant, and only 58% of low-income regions surrounded by high-income regions remain in their initial quadrant. This shows a significant mobility process of Maghreb regions in terms of GDP per capita. In particular, the HH quadrant attracts 61.8% of the changes corresponding to the three other spatial associations. This is an indication that the high-income regions have spatially driven the convergence process identified in Section 1. In addition, quadrant HL has attracted 14.6% of the transitions from the other quadrants. Conversely, the LL quadrant has attracted only 11.7% of the changes in the other quadrants.

The final step consists of identifying the shape of the long-run spatial associations through the use of Markov chains, which make it possible to derive unique stationary distribution related to the transition matrix. Basically, for a group of m spatial associations, a Markov chain is irreducible if all groups form a unique equivalent class (each association is accessible from any other association). Consequently, the chain has a unique stationary distribution $\Pi = \begin{pmatrix} \Pi_1 & \cdots & \Pi_i & \cdots & \Pi_m \end{pmatrix}$ as the solution of the following system:

$$\begin{cases} \Pi A = \Pi \\ \sum_{i=i}^{m} \Pi_i = 1 \end{cases} \tag{4}$$

where Π_i denotes the proportion of the regional units in group I, and A is the transition matrix defined as :

$$A = \begin{pmatrix} e_{11} & \cdots & e_{1i} & \cdots & e_{1m} \\ \vdots & \ddots & \cdots & \cdots & \cdots \\ e_{i1} & \vdots & e_{ii} & \cdots & e_{im} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ e_{m1} & \cdots & e_{mi} & \cdots & e_{mm} \end{pmatrix} \tag{5}$$

e_{ij} is the percentage of the regional units which have shifted from the state i at year t to the state j at the year t+1. The units on the main diagonal (e_{ii}) denote the percentage of the regional units that remain in the initial state between t and t+1. In order to derive the stationary distribution, we consider:

$$\begin{pmatrix} \Pi_1 & \cdots & \Pi_i & \cdots & \Pi_m \end{pmatrix} \begin{pmatrix} e_{11} & \cdots & e_{1i} & \cdots & e_{1m} \\ \vdots & \ddots & \cdots & \cdots & \cdots \\ e_{i1} & \vdots & e_{ii} & \cdots & e_{im} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ e_{m1} & \cdots & e_{mi} & \cdots & e_{mm} \end{pmatrix} = \begin{pmatrix} \Pi_1 & \cdots & \Pi_i & \cdots & \Pi_m \end{pmatrix}$$

with

$$\sum_{i=i}^{m} \Pi_i = 1 \tag{6}$$

or

$$\begin{pmatrix} \Pi_1 & \cdots & \Pi_i & \cdots & \Pi_m \end{pmatrix} \left[\begin{pmatrix} e_{11} & \cdots & e_{1i} & \cdots & e_{1m} \\ \vdots & \ddots & \cdots & \cdots & \cdots \\ e_{i1} & \vdots & e_{ii} & \cdots & e_{im} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ e_{m1} & \cdots & e_{mi} & \cdots & e_{mm} \end{pmatrix} - \begin{pmatrix} 1 & & & & \\ & 1 & & & \\ & & 1 & & \\ & & & 1 & \\ & & & & 1 \end{pmatrix} \right] = \begin{pmatrix} 0 & \cdots & 0 & \cdots & 0 \end{pmatrix} \tag{7}$$

This implies:

$$\begin{pmatrix} \Pi_1 & \cdots & \Pi_i & \cdots & \Pi_m \end{pmatrix} \begin{pmatrix} e_{11}-1 & \cdots & e_{1i} & \cdots & e_{1m} & 1 \\ \vdots & \ddots & \cdots & \cdots & \cdots & \vdots \\ e_{i1} & \vdots & e_{ii}-1 & \cdots & e_{im} & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ e_{m1} & \cdots & e_{mi} & \cdots & e_{mm}-1 & 1 \end{pmatrix} = \begin{pmatrix} 0 & \cdots & 0 & \cdots & 0 & 1 \end{pmatrix} \tag{8}$$

And then:

$$\Pi M = V \quad \Leftrightarrow \quad \Pi M M' = V M' \quad \text{with} \quad \sum_{i=i}^{m} \Pi_i = 1 \tag{9}$$

Finally, the long run stationary distribution is given by:

$$\Pi = V M' (M M')^{-1}, \ \sum_{i=i}^{m} \Pi_i = 1 \tag{10}$$

Starting from the transition matrix developed in Figure 2b, the application of this method to the Maghreb regions leads to the following stationary distribution Π_s as the solution of the following system:

$$\pi^{(s)} W(T) = \pi^{(s)} \text{ or } \Pi^{(s)} = V(W(T)-I)'\left[(W(T)-I)(W(T)-I)'\right]^{-1}, \tag{11}$$

where V is similar to that in equation (9) and I is the identity matrix.

Calculations (Table 3) show that the stationary distribution is significantly different from the standard one. It shows that, based on the long-run distribution, the proportion of high-income regions surrounded by similar rich regions has significantly increased detrimentally to the other spatial associations (quadrants HL, LH, and LL), especially the LL quadrant, but also the LH quadrant to a lesser extent. This result confirms the result found in Section 1 with the parametric model, but it provides additional details about the location of the spatial associations in the various quadrants.

3. Conclusion and policy implications.

This paper has provided two complementary approaches that characterize the convergence process in Maghreb countries' regional units. The results of the first approach (parametric) suggest that the regions are converging in terms of GDP per capita. However, the convergence process is slow. This approach also highlights significant spatial interactions across regions and positive spillover effects, i.e., high-income regions have beneficial effects on neighboring regions in terms of GDP per capita. These effects can be explained by increased supply and demand opportunities offered by the proximity to rich areas. These opportunities are profitable to the neighboring regions. In addition, rich regions are also generally well-endowed in terms of human capital (especially education and technology) and also

International Journal of Business and Social Science Research
Vol: 2, Issue: 1
January/2021
https://ijbssrnet.com/index.php/ijbssr
DOI: 10.47742/ijbssr.v2n1p2

in terms of transport and infrastructure (ports, highways, internet, and other networks), as well as in terms of public services that can also benefit neighboring regions. Overall, these spatial interactions (spillover effects) can speed up the convergence process and reduce inequalities across regions.

The non-parametric approach complements these results by characterizing the dynamics of the location of these spatial interactions. This approach clearly shows that a significant number of regional areas did not remain in the same state (in terms of GDP per capita) between 1990 and 2005. In particular, the analysis of stationary spatial associations confirms that the proportion of high-income regions surrounded by similar rich regions has significantly increased detrimentally to the other spatial associations. This suggests that the convergence process in Maghreb countries is *global*, as only one spatial régime is increasing, instead of being *polarized* (local convergence in two spatial régimes) or *stratified* (local convergence with three spatial régimes).

References

Alexiadis, S. (2013), Convergence Clubs and Spatial Externalities: Models and Applications of Regional Convergence in Europe, Advances in Spatial Science. New York and Heidelberg: Springer, pp. xiv, 244.

Bailey.T. & Gatrell, A. (1995). Interactive Spatial Data Analysis, Longman, Harlow.

Baumont, C., Ertur, C. & Le Gallo, J. (2000). Convergence des régions européennes: Une approche par l'économétrie spatiale. Revue d'Economie Régionale et Urbaine, 2002, vol. 2, pp. 203-216.

Dall'Erba, S. and J. Le Gallo (2008) "Regional convergence and the impact of European structural funds over 1989-1999: a spatial econometric analysis", Papers in Regional Science, vol. 87(2): 219-244.

Davor, M., Andrea, G., Zeljko, L (2013). Regional convergence in the European Union, new Member States and Croatia, South East European Journal of Economics and Business, Volume 8(1), 7-19.

Ferrer, E (2017). Regional convergence and productive structure in Iberian regions: A spatial approach, Revista Portuguesa de Estudos Regionais, nº 47.

Guétat, I. and F. Serranito (2010), "Convergence et Rattrapage Technologique : Un Test par les Séries Temporelles dans le Cas de Pays de la Région MENA », Revue d'Economie du Développement, 2 : 5-45.

Haining, R. (1990). Spatial Data Analysis in the Social and Environmental Sciences, Cambridge University Press, Cambridge.

Hammouda, H., S. Karingi, A. Njuguna and M. Sadni-Jallab (2009) "Why Doesn't Regional Integration Improve Income Convergence in Africa?", African Development Review, 21(2): 291-330.

Kosfeld, R. and J. Lauridsen (2009) "Dynamic Spatial Modelling of Regional Convergence Spatial Econometrics: Methods and Applications, pp. 245-61, Studies in Empirical Economics. New York: Springer, Physica.

Le Gallo, J. (2002). Econométrie spatiale: L'autocorrélation spatiale dans les modèles de régression linéaire. Economie et prévision, 155, 139- 157.

Matsuura, K. and C. Willmott (2009) "Terrestrial Precipitation and Temperature: 1900-2008 Gridded Monthly Time Series", Center for Climatic Research, Department of Geography,

Péridy, N. and C. Bagoulla (2012) "An Analysis of Real Convergence and its Determinants: Evidence from MENA countries (with C. Bagoulla), Journal of Economic Integration, 27(1): 80-114

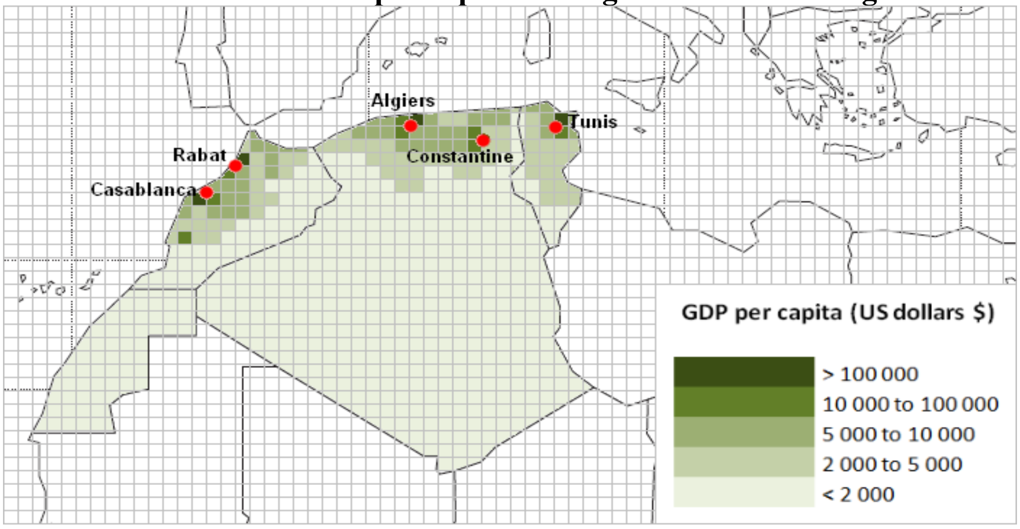
Péridy, N., M. Hazem and M. Brunetto (2013) Some new Insights into Real Convergence in MENA countries' regional areas: A Spatial Econometric Analysis, Economics and Business Letters, 2(4).

Soundararajan, P. (2013) "Regional income convergence in India: A Bayesian Spatial Durbin Model approach", MPRA Paper No. 48453.

Zachary. S, Harper. A. (2013). Spatial Econometric Analysis of Regional Income Convergence: The Case of North Carolina and Virginia. Research in Business and Economics Journal.

International Journal of Business and Social Science Research
Vol: 2, Issue: 1
January/2021
https://ijbssrnet.com/index.php/ijbssr
DOI: 10.47742/ijbssr.v2n1p2

Figure 1: The Gross Cell Products per capita in Maghreb countries' regional units (2005).



Source: own calculations from GEcon 3.3 database.

Table 1a: Estimation of the a-spatial absolute convergence model

α	2.0511 (0.0015)***
β	-0.0245 (0.0012)***
LogL	-1520.451
AIC	1222.59
Jarque-Bera	25.4521 (0.0005)***
Breush-Pagan	8.1254 (0.0052)***
Convergence speed	3.05%
Half-time	27.9 years

***, **, * : significant at respectively 1%, 5% and 10% ; AIC : Akaïke information criteria; Jarque Bera: error normality test.

Table 1b: The spatial model specifications

	W(dist)	*W(5)*	*W(10)*
IM-Err	0.5475 ($2.2.10^{-4}$)***	0.4512 ($2.2.10^{-4}$)***	0.4952 ($2.2.10^{-4}$)***
RLM-Lag	10.1051 (0.0042)***	6.1582 (0.0125)**	7.35216 (0.0052)***
RLM-Err	5.5652 (0.0165)**	3.1235 (0.014)**	3.8212 (0.0352)**

Note: IM-Err is the Moran test; RLMerr and RLMlag are respectively the robust Lagrange Multiplier test applied on the spatial error and spatial lag models.

International Journal of Business and Social Science Research

Vol: 2, Issue: 1
January/2021
https://ijbssrnet.com/index.php/ijbssr
DOI: 10.47742/ijbssr.v2n1p2

Table 2: Results of the spatial SAR models

	SAR absolute convergence	SAR conditional convergence model
α	3.1654 (0.0056)***	2.9851 (0.004)***
β	-0.0301 (0.0011)***	-0.0313 (0.0032)**
δ	-	-2.4514 (0.0054)***
δ_2	-	0.28541 (0.0072)***
Convergence speed	4.0%	4.2%
Half-time	22.7 years	21.8 years
ρ	0.7010 ($2..10^{-4}$)***	0.6452 ($2.2.\ 10^{-4}$) ***
LogL	-675.85	-5951.452
AIC	1110.45	1330.560
Breush-Pagan	4.5857 (0.0432)**	3.458 (0.0981)*
LRT	15.139 (0.0000)*	21.522 (0.0000)*

Note: LRT: likelihood test.

Figure 2: The standard Moran Scatterplot

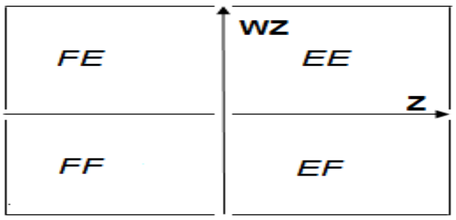


Table 3: Spatial Associations of Maghreb regional units (Moran Diagram)

Year	HH	HL	LH	LL
1990	29.1%	15.4 %	18.3 %	37.1 %
2005	37.4%	14.3%	15.4%	32.9%

Figure 3: The standard transition matrix (1990-2005)

$$
W(T) = \begin{array}{c} \\ HH \\ HL \\ LH \\ LL \end{array}
\begin{array}{c} \begin{array}{cccc} HH & HL & LH & LL \end{array} \\
\begin{pmatrix} 0.912 & 0.052 & 0.023 & 0.013 \\ 0.145 & 0.825 & 0.011 & 0.019 \\ 0.321 & 0.012 & 0.582 & 0.085 \\ 0.152 & 0.082 & 0.081 & 0.685 \end{pmatrix} \end{array}
$$

Table 4: Stationary Spatial Associations of Maghreb regional units

Year	HH	HL	LH	LL
2005 : $\Pi^{(S)}$	68.1%	6.5%	8.3%	17.1%
1990: $\Pi^{(I)}$	29.1%	15.4 %	18.3 %	37.1 %