Economics Bulletin

Volume 35, Issue 3

Exploring spatial convergence of Maghreb regional areas: An application of a Markov chains approach

Alexandra Schaffar
Université de Toulon, Léad (France)

Nicolas Péridy
Université de Toulon, Léad (France)

Abstract

This paper explores the real convergence process of 360 regional areas in Maghreb countries using a non-parametric approach based on classical and spatial Markov chains. This approach investigates the long-term spatial associations between regional units. The advantage of this method is that is does not require the use of control variables which are very often non available at a disaggregated geographical level. We show that there is a trend of regional convergence of GDP per capita in Mena regions. However, this process is very slow and there is an important spatial clustering movement. We also show that although almost 75% of the regional areas seem to converge towards a higher GDP per capita level in the stationary state, 25% are trapped in low development trends. These results suggest that the economic performance of a given region strongly depends of that of its neighbor regions. This in turn implies reconsidering regional development policies within these countries.

We are grateful to Mohamed Hazem and Marc Brunetto for initial data management
Citation: Alexandra Schaffar and Nicolas Péridy, (2015) "Exploring spatial convergence of Maghreb regional areas: An application of a Markov chains approach", *Economics Bulletin*, Volume 35, Issue 3, pages 1848-1855
Contact: Alexandra Schaffar - schaffar@univ-tln.fr, Nicolas Péridy - nicolas.peridy@univ-tln.fr.
Submitted: July 11, 2015. **Published:** September 02, 2015.

1. Introduction

In recent years, a new empirical literature attempts to measure the convergence process and to identify the main driving forces of economic growth in Middle-East and North African 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 convergence process appears, it can be explained by different variables, such as human capital, trade and regional integration, transports equipment and public infrastructures (Hammouda and al., 2009; Guetat and Serranito, 2010; Péridy and Bagoulla, 2012).

Most of these studies deal with national data, which do not allow to explore the existence of spatial spillover effects and inequalities among regions. Recent developments in spatial econometrics and statistics on the one hand and the increasing availability of regional data on the other hand have extended the opportunities to describe and to characterize the convergence process at a more detailed geographical level (Kosfeld and Lauridsen, 2009; Alexiadis, 2013; Soundararajan, 2013). Referring to MENA countries, Peridy and al (2013) have launched a first study to explore the per capita income convergence process at a regional level through the estimation of beta-convergence models. However, the main limitation of this research is the absence of appropriate control variables, given the lack of data at regional level in Maghreb countries.

The present study provides a much more detailed analysis on regional convergence in Maghreb countries (Algeria, Morocco and Tunisia) by adapting a previous original work from Rey and Montouri (1999) and Rey (2001) who use a non-parametric approach, based on the Markov chains, to explore the long-term spatial associations between regional units. The advantage of this method is that is does not require the use of control variables (which are necessary in parametric models). Rey's (2001) work uses several "spatial" extensions from classical Markov matrices, allowing not only to identify the transition process in the income distribution but also to characterize its spatial dependency. This idea goes back to Quah (1996), who questioned the existence of regional convergence by studying the European regions' income relatively to the European average, or relatively to their home-nation average, or to the average income of their geographical neighbors.

The present study shows that Maghreb countries feature a significant regional convergence rate process, that is, the convergence of the different sub-national areas' GDP per capita relatively to the Maghreb's average GDP per capita. Inequalities subsist however, with many lower income zones failing to converge towards the Maghreb average. Spatial convergence, that is, each area's GDP per capita convergence to the average GDP of its neighbors reveals important spatial clustering, with some areas forming regional sub-groups more or less "trapped" in a low GDP per capita situation. This result implies reconsidering regional development policies within these countries.

Data is provided by the Yale University G-Econ research project that measures every Gross Cell's Product, i.e. the economic activity (GDP) of each area corresponding to a one-degree longitude by one-degree latitude (approximately 10 000 km²) for 1990, 1995, 2000 and 2005 (for more details refer to http://gecon.yale.edu/). This method makes it possible to estimate 366 geographical areas' GDP per capita in North Africa. In this study, we only consider the 361 lowest GDP per capita areas, which means that we withdraw the 5 highest GDP per capita areas of the distribution. The latter correspond to the oil production desert areas in Algeria, characterized by a very low population but an extremely high GDP.

The paper is organized as follows. Section 2 explores regional convergence in the Maghreb by using classic Markov chains. Section 3 tests for spatial autocorrelation effects and delivers results on spatial clustering, following Rey's (2001) spatial Markov chains approach. Section 4 concludes and discusses convergence issues and regional policies in the Maghreb region.

2. Regional convergence in the Maghreb region 1990-2005: a classic Markov chains analysis

The Markov chains deliver an interesting analysis on the dynamics of the distribution of regional GDP per capita. This distribution is divided into a certain number of classes and the Markov chains specify a vector of probabilities corresponding to each area's probability to be a member of a particular GDP per capita class in a given year. The transition matrix measures the convergence rate within the distribution, with $p_{ij,t}$ the probability for an area with a GDP per capita y in the class i at the period t, to move to a class j, in $t+1$:

$$\Pr\left(y_{t+1} = j \mid y_0 = i_0, y_1 = i_1, \ldots, y_t = i_t\right) = \Pr\left(y_{t+1} = j \mid y_t = i_t\right)$$

In the present work, we follow the classical Markov chains method with the distribution divided in five classes (Quah, 1993) of per capita GDP. The cut-off points are chosen in order to have five rather homogenous classes. Table 1 gives the initial classes of the distribution of the 361 Maghreb areas' GDP per capita in 1990, where y_i is the per capita GDP of an area i and Y is the Maghreb average per capita GDP:

Table 1: Distribution of the Maghreb areas' GDP per capita in 1990

	C1	***C2***	***C3***	***C4***	***C5***
Cut-off points	$y_i<0.8Y$	$0.8Y<y_i<Y$	$Y<y_i<1.2Y$	$1.2Y<y_i<1.4Y$	$1.4Y<y_i$
Number of areas	*78*	*93*	*68*	*65*	*57*
% of areas	*0.2161*	*0.2576*	*0.1884*	*0.1801*	*0.1579*

In a preliminary work, we perform a χ^2 test (Basawa et Prakasa Rao, 1980) to check the Markov property and to confirm that we get a first-order discrete Markov chain. Then, following Bickenbach and Bode (2003) we also test for time-homogeneity (time stationarity), which controls for exogenous shocks and structural breaks in the distribution over time. The K-statistics rejects the H_0 hypothesis for such shocks. This means that the Markov chains are time-invariant and allows to estimate the limiting transition probabilities within a steady-state distribution vector (ergodic distribution).

Table 2 delivers information about the intra-distributional mobility of the Maghreb areas, when considering their GDP per capita, from 1990 to 2005. The transition probabilities are estimated with the maximum likelihood method. The diagonal elements indicate the percentage of areas that don't change a class overtime. These elements can be considered as a measure of stability of the time-dynamics of the distribution. The closest to 1 indicates the lowest increasing or decreasing changes within the distribution.

Table 2: The Intra-distributional mobility of Maghreb areas measured by their GDP per capita

p_{ij}	C1	C2	C3	C4	C5
C1	0.9324 (0.011)	0.0676 (0,014)	0	0	0
C2	0	0.8361 (0.013)	0.0378 (0.018)	0.1261 (0.010)	0
C3	0	0.0298 (0.009)	0.9007 (0.015)	0.0597 (0.0011)	0.0099 (0.0008)
C4	0	0	0.0177 (0.0013)	0.8230 (0,011)	0.1593 (0,024)
C5	0	0	0.0051 (0.0007)	0.0205 (0,002)	0,9744 (0,003)

Standard deviation in brackets

Two series of conclusions can be drawn: firstly, instability increases with GDP per capita. This means that the areas with the lower GDP per capita, mainly those belonging to class C1, show a rather high probability of staying in the same class over time (93.24%); secondly, upward mobility (e.g. from C1 to C2) is stronger than downward mobility (e.g. from C2 to C1), which means that the development trends in Maghreb over the last twenty years are characterized by continuous growth in GDP per capita. However this is not necessarily synonymous of full convergence. In this regard, Table 3 displays the ergodic distribution, that is, the distribution of the Maghreb areas in the stationary state.

Table 3: Initial and ergodic distributions of Maghreb areas measured by their GDP per capita

	C1	C2	C3	C4	C5
Initial 1990 state	0.2161	0.2576	0.1884	0.1801	0.1579
Ergodic state	0	0.0144	0.0952	0.1184	0.7721

One can easily observe the ascending trend in the different Maghreb areas' GDP per capita, with 77.21% of these areas attaining the highest income class in the stationary state. This can be considered as a rather clear sign of convergence process in regional GDPs per capita. However, the regional process is very slow. In addition, it remains partial since almost a quarter (22.79%) of the Maghreb areas fail to complete this upward mobility trend until the last class C5 and get "stuck" in lower GDP per capita classes.

3. Spatial convergence in the Maghreb region 1990-2005: Results from the spatial Markov chains

In order to test whether there is spatial convergence, i.e. a convergence of an area's GDP per capita to its closest neighbors' average GDP per capita, Rey's (2001) builds spatially defined Markov matrices. The question here is whether an area meets variations in its GDP per capita relatively to its neighbors and not the whole Maghreb region. As Rey (2001) states it in a very clear way, the spatial Markov chains allow to test the stickiness or propulsive influence of an area's neighbors to this area's economy. This type of analysis not only provides a more detailed view of the geographic dimension of the GDP distribution dynamics but also allows to identify the existence (or not) of convergence clusters. Section 2's results deliver evidence of a partial convergence process in regional per capita GDPs with almost a quarter of the identified areas missing the process. Spatial Markov chains make it possible to test whether these areas cluster or not.

In this work, spatial effects are identified through a second order contiguity matrix. This means that we consider as neighbors of a given area all its direct neighboring areas sharing a common border, but also all the second closest neighbors, that is, the areas that are accessible only when crossing two borderlines. For each of the 361 areas we have calculated their neighbors' average GDP per capita for different time sequences.

Table 4 delivers the results from the spatial Markov transition matrix. The first column corresponds to the five spatial-lag classes, that is, the classes containing the neighbors' average GDP per capita. These classes are defined in the same way as is the classic Markov chains in section 2 (with cut-off points at 0.8, 1, 1.2 and 1.4 of the Maghreb average). The first class includes all neighboring areas featuring a low GDP per capita average; the last one involves all neighboring areas featuring a high GDP per capita average.

The second column corresponds to the different areas' per capita GDP, also divided in 5 classes according to the previous rule for spatial lag classes. When its neighbors feature a low per capita GDP average –for example under 0.8 of the Maghreb average– a given area may feature a GDP that belongs to the same low-GDP class or to a higher class, corresponding to a wealthiest area; there are 25 possible combinations. Finally, the last five columns show the transition possibilities of an area. For example, the first line indicates the transition probabilities of all areas with a GDP per capita below 0.8 of the average Maghreb GDP per capita that are initially surrounded by areas that also feature a poor average GDP per capita. In this regard, 94% of poor regions surrounded by other poor regions remain in the same poor class (C1). Only 5.83% of these areas follow a limited upward trend towards class C2. For all the other areas with a higher GDP than the surrounding areas' average per capita GDP, we observe a strict immobility pattern (the diagonal elements are equal to 1).

Another example can be taken for areas surrounded by neighboring areas with an average GDP per capita ranging between the Maghreb average and 1.2 times this average (class C3). These "neighborhoods" don't count any area with a GDP in the lowest class C1 (all elements of the 11^{th} row are equal to 0). However, when an area with a per capita GDP belonging to class C2 is surrounded by areas with an average GDP in class C3, it tends either to stay in its initial state (84.38% of the concerned areas) or to "catch up" with the rest of its neighboring areas (for 15.62% of these areas). The next line shows that, comparing to other classes, immobility is rather low (82.2%) for areas with a per capita GDP close to the average of its neighbors (C3) while 10.26% and 1.71% of these areas follow an ascending trend towards the classes C4 and C5. Areas with a slightly higher GDP than their neighbors are even more volatile: only 66.67% of these areas C4 surrounded by C3 areas remain to their initial state C4. 25.64% of these areas show an increase in their GDP per capita over time (C5), while 7.69% meet a decrease (C3). Finally, when a higher per capita GDP (class C5) is surrounded by a C3 class neighborhood, it features strong immobility, since 92% of these rich areas remain rich.

Table 4: The Spatial Markov transition matrix in the Maghreb region

SPATIAL LAG	**AREA'S GDP/CAP**	P_{IJ}				
		C1	C2	C3	C4	C5
C1	C1	0.9417	0.0583	0	0	0
	C2	0	1	0	0	0
	C3	0	0	1	0	0
	C4	0	0	0	0	0
	C5	0	0	0	0	0
C2	C1	0.8125	0.1875	0	0	0
	C2	0	0.7643	0.0214	0.2143	0
	C3	0	0	0.8889	0.0556	0.0556
	C4	0	0	0	1	0
	C5	0	0	0	0	1
C3	C1	0	0	0	0	0
	C2	0	0.8438	0.1562	0	0
	C3	0	00484	0.8220	0.1026	0.0171
	C4	0	0	0.0769	0.6667	0.2564
	C5	0	0	0.050	0	0.9500
C4	C1	0	0	0	0	0
	C2	0	1	0	0	0
	C3	0	0	1	0	0
	C4	0	0	0.0056	0.8483	0.1461
	C5	0	0	0	0.0714	0.9286
C5	C1	0	0	0	0	0
	C2	0	0.9615	0.0385	0	0
	C3	0	0.0303	0.9697	0	0
	C4	0	0	0	1	0
	C5	0	0	0	0.0189	0.9819

The Spatial Markov transition matrix in table 4 delivers three series of results: firstly, there are rather strong immobility patterns for spatial-lag classes C1 and C5, which means that intra-distributional volatility is much stronger for the medium GDP per capita classes. This clearly indicates the appearance of regional "neighborhoods" of very low and very high GDP per capita areas. Secondly, in a more general way, when spatial convergence exists, it is a very slow process. Considering that the minimum amount of spatial change is represented by all observations experiencing no transition, Rey (2001) defines a measure of the stability of the space-time dynamics such as:

$$S_t = \frac{F_{0.T}}{F_{..T}}$$

with $F_{0.T}$ denoting all observations experiencing no movement of class and $F_{..T}$ reflecting all observations of the spatial Markov matrix. The values of S_T go from 0 to 1 ($0 < S_t < 1$) with higher values indicating a higher stability. In the case of the Maghreb, S_T is equal to 0.786 which reveals the presence of a slow intra-distributional mobility. Thirdly, the spatial Markov chains reveal important clustering effects. In this regard, C_T measures spatial cohesion, i.e. the number of transitions which occur when both an area's per capita GDP and its neighbors' average move in the same direction.

$$C_t = \frac{F_{.iT}}{F_{..T}}$$

where $F_{.iT}$ is the number of transitions allowing an area to have the same per capita GDP as its directs neighbors' average ($F_{.iT}$ includes one diagonal element for each spatial lag class including the number of areas that don't move when their neighbors' average GDP belongs to the same class as theirs). When C_T is equal to 1, all areas have the same per capita GDP that their neighbors' average, which indicates strong convergence trends. In the case of the Maghreb, C_T is equal to 0.8913, which reveals strong spatial clustering.

Table 5 delivers the results of the ergodic spatial matrix, that is, the distribution of the Maghreb areas per capita GDP compared to the average per capita GDP of their neighbors in the stationary state. Each line provides useful information about the final destination of an area within each spatial lag group. For example, line 1 shows that when an area belongs to a C1 neighborhood, it will converge to the C2 GDP per capita class. This features mainly an ascending trend for most of the areas to the C2 class with no further upwards. Line 3 shows less convergence. When an area belongs to a C3 per capita GDP class it will either stay within the same class as its neighbors (for 47.49% of these areas) or follow an ascending trend towards the highest per capita GDP class (for 38.73% of these areas).

Table 5: The ergodic spatial Markov transition matrix in the Maghreb region

Spatial lag	C1	C2	C3	C4	C5
C1	0	1	0	0	0
C2	0	0	0	0	1
C3	0	0.0862	0.4749	0.0606	0.3873
C4	0	0	0	1	0
C5	0	0	0.0407	0	0.9593

The ergodic matrix confirms the previous results from the spatial transition matrix. All areas feature ascending per capita GDP trends except for those within a C3 class neighborhood, which feature a more volatile final distribution. However, it is obvious that while an important number of areas converge towards the C4 and C5 classes, those belonging to a C1 neighborhood only climb one class. When taking into account the previous results from the classic Markov chains, this means that almost three quarters of the areas converge to a high per capita GDP level but the last quarter converge to a lower level. Since regions within this last quarter are neighbors, this means that there are some important geographical areas that found themselves trapped in a lower income development trend.

4. Conclusion and policy implications.

This paper provides two complementary methods allowing to characterize the regional and the spatial convergence process in the Maghreb region using in both cases a Markov chains' non-parametric analysis. The paper uses a dataset provided by the Yale University's G-Econ research project that makes possible to to define 361 geographical areas' GDP per capita in the Maghreb for 1990, 1995, 2000 and 2005.

The paper provides three series of findings: firstly, Maghreb areas show a significant trend of regional convergence in GDP per capita, independently of national parameters; secondly, there is an important spatial clustering process; thirdly, although almost 75% of the areas seem to converge towards a rather high GDP per capita level in the stationary state, the other ones find themselves trapped in a lower development trend. The latter seem to be spatially auto-correlated.

This means that, in the Maghreb region, a given geographical area depends on its neighbors' performance in terms of GDP per capita growth. In terms policy implications, this means first that, public policies aiming to accelerate the convergence process should be considered at a rather high aggregated regional level. Secondly, specific structural policies should be implemented in order to allow some areas trapped in a lower development trend to boost their economic growth. These structural policies must also be carried out at a high aggregated regional level.

These conclusions should take into account some methodological considerations. The results derived from this paper are based on a dataset which raises specific problems when it comes to policy implications. Firstly, the spatial units used in this study are geographical areas which don't necessarily correspond to institutionally defined areas (administrative regions). In other words, it is rather difficult to associate spatial issues and specific local policy solutions. Secondly, while we observe spatial clustering and regional differentiation for a quarter of these geographical areas, we can't identify at this stage the reasons for such a behavior. Why some aggregated areas are trapped in lower development trends? This remains a very important question but also extremely difficult to handle with, since we definitely lack of any data at a disaggregated regional and local level that could be used to identify possible explanatory variables. There doesn't seem to be a short-term solution to this issue, since Maghreb countries' statistical offices don't produce significant regional and local databases.

However, when taking into account these methodological issues, the results delivered from this study remain quite interesting for public policies' planners. Moreover, they represent the first findings on regional and spatial convergence in the Maghreb area.

5. 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, 232-244

Guétat, I., Serranito F. (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.

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

Kosfeld, R., Lauridsen J. (2009). Dynamic Spatial Modelling of Regional Convergence Spatial Econometrics: Methods and Applications, *Studies in Empirical Economics*: 245-261.

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

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

Quah D. (1996). Regional Convergence clusters across Europe, *European Economic Review*, 40, 1353-1375.

Rey S. (2001). Spatial Empirics for Economic Growth and Convergence, *Geographical Analysis*, 33(3), 195-214.

Rey S., Montouri D. (1999). US Regional income convergence: a spatial econometric perspective, *Regional Studies*, 33, 146-153.

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