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Disparities and Regional Convergence of Literacy Rate in India: A Spatial Econometric Approach

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Abstract: Income growth and convergence also known as the catch-up effect has been studied extensively in the literature and 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 Indian districts considering the spatial dependence and to explore a non-parametric approach for characterizing convergence of literacy rate. This study utilizes growth theory as the theoretical foundation to explore the convergence hypothesis. The methodology consists in 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. 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 districts surrounded by similar districts has significantly increased detrimentally to the other spatial associations. This non-parametric approach complements the standard parametric method (absolute and conditional β-convergence) which shows that 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 districts.

Key Words: Spatial Econometrics, Stationary Moran Scatter Plot, Exploratory Spatial Data Analysis, Regional Convergence, Indian Literacy, Markov Chain.

I. INTRODUCTION

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). Convergence is a concept that has gained popularity among economists, not only because of the importance of the issue about poor countries catching up with rich ones, but also because this analysis can serve as a way to verify the validity of different growth models (Varblane et Vahter, 2005). 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). Furthermore, 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). So, 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).

The spatial econometric approach has been employed in several studies alongside convergence models, both unconditional (Rey & Montouri, 1999) and conditional (LópezBazo et al., 1999; Fingleton & López-Bazo, 2006; Ezcurra & Rios, 2015). In the other hand, econometric analysis of convergence processes across countries or regions usually refers to a transition period between an arbitrary chosen starting year and a fictitious steady state (Kosfeld & Lauridsen, 2004).

One limitation of these studies is the use of national data, which do 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 Indian districts between 1991 et 2001. 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 article is organized as follows: In the second section, after a brief review of the theoretical framework applied, we define the classic notion of the Moran scatter plot and explain its utility as a tool for local spatial exploratory analysis, after which we present the stationary form of the Moran scatter plot. In the third section, we apply the method to literacy data at the district level in India. In the fourth section, we use the same data to test regional convergence by using the absolute convergence model and finally we specify the most adequate model of spatial convergence. Section five concludes and discusses the contributions and the complementarity of the non-parametric approach developed in section 2 with regard to the convergence model derived in section 4.

II. THE STATIONARY MORAN SCATTER PLOT

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). These methods are frequently used for measuring both local and global spatial autocorrelation. In this approach, local exploratory analysis involves calculating local indices of spatial association which are derived from global indices, where the matrix of spatial weights[1] is replaced by the vector or the row that corresponds to the regional unit (Xie & al, 2000). 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 scatter plot (Figure 1) is a graphic representation that enables a description of the schema of local spatial association, identifies the atypical points and detects the extreme observations. Let Z be the standardized value of the variable on the horizontal axis and WZ the standardized lagged value on the vertical axis[2]. The use of standardized values enables the comparison of the Moran scatter plot in time. The scatter plot has four different quadrants, where each quadrant corresponds to a specific spatial affiliation that can exist between a region and its neighbors. The quadrant HH includes the regions which are associated with a high value of the relevant variable, surrounded by regions which also have high values of the same variable. Similarly, the quadrant LL contains only the regions that are associated with low values surrounded by regions that also have low values of the variable. The quadrant LH corresponds to regions associated with low values surrounded by regions associated with high values (districts in this quadrant are called "black sheep"). Finally, the quadrant HL contains regions that are associated with high values surrounded by regions associated with low values (The districts which are grouped in this quadrant are called "islands of wealth"). The associations of the two quadrants HH and LL give a local spatial autocorrelation that is positive between the regions and their neighbors while the quadrants HL and LH have a local spatial autocorrelation that is negative. For each unit of time, we can construct a Moran scatter plot, which can demonstrate the dynamics of regional inequalities of spatial associations. In order to highlight this issue, we propose a stationary form of the Moran scatter plot in which we focus on long-term forms of spatial associations. To do this, we use the transition matrix constructed from the distributions of the initial and final years and the Markovian method to determine the stationary distribution of spatial associations relative to the four quadrants of the Moran scatter plot.

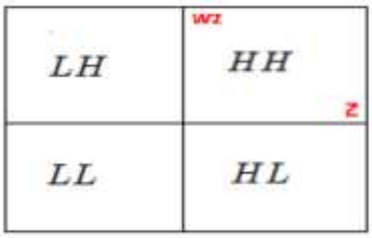

Figure1: Moran Scatterplot

Let *m* be a set of spatial associations. A Markov chain is called irreducible if all the groupings form a single equivalence class, and each association is accessible from any other association. This chain has a unique stationary distribution, $\Pi = (\Pi_1, \Pi_2, ..., \Pi_m)$, which is a solution of the following system:

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

where Π_i is the percentage of the regional units in the state **i** and **A** is the transition matrix defined by:

[1] W is a square matrix of spatial weights. For any two regions, the term wij reveals their degree of interaction and reflects the accessibility of the region i to the region j.

[2] The i^{th} element of this variable is defined by the weighted mean of the observations for the neighboring regions of the regional unit *i*. Also, since W is standardized, the statistics of Moran (I = (Z'WZ)/(Z'Z)) is the slope of the linear regression of WZ with respect to Z. This relationship is frequently represented in Moran's diagram.

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1i} & \cdots & a_{1m} \\ \vdots & \ddots & \cdots & \cdots & \vdots \\ a_{i1} & \cdots & a_{ii} & \cdots & a_{im} \\ \vdots & \cdots & \cdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mi} & \cdots & a_{mm} \end{pmatrix} \qquad (2)$$

where a_{ij} is the percentage of regional units which were in the state i at the period t and have made a transition towards the association j at the period t + 1. The elements of the principal diagonal (a_{ii}) specify the percentage of these regional units which have remained in their state of origin between t and t+1.

In order to determine the stationary distribution, we consider:

$$\begin{pmatrix} \Pi_1 & \cdots & \Pi_i & \cdots & \Pi_m \end{pmatrix} \begin{pmatrix} a_{11} & \cdots & a_{1i} & \cdots & a_{1m} \\ \vdots & \ddots & \cdots & \cdots & \vdots \\ a_{i1} & \cdots & a_{ii} & \cdots & a_{im} \\ \vdots & \cdots & \cdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mi} & \cdots & a_{mm} \end{pmatrix} = \begin{pmatrix} \Pi_1 & \cdots & \Pi_i & \cdots & \Pi_m \end{pmatrix}, \sum_{i=1}^{m} \Pi_i = 1 \qquad (3)$$

Or,

$$\begin{pmatrix} \Pi_1 & \cdots & \Pi_i & \cdots & \Pi_m \end{pmatrix} \times \left[\begin{pmatrix} a_{11} & \cdots & a_{1i} & \cdots & a_{1m} \\ \vdots & \ddots & \cdots & \cdots & \vdots \\ a_{i1} & \cdots & a_{ii} & \cdots & a_{im} \\ \vdots & \cdots & \cdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mi} & \cdots & a_{mm} \end{pmatrix} - \begin{pmatrix} 1 & & & & \\ & \ddots & & & \\ & & 1 & & \\ & & & \ddots & \\ & & & & 1 \end{pmatrix} \right] = \begin{pmatrix} 0 & \cdots & 0 & \cdots & 0 \end{pmatrix}, \sum_{i=1}^{m} \Pi_i = 1 \qquad (4)$$

$$\Leftrightarrow \begin{pmatrix} \Pi_1 & \cdots & \Pi_i & \cdots & \Pi_m \end{pmatrix} \times \begin{pmatrix} a_{11}-1 & \cdots & a_{1i} & \cdots & a_{1m} \\ \vdots & \ddots & \cdots & \cdots & \vdots \\ a_{i1} & \cdots & a_{ii}-1 & \cdots & a_{im} \\ \vdots & \cdots & \cdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mi} & \cdots & a_{mm}-1 \end{pmatrix} = \begin{pmatrix} 0 & \cdots & 0 & \cdots & 0 \end{pmatrix}, \sum_{i=1}^{m} \Pi_i = 1 \qquad (5)$$

$$\Leftrightarrow \begin{pmatrix} \Pi_1 & \cdots & \Pi_i & \cdots & \Pi_m \end{pmatrix} \times \begin{pmatrix} a_{11}-1 & \cdots & a_{1i} & \cdots & a_{1m} & 1 \\ \vdots & \ddots & \cdots & \cdots & \vdots & \vdots \\ a_{i1} & \cdots & a_{ii}-1 & \cdots & a_{im} & 1 \\ \vdots & \cdots & \cdots & \ddots & \vdots & \vdots \\ a_{m1} & \cdots & a_{mi} & \cdots & a_{mm}-1 & 1 \end{pmatrix} = \begin{pmatrix} 0 & \cdots & 0 & 1 \end{pmatrix}, \sum_{i=1}^{m} \Pi_i = 1. \qquad (6)$$

Hence, we have:

$$\Longleftrightarrow \begin{cases} \Pi\Omega = V \\ \sum_{i=1}^{m} \Pi_i = 1. \end{cases} \Longleftrightarrow \begin{cases} \Pi\Omega\Omega' = V\Omega' \\ \sum_{i=1}^{m} \Pi_i = 1. \end{cases} \qquad (7)$$

Where,

$$\Omega = \begin{pmatrix} a_{11}-1 & \cdots & a_{1i} & \cdots & a_{1m} & 1 \\ \vdots & \ddots & \cdots & \cdots & \vdots & \vdots \\ a_{i1} & \cdots & a_{ii}-1 & \cdots & a_{im} & 1 \\ \vdots & \cdots & \cdots & \ddots & \vdots & \vdots \\ a_{m1} & \cdots & a_{mi} & \cdots & a_{mm}-1 & 1 \end{pmatrix}$$

And $$V = \begin{pmatrix} 0 & \cdots & 0 & 1 \end{pmatrix}$$

Finally, the long-term stationary distribution is defined by :

$$\Pi = V\Omega'(\Omega\Omega')^{-1}, \sum_{i=1}^{m} \Pi_i = 1 \quad (8)$$

For Moran scatter plot where $m = 4$, the stationary distribution is defined by:

$$\Pi_S = \begin{pmatrix} \Pi_{HH}^{(S)} & \Pi_{HL}^{(S)} & \Pi_{LH}^{(S)} & \Pi_{LL}^{(S)} \end{pmatrix} \quad (9)$$

3. APPLICATION: LITERACY RATE OF INDIAN DISTRICTS BETWEEN 1991 AND 2001

Literacy and educational attainment are primary indicators which helps in social and economic development of any community. In world scenario spread of literacy is generally associated with importance of modern civilization such as modernization, urbanization, industrialization, communication and commerce (Biswas, 2016). It has also been looked upon that the benefits of educational programs have been shared disproportionately by the advantaged and the disadvantaged sections of population (Ahamed, 2014). In this application, in the context of spatial interdependencies, regional inequalities and the determinants of growth in India, we focus on a variable that partially characterizes human capital: the literacy rate. We use the data of the last two Population Census (1991 and 2001) at the level of the 563 administrative districts into which India was divided[3]. We use the data base of a Geographical Information System (GIS) to analyze the geographical map of India in order to determine t he geographical coordinates of the districts.

According to the Human Development Report 2011[4] of the United Nations Development Program, with an average Human Development Index (HDI) of 0.547, India ranks 134th worldwide among 187 classifieds States[5]. Figures (2) indicates that literacy rate[6] varies considerably according to respective districts for the years 1991 and 2001. In fact, a quasitotality of low levels[7] is witnessed in the districts located in Central India such as the districts in the states of Madhya Pradesh, Orissa and Chhattisgarh[8]. In contrast, high levels can be discerned in the frontiers and to a great extent in the two extremities of North and South (districts in the states of Jammu & Kashmir, Punjab, Himachal Pradesh and Uttaranchal in the North and districts in the states of Andhra Pradesh, Kerala, Tamil Nadu and Karnataka to the south of the country). In 2001, the highest literacy rate (96.6%) has been noted in the Aizawl district in the state of Mizoram, while it was 95.7% in 1991, recorded in the district of Kottayam in the state of Kerala[9]. One might take note of the fact that the highest literacy rate recorded in 1991 is 5.8 times higher than the lowest recorded in the same year, whereas in 2001, this ratio is reduced to 3.22. In a similar way, among the ten highest levels, eight (respectively seven) were recorded in the districts of Kerala in 1991 (respectively in 2001).

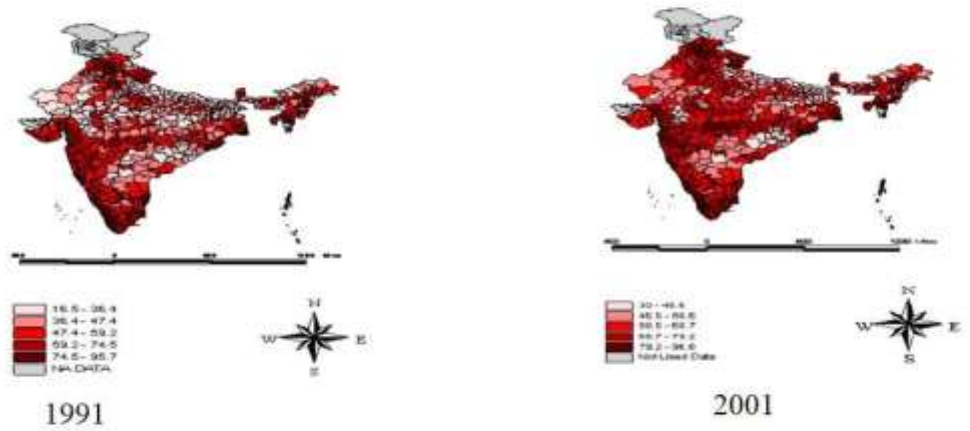

Fig 2: Literacy rates of Indian districts in 1991 and 2001

[3] We use only the districts that existed both in 1991 and 2001.
[4] DP, Human Development Report 2011, statistical tables.
[5] HDI comprises of three elements: health, in terms of life expectancy at birth; the level of education, in terms of the rate of literacy and the rate of scalarization; and the GDP per inhabitant. The highest index is equal to 1, and 0 represents the lowest level (Sabot, 2005).
[6] UNESCO defines a non-literate person as someone who, while understanding a situation, cannot read or compose a simple statement on his or her own daily life. UNESCO defines a literate person as someone who has acquired the essential knowledge and competence which enable him or her to engage in all activities that require literacy for an effective social functioning.
[7] A low value (respectively elevated) is one which is inferior (respectively superior) to an average value in the sample.
[8] The lowest value has been seen in the district Dantewada in the state of Chhattisgarh: it was raised to 16.5% in 1991 (respectively 30% in 2001).
[9] Among the success stories in the field of literacy, Kerala remains an emblematic case in India (Buisson, 2007).

Similarly, in Table (1) we observe the evolution of literacy rates in Indian districts during the periods specified. The average moved from 50.94% in 1991 to 64.45% in 2001[10]. In fact, during the decade 1991-2001, the number of non-literates comes down for the first time since the Census of 1951 by approximately 32 million in absolute terms[11]. This is a result of the development of basic education system and more precisely improvements in female education. During this decade, the increase in female literacy rate is relatively higher than that for men, thereby reducing gender disparity. This can be partly explained in terms of the general expansion of the education system, the policy of affirmative action favoring the girlchild, the very low starting point and the execution of the various programs of promotion of education, such as the primary education program of Bihar, the basic education project of Uttar Pradesh, so on and so forth.

Table 1: Trend in literacy rates in India between 1991 and 2001

year	1991	2001
Lowest rate	16,5%	30%
Highest rate	95,7%	96.60%
Average lowest rates (for 10 districts)	21,27%	33,18%
Average of the highest rates (for 10 districts)	92,34%	94,07%
Average lowest rates (for 100 districts)	30,09%	44,79%
Average of the highest rates (for 100 districts)	73,90%	81,82%

If we now re-turn to table (1), we would notice that the difference between the two values (maximum and minimum) of literacy rate is very high: it is as high as 79.2% in 1991 and is reduced to 66.6% in 2001. Therefore, the difference between the average of 10 (respectively 100) most literate districts and that of 10 (respectively 100) almost non-literate districts is 71.07% (respectively 43.812%) in 1991 and is reduced to 60.89% (respectively 37.025%) in 2001. This result brings us to a fundamental question in regional studies about the notion of regional convergence.

The evaluation of global spatial autocorrelation is the preliminary phase of Exploratory Spatial Data Analysis. It is said to be positive if the observations (low or high) form a concentration in space. This happens when the regional units are neighbors and their attributes are similar. (William et al, 2004). On the other hand, it is negative when there is a concentration of opposing values around each regional unit. Finally, spatial autocorrelation is said to be null if the observations are randomly distributed in space, that is, the values are independent of the localization of regional units. Moran's index is the most powerful statistic for testing the presence of global spatial autocorrelation. This statistic (Cliff and Ord (1981), Upton and Fingleton (1985) and Anselin (1992)) is defined by:

$$I_M = \frac{N}{K}\frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum (x_i - \bar{x})^2}$$

where $\boldsymbol{x_i}$ is the level of literacy in the district i; $\bar{x}$ is the overall mean, N is the number of districts in India, w_{ij} measures the intensity of the interaction between the districts i and j, $k=\sum w_{ij}$ is the sum of the coefficients of interaction. I_M is calculated by using the matrix of the inverse of distances. Inference for Moran's I is based on a random permutation procedure, which recalculates the statistic many times to generate a reference distribution (Anselin, 2001).

Table (2) shows that the literacy rates of Indian districts have positive spatial correlation and the statistics of Moran are strongly significant. This result shows that the districts having relatively high (low) literacy rates have a tendency to be located close to districts that are highly literate (respectively districts with low literacy). Similarly, the standardized values of the Moran statistics appear to be very high, a fact that could indicate a problem of spatial levels in our sample: a part of the autocorrelation detected could therefore be a result of administrative subdivision (Le Gallo, 2002) or the result of the presence of extreme observations that could affect the value of the global spatial autocorrelation. For 1991, there are two extreme observations that affect the spatial autocorrelation at the higher levels. However, that should not put to question the presence of real positive spatial interdependences among the states. Similarly, the number of these extreme points appears negligible compared to the size of our sample that comprises of 563 districts. In contrast, for the year 2001, no extreme observation is detected. It proves that a global analysis can at times hide spatial peculiarities, while local analysis helps to bring out atypical data. As a result, local analysis can contradict the results of global analysis. It consists of a calculation of local indices of spatial association derived from global indices where the neighborhood matrix is replaced by the vector or the line that corresponds to the object (Xie et al, 2000).

[10] The average rate of literacy was 18.3% in 1951 and 43.6% in 1981. [11] National Human Development Report, 2001.

Table 2: Moran statistics with literacy rates

Year	I-Moran	Expected value	Standard deviation	Critical value
1991	0.2586	−0.0018	0.0089	10^{-4}
2001	0.2561	−0.0018	0.0090	10^{-4}

Figure 3 gives an idea of the forms of spatial association for these two years. The table 3 shows that in 1991 (respectively 2001), 68.02% (respectively 70.51%) of the districts are represented by a spatial association of similar values, 30.02% (respectively 36.94%) of districts are localized in the quadrant HH and 38.01% (respectively 33.57%) are in the quadrant LL.
Also, 31.97% (respectively 29.48%) of the districts have a negative spatial association, 15.98% (respectively 15.27%) are in the quadrant HL (island of wealth) et 15.98% (respectively 14.21%) are localized in the quadrant LH (black sheep). Through these two results, we note that the percent-age of districts of the quadrant HH has increased to the detriment of the three other quadrants. Hence the need to study the dynamics of spatial associations.

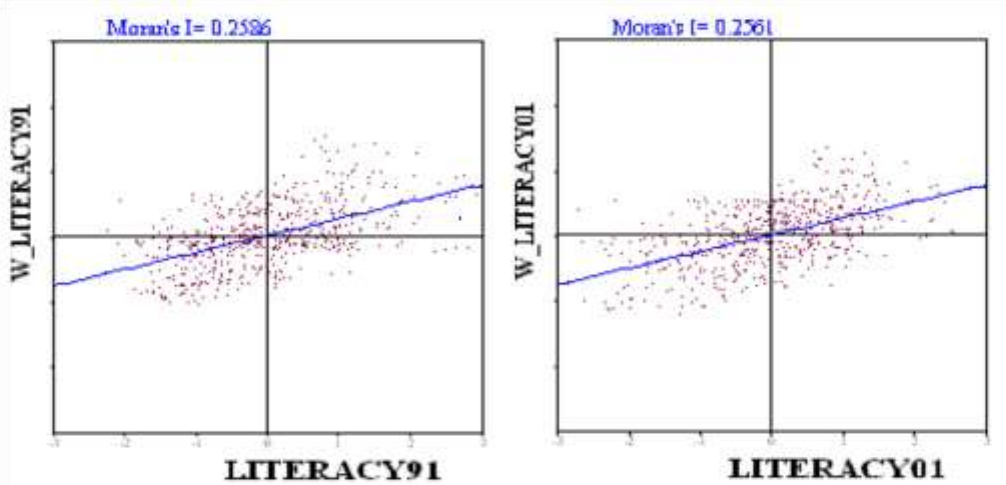

Figure 3: Moran Scatter Plot for 1991 et 2001

Table 2: Spatial Associations of Indian districts in Moran Scatter Plot for 1991and 2001

Matrice	HH	HL	LH	LL
1991	30.017%	15.985%	15.985%	38.010%
2001	36.944%	15.275%	14.209%	33.570%

Each of the districts can carry out a transition towards a different quadrant. This transition can be horizontal (LH HH; HH LH; LL HL; HL LL) where only the district in question carries out a movement towards a different quadrant, or vertical (LL LH; LH LL; HL HH; HH HL) where only the neighboring districts change quadrants, or diagonal (LL HH; HH LL; LH HL; HL LH) where a parallel movement of the district and its neighbors is registered. Also, another form of transition can be carried out by a district and its neighbors: they occupy together the same quadrant (HH HH; HL HL; LH LH; LL LL). We call this type of movement " Transition of the Top".

By referring to the two Moran scatter plots of 1991 and 2001 and to the forms of transition carried out by the 563 districts during this period, we have constructed the following transition matrix:

$$W_{91/01}^{(T)} = \begin{array}{c} \\ HH \\ HL \\ LH \\ LL \end{array} \begin{array}{c} \begin{array}{cccc} \mathrm{HH} & \mathrm{HL} & \mathrm{LH} & \mathrm{LL} \end{array} \\ \begin{pmatrix} 0,899408284 & 0,029585799 & 0,059171598 & 0,01183432 \\ 0,1 & 0,833333333 & 0,011111111 & 0,055555556 \\ 0,333333333 & 0 & 0,566666667 & 0,1 \\ 0,070093458 & 0,042056075 & 0,065420561 & 0,822429907 \end{pmatrix} \end{array}$$

In the principal diagonal of this matrix, we have the percentage of districts which stayed in the same state between 1991 and 2001. This corresponds to 89.94% of the districts for HH. Also, 83.33% of the districts of the type "islands of wealth" have occupied the same quadrant
HL during the decade. The percentage of districts which have stayed in the quadrant LL is equal to 82.24%. However, 56.66% of the districts with low rates of literacy 1991 that have as neighbors' districts with high rates of literacy have not changed their state

(quadrant) LH (black sheep) in 2001. This denotes a high rate of mobility of districts and their neighbors in this last quadrant. In other words, a column-wise reading of this matrix shows the quadrant had received 50.34% of the movements of the districts of the three other spatial associations. Also, 7.16% of the transitions realized by the districts of the quadrants HH; LH et LL are attributed to the quadrant HL. Also 13:57% of the districts which had been in the three quadrants HH; HL et LL in 1991 had carried out movements towards the quadrant LH in 2001. Finally, 16:73% of the districts have migrated towards LL in 2001; given that they were in the quadrants HH, HL and LH in 1991: Consequently, since we expected other transitions in the preceding years, question on the forms of long-term spatial association are open. In this sense, the stationary distribution (Π_s) is the solution of the following system:

$$\Pi_S W_{91/01}^{(T)} = \Pi_S$$

Where,

$$\left(\Pi_{HH}^{(S)} \quad \Pi_{HL}^{(S)} \quad \Pi_{LH}^{(S)} \quad \Pi_{LL}^{(S)} \right) W_{91/01}^{(T)} = \left(\Pi_{HH}^{(S)} \quad \Pi_{HL}^{(S)} \quad \Pi_{LH}^{(S)} \quad \Pi_{LL}^{(S)} \right)$$

And the stationary distribution is given by:

$$\Pi_S = (\ 0,60236 \quad 0,14374 \quad 0.10796 \quad 0,14592 \ )$$

While the initial distribution (Π_I) was:

$$\Pi_I = (\ 0.30017 \quad 0.15985 \quad 0.15985 \quad 0.38010 \ )$$

This stationary distribution shows the percentage of districts associated with high values of literacy surrounded by districts that are strongly literate (quadrant HH) which were 30.02% in 1991 and which increased to 60.23% in the long term, to the detriment of districts in the three other quadrants (HL, LH et LL) and mainly to the districts of the quadrant LL: A remarkable decrease of 38.01% to 14:592%. This confirms the hypothesis of regional convergence (the catching up of districts that are strongly literate by districts that are weakly literate). This is explained by the rise in the growth rate of female literacy in almost a majority of districts. This naturally reduces the distance between the districts. Hence, this last result leads us to study regional convergence through the model of β-convergence.

4. REGIONAL CONVERGENCE OF LITERACY RATE IN INDIAN DISTRICTS: AN APPLICATION OF A BETA-CONVERGENCE MODEL

Income growth and convergence 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). In the other hand, Econometric analysis of convergence processes across countries or regions usually refers to a transition period between an arbitrary 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. 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 modelling of convergence are demographic variables, labor market conditions, industrial structure, institutional factors and overall government policy (Davor & Andrea, 2013).

4.1. The model of absolute β-convergence

We relate the previous results to the notion of absolute convergence in order to show the role played by spatial factors in improving the convergence model. We consider the following standard convergence model:

$$\begin{aligned} TXCLit &= \alpha S + \beta \log Lit_{1991} + \varepsilon \\ \varepsilon &\sim N(0, \sigma^2 I) \end{aligned} \tag{10}$$

where $T\,XCL$ it is the vector of average annual growth rates of literacy of the 563 districts during the period 1991-2001, $logLit_{1991}$ is the vector of rates of literacy expressed in logarithm at the initial date (1991), S is the sum vector of the dimension (563; 1), and are the parameters of interest to be estimated. The table (3) shows that the parameter is negatively significant (0.036). This confirms the hypothesis of global convergence of Indian districts. In fact, the speed of convergence[11] and the half-life[12] are respectively equal to 4**.**602% and 18**.**442 years.

4.2. **Specification of the convergence spatial model**

The two models that are most commonly used to describe or characterize spatial dependence are the model of the spatial autocorrelation of errors and the model of the spatial autocorrelation of the endogeno us variable.

According to Cliff and Ord (1981), the Moran test when applied on the residue of classic regression is most frequently used to detect the spatial dependence that may exist among regional units. Nonetheless, in spite of its strength, the test does not help to discriminate the various forms of spatial autocorrelation. For this purpose, the Lagrange multiplier test (LMLag and LM-Error) as well as its robust version (RLM-Lag and RLM-Error) are frequently used. LM-Lag helps to test the existence of spatial autocorrelation in the endogenous variables, while LM-Error helps to test a spatial autocorrelation in terms of error.

The results of the regression show that the error terms are strongly heteroscedastic. In other words, the high value of Moran's test (0.208493) shows that there is a strong positive global spatial autocorrelation between the residuals arising out of the estimation of the model of absolute convergence by the OLS method. This model is misspecified. The convergence model with spatial autocorrelation of errors is the most appropriate model because the LMLag robust statistic is non-significant. Taking into account spatial interdependence between the residuals improve the classical model. The model of absolute convergence needs to be modified in order to integrate explicitly this new form of the spatial dependence of error terms[13].

Table 3: Estimation of convergence model.

$\beta - convergence$ model		
$\hat{\alpha}$	0.169	(0.0000000)
$\hat{\beta}$	-0.036	(0.0000000)
Log likelihood	1911.31	
Akaike info criterion	-3818.61	
Schwarz criterion	-3809.94	
Jarque-Bera	202.920	(0.0000000)
Breusch-Pagan	224.642	(0.0000000)
White	103.522	(0.0000000)
Moran's I (error)	0.208493	(0.0000000)
Lagrange Multiplier (lag)	99.8707558	(0.0000000)
Robust LM (lag)	1.8542228	(0.1732931)
Lagrange Multiplier (error)	809.8044393	(0.0000000)
Robust LM (error)	711.7879063	(0.0000000)
Lagrange Multiplier (SARMA)	811.6586621	(0.0000000)

4.3 Estimation of the convergence Spatial Error Model by Maximum Likelihood

When errors follow an autoregressive spatial process, the structural form of the model is defined by:

$$\begin{cases} TXCLit = \alpha S + \beta \log Lit_{91} + \varepsilon \\ \varepsilon = \lambda W \varepsilon + \nu, \qquad \nu \sim N(0, \sigma^2 I) \end{cases} \tag{10}$$

Where ε is generated by an autoregressive spatial process. The parameter λ measures the intensity of the spatial correlation that exists between the error terms and *W* the matrix of spatial weights.

[11] $\mu = -\ln(1 + T\beta)/T$

[12] The time necessary for an economy to cover half the distance that separates it from its stationary state is defined by θ= ln(2)= ln(1 +))

[13] 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.

$$\varepsilon = (I - \lambda W)^{-1}\nu \quad et \quad \nu \curvearrowright N(0, \sigma^2 I)$$

and the variance-covariance matrix of the residuals is defined by :

$$E(\varepsilon\varepsilon') = \sigma^2 \left[(I - \lambda W)^{-1}\right] \left[(I - \lambda W)^{-1}\right]'$$

The results of the estimation (second column of table 5) shows that the parameter is negatively significant, which confirms the hypothesis of global spatial convergence. The speed of convergence and the half-life are respectively equal to 4.396% and 19.136 years. We note that there is strong positive spatial autocorrelation of the residuals (λ= 0.901). We respecify the convergence model with a special lag model in the following way:

$$\begin{cases} TXCLit = \alpha S + \rho W TXCLit + \beta \log Lit_{91} + \varepsilon \\ \varepsilon \curvearrowright N(0, \sigma^2 I) \end{cases} \quad (11)$$

With,

$$(I - \rho W) TXCLit = \alpha S + \beta \log Lit_{91} + \varepsilon \quad (12)$$

where is the autoregressive spatial parameter which measures the intensity of the spatial interaction that exists between a district and its neigh-bours. We consider the following transformation:

$$TXCLit = (I - \rho W)^{-1}(\alpha S + \beta \log Lit_{91}) + (I - \rho W)^{-1}\varepsilon \quad (13)$$

This expression shows that the average annual rate of growth of literacy of a district is simultaneously affected by the rate of initial literacy registered in the district and that of neighboring districts, via a spatial multiplier effect. A random shock which happens in a district does not have a unique effect on the growth rate of literacy of the district, but also affects the rate of growth of literacy in the neighboring districts. The third column of table 5 shows clearly that the process of convergence seems to be low/weak: the speed of convergence is 3.8563% and the half-life is equal to 21.3137 years. On the other hand, the same estimation shows that districts in India interact in terms of rate of increase in literacy rate: the parameter of interaction is statistically significant (ρ= 0.320). The Breush-Pagan test remains significant. This results in the problem of over (under)-estimation of the parameters of the real model of β-convergence. Finally, on the basis of the information criteria, we conclude that the model with the spatial autocorrelation of errors is the most appropriate specification.

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

Table 4: Estimation of spatial convergence models

	Spatial Error Mode		Spatial Lag Model	
$\hat{\alpha}$	0.1634155	(0.0000000)	0.1380478	(0.0000000)
$\hat{\beta}$	-0.0355737	(0.0000000)	-0.03199804	(0.0000000)
$\hat{\lambda}$	0.9009087	(0.0000000)	-	
$\hat{\rho}$	-		0.4697668	(0.0000000)
Log likelihood	1978.753918		1944.96	
Akaike info criterion	-3953.51		-3883.92	
Schwarz criterion	-3944.841277		-3870.92	
Breusch-Pagan	189.779	(0.0000000)	198.8029	(0.0000000)
Likelihood Ratio Test	135.2098	(0.0000000)	67.61938	(0.0000000)

V. CONCLUSION

This paper provides two complementary approaches that characterize the convergence process in Indian districts. We have proposed a stationary form of the Moran scatter plot based on Markovian method that characterize the convergence process in Indian districts. This approach clearly shows that a significant number of districts did not remain in the same state (in terms of literacy rate) between 1991 and 2011. In particular, the analysis of stationary spatial associations confirms that the proportion of HH districts surrounded by similar HH districts has significantly increased detrimentally to the other spatial associations. This suggests that the convergence process in Indian districts is *global*, as only one spatial régime is increasing, instead of being *polarized* (local convergence in two spatial régimes) or *stratified* (local convergence with multiple spatial régimes).

The results of the β-convergence approach suggest that the districts are converging in terms of literacy rate. This approach highlights significant spatial interactions across districts and positive spillover effects, i.e., high-literacy rate districts have beneficial effects on neighboring districts. These opportunities are profitable to the neighboring districts. In addition, districts with high literacy rate are also generally well-endowed in terms of human capital (especially education and technology) and also 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 districts. Overall, these spatial interactions (spillover effects) can speed up the convergence process and reduce inequalities across Indian districts. This approach complements the stationary Moran approach results by characterizing the dynamics of the location of these spatial interactions.

It appears that the long-term Moran diagram and the regional convergence model both incorporate regional proximity effects between georeferenced units and lead to the same results. The new non-parametric approach brings the advantage of identifying the location of spatial associations.

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