

## EDUCATIONAL PERFORMANCE AND SPATIAL CONVERGENCE IN PERU

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**Abstract** - While an enormous and growing literature exists on the topic of regional income convergence, other aspects of socioeconomic well-being and development have attracted much less attention. Social indicators are a valuable complement to economic indicators when analyzing spatial patterns in a given geographic region, and can often yield a more comprehensive view about regional socioeconomic behavior. In poorer nations dominated by many low income areas that exhibit similar economic performance, social indicators may reveal further insight into the differences among regions. This paper explores the issue of educational convergence in Peru over the period 1993 to 2005. Using both exploratory spatial data analysis and spatial econometrics, the study is conducted at province level in order to uncover potential spatial patterns that help explain variation in educational performance over time, among regions, and across different terrain.

**Key-words:** SPATIAL CONVERGENCE, EDUCATION, PERU.

**JEL classification:** I20, R10, R11, R12

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## INTRODUCTION

Most research on regional convergence focuses on income dynamics. Economic convergence is a long term process through which income or other economic indicators tend to equalize (Abreu et al., 2005; Lim, 2003; Mossi et al., 2003; Rey and Montouri, 1999; Rey and Janikas, 2005). Generally, the analysis of spatial convergence has focused on income indicators while ignoring other dimensions of socioeconomic well-being. Social indicators are a complement to analyze spatial patterns and can sometimes give a more comprehensive view about how a region behaves. Particularly in developing countries, the analysis of social indicators such as educational performance, life expectancy or per capita caloric intake of food can more realistically represent the performance of a region (Baumol et al., 1994). In developing countries where most regions are considered low income areas and show a similar economic performance, social indicators may reveal more insights into the differences between regions. This research will focus on analyzing social and geographical patterns in all Peruvian regions. Peru is hierarchically divided in departments, provinces and districts, with districts being the smallest autonomous region. In this case, the objective is to study the relationships between province regions over a period of time (1993- 2005) and try to determine if spatial convergence exists. For this study, a social indicator will be used in order to measure convergence in Peru. Specifically, an educational indicator will be selected as the variable of analysis.

In developing countries, education has been always an important socioeconomic measure. In countries with high levels of poverty, levels of education are often correlated with the economic performance of a region (Baumol et al., 1994; World Bank, 1999). In Peru, there is a constant effort to improve the level of education. In 2004, the Ministry of Education confirmed that the probability that a student in elementary school finishes his or her education in the expected period of time was only 37%. Moreover, 39% of the elementary school students attend a grade below what is typical for their age level, with this percentage being even lower in rural regions with extreme poverty (Minedu, 2005). In addition, most of the main services of education, health, and transportation are located in the capital city (Lima) and service flows radiate from this hub. This centralization causes a problem of disarticulation among regions and makes the gap between Lima and other areas even wider. Whole sectors of the population are often severed from one or more government services. Even though Peru is involved in a process of decentralization, the complexity of its geography makes it all the more difficult to accomplish. Peru's rough terrain frequently limits access to basic services, thereby making educational development and equity even more of a challenge for its inhabitants. Geography may reveal important differences in a region's welfare and may play an important role in explaining educational development across the country (Escobal and Torero, 2000).

Peruvian diversity (social, cultural and physical) and the complexity of its territory make very difficult an equal distribution of educational services. At the beginning of the 1990's, the Peruvian government decided to implement important educational reforms in order to improve the quality of education as well as to facilitate the access to elementary school. Investments in infrastructure,

training of teachers, and changes in the educational curriculum were some of their principal goals (Arregui et al., 2004). This research will analyze the state of education in Peru at the beginning of this period of reforms and its performance over a twelve year period of time. The objective of this research is to provide a better understanding of the geographical dynamics of the educational variables, and also to measure if there is a tendency towards equalization of education.

The remainder of the paper begins with an overview of the research on regional education convergence. Next, the specific methods and models to analyze the convergence process are introduced. In this section the focus will be an exploratory spatial analysis of the educational variable over the period 1993-2005, and then a confirmatory spatial econometric analysis of the regional education convergence. The research closes with a summary of expected results, limitations and significance of this study.

## **1. BACKGROUND**

### **1.1. Educational Indicators**

A growing body of literature suggests that educational indicators seem to be a good way of measuring the change of a country due to a positive relationship between education and growth. For example, according to Azzoni and Servo (2002), education is the most important variable in explaining wage differentials across regions in Brazil. Other studies show that regions that invest more in education grow faster (Azzoni and Servo, 2002; Cardenas and Pontoon, 1995). In addition, as stated by The World Bank (1999, p.18), "education is one important explanation of why some people have higher incomes than others. People who have had little education tend also to be less productive and are more likely to be unemployed and economically and socially marginalized than are people with more education." According to Baumol et al. (1994), a given increase in per capita Gross Domestic Product (GDP), especially in very low income developing countries, is generally associated with improvements in social indicators that measure human welfare. Therefore, we cannot separate social and economic aspects; it is highly likely to find high correlations between them (Azzoni and Servo, 2002; Baumol et al., 1994; Cardenas and Pontoon, 1995). The causality can flow in both directions; for example, education can sometimes be explained by income variables and income can also be explained by educational variables (Tolley and Olson, 1971). Moreover, these two variables are not the only ones that influences the growth of a region, but both are highly important in a region's development.

The interest in education has led to numerous studies in developing countries (Azzoni and Servo, 2002; Bonal, 2004; Habibi et al., 2003; UMC, 2004; UNESCO, 2004; White, 2005; World Bank, 2003, 2004). Most of them have focused their research only on education itself, analyzing, for example, the educational performance between urban and rural areas, between genders, or among levels of poverty. However, to date, it appears that not many studies have focused on the education variable from a spatial econometric perspective. In this research, the focus is on the variation in educational performance over time, among regions

and within different terrains (coast, highlands and rainforest), and will try to draw conclusions about any patterns of educational convergence that may exist.

Education can be a powerful means for reducing poverty and inequality, but at the same time it can lead to exclusion and marginalization. In that way, inequalities in access to education, educational environments, and learning outcomes may influence regional growth (World Bank, 1999). The educational indicator may reveal socio-economic patterns and provide a more comprehensive understanding of the spatial asymmetries and imbalances within a given region and among different regions. In summary, this research adopts a different perspective of the analysis of spatial convergence in developing countries. The goal is to apply existing measures of convergence from a spatial econometric perspective with a different variable of analysis.

### **1.2. Importance of Geography**

As is the case for most regional growth studies, it is necessary to consider the importance of geography and accept the role of space. There is a growing recognition of the importance of space in economic convergence analysis (Goodchild et al., 2000; Janikas and Rey, 2005; Lim, 2003; Mossi et al., 2003). According to Mossi et al., 2003, p.394), "the economic growth of a region may be affected by the performance of neighboring economies: proximity to a prosperous area may have a positive influence on a region's economic performance, and alternatively, being close to a deprived economic environment may have an adverse effect." In addition to neighbor's influence, the geography of a place might also play a fundamental role in understanding regional growth. The geographic diversity in Peru may influence the region's development, for example, coastal areas might behave different from highland areas or rainforest areas.

The complexity of Peru's terrain sometimes limits access to basic services and makes equitable development more difficult (Escobal and Torero, 2000). Peru has a large variety of ecological areas, different climates zones and landscapes, and this geographic diversity is linked to development and may influence the welfare of regions. These regions not only represent a different type of landscape, but also represent something much more complex: the differences in social and cultural aspects (Escobal and Torero, 2000; World Bank, 2007).

Peru is mainly divided in three natural regions: Costa, Sierra and Selva (coast, highlands and rainforest respectively). This analysis considers the three regions in order to explore specific spatial patterns for each zone. The research analyzes if the geographic characteristics of regions are among the variables that determine students' performance (Figure 1).

### **1.3. Convergence Measures**

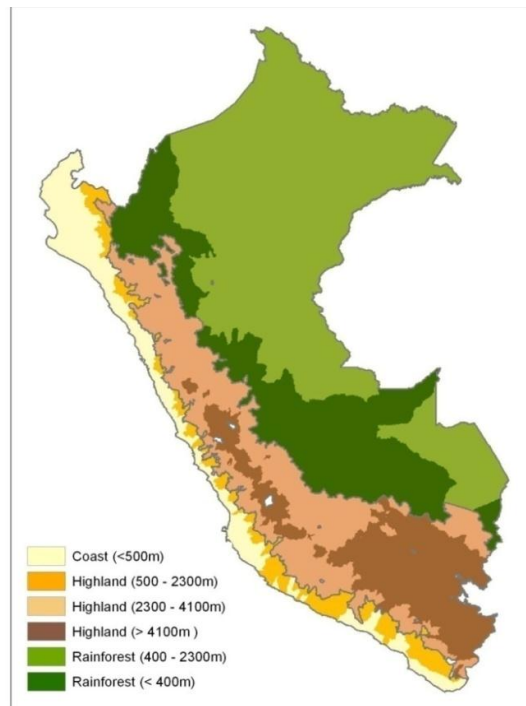
On the topic of convergence measures, Rey and Montouri (1999, p.144) stated that "the interest in regional convergence has not followed a uniform path. Instead, several distinct types of convergence have been suggested in the literature each being analyzed by distinct groups of scholars employing different

methods." The analysis of spatial convergence can be done using cross-sectional, time series or panel data measures. Cross-sectional analysis evaluates the performance of several regions at one specific time. This kind of convergence measures the decline of the cross-sectional dispersion of the variable of study. Another kind of cross-sectional convergence occurs when poor regions grow faster than rich regions, resulting in the former eventually catching up to the latter. These forms of convergence have been referred to as  *$\alpha$ -convergence* and  *$\beta$ -convergence* respectively. Time series analysis measures convergence of regions over a period of time. Here, convergence requires that the differences of the variable of analysis between two regions tend to go to 0 after a period of years. This form of convergence has been referred to as *stochastic convergence*. Finally, panel data analysis incorporates cross-sectional and time series data (Rey and Montouri, 1999; Rey and Janikas, 2005).

## 2. METHODOLOGY

In order to analyze the relationships between regions over a period of time and to determine if spatial convergence exists, this study did first an exploratory spatial data analysis of the educational indicator convergence and then, a confirmatory spatial econometric analysis of that convergence.

**Figure 1: Peru natural regions**



This section is divided into three main sections. The first and the second sections deal with the process of data collection, the variables of education that were used and the scale of the analysis. The third and last section describes the methods performed to analyze spatial convergence. The software used for the data process was ArcGis 9.2.; for the ESDA section, STARS 0.8.2 (Space Time Analysis of Regional Systems) and for the confirmatory section GeoDa.

### 2.1. Data Collection and Selection

Data availability constituted a big constraint on this research. The current spatial databases may contain some inconsistencies and gaps that require correction and manipulation. One of the biggest problems of the data is that it has been produced by different institutions using different methods of collection and management.

*Figure 2: Peruvian departments*

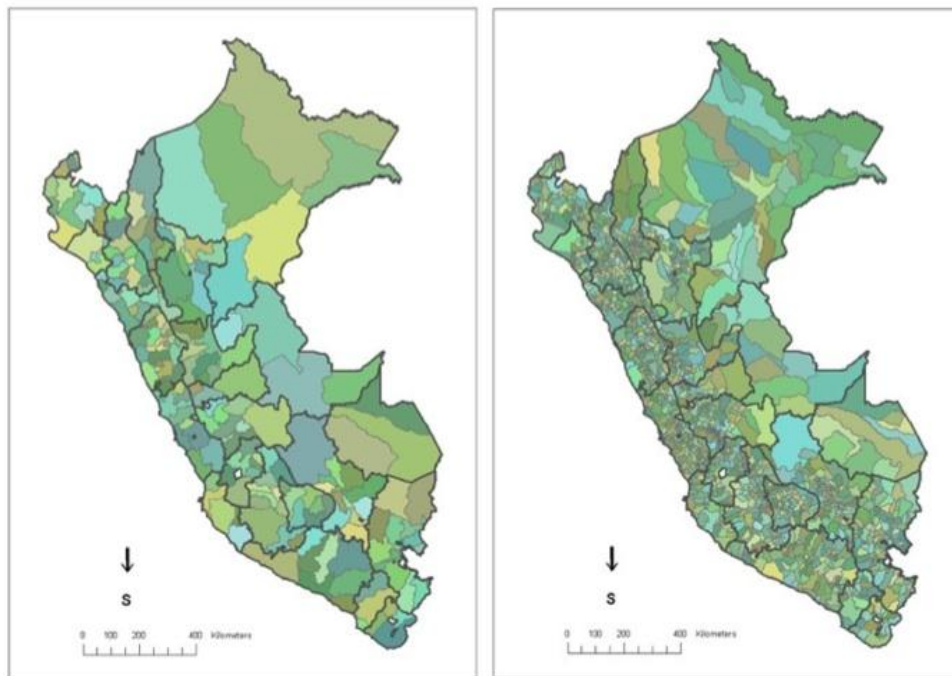


Data from two main organizations were used. The educational data were obtained from the Educational Census of the Ministry of Education of Peru (1993 -

2005 period) and the other population variables came from the INEI<sup>1</sup>. However, for consistency, all the data from the Ministry of Education was used and only the INEI data that matches with it was incorporated (part of the reason of choosing 1993 - 2005 period is due to Peruvian national census).

Peru is divided in 25 departments (departamentos), 194 provinces (provincias) and 1,829 districts (distritos). For this case, due to availability data only 189 provinces were analyzed.<sup>2</sup> See Figures 2 and 3.

**Figure 3: Peruvian provinces and districts**



## 2.2. Measures of Educational Performance

Some studies have considered educational indices in order to analyze spatial patterns in regions, such as using the outcomes of math tests with the purpose of measuring the educational performance of students (Fotheringham et al., 2001). However, it is important to differentiate that in developing countries it is challenging to find an appropriate index due to large discrepancies among regions, and thereby large discrepancies in educational performance. It is important to find an appropriate index since the standard measures of educational

<sup>1</sup>Instituto Nacional de Estadística e Informática

<sup>2</sup>These numbers correspond to 2005. The number of departments remains static; however, provinces and districts may increase over time.

level might not be truly representative in countries with high levels of inequality (MECEP, 2002; Minedu, 2004, 2005).

For that reason, for a better representation of the educational performance in Peruvian regions, not only one but four educational variables were used. One of them may not represent properly the behavior of a region but all of them together may show interesting results. The four variables are described below:

- **Percentage of approved students.** This includes all students that passed the school year with respect to all the ones that are enrolled.
- **Probability that students finish elementary school on time.** This means finishing elementary school in a period of time of 6 years.
- **Percentage of students that start school late.** This includes all students that start school later than the official time (older than 5-6 years old).
- **Percentage of designated teachers.** There are two kinds of teachers in Peru: *designated* and *hired* teachers. Designated teachers have generally applied for and received a permanent place in the educational system, analogous to the concept of tenure in the United States. This secure arrangement yields access to a variety of labor benefits, such as insurance and retirement plans, but has been criticized for eliminating performance incentives and therefore depressing standards. In response, the government shifted toward hired teachers, who work for a contractually-specified time period. These teachers are motivated by an evaluation process, and have their contracts renewed according to their performance.

The goal is to test all of these variables independently, and see how each of them represents the educational performance of the country. In addition, an appropriate composite variable is built in order to create an index of educational performance. For this index, the principal component analysis (PCA) was used to construct the weights for the variables. This model reduces the multidimensional educational variables into one single dimension or class. The idea was to create an index in which each of the four variables is well represented. The "negatives" variables, which means the higher the value the worse it is, needed to be changed to their opposite way, so instead of using the percentage of students that start school late and the percentage of designated teachers, it was used the percentage of students that start school at 5-6 years old and the percentage of hired teachers. This index needed the same type of hierarchy to be built: the higher the best for the four of them<sup>3</sup>.

As a complement, an economic variable derived from the INEI data is analyzed. According to the literature, there is generally a positive relationship between education and regional growth (Azzoni and Servo, 2002; Baumol et al.,

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<sup>3</sup>PCA 1993, Component Matrix: Finish school: 0.955, Approved: 0.945, Start late: 0.794, Hired teachers: 0.419. PCA 2005, Component Matrix: Finish school: 0.981, Approved: 0.972, Start late: 0.280, Hired teachers: 0.377.

1994). Thereby, in addition to the educational variable, an economic variable or a proxy in this case (access to electricity and water) is incorporated for comparative analysis. The purpose is to investigate whether the rates of convergence are similar for both measures across the regions. It is assumed that both variables will provide a more comprehensive view of regional development.

### 2.3. Analysis of Spatial Convergence

The analysis includes an exploratory spatial analysis of the educational variable and then a confirmatory spatial econometric analysis of the regional education convergence. First, *α-convergence* is analyzed, as well as its related spatial patterns with respect to the educational variable, followed by a confirmatory spatial econometric analysis of *β-convergence* that might support those findings.

The analysis of spatial convergence can be done using cross-sectional, time series or panel data measures as previously noted. This research analyzes convergence using the cross-sectional method, which evaluates the performance of several regions at one specific time. There are two kinds of measures:

- *α-convergence*. Occurs when there is a decline in the cross-sectional dispersion of the variable of study. Measures like the standard deviation and coefficient of variation of the log of the variable of analysis are employed to examine this form of convergence.
- *β-convergence*. Occurs when low performance regions grow faster than high performance regions, resulting in the former eventually catching up to the latter in educational performance (for this study case). To test this form of convergence, numerous studies have used the following regression:

$$\ln\left(\frac{Y_{i,t+k}}{Y_{i,t}}\right) = \alpha + \beta \ln(Y_{i,t}) + \varepsilon_{it} \quad (1)$$

Where  $Y_{i,t}$  is educational variable in region  $i$  year  $t$ ,  $\alpha$  and  $\beta$  are parameters to be estimated, and  $\varepsilon_{it}$  is a stochastic error term.

#### 2.3.1. Exploratory Spatial Data Analysis of Educational Convergence

The exploratory spatial data analysis (ESDA) is done in order to explore the structure of spatial data and determine the nature of spatial dependencies. This analysis considers the application of techniques in order to generate hypotheses about underlying dynamics of spatial distribution, the identification of atypical locations (spatial outliers), and possible spatial agglomerations or clusters, as well as to suggest different spatial patterns or other forms of spatial instability (Serrano and Valcarce, 2000).

An analysis of spatial autocorrelation is performed using Moran's I statistic and local Moran's statistic in order to evaluate any possible connection between spatial autocorrelation and the spatial convergence results. The research attempts

to answer questions such as whether the measure of spatial autocorrelation tends to co-move with the measure of the dispersion of the educational variable, or if the development of the educational variable distribution appears to be clustered in nature. Finally, the local Moran's statistic is applied in order to have a more disaggregated view of the nature of the spatial autocorrelation.

Two different kinds of measures will be used in this part:

- *a-convergence and global spatial autocorrelation.* This measure is only concerned with the spread or dispersion of the educational variable distribution.

$$I_t = \left( \frac{n}{s_0} \right) \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} x_{i,t} x_{j,t}}{\sum_{i=1}^n \sum_{j=1}^n x_{i,t} x_{j,t}} \quad (2)$$

Where  $w_{ij,t}$  is an element of a binary spatial weights matrix  $\mathbf{W}$  such that  $w_{ij} = 1$  if regions  $i$  and  $j$  share a border and zero otherwise;  $x_{i,t}$  is the natural log of real educational variable in state  $i$  in year  $t$  (measured as  $x_{i,t} - u$ );  $n$  is the number of states; and  $s_0$  is a scaling factor equal to the sum of all the elements of  $\mathbf{W}$  (Rey and Montouri, 1999).

- *a-convergence and local spatial autocorrelation.* This measure has a more disaggregated view of the structure of spatial dependence in regional education performance. The local Moran for region  $i$  takes the following form:

$$I_{i,t} = \left( \frac{x_i}{m_o} \right) \sum_{j=1}^n w_{ij} x_{j,t} \quad (3)$$

with:

$$m_o = \sum_i^n x_{i,t}^2$$

The next step is a confirmatory spatial econometric analysis of the convergence hypothesis in order to model the possible spatial patterns.

### 2.3.2. Confirmatory Analysis of $\beta$ -Convergence

The confirmatory analysis is the second part of the analysis of spatial convergence<sup>4</sup>. This analysis tests the data against spatial models. Econometric models that incorporate spatial effects are used. These models are relevant when there are technology spillovers between adjacent states (*substantive spatial dependence*) or when an artificial spatial framework (the states or departments in this case) does not correspond to market processes (*nuisance dependence*) (Anselin and Rey, 1991).

The confirmatory analysis is done for the educational index due to the fact that is the variable that best represents educational performance. In addition, two

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<sup>4</sup>It is important to mention that this study will measure absolute convergence for the entire country.

other socioeconomic variables are explored to see if the convergence pattern, if any, tends to move together with the educational one. Percentage of population with access to water and electricity is used.

The starting point of the analysis of convergence is the Ordinary Least Squares (OLS) model, followed by a spatial diagnostics that accounts for the presence of spatial effects:

$$\ln\left(\frac{Y_{t+k}}{Y_t}\right) = \alpha + \beta \ln(Y_t) + \varepsilon_t \quad (4)$$

where the vector  $Y_t$  contains the observations on real educational variable from all regions in a given year.

In order to evaluate the presence of spatial effects, a total of 5 test statistics are analyzed. The first statistic test is Moran's I, however, as reported in Anselin and Rey (1991), while this test is very powerful against both forms of spatial dependence (spatial lag and spatial error autocorrelation), it does not suggest which of these two forms of misspecification should be considered. For that reason, the Lagrange Multiplier test statistic is also incorporated. Four Lagrange Multiplier test statistics are reported in the diagnostic output. The first two (LM-Lag and Robust LM-Lag) pertain to the spatial lag model as the alternative. The next two (LM-Error and Robust LM-Error) refer to the spatial error model as the alternative. The Robust versions of the statistics only can be considered when the standard versions (LM-Lag or LM-Error) are significant<sup>5</sup>. The results of the diagnosis will point to a particular presence of spatial dependence, and therefore, to the model that should be estimated next.

Following Rey and Montouri (1999), three spatial dependence models can be used. Each of these models holds different interpretations for the nature of the convergence process, the goal in this research is to analyze which one represents better the spatial dependence problem (see equations 5, 6 and 7).

- *Spatial error models*: This specification is relevant when the dependence works through the error process in that the errors from different states may display spatial covariance (*nuisance dependence*):

$$\ln\left(\frac{Y_{t+k}}{Y_t}\right) = \alpha + \beta \ln(Y_t) + (I - \zeta W)^{-1} u_t \quad (5)$$

where  $\zeta$  is a scalar spatial error coefficient and  $u \sim N(0, \sigma^2 I)$ .

- *Spatial lag model*: In contrast to the nuisance form of dependence accounted for the spatial error model, the lag model deals with a substantive form of dependence. This means that the spatial dependence is within the structural part of the model:

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<sup>5</sup>For technical details, see Exploring Spatial Data with GeoDaTM: A Workbook. Luc Anselin, 2005.

$$\ln\left(\frac{Y_{t+k}}{Y_t}\right) = \alpha + \beta \ln(Y_t) + \rho W \ln\left(\frac{Y_{t+k}}{Y_t}\right) + \varepsilon_t \quad (6)$$

where  $\rho$  is the scalar spatial autoregressive parameter.

- *Spatial cross-regressive model*: A closely related model to that of the lag is the crossregressive model. This is a second possibility for dealing with substantive spatial spill-over effects. Here the lag is taken with respect to a subset of the exogenous variables in the design matrix, rather than the dependent variable itself:

$$\ln\left(\frac{Y_{t+k}}{Y_t}\right) = \alpha + \beta \ln(Y_t) + \tau W \ln\left(\frac{Y_{t+k}}{Y_t}\right) + \varepsilon_t \quad (7)$$

### 3. RESULTS AND DISCUSSION

This section includes an exploratory spatial analysis of the educational variables and then a confirmatory spatial econometric analysis of the regional education convergence. First, *a-convergence* is analyzed, as well as its related spatial patterns with respect to the educational variable, followed by a confirmatory spatial econometric analysis of  *$\beta$ -convergence* that might support those findings.

#### 3.1. Descriptive Results

##### 3.1.1. Descriptive Distribution

According to the distribution of the first variable (approved students), the coefficient of variation and the standard deviation are low for both years, which represents similar dispersion behavior over time. The first year does not show any extreme values or outliers and the second one shows only one: the province of Purus, Ucayali (65.96%), located in the rainforest. This is an interesting case due to the fact that for the year 2005 both extremes are located in the rainforest. Table 1 shows the descriptive summary for all the variables.

For the second variable (students that finish on time), the coefficient of variation for both years is higher than the one from the first variable, but both variables present a lower dispersion for the second year. Regarding outliers, 1993 has two provinces with extreme high values, one in Ilo, Moquegua with 56% and Jorge Basadre, Tacna with 63%, both located in the southern coast. For 2005, one outlier is found: the province of Requena (Loreto department) located in the northern rainforest, presents a very high probability of finishing school on time (78%) with respect to its neighbors.

The third variable (students that start late) presents a large decrease in the percentage of students that start school late. However, the coefficient of variation and the standard deviation show higher dispersion for the last year. The first year presents 3 outliers with high values, Pachitea in Huanuco (65.22%), Carabaya in Puno (59.97%) and Sanchez Carrion in La Libertad (56.71%). The year 2005 has several outliers, most of them are regions with high percentage of students that start school late (the majority is located in the highlands).

The last variable (designated teachers) shows higher dispersion for the second year. The coefficient of variation and the standard deviation are similar, but the results show that the first year is more homogeneous. According to outliers, both years have several ones. Most of the outliers for 2005 are located on the coast and rainforest. They are regions with low percentage of designated teachers surrounded by regions with higher values.

The educational index presents similar results for the two periods but the year 2005 exhibits an improvement over time (Table 1). For both years the coefficient of variation and the standard deviation is similar. There are no outliers with this index.

**Table 1: Descriptive Summary**

| Approved students  |        |        |        |       |        |        |
|--------------------|--------|--------|--------|-------|--------|--------|
| Year               | mean   | median | s      | cv    | sk     | kurt   |
| 1                  | 73.085 | 73.031 | 8.963  | 0.123 | 0.009  | -0.822 |
| 2                  | 83.044 | 83.181 | 6.101  | 0.073 | -0.253 | -0.459 |
| Finish on time     |        |        |        |       |        |        |
| Year               | mean   | median | s      | cv    | sk     | kurt   |
| 1                  | 0.210  | 0.179  | 0.127  | 0.605 | 0.871  | 0.055  |
| 2                  | 0.359  | 0.338  | 0.145  | 0.403 | 0.476  | -0.507 |
| Start late         |        |        |        |       |        |        |
| Year               | mean   | median | s      | cv    | sk     | kurt   |
| 1                  | 28.396 | 27.205 | 10.195 | 0.359 | 0.624  | 0.228  |
| 2                  | 1.078  | 0.827  | 0.983  | 0.912 | 1.993  | 4.687  |
| Designated teacher |        |        |        |       |        |        |
| Year               | mean   | median | s      | cv    | sk     | kurt   |
| 1                  | 85.721 | 86.911 | 8.742  | 0.102 | -1.015 | 0.851  |
| 2                  | 79.496 | 80.952 | 11.512 | 0.145 | -1.061 | 1.173  |
| Educational index  |        |        |        |       |        |        |
| Year               | mean   | median | s      | cv    | sk     | kurt   |
| 1                  | 48.815 | 47.155 | 8.858  | 0.181 | 0.539  | -0.474 |
| 2                  | 58.029 | 56.415 | 8.283  | 0.143 | 0.456  | -0.507 |

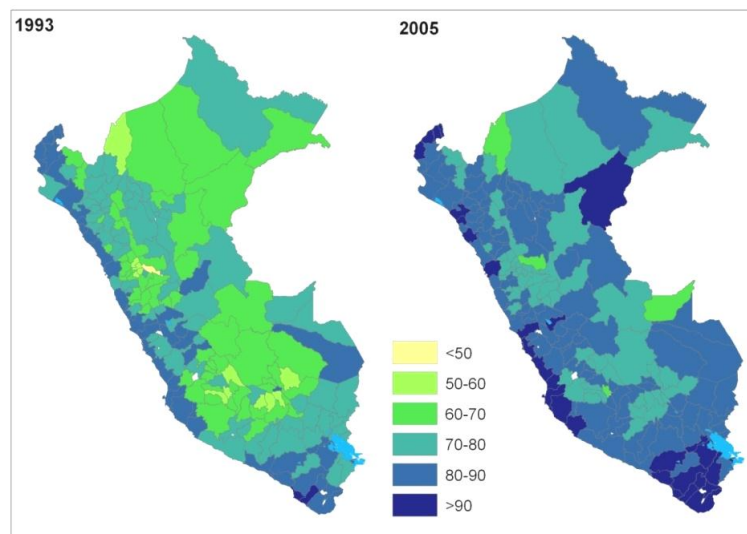
Over time the results reflects an improvement in educational performance. The mean is higher for the second period for the variables related with student performance and also the province variables distribution is less dispersed. The results for the other two variables have decreased over time, there are more students that start school on time and also more teachers that have been hired, however, both present a higher dispersion over time.

### 3.1.2. Maps

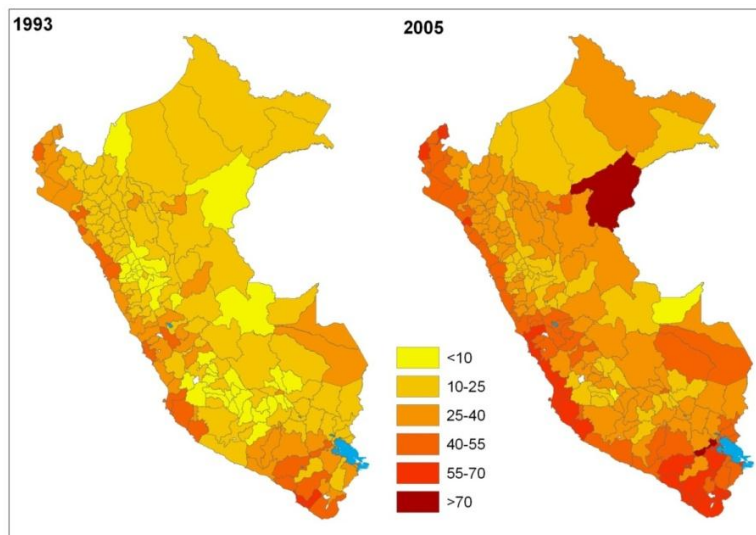
The maps shown below help to detect some possible province spatial patterns that remain constant through time. The students that have a higher probability of finish school on time are located in the coast, as well as the ones with higher percentage of approval rate. In contrast, the maps show some spots with lower values located in the highlands and some areas of the rainforest. This

low performance is related with the poorest provinces in Peru, usually with higher percentage of rural population. The rainforest region behaves differently over time, the first year seems more homogeneous but the second one has high and low values together and it is hard to find any pattern (Figures 4 and 5).

**Figure 4: Percentage of approved students**



**Figure 5: Probability of finishing elementary school on time**

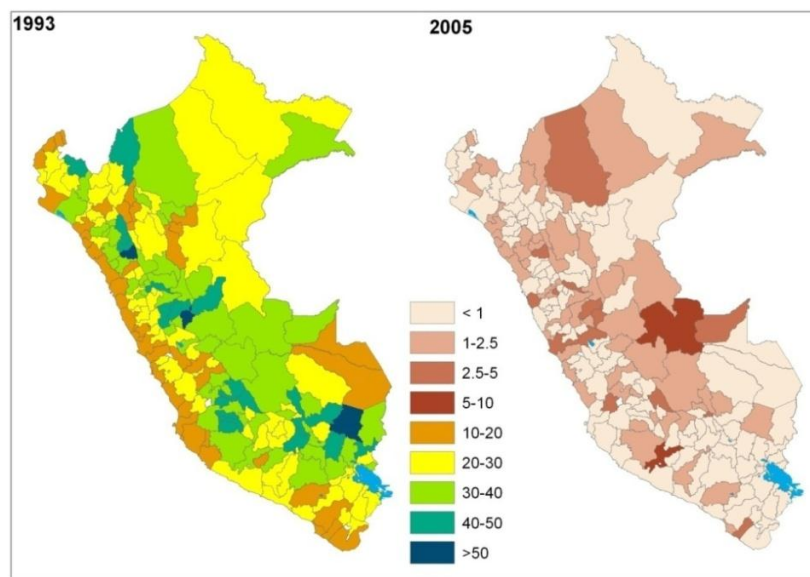


According to the map of students that start school late, there are also some interesting results. For the year 1993, all the coast line shows low percentage contrasting with some areas of the highlands and rainforest. For the year 2005, there are several provinces with less than 1% of students that start late (Figure 6).

For the last variable, the rainforest and part of the coast present the lowest percentage of designated teachers. The southern part presents a strong cluster that remains over time (Figure 7).

The educational index map for provinces represents the overall educational performance over time. The coast shows a constant pattern for both years performing better than the rest of the country, especially the southern part. The central part of the country (highlands) varies over time but is characterized by moderate to lower values. The rainforest is very diverse for both periods but the southern area tends to performs better (Figure 8).

**Figure 6: Percentage of students that start school late**

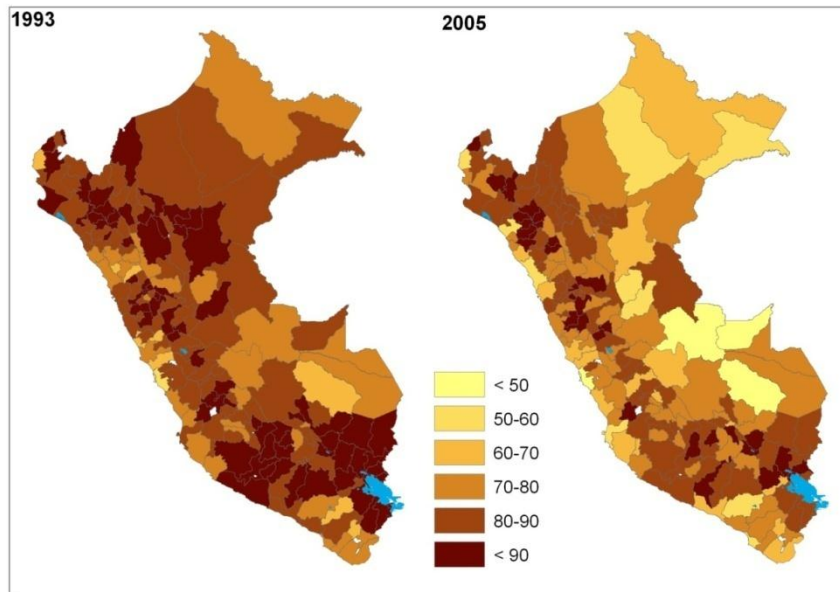


### 3.2. Global Moran

This section analyses the dispersion of the educational variables in the two periods. Global spatial autocorrelation represents the extent of overall clustering that exists in a dataset. There are two kinds of spatial autocorrelation, positive spatial autocorrelation which means presence of spatial clusters of high/low

values and negative spatial autocorrelation which means presence of spatial outliers<sup>6</sup>.

**Figure 7: Percentage of designated teachers**



Positive spatial autocorrelation represents Tobler's First Law of Geography whereby closer areas are more similar in value than distant ones. The results show the presence of positive spatial autocorrelation at the province level as the statistics are significant at  $p \leq 0.01$  for both years. The provinces with high (low) values tend to be located nearby other provinces with high (low) values more often than would be expected due to random choice (Table 2). The province level maps in the previous section showed some potential spatial dependence for both periods, and global Moran result is supporting those patterns.

In addition, Table 3 shows for the first three variables that the measure of spatial autocorrelation tends to co-move with the measure of educational dispersion. Even though the spatial dependence decreases as the educational dispersion also decreases, the spatial dependence is still highly significant. On the other hand, the last two variables from the table perform different, here the level of spatial dependence also decreases over time but the dispersion of the education variables tends to increase. Besides the difference in the movement over time, all of them indicate that the development of the distribution seems to be clustered at the province level.

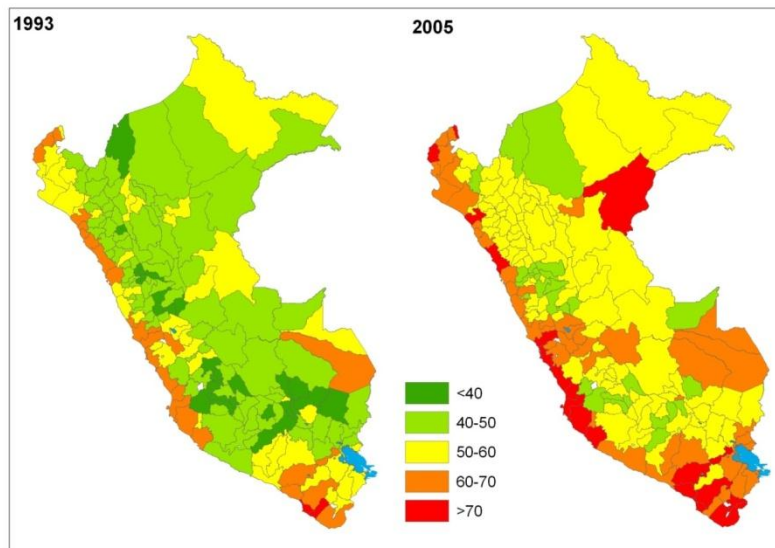
<sup>6</sup>All the analysis in this section has used the Rook weight matrix and 999 permutations. The Queen weight matrix was also used but it was not incorporated into the analysis due to similar results.

### 3.3. Local Moran

Local Moran analysis provides a more disaggregated view of the spatial autocorrelation presented in the educational variables. It indicates the location of local clusters and spatial outliers. The Moran scatter plot is a way to visualize the type and strength of spatial autocorrelation in the educational data distribution. The scatter plot provides a statistic (Moran's I) to determine the extent of linear association between the values in a given location (x-axis) with values of the same variable in neighboring locations (y-axis) (Spatial Analysis Lab, University of Illinois, 2006).

The four different quadrants of the scatterplot identify four types of local spatial association between a region and its neighbors: (HH) a high educational value region with high educational value neighbors (Quadrant I); (LH) a low educational value region surrounded by high educational value neighbors (Quadrant II); (LL) a low educational value region surrounded by low educational value neighbors (Quadrant III); and (HL) a high educational value region with low educational value neighbors (Quadrant IV, Quadrants I and III belongs to positive forms of spatial dependence while the other two represent negative spatial dependence. The significance level ( $p \leq 0.05$ ) used in the local Moran is based on a conditional randomization approach involving 999 random permutations of the neighboring regions for each observation.

**Figure 8: Educational index**



The local Moran results illustrate for the first variable (approved students), 72 provinces for which the local statistic provides an indication of clustering for one of the years and 38 provinces that present clustering for the two periods. More than 97% of the local indicators that are significant fall in either quadrant I or III of the scatterplot, reflecting HH and LL clustering respectively (Figure 9).

For the second variable (finish school), there are 68 clusters for at least one of the years and 38 clusters that remain constant through time. Also more than 95% of the local indicators that are significant fall in either quadrant I or III of the scatterplot (Figure 10). For the third one (start school late), there are 67 provinces for which the local statistic provides an indication of clustering for one of the years and only 6 provinces that present clustering for the two periods. Also more than 82% of the local indicators that are significant fall in either quadrant I or III of the scatterplot (Figure 11). For the fourth one (designated teacher), there are 56 clusters for at least one of the years and 12 for the two periods. Also more than 94% of the local indicators that are significant fall in either quadrant I or III of the scatterplot (Figure 12).

Finally, the local Moran for the educational index shows 70 provinces for which the local statistic provides an indication of clustering for one of the years and 40 provinces that present clustering for the two periods. Also over 98% of the local indicators that are significant fall in either quadrant I or III of the scatterplot (Figure 13).

The results demonstrate that the local pattern of spatial association reflects also the global trend of positive spatial association. For the first two variables and for the educational index, most of the HH clusters are located in the coast line; the north and the south coast have notorious positive clusters, as well as Lima and surrounding. And most of the LL clusters are located in the highlands areas.

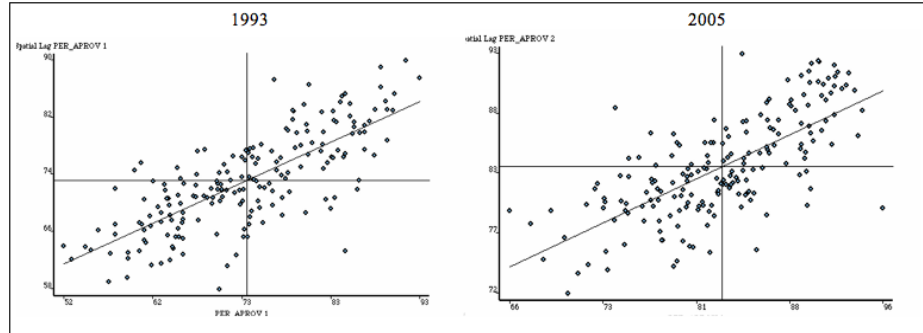
**Table 2: Moran's I**

| Moran's I expected Value: -0.005 |       |        |       |       |
|----------------------------------|-------|--------|-------|-------|
| Approved students                |       |        |       |       |
| Year                             | MI    | z      | p-(N) | p-(P) |
| 1                                | 0.562 | 12.259 | 0.000 | 0.000 |
| 2                                | 0.497 | 10.860 | 0.000 | 0.000 |
| Finish on time                   |       |        |       |       |
| Year                             | MI    | z      | p-(N) | p-(P) |
| 1                                | 0.569 | 12.403 | 0.000 | 0.000 |
| 2                                | 0.509 | 11.123 | 0.000 | 0.000 |
| Start late                       |       |        |       |       |
| Year                             | MI    | z      | p-(N) | p-(P) |
| 1                                | 0.453 | 9.913  | 0.000 | 0.000 |
| 2                                | 0.080 | 1.850  | 0.032 | 0.017 |
| Designated teachers              |       |        |       |       |
| Year                             | MI    | z      | p-(N) | p-(P) |
| 1                                | 0.346 | 7.602  | 0.000 | 0.000 |
| 2                                | 0.316 | 6.951  | 0.000 | 0.000 |
| Educational index                |       |        |       |       |
| Year                             | MI    | z      | p-(N) | p-(P) |
| 1                                | 0.573 | 12.489 | 0.000 | 0.000 |
| 2                                | 0.507 | 11.063 | 0.000 | 0.000 |

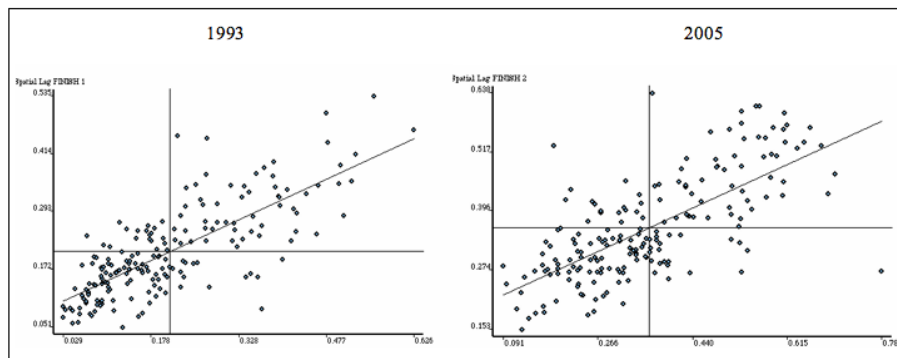
**Table 3: Educational Convergence and Spatial Autocorrelation**

| Approved students   | MI    | CV    |
|---------------------|-------|-------|
| Year 1              | 0.562 | 0.123 |
| Year 2              | 0.497 | 0.073 |
| Finish on time      | MI    | CV    |
| Year 1              | 0.569 | 0.605 |
| Year 2              | 0.509 | 0.403 |
| Educational index   | MI    | CV    |
| Year 1              | 0.573 | 0.181 |
| Year 2              | 0.507 | 0.143 |
| Start late          | MI    | CV    |
| Year 1              | 0.453 | 0.359 |
| Year 2              | 0.080 | 0.912 |
| Designated teachers | MI    | CV    |
| Year 1              | 0.346 | 0.102 |
| Year 2              | 0.316 | 0.145 |

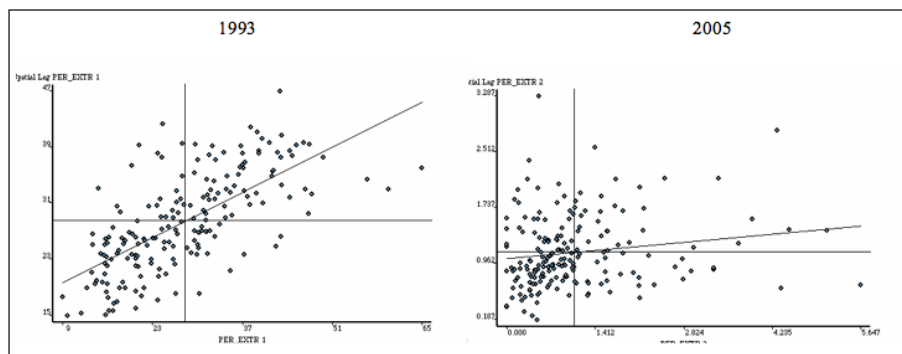
**Figure 9: Percentage of approved students**



**Figure 10: Probability of finishing on time**



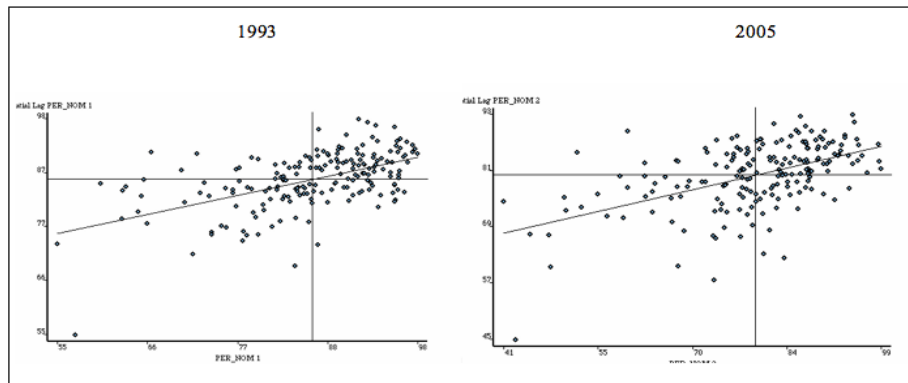
**Figure 11: Percentage of students that start school late**



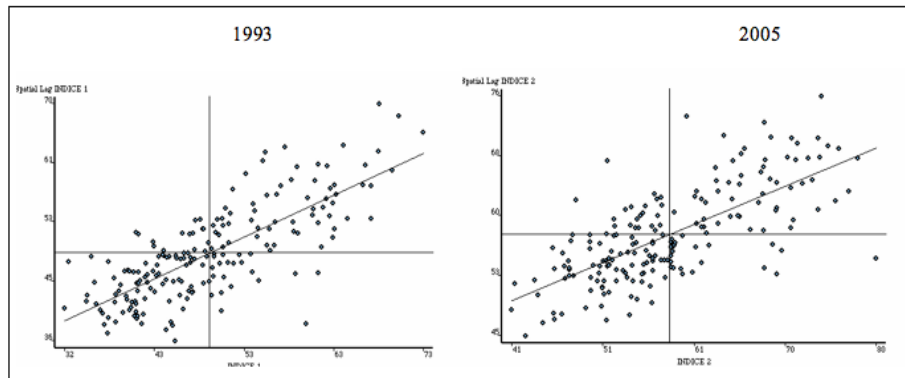
According to the maps, there are clear spots of LL clusters in the central and southern highlands. Regarding the HL - LH regions, there are two outliers in the north part of the rainforest (and only one regarding the educational index). The map regarding students that start school late, on the other hand, behave the opposite way. The LL clusters are located among the coast line and the HH

clusters are located in the highlands and some areas of the rainforest (Figures 14 and 15).

**Figure 12: Percentage of designated teachers**



**Figure 13: Educational index**

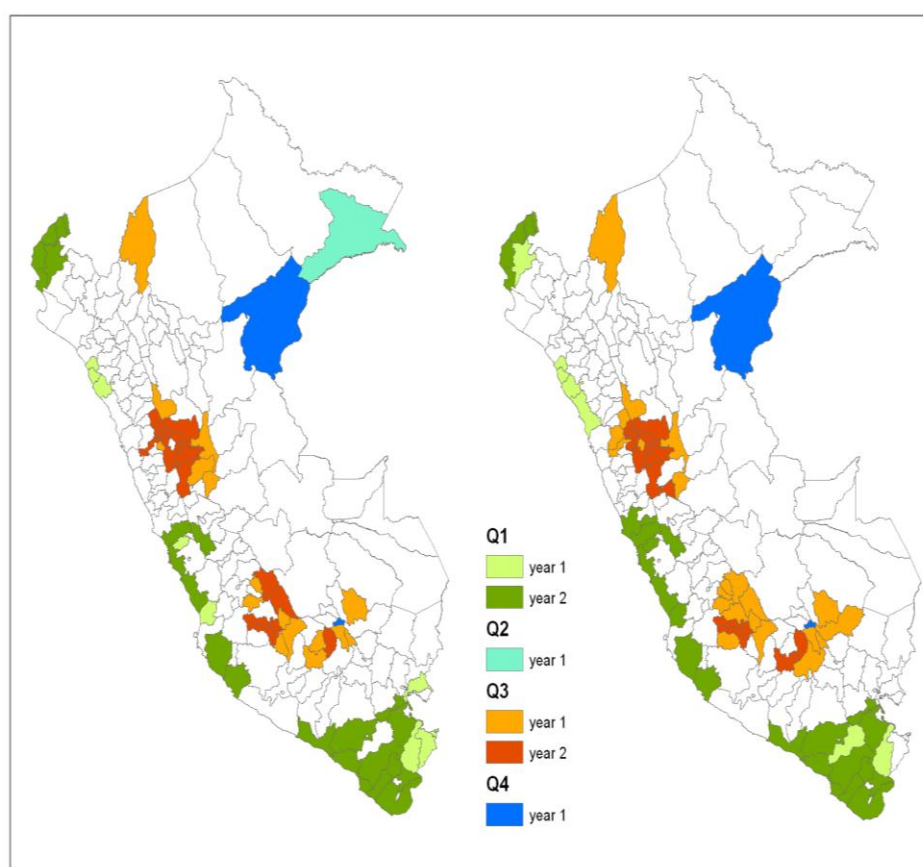


This section has shown the presence of some spatial patterns in Peruvian regions. The results showed a general improvement in educational performance over time as well as a decrease in the dispersion of the educational variables. Moreover, the results revealed the differences between natural regions: the coastal regions tend to perform better than the highlands and rainforest. For the first year, the variables regarding educational performance present higher values in the coastal regions. In the same manner, the year 2005 also shows that the coast is the one with the best performance. The rainforest showed some particular behavior with respect to the educational performance. It showed very high results for some of the regions, a result that might need further analysis to understand the inside dynamics of these specific places.

Something interesting to mention is the relationship found in the first period between natural regions and the percentage of students that start school late (Figure 16). For this year, there is a strong spatial pattern regarding this variable.

The more isolated places are the ones that have higher percentage of students that start school late, such as the rainforest and the very high altitude areas. These places usually have a very difficult access to services due to their rough geography and limited public resources. The year 2005 does not present any pattern due to the general decrease in the percentage of students that start late. Even though to date there is an increment in school infrastructure<sup>7</sup>, the more isolated regions dominated by high altitudes or dense rainforest still have serious problems regarding enrollment.

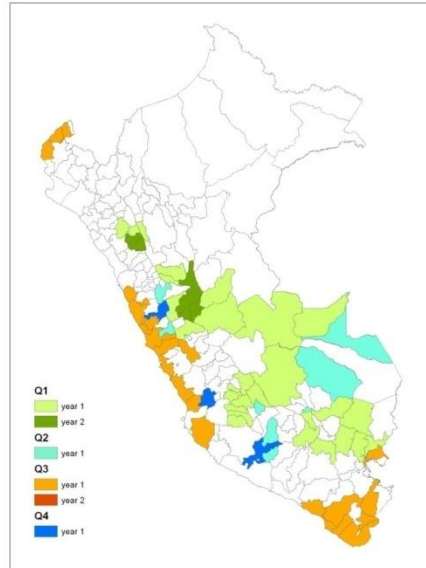
**Figure 14: Local Moran: finish on time (left) and educational index (right)**



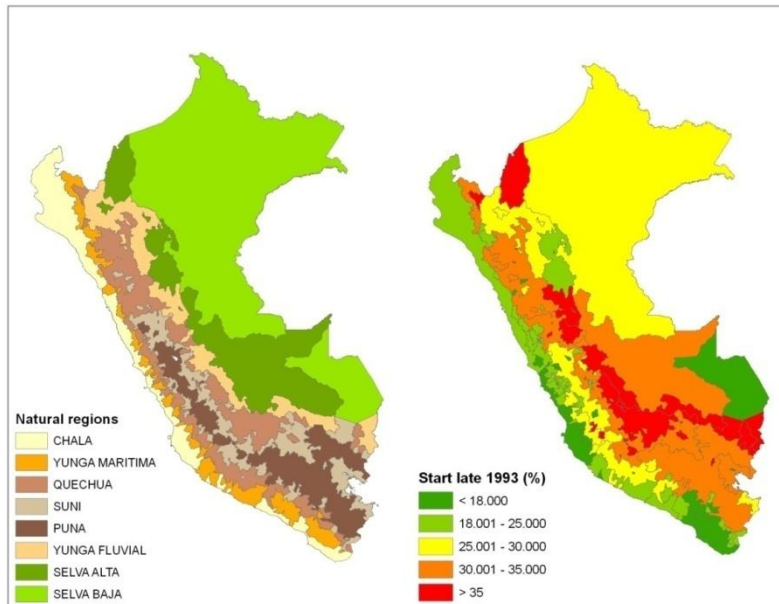
In addition, the results from the global and local Moran analysis supported the spatial patterns founded in the maps. This section has revealed the presence of positive spatial association over time and it has provided a better understanding of the dynamics between regions over the 12 period of time.

<sup>7</sup> According to the Ministry of Education database, an increase of about 25% from 1993 to 2005 regarding all types of elementary schools.

**Figure 15: Local Moran: students that start late**



**Figure 16: Peru natural regions and percentage of students that start school late (1993)**



### 3.4. Confirmatory Analysis of $\beta$ -Convergence

After the exploratory analysis, the next step is a confirmatory spatial econometric analysis of the convergence hypothesis in order to model the pos-

sible spatial patterns. The starting point of the analysis of convergence is the Ordinary Least Squares (OLS) model, followed by a spatial diagnostics that accounts for the presence of spatial effects. The first variable of analysis is the educational index followed by an analysis of two socioeconomic variables.

### 3.4.1 Educational Index

Table 4 presents the results obtained from the Ordinary Least Squares (OLS) model of the educational index. The regression yields highly significant and negative coefficient for the starting level, confirming the presence of  $\beta$  convergence for the Peruvian provinces. In column 6 of Table 4 the rate of convergence over the study period is reported to be 3.2%. This indicates that the gap between provinces with high educational performance and provinces with low educational performance reduces by 3.2% every year.

**Table 4: OLS Estimation**

| Period    | R <sup>2</sup> | AdjR <sup>2</sup> | AIC     | $\beta$ (p-value) | Convergence Rate $\theta$ |
|-----------|----------------|-------------------|---------|-------------------|---------------------------|
| 1993-2005 | 0.39           | 0.38              | -462.49 | -0.315 (0.000)    | 0.032                     |

AIC: Value of Akaike Information Criterion.

Convergence rate  $\theta$  is obtained using  $\theta = \ln(\beta + 1)/-k$ , where  $k$  is the number of years in the period.

**Table 5: Diagnosis for Spatial Dependence**

| Test                        | MI/DF    | z-value       | p-value       |
|-----------------------------|----------|---------------|---------------|
| Lagrange Multiplier (error) | 1        | 12.381        | 0.0004        |
| <b>Robust LM (error)</b>    | <b>1</b> | <b>10.215</b> | <b>0.0014</b> |

Even though the OLS results show the presence of convergence, a diagnostics for the presence of spatial effects should be applied. According to the results in table 5, there is evidence of error dependence<sup>8</sup>. In addition, table 6 reports the estimation results for the spatial error model over the study period. As expected from the findings of the diagnostic tests, the spatial error model has the best fit. This indicates a misspecification of the OLS model due to omitted spatial dependence. The result shows that taking the error dependence into account also affects the estimated of the annual rate of convergence at province level. It shows a faster rate of convergence than the one based on the OLS estimate (0.034 and 0.032 respectively). For more details review Rey and Montouri (1999).

### 3.4.2. Socioeconomic Variables

The next step will be the comparison of the educational results with the socioeconomic ones. The results in Table 7 tend also to follow the same pattern as the educational index variable. The regression yields highly significant and negative coefficient for the starting level, confirming also the presence of  $\beta$

<sup>8</sup>While the results show a strong evidence of spatial dependence, the White test for heteroskedasticity is not significant. For that reason, further consideration for this problem is omitted.

convergence for the Peruvian provinces. However the rate of convergence over the study period is much higher: 6.9% for electricity and 8.7% for water. This indicates that the gap between provinces with higher and lower access to these services reduces much faster than the gap regarding education.

**Table 6: Spatial Error Model**

| Model specification                                                             | $AIC^1$        | $\beta$ ( $p$ - value) <sup>2</sup> | $\gamma, \rho, \tau^3$<br>p-value | Test <sup>4</sup><br>p-value |
|---------------------------------------------------------------------------------|----------------|-------------------------------------|-----------------------------------|------------------------------|
| <b>Spatial error (ML)</b>                                                       | <b>-472.24</b> | <b>-0.333(0.000)</b>                | <b>0.002</b>                      | <b>0.002</b>                 |
| Convergence rate based on spatial error (ML) estimates( $\theta$ ) <sup>5</sup> |                |                                     |                                   | 0.034                        |

Notes:

1. Value of Akaike Information Criterion.

2. Estimate for  $\beta$  and its p-value.

3. p-value for the spatial coefficient.

4. p-value for the Lagrange Multiplier Test for the alternative model.

5. Convergence rate  $\theta$  is obtained using  $\theta = \ln(\beta+1)/-k$ , where  $k$  is the number of years in the period.

**Table 7: OLS Estimation**

| Period    | Variable | $R^2$ | Adj $R^2$ | AIC    | $\beta$ ( $p$ - value) | Conv. Rate $\theta$ |
|-----------|----------|-------|-----------|--------|------------------------|---------------------|
| 1993-2005 | Elec     | 0.71  | 0.71      | 126.21 | -0.561 (0.000)         | 0.069               |
| 1993-2005 | Water    | 0.65  | 0.65      | 283.29 | -0.649(0.000)          | 0.087               |

The diagnostic for the presence of spatial effects points to the presence of spatial error autocorrelation for both variables. Similar to the educational index, the result shows that taking the error dependence into account affects the estimated of the annual rate of convergence. It shows also a faster rate of convergence than the one based on the Ordinary Least Squares estimate. It changes from 0.069 (OLS) to 0.071 (Error model) for electricity and from 0.087 to 0.091 for water (Tables 8 and 9).

**Table 8: Diagnosis for Spatial Dependence**

| Elec Test                   | MI/DF    | z-value       | p-value       |
|-----------------------------|----------|---------------|---------------|
| Lagrange Multiplier (error) | 1        | 25.000        | 0.0000        |
| <b>Robust LM (error)</b>    | <b>1</b> | <b>17.779</b> | <b>0.0000</b> |
| Water Test                  | MI/DF    | z-value       | p-value       |
| Lagrange Multiplier (error) | 1        | 13.874        | 0.0002        |
| <b>Robust LM (error)</b>    | <b>1</b> | <b>11.400</b> | <b>0.0007</b> |

The aim of this model was to eliminate the nuisance found in the error term. This spatial error autocorrelation could be due to the poor match between the spatial extent of the phenomenon of interest (in this case, educational performance or access to electricity/water) and the administrative units for which

data are available (Anselin and Rey, 1991). Looking at the results in the exploratory section, it is possible that the political-administrative boundaries can restrict the analysis of educational performance. The use of models that deal with spatial dependence problems have provided more accurate results regarding the convergence process within Peruvian regions.

**Table 9: Spatial Error Model (ML)**

| Variable                                                            | AIC     | $\beta$ (p-value) | $\lambda$ p-value | Test p-value |
|---------------------------------------------------------------------|---------|-------------------|-------------------|--------------|
| Elec                                                                | 102.70  | -0.575(0.000)     | 0.0000            | 0.0000       |
| Convergence rate based on spatial error (ML) estimates ( $\theta$ ) |         |                   |                   | 0.0710       |
| Water                                                               | 270.054 | -0.664(0.000)     | 0.0000            | 0.0003       |
| Convergence rate based on spatial error (ML) estimates ( $\theta$ ) |         |                   |                   | 0.0910       |

#### 4. CONCLUSIONS

Social indicators such as education, poverty or access to services seem to be an appropriate way to evaluate a Peruvian region.

This study provides a better understanding of the geographical dynamics of the educational variables, and also measure if there was a tendency towards equalization of education. It has looked for spatial patterns in order to explain how educational performance behaves over time, among regions and within different terrains. Moreover this research has provided insights to the nature of regional educational convergence patterns in Peru for the 1993- 2005 period. This period was important because it analyzed the state of education in Peru at the beginning of a period of reforms and its performance over a twelve year period of time. The study has evaluated if educational convergence exists, as well as analyzed if there were different results for the analysis of spatial convergence within other socioeconomic variables.

The results in this analysis confirmed the presence of educational convergence throughout the 12 year period. Previously to this finding, an exploratory spatial data analysis was done in order to find some spatial patterns that helped understand the convergence process.

According to the ESDA results, strong positive spatial autocorrelation was found. Interestingly, the province level showed that the measure of spatial autocorrelation tends to co-move with the measure of the educational dispersion. Even though the spatial dependence weakens as the educational dispersion decreases, the spatial dependence is still highly significant. Moreover, the clusters maps provided a more disaggregated view of the nature of the spatial autocorrelation. They showed a strong spatial pattern; HH clusters tend to be located in the coastal regions while LL clusters tend to be located in the rainforest and highlands.

While the exploratory section was concerned about finding spatial patterns, the convergence hypothesis focused in the inverse relationship between the

growth rate in educational performance and the initial level of this educational variable. The findings showed that a region's educational growth also displayed strong spatial autocorrelation, indicating that the region's movement towards convergence tends to be similar to their neighbors.

The results showed the presence of spatial convergence for the educational and socioeconomic variables. The confirmatory analysis revealed that the traditional model (OLS) was misspecified due to the presence of strong spatial error dependence. And after taking into account the spatial dependence, there were no longer misinterpretations in the Peruvian convergence process for the 12 year period. With respect to the other socioeconomic variables, the results showed that the convergence rate is different from the educational index. Even though the socioeconomic variables tend to co-move with the educational one, their pace is different. The gap between regions with high percentage and low percentage of population with access to water and electricity tends to decrease much faster than the one from the educational variable. These results were expected due to the fact that bringing infrastructure into regions is easier than changing people's performance.

An important aspect of this research was the analysis of spatial convergence using a different perspective: the use of a social indicator as the variable of analysis. This research has applied existing measures of convergence from a spatial econometric perspective with a different variable of analysis: education. In the Peruvian case, the use of educational variables, as well as other socioeconomic variables, brought interesting results regarding regional development.

Unfortunately, even though the results showed a general improvement in education, as well as an increment in infrastructure, there is still a big gap among regions. Inequity is one of the biggest problems in Peru. The constant migration, the inequities among regions, the cultural disparities and the high poverty rates (some regions with more than 90% of poverty) makes crucial the search for new policies of development. Peru's centralization causes a problem of disarticulation among regions. The total population for 2005 was 27,219,264 from which 33% lives in Lima and Callao. The gap between Lima provinces and its neighbors is impressive. Lima province has 6,954,583 inhabitants while the following province regarding population is Arequipa with only 861,746 inhabitants. The capital, the big cities and, in general, the coastal regions, tend to centralize the main services, such as education, health and transportation. It easy to believe then, that Lima and surroundings are the more beneficiaries in all aspects.

Education is vital for regional growth but it cannot improve alone. Peruvians regions need policy makers that think in long term projects and that take into account not only the education aspect but also to be able to provide better public services, improve market competition, generate local employment, improve roads and connectivity, among others. It is not an easy job for such a complex country and understanding the spatial behavior of educational performance over time, among regions, and within different terrains might help planners and policy makers to take better decisions regarding regional development.

The results of this research suggest a number of areas for further study, including aspects such as Lima's influence, migration, urban - rural population differences, connectivity between cities and regions, poverty rates, among others, might bring interesting conclusions regarding Peruvian's education, and might also complement these research findings. Moreover, it would be interesting to measure spatial convergence for longer periods of time in order to find more insights regarding Peruvian regions.

To conclude, it is important to mention some limitations that were found during this research. Peru is mainly divided in three natural regions: coast, highlands and rainforest. This analysis considered these three regions to explore specific spatial patterns. It is possible that this simplification of Peru complex territory in only three natural regions might mask the existence of more localized educational growth trajectories. However, it is a first approach to a general comprehension of geographic patterns. It might be interesting to realize further studies regarding different classification of natural regions. Another aspect to mention is that the short period of time was a limitation for the analysis of spatial convergence and could have influenced the results. In general data availability was the main problem. There is not reliable socioeconomic data at province level for previous periods and also the 2005 census was the latest census available. Regarding the educational data, there is no data available for previous years at province level, and doing the analysis only at department level might cover important internal patterns.

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#### PERFORMANCES DU SYSTÈME ÉDUCATIF ET CONVERGENCE SPATIALE AU PÉROU

**Résumé** - Alors qu'une littérature importante existe autour de la convergence régionale des revenus, peu de travaux se sont intéressés aux disparités régionales des indicateurs sociaux. Ce article étudie la convergence des performances en matière d'éducation des régions péruviennes entre 1993 et 2005 en s'appuyant sur différents outils de statistique et d'économétrie spatiale.