Economic and social convergence in Colombia

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Abstract

GDP has usually been used as a proxy for human well-being. Nevertheless, other social aspects are to be considered, such as life expectancy, infant mortality, educational enrolment, or crime issues. With this paper we investigate not only economic convergence but also social convergence between regions in a developing country, Colombia in the 1975-2005 period. We consider several techniques in our analysis: sigma convergence, stochastic kernels estimations, and also several empirical models to find out the beta convergence parameter (cross section and panel estimates, with and without spatial dependence). The main results confirm that we can talk about convergence in Colombia in key social variables (household available income, literacy rate, life expectancy at birth and non-murder rate), while in others (GDP per capita and infant survival rate) it is not the case. We have also found that spatial autocorrelation reinforces convergence processes through deepening market and social factors, while isolation condemns regions to non convergence.

1. Introduction

GDP has usually been used as a proxy for human well-being. In this line, macroeconomic convergence has been studied in a wide number of studies at different levels: international (Barro and Sala-i-Martin, 1995; (Mankiw et al. 1992, Quah 1996), regional (Lopez-Bazo et al. 1999, Bivand and Brunstad 2005) and even local (Royuela and Artis 2006). Improving GDP will help to increase life expectancy, better access to basic education, etc. As Kenny (2005) argues “it appears that improving incomes will improve whatever your chosen [quality of life] measure happens to be” (Kenny, 2005, p 1).

Nevertheless, other aspects are important in the development agenda. The Millennium Development Goals stress eight international development goals to achieve by the year 2015. They include reducing extreme poverty, reducing child mortality rates, fighting disease epidemics such as AIDS, and developing a global partnership for development. Some previous literature (Easterly, 1999) stress the fact that many of the improvements in quality of life variables are many times not correlated with economic growth rates. Indeed, if some studies fail to find economic convergence at the international level (Ram, 1992, and others finds weighted income convergence but unweighted stagnation, mainly due to big changes in big countries such as China and India), others (Kenny, 2005, Crafts, 2000, Ram, 1992) find convergence in well being indicators.

The list of the analysed social indicators to test convergence is quite wide, such as life expectancy, infant mortality, educational enrolment, literacy, environmental degradation, etc. (Neumayer 2003, Goesling and Firebaugh 2004, Bourguignon and Morrisson 2002, Becker et al. 2005, Dorius 2008). Usually the results come to mixed conclusions with respect to convergence, depending on the time frame considered and the selection of countries and indicators. These papers are usually referred at the international context, and only few of them are devoted to the regional level (Giannias et al. 1999, Liargovas and Fotopoulos 2009, Marchante and Ortega 2006), and even some of them at the local level (Royuela and Artís, 2006).

In this paper we focus our attention on multidimensional convergence at the regional level in a single country, Colombia, for the 1975-2005 period. There is a wide literature analysing economic convergence in Colombia, but the list of works focused on convergence in social indicators in quite short, and with ambiguous results.

Additionally, many techniques have been used for finding convergence in living standards: β-convergence, σ-convergence, and kernel density estimates among others. Besides, the fact that the spatial distribution matters, particularly at the regional level, has driven special attention to spatial statistics and spatial econometrics. In this paper we try to find robust results on convergence using a wide list of available techniques in our analysis. In this line we also plan to answer a question posed in the literature: what is the relationship between convergence and spatial autocorrelation.

Our findings suggest convergence in four out of six considered variables (household available income, literacy rate, life expectancy at birth and non-murder rate). This evidence is strong enough to affirm that there is a convergence process at the regional level in Colombia. In any case it is also the case that we have found important levels of polarisation in variables such as GDP, and that in other variables the convergence process has been to dramatic changes in a small number of departments (such as crime in Antioquia). We have also found that spatial autocorrelation reinforces convergence processes through deepening market and social factors, while isolation (such as the one experienced by Chocó) condemns to non convergence.

The structure of this article is as follows. The next section overviews the recent research on regional income convergence. Section 3 displays the case of study and the employed databases. The empirical evidence is presented in section 4. Finally, section 5 concludes.

2. Convergence concepts

The contribution of (Baumol 1986) stimulated a large number of studies examining the convergence hypothesis, being initial followers Barro (1991) and Barro and Sala-i-Martin (1991 and 1992). These works can be derived from the neo-classical model of economic growth by Solow (1956), and use the so-called *β-convergence* approach, where the economic growth of a list of economies depends on their initial level. If a significant coefficient of this *convergence equation* is found, then poor countries grow more than rich countries, and consequently a convergence process exists.

Another indicator of convergence has to see with distribution of the variable in two different periods of time. The more basic measure is the called *σ-convergence* (Quah, 1993), usually measured either by the standard deviation or by the coefficient of variation in two different periods of time. Through σ-convergence it is possible to find if a variable is becoming increasingly similar across the studied economies.

As explained by Quah, the first kind of convergence is necessary but not sufficient to achieve the second one, and consequently β-convergence should be complemented by the analysis of σ-convergence (Sala-i-Martin, 1996). Magrini (2007) exposes that the distribution dynamics approach proposed by Quah (1993a and b, 1996 and 1997) contends explicitly the σ-convergence point of view, and expands it with the use of stochastic kernels to capture the time evolution of the behaviour of the entire cross-sectional distribution of a variable.

Finally, we remember that several works as Bernat (1996) and Rey and Montouri (1999) were among the first to include spatial effects in growth regressions, with special attention on the spatial distribution of the variable. When inspecting the dynamics of the distribution of a variable, they assume that both the magnitude and spatial distribution of a variable are important. More recently Rey and Janikas (2005) provides a review of methodological approaches with spatial effects of regional growth processes, proposing several research questions for such as "What is the relationship between convergence, inequality and spatial autocorrelation?" (Rey and Janikas, 2005, p. 168).

As our main aim is to analyse convergence and growth patterns in socio-economic variables, we assume that we have to inspect all possible techniques and sources of convergence. Although many works have surveyed these techniques (see the excellent proposal of Magrini, 2007), next we display a brief summary of these alternatives.

2.1. The regression approach: β-convergence approach

The neoclassical growth theory (Solow 1956, Swan, 1956, Cass, 1965 and Koopmans 1965), inspired works on economic convergence such as (Baumol 1986) and several hundreds more. The model drives to a saddel-patrh stability, namely the steady state, where the final driver of income and consumption per capita growth is the rate of technological progress of the economy.

If a Cobb-Douglas production function is assumed, a testable expression for the convergence debate is derived. In particular, Barro and Sala-i-Martin (1991) suggest the following growth equation:

$$\left(\frac{1}{T}\right)\log\left(\frac{y_t}{y_0}\right) = c - \frac{\left(1-e^{-\beta t}\right)}{t}\log y_0 + u_t$$

Where the average growth rate of per capita income depends negatively on its initial level, conditioned on the exogenous growth rate of technology, on the steady state value per effective worker and on the initial level of technology. Parameter *c* summarises the unobserved parameters, such as the steady state values. The speed of convergence to the steady state, β, is the rate at which the representative economy approaches its steady state growth path, and consequently this procedure of convergence analysis is known as β-convergence.

There has been a huge literature on convergence, but in empirical terms there are three estimation alternatives: cross sectional, panel data and time series analysis.

The more basic analysis is the use of OLS estimation on a ***cross section*** of data. The basic assumption is that the considered economies of the data base belong to a homogeneous system. Of course, it can be the case that this hypothesis does not hold. The solution for this is the use of an additional set of explanatory variables (*X*) that represent proxies for different steady states in the cross-section regression, capturing different technological levels, saving rates, etc. In this case the growth equation becomes:

$$\left(\frac{1}{T}\right)\log\left(\frac{y_t}{y_0}\right) = c - \frac{\left(1-e^{-\beta t}\right)}{t}\log y_0 + \delta X + u_t$$

As it is not easy to find these explanatory variables proxying the steady state of every economy, a popular empirical alternative is the use of panel data methods. Through the use of fixed effects one can estimate the steady state of every economy. A simple model can be:

$$\log\left(\frac{y_t}{y_{t-1}}\right) = c_0 + c_1(t) - b\log y_{t-1} + u_t$$

Where c_0 is an unobservable economy-specific effect, and c_1 is a time specific fixed effect affecting all economies. Nevertheless, panel data estimations have also a list of drawbacks: if most of the variation in the key variables is cross-sectional rather than within regions, fixed effect approaches could produce misleading results (Barro, 2000). That is, if the underlying causal factors in the growth process are persistent, the long-run cross-sectional effects will be subsumed into the region fixed effects, which mean the explanatory variable coefficients would be much less informative.

Consequently, OLS cross-sectional models capture how persistent cross-sectional differences in inequality affect long-run growth rates, which is more relevant to understanding growth disparities, while panel techniques capture how time-series changes in inequality within a region affect changes in its growth rate over a short period. Therefore, the two methods are complementary and may reflect different responses.

The regression approach can be also operationalised using time series methods, in which the definition of convergence relies on the notions of unit roots and cointegration. Bernard and Durlauf (1995 and 1996) argue that convergence is defined as the equality across economies of long-term forecasts of per capita income taken at a given fixed date. The main idea is that convergence will exist if the difference between per capita income series of two economies is a mean zero stationary process. This analysis has been rather uncommon in regional analysis.

While the cross section and panel data approaches usually confirm economic convergence around a speed of 2% (depending on the employed technique), the time series way of estimation usually reject convergence, probably due to it uses a stricter notion of convergence. Besides, regressions such as the cross-section approach, is unable to test the neoclassical model implying convergence against alternative and conflicting models. Finally, Friedman (1992) and Quah (1993b) argue that it is possible to observe a negative parameter in the regression approach together in a diverging distribution. This aspect is subsequently analysed under the label of σ-convergence.

2.2. Analysis of the evolution of dispersion: σ-convergence approach and the analysis of inequality

σ-convergence corresponds to the decline of the cross-section dispersion in the variable under analysis. Different measures have been employed to analyse dispersion: standard deviation (Carlino and Mills, 1996) and the coefficient of variation (Bernard and Jones 1996). In order to find σ-convergence there is a necessary but not sufficient condition: to find β-convergence. That's why Sala-i-Martin (1996) suggests complementing the convergence analysis using both procedures.

In any case, the analysis of the cross-section dispersion is again non conclusive. As shown by Quah (1996a), a constant standard deviation can be consistent with very different dynamics. Consequently, it is not fully clear that a decreasing dispersion measurement is the definitive prove of the existence of convergence.

Together with the analysis of the variance, the literature has used inequality statistics in order to see if there is a convergence process. Some examples are the Gini index, the Mehran index, the Piesch index, the Kakwani index, and the Theil index, being the latter one of the more popular ones. This index is based in the notion of entropy, and is computed as follows:

$$Theil\ \ Index = \sum_{i=1}^{N} \frac{y_i}{Y} \log\left(\frac{y_i}{Y} \Big/ \frac{n_i}{N} \right)$$

where: y_i = Total amount of the variable that belongs to individual i.
$Y = \Sigma\, y_i$ = Sum of the whole amount of the variable for all individuals.
n_i = size of individual i
N = total amount of individuals

When there is total equality, every individual has the same amount of the variable. Consequently, $\log\left({}^{y_i}\!/_{Y} \Big/ {}^{1}\!/_{N} \right)$ would be equal to zero, and the total sum would be equal to zero as well. As the inequality rises, the index grows higher and higher, reaching its maximum value at –log(n_i/N). The Theil index is particularly appropriate when looking at inequality measurements because it has the property of mathematical fractals: it can be decomposed additively between groups, with the total Theil index being equal to sum of the Theil index between groups and the weighted average of the Theil indices within each group. This property greatly simplifies many calculations (as in Royuela and Vargas, 2009).

2.3. The distribution dynamics approach: computing stochastic kernels

This approach analysis the evolution of the cross sectional distribution of a variable by means of computing stochastic kernels to describe the change in the shape of the distribution and also the dynamics of changes within the distribution. As is clearly exposed is Magrini (2007), being $f_{X(t)}$ the probability density function associated to a variable X at time t, then:

$$f_{X(t+s)} = M_{t,s}\, f_{X(t)}$$

the stochastic kernel, $M_{t,s}$, allows for analysing the dynamics of the entire distribution of a variable between two different periods of time, providing information not only on the change in the external shape of the distribution but also, and more importantly, on the movement of the economies from one part of the distribution to another.

Analysing the shape of a three-dimensional plot of the stochastic kernel or the corresponding contour plot is the way we can inspect the existence of convergence. The main diagonal in these graphs represents persistence, as the elements in the crosssectional distribution remain where they started. We will find perfect convergence if most of the graph is around the average of the time $t+s$ axis and parallel to the time t axis. Finally, the intra distribution analysis can be made searching for the formation of separate modes, a signal of polarization (stratification) in the distribution.

2.4. The relationship between convergence and the spatial autocorrelation

"The problem with aspatial empirical analyses that have ignored the influence of spatial location on the process of growth is that they may have produced biased results, and hence misleading conclusions" (Fingleton and Lopez-Bazo 2006, p. 178). In other words, the basic assumption of independence between observations was usually violated in the analysis of convergence. (Rey and Montouri 1999) checked for σ and β convergence under spatial heterogeneity and spatial dependence, and found that, because of these spatial behaviours, convergence processes may display complicated transitional dynamics, which have to be taken into account.

Two aspects are to be considered here. Firstly, spatial econometrics estimation tools have to be considered, both in the cross-section estimates and in the panel data approach. (Abreu et al., 2005 surveys the existing evidence of the empirical evidence).

Basic references of these methods are Anselin, 1988; Anselin, 1995; Anselin and Bera, 1998; Anselin and Florax, 1995; Anselin and Rey, 1991; Anselin et al., 1996; Getis and Ord, 1992). In the cross-section approach, several estimation alternatives arise, such as the spatial error model, the spatial lag model, and the spatial cross–regressive model, and even autoregressive and spatial error model. In our paper we will consider only two basic models: the spatial error model and the spatial lag model. Thus, we will not consider the autoregressive and spatial error model. Even though it may appear convenient to combine both the spatial lag and the spatial error dependence, it is difficult to disentangle which one is more relevant, and also it is also more difficult to interpret the spatial coefficients:

spatial error model	$\ln\left(\frac{Y_{t+k}}{Y_t}\right) = \alpha + \beta \ln(Y_t) + \varepsilon_t$, where $\varepsilon_t = \lambda W \varepsilon_t + u_t$
spatial lag model	$\ln\left(\frac{Y_{t+k}}{Y_t}\right) = \alpha + \beta \ln(Y_t) + \rho W \ln\left(\frac{Y_{t+k}}{Y_t}\right) + \varepsilon_t$

The panel data approach with spatial effects is more recently developed in Elhorst (2001 and 2003), and recent applications are Arbia and Piras (2005) Arbia, Basile and Piras (2005) Arbia, Elhorst and Piras (2005) and Elhorst (2005).

And secondly, the distribution dynamics of the spatial dimension of the variables also matter. In this line, the use of global and local spatial measurements deserves a particular attention. Global statistics of spatial patterns of a variable *x*. We consider here three alternatives: Moran's I, Geary's C, and Getis and Ord's G.

Moran's I	$I = \frac{N}{S_0} \frac{\sum_{ij}^{N} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i}^{N}(x_i - \overline{x})^2}, i \neq j$
Geary's C	$C = \frac{N-1}{2S_0} \frac{\sum_{ij}^{N} w_{ij}(x_i - x_j)}{\sum_{i}^{N}(x_i - \overline{x})^2}, i \neq j$
Getis and Ord's G	$G = \frac{\sum_{i}^{N}\sum_{j}^{N} w_{ij}(d) x_i x_j}{\sum_{i}^{N}\sum_{j}^{N} x_i x_j}, i \neq j$

Where: N: sample size
w_{ij}: spatial weight of the W contact matrix
$S_0 = \sum_{i}^{N}\sum_{j}^{N} w_{ij}$

Local statistics of spatial patterns: despite there are several local statistics (such as Moran's Ii, Geary's Ci, Getis and Ord's G1i, Getis and Ord's G2i), here we will only consider the local Moran's I statistic for a region *i*:

$$I_i = \frac{z_i}{\sum_i z_i^2 / N} \sum_{j \in J_i} w_{ij} z_i$$

Where: z_i : standardized value of x_i
J_i: amount of regions neighbouring region *i*

3. The case of study: Continental Colombian regions

Colombia is a medium-income nation with some 44 million inhabitants and a land area of about 1.200.000 km^2. It is a country located in northwestern South America that shares borders with several countries and it has access by the north to the Caribbean Sea and by the west to the Pacific Ocean (see figure 1). Colombia is conformed by thirty-two departments and a Capital District that is the country's capital, Bogotá[1]. Departments are country subdivisions similar to US states and are granted a certain degree of autonomy (see figure 1 of the annexes).

To late twentieth century Colombia had an economic growth low but stable which was accompanied by high levels of poverty, inequality and violence. The annual growth rate of per capita GDP between 1990 and 2007 was around of mean of the region but the percentage of people living below the poverty line was 28 percent and the Gini coefficient was 58 percent, which was the highest of the region. The homicides rate including the deaths by the internal war was 42 per 100,000 people in 2007 and the conflict and insecurity induced an internally displaced of more than 3 million persons in 2008 (see table 1).

Table 1. Economics and social indicators in Colombia and others country

	Colombia	Brazil	Chile	Argentina	Mexico	United States
Per capita GDP 2007 (US$)	4,724	6,855	9,878	6,644	9,715	45,592
Annual Growth rate of per capita GDP 1990-2007 (at constant prices)	1.2%	1.2%	3.7%	1.5%	1.6%	2.0%
Gini coefficient 2007	58.5	55.0	52.0	50.0	48.1	40.8
Population below income poverty line (US$2 a day) 2007	27.9%	12.7%	2.4%	11.3%	4.8%	-
Adult Illiteracy rate (% aged 15 and above) 1999-2007	7.3%	10.0%	3.5%	2.4%	7.2%	-
Life expectancy at birth 2007	72.7	72.2	96.5	75.2	92.8	79.1
Conflict and insecurity induced movement internal 2008 (Total in thousands)	2,650–4,360	-	-	-	6	-

Source: UNDP, 2009.

Colombia is a country of regions, each region has different characteristics geographic, economics and socio-cultural. The first one has influenced the last two. The majority of the urban centres are located in the highlands of the Andes Mountains or cordilleras. There are three mainly cities located in the cordilleras: Bogotá, Medellín (capital of Antioquia) and Cali (capital of Valle). Between these three cities are concentrated the

[1] Colombia is politically divided into departments, districts and municipalities. Before the Constitution of 1991, there were also intendencias and comisarias. The intendencias and comisarias are the "New Departments", and the departments that existed before 1991 are known as the old departments. The "New Departments" included: Arauca (Ara), Casanare (Cas), Putumayo (Put), the islands of San Andrés and Providencia, Amazonas, Guainía, Guaviare, Vichada and Vaupés; and the old departments included: Antioquia (Ant), Atlántico (Atl), Bogotá (Bog), Bolívar (Bol), Boyacá (Boy), Caldas (Cal), Caquetá (Caq), Cauca (Cau), Cesar (Ces), Córdoba (Cór), Cundinamarca (Cun), Chocó (Cho), Huila (Hui), La Guajira (La Gua), Magdalena (Mag), Meta (Met), Nariño (Nar), Norte de Santander (Nors), Quindío (Qui), Risaralda (Ris), Santander (San), Sucre (Suc), Tolima (Tol) and Valle (Val).

41% of total population and about of 80% of economic activity (Galvis, 2001). In contrast, regions located in the periphery or in geographical areas of difficult access are the regions poorest, as Chocó, the Amazonía, Nariño and La Guajira. Others poor regions are located close to maritime borders, such as Bolivar, Magdalena, Sucre and Cauca.

On the other hand, the discovery of important mineral resources in the 80's and 90's increasing the importance of some departments in the national production, this is the case of the departments of Arauca and Casanare which have the largest oil fields of country (Caño Limón and Cusiana-Cupiagua, respectively), and La Guajira which has the Cerrejon mines which are largest open coal mine in Latin America and the salt mines in Manaure which are the salt mines to opened sky largest of world.

The inequality regional and the locating geographic of poverty in the coastal departments are one of the main characteristic in Colombia. Besides, economic and social disparities have deepened in the last 15 years (Meisel, 2007). Consequently, the study of these disparities and the processes of convergence are quite important. In this sense this work attempts to advance in the analysis of regional economic and social convergence in Colombia.

Figure 1. Map location of Colombia

3.2. Literature review in Colombia

The results found on economic convergence in Colombia are ambiguous. These results have depended of analysis period and the technique applied. The works by Cárdenas (1993 and 1995) and Cárdenas *et al*. (1993) are the firsts study of convergence in Colombia, concretely, the convergence departmental of GDP in the period 1950-1990. By applying usual analysis β-convergence by Barro and Sala-i-Martin (1991) and with information provided by DANE, the authors show that Colombia is a successful case of convergence with a convergence rate of GDP of 4.2%. Cárdenas' papers were criticized by many authors. One of the most critical was Meisel (1993) that with similar database of DANE and period of GDP used by Cárdenas found that even though in the period 1950-1960 there was convergence, it was not the case for the period 1960-1990. The results by Meisel (1993) suggest that findings by Cárdenas were biased by misinterpreted and errors in the database.

Birchenall and Murcia (1997) performed the first empirical study of economic convergence where is use the stochastic kernel estimation in the per capita income at departmental level. The results for the period 1960-1994 with information provided by DANE suggest that there is not economic convergence in Colombia and the existence of processes of mobilization of poor regions were due to the income of the mining industry (oil fields) in the last years. One step forward in the analysis of economic convergence is the work by Rocha and Vivas (1998), who applied an alternative methodology (Exchangeability Priors). They used a database at the departmental (regional) level provided by DANE and Banking Superintendence of Colombia, measuring alternatively the GDP. They related the processes of regional convergence with the heterogeneity of regional conditions (socio-political instability, credit restrictions and the low level of education). The results show that in Colombia was a process of regional polarization in the period 1980-1994. Finally, the authors stress that there are different regional steady states and the hypothesis of economic convergence is not fulfilled.

Bonet and Meisel (1999) also use the GDP measure from Banking Superintendence of Colombia, and nalyze the regional convergence by applying usual absolute β-convergence and σ-convergence, together with others measures of dispersion and inequality, as the weighted coefficient of variation, the Theil index, the Gamma and Alfa indicators and the Herfindahl-Hirschman concentration index. In this work they analyzed two periods, 1926-1960 and 1960-1995. The results found show that in the first period there was economic convergence, while it was not found in the second period. On the contrary: there was a process of polarization in departmental per capita income levels.

Others papers that use an alternative database on GDP at the municipal level are the works by Sánchez and Núñez (2000) and Galvis and Meisel (2000). In these papers it is estimated the absolute and conditional β-convergence at the municipal level, using as controls geographic, infrastructure, human capital and living standard variables. The general conclusion is that there was conditional convergence between the 70s and 90s, while that the evidence of absolute convergence is not very strong.

Several other papers have made empirical researches of convergence for the 80s and 90s. Using data from DANE the works by Acevedo (2003), Barón and Meisel (2003), and Barón (2003), finds convergence during the eighties but not during the nineties. The last one, by Barón (2003), by means of spatial dependence techniques (Moran's I and

Geary's C) find that the departmental per capita GDP does not show any pattern, so the wealth or poverty in Colombia is randomly distributed geography.

In the 2004 and 2006 the Centro de Estudios Ganaderos (CEGA) produced new estimates of GDP and income at the departmental level in Colombia for the period 1975-2000. The first authors who used this information for analyzing regional convergence were Gómez (2006) and Bonet and Meisel (2006 and 2008). The first one analyzed absolute and conditional convergence and univariate kernel density estimators, and used the monetary supply and the regional export rate as controls in conditional convergence analysis. He did not find strong evidence of regional absolute convergence, but he did for conditional convergence.

Bonet and Meisel (2006 and 2008), analyzed the convergence in gross per capita income and departmental per capita household income using measures of dispersion and inequality, together with kernel density estimators. The results show that there is not convergence in the per capita income, but that there is a decrease in sigma convergence in household available income. In their conclusions they stressed the process of polarization in the income between Bogotá and the rest of the nation.

Similarly, the works by Branisa and Cardozo (2009a) and Franco and Raymond (2009) analyze the economic convergence in Colombia with CEGA data. The first one analyzed the convergence of the GDP and income available to household estimating the β-convergence, σ-convergence and stochastic kernels. According to their results there exists evidence of slow convergence in household available income but there is not in GDP. The convergence observed in income can be explained by recent redistributive policies, particularly higher public spending in social sectors and infrastructure. The public spending affected the relative position of some departments, although not the distribution as a whole. The second one, by Franco and Raymond (2009), study the existence of clubs of convergence of GDP between the regions in Colombia. Their results suggest that there are four clubs of convergence, but that there is not convergence between these clubs. In fact there are big differences between regions poor and rich and there is a persistence of the disparities since the 1970's. Again, the polarization stressed by Bonet and Meisel arises.

All these works focus only on economic convergence (GDP and income). Few studies consider the convergence in non economic social indicators probably due to the lack of available data. There are only five works dealing with convergence in social indicators: Meisel and Vega (2007), Ardila (2004), Aguirre (2005), Ventura (2006) and Branisa and Cardozo (2009b). The first one studied convergence in the height of Colombians in the last century using absolute β-convergence and σ-convergence. With a wide database the authors show that the average height of Colombians increase throughout the 20th century in every decade and there is convergence in this indicator also between men and women, an proxy of social development. The second one, Ardila (2004), using DANE data for period 1985-1996 and applying stochastic kernel estimation (both conditional and unconditional) looked at the percentage of people with unsatisfied basic needs and the index of living conditions. They found geographical persistence in the social indicators and also the fact that policy variables such as the public expenditure affect the relative position of some departments, although not the dynamic of the distribution as a whole.

Aguirre (2005), Ventura (2006) and Branisa and Cardoso (2009b) used health and education indicators for analyze the social convergence between 1973 and 2005, with DANE data. The two first works, by means of the estimation of β-convergence and univariate kernels, found that while the infant mortality rate converges, the education indicators (the illiteracy rate and the basic education variable) did not converge. Similarly, Aguirre (2005) also found convergence in life expectancy at birth. Contrary to these results Branisa and Cardoso (2009b) found convergence in education indicators but not in the health ones. The main difference between both works is the exclusion of outliers in the analysis developed by in Branisa and Cardoso (2009b). Besides, in Branisa and Cardozo all variables are expressed as a ratio to the national value and they use literacy rates while that Aguirre uses illiteracy rates.

Overall, we have seen that there are conflicting results in the literature, both in economic and social variables, and consequently some additional work will be helpful to analyse convergence from a multidimensional point of view.

3.3. Data base description

When analyzing social indicators a key issue is the selection of the considered variables under study. Following Sen, a 'good life' is composed of four key elements: material well-being, health and survival, education and personal development and social inclusion / participation. Our selection include two economic variables (real GDP per capita and real household available income), two related with health (life expectancy at birth and infant survival rates), one concerning education (literacy rates), and finally one related with a key aspect of social life in Colombia: crime (murder rate). Next we describe the sources and implementation issues of every variable.

In Colombia there are two different data sources of departmental information of GDP: the National Department of Statistics (DANE) and the Centro de Estudios Ganaderos (CEGA). Both series produced for these two institutions have serious limitations. DANE only provides homogeneous data of GDP between 1990 to 2005 at disaggregate level for all the 33 departments (including Bogotá), while the CEGA even though provides data of GDP and income since 1975, only includes 23 departments, the capital district of Bogotá, and the nine "New Departments" grouped into one observation (a total of 25 departments). Besides, CEGA databases finishes in 2000.

Having into account that departmental results coincide between CEGA and DANE from 1990 onwards because both use the same system of accounts (System of National Accounts of 1993, CEGA, 2006), we try to build a series consistent of GDP that account the heterogeneity of departments. Two procedures have been followed. The first procedure consisted in use as baseline the data of CEGA and uses the series of GDP computed by DANE since 2000 to 2005 for calculating department growth rates. Subsequently we applied these growth rates to the CEGA database for update the series up to 2005. The second procedure consisted in assign values of GDP to each of the nine "New Departments". We used the data computed by DANE of GDP for the period 1990 to 2005 to find the relative position of the new departments, and subsequently we filled the DANE data between 1975 and 1989 maintaining the relative positions between these new departments in 1990 CEGA data. This way we consider a data set ranging from 1975 to 2005 (31 years) for 26 departments, Bogotá and the Amazonía Group (GA) (thus, a total of 28 spatial units)[2].

For income variable we only used the data of CEGA because it is not supplied by DANE, and consequently it is not possible to enlarge the database for "New Departments". Hence, we prefer excluded to the nine "New Departments" to avoid bias by omission of regional heterogeneity. Consequently, for the income variable we have data of 23 departments and Bogotá for the period 1975 through 2000: 24 units during 26 years.

In summary, we have two key variables relevant for economic convergence analysis, gross departmental product and gross departmental household available income. The first variable reflects production by residents in each department, while the second reflects the primary income received by those residents. The latter is the result of households' income after subtracting taxes on property and rental income and net payments to the social security, and adding other net current transfers. As is mentioned in others studies (Bonet and Meisel, 2008) the income variable is a more accurate measure of a population's welfare than merely using GDP. And in our view, in order to analyze well being, it is more useful using household available income, as it considers the net amount of economic flows finally available for people.

Concerning the other social indicators we use the literacy rate, the life expectancy at birth and the infant survival rate and non-murder rate. Our main source of data at department level is DANE. The first variable was taken of Census facts by DANE in the years 1973, 1985, 1993 and 2005. Both health variables, were considered for the periods 1985-1990, 1990-1995, 1995-2000 and 2000-2005; and finally the crime variable is computed yearly for the period 1990-2005.

It is noted that the literacy rate, infant survival rate and non-murder rate are positive variables or complement of original variable. Although the results of convergence analysis may change depend upon whether one uses a variable or its complement (Micklewright and Stewart, 1999), we prefer the positive variables and follow the arguments of Kenny (2005). He argues that the measurements of convergence toward zero are more sensible to favors very small changes close to zero than very large changes further from zero. Besides, he claims that convergence towards a positive value is the standard in the literature. The same approach is followed in Braniza and Cardozo (2009).

The literacy rate is defined as the complement of illiteracy rate, so that measure the percentage of literate population greater than age 5 and it is show the level of education of each region. Life expectancy at birth measures the number of years of life remaining at a given age. The infant survival rate is calculated as 1000 menus the infant mortality rate and it measure the number of infants that survive their first year of life over 1000 births. Lastly, the non-murder rate is computed as the complementary measure of the murder rate: violent deaths per 10,000 inhabitants. Consequently it is computed as the amount of people who is not murdered per 10,000 inhabitants. This variable shows the regional safety level, and we use is a proxy of social inclusion.

[2] We excluded the islands of San Andrés and Providence because these are not in continental Colombian regions. The Amazonía group included to Amazonas, Guainía, Guaviare, Vichada and Vaupés.

4. Empirical evidence. Convergence analysis for economic and social variables

4.1. Analysing economic variables: real GDP per capita and real departmental per capita household income

As has been highlighted above, there is a wide list of statistical methods to test the existence of convergence. Next we analyse convergence in economic variables: product and income. The product variable is real GDP per capita, while the income variable is real departmental per capita household income, computed by CEGA.

We firstly look at the **real GDP per capita**. The real production in Colombia during the 31 considered years has grown at an average annual rate of 1.7%. There has been important expansion periods (1986-1987, 1994-1996) and also experienced recessions (end of nineties). This growth has been unequally distributed between regions, what has forced significant changes in the dispersion of the variable. While annex 1 shows the table with all key statistics of real GDP per capita, in picture 1 we see the evolution of the a σ-convergence measurement, the coefficient of variation (CV), and a spatial autocorrelation statistic, the standardized value of the Moran's I.

In the period 1975-2005 we see very different paths. Firstly, since 1975 to 1986 there is a quite stable situation, with low levels of dispersion. In 1986 starts a huge increase in the CV, with maximum values in 1997. After this year we see an important decrease in CV, although in 2000 it is still above its initial level in 1975. Consequently, if we focus only on the sigma convergence path, we cannot talk about sigma convergence (as it is generally found in the existing literature).

And, how about the changes in shape of the distribution? And the dynamics of changes within the distribution? The stochastic kernels help us to answer these questions. Figures 3 to 5 display the Univariate kernel density estimate of relative per capita GDP in the years 1975 and 2005, and the three-dimensional plot of the stochastic kernel and its corresponding contour plot. We see in the kernels shapes (figure 3) that at the beginning of the considered period, there lower part of the distribution is significantly away of the rest. Figures 4 and 5 show that this peak in the 1975 distribution belongs to the region of Putumayo, and that this region is displaying a particularly strong convergence process, as in 2005, although it is still a poor department, it is much closer to average values of the distribution. Bogotá is experiencing a convergence picture: in 2005 it is not the richer department in Colombia, due to the strong growth in Casanare and Grupo Amazonía. This group of regions was growing at average year rates over 15%, a positive cluster close to Orinoco River and with oil fields. It is mainly due to the start of works in Caño Limón, in Casanare, the main oil field in Colombia, which started to work in 1986.

The rest of the distribution is quite away of any convergence path. On the contrary, we see a quite persistent picture, with most of the regions close to the main diagonal of the kernel density estimate, and even a group of regions forming a local mode over average of the distribution. Consequently we see again a non convergence dynamics in Colombian regions, with few exceptions that clearly does not allow generalizing the convergence process.

Spatial autocorrelation follows a parallel path to the CV: small values at the beginning, a huge increase after 1986 (with the start of the works in the oil fields Orinoco River) until 2000, and then an important decrease. Thus, real GDP per capita dispersion and spatial dependence display a strongly positive covariance throughout time (the correlation equals 0.93). This finding has been highlighted previously in works as Rey and Montouri (1999), while Rey and Janikas (2005) inspect the relationship between inequality and spatial autocorrelation: “what is the relationship between convergence, inequality and spatial autocorrelation?” (Rey and Janikas, 2005, p 168). In our case the Theil index display the same behaviour as the CV (see annex 1), and consequently we focus our analysis in the typical measurement of sigma σ-convergence. What we see is a positive relationship between dispersion and spatial dependence. This evidence is basically the same that the one found in Rey and Montouri (1999) and Rey and Janikas (2005) for the USA case. The consequence of this result is that low levels of dispersion would imply low spatial dependence, and subsequently convergence would drive to low levels of spatial dependence. This aspect will be considered again in the rest of the considered variables, what will help to answer, at least partially, to the research question posed by Rey and Janikas.

Figures 6 and 7 display the cloropleth and LISA maps in order to find the spatial distribution dynamics in Colombia. There are interesting changes in the distribution of the variable. Significant clusters with negative values at the beginning of the period (the ones formed by Chocó, Nariño and Putumayo) are non significant after 1986. Bogotá is displaying a significant positive cluster only at the beginning of the period. On the contrary, a positive cluster is developed after 1986, formed by Amazonía, Arauca and Casanare, the departments with oil fields. Consequently, we see a much higher spatial heterogeneity at the beginning of the period than at the end. Besides, Casanare is the typical example of a catching up region: while its GDP per capita in 1975 was 38% below the national average (24th position out of 28 regions), in 2000 it was 250% above the national average, and 150% in 2005 (2nd position). Annex 2 displays a list of tables detailing the significant local spatial autocorrelation measurements of every Department for every considered year. There we see clearly the break that is experienced in 1986, with the creation of the above mentioned positive cluster and the disappearance of the negative cluster.

Figure 1. Real GDP per capita statistics

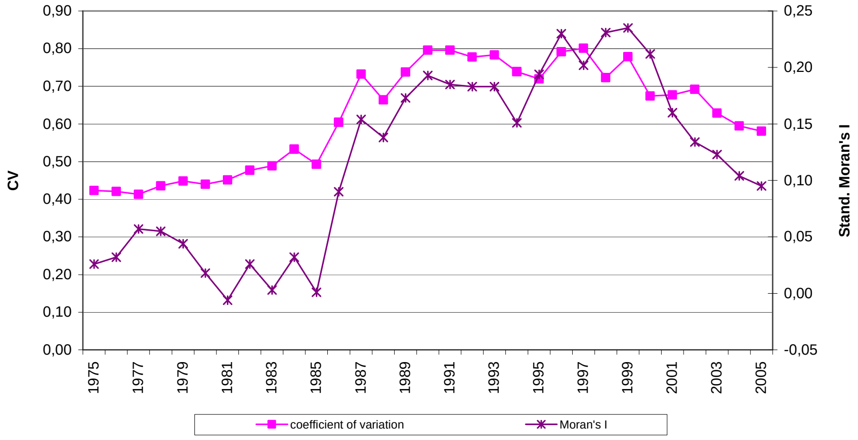
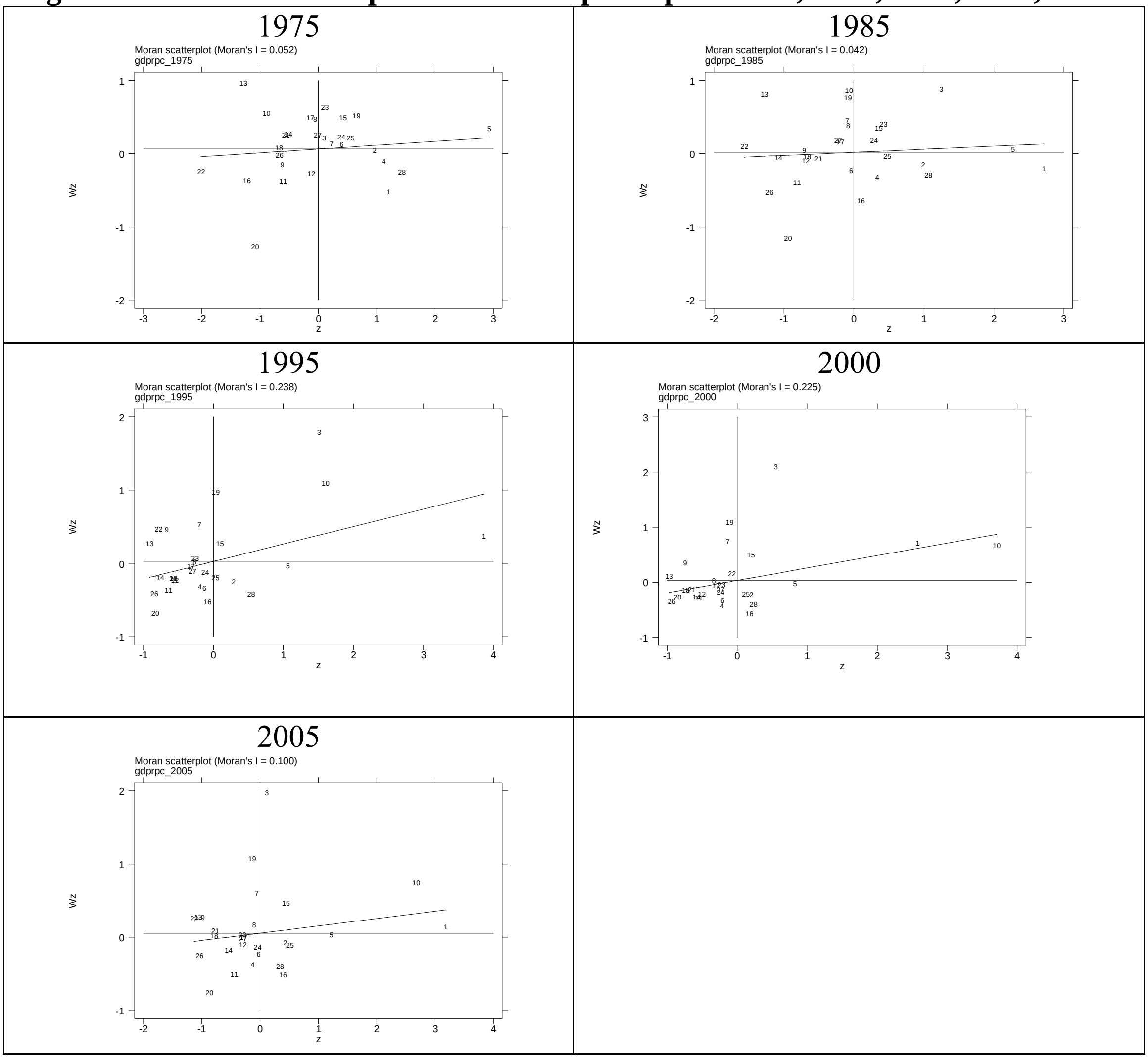


Figure 2. Moran's Scatterplot. Real GDP per capita. 1975, 1985, 1995, 2000, 2005



Finally we refer to the beta convergence estimates. Table 1 shows the main results of the developed estimations, and displays both the long run cross section analysis and the panel estimations.

In the long run estimates, despite the low adjustment (adj R^2 =15%) we find significant negative parameters, and also a non significant influence of spatial dependence. Both AIC statistics and LM tests drive to the same conclusion: OLS estimates are preferred to the ones using spatial autocorrelation techniques. The parameter in the OLS estimation implies the existence of β convergence, at a speed over the 2%, which is contrary to the evolution of dispersion over the 31 years under study that we saw above.

Panel data estimates use annual growth rates as dependent variable. As there are conflicting results between the Hausman test and the Breusch and Pagan test, being conservative, we prefer the fixed effects estimation procedure. Although not reported, the within dispersion exceeds by large the between dispersion, which is mainly controlled using time series fixed effects, and consequently most of the variation of the endogenous variable relates to the time series dimension. Consequently time series fixed effects are important, and consequently are controlled.

Consequently, there are conflicting results in the overall evidence: our analysis of sigma convergence and the kernel estimates was not strongly supportive of convergence for the whole period. Alternatively, the beta convergence analysis, both in the long run and in the panel data estimates, supports the idea of convergence. Previous literature had already pointed to the fact that once mining departments are excluded, convergence disappears (Birchenall and Murcia, 1997). This evidence is supported here with kernel analysis. Nevertheless, if the correlation coefficient between GDP growth and the log of initial GDP is -0.43, when excluding Amazonía, Arauca, Casanare, La Guajira, and Putumayo, the mining departments (more than 10% of their GDP), the coefficient drops to 0.01. Consequently, it cannot be argued that any convergence process is due to the neoclassical growth theory, based in factors mobility and decreasing marginal returns, but on changes in the steady state conditions of a list of departments. Precisely because of these aspects is why we find simultaneously a significant beta convergence parameter together with a non decreasing path in the sigma convergence measures and an increase in the spatial autocorrelation.

Table 1. Beta convergence estimates. Real GDP per capita.

	OLS	**Spatial Lag**	**Spatial Error**	**Panel estimation (CS, TS, Fixed Effects)**	**Panel estimation (CS, Random Effects + TS Fixed Effects)**
Log GDP t-1	-0.041*	-0.042*	-0.041*	-0.091***	-0.018***
	0.017	*0.017*	*0.017*	*0.012*	*0.006*
Implicit yearly speed of convergence	2.67%	2.72%	2.67%	8.7%	1.8%
rho		0.092			
		0.262			
lambda			0.145		
			0.273		
LM test		0.116	0.26		
		0.734	*0.61*		
Robust LM test		0.179	0.323		
		0.672	*0.57*		
Cross section				Fixed Effects ***	Random Effects
Time Series				Fixed Effects ***	Fixed Effects ***
Breusch-Pagan test				11.07	
p-value				*0.001*	
Hausman test				45.3	
p-value				*0.000*	
AIC	99.49	103.22	103.37	-1913.6	
Adj- R-squared	0.146	0.183	0.178	0.140	0.135
N	28	28	28	840	840

* p<0.05, ** p<0.01, *** p<0.001. Standard errors are displayed in italics.

The second economic variable we face is **real departmental per capita household income**. One of the limitations in the debate the regional convergence in Colombia is that there did not exist, until recently, a direct measurement of departmental per capita household income, until in 2006 CEGA estimated this series. The advantage of income with respect to GDP is that the latter is a measure of the production generated by individuals within a department while the former is an estimate of the received income by individuals residing in this region. In others words, the data on GDP do not reflect well the level of prosperity of the regions (Bonet and Meisel, 2006), while reproduces the portion of the generated production that is captured by individuals, and then it is not affected by the sectoral composition of production. A typical example of the differences between GDP and income is the production of energy, a sector with high apparent productivity (GDP per worker) but its correspondence in personal income is usually quite low. As we have seen above, sectoral composition is a huge aspect to be considered in Colombian departments.

Nevertheless we face a trade off in the use of personal income in Colombia. The available series, computed by CEGA, is available from 1975 to 2000, and is not available for a list of departments (Arauca, Casanare, Putumayo and Amazonía, which are the ones with oil fields). Consequently, the analysis will be at the same time partial but away from the influence of mining activities.

We firstly look at the evolution of dispersion. Inversely to what happened with real GDP, there is a decrease in the coefficient of variation of income (from 0.46 in 1975 to 0.33 in 2000), especially after 1987. Figures 11 to 13 show the kernel estimates and contour plot of the distribution of real departmental per capita household income at the beginning and at the end of the 1975-2000 period. What we see is that any convergence process is observed at the tails of the distribution, both the highest and the lowest. The poorest in 1975 (Chocó, 39% of the national average) was less poor in 2000 (51%), and the richest in 1975 (Bogotá, 275% oif the national average) was less rich in 2000 (206%). Additionally, there is an important increase of the density close to the average of the distribution.

Inversely to what happened with real GDP, now we see that spatial autocorrelation is non significant and the standardized value of the Moran's I statistic experiences a very small increase (see the Moran's scatterplots in figure 10). Consequently now we do not find the positive relationship between dispersion and spatial autocorrelation. On the contrary, we find a negative correlation between both statistics of -0.33. Part of this result is due to the dataset we are using. In the previous analysis if real GDP per capita we found a positive cluster formed by Arauca, Casanare and Amazonía, three out of the four Departments we are not considering now. Consequently we perform the analysis of real GDP per capita in the narrow data set of 24 departments. The results of the CV and Moran's I is displayed in figure 9. The correlation between the CV and the Moran's I in real GDP per capita of the 24 departments is equal to -0.44 between 1975 and 2005 (and equal to -0.31 between 1975 and 2000). Our conclusion is that the positive relationship in Colombia between CV and Moran's I in economic variables is only due to the birth in 1986 of a positive cluster of small departments related with oil fields. What the rest of the country experiences is an absolute absence of spatial autocorrelation, as is displayed in the four Moran's scatterplots of figure 10.

Finally, figure 15 shows the local spatial autocorrelation measures. There we see permanently a department with low levels of departmental per capita household income and surrounded of richer departments. We talk about Chocó, the 'low-high' department at the west side of the country. This region is at the Pacific coast and has a natural barrier of deep forest that separates it from the rest of the country. The transportation to the main city (Quibdó) of the rest of the country is done by air, for instance, Quibdó only is 136 km away from the Medellín (second city of Colombia) but the access by road takes approximately 18 hours, while that by plane takes only 30 minutes (Bonet, 2007). Its isolation is a key aspect to explain the big difference in departmental per capita household income levels with neighbouring regions. Bogotá displays a significant local autocorrelation measure in 21 out of the 26 considered years. Cundinamarca, a neighbouring region to Bogotá, joints the capital in a positive High-High cluster in 1994.

Figure 8. Real Household Income per capita statistics (24 Departments)

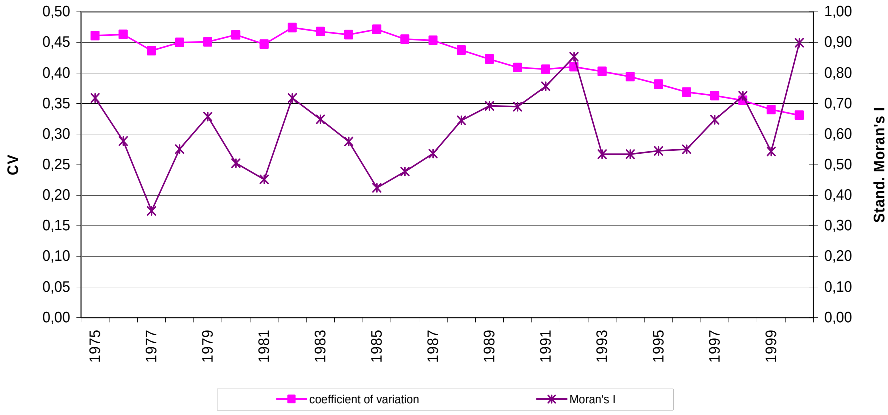
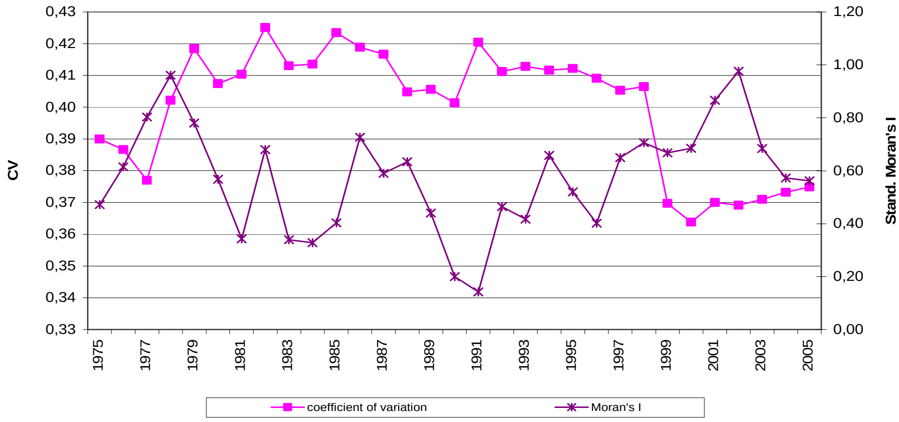


Figure 9. Real GDP per capita statistics (24 Departments)



The beta convergence analysis displayed in table 2 is quite close to the one observed in the product variable: the long run estimates (where OLS is preferred to spatial models) drive to assume beta convergence, as happens with the panel data estimates (fixed effects are clearly preferred here), which drive to a parameter suggesting strong convergence. Now the estimates enjoy a better adjustment, and consequently, despite the estimates are lower, are more reliable than before, particularly because now we are not considering the mining departments.

The whole evidence is supportive of the idea of convergence: the CV decreases, particularly after 1985, the kernel estimates show that convergence happens particularly at the tails of the distribution, and finally the estimations of beta convergence are significant. And interestingly, this happens with a total absence of spatial autocorrelation.

Figure 10. Moran's Scatterplot. Real Household Income per capita. 1975, 1985, 1995, 2000

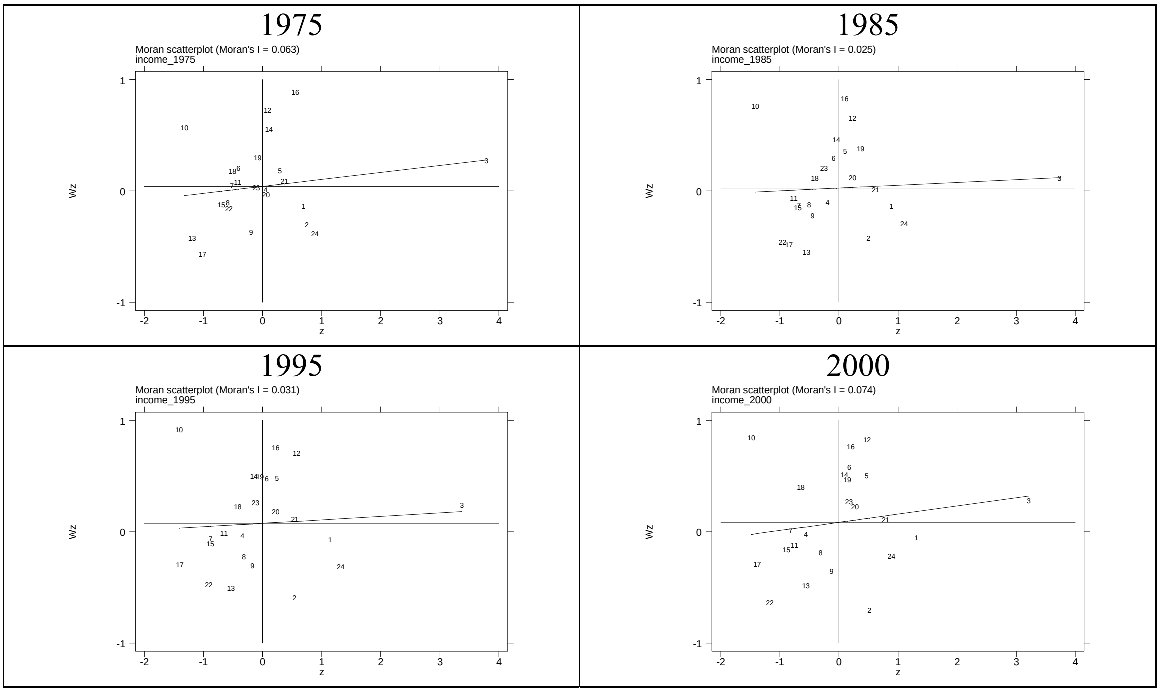


Table 2. Beta convergence analysis. Real Household Income.

	OLS	Spatial Lag	Spatial Error	Panel estimation (CS, TS, Fixed Effects)	Panel estimation (CS, Random Effects + TS Fixed Effects)
Log Income t-1	-0.0174**	-0.0170***	-0.0171***	-0.1319***	-0.0149**
	0.0046	*0.0044*	*0.0044*	*0.0195*	*0.0044*
Implicit yearly speed of convergence (divergence)	1.45%	1.42%	1.43%	12.39%	1.48%
rho		0.216			
		0.277			
lambda			0.22		
			0.289		
LM test		0.456	0.468		
p-value		*0.499*	*0.494*		
Robust LM test		0.013	0.025		
p-value		*0.909*	*0.876*		
Cross section				Fixed Effects ***	Random Effects
Time Series				Fixed Effects ***	Fixed Effects ***
Breusch-Pagan test					0.21
p-value					*0.6496*
Hausman test					35.55
p-value					*0.000*
AIC	-156.18	-152.73	-152.76	-2186.4	
Adj- R-squared	0.363	0.382	0.362	0.271	0.281
N	24	24	24	600	600

* p<0.05, ** p<0.01, *** p<0.001. Standard errors are displayed in italics.

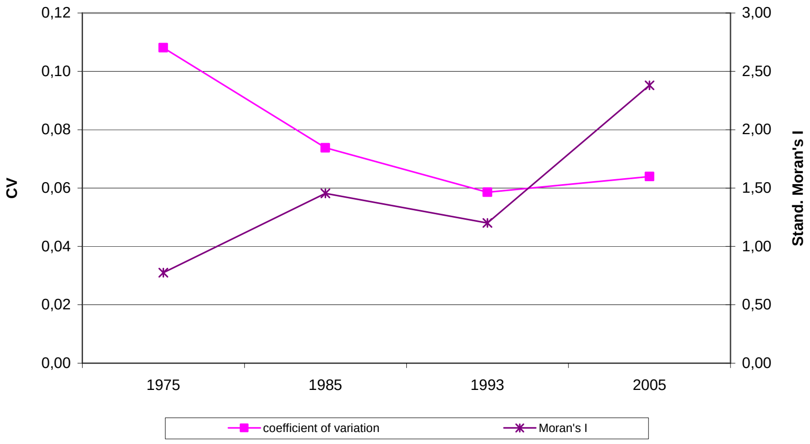
4.2. Literacy rate

Once we have looked at the economic variables we turn to analyse the **social variables**, concerning education, health and crime.

Depending on the country, the education variable that has to be used to see if there are important inequalities in the territory can change. In our case we will use the **literacy rate** (percentage of literate population above 5). This variable is computed from the results coming from different census and consequently is only available for four different years: 1973, 1985, 1993 and 2005. We have used the micro data available in IPUMS data bases to build our variables for the 28 departments, and we have also turn the variable rate of illiteracy rate into positive terms: the proportion of individuals who can read.

In general terms we see a positive evolution of this variable. The evolution of people who can read has been growing steadily from 78,4% in 1975 to 89,2% in 2005. The point we face now is how has been this evolution in the territory. Again, annex 1 shows the table with all key statistics of the considered variable. In figure 16 we see the evolution of the coefficient of variation (CV) and the standardized value of the Moran's I.

Figure 16. Literacy rate statistics

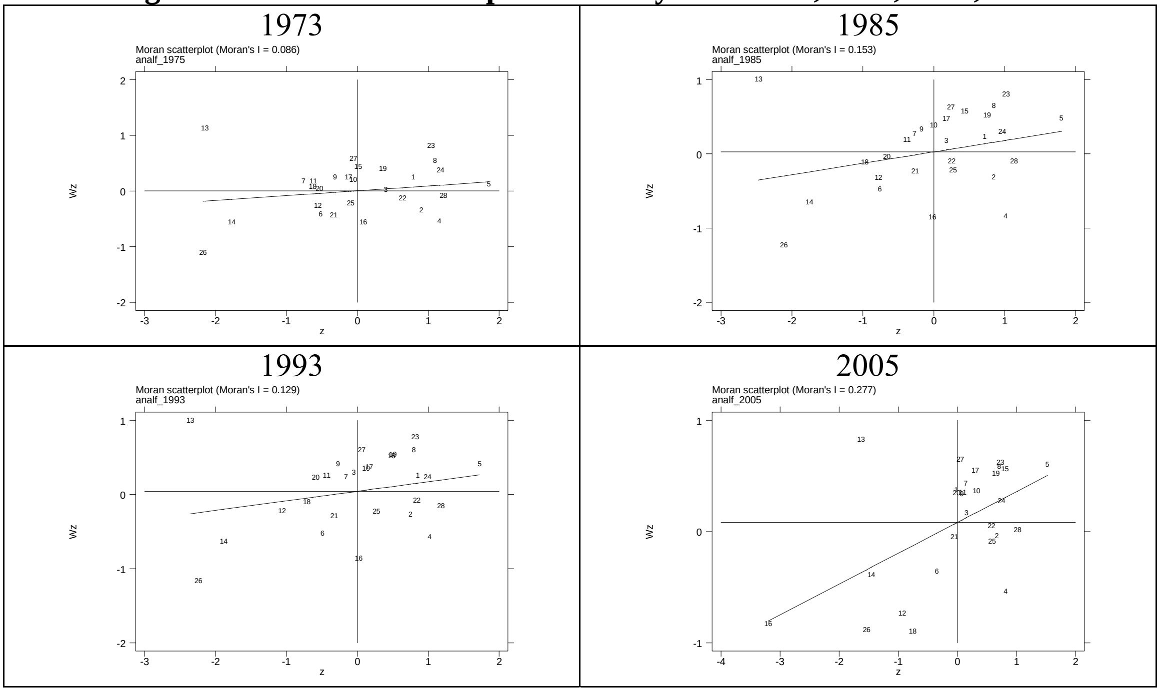


What we find is a decreasing path of sigma convergence, which stops in 2005. Figures 18 to 20 display the kernel density estimate of relative literacy rate in the years 1973 and 2005, and the three-dimensional plot of the stochastic kernel and its corresponding contour plot. Again, we see an important decrease in the dispersion of the variable: the kernel concentrates much more density close to the mean in 2005. Nevertheless several modes below the average suggest a persistence of several departments to join the rest of the country. Besides, figure 20 shows a quite flat contour plot with few exceptions (mainly La Guajira, which worsens its position in 2005).

Parallel to this evolution we see an increasing evolution of the global spatial autocorrelation measurement, which always display a positive sign, although only arises as significant in 1985 (10% of significance) and 2005 (1% of significance). Figure 17 show the Moran's scatter plot of all four considered years, and can be clearly seen the increase in the Moran's I statistic is affected by a region, Chocó (the naturally isolated department at the Pacific coast, posed as number 13 in the considered graphs), which is away from the rest of the observations. In 2005 the Moran's I displays a value of 0.27.

If Chocó had had a value equal to the average of the country, the Moran's I would have been a figure close to 0.29. Instead, what we find is this Department with low values in the literacy rate and surrounded by Departments with high values. We have to remember that this situation also happened in economic variables, such as real per capita GDP and Income. Consequently, this variable displays a positive spatial autocorrelation that is increasing in time while the σ-convergence measure decreases (the correlation between these two measurements is equal to -0.63).

Figure 17. Moran's Scatterplot. Literacy rate. 1973, 1985, 1993, 2005



Finally, figures 21 and 22 display the cloropleth and LISA maps in order to find the spatial distribution dynamics in Colombia. We have seen above that the increasing trend in the literacy rate has been accompanied by a growing degree of global spatial autocorrelation, and an increasing heterogeneity, basically due to birth of a positive high-high cluster in the departments close to Bogotá, and the strengthen of the low-low cluster of northern Departments (Cesar, La Guajira and Magdalena).

Finally we focus our attention in the beta convergence analysis. We find strong convergence results, both because of the significant parameters in the regressions and because the high adjustment levels of the estimates: only with one explanatory variable (the initial level of the endogenous variable) we can explain more than the 60% of the variance of literacy rate growth rates. In this case the spatial error model is preferred to the OLS and the spatial error models. It means that there are non observed aspects in the growth rate following spatial patterns. In these situations conditional models deserve particular attention.

Panel data estimates show higher estimates of the speed of convergence: we find a higher speed of convergence in the conditional models displayed in panel specifications. The preferred fixed effects model almost doubles the spatial lag cross section estimate. Following Islam (1995), a higher beta convergence in panel estimates, contrary to what may appear, calls for more policy activism. The main reason is because improvements in every particular region (every steady state) will lead also to higher transitional growth rates (higher speed of convergence).

Table 3. Beta convergence analysis. Literacy rate.

	OLS	**Spatial Lag**	**Spatial Error**	**Panel estimation (CS, TS, Fixed Effects)**	**Panel estimation (CS, Random Effects + TS Fixed Effects)**
Log Literacy rate t-1	-0.023***	-0.024***	-0.023***	-0.060***	-0.030***
	0.003	*0.003*	*0.003*	*0.011*	*0.004*
Implicit yearly speed of convergence (divergence)	1.74%	1.79%	1.74%	3.39%	2.12%
rho		0.098			
		0.225			
lambda			0.607**		
			0.212		
LM test		0.134	3.759		
p-value		*0.714*	*0.053*		
Robust LM test		2.036	5.662		
p-value		*0.154*	*0.017*		
Cross section				Fixed Effects	Random Effects
Time Series				Fixed Effects ***	Fixed Effects ***
Breusch-Pagan test				0.04	
p-value				*0.8451*	
Hausman test				7.13	
p-value				*0.0076*	
AIC	-275.00	-276.19	-271.19	-799.3	
Adj- R-squared	0.683	0.698	0.695	0.623	0.707
N	28	28	28	600	600

* p<0.05, ** p<0.01, *** p<0.001. Standard errors are displayed in italics.

4.3. Health variables: life expectancy at birth and infant survival rate.

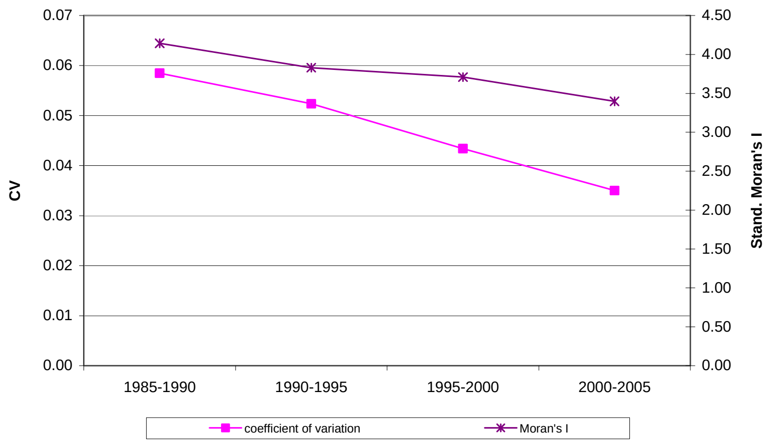
The next social variables we are facing are the ones related with health. Here we consider two of them: life expectancy at birth and infant survival rate. These variables are available for four different periods: 1985-1990, 1990-1995, 1995-2000 and 2000-2005, and are available for all 28 considered departments.

The first variable we look at is **life expectancy at birth**. We have to remark the important increase of this variable during the 30 years considered. If in 1975 the life expectancy at birth was 66.3, in 2005 it grow up to 71.1. As the standard deviation decreases, the CV experiences an important decrease: from 5.8% in 1975 to 3.5% Figures 25 to 27 show the kernel estimates. They show clearly the decrease in the dispersion of the variable (figure 25) and a contour plot that moves away from the diagonal of the box and approaches to the horizontal line.

This evolution has been parallel to a decrease in the measure of spatial autocorrelation, which, in any case, is always positive and highly significant (see figure 23). The comovement between the CV and the Moran's I can be summarized into a correlation throughout time close to 0.98. In any case, the Moran's scatter plots clearly show the strong spatial dependence in this variable and only the evolution of the department of Chocó (numbered as 13) imposes a decrease in the Moran's I.

The spatial distribution of the variable is showing also an important degree of heterogeneity, as there are permanently two clear clusters: a positive high-high cluster formed by Atlántico, Bolívar, Córdoba and Sucre, and a negative low-low cluster, formed by Amazonía, Arauca, Caquetá, Casanare and Putumayo. These clusters are quite stable (see annex 2) and demonstrate an important persistence in this variable, in our view basically due to natural conditions in every part of the country, such as deep forest in the new departments close to Amazonía. Additionally it demonstrates the difficulty of the public policies in improving health facilities and/or life expectancy.

Figure 23. Life expectancy at birth statistics



The estimates of beta convergence display significant parameters together with high levels of adjustment in all regressions. Despite finding strong spatial autocorrelation, cross section OLS estimates are preferred to spatial model specifications. Contrary to what happened to literacy rates, now panel estimates (random effects are preferred here) show similar speed of convergence to long run cross section models. Consequently the convergence process can be seen as a national phenomenon, probably based on the overall economic growth of the country.

Figure 24. Moran's Scatterplot. Life expectancy at birth. 1985-2005

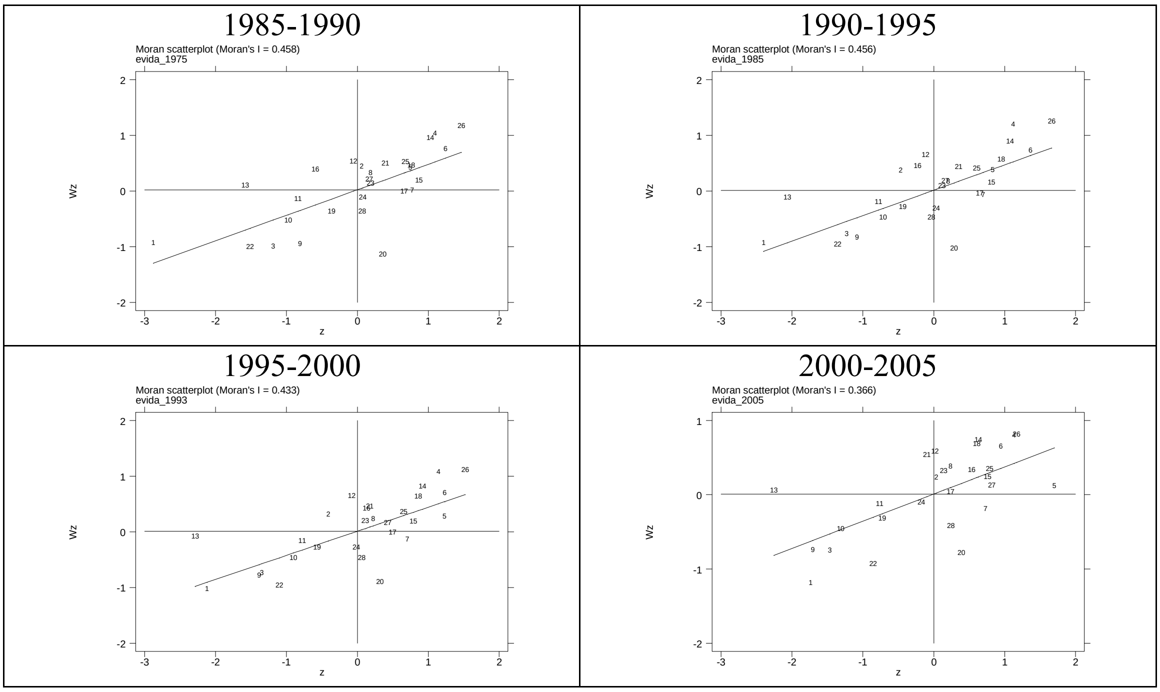


Table 4. Beta convergence estrimates. Life expectancy at birth.

	OLS	**Spatial Lag**	**Spatial Error**	**Panel estimation (CS, TS, Fixed Effects)**	**Panel estimation (CS, Random Effects + TS Fixed Effects)**
Log Life Exp t-1	-0.017***	-0.0196***	-0.017***	-0.029***	-0.019***
	0.002	*0.002*	*0.001*	*0.009*	*0.003*
Implicit yearly speed of convergence (divergence)	1.40%	1.54%	1.37%	2.08%	1.48%
rho		-0.293			
		0.182			
lambda			-0.551		
			0.355		
LM test		2.202	1.142		
p-value		*0.138*	*0.285*		
Robust LM test		1.069	0.01		
p-value		*0.301*	*0.92*		
Cross section				Fixed Effects ***	Random Effects
Time Series				Fixed Effects ***	Fixed Effects ***
Breusch-Pagan test				9.04	
p-value				*0.0026*	
Hausman test				1.39	
p-value				*0.2378*	
AIC	-330.16	-328.37	-328.62	-985.9	
Adj- R-squared	0.726	0.763	0.736	0.551	0.572
N	28	28	28	84	84

* p<0.05, ** p<0.01, *** p<0.001. Standard errors are displayed in italics.

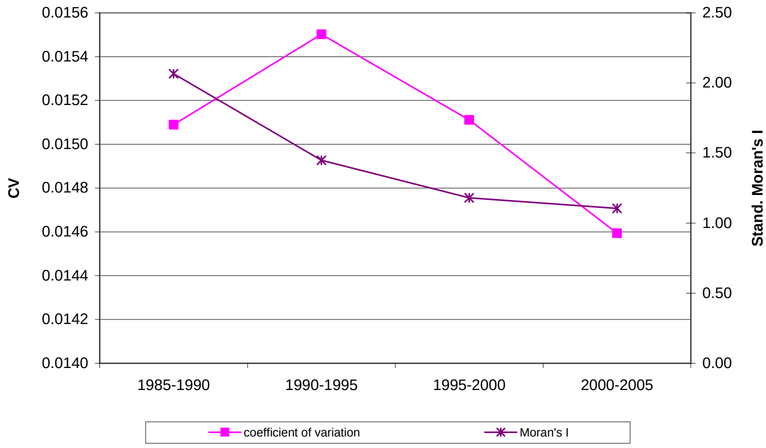
The next health variable is **infant survival rate**, which is the positive variable of the more commonly defined infant mortality rate, is usually assumed to reflect more directly the health condition of population than life expectancy at birth, due to the influence coming form the availability of health facilities.

Parallel to the increase in life expectancy at birth that we have seen above, the infant survival rate increases from 95.2% survived infants under 5 years old in the period 1985-1990 to 96.4% in 2000-2005.

Again, we see a small decrease in the dispersion of the variable, with a CV moving from 1.51% to 1.46% in the considered period of study. Figures 32 to 34 display the kernel estimates. While the mode represented by the department of Chocó (quite away from the rest of the departments) shows a strong persistence over time, there are several changes close to the average. Some initially bad placed departments experience a positive convergence process while other departments who were over the average move towards the maximum.

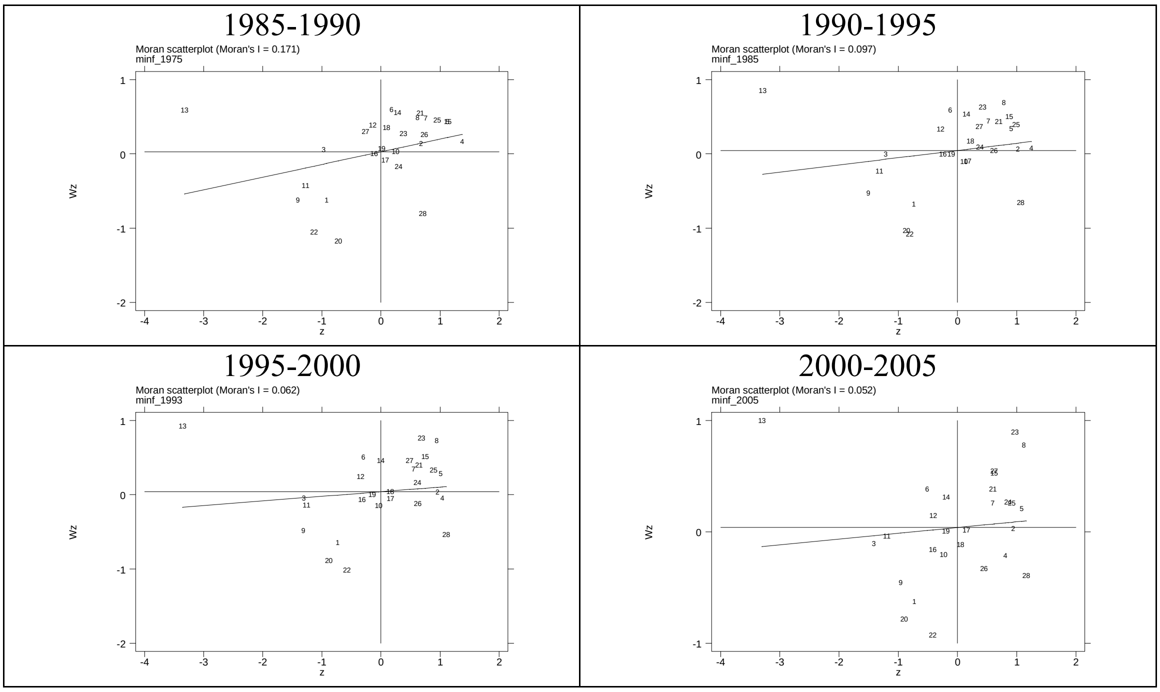
These movements in the dispersion of the variable has been observed together with a fall in the Moran's I statistic, from 0.18 in 1985-1990 to 0.08 in 2000-2005 (the correlation though time is close to 0.90). The Moran's I stops being significant at 10% in the 1995-2000 period. In order to understand what is going on, the inspection of the Moran's scatterplots (fugure 31) is helpful. Firstly we see that most of the observations are close to a positive and significant spatial autocorrelation. Nevertheless, again due to Chocó, the final Moran's statistic is low, and decreasing (as the Choco's neighbours increase their performance in this indicator). If Chocó would have an infant survival rate equal to the average of the distribution, the Moran's I statistic would have been, although decreasing, always significant: 0.44 in 1985-1990 and 0.37 in 2000-2005.

Figure 30. Infant survival rate statistics



The spatial distribution of the variable is quite close to the maps of life expectancy at birth. Again, there is a low-low significant cluster in the Amazonia part of the country, but now the positive high-high cluster is now close to Bogotá. In our view it reflects much more the availability of health facilities than the life expectancy at birth, probably more related with the natural environment of the regions. The urban growth experienced in Colombia during this period clearly helped to improve this indicator, as providing social services to urban residents is easier than to rural populations (Kenny, 2005). In our view it implies that there is a wide margin of improvement in this indicator if additional investments in health facilities are extended to rural areas.[3]

Figure 31. Moran's Scatterplot. Infant Survival Rate. 1985-2005



The beta convergence estimates displayed in table 5 are insignificant for all cross section estimates. There the spatial specifications matter, but any of them does change the non-significance of the parameter. On the contrary, the panel data models are displaying significant parameters. Breusch Pagan and Hausman tests report conflicting results, and consequently fixed effects are preferred. The estimate result reports a small amount of convergence. At this stage we can recommend the spatial specification of the panel, what will probably remove the significany of the convergence parameter.

[3] In this line, Chay and Greenstone, (2000), claims that federal interventions during the War on Poverty in the md-1960's in rural parts of the USA are the main responsible for convergence in infant survival rates.

Table 5. Beta convergence estrimates. Infant Survival Rate.

	OLS	Spatial Lag	Spatial Error	Panel estimation (CS, TS, Fixed Effects)	Panel estimation (CS, Random Effects + TS Fixed Effects)
Log Inf Surv Rate. t-1	-0.00379	-0.0013	-0.0006	-0.006 *	-0.051 ***
	0.002	*0.002*	*0.002*	*0.003*	*0.009*
Implicit yearly speed of convergence (divergence)	0.36%	0.13%	0.06%	0.55%	3.09%
rho		0.618***			
		0.164			
lambda			0.637***		
			0.163		
LM test		10.891	9.095		
p-value		*0.001*	*0.003*		
Robust LM test		2.94	1.144		
p-value		*0.086*	*0.285*		
Cross section				Fixed Effects ***	Random Effects
Time Series				Fixed Effects ***	Fixed Effects ***
Breusch-Pagan test				17.05	
p-value				*0.000*	
Hausman test				21.35	
p-value				*0.000*	
AIC	-396.39	-401.38	-401.72	-1262.6	
Adj- R-squared	0.047	0.432	0.047	0.026	0.056
N	28	28	28	84	84

* p<0.05, ** p<0.01, *** p<0.001. Standard errors are displayed in italics.

4.4. Crime statistics

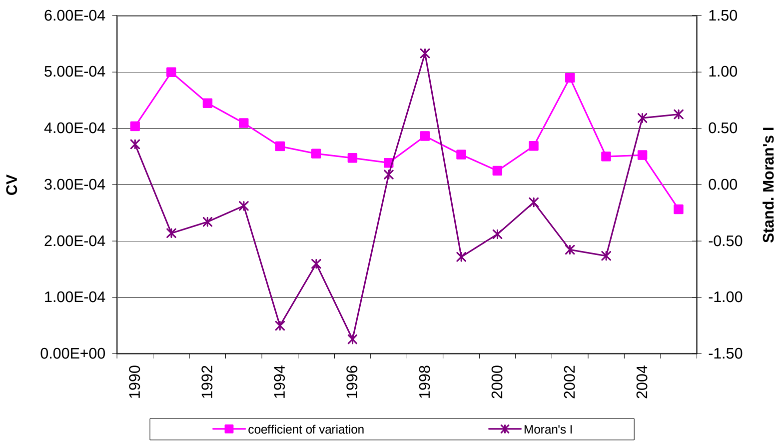
The final social variable we are using is the one related with crime. Again, we turn this variable into positive and thus we use **non-murder rate**, which considers namely the total amount of people who is not being killed over 10,000 inhabitants. This variable is observed along the period 1990-2005, and consequently this is the variable with the shortest period of study. In any case, 16 years is a wide span of years and consequently it is worth to analyse a key variable in a country as Colombia, where violence is a key issue in the country.

The *murder rate* we experienced an important increase between 1990 (5.2 murders per 10,000 inhabitants) and 2002 (7.9). Nevertheless it rebounded and in 2005 the figure was 4.6. The CV of the *non-murder rate* experienced a significant decline during the considered period: it was close to 0.05% in 1991, while in 2005 it reduced up to 0.025% (see figure 37).

The kernel estimates show a much richer picture of changes in the distribution. Firstly we see that in 1990 there was a significant mode below the average. In 2005 this mode has completely disappeared and in the contour plot we see how the department of Antioquia has experienced a dramatic change towards the average of the distribution. Contrary to this, there is a big part of the distribution below the average moving away of the convergence process (particularly Arauca and Caquetá, which move from the 9th and 10th position in the crime ranking to the 1st and 2nd respectively). In these departments, together with Putumayo and others, there is an important presence of illegal military (guerrilla and paramilitars) and the war has been a constant for decades.

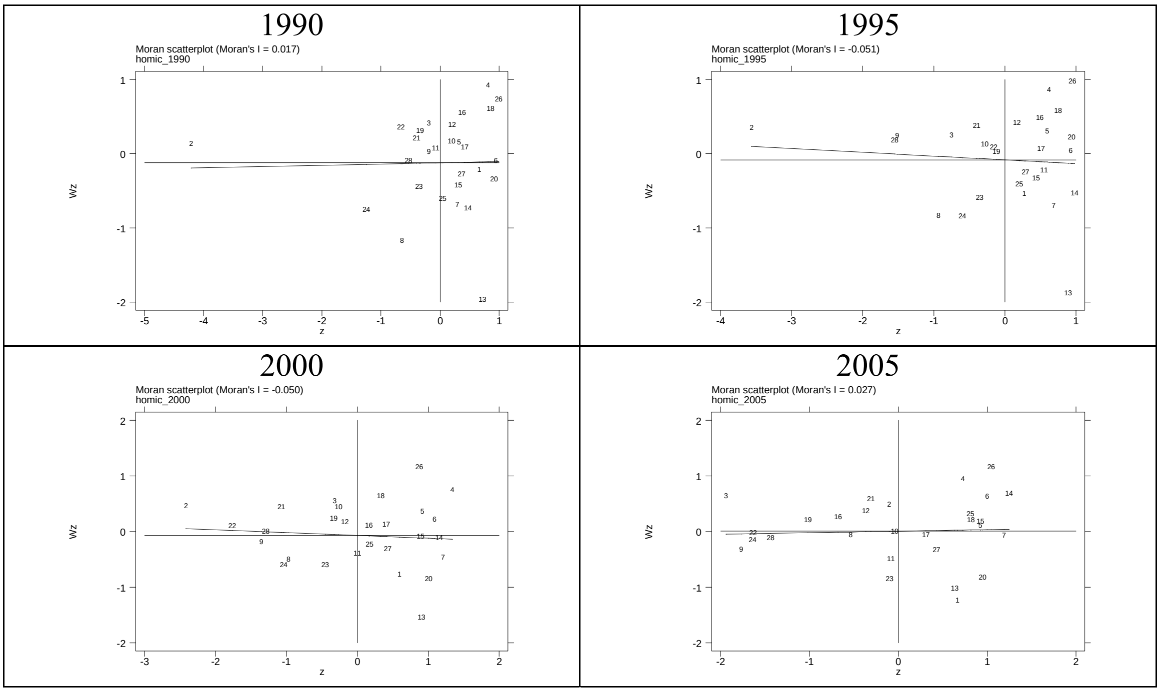
The strong position from president Uribe at the beginning of the XXI century against these groups may have increased crime statistics. In a similar way Antioquia has had high presence of groups outside the law as drug cartels and urban militia, what generated strong violence episodes in the nineties, for instance in Medellin (its capital). This situation has experienced a dramatic decline since 2000, what has reinforced the convergence path in this variable.

Figure 37. Non murder rate statistics



The spatial autocorrelation was simply non existent in any of the periods under analysis and additionally there is no trend on them. The Moran's scatterplots (figure 38) clearly show the lack of any spatial behaviour on the variable. Spatial heterogeneity is analysed through the inspection of the LISA maps. We see that there is a significantly high variation from the beginning of the period to the end, and also that the maps show an important number of high-low and low-high regions (such as Antioquia). A significant positive high-high cluster at the north of the country is finally found in 2005, as violence in Antioquia decreases. On the contrary, a negative low-low cluster arises in the south, linked to the increasing relative importance of crime figures at the zone where the guerrilla is important.

Figure 38. Moran's Scatterplot. Non murder rate. 1990-2005



Beta convergence is significant in all estimates and at high rates. As can be expected, spatial specifications are not important at the cross section models. Panel estimates (fixed effects are preferred) show a lower speed of convergence. As can be expected these estimates are affected by the dramatic decline of violent episodes in Antioquia. If the correlation coefficient between the growth rate and the log of initial non/murder rate is -0.78, when excluding Antioquia this statistic collapses to -0.16. Consequently, any convergence process in crime statistics is due to decrease of violent episodes in Antioquia.

Table 6. Beta convergence estrimates. Non-murder rate.

	OLS	**Spatial Lag**	**Spatial Error**	**Panel estimation (CS, TS, Fixed Effects)**	**Panel estimation (CS, Random Effects + TS Fixed Effects)**
Log Crime t-1	-0.708 ***	-0.698 ***	-0.684 ***	-0.353 ***	-0.099 ***
	0.110	*0.102*	*0.020*	*0.040*	*0.019*
Implicit yearly speed of convergence (divergence)	15.70%	15.61%	15.50%	11.84%	5.92%
rho		0.255			
		0.172			
lambda			0.241		
			0.249		
LM test		1.956	0.843		
p-value		*0.162*	*0.359*		
Robust LM test		1.113	0.000		
p-value		*0.291*	*0.988*		
Cross section				Fixed Effects ***	Random Effects
Time Series				Fixed Effects ***	Fixed Effects***
Breusch-Pagan test				1.31	
p-value				*0.253*	
Hausman test				48.17	
p-value				*0.000*	
AIC	-387.29	-384.12	-385.3	-6262.4	
Adj- R-squared	0.597	0.629	0.597	0.163	0.238
N	28	28	28	420	420

* p<0.05, ** p<0.01, *** p<0.001. Standard errors are displayed in italics.

5. Conclusions

In this paper we have analyzed social convergence in Colombia, not only considering economic variables but also social indicators of education, health and crime. We have developed our analysis inspecting sigma convergence, the distribution dynamics of the variables and the beta convergence, both in the long run (using cross section specifications) and in the short run (suing panel data techniques). We have also focused on the spatial distribution of the variables, through the inspection of global spatial autocorrelation statistics, local autocorrelation statistics and also through the use of spatial econometrics techniques for estimating beta convergence.

We have found that the economic variables display conflicting results. Despite GDP significant beta convergence parameters, there was a growing sigma convergence between 1975 and 2005. The start of works in the Casanare's oil fields in 1986, implied important growth rates of formerly poor departments. In any case, this process had nothing to see with the grounds of the neoclassical growth theory convergence, based on labour mobility and decreasing marginal returns. The rest of the country maintained the same distribution along the years and consequently we understand that there was no convergence in this variable.

When inspecting real household available income we find simultaneously three results related with convergence: significant decline in sigma convergence, particularly after 1986; decrease of both tails of the distribution between 1975 and 2005, in both cases towards the average; and finally significant beta convergence estimates. A detailed analysis of the kernel estimates shows that both the richest and the poorest departments were the main responsible of convergence.

Literacy rate is a clear example of convergence: huge decrease in sigma convergence, dramatic change of the distribution concentrating much more density close to the average at the end of the period, and significant beta estimates. We find a higher speed of convergence panel specifications what, in our view, calls for more policy activism, as improvements in every region's steady state will also lead to higher transitional convergence processes.

Both health variables, life expectancy at birth and infant survival rates, show declines in sigma convergence. Nevertheless, the former also shows significant changes in the kernel estimates towards the average and significant parameters of beta convergence, while the latter doesn't display the same convergence evidence. Life expectancy at birth beta estimates display similar results at the cross section and panel estimations, what drive us to assume that the convergence process can be seen as a national phenomenon, probably based on the overall economic growth of the country. On the contrary, infant survival rate does not show any significant convergence path.

Finally, crime statistics are highly influenced by the evolution of Antioquia, the more violent department in 1990, which is positioned over the average in 2005. This dramatic change is counterbalanced by the negative evolution of several departments partially controlled by the guerrilla and paramilitars, where violence increased. Overall one can talk about polarisation of the murder rate in a small amount of departments (although with big areas) close to the Amazonía, and that finally that convergence has a main name: Antioquia.

Our results suggest that there is robust evidence of convergence in Colombia over the last 30 years. Convergence both in economic (income) and social variables (literacy rate, life expectancy at birth, and non-murder rate) are evident and robust results. Our results are in line with Kenny (2005): convergence in quality of life indicators can be achieved even in the absence of sustained economic growth and convergence. Thus, income is only one among a number of factors in determining well being. Despite technology improvements in health and education, there is still a wide margin for government intervention.

We have also found that other social issues show more conflicting results. Polarisation in the GDP and in the non-murder rate has to be pointed out as significant and important aspects to be considered, particularly when some of the social and economic phenomena arise in the same regions.

These spatial trends drive us to answer to the second main question posed in our paper: the joint analysis of the spatial distribution of the variables and the convergence processes, trying to answer to the Rey and Janikas question of what is the relationship between convergence and spatial autocorrelation.

We have found a huge diversity of results, summarised in the table 7. We find all kind of possible results: convergence and non convergence with and without global spatial autocorrelation. Interestingly, we have found convergence associated with increasing spatial autocorrelation in three out of four variables. In other words: decreasing CV has been accompanied by increases (significant or not) in the Moran's I: global measure of spatial autocorrelation. Consequently, in order to find evidence linked to the neoclassical growth theory of convergence, based on labour mobility and decreasing marginal returns linked as well with capital mobility, there has to be found some kind of link between regions. The fourth variable experiencing convergence together with decreases in the Moran's I (Life Expectancy at Birth) displays a significant value of the global statistic of spatial autocorrelation.

Table 7. Summary of results

Indicator	**Convergence**	**Global Spatial Autocorrelation**	**Local Spatial Autocorrelation**	**Corr(CV, Moran's I)**
GDP	NO	Non significant	Significant (positve mining depts)	0.90
Houshold Available Income	YES	Non significant	Significant (positive Bogota and neighbouring depts, negative Chocó)	-0.33
Literacy Rate	YES	Significant	Significant (positive Bogota and neighbouring depts; negative northern depts)	-0.63
Life Expectancy at Birth	YES	Significant	Significant (positive, northern depts, negative mining depts)	0.98
Infant Survival Rate	NO	Significant	Significant (positive, centre depts, negative mining depts)	0.34
Non-Murder Rate	YES	Non significant	Significant (positive cluster northern depts, negative mining depts in 2005)	-0.15

Our results for social variables are in line with Aroca and Bosch (2000), who find for GDP per capita opposite evolutions of the sigma convergence (decreasing) and the Moran's I (increasing) for the Chilean case. On the contrary, Rey and Montouri (1999) and Rey and Janikas (2005) find, again for GDP per capita, huge decreases in the CV and Theil indices together with a decreases in the Moran's I in the USA. In any case we have to indicate that these convergence processes are developed in significant spatial autocorrelation scenarios, what partly support our intuition.

An example of this situation is the department of Chocó. Chocó is located at the Pacific coast but having a natural barrier of deep forest that separates it from the rest of the country, obliging to last 18 hours to drive to Medellín, the closest big capital, only at 136 km. Its isolation is a key aspect to explain low levels in GDP, income, literacy rate and infant survival rate despite being surrounded by departments with high levels in all these variables. In these indicators Chocó has a significant low-high cluster.

Consequently, in our view, spatial autocorrelation reinforces convergence processes through deepening market and social factors. We have also found that the public action may play a key role, as panel data estimates of beta convergence has been found in many cases larger than the cross section estimates, what indicates the fact that influencing every department's steady state will increase the speed of convergence and consequently overall well-being of the country.

Future research: two key questions arise from this paper. First, what is the relationship in the evolution between social and economic variables at the regional level? And second, is it really the case that convergence is achieved together with significant or increasing spatial autocorrelation?

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Annex 1. Socio-economic variables statistics

Real GDP per capita

	Mean	Standard Deviation	coefficient of variation	Gini coefficient	Theil entropy measure	Moran's I	Geary's c	Getis & Ord's G
1975	909939.6	385580.3	0.4237	0.2269	0.08835	0.589	-1.409	1.423
1976	967468.4	407520.2	0.4212	0.2302	0.09003	0.629	-1.349	1.635
1977	1028713	425143.3	0.4133	0.2291	0.08879	0.852	-1.609	1.77
1978	1055199	459615.6	0.4356	0.2403	0.09529	0.829	-1.564	1.626
1979	1062903	476684.3	0.4485	0.2448	0.09910	0.74	-1.411	1.568
1980	1094027	481291.9	0.4399	0.2396	0.09462	0.504	-1.213	1.412
1981	1100815	497012.1	0.4515	0.2453	0.09822	0.284	-0.965	1.196
1982	1102065	525606.9	0.4769	0.2568	0.10697	0.577	-1.167	1.27
1983	1133480	553781.2	0.4886	0.2598	0.11045	0.369	-0.954	0.96
1984	1174048	626075.7	0.5333	0.2739	0.12457	0.66	-0.892	0.938
1985	1159027	571415.9	0.493	0.2618	0.11283	0.348	-0.891	0.919
1986	1322786	799599.4	0.6045	0.2972	0.14968	1.256	-0.946	0.958
1987	1463763	1072261	0.7325	0.3283	0.19691	1.996	-1.02	1.227
1988	1456398	967140.4	0.6641	0.3067	0.16821	1.795	-1.002	1.191
1989	1568846	1157677	0.7379	0.3282	0.19669	2.206	-1.06	1.225
1990	1656302	1318391	0.796	0.3434	0.22051	2.464	-1.09	1.306
1991	1665865	1325760	0.7958	0.3463	0.22190	2.387	-1.038	1.231
1992	1664520	1294495	0.7777	0.3375	0.21180	2.388	-0.997	1.387
1993	1683532	1319034	0.7835	0.3385	0.21422	2.398	-0.969	1.488
1994	1713296	1265828	0.7388	0.3234	0.19444	2.072	-0.807	1.423
1995	1812272	1303983	0.7195	0.3268	0.19144	2.426	-1.031	1.706
1996	1915357	1517315	0.7922	0.3491	0.22352	2.782	-1.112	1.839
1997	1967532	1575874	0.8009	0.3466	0.22452	2.569	-0.889	1.813
1998	1894158	1369473	0.723	0.3253	0.19247	2.757	-1.1	1.881
1999	1847497	1438310	0.7785	0.3270	0.20850	2.957	-0.949	1.953
2000	1797015	1211703	0.6743	0.2969	0.16683	2.604	-0.96	1.866
2001	1770096	1198720	0.6772	0.2960	0.16839	2.016	-0.749	1.791
2002	1740011	1204001	0.692	0.3034	0.17522	1.766	-0.627	1.755
2003	1736348	1092016	0.6289	0.2924	0.15505	1.597	-0.717	1.706
2004	1755273	1044104	0.5948	0.2856	0.14411	1.377	-0.725	1.645
2005	1806356	1049326	0.5809	0.2815	0.13842	1.285	-0.701	1.577

Note: All measures of global spatial autocorrelation are standardized.

Real Income per capita (24 Departments)

	Mean	Standard Deviation	coefficient of variation	Gini coefficient	Theil entropy measure	Moran's I	Geary's c	Getis & Ord's G
1975	694635	320279	0.4611	0.2151	0.0860	0.718	-1.138	1.064
1976	728942	337435	0.4629	0.2171	0.0876	0.577	-1.094	1.013
1977	764764	333814	0.4365	0.2065	0.0799	0.349	-1.119	0.938
1978	785971	353600	0.4499	0.2125	0.0835	0.551	-1.100	1.021
1979	800068	360515	0.4506	0.2141	0.0837	0.657	-1.115	1.111
1980	818611	378469	0.4623	0.2184	0.0869	0.505	-1.044	1.048
1981	816316	364738	0.4468	0.2145	0.0827	0.452	-0.998	1.025
1982	804347	381307	0.4741	0.2232	0.0911	0.718	-1.077	1.130
1983	797033	372869	0.4678	0.2195	0.0890	0.648	-1.046	1.078
1984	816519	377649	0.4625	0.2192	0.0878	0.576	-1.032	1.058
1985	807775	380583	0.4711	0.2224	0.0899	0.424	-0.914	0.986
1986	859018	391044	0.4552	0.2142	0.0836	0.477	-0.897	0.960
1987	895112	405777	0.4533	0.2144	0.0836	0.536	-0.914	1.066
1988	922847	403485	0.4372	0.2092	0.0786	0.645	-0.960	1.150
1989	948558	400779	0.4225	0.2041	0.0741	0.692	-0.985	1.133
1990	928439	379470	0.4087	0.1983	0.0701	0.690	-1.047	1.119
1991	936398	380169	0.4060	0.1985	0.0700	0.756	-1.116	1.206
1992	950654	389722	0.4100	0.2014	0.0714	0.853	-1.160	1.316
1993	967812	389339	0.4023	0.2000	0.0699	0.534	-1.028	1.331
1994	976528	384574	0.3938	0.1956	0.0669	0.534	-1.043	1.394
1995	980368	374231	0.3817	0.1911	0.0634	0.545	-1.047	1.515
1996	982098	361941	0.3685	0.1840	0.0590	0.550	-1.028	1.521
1997	968181	351332	0.3629	0.1831	0.0577	0.647	-1.089	1.638
1998	978657	347567	0.3551	0.1789	0.0553	0.725	-1.130	1.553
1999	949657	322991	0.3401	0.1732	0.0511	0.543	-1.049	1.584
2000	944975	312636	0.3308	0.1703	0.0492	0.899	-1.262	1.783

Note: All measures of global spatial autocorrelation are standardized.

Literacy Rate

	Mean	Standard Deviation	coefficient of variation	Gini coefficient	Theil entropy measure	Moran's I	Geary's c	Getis & Ord's G
1975	78.39679	8.477802	0.108	0.0588	0.00576	0.04900	0.689	0.171
1985	84.89214	6.265671	0.074	0.0397	0.00268	0.12200	0.617	0.172
1993	88.58929	5.190908	0.059	0.0314	0.00168	0.09500	0.632	0.171
2005	89.17143	5.702428	0.064	0.0323	0.00204	0.21400	0.443	0.173

Note: All measures of global spatial autocorrelation are standardized.

Life Expectancy at Birth

	Mean	Standard Deviation	coefficient of variation	Gini coefficient	Theil entropy measure	Moran's I	Geary's c	Getis & Ord's G
1985-1990	66.278	3.876	0.058	0.0313	0.00168	4.14300	-2.965	0.207
1990-1995	67.456	3.533	0.052	0.0287	0.00134	3.83000	-3.271	-0.091
1995-2000	69.250	3.005	0.043	0.0237	0.00092	3.70900	-3.372	-0.159
2000-2005	71.120	2.491	0.035	0.0191	0.00060	3.39700	-3.236	-0.101

Note: All measures of global spatial autocorrelation are standardized.

Infant Survival Rate

	Mean	Standard Deviation	coefficient of variation	Gini coefficient	Theil entropy measure	Moran's I	Geary's c	Getis & Ord's G
1985-1990	95.216	1.437	0.0151	0.0078	0.00011	2.06500	-1.861	0.596
1990-1995	95.658	1.483	0.0155	0.0080	0.00012	1.44800	-1.500	0.866
1995-2000	96.026	1.451	0.0151	0.0078	0.00011	1.18000	-1.386	0.879
2000-2005	96.430	1.407	0.0146	0.0076	0.00010	1.10500	-1.359	0.974

Note: All measures of global spatial autocorrelation are standardized.

Non-murder rate

	Mean	Standard Deviation	coefficient of variation	Gini coefficient	Theil entropy measure	Moran's I	Geary's c	Getis & Ord's G
1990	9994.8	4.036	4.04E-04	1.80E-04	7.86E-08	0.359	1.520	-2.100
1991	9993.7	4.994	5.00E-04	2.36E-04	1.21E-07	-0.430	1.670	-1.936
1992	9993.8	4.445	4.45E-04	2.11E-04	9.54E-08	-0.329	1.634	-2.064
1993	9994.1	4.091	4.09E-04	2.00E-04	8.08E-08	-0.188	1.530	-1.927
1994	9994.5	3.681	3.68E-04	1.79E-04	6.54E-08	-1.251	1.974	-1.575
1995	9995.0	3.550	3.55E-04	1.75E-04	6.08E-08	-0.702	1.759	-1.762
1996	9994.7	3.472	3.47E-04	1.73E-04	5.82E-08	-1.372	2.222	-1.299
1997	9994.7	3.386	3.39E-04	1.77E-04	5.54E-08	0.090	1.205	-1.513
1998	9993.8	3.860	3.86E-04	2.07E-04	7.20E-08	1.166	-0.502	-1.295
1999	9994.0	3.533	3.54E-04	1.92E-04	6.03E-08	-0.640	1.023	-1.130
2000	9993.4	3.247	3.25E-04	1.79E-04	5.09E-08	-0.439	1.045	-1.207
2001	9993.0	3.685	3.69E-04	2.05E-04	6.56E-08	-0.156	0.750	-1.422
2002	9992.1	4.894	4.90E-04	2.62E-04	1.16E-07	-0.577	0.249	-0.777
2003	9993.5	3.497	3.50E-04	1.92E-04	5.90E-08	-0.631	-0.088	-0.818
2004	9994.2	3.524	3.53E-04	1.89E-04	5.99E-08	0.592	-0.843	0.010
2005	9995.4	2.563	2.56E-04	1.41E-04	3.17E-08	0.625	-0.738	-0.158

Note: All measures of global spatial autocorrelation are standardized.