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# Economic and Social Disparities across Subnational Regions of South America: A Spatial Convergence Approach

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## Abstract
This paper studies the evolution of economic and social disparities across South America. By exploiting a novel multi-country subnational dataset, we evaluate the evolution of gross national income per capita (GNI) and the human development index (HDI) across 151 subnational regions over the 1990–2018 period. In particular, regional dynamics are evaluated through the lens of two spatial convergence models. The first model deals with the role of spatial dependence. Results indicate that for both GNI and HDI, there is an overall process of regional convergence. Furthermore, spatial dependence plays a significant role in this process. A spatial error specification suggests that spatial dependence accelerates the speed of convergence in some decades, but decelerates it in others. The second model deals with the role of spatial heterogeneity. Results indicate that for both GNI and HDI, the speed of convergence is largely heterogeneous across space and time. Moreover, economic and social disparities are characterized by multi-country spatial clusters that show both converging and diverging trends. Taken together, these results emphasize the importance of accounting for spatial dependence and heterogeneity when evaluating the dynamics of economic and social inequality in South America.

**Keywords** Convergence · Spatial dependence · Spatial heterogeneity · Human development · South America

**JEL Classification** O47 · R10 · R11 · R58

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## Introduction

South America is a geographically compact portion of the American continent that is characterized by high economic and social inequality. At the national level, the dynamics of inequality in economic and social well-being have been largely documented and comparatively evaluated (Barrios et al. 2019; Dobson and Ramlogan 2002; Galvao and Reis Gomes 2007). Therefore, given the development gaps across countries in South America, studying inequality per se is of utmost importance. Moreover, in a continent that is aiming to integrate, the study of regional convergence is also important to systematically monitor the degree of socio-economic integration. Relatively free movement of labor, similar institutions and common historical legacies are among the shared characteristics of the regions of South America. For these reasons, regional convergence is to a certain extent expected. Nevertheless, regional convergence is rarely a smooth process, and caveats and heterogeneous processes need to be thoroughly documented and explained.

In order to unveil whether regional convergence in well-being is taking place across South American subnational regions, this paper exploits a novel dataset to evaluate the dynamics of economic and social well-being across the first-level subnational regions of South America. The paper's main contribution highlights the role of the spatial dimension on the regional dynamics of well-being. Specifically, the paper evaluates the role of spatial dependence as well as spatial heterogeneity in accelerating the process of regional convergence in gross national income per capita (GNI) and the human development index (HDI).

Well-being is measured based on the human development index as proposed by the United Nations. Specifically, this paper uses a subnational version of the human development index and one of its components: gross national income per capita. This new dataset allows us to consistently evaluate social and economic inequalities across 151 subnational regions of South America over the 1990–2018 period. Compared to previous studies, this dataset provides a richer setting for evaluating the relationship between well-being and spatial effects in South America (Martín-Mayoral and Zúñiga 2013; Barrios et al. 2019; Galvao and Reis Gomes 2007; Dobson and Ramlogan 2002). Previous studies that focus on subnational-level data for a single country usually fail to thoroughly identify statistically significant and robust spatial effects, in part because of the reduced number of subnational units in a single country (Royuela and Garcia 2015; Magalhães et al. 2005; Resende 2013). In this paper, we use one of the largest and latest regional datasets available to overcome these limitations (Smits and Permanyer 2019).

Furthermore, this paper also speaks to the literature that deals with testing regional convergence across multiple contries. This literature on multi-country convergence has been recently expanding (Lessmann and Seidel 2017; Mendez and Santos-Marquez 2020; Ayouba et al. 2020) in line with the discussion by Rey and Janikas (2005). These authors indicate that despite the large body of studies on inequality and convergence for single countries, very few studies compare rates of regional convergences across multiple countries. Furthermore, Rey and Janikas (2005) point out that studying the role of space in the dynamics of different continental systems is a promising research question for future studies.

In terms of analytical methods, this paper uses a spatial convergence model to study the dynamics of regional inequality and spatial effects. Specifically, convergence is usually defined as a process in which initially poor regions tend to grow faster than initially rich regions. In regards to a regression model, this process implies that the initial level of a variable shows an inverse relationship with its subsequent growth rate. The role of spatial dependence in the convergence process is evaluated using spatial error and the spatial lag models (Akçagün 2017; Arbia 2006; Rey and Montouri 1999). In addition, the role of spatial heterogeneity is evaluated using a geographically weighted regression framework (Brunsdon et al. 1996; Eckey et al. 2007; Öcal and Yildirim 2010).

Overall, our results indicate that for both GNI and HDI, there is an ongoing process of regional convergence; moreover, spatial effects play an important role in this process. The first set of results points to the role of spatial dependence on the speed of regional convergence. A spatial error specification indicates that spatial dependence accelerates the speed of convergence in some decades, but decelerates it in others. The second set of results points to the role of spatial heterogeneity in the convergence process. For both GNI and HDI, the speed of convergence is largely heterogeneous across space. Specifically, economic and social disparities are characterized by multi-country spatial clusters that show strongly localized converging and diverging trends.

The results of this paper contribute to the literature of spatial dependence and regional convergence in South America in three fronts. First, we use a novel dataset of well-being and income to test the degree of regional convergence. Secondly, to the best of our knowledge, this is the first study to analyze convergence patterns across multiple countries in South America. Lastly, by dividing the sample in different sub-periods, this paper shows that the convergence process has not been smooth and the speed of convergence has significantly varied over time.

The rest of the paper is organized as follows. Section 2 provides an overview of the related literature. In Sect. 3, the well-being and income data are described, and the methods of regional convergence, spatial dependence and spatial heterogeneity are briefly explained. Section 4 presents the results of the spatial analysis of regional convergence. Lastly, Sect. 5 offers some concluding remarks.

## Related Literature

There are several convergence frameworks in the literature. The most common methodology is known as beta convergence (Barro and Sala-i Martin 1992a). In terms of output, beta convergence occurs when economies with initially low levels of output tend to grow faster than rich economies. This type of convergence was originally tested using cross-country and cross-regional regressions (Barro 1991; Barro and Sala-i Martin 1992a). Ever since, the literature has largely expanded, and convergence has been tested across a variety of observational units. For instance, firms (Val et al. 2009; Matos and Faustino 2012), households (Wan 2005; Zhang et al. 2020), subnational regions (Lessmann and Seidel 2017; Mendez and Santos-Marquez 2020), industries (Domínguez and Mendez 2019; Rodrik 2013), etc. and for a large number socio-economic variables.

In the following subsections, we have divided the literature review according to the topic and geographical scale (national and sub-national). In this literature review, the term "human development" is hereafter understood in terms of well-being.

#### Human Development Convergence

One of the first systematic studies of beta and sigma convergence for the human development index is Konya and Guisan (2008). In that paper, the authors test beta convergence of the HDI across 101 countries between 1975 and 2004. They report that countries tend to halve the gap with respect to their long-run equilibrium in about 88 years, which is significantly higher than the average 40 years found for regional income convergence in several studies (Barro and Sala-I-Martin 2004; Barro and Sala-i Martin 1992b). The authors also find that the cross-sectional disparities, decreased over the same time period.

Other earlier studies include Mazumdar (2002), who finds divergence using linear and nonlinear beta regression models over the period 1960–1995. However, Konya and Guisan (2008) express their concern about the quality of the data used by Mazumdar as most HDI data have been collected from 1975. Sutcliffe (2004) finds strong patterns of beta convergence for the 1975–2001 period. Moreover, the author argues that beta convergence is almost certain as the index is bounded by definition. Lastly, Noorbakhsh (2007) also studies convergence in HDI for the years 1975 to 2002. However, the author excludes the most developed nations and focuses on the convergence among a sub-sample of of 93 medium and low human development countries.

Recent studies have also incorporated alternative convergence frameworks. For example, Jordá and Sarabia (2014) uses a nonparametric kernel density approach to conclude that the HDI distribution has largely shifted to the right from 1980 to 2012. Moreover, the authors find strong signs of a bimodal HDI distribution at the end of the period, which suggests the formation of convergence clubs. In addition, the authors also test sigma convergence using three different measurements, the Gini, Theil and Attkinson indicators and find that overall HDI disparities have been decreasing over time. In a later article, the same authors Jordá and Sarabia (2015) analyze beta convergence using the traditional linear model and a semi-parametric approach. Based on the linear model, the authors find weak beta convergence in the global index. However, they indicate that the income and education components exhibit nonlinear trends.

The human development index is just one of a group of indicators that attempt to summarize developmental outcomes beyond purely economic variables. In the convergence literature, other indicators have also been analyzed. For example, Peiró-Palomino (2019) aggregates variables from a regional OECD dataset into a new well-being indicator. Using a distribution dynamics framework, Peiró-Palomino (2019) reports strong signs of polarization in the cross-sectional distribution.

### National Human Development Convergence in South America

In terms of well-being convergence in South America or Latin America, the literature is scarce. Martín-Mayoral and Zúñiga (2013) study the convergence of the HDI index and its components over the 1970–2010 period in Latin American countries. The authors report strong signs of sigma convergence of the HDI until the early 2000s. Among the HDI components, the life expectancy index shows the smallest disparities across all countries and regional geographic groups. In contrast, the income component presents signs of beta convergence but not sigma convergence from the early 2000s.

### Subnational Human Development Convergence in South America

At the subnational level, to the best of our knowledge, there are no studies about regional convergence in well-being covering multiple countries of South America[1]. Nevertheless, there are some papers that test convergence within individual countries. One these studies, Hernández and Nieto (2013) test the convergence of the HDI components across Colombian departments in the years 1990–2010. The authors report income divergence at the end of the period and convergence for the health and education components. In a study of Bolivia's development, Urquiola et al. (2000) report weak signs of HDI divergence at the departmental level between 1976 and 1992. Nevertheless, the authors find that a visual inspection of growth rates and initial values suggests beta convergence over the same period. Mendez (2018), in a more recent study about Bolivia, analyzed the convergence patterns of the HDI across municipalities over the 1992–2013 period. Beta and sigma convergence were reported for the entire period, though HDI disparities were reduced over the 2001–2013 sub-period at a faster speed. The author also uses nonparametric kernel density estimates and finds three convergence clubs for the period 1992–2001 and two convergence clubs in the later period 2001–2013.

In terms of income convergence, the body of literature for within-country convergence is considerably larger. Some of the studies for selected countries are presented as follows. For the case of Colombia, Royuela and Garcia (2015) report a significant convergence for income per capita for 24 states from 1975 to 2000 using cross-sectional and panel data models. Garrido et al. (2002) report weak and non-significant beta convergence across Argentinean provinces from 1970 to 1995. For the Brazilian states, Magalhães et al. (2005) report a slow and significant convergence speed of 0,8% between 1970 and 1995 for per capita income. Duncan and Fuentes (2006) report absolute beta convergence of income per capita in Chilean regions from 1987

[1] Although, in this paper, we focus on the study of the convergence process in South America, there is a related stream of literature that analyses trends in well-being indicators using spatial econometric methods. Such studies consider different aspects of well-being such as educational outcomes (Delboy 2019; Cepeda-Cuervo and Núñez-Antón 2013; Fujita et al. 2021; Elias and Rey 2011), poverty (Agudelo Torres et al. 2015; Ponce et al. 2020; Álvarez-Gamboa et al. 2021) crime (Ingram and Marchesini da Costa 2019; Santos-Marquez et al. 2021) environmental degradation (de Barros and Stege 2019; Ferrer Velasco et al. 2020) to name but a few.

to 2000. The authors use cross sectional and pooled panel data, being the convergence statistically significant in the latter model only. A more detailed review of studies of income convergence in some of these and other South American countries is presented in González (2004).

## Data and Methods

### Data: The Subnational Human Development Index

A new regional dataset on the human development index has been assembled by Smits and Permanyer (2019). The dataset is an extension of the country level HDI to the first-level administrative divisions across various countries of the world. Similarly to the country level index, the subnational HDI is constructed from data of the following three dimensions: education, health and income. For instance, the income component is measured as Gross National Income per capita in thousands of US Dollars (2011 PPP). More details regarding the construction of the database, and the handling of missing data and interpolations can be found in Smits and Permanyer (2019).[2]

In this paper, we use data for 151 subnational regions of South America over the 1990–2018 period. Specifically, two variables were considered: the human development index (HDI) and the per-capita gross national income (GNI). We use the 4.0 version of the database that was released in March 2020. Moreover, the shapefile of the world provided in the aforementioned website was utilized. From this shapefile, 151 contiguous regions were selected. In order to conduct the spatial regression analyses with a contiguity weight matrix, islands were removed.

In the first four columns of Table 1, descriptive statistics of Gross National Income per capita for 1990, 2000, 2010 and 2018 are shown. There is a clear upward trend in income for the first three years as both the mean and median steadily increase. However, the median slightly falls in 2018. In terms of dispersion, the interquartile range and the standard deviation do not provide a conclusive trend. While the standards deviation steadily increases over time, the IQR increases in the first three periods and then declines in 2018. Therefore, based on the dispersion of the data, it is not possible to conclude that there are signs of sigma convergence (that is, a systematic reduction in the cross-sectional dispersion over time).

These results contrast with the findings in the paper by Lessmann and Seidel (2017). The authors report strong signs of a sigma convergence process within all countries in South America except Suriname in the 1992–2012 period. Nevertheless, it appears that within country convergence is not sufficient for global convergence when considering a pool of all sub-national regions in South America.

In terms of the subnational human development index, summary statistics for selected years are shown in columns 5–8 of Table 1. HDI appears to be improving over time, as the mean and the median have continuously increased. Though there is

[2] All data are accessible from the website of the Global Data Lab https://globaldatalab.org/

**Table 1** Descriptive statistics for selected years: Human development index (HDI) and gross national income per capita (GNI)

| Year | GNI | | | | HDI | | | |
|---|---|---|---|---|---|---|---|---|
| | 1990 | 2000 | 2010 | 2018 | 1990 | 2000 | 2010 | 2018 |
| Mean | 8.10 | 9.43 | 12.01 | 12.11 | 0.61 | 0.67 | 0.72 | 0.74 |
| SD | 3.98 | 4.40 | 4.99 | 5.12 | 0.07 | 0.06 | 0.06 | 0.06 |
| Min | 0.53 | 0.97 | 1.74 | 1.65 | 0.41 | 0.48 | 0.51 | 0.52 |
| Q1 | 5.31 | 5.45 | 7.94 | 8.41 | 0.56 | 0.62 | 0.68 | 0.71 |
| Median | 7.93 | 9.54 | 11.96 | 11.33 | 0.62 | 0.66 | 0.72 | 0.74 |
| Q3 | 10.67 | 12.99 | 15.74 | 15.56 | 0.66 | 0.70 | 0.74 | 0.78 |
| Max | 20.71 | 20.76 | 24.06 | 26.01 | 0.75 | 0.82 | 0.86 | 0.87 |
| MAD | 3.97 | 5.38 | 5.70 | 5.26 | 0.07 | 0.06 | 0.05 | 0.05 |
| IQR | 5.36 | 7.53 | 7.80 | 7.15 | 0.09 | 0.08 | 0.06 | 0.07 |
| Skew | 0.35 | 0.15 | 0.01 | 0.46 | −0.41 | −0.12 | −0.46 | −0.50 |
| Kurtosis | −0.11 | −0.99 | −0.86 | −0.36 | −0.02 | 0.19 | 1.05 | 1.24 |
| Observations | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 |

SD represents the standard deviation. Q1 and Q3 stand for the first and third quartiles of the distribution and IQR is the interquartile range. MAD refers to the median absolute deviation

fluctuation in the interim years between 1990 and 2018, the cross-sectional dispersion as measured by the IQR and the standard deviation were greater in 1990 than in 2018. Nevertheless, the standard deviation has barely changed over the 28-year period. Similar to GNI, it appears that HDI is not converging in terms of sigma convergence.

## Classical Convergence Framework

According to the seminal works of Barro (1991) and Barro and Sala-i-Martin (1991, 1992a), the convergence hypothesis can be tested using the following regression model:

$$g(y)_{i,0-T} = \alpha - \frac{[1 - e^{-\gamma T}]}{T} \cdot log(y_{i0}) + \epsilon_i, \tag{1}$$

where $i$ is the index for each region, 0 and $T$ represent the initial and final times, $y$ is the variable under study. Also, $g(y)_{i,0-T}$ represents the growth rate of $y$ for region $i$ over the time period $(0 - T)$, $\gamma$ is the speed of regional convergence, $\alpha$ is a constant term and $\epsilon_{i,0T}$ is the error term.

For estimation purposes, Eq. 1 is re-expressed as

$$g(y)_{i,0-T} = \alpha + \beta \cdot log(y_{i0}) + \epsilon_i, \tag{2}$$

where the speed of convergence $\gamma$ can still be recovered from the estimated coefficient $\beta$. In this setting, cross-sectional data and the ordinary least squares (OLS) method are used to estimate the $\beta$ coefficient. Besides the speed of convergence ($\gamma$), a second parameter known in the convergence literature as the “half-life” can be computed as

$$half \cdot life = \frac{log2}{\gamma}. \tag{3}$$

This parameter (usually measured in years) represents the time that it would take for an economy to reduce by 50% the income gap between its initial state and its long-run equilibrium.

In addition, a second test of convergence is the so-called $\sigma - convergence$. According to this test, convergence is reported if the cross-sectional dispersion systematically decreases over time. There are several statistical measures of dispersion that may be used to study $\sigma - convergence$, being the standard deviation one of the most commonly used in the convergence literature. In this paper, we focuses our analysis on beta convergence. However, sigma convergence is implicitly evaluated in Table 1 as one can identify how the different indicators of dispersion, such the standard deviation or the coefficient of variation, change over time.

Although the econometric specification of Equation 2 is consistent with that used in Barro (1991) and Barro and Sala-i Martin (1991, 1992a), there are at least two caveats to consider. First, the specification may suffer from unobserved heterogeneity. To handle this issue, Islam (1995) suggests using panel data methods. However, Barro (2015) shows that when the time dimension is relative short (as in our case, $t < 50$), standard panel data methods tend to overestimate the speed of convergence. Since a comprehensive analysis using panel data methods is beyond the scope of this paper, we opt to use cross-sectional methods.

Second, the specification may suffer from endogeneity due omitted variable bias. Add indicated by Barro and Sala-i Martin (1991), endogeneity a more acute problem when Equation 2 is estimated using cross-country data. Within countries, however, smaller institutional and technological differences tend to reduce the need to control for additional variables. Nevertheless, we acknowledge that endogeneity is still a concern in our study due to its multi-country coverage. Although one would like add further controls variables to reduce endogeneity concerns, finding a systematic multi-country set of control variables at the subnational level is out of the scope of our current research. Even in this limited scope, our analyses and results are still informative as they may serve as a first benchmark for future studies that use more control variables.

### Measuring Spatial Dependence

Global spatial dependence refers to the existence of an overall pattern of spatial clustering of the data. There are several statistics to measure the spatial dependence of data, being the Moran's I statistic one of the most widely used. In the context of subnational regions, the Moran's I measures the correlation of the level of the variable at one location with the levels at nearby locations (Anselin 1995; Anselin et al. 2007). For any time period $t$, the global Moran's I statistic is defined as

$$I_t = \frac{N}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \left[ \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(X_i - \bar{X}\right)\left(X_j - \bar{X}\right)}{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2} \right], \tag{4}$$

In the context of this study $N$ is the number of subnational regions, $w_{ij}$ is the element of the spatial weights matrix ($W$), $X_i$ and $X_j$ are the values of income or well-being (HDI) of regions $i$ and $j$, respectively, and $\bar{X}$ is the mean. When the Moran's I is statistically different from zero, then the null hypothesis of spatial randomness can be rejected. Intuitively similar to a standard correlation coefficient, the numerical value of the Moran's I statistic lies between plus one and minus one. When its value is close to one, it indicates positive spatial autocorrelation. That is, evidence of an overall clustering pattern of similar values. On the other hand, when its value is close to minus one, it indicates negative spatial autocorrelation. That is, evidence of spatial dissimilarity, which at its limit it could be similar to a chessboard-like pattern where low values are surrounded by high values and vice versa.

### Spatial Dependence Models

The coefficients of the standard beta regression in model (1) are computed using an ordinary least squares (OLS) framework. Such framework requires cross-sectional independence among observations (regions). Nevertheless, if the data present patterns of spatial clustering, the assumption of cross-sectional independence is usually violated. In order to overcome this problem, several spatial econometric models have been used in the literature to account for spatial dependence.

For cross-sectional data, many plausible spatial models can be used. Some of these models include: the spatial lag model (SLM), the spatial error model (SEM), the spatial cross-regressive model (SLX), the spatial Durbin model (SDM), among others. In this paper, the approach suggested by Anselin (2013) and Anselin and Rey (2014), is used to select the most appropriate model between SLM and SEM.

Accordingly, the spatial model specification depends on the significance of the Lagrange Multiplier (LM) test. This approach can be summarized as follows. First, the LM test is performed on both the spatial error (SEM) and spatial lag model (SLM). If neither of them is significant the best specification is the standard OLS model. If one of them is significant the associated spatial model should be used. In contrast, if both are significant, a different test known as the robust Lagrange Multiplier test is performed. The significance of the robust LM test indicates which model should be used.

The two most basic spatial models are described in Eqs. 5 and 6. The spatial lag model (SLM) is

$$g(y)_{i,0-T} = \alpha + \beta \cdot log(y_{i0}) + \rho W \cdot g(y)_{i,0-T} + \epsilon_i; \tag{5}$$

and the spatial error model (SEM) is

$$g(y)_{i,0-T} = \alpha + \beta \cdot log(y_{i0}) + \lambda W \epsilon_i + u_i, \tag{6}$$

where $g(y)_{i,0-T}$ represents the growth rate of the variable $y$ for region $i$ over the time period 0 to $T$, $W$ represents the spatial connectivity structure among regions and is constructed using a queen contiguity criterion, $\alpha$ is the intercept, $\beta$, $\lambda$ and $\rho$ are the coefficients of the spatial regressions, and $\epsilon_i$ and $u_i$ are error terms.

### Spatial Heterogeneity Model

The statistical relationship between two or more variables often differs across space. This phenomenon is known as spatial non-stationarity and implies that locally different parameters should be estimated. For this purpose, the geographically weighted regression (GWR) approach of Brunsdon et al. (1996, 1998, 1999) has been proved useful in the regional development and convergence literatures (Eckey et al. 2007; Ingram and Marchesini da Costa 2019; Öcal and Yildirim 2010). In the following paragraphs, we present a brief sketch of the GWR framework. For a more extensive presentation and discussion, see Brunsdon et al. (1996).

Consider the following beta convergence model that is estimated using ordinary least squares (OLS):

$$g(y)_{i,0-T} = \alpha + \beta \cdot log(y_{i0}) + \epsilon_i. \tag{7}$$

In this model, $i$ represents the regional units in a geographical space and $\alpha$ and $\beta$ represent the regression coefficients for the intercept and slope, respectively. Equation 7 is a global model in the sense that the regression coefficients are homogeneous across all units of the geographical space. In a GWR framework, the coefficients of the global model are replaced by local parameters that indicate the potential existence of spatial heterogeneity. Specifically, Eq. 7 is re-expresed as

$$g(y)_{i,0-T} = \alpha_{(lat_i,long_i)} + \beta_{(lat_i,long_i)} \cdot log(y_{i0}) + \epsilon_i, \tag{8}$$

where the main difference is the variation of the regression coefficients across space based on the latitude and longitude of each geographical unit. Note that Eq. 8 is a generalized version of Eq. 7. If the regression coefficients of Eq. 8 do not vary across space, the GWR model becomes the OLS model. That is,

$$\alpha_{(lat_i,long_i)} \rightarrow \alpha$$
$$\beta_{(lat_i,long_i)} \rightarrow \beta,$$

when the regression model is stationary across space. The GWR framework uses a nonparametric approach to estimate locally weighted regression coefficients. A weighting kernel function based on geographical distances is used to estimate these local coefficients. After calibrating an optimal kernel bandwidth, observations closer to an estimation point (focal region) have a greater influence on the estimation.

## Results

### Convergence and Spatial Dependence

Table 2 shows per-capita GNI beta convergence estimates for the three sub-periods: 1990–2000, 2000–2010 and 2010–2018. The first, fourth and seventh columns contain regression coefficients for the classical convergence, which was presented in Eq. 1. The intercept $\alpha$ and the coefficient of the initial income per capita $Y_{T0}$ are highly significant for the three sub-periods. Moreover, the negative sign of the coefficient of $Y_{T0}$ indicates that there are signs of beta convergence in income at the first subnational level in South America for all periods.

The speed of convergence and the half-live vary over time as it can be seen in Table 2. The speed of convergence is about 2.8% from 1990 to 2000, then it decreases to 2.3% from 2000 to 2010, and finally it grows to 3.4% in the last 8-year period. Accordingly, the half-life is also dramatically reduced in the last sub-period. Even though convergence in GNI was faster in the last sub-period (2010–2018), there was little improvement in the estimates (see the mean and median in Table 1). This suggests that the convergence process in the last period was driven by overall income stagnation.

The dynamics of income per capita in South America are characterized by a faster convergence speed when comparing them to a study that analyses beta convergence for subnational regions in other countries. In the case of ASEAN, Mendez and Santos-Marquez (2020) find that over the 1998–2012 period, the convergence speed was only 1,7%, with an associated half-life of 41.8 years. However, the slower convergence process in ASEAN may be partly due to a rapid and continuous growth trend in output, which is not the case for South America in the last sub-period. In addition, in the first two sub-periods of our sample, the half-lives are much lower than to the standard 35 years reported for states of the United States and prefectures of Japan (Barro and Sala-i Martin (1991, 1992a)). Thus, it can be concluded that for the South American regions, the catch-up process was relatively faster than the reported for the subnational regions of the United States or Japan.

Moreover, beyond the case of high-income countries, studies that consider multi-country sub-national regions such as Gennaioli et al. (2014), show that a 2% convergence speed is the norm in various regional studies, a speed to which the authors refer as Barro's "iron law". The findings of this paper suggest that the convergence process in GNI per capita in South America is relatively high when focusing in periods of sustained growth (1990–2010). Also, this swift convergence process is to a certain extent robust to the inclusion of spatial effects, which is shown in detail in the following section.

Similarly, the HDI beta convergence estimates are presented in Table 3. The first, fourth, and seventh columns show the regression results for the classical convergence model (Equation 1) for the 10-year and 8-year time frames, respectively. The intercepts $\alpha$ and the coefficients of the initial HDI $Y_{T0}$ are all highly significant at $p < 0.01$. Also, the regression coefficients of $Y_{T0}$ have the expected

**Table 2** GNI per capita beta convergence estimates

| | Dependent variable | | | | | |
|---|---|---|---|---|---|---|
| | GNI per capita 2000 | | | GNI per capita 2010 | | |
| | No spatial effects | Spatial error | Spatial lag | No spatial effects | Spatial error | Spatial lag |
| $\alpha$ | 1.69*** | 1.66*** | 0.56*** | 1.77*** | 1.84*** | 0.83*** |
| | (0.06) | (0.08) | (0.09) | (0.07) | (0.08) | (0.13) |
| $Y_{T0}$ | −0.24*** | −0.21*** | −0.13*** | −0.21*** | −0.25*** | −0.14*** |
| | (0.03) | (0.03) | (0.02) | (0.03) | (0.03) | (0.03) |
| Speed of convergence | 0.028 | 0.024 | 0.014 | 0.023 | 0.029 | 0.015 |
| Half life | 24.99 | 28.77 | 50.66 | 29.65 | 23.9 | 45 |
| $\lambda$ | | 0.819*** | | | 0.724*** | |
| $\rho$ | | | 0.745*** | | | 0.598*** |
| Adjusted $R^2$ | 0.29 | 0.692 | 0.656 | 0.234 | 0.527 | 0.459 |
| Akaike Inf. Crit. | 8.6 | −114.7 | −97.9 | −32.9 | −102.6 | −82.4 |
| LM test SEM | 145.52*** | | | 83.95*** | | |
| LM test SAR | 122.34*** | | | 63.74*** | | |
| Robust LM test SEM | 23.37*** | | | 21.75*** | | |
| Robust LM test SAR | 0.18 | | | 1.54 | | |
| Observations | 151 | 151 | 151 | 151 | 151 | 151 |

| | Dependent variable | | |
|---|---|---|---|
| | GNI per capita 2018 | | |
| | No spatial effects | Spatial error | Spatial lag |
| $\alpha$ | 1.62*** | 1.46*** | 0.48*** |
| | (0.09) | (0.11) | (0.10) |
| $Y_{T0}$ | −0.24*** | −0.16*** | −0.10*** |
| | (0.04) | (0.04) | (0.03) |
| Speed of convergence | 0.034 | 0.021 | 0.013 |
| Half life | 20.64 | 32.62 | 52.89 |
| $\lambda$ | | 0.803*** | |
| $\rho$ | | | 0.774*** |
| Adjusted $R^2$ | 0.192 | 0.632 | 0.628 |
| Akaike Inf. Crit. | 7.7 | −108.1 | −106.3 |
| LM test SEM | 139.57*** | | |
| LM test SAR | 134.29*** | | |
| Robust LM test SEM | 7.08*** | | |
| Robust LM test SAR | 1.8 | | |
| Observations | 151 | 151 | 151 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

negative sign. Therefore, it is possible to conclude that on average, subnational regions in South America are converging in all time periods.

The half-lives and convergence speeds associated to each sub-period show a high degree of heterogeneity. Though the speeds of convergence in the first two sub-periods are about 2.4%, the speed of convergence plummets to about 1.3% in the last period (2010–2018). Thus, the half-life value for the first two periods is about 28 years and 52 years in the later period. In addition, the $R^2$ shows a decreasing trend over time. Initially, about 38% of the variation in HDI growth rates could be explained by the HDI in 1990. This figure declines in the second and third periods to 23% and 5%, respectively.

Taken together, these results shown contrasting patterns between the convergence trends of GNI per capita and HDI. While the convergence speed of GNI per capita rises in the last period, the convergence speed of HDI dramatically drops.

Using the classical convergence model (Eq. 1) requires that the residuals of the OLS regression are spatially independent. In terms of spatial effects, a common test for spatial dependence is the global Moran's I test. The results of this test for each of the six OLS regressions are shown in Table 4. In order to test the robustness of the Moran's I, six different spatial weight matrices where used. With the queen contiguity criterion, two subnational regions are considered neighbours if they share at least a single boundary point. In contrast, to meet the rook contiguity condition more than one shared boundary point is required. Also, three k-nearest neighbours criteria where used, with k equal to 4, 6 and 8. Lastly, a distance band of 771 km was utilized to construct the spatial weight matrix. The distance of 771 km was chosen because this is the distance for which all subnational regions have at least 1 neighbour. Overall, the Moran's I of the regression residuals is significant for all weight matrices.

Regarding GNI per capita, the residuals are highly correlated across space for all the three sub-periods. Moreover, the test shows that the global Moran's I of the regression residuals reached its highest value (0.65) in the 1990–2000 sub-period. Likewise, the residuals of the HDI regressions are also highly correlated across space. The maximum value of this spatial dependence test is reported in the last period. The fact that the spatial dependence test is highly significant for all regressions indicates that the simple non-spatial convergence equation represents a misspecified model. These results suggest that spatial models are more appropriate convergence models for analysing income and HDI disparities in South American regions.

Two spatial models, the spatial error model and the spatial lag model, are used to test convergence for both GNI and HDI and for each of the three sub-periods. Starting with GNI, the regression coefficients for both spatial models are reported in Table 2. For the first sub-period (1990–2000), all coefficients are highly significant, including $\lambda$ and $\rho$. In order to choose the best fitting model, the approach suggested by Anselin and Rey (2014) is followed. Although both Lagrange multipliers tests for the SEM and SAR models are statistically significant, the Robust Lagrange multipliers test is significant only for the former model. Similar results are found for GNI in the sub-periods 2000–2010 and 2010–2018. Therefore, the

**Table 3** HDI beta convergence estimates

| | Dependent variable | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | HDI 2000 | | | HDI 2010 | | | HDI 2018 | | |
| | No spatial effects | Spatial error | Spatial lag | No spatial Effects | Spatial error | Spatial lag | No spatial effects | Spatial error | Spatial lag |
| $\alpha$ | 2.01*** | 2.11*** | 1.27*** | 1.98*** | 2.07*** | 1.20*** | 1.46*** | 1.30*** | 0.41*** |
| | (0.10) | (0.10) | (0.15) | (0.13) | (0.15) | (0.18) | (0.15) | (0.13) | (0.12) |
| $Y_{T0}$ | −0.22*** | −0.25*** | −0.17*** | −0.22*** | −0.24*** | −0.16*** | −0.10*** | −0.06** | −0.04* |
| | (0.02) | (0.02) | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.02) |
| Speed of convergence | 0.025 | 0.028 | 0.019 | 0.024 | 0.027 | 0.018 | 0.013 | 0.008 | 0.005 |
| half life | 27.44 | 24.48 | 36.05 | 28.49 | 25.55 | 38.96 | 52.19 | 85.96 | 126.23 |
| $\lambda$ | | 0.653*** | | | 0.601*** | | | 0.791*** | |
| $\rho$ | | | 0.497*** | | | 0.525*** | | | 0.783*** |
| Adjusted $R^2$ | 0.376 | 0.57 | 0.508 | 0.233 | 0.421 | 0.382 | 0.048 | 0.551 | 0.55 |
| Akaike Inf. Crit. | −604 | −657.2 | −636.8 | −564.5 | −604.1 | −594.2 | −578.8 | −689.2 | −688.8 |
| LM test SEM | 68.14*** | | | 49.91*** | | | 136.01*** | | |
| LM test SAR | 40.09*** | | | 34.74*** | | | 133.77*** | | |
| Robust LM test SEM | 29.51*** | | | 16.94*** | | | 2.69 | | |
| Robust LM test SAR | 1.46 | | | 1.76 | | | 0.45 | | |
| Observations | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 |

*p<0.1; **p<0.05; ***p<0.01

**Table 4** Moran's I test of the regression residuals

| Regression | Spatial weights | | | | | |
|---|---|---|---|---|---|---|
| | Queen | Rook | K = 4 | K = 6 | K = 8 | Distance band = 771 km |
| GNIpc 1990–2000 | 0.65*** | 0.65*** | 0.67*** | 0.62*** | 0.58*** | 0.48*** |
| GNIpc 2000–2010 | 0.5*** | 0.5*** | 0.48*** | 0.47*** | 0.46*** | 0.45*** |
| GNIpc 2010–2018 | 0.64*** | 0.64*** | 0.63*** | 0.6*** | 0.59*** | 0.38*** |
| HDI 1990–2000 | 0.45*** | 0.45*** | 0.41*** | 0.4*** | 0.38*** | 0.3*** |
| HDI 2000–2010 | 0.38*** | 0.39*** | 0.39*** | 0.38*** | 0.34*** | 0.22*** |
| HDI 2010–2018 | 0.63*** | 0.63*** | 0.65*** | 0.61*** | 0.62*** | 0.42*** |

***Means that value of Moran's I test is statistically significant at 1 percent level

SEM is the best fitting model to account for the variation of the growth rates and spatial dependence.

The speed of convergence and half-lives are also reported for the SEM model. For all sub-periods, the speeds of convergence of the SEMs are between 2% and 3%. This implies that half-life had values between 24 and 33 years. These results reinforce the previous findings in the literature that have reported a 2% speed of convergence as a benchmark in regional income convergence (Barro and Sala-i Martin 1992a).

The SEM and SAR estimates for HDI are reported in Table 3. The coefficients for all periods and for the two spatial models are highly significant with *p-values* below 0.01. Overall, the first two sub-periods present similar patterns. In both sub-periods, the SEM was found to be the best fitting model, according to the Robust Lagrangian multipliers test. Additionally, the speed of convergence is about 2.7% in both periods and the half-lives also have similar magnitudes.

In contrast, in the last sub-period (2010–2018), the Lagrangian multiplier test results are inconclusive. The test results for the SEM and SAR models are significant, with values of 136.01 and 133.77, respectively. Nonetheless, the robust Lagrangian multiplier test is not significant for either model. These results suggest that more complex spatial models such as the spatial Durbin model, the spatial Durbin error model, among others, may be better suited to account for the spatial dependence in the last period. This extension of the paper is left for further research.

The convergence speeds of the SEM and SAR models in the last period are significantly smaller than those reported for the classical model. For the SEM model, the speed is about 0.8% and the half-life is about 86 years. For the SAR model, the speed is much smaller at about 0.5% and the half-life is about 126 years. Although there is not a conclusive answer over the best fitting model, the weaker speeds reported in the spatial models indicate that spatial effects may be responsible for a slower convergence process in HDI from 2010 to 2018.

Overall, our spatial specifications suggest that accounting for spatial dependence accelerates the speed of convergence in some decades, but decelerates it in others. When comparing the SEM and SAR specifications, the former is found to be the

**Table 5** Convergence coefficients for GNI per capita

| | Sub-period | | |
|---|---|---|---|
| | 1990–2000 | 2000–2010 | 2010–2018 |
| *OLS Global Estimate* | | | |
| Estimate | −0.242*** | −0.208*** | −0.236*** |
| R-squared | 0.295 | 0.239 | 0.198 |
| AIC | 6.5 | −34.9 | 5.7 |
| *GWR Local Estimates* | | | |
| Mean | −0.123 | −0.245 | −0.316 |
| Stand. Dev. | 0.174 | 0.183 | 0.218 |
| Min | −0.386 | −0.793 | −0.914 |
| Median | −0.153 | −0.204 | −0.273 |
| Max | 0.175 | 0.034 | −0.006 |
| R-squared | 0.753 | 0.692 | 0.682 |
| AIC | −125 | −145 | −108 |

***Means that the coefficient is statistically significant at 1 percent level. An evaluation of statistical significance for the GWR estimates is presented in Figs. 1, 2 and 3

best fitting model. This result is consistent with the seminal work of Rey and Montouri (1999), which finds that the SEM model provides a better characterization of the regional income convergence in the US. A limitation of the SEM model, however, is that—by construction—the specific magnitude of spillovers is not measurable (Le-Gallo 2019).

### Convergence and Spatial Heterogeneity

Convergence results based on the spatial heterogeneity model are presented in Table 5 and 6 for GNI and HDI, respectively. Each table first presents the results of a global convergence estimate, which is based on the ordinary least squares (OLS) method. The second part of the table presents the results of local convergence estimates, which are based on the geographically weighted (GWR) regression method described in Sect. 3.4.

Table 5 presents the convergence coefficient estimates of GNI for each sub-period of the study. Although a process of regional convergence occurs over the entire 1990–2018 period, the speed with which this process happens varies over time. For instance, the global estimate of the convergence coefficient indicates the speed of regional convergence was highest during the 1990–2000 sub-period. It then decreased (in absolute value) to 0.208 in the next decade and increased to 0.236 in the 2010–2018 sub-period. The local estimates of the convergence coefficient also show variation over time, but with a different pattern. As indicated by the mean and median of the estimates, the convergence speed is monotonically increasing over time.

One of the most appealing features of the GWR framework is the visualization of the estimated parameters across space. Figures 1, 2 and 3 present the spatial

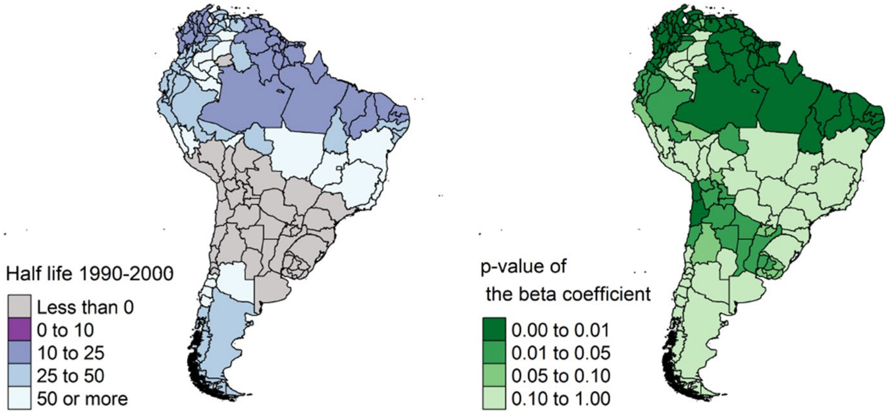


**Fig. 1** GNI per capita 1990–2000

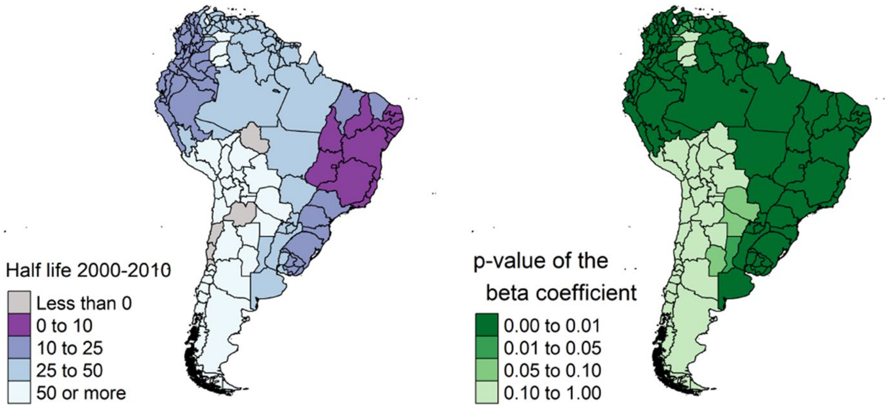


**Fig. 2** GNI per capita 2000–2010

variation of the convergence speed of GNI. To facilitate the interpretation of the convergence speed, the half-life indicator is used in all figures. This indicator is measured in years and represents the time that a region needs to halve the distance between its current state and its long-run equilibrium. Each figure contains two maps. The map on left shows the spatial distribution of the half-life indicator, which was derived from the estimated local convergence coefficients. The map on the right shows the spatial distribution of the p-value of each coefficient.

The central message of Figs. 1, 2 and 3 is that the economic convergence process of South America is characterized by multi-country spatial clusters. For instance, during the 1990–2000 sub-period, Fig. 1 shows that the regions experiencing a diverging process (less than 0 in terms of half-lives) are located along the bottom center of South America. Specifically, those regions belong to the southern part of Brazil and Peru, the entire country of Uruguay and Paraguay,

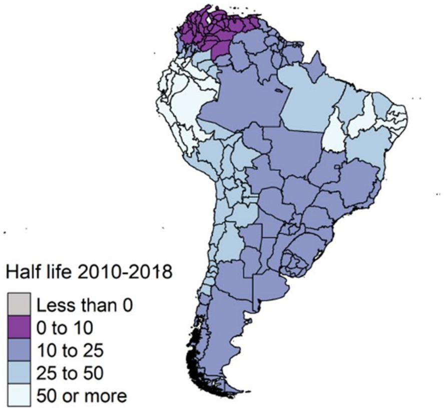


**Fig. 3** GNI per capita 2010–2018

**Table 6** Convergence coefficients for HDI

| | Sub-period | | |
|---|---|---|---|
| | 1990–2000 | 2000–2010 | 2010–2018 |
| *OLS Global estimate* | | | |
| Estimate | −0.223*** | −0.216*** | −0.101*** |
| R-squared | 0.38 | 0.238 | 0.055 |
| AIC | −605 | −566 | −580 |
| *GWR Local Estimates* | | | |
| Mean | −0.256 | −0.293 | −0.184 |
| Stand. Dev. | 0.123 | 0.257 | 0.136 |
| Min | −0.562 | −0.939 | −0.537 |
| Median | −0.259 | −0.191 | −0.169 |
| Max | −0.051 | 0.031 | 0.057 |
| R-squared | 0.702 | 0.629 | 0.624 |
| AIC | −690 | −648 | −693 |

***Means that the coefficient is statistically significant at 1 percent level. An evaluation of statistical significance for the GWR estimates is presented in Figs. 4, 5 and 6

the northern part of Argentina and Chile, and most regions of Bolivia.[3] During the 2010–2018 sub-period, Fig. 3 shows a clear cluster of regions sharing similar convergence speeds (half-lives from 10 to 25 years). The regions belonging to this cluster are from multiple countries including Venezuela, Brazil, Bolivia, Colombia Paraguay, Uruguay, Argentina, and Chile.

Table 6 presents the convergence coefficient estimates of HDI for each sub-period of the study. Although a process of regional convergence occurs over the

[3] Nevertheless, as indicated by the p-value map associated with Fig. 1, many of the regions belonging to this cluster show no significant values.

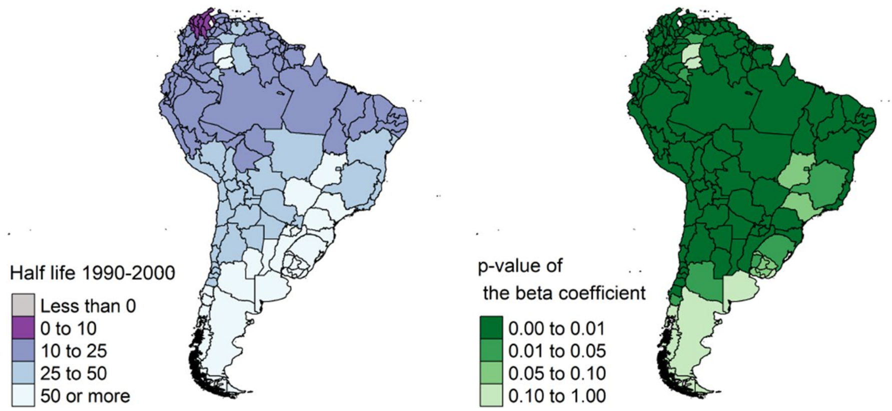


**Fig. 4** HDI 1990–2000

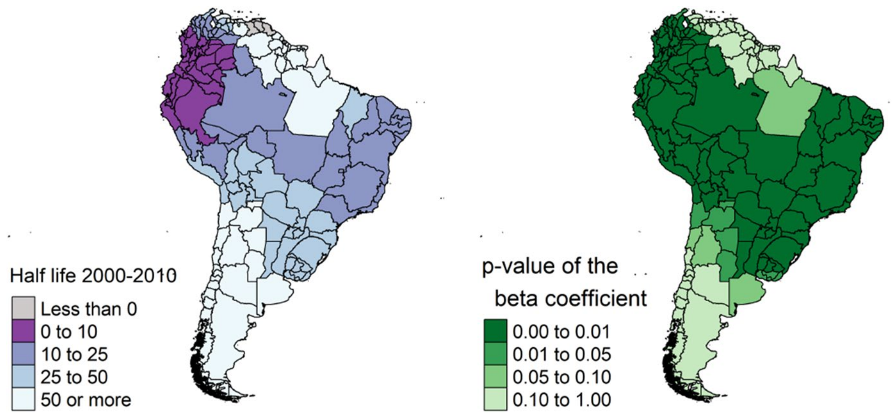


**Fig. 5** HDI 2000–2010

entire 1990–2018 period, the speed of convergence has been decreasing over time. For instance, the global estimate of the convergence coefficient indicates the speed of regional convergence (in absolute values) was highest during the 1990–2000 sub-period. During the 2010–2018 period, the absolute value of the convergence coefficient was less than half of that in the 1990–2000 sub-period. To a large extend, the GWR local estimates confirm this slowdown in the convergence coefficient. In the 1990–2000 sub-period, the absolute value of the median convergence coefficient was 0.259. By the 2010–2018 sub-period, however, this value has reduced to 0.169.

Figures 4, 5 and 6 show the spatial variation of the convergence speed (measured in years) of HDI. Similar to the spatial distribution of GNI, the convergence speed shows marked spatial clusters that are composed by subnational regions from multiple countries. For instance, in the 1990–2000 sub-period (Fig. 4), regions in the north of South America were converging at a faster speed than those in the south.

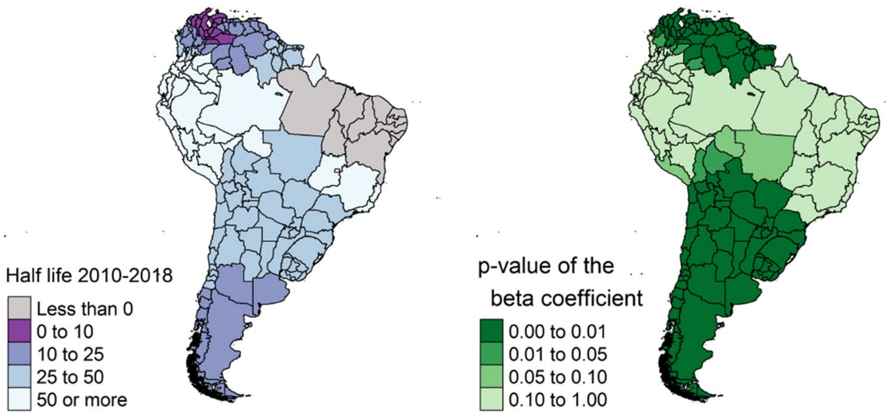


**Fig. 6** HDI 2010–2018

During the 2000–2010 sub-period, a fast convergence cluster has appeared in the northeast of the South America. This cluster is composed by the northern regions of Peru, all the regions of Ecuador, and some regions of Colombia. In this cluster, regions are expected to halve their HDI gaps in less than 10 years. Interestingly, in the 2010–2018 sub-period, that cluster has suffered a large slowdown in its speed of convergence. Regional HDI gaps are now expected to be reduced by half after 50 years or more. This result, however, needs to be interpreted with caution as the p-value map of Fig. 6 indicates that the convergence coefficients of these regions are not statistically significant.

## Concluding Remarks

Many studies have analyzed convergence of social and economic indicators across countries. Fewer studies, however, have evaluated convergence across the subnational regions of multiple countries. By using a novel multi-country subnational dataset on the human development index (HDI), we evaluate the evolution of economic and social disparities across 151 subnational regions of South America over the 1990–2018 period.

Our main results are as follows. First, for both gross national income per capita (GNI) and human development index (HDI), spatially adjusted specifications should be used as the residuals of standard OLS regressions show strong and significant spatial dependence patterns. Second, there is an overall process of regional convergence for both GNI and HDI. Third, a spatial error specification suggests that spatial dependence accelerates the speed of convergence in some decades, but decelerates it in others. Forth, results from the geographically weighted regression framework indicate that the speed of convergence is largely heterogeneous across space. Fifth, the evolution of economic and social disparities are characterized by multi-country spatial clusters that show localized converging and diverging patterns. Taken together, these results emphasize the importance of accounting for spatial dependence and heterogeneity when evaluating the dynamics of economic and social inequality in South America.

In this study, the convergence patterns of a subnational version of GNI and HDI are analyzed. Nevertheless, the dataset assembled by Smits and Permanyer (2019) also includes information on the other two components of HDI: educational and health indexes. The analysis of the convergence of these indicators is a possible extension that is left for further research.

The results presented in this paper also indicate possible avenues for further research in terms of methodological approaches. Firstly, other spatial econometric specifications may be used to study spatial dependence. Although the seminal contribution of Rey and Montouri (1999) suggests that the spatial error (SEM) specification is the most adequate to model the convergence process, more recent convergence studies argue in favor a spatial Durbin (SDM) specification (Fischer 2011, 2016). In addition, this paper did not present an exploratory spatial data analysis; thus, the study of hot and cold spots by computing local indicators of spatial association is also left for future studies. Lastly, to explicitly account for the spatial dimension of the growth process, one could also apply the spatial filter approach of Getis and Griffith (2002) and Getis and Ord (2010). Evaluating the role of spacial dependence through spatial filters may prove useful to delve deeper into the nature of the spatial convergence process (Fischer and Stumpner 2008; Santos-Marquez et al. 2021).

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## References

Agudelo Torres, G., L.E. Franco Ceballos, and L.C. Franco Arbeláez. 2015. Aplicación de la econometría espacial para el análisis de la miseria en los municipios del departamento de antioquia. *Semestre Económico* 18 (37): 103–127.

Akçagün, P. 2017. Provincial growth in Turkey: A spatial econometric analysis. *Applied Spatial Analysis and Policy* 10 (2): 271–299. https://doi.org/10.1007/s12061-016-9183-5.

Álvarez-Gamboa, J., P. Cabrera-Barona, and H. Jácome-Estrella. 2021. Financial inclusion and multidimensional poverty in ecuador: A spatial approach. *World Development Perspectives* 22: 100311.

Anselin, L. 1995. Local indicators of spatial association-lisa. *Geographical Analysis* 27 (2): 93–115.

Anselin, L. 2013. *Spatial Econometrics: Methods and Models*, vol. 4. Springer.

Anselin, L., and S.J. Rey. 2014. *Modern spatial econometrics in practice: A guide to GeoDa, GeoDaSpace and PySAL*. GeoDa Press LLC.

Anselin, L., S. Sridharan, and S. Gholston. 2007. Using exploratory spatial data analysis to leverage social indicator databases: The discovery of interesting patterns. *Social Indicators Research* 82 (2): 287–309.

Arbia, G. 2006. *Spatial Econometrics: Statistical Foundations and Application to Regional Convergence*. Springer.

Ayouba, K., J. Le Gallo, and A. Vallone. 2020. Beyond gdp: An analysis of the socio-economic diversity of european regions. *Applied Economics* 52 (9): 1010–1029.

Barrios, C., E. Flores, and M.Á. Martínez. 2019. Convergence clubs in Latin America. *Applied Economics Letters* 26 (1): 16–20. https://doi.org/10.1080/13504851.2018.1433288.
Barro, R. 2015. Convergence and modernisation. *The Economic Journal* 125 (585): 911–942.
Barro, R., and X. Sala-i Martin. 1991. Convergence across states and regions. *Brookings papers on economic activity* 1991 (1): 107–182.
Barro, R., and X. Sala-i Martin. 1992. Convergence. *Journal of Political Economy* 100 (2): 223–251.
Barro, R., and X. Sala-i Martin. 1992. Regional growth and migration: A Japan-united states comparison. *Journal of the Japanese and International Economies* 6 (4): 312–346.
Barro, R.J. 1991. Economic growth in a cross section of countries. *The Quarterly Journal of Economics* 106 (2): 407–443.
Barro, R.J., and X. Sala-I-Martin. 2004. *Economic growth*. Cambridge, Mass: MIT Press.
de Barros, P.H.B., and A.L. Stege. 2019. Deforestation and human development in the brazilian agricultural frontier: An environmental kuznets curve for matopiba. *Revista Brasileira de Estudos Regionais e Urbanos* 13 (2): 161–182.
Brunsdon, C., A.S. Fotheringham, and M.E. Charlton. 1996. Geographically weighted regression: A method for exploring spatial nonstationarity. *Geographical Analysis* 28 (4): 281–298.
Brunsdon, C., A.S. Fotheringham, and M. Charlton. 1998. Spatial nonstationarity and autoregressive models. *Environment and Planning A* 30 (6): 957–973.
Brunsdon, C., A.S. Fotheringham, and M. Charlton. 1999. Some notes on parametric significance tests for geographically weighted regression. *Journal of Regional Science* 39 (3): 497–524.
Cepeda-Cuervo, E., and V. Núñez-Antón. 2013. Spatial double generalized beta regression models: Extensions and application to study quality of education in Colombia. *Journal of Educational and Behavioral Statistics* 38 (6): 604–628.
Delboy, M. 2019. Determinants of school attendance rate for Bolivia: A spatial econometric approach. *The e-Jounal of Economics & Complexity* 1: 89–112.
Dobson, S., and C. Ramlogan. 2002. Economic growth and convergence in Latin America. *Journal of Development Studies* 38 (6): 83–104.
Domínguez, A., and C. Mendez. 2019. Industrial productivity divergence and input-output network structures: Evidence from Japan 1973–2012. *Economies* 7 (2): 52.
Duncan, R., and R. Fuentes. 2006. Regional convergence in Chile: New tests, old results. *Cuadernos de economía* 43 (127): 81–112.
Eckey, H.F., R. Kosfeld, and M. Türck. 2007. Regional convergence in Germany: A geographically weighted regression approach. *Spatial Economic Analysis* 2 (1): 45–64. https://doi.org/10.1080/17421770701251905.
Elias, M., and S. Rey. 2011. Educational performance and spatial convergence in Peru. *Région et Développement* 33: 107–135.
Ferrer Velasco, R., M. Köthke, M. Lippe, and S. Günter. 2020. Scale and context dependency of deforestation drivers: Insights from spatial econometrics in the tropics. *PloS One* 15 (1): e0226830.
Fischer, M., and P. Stumpner. 2008. Income distribution dynamics and cross-region convergence in Europe. *Journal of Geographical Systems* 10 (2): 109–139. https://doi.org/10.1007/s10109-008-0060-x.
Fischer, M.M. 2011. A spatial Mankiw–Romer–Weil model: Theory and evidence. *Annals of Regional Science* 47 (2): 419–436. https://doi.org/10.1007/s00168-010-0384-6.
Fischer, M.M. 2016. Spatial Externalities and Growth in a Mankiw–Romer–Weil World: Theory and Evidence. *International Regional Science Review* 41 (1): 45–61. https://doi.org/10.1177/0160017616628602.
Fujita, L.D.V., I.P. Bagolin, and A. Fochezatto. 2021. Spatial distribution and dissemination of education in Brazilian municipalities. *The Annals of Regional Science* 66 (2): 255–277.
Galvao, A., and F. Reis Gomes. 2007. Convergence or divergence in Latin America? A time series analysis. *Applied Economics* 39 (11): 1353–1360.
Garrido, N., A. Marina, and D. Sotelsek. 2002. Dinámica de la distribución del producto a través de las provincias argentinas (1970–1995). *Estudios de Economía Aplicada* 20 (002): 123–140.
Gennaioli, N., R. La Porta, F.L. De Silanes, and A. Shleifer. 2014. Growth in regions. *Journal of Economic growth* 19 (3): 259–309.
Getis, A., and D.A. Griffith. 2002. Comparative spatial filtering in regression analysis. *Geographical Analysis* 34 (2): 130–140.
Getis, A., and J.K. Ord. 2010. The analysis of spatial association by use of distance statistics. In *Perspectives on Spatial Data Analysis*, Springer, pp. 127–145

González, L.M.C. 2004. Estudios de convergencia y divergencia regional en américa latina: balance y perspectivas. *Investigaciones Regionales= Journal of Regional Research* 5: 29–66.
Hernández, H.R., and D.I.L. Nieto. 2013. Convergencia regional en el índice de desarrollo humano en colombia. *Equidad y desarrollo* 20: 105–141.
Ingram, M.C., and M. Marchesini da Costa. 2019. Political geography of violence: Municipal politics and homicide in Brazil. *World Development* 124: 104592. https://doi.org/10.1016/j.worlddev.2019.06.016.
Islam, N. 1995. Growth empirics: A panel data approach. *Quarterly Journal of Economics* 110 (4): 1127–1170.
Jordá, V., and J.M. Sarabia. 2014. Well-Being Distribution in the Globalization Era: 30 Years of Convergence. *Applied Research in Quality of Life* 10 (1): 123–140. https://doi.org/10.1007/s11482-014-9304-8.
Jordá, V., and J.M. Sarabia. 2015. International Convergence in Well-Being Indicators. *Social Indicators Research* 120 (1): 1–27. https://doi.org/10.1007/s11205-014-0588-8.
Konya, L., and M.C. Guisan. 2008. What Does the Human Development Index Tell Us About Convergence? *Applied Econometrics and Human Development* 8 (1): 19–40.
Le-Gallo, J. 2019. Cross-Section Spatial Regression Models. In *Handbook of Regional Science*, 2nd ed., ed. M. Fischer and P. Nijkamp, 1–24. Spring-Verlag. https://doi.org/10.1007/978-3-642-36203-3_85-1.
Lessmann, C., and A. Seidel. 2017. Regional inequality, convergence, and its determinants A view from outer space. *European Economic Review* 92 (November 2016): 110–132. https://doi.org/10.1016/j.euroecorev.2016.11.009.
Magalhães, A., G.J. Hewings, and C.R. Azzoni. 2005. Spatial dependence and regional convergence in brazil. *Investigaciones Regionales-Journal of Regional Research* 6: 5–20.
Martín-Mayoral, F., and J.Y. Zúñiga. 2013. Evolución de las disparidades en el desarrollo económico y humano de América Latina: Análisis del IDH y sus componentes. *Economia Mexicana, Nueva Epoca* 22 (3): 203–246.
Matos, P.V., and H.C. Faustino. 2012. Beta-convergence and sigma-convergence in corporate governance in europe. *Economic Modelling* 29 (6): 2198–2204.
Mazumdar, K. 2002. A note on cross-country divergence in standard of living. *Applied Economics Letters* 9 (2): 87–90.
Mendez, C. 2018. Beta, sigma and distributional convergence in human development? Evidence from the metropolitan regions of Bolivia. *Revista Latinoamericana de Desarrollo Económico* 30: 87–115.
Mendez, C., and F. Santos-Marquez. 2020. Regional convergence and spatial dependence across subnational regions of ASEAN: Evidence from satellite nighttime light data. *Regional Science Policy & Practice*. https://doi.org/10.1111/rsp3.12335.
Noorbakhsh, F. 2007. International Convergence or Higher Inequality in Human Development? Evidence for 1975–2002. In *Advancing Development*, Palgrave Macmillan UK, London, pp 149–167, https://doi.org/10.1057/9780230801462_9
Öcal, N., and J. Yildirim. 2010. Regional effects of terrorism on economic growth in Turkey: A geographically weighted regression approach. *Journal of Peace Research* 47 (4): 477–489. https://doi.org/10.1177/0022343310364576.
Peiró-Palomino, J. 2019. Regional well-being in the OECD. *The Journal of Economic Inequality* 17 (2): 195–218. https://doi.org/10.1007/s10888-018-9398-6
Ponce, P., N. Aguirre-Padilla, C. Oliveira, J. Álvarez-García, MdlC. del Río-Rama, et al. 2020. The spatial externalities of tourism activities in poverty reduction. *Sustainability* 12 (15): 6138.
Resende, G.M. 2013. Spatial dimensions of economic growth in brazil. International Scholarly Research Notices 2013
Rey, S., and B.D. Montouri. 1999. US regional income convergence: A spatial econometric perspective. *Regional Studies* 33 (2): 143–156. https://doi.org/10.1080/00343409950122945.
Rey, S.J., and M.V. Janikas. 2005. Regional convergence, inequality, and space. *Journal of Economic geography* 5 (2): 155–176.
Rodrik, D. 2013. Unconditional convergence in manufacturing. *The Quarterly Journal of Economics* 128 (1): 165–204.
Royuela, V., and G.A. Garcia. 2015. Economic and social convergence in colombia. *Regional Studies* 49 (2): 219–239.

Santos-Marquez, F., A. Gunawan, and C. Mendez. 2021. Regional income disparities, distributional convergence, and spatial effects: Evidence from Indonesian regions 2010–2017. *GeoJournal*. https://doi.org/10.1007/s10708-021-10377-7.

Smits, J., and I. Permanyer. 2019. The subnational human development database. *Scientific data* 6: 190038.

Sutcliffe, B. 2004. World Inequality and Globalization. *Oxford Review of Economic Policy* 20 (1): 15–37. https://doi.org/10.1093/oxrep/grh002.

Urquiola, M., A. Lykke, E. Antelo, J.L. Evia, O. Nina, and B.I. de Desarrollo. 2000. Geography and development in Bolivia: Migration, urban and industrial concentration, welfare, and convergence: 1950-1992. Bid (Banco Interamericano de Desarrollo)

Val, M.M.S., D.G.P. de Lema, and F.A.L. Hernández. 2009. Spatial effects in the productivity convergence of spanish industrial sme's. *Spanish Journal of Finance and Accounting/Revista Española de Financiación y Contabilidad* 38 (141): 13–36.

Wan, G.H. 2005. Convergence in food consumption in rural China: Evidence from household survey data. *China Economic Review* 16 (1): 90–102.

Zhang, H., X. Shi, T.S. Cheong, and K. Wang. 2020. Convergence of carbon emissions at the household level in China: A distribution dynamics approach. *Energy Economics* 92: 104956.

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