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 the 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 frameworks. The first framework highlights 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 framework highlights 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, the dynamics of economic and social inequality in South America 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 Codes: R10, R11, R58

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1. 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. There is little evidence, however, on the spatial variation of well-being at the subnational level. This paper exploits a novel dataset to evaluate the dynamics of well-being and its determinants across almost all 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 regional convergence in well-being.

Well-being is measured based on the human development index of the United Nations. Specifically, this paper uses subnational version of the human development index and one of its components: 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 more suitable setting for evaluating the relationship between well-being and spatial effects. Previous studies that focus on national-level data usually fail to identify statistically significant and robust spatial effects. Other studies that focus on a few selected countries fail to provide a comprehensive evaluation of South America. In this paper, we use the largest and latest regional dataset to overcome these limitations.

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 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 the spatial error and the spatial lag models. In addition, the role of spatial heterogeneity is evaluated using a multi-scale geographically weighted regression.

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 balanced dataset of well-being and income to test beta convergence. Secondly, to the best of our knowledge this is the first study to analyze the convergence patterns across subnational regions in South America. Lastly, by diving the sample in different time periods this paper shows that the convergence process has not been completely 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 section 3 the well-being and income data is described, and the methods of regional convergence and spatial dependence and heterogeneity are briefly explained. Section 4 presents the results of the spatial analysis of convergence. Lastly, section 5 offers some concluding remarks.

2. Related literature

There are several convergence frameworks in the literature. The most common methodology is known as beta convergence. In terms of output, beta convergence occurs when countries with initially low levels of output tend to grow faster than rich countries. This type of convergence was originally tested in cross-country regressions (Barro (1991); Barro and Sala-i

Martin (1992a)). Ever since, the literature has expanded, and convergence has been tested across a variety of observational units (firms, households, regions, etc.) and socio-economic variables.

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 their steady state development in about 88 years, which is significantly lower 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, a phenomenon that is known as sigma-convergence.

Other earlier studies include Mazumdar (2002) who finds divergence using linear and non-linear 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 since most HDI data has been collected from 1975. Sutcliffe (2004) though finding strong sings of beta convergence for the 1975-2001 period, claims that the convergence is almost certain as the index is bounded by definition. The author goes further to claim that ”HDI convergence,.. is more a logical than an empirical result, arising from the index's definition, and so is of little interest in the debate about world inequality”. 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 new convergence frameworks. For example, Jordá and Sarabia (2014) using nonparametric kernel density estimates conclude that the HDI distribution has shifted to the right from

1980 to 2012, signalling higher development outcomes. 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 coefficients 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. Using the linear model, the authors find weak absolute 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 indices beyond HDI have also been analyzed. For example, Peiró-Palomino (2019) aggregates variables from a regional OECD dataset into a new well-being indicator. The author studies the convergence of this indicator using distribution dynamics analysis and conditional density estimation. He reports strong signs of polarization, with the well-being distribution showing two convergence clubs.

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 of sigma convergence from the early 2000s.

At the subantional level, to the best of our knowledge there are no studies of well-being convergence across this type of regions in South America. Nevertheless, there are some papers that test convergence within individual countries. One of these studies is Hernández and Nieto (2013) in which the authors 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. In a more recent study of Bolivia's development, Mendez-Guerra (2018) 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 subperiod 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 much 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 1.995. For 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 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).

3. Data and methods

3.1 Data: The subnational human development index

A new Human development index dataset for a large sample of sub-national regions of the world has been assembled by Smits and Permanyer (2019). The dataset is an extension of the country level HDI to the first administrative level regions across the world. Similarly to the country level index, the subnatinal HDI is the average of the values of the following three dimensions: education, health and income. More details regarding the construction of the database, and the handling of missing data and interpolations can be found in Smits and Permanyer (2019).[1]

For this research, data for the sub-national regions in South America were selected for the period 1990-2018. In addition, two variables were considered: the HDI and Gross National Income per capita (PPP, 2011 US$). We use the version 4.0 of the database that was released in March 2020. Moreover, the world shapefile provided in the aforementioned website was utilized. In order to conduct the spatial regression analysis with a contiguity weight matrix, islands were removed from the shapefile of South America. The final shapefile includes 151 sub-national regions.

In the first four columns of table 1 descriptive statistics of Gross

[1] All data are freely accessible on the website of the Global Data lab (https://globaldatalab.org/)

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 the last year. 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.

In terms of the subanational Human Development Index, sumamry statistics for selected years are shown in columns 5 to 8 of table 1. HDI appears to be improving over time, as the mean and the median have steadily increased. Though there is fluctuation in the interim years between 1990 and 2018, the dispersion as measured by the IQR and the standard deviation were greater in 1990 than in 2018.

3.2 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:

$$(1/T) \cdot log\frac{y_{iT}}{y_{i0}} = \alpha - \frac{[1 - e^{-\beta T}]}{T} \cdot log(y_{i0}) + w_{i,0T} \tag{1}$$

Where i is the index for each region, 0 and T represent the initial and final times, y is the economic level, β is the speed of regional convergence, α is a constant term and $w_{i,0T}$ represents the error term. besides the β coefficient, a second parameter known in the convergence literature as the ”half-life” can be computed as

$$half \cdot life = \frac{log2}{\beta} \tag{2}$$

Table 1: descriptive statistics for selected years for Human Development Index and gross national income per capita

	GNI				HDI			
Year	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

Notes: 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.

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

3.3 Spatial dependence analysis

The coefficients of the standard beta regression model (1) are computed using an OLS framework. Such framework requires the independence among observations (regions). Nevertheless, if the data presents patterns of spatial clustering, the assumption of ”independence” may be violated. In order to overcome this problem, several econometric models have been used in the literature to account for spatially autocorrelated variables.

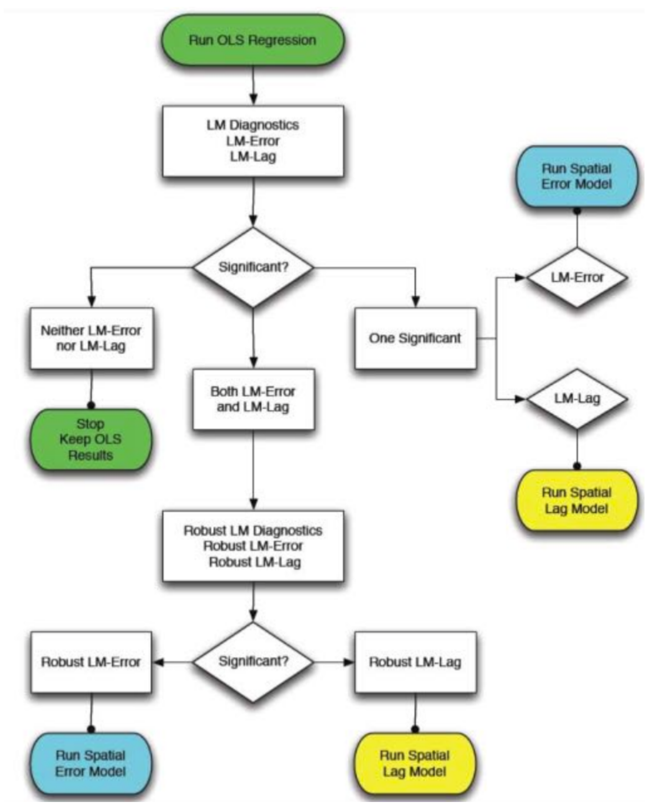

Figure 1: Model Selection. Figure adapted from Anselin and Rey (2014)).

In principle, for cross-sectional data many plausible spatial models can be used. Some of these models include: the spatial lag model, the spatial cross-regressive model and the spatial Durbin model, among others. In this paper, the approach suggested by Anselin (2013) and Anselin and Rey (2014), will be used to select the best fitting model. A visual representation of this approach is shown in figure 1.

According to figure 1 the spatial model specification depends on the significance of the Lagrange Multiplier (LM) test. The significance of the LM test or the robust LM test indicates which model should be used. In this approach there are two available models, the spatial error model and the spatial lag model. These models are described in equations 3 and 4.

The spatial lag model:

$$log\frac{y_{iT}}{y_{i0}} = \alpha + \beta \cdot log(y_{i0}) + \rho W \cdot log\frac{y_{iT}}{y_{i0}} + \epsilon_t \tag{3}$$

The Spatial error model:

$$log\frac{y_{iT}}{y_{i0}} = \alpha + \beta \cdot log(y_{i0}) + \lambda W \epsilon_t + u_t \tag{4}$$

3.4 Spatial heterogeneity analysis

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 an ordinary linear regression model, which can be expressed as:

$$y_i = \beta_0 + \sum_{k=1}^{m} \beta_k \cdot x_{ki} + u_i, \tag{5}$$

where y_i represents the observations of the dependent variable, β_k represents the regression coefficient of each explanatory variable x_k, and x_{ki} represents the observations of each of the k explanatory variables. Equation 5 represents a global model in which the regression coefficients, β_k, are homogeneous across the geographical space. In a GWR framework, the coefficients of the the global model are replaced by local parameters that indicate the potential existence of spatial heterogeneity. Specifically, Equation 5 is re-expresed as

$$y_i = \beta_{0i} + \sum_{k=1}^{m} \beta_{ki} \cdot x_{ki} + u_i, \tag{6}$$

where the main difference is the variation of the regression coefficients, β_{ki}, across space.

4. Results

4.1 Convergence and spatial dependence

Table 2 shows the GNI per capita beta convergence estimates for the three transitions: 1990-2000, 2000-2010 and 2010-2018. The first, fourth and seventh columns contain the regression coefficients for the classical convergence equation 1. The intercepts α and the coefficients of the initial income per capita Y_{T0} are highly significant for the three transitions. Moreover, the negative sign of the coefficient of Y_{T0} indicates that there are signs of beta convergence in Income at the subnational level in South America for all periods.

The speed of convergence and the half-lives 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 transition up to 2018. Accordingly, the half-life is also dramatically reduced in the last period. Even though the convergence of GNI was faster in the last period (2010-2018), there was little improvement in centrality estimates (see the mean and median in table 1). This suggest that the convergence process in the last period was driven by overall income stagnation.

Similarly, the HDI beta convergence estimates are presented in table 3. The first, fourth and seventh columns have the regression results for the classical convergence model (equation 1) for the 10-year and 8-year timeframes. The intercepts α and the coefficients of the initial HDI Y_{T0} are all highly significant with a $p < 0.01$. Also, the regression coefficients of Y_{T0} have the expected negative sign. Therefore, it is possible to conclude that on average subnational regions in South America are converging to a common steady state in all time periods.

The half-lives and convergence speeds associated to each time transitions show a high degree of heterogeneity. Though, the speeds of convergence in the first two transitions are about 2.4%, in the last period (2010-2018) the speed of convergence plummets to about 1.3%. 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 (1) requires that the residuals of the OLS regression are uncorrelated. In terms of spatial effects, a common test for spatial dependence is the Moran's I test. The estimates of this spatial dependence test of the residuals for each of the 6 OLS regressions are shown in table 4.

Table 2: GNI per capita beta convergence estimates

	Dependent variable:								
	GNI per capita 2000			GNI per capita 2010			GNI per capita 2018		
	no spatial effects	spatial error	spatial lag	no spatial effects	spatial error	spatial lag	no spatial effects	spatial error	spatial lag
α	1.69***	1.66***	0.56***	1.77***	1.84***	0.83***	1.62***	1.46***	0.48***
	(0.06)	(0.08)	(0.09)	(0.07)	(0.08)	(0.13)	(0.09)	(0.11)	(0.10)
Y_{T0}	−0.24***	−0.21***	−0.13***	−0.21***	−0.25***	−0.14***	−0.24***	−0.16***	−0.10***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)
speed of convergence	0.028	0.024	0.014	0.023	0.029	0.015	0.034	0.021	0.013
half life	24.99	28.77	50.66	29.65	23.9	45	20.64	32.62	52.89
λ		0.819***			0.724***			0.803***	
ρ			0.745***			0.598***			0.774***
Adjusted R^2	0.29	0.692	0.656	0.234	0.527	0.459	0.192	0.632	0.628
Akaike Inf. Crit.	8.6	-114.7	-97.9	-32.9	-102.6	-82.4	7.7	-108.1	-106.3
LM test SEM	145.52***			83.95***			139.57***		
LM test SAR	122.34***			63.74***			134.29***		
Robust LM test SEM	23.37***			21.75***			7.08***		
Robust LM test SAR	0.18			1.54			1.8		
Observations	151	151	151	151	151	151	151	151	151

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

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
α	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
λ		0.653***			0.601***			0.791***	
ρ			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

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

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

Regression	Moran's I	Expectation
GNIpc 1990-2000	0.65***	-0.01
GNIpc 2000-2010	0.50***	-0.01
GNIpc 2010-2018	0.64***	-0.01
HDI 1990-2000	0.45***	-0.01
HDI 2000-2010	0.38***	-0.01
HDI 2010-2018	0.63***	-0.01

Notes: *** means that value of Moran's I test is statistically significant at 1 percent level.

Regarding GNI per capita, the residuals are highly auto-correlated for all the three sub-period. Moreover, the test shows that the Moran's I of the regression residuals reached its highest value (0.65) in the 1990-2000 transition. Likewise, The residuals of the HDI regressions are also highly autocorrelated. The maximum value of this spatial autocorrelation 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 were used to test convergence for both Income and HDI variables and for each of the three transitions. Starting with GNI, the regression coefficients for both spatial models are reported in table 2. For the first period (1990-2010) all coefficients are highly significant, including λ and ρ. In order to choose the best fitting model, the approach suggested by (Anselin and Rey (2014)), among others, is followed (see figure 1). Although both the Lagrange multipliers test for the SEM and SAR models are significant, the

Robust Lagrange multipliers test is significant only for the former model. Similar results are found for the GNI per capita transitions in 2000-2010 and 2010-2018. Therefore the SEM is the best fitting model to account for the variation of the growth rates and the spatial dependence in the GNI per capita data.

The speed of convergence and half-lives are also reported for the SEM model. For all sub-periods SEM the speeds of convergence lie between 2% and 3%. This implies that the 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.

The SEM and SAR estimates for the HDI transitions 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 periods present similar patterns. In both 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 period (2010-2018), the Lagrangian multiplier test results are inconclusive. The test results for the SEM and SAR models are significant, with valued 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 model the spatial dependence in the last period. This extension is left for further research.

Furthermore, the convergence speeds of the SEM and SAR models in the last period are significantly smaller that the speed reported for the classical model. For the SEM the speed is about 0.8% and the half-life is about 86 years. For the SAR 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.

4.2 Convergence and spatial heterogeneity

Convergence results based on the spatial heterogeneity framework are presented in Table 5 and Table 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.

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 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 parameter across space. Figures 2-4 present the spatial variation of the convergence speed of GNI. To facilitate the interpretation of the convergence speed, the half-life indicator is used in all

Table 5: Convergence coefficient 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

Notes: *** means that the coefficient is statistically significant at 1 percent level. An evaluation of statistical significance for the GWR estimates is presented in Figures 2-4.

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 Figures 2-4 is that the economic convergence process of South America is characterized by multi-country spatial clusters. For instance, during the 1990-2000 sub-period, Figure 2 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, the northern part of Argentina and Chile, and most

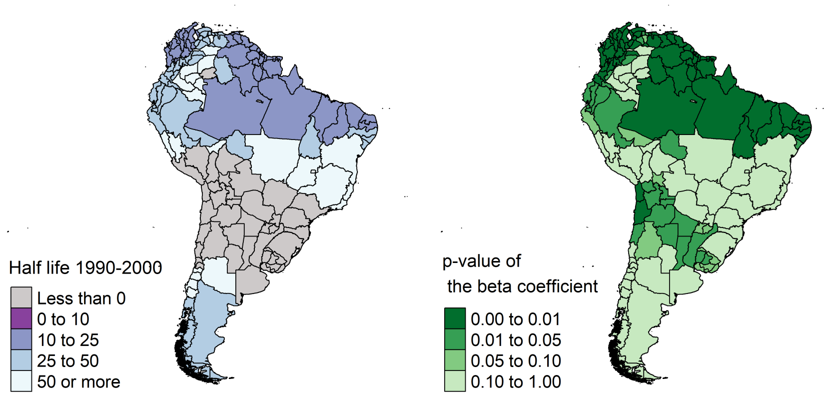

Figure 2: GNI per capita 1990-2000

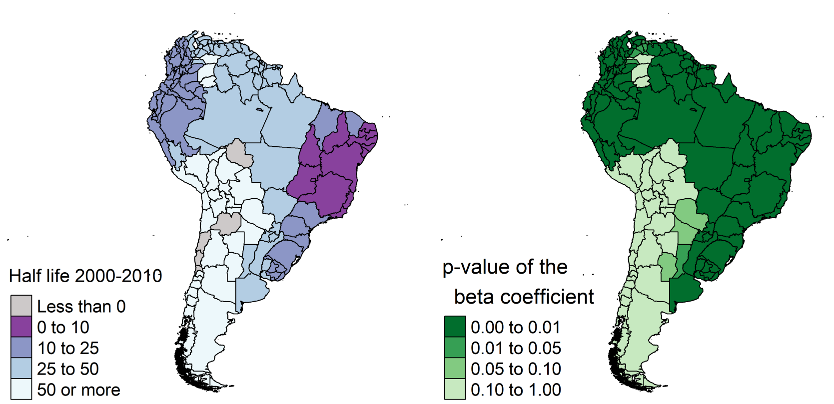

Figure 3: GNI per capita 2000-2010

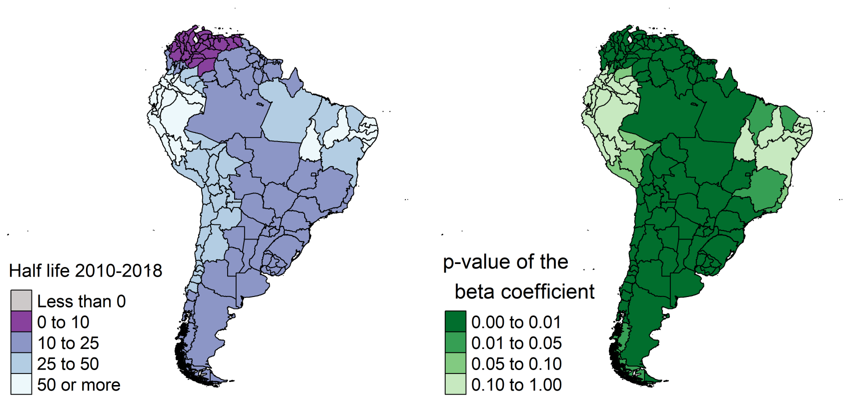

Figure 4: GNI per capita 2010-2018

regions of Bolivia.[2] During the 2010-2018 sub-period, Figure 4 shows a clear cluster of regions sharing similar convergence speeds (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 entire 1990-2018 period, the speed of convergence has been decreasing over time. For instance, the global estimate of the convergence coefficient indicates the 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

[2]Nevertheless, as indicated by the p-value map associated with Figure 2, many of the regions belonging to this cluster show no significant values.

reduced to 0.169.

Table 6: Convergence coefficient 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

Notes: *** means that the coefficient is statistically significant at 1 percent level. An evaluation of statistical significance for the GWR estimates is presented in Figures 5-7.

Figures 5-7 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 (Figure 5), regions in the north of South America were converging at a faster speed than those in the south. During the 2000-2010 sub-period, a fast convergence cluster has appear 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 from 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

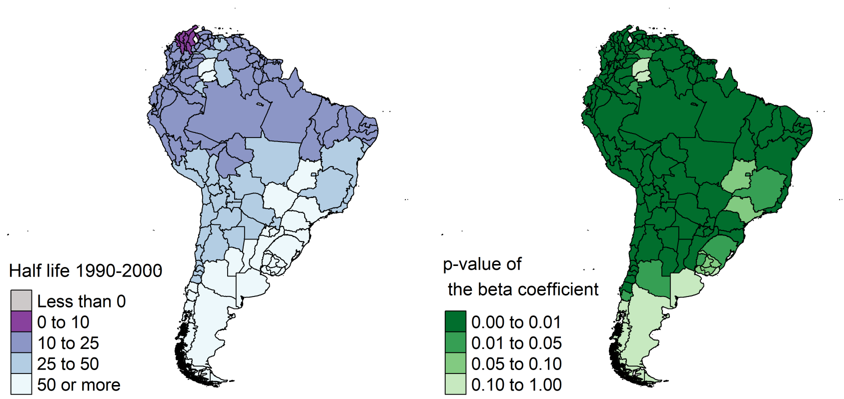

Figure 5: HDI 1990-2000

be interpreted with caution as the p-value map of Figure 7 indicates that the convergence coefficients of these regions are not statistically significant.

5. Concluding remarks

A large number of studies analyze the convergence of social and economic indicators across countries. Relatively few studies, however, have evaluated convergence across the subnational regions of multiple countries. By using a novel multi-country subnational dataset of 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), spatial convergence models should be used since the residuals of a standard OLS regression show strong and significant patterns of spatial dependence. 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,

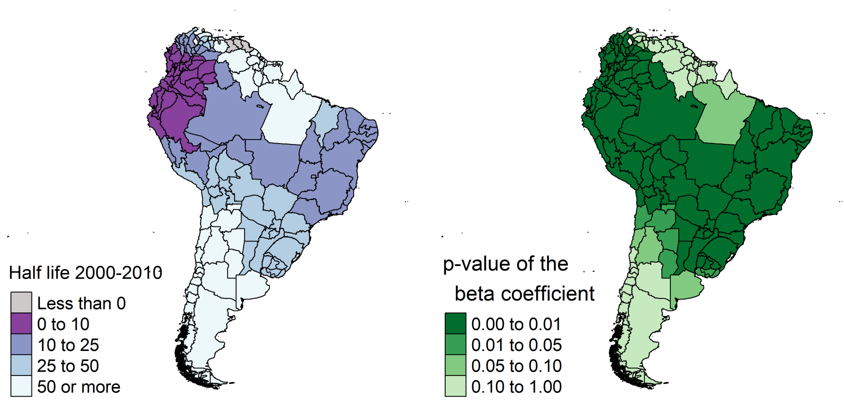

Figure 6: HDI 2000-2010

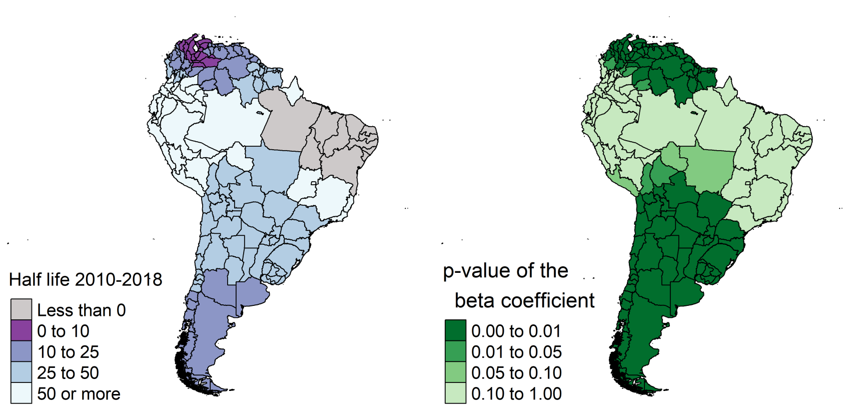

Figure 7: HDI 2010-2018

results from the geographically weighted regression framework indicate that for both GNI and HDI, the speed of convergence is largely heterogeneous across space. Fifth, the dynamics of economic and social inequality 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.

In this study, the convergence patterns of a subnational version of the HDI and GNI are analyzed. Nevertheless, the dataset assembled by Smits and Permanyer (2019) also includes information of the other two components of HDI: educational and health. The analysis of the convergence of these indicators is a possible extension that is left for further research. Moreover, these methodologies can also be applied to data from other developing regions of the world such as Africa or South East Asia.

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