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Abstract

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Keywords: Colombia, convergence, departments, distribution dynamics, spatial spillovers, weights

JEL classification: C16, O18, O47, R11

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1. Introduction

Concerns about countries' wealth have triggered a vast literature on growth and convergence. Conclusions as to the validity of the convergence hypothesis vary depending on methodologies, units of study (countries/regions), or sample years. The relevance of the issue has prompted a vast body of literature dealing with the topic, nicely reviewed by Islam (2003) and, more recently, Johnson and Papageorgiou (2019). Although most of this wave of research focused initially on international income convergence, regional convergence has become a large area in itself.

If we also factor in the growing inequality in income distribution in rapid-growth countries at a global level (Johnson and Papageorgiou, 2019), these global tendencies would indicate that examining convergence at sub-national levels seems to be as important as at the country level. As Jerzmanowski (2006) indicate, over time, growth experiences differ within a country (almost) as much as they differ among countries. Indeed, in some relevant regional contexts such as the European Union, the objective of convergence has involved specific policies (the so-called "cohesion policies", Farole et al., 2011) and a large amount of economic resources (Sala-i-Martin, 1996a; Giannetti, 2002; Geppert and Stephan, 2008; Ramajo et al., 2008). With a much more limited budget, this is also the case of some developing countries such as Colombia, the country on which we focus, and whose high levels of income disparities are a major concern among its policymakers.

Colombia is a highly unequal country with historical economic and social gaps due to disparities in human and physical capital, low-quality institutional settings and civil conflicts that have caused wealth inequities among and within regions (García and Benitez, 1998; Galvis and Meisel, 2010; Galvis-Aponte et al., 2017). It is well-known that great inequalities have an impact on redistributive tax pressures, deterring investment incentives and, ultimately, leading to more unstable socio-political environments with detrimental effects for economic activities (see, for instance Alesina and Perotti, 1996; Alesina and Rodrik, 1994). Although Colombia is one of Latin America's most solid performers in terms of economic growth over the last decades, this has not been felt equally throughout the country. In terms of population, the country is comparable to some developed countries such as Spain, but its regional inequalities are five 5 times higher than those of the United States and Canada, and 42 times larger than in Australia (OECD, 2014). These persistent regional disparities present a challenge, and thwart the future development of the country, particularly in terms of *balanced* development (World Bank, 2018).

Different regional convergence patterns can be distinguished from 1960 to the mid 2000s.

There was a first period of convergence from 1960 to 1980, mainly driven by transport infrastructure investments (Bonet and Meisel, 1999). This was followed by a period of divergence from 1980 to 1990, when the central region led economic development (Galvis et al., 2001; Acevedo, 2003a). Finally, disparities persisted from 1990 onwards, when mobility between rich and poor regions was negligible (Bonet and Meisel, 2008). The absence of economic convergence becomes a structural bottleneck, hindering equal opportunities for social and economic development in the country, while at the same time showing up poor performance of public policies in providing favorable conditions to push the lagged economies towards a sustainable growth pattern.

The reasons underlying these persisting regional imbalances are varied, and include the limited physical government presence in isolated regions, imbalances in essential public infrastructures, the country's uneven topography (representing natural barriers isolating some areas, which remain disconnected), or the long armed conflict that has eroded the human, physical and even social capital of the most affected areas—particularly rural ones (World Bank, 2018). However, given the limited performance of the more traditional neoclassical model to explain income dynamics among the Colombian regions, some of the pioneering contributions to the field such as Cárdenas (1993) or Cárdenas and Pontón (1995) suggested the need for alternative theories able to better explain the Colombian reality. As a result, endogenous growth models with increasing technological returns to scale based on human and physical capital spillovers were postulated as good candidates to explain the evolution of income convergence. In addition, geographical comparative advantages and demographic factors might have better capacity to explain the polarization patterns found. In this regard, more recent papers by Galvis et al. (2010) and Galvis-Aponte and Hahn-De-Castro (2016) have highlighted the role of spatial dependence and neighbor effects, which can be essential for the diffusion of the above-mentioned spillovers. Observed trends also reveal that fiscal policy decentralization has not been successful in closing per capita income gaps among central and peripheral regions in Colombia. In response, the new strategies for regional policy are based on a Regional Compensation Fund (RCF) to level up social and economic opportunities. The RCF is a long-term regional development policy proposal based upon human capital investments within a spatial and integrated approach designed to overcome an unequal wealth distribution (see Galvis et al., 2010).

Against this background, we examine the complexity of the convergence process in per capita income across Colombian departments over the period 2000–2016. The literature in this regard is already ample, and has been recently reviewed by Galvis-Aponte et al. (2017). They document 20 years of studies evaluating different facets of regional convergence in Colombia, which vary in the methods used, periods considered or even variables assessed—not only economic magnitudes such as income per capita but also social variables. Because of these heterogeneities, results are not always entirely coincidental, but if the analysis is restricted to some specific methods they are generally more robust. In this study, and unlike several contributions that apply either σ- or β-convergence (which sometimes require strong assumptions), we follow the distribution approach initially developed by Quah (1993a,b), which allows data to reveal the nature of the relationship of interest by using nonparametric techniques, and does not impose any assumption or restriction on the specification of the income distribution. In the analysis of Colombian regional convergence (we will discuss this question below), several studies consider the distribution approach have found that, in general, convergence has been weak—although results also vary depending on the period considered—and regional disparities persist.

These conclusions have been reached by Ardila Rueda (2004), Birchenall and Murcia (1997), Bonet and Meisel (2007), Branisa and Cardozo (2009b), Martínez (2006), Royuela and García (2015), Gómez (2006), all of whom consider different variants and instruments within the general context of the distribution approach. However, there are some gaps in this literature that we attempt to fill, and that constitute our contributions. The first one relates to the sample and the period analyzed. To our knowledge, this is the first study to consider all 33 Colombian departments existing nowadays. The period considered is also novel; there is no evidence for the last 15 years, so the analysis provides a recent view of the convergence process. In addition to this, although it is critical to evaluate intra-distribution mobility (i.e., changes in departments relative positions), very few contributions have measured it explicitly via transition probability matrices (Ardila Rueda, 2004; Bonet and Meisel, 2007). Although several studies consider their continuous counterparts, represented by stochastic kernels, disregarding transition probability matrices constitutes an impediment to evaluate the ergodic (or stationary) distributions; we avoid this problem by also considering also the continuous state-space approach proposed by Johnson (2005b). A further contribution we make to the convergence literature in Colombia is to explicitly measure intra-distribution mobility, by calculating mobility indices (Birchenall, 2001, in an analysis for an earlier period), as well as the asymptotic half-life of convergence—that is, when will the hypothetical stationary distribution be achieved? These are all relevant questions which to date remain either partly or wholly unanswered.

However, we consider a more relevant contribution of the study to control explicitly for the role of demography and geography—two issues which, in the case of Colombia, are particularly pertinent. Considering demography, and taking into account population matters, convergence might be weak in purely *geographic* terms, but the patterns can differ when considering how many inhabitants live in each region—in our case, departments. As Sala-i-Martin (2006) notes, the unweighted approach is not useful if one is concerned about human welfare, since different regions have varying population sizes, and therefore a different share of the Colombian population living in poverty. This shift to population-weighted comparisons has obvious implications for the importance that we assign to the growth of the largest departments (Schultz, 1998). This population-weighted analysis also constitutes a different approach to evaluate the "people follow jobs" hypothesis (Muth, 1971; Carlino and Mills, 1987; Hoogstra et al., 2017).

In turn, geographical features such as large mountain ranges and rain forest areas represent frictions that hinder connections and, therefore, make some areas more isolated. This can ultimately exacerbate regional disparities and heavily impact the convergence process. Other authors have taken similar approaches to the ones we consider here to examine these questions for both developed (e.g., Tortosa-Ausina et al., 2005) and emerging economies (e.g., Herrerías et al., 2011). In the specific context of Colombia, only Galvis-Aponte and Hahn-De-Castro (2016) have partly dealt with these issues, although from a different point of view. As an additional contribution, the transition probability matrices enable the computation of ergodic (steady-state) distributions, which have not previously been considered for the case of Colombian regional convergence. We compute these distributions considering not only the unconditional analysis but also analyses for the two conditioning schemes (geography and demography), as well as their continuous counterparts, following Johnson's (2005b) proposals. The information provided by transition probability matrices is also complemented via the explicit measurement of intra-distribution mobility (Shorrocks, 1978) and asymptotic half-life of convergence (Kremer et al., 2001), which tells us how far we are from reaching the ergodic distribution.

The results suggest that convergence in terms of GDP per capita is not taking place across Colombian departments in the analyzed period. In contrast, we observe a bimodal distribution, with a strong polarization between poor and rich departments that is more compatible with the concept of *club convergence*. This pattern changes when distributions are weighted by population. For that case, the resulting distribution is clearly unimodal and sharper than the unweighted one, showing a strong convergent process when we account for demography. Similarly, geography is also relevant, as convergence is much more evident when departments are compared with their neighbors than with the country mean.

The rest of the paper is organized as follows. Section 2 provides a review of the literature. Section 3 explains the methodology. In Section 5 the results are presented and, finally, Section 6 concludes.

2. Background and literature review

There is a fairly large body of literature analyzing convergence in Colombia, either focusing on per capita income or other related economic or social variables is relatively large, although most of it is in Spanish[1] and only a few studies have been written in English. In addition, some of the most relevant contributions were published before more recent important events, such as the international financial crisis or the end of the armed conflict. A review of the latest research on economic and social convergence in Colombia, either focusing on per capita income or other related economic or social variables, has mainly shown a polarized country, a situation that is persistent over time among departments (Galvis-Aponte et al., 2017).

Some of these studies, particularly the oldest ones, adopted σ and β-convergence approaches. This is the case of Cárdenas and Pontón (1995) (see also Cárdenas, 1993; Cárdenas et al., 1993), who evaluated per capita income convergence across departments for the 1950–1990 period, finding a robust convergent pattern. However, this result was not robust across studies, since other authors found convergence in the 1950–1960 period, but not for 1960–1990 (Meisel, 1993). Similarly, Birchenall and Murcia (1997) and, to a lesser extent, Birchenall (2001), considered Quah's distribution dynamics approach, finding weaker evidence supporting convergence. In another relevant study, Bonet and Meisel (2008), also using the distribution approach and with a new database, found that there was no clear pattern towards convergence between 1975 and 2000, and that Bogotá was playing a fundamental role in this process due to its size, both in population and economic terms.

Bonet and Meisel (1999) also found a significant negative relationship between initial income levels and growth rates and a reduction in the dispersion around the national income average from 1926 to 1960 due mainly to investment in roads and railways around the country. Nevertheless, the convergence trend changed from 1960 to 1995, when it showed a polarization in per capita income levels in which Bogotá was the dominant economic force in the country. The main factors behind the polarization process were the import substitution policy implemented to protect national industry and public consumption, which were more relevant in the capital city.

In turn, Rocha and Vivas (1998), Acevedo (2003b), Galvis et al. (2001), and Galvis-Aponte and Hahn-De-Castro (2016) showed how factors such as human and physical capital, market imperfections, political stability, international trade, telecommunications infrastructure, among others, matter when explaining regional growth. In this sense, there was a change in research focus, which shifted to the relevance of knowledge externalities

[1] This is not bad in itself, but prevents the research from reaching larger readerships.

together with increasing returns to scale to explain why some regions grew faster than others. In this new research trend, both these factors received particular attention, together with spatial dependence, spillovers and labor migration, effects that were included in econometric analyses. The results confirmed a higher concentration of economic activity, population and infrastructure in a few cities, located mostly in the central region. In contrast, peripheral regions are left behind, unable to close the regional income gap (Bonet, 2007). Also, Ardila Rueda (2004) found that the decentralized fiscal policy has not been successful in promoting lower regional gaps. In this sense, regional public investment and regional public consumption only showed positive effects on the relative position of each region within the income distribution, but income distribution remained virtually unaltered between 1985 and 1996.

From a poverty convergence perspective, Galvis et al. (2010) found more evidence of convergence clubs (Phillips and Sul, 2009) where income inequalities are lower compared to the distribution of all departments around the national average. They also found a polarization trend among convergence clubs, driven by spatial factors that are creating persistent poverty traps in peripheral regions. One of the most recent applications of the distribution dynamics approach (although they also considered σ and β-convergence) to the case of the Colombia is the study by Royuela and García (2015), have analyzed not only the evolution of per capita income convergence, but extended the analysis to well-being indicators such as life expectancy, infant mortality, educational enrolment and crime issues. Their study, focusing on the period 1975–2005, found different patterns depending on the indicator considered. Although convergence was found for some social indicators (education, health, crime), per capita income exhibited a divergent pattern, a similar finding to Branisa and Cardozo (2009a) and Franco and Raymond (2009).[2]

3. Methodology

We consider the distribution approach initially proposed by Danny Quah in a series of contributions. With respect to other methods and concepts, particularly σ and β-convergence, it has the advantage of analyzing how the entire distribution of per capita income evolves. Although, as mentioned in the preceding section, some contributions have already considered its application to the Colombian case, we introduce certain variations in the methodology that are novel in this context, and which provide more thorough conclusions. The advantages of analyzing the entire cross-sectional distribution of per capita income are multiple and include, for

[2]Other contributions also considering social indicators are Branisa and Cardozo (2009b), Aguirre (2005) and Martínez (2006).

instance, a better ability to detect multi-modality, polarization, or the existence of convergence clubs (Phillips and Sul, 2007).

Apart from choosing a methodology, any convergence study must take some additional decisions (Islam, 2003). Some of them concern which *concept* of convergence to use; in our we use convergence within an economy (Colombian departments), and GDP per capita-convergence. In addition, although in the first stages of the analysis we focus on *unconditional* (absolute) convergence, we will also examine several *conditioning* scenarios, by evaluating the role of geographic proximity, as well as the relevance of weighting—either using economic or population weights.

3.1. On the shape of the distributions and their evolution: densities estimated via kernel smoothing and local polynomials

In the first stage of the model, we report the non-parametric estimation of per capita income density functions via kernel smoothing for different years. A concentration of the probability mass would indicate convergence, while flatter densities would indicate divergence. In addition, a multiplicity of scenarios could also emerge, such as the existence of convergence/divergence clubs (Ben-David, 1994; Phillips and Sul, 2009) shown by multi-modal shapes.

In our setting, where $x_{i,t}$ refers to department i's normalized per capita GDP in period t, the corresponding kernel estimator will be:

$$\hat{f}(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\Big(\frac{\|x - X_i\|_x}{h}\Big) \tag{1}$$

where X is departmental per capita income, N is the number of departments, x is the point of evaluation, $\|\cdot\|_x$ is a distance metric on the space of X, h is the bandwidth, and $K(x)$ is a kernel function. Our selection is the Gaussian kernel, which is both relatively straightforward to apply and fits most contexts well.[3] The choice of the bandwidth, h, has a much greater impact than the choice of kernel, however. We follow the local likelihood variant of density estimation, which allows us to overcome some notorious problems in kernel estimation (see Loader, 1996; Hjort and Jones, 1996).[4]

As Loader (1996) showed in his comparison of the relative efficiencies of kernel and local

[3]Formally, $K(x) = (1/\sqrt{2\pi})e^{-\frac{1}{2}x^2}$. See, for more details, Härdle and Linton (1994), Silverman (1986) and, more recently, Li and Racine (2007), among others.

[4]Increasing bandwidths for data sparsity can lead to severe bias, essentially because of the kernel being based on a local constant approximation which might suffer from problems in the tails, or trimming of peaks. See Loader (1999).

log-polynomial methods, the latter might perform better in settings such as ours, where several types of densities (unweighted, weighted, spatially-conditioned, ergodic) are considered. Therefore, we consider changes in the local likelihood criterion as follows:

$$\sum_{i=1}^{N} \omega_i(x)\ln(f(X_i)) - N \int W\Big(\frac{u-x}{h}\Big) f(u)du \tag{2}$$

where the log-link is used, i.e., $\ln(f(x))$ is modeled by local polynomials, where W indicates that we specify a locally weighted least squares criterion for each fitting point (x), $\omega_i(x)$ refers to the localization weights, the log-link is used (i.e., $\ln(f(x))$ is modeled via local polynomials), and the term on the right is the added penalty term.[5]

3.2. How densities evolve: intra-distribution mobility

Although two identical densities would in principle imply, neither convergence nor divergence, this could be concealing changes in departments' relative positions—or *churning*. Therefore, apart from the evolution of the external shape of the distribution, it is also interesting to analyze its internal mobility. To do so, and considering our $x_{i,t}$ variable referring to department i's normalized per capita GDP in period t, $F_t(x)$ is the cumulative distribution of $x_{i,t}$ across departments. A probability measure $\lambda_t((-\infty, x]) = F_t(x)$, $\forall x \in \mathbb{R}$, λ_t being the probability density function for each indicator across departments in period t.

We will look for the operator, P^*, that discloses information on how the distribution of per capita GDP at time $t-1$ transforms into a different distribution at time t. To do this, we focus on a stochastic difference equation $\lambda_t = P^*(\lambda_{t-1}, u_t)$, integer t, which takes into account that $\{u_t : \text{integer } t\}$ is the sequence of disturbances of the entire distribution. In this context, P^* is the operator mapping disturbances and probability measures into probability measures, and which encodes the information on intra-distribution mobility. If we assume that operator P^* is time invariant, and that the stochastic difference equation is of first order (Redding, 2002), by setting null values to disturbances and iterating for $\lambda_t = P^*(\lambda_{t-1}, u_t)$ the future evolution of the distribution can be obtained, i.e., $\lambda_{t+\tau} = (P^*)^\tau \lambda_t$.

If the set of possible values of x is discretized into a finite number of classes (grids), to which we can also refer as states or intervals, e_k, $k \in \{1, \dots, K\}$, then P^* will become a transition probability matrix as in:

$$\lambda_{t+1} = P^* \cdot \lambda_t \tag{3}$$

Accordingly, λ_t turns into a $K \times 1$ vector of probabilities that the per capita GDP of a given

[5] Additional details can be found in Loader (1996, 1999).

department is located on a given grid at time t. It is then possible to evaluate the probability of a given department moving to a higher (or lower) position on the grid. We start by discretizing the set of observations into the states e_k.[6] Each p_{kl} entry in the matrix indicates the probability that a department initially in state k will transit to state l during the period (T) under analysis.

The limits between states are chosen so that all department-year observations are uniformly distributed among the cells.[7] Accordingly, each cell in the transition probability matrices is computed by counting the number of transitions out of and into each cell. Therefore, each cell's p_{kl} value is:

$$p_{kl} = \frac{1}{T-1} \sum_{t=1}^{T-1} \frac{n_{kl}^t}{n_k^t} \tag{4}$$

where n_{kl}^t is the number of departments moving during one period from state k to class l, n_k^t is the total number of departments starting the period in state k, and T is the length of the sample period.

3.3. Ergodic distributions, transition path analysis and mobility indices

The transition probability matrices allow us to characterize the ergodic or stationary distribution—under current trends. The resulting scenarios can be diverse, from distributions with the probability mass concentrated mainly in the central classes (indicative of convergence to the mean) to more polarized distributions with the probability mass distributed in the extreme classes (tails) of the distribution, indicating increasing separation between the poorest and richest, shown by twin peaks (Quah, 1996c).

We compute the ergodic distributions following the algorithms proposed by Kremer et al. (2001). We also overcome the intrinsic disadvantages to transition probability matrices and ergodic distributions via transition probability matrices (i.e., the need to *discretize* per capita income into five states) by considering their continuous counterparts, following relevant proposals by Johnson (2000, 2005a).

This "continuous state approach" (Johnson, 2000, 2005a) therefore provides a natural continuous counterpart to the discrete ergodic distributions, with the advantage of not having to summarize information in a few states only. Although the information provided is basically similar, this strategy overcomes the subjectivity intrinsic to discretizing into only a few states.

[6] Once each department-year observation has been classified in one of the K states, a 5×5 matrix is built (other popular dimensions are, for instance, 7×7).

[7] Other criteria for choosing the limits between states exist, including arbitrary (albeit 'reasonable') choices (Kremer et al., 2001; Quah, 1993a). An alternative to avoid the discretization issue is to consider *continuous* stochastic kernels (Quah, 1996b). They, however, are not trouble-free, particularly when trying to estimate the corresponding ergodic distributions.

The ergodic distribution might not be reached quickly. Actually, it is unclear whether it would be ever reached, given it could only happen under current trends, which can vary. However, we can use the concept of asymptotic half-life of the chain ($H - L$), which refers to the time it takes to cover half of the distance to the ergodic distribution. We define the asymptotic half-life as:

$$H - L = -\frac{\ln 2}{\ln |\lambda_2|} \tag{5}$$

where $|\lambda_2|$ is the second largest eigenvalue (after 1) of the transition probability matrix, ranging between infinity (when the stationary distribution does not exist and the second eigenvalue is equal to 1) and 0 (when $\lambda_2 = 0$ and the system has already reached its stationary equilibrium).[8]

In order to *quantify* the mobility underlying each transition matrix, we also consider mobility indices such as those considered in the economic inequality literature. Specifically, we follow Shorrocks (1978), Geweke et al. (1986) and Quah (1996a), some of whose proposals evaluate the trace of the transition probability matrix, providing information on the relative magnitude of on-diagonal and off-diagonal terms. Following Quah (1996a), its expression is:

$$\mu_1(P^*) = \frac{K - \mathrm{tr}(P^*)}{K - 1} = \frac{\sum_j (1 - p_{jj})}{K - 1} \tag{6}$$

where p_{jj} is the j-diagonal entry of matrix P^*, representing the probability of remaining in state j, and K is the number of classes. Large values of μ_1 indicate more mobility (less persistence) in P^*. This concept is identical to the inverse of the harmonic mean of expected durations of remaining in a certain state.

3.4. Conditioning schemes: demography and geography

The methods presented in the previous sections provide a full analysis of departmental per capita income dynamics. But, as indicated by Herrerías et al. (2011), using departments as units of analysis will be less useful when the issue under analyzed is the number are "How many people in Colombia live in poverty". In this section we propose a weighting scheme for the methods presented in the preceding paragraphs. We do this for both density functions as well as transition probability matrices, and the proposed weighting schemes can take several factors into account—in our case we will consider both population and economic size (GDP). The rationale for this is based on the relatively greater impact on per capita income convergence (or divergence) of a large department (either in population or GDP terms) than that of a smaller one.

[8] See Magrini (1999) and, more generally, Shorrocks (1978).

In the specific case of the population-weighted analysis, we would not be counting transitions of departments but rather of people living in each department—i.e., the unit of analysis is the *person*. However, this issue has only rarely been taken into account in convergence studies applying the distribution dynamics approach, some exceptions being Tortosa-Ausina et al. (2005), Kremer et al. (2001) and Jones (1997).

Regarding the expressions corresponding to the non-parametric estimation of density functions, the modified kernel estimator becomes:

$$\hat{f}_\omega(x) = \frac{1}{h}\sum_{i=1}^{N}\omega_i K\Big(\frac{\|x - X_i\|_x}{h}\Big) \tag{7}$$

where, depending on the type of weighting considered, ω_i corresponds to the share of Colombian population or GDP corresponding to department i. In our local likelihood approach for density estimation, the weights can be entered directly into Equation (2). As indicated in the introduction, this is our strategy for testing the 'jobs follow people' (GDP-weighting) and 'people follow jobs' (population-weighting) hypotheses (Carlino and Mills, 1987; Hoogstra et al., 2017).

Regarding the transition probability matrices, Equation (4) now takes into account the number of people (if we weighted by population) that moves from one class to another. In this *weighted* transition probability matrix the expression corresponding to each cell will be:

$$p_{kl}^{\omega} = \frac{1}{T-1}\sum_{t=1}^{T-1}\sum_{i=1}^{n_{kl}}\frac{W_{ikl}^t}{W_{ik}^t} \tag{8}$$

where W_{ikl}^t is the population (or GDP) corresponding to department i, that moves from state k to state l in period t, and W_{ik}^t is the population (or GDP) corresponding to department i starting the period in state k.

In turn, the effect of geography on convergence processes cannot be overlooked. Increasing returns to scale, knowledge spillovers, access to markets, labor mobility and vertical linkages between industries largely explain regional income and its geographical patterns. These issues have been widely explored, particularly intensity for the European regional context (see, for instance Breidenbach et al., 2019), although there are also some initiatives for the Colombian regional context such as Gómez Rodríguez and Santana Viloria (2016). The importance of explicitly taking spatial processes into account when assessing regional convergence has been repeatedly highlighted in the last years (Fischer and Stumpner, 2008; Le Gallo and Fingleton, 2019; Kelejian and Piras, 2020). However, according to Gerolimetto and Magrini (2017), whereas convergence studies based on regression analysis devote a great deal of attention to the spatial phenomenon, within the nonparametric literature this issue has received much less attention.

In an attempt to address this issue, we conducted an analysis which compares the *state-relative* GDP per capita used in the previous sections and *neighbor-relative* per capita GDP, where we normalize each department's per capita GDP by the average per capita GDP of the neighbor departments, excluding the department itself. The spatial econometrics literature provides many alternatives to define each department's neighborhood, including distance, *k*-nearest criterion, a variety of economic and non-economic attributes or simply contiguity between two given regions. In this paper we follow this latter strategy, as contiguity matrices have been proved to capture spatial spillovers appropriately, while still being intuitive and simple in structure (LeSage, 2014). Accordingly, those departments sharing borders are considered neighbors. Formally, the expression corresponding to the neighbor-relative per capita GDP series is:

$$x_i^{NR} = \frac{\ln y_i}{\ln \frac{1}{NE-1}\left(\sum_{j \in NE \setminus i} y_j\right)} \tag{9}$$

where NE is the number of neighbors each i department has, and nr is the super-index indicating that we are referring to the neighbor-relative per capita GDP series. The closer the values of the neighbor-relative series are to unity, the lower the disparities among neighbor departments and the larger the magnitude of the spillover effects.

4. Data and descriptive statistics

Two variables are used in the analysis: GDP per capita and population. Information on both variables was provided by the National Administrative Department of Statistics (DANE, *Departamento Administrativo Nacional de Estadística*). We consider the period 2000–2016. In contrast to other analyses considering previous periods, our selection allows us to consider of all 33 Colombian departments. Data on GDP per capita is measured in constant 2010 pesos.

Summary statistics are reported in Tables 1 and 2. The different columns provide information for income per capita (Table 1) and population (Table 2), both in levels as well as in growth rates. The information is split for selected years and periods. The period of analysis is 2000–2016, for a variety of reasons. Although, ideally, a longer period of analysis would have been more informative, particularly for the sake of comparison with previous literature, this would have impeded using all 33 departments in which Colombia's territory is organized today. When deliberating this trade-off (i.e., having to choose either more years or more departments) we chose to drop some years in order to focus on the 33 departments, for which analyses of convergence are scarce.

In contrast to other recent convergence studies for Colombia, such as Acevedo (2003a), Ardila Rueda (2004), and Galvis and Meisel (2012), the following description includes all 33 departments, which is a relevant contribution to regional income distribution research in this context. Although available data would give us greater insight into distributional patterns at the municipal level, our key variable, per capita income, is not available at this level of disaggregation.

Table 1 reports data on per capita income and population in 2010 Colombian pesos per person for years 2000, 2008 and 2016, along with growth rates for the three subperiods considered (2000–2016, 2000–2008 and 2009–2016). There are remarkable discrepancies among both departments and natural regions.[9] For instance, for the whole country, the year 2000 average for GDP per capita was about 8 million Colombian pesos per person (in 2010 pesos). Between 2000 and 2016, the per capita income grew in real terms at an annual rate of 2.3% to reach a level of 11 million per person (in 2010 pesos). Although all regions did show favorable growth rates in per-capita income, the Andean (*región Andina*) and Orinoco (*región de la Orinoquía*) regions exhibited the highest levels of per capita GDP. In contrast, the highest per capita income growth rates corresponded to the Pacific Region, which has been considered the country's poorest natural region. Moreover, the Caribbean (*región Caribe*) and Andean regions also showed higher growth rates than the Orinoco region, which has the most important oil reserves in the country.

Having better growth rates in regions that are not endowed with natural resources, and having higher growth rates in poor regions are usually considered as evidence of per capita income convergence in terms of the traditional neoclassical approach (Rocha and Vivas, 1998). However, some work using non-parametric methods (Bonet and Meisel, 1999) has found a polarization process in per capita income levels, according to which the capital city, Bogotá, was the dominant economic force. Indeed, there is evidence of a reduction in the coefficient of variation in per capita income levels for each sub-period, but it happened simultaneously with an increase in per capita income growth dispersion for each sub-period.

Although the Andean and Orinoco regions had the best performance in terms of real per capita GDP levels, they also exhibited the most volatile evolution of the per capita GDP trend in each period, as shown by the standard deviation. In contrast, the coefficient of variation for the Amazon region almost doubled between 2000 and 2016—as some departments grew much

[9]Note that Colombian natural or *geographical* regions do not hold specific powers (they are not administrative units), and in some cases their geographical limits do not coincide with departments' limits—i.e., some departments are part of different regions. However, given Colombia's peculiar geography and orography, which both have a critical impact on the development of infrastructures, we consider they help to understand some facts and trends.

faster than others—, a similar trend to that observed in the Caribbean region. In the Pacific region, however, another relatively poor area, per capita income grew much faster (it almost doubled between 2000 and 2016) than its dispersion and, as a consequence the coefficient of variations declined sharply. These descriptive findings show that there was a convergence process with winners and losers that might have offset the initial positive trend in terms of per capita GDP levels and growth rates for all regions.

In this sense, it is clear that the Andean region, particularly Bogotá and the department of Antioquia, are winners compared to the departments in the Pacific and Amazon regions. In all, performance of the departments of Antioquia, Valle del Cauca, and the capital city, Bogotá, which enjoy better transportation and communication infrastructures (and also better access to finance), improved in relation to regional and national averages. In this sense, it is clear that progress in communication, transportation, and financial infrastructures are essential to explaining both the gains in per capita GDP for the winners and the increase in the standard deviation of per capita GDP distribution for the rest of the regions and departments in the country. This descriptive finding reveals that there is a 'golden triangle' of economic development in the departments of Antioquia, Valle del Cauca, and the city of Bogotá, partly driven by higher investments in public infrastructures and urbanization processes, and also due to labor migration patterns that have attracted people to these areas of the country.

A closer look at the data reveals a population trend that has a bearing on our understanding of migration patterns driven by the economic outlook in each province. The Andean region, particularly the departments of Antioquia and Bogotá, and the department of Valle del Cauca (in the Pacific region), have the highest population levels in the sample for each of the periods considered (see Table 2). However, the Orinoco and Caribbean regions have the highest population growth rates. In contrast, the Pacific and Amazon regions do not show an increase in population growth and remain the regions with the lowest population levels. This finding seems to be related to better employment opportunities and the presence of an urbanization process that had taken place in the economic triangle comprising the departments of Antioquia, Valle del Cauca, and the city of Bogotá. At the same time, the oil industry is also an important factor in explaining the positive population growth in the Orinoco region. There was also an economic diversification process that helped to increase the financial incentives to migrate from rural areas to urban areas, which is the case of the Caribbean and Andean regions. While Bogotá and the departments of Antioquia and Valle del Cauca dominate in terms of population *trends* (growth), the departments of Atlántico and Bolívar show the most significant population *levels* in the Caribbean region.

The figures reported in the table give a clear idea of the remarkable discrepancies among departments and regions in terms both of wealth and population. Figure 1 provides a more visual picture in the form of a map of Colombian departments in which the lightest colors indicate lower per capita GDP, and the darkest colors, the highest. Here we see that more wealth is concentrated in the central areas (Orinoco and Andean regions), whereas the periphery (Pacific, Amazon and Caribbean regions) is not only poorer but actually grows poorer over time—the colors corresponding to the Amazon region, for instance, have become lighter in general. Therefore, wealth discrepancies are not only high but, as documented in previous literature, persistent. We disentangle these trends in the following sections.

5. Results

We provide results for all methods described in Section 3, including transition probability matrices, ergodic (stationary) distributions, mobility indices and asymptotic half-life convergence. We also report continuous counterparts (density functions) when possible, as well as results for the different conditioning schemes—GDP-weighted, population-weighted and physically-contiguous conditioned. For the transition probability matrices, we present tables for the different periods and sub-periods considered (2000–2016, 2000–2008 and 2008–2016), for the unweighted analysis (Table 3), GDP-weighted (Table 6), population-weighted (Table 7), and physically-contiguous conditioned (Table 8). The last three rows in each panel display information on the initial, final and ergodic distributions of (normalized) departmental per capita income.

The variable of analysis is the normalized logarithm of per capita GDP. We normalize by dividing per capita GDP of department i in year t by that year's national average, i.e., $x_{it} = \ln y_{it}/\ln \bar{y}_t$, where y_{it} is the per capita GDP of department i in year t, and $\bar{y}_t$ is the cross-sectional average of y_{it}. By normalizing the data we can assess more easily how far a given department is from the rest of the country—the closer a given (normalized) value is to unity, the closer it will be to the national average. This naturally implies that the more values closer to unity, the faster the convergence to the national average. Similar normalization strategies can be found in, for instance, Sakamoto and Islam (2008).

5.1. Unweighted distribution dynamics

Transitions for normalized departmental per capita GDP are reported in Table 3. The top panel reports results for the entire period (2000–2016), and the middle and bottom panels, for each sub-period (2000–2008 and 2008–2016, respectively). Since our period of analysis is not particularly long, we consider two-year transitions (i.e., from 2000 to 2002, from 2001 to 2003, and so on) instead of more popular choices (such as five-year transitions) in order to minimize information loss.

For each of the matrices in Table 3, the cut-off points (upper limits) differ slightly because the period analyzed is different. Although several criteria are available, one of the most widely accepted ones is to consider all observations for the analyzed period (2000–2016, 2000–2008 or 2008–2016), and divide them into five similarly-sized intervals. Accordingly, the numbers in brackets to the left of each matrix correspond to the number of observations (departments) starting the period in a given state (or class). In the case of the upper panel in Table 3, given we are considering two-year transitions, they sum to 495 (instead of 528), since the last two years (2015 and 2016) would be excluded (i.e., $495 = 33$ departments $\times$ 15 transitions).

The first row of each panel displays the cut-off points that delimit the intervals (upper limits), and should be interpreted as follows: the upper limit for the first state of 0.970 implies that approximately one fifth of the total number of observations lie below 97% of the average. For the other tail of the distribution, the upper-state has observations above 1.023 (102.3%) of the average. Although this is a relatively narrow range of variation, note that the average is unity, since our data have been normalized by the mean, after taking logs.

Inside each 5×5 matrix in Table 3, entries (cells) should be interpreted as the probability of *remaining* in a particular state after two years—since we are considering 2-year transitions. For instance, in the case of the entire 2000–2016 period (top panel in Table 3), its value would indicate that 81% of the observations starting in the lowest relative per capita GDP state (105 observations, below 0.970) would remain in that state, whereas the remaining 19% would move to states of higher relative per capita income—in this case, to state 2. This high persistence is greater for richer departments, as shown by the probability in the lower right of the matrix, which shows that 92% of the observations in the richest state remain there after two years—with 8% moving to state 4. The rest of the values on the main diagonal show less persistence. Actually, the higher the probability off the main diagonal, the higher the mobility, whereas values on the main diagonal closer to one indicate more persistence.

Regarding the implicit mobility shown in Table 3, the values on the main diagonals of each matrix average to 0.784, 0.814 and 0.774 (for 2000–2016, 2000–2008 and 2008–2016, respectively), which suggests that most changes in the relative positions took place during the most recent period. These average values represent a good starting point to measure mobility. However, we can consider more precise measures which are less frequently used in distribution dynamics studies such as the mobility indices presented in Section 3.3.

We report results for mobility indices in Table 4. They do not entirely corroborate what was found for the average values on the main diagonal, since μ_1 shows quite similar values for the three periods. However, apart from the absolute value found for mobility, it is important to assess its implicit trends—i.e., whether it leads to convergence, divergence or other possible outcomes.

Specifically, the last three rows in each of the panels in Table 3 display information on the initial (2000), final (2016) and ergodic (steady-state) distributions for the selected periods. The top panel indicates that, under 2000–2016 trends, intra-distribution mobility drives probability mass to concentrate in the states of relatively high per capita income—with 69% of probability mass concentrated in states 4 and 5, and only 20% in the poorest states (1 and 2). This process of convergence to richer states, however, is the result of different dynamics, as shown in the central and bottom panels in the Table, since intra-distribution mobility in the first sub-period (2000–2008) leads probability mass to concentrate strongly (75%) in state 5. In contrast, under 2008–2016 trends (Table 3.c), although convergence still existed, it was more concentrated in poorer states—with state 2 absorbing, in the long run, 26% of probability mass. Therefore, we observe that convergence largely took place before 2008, whereas the last few years saw more stable patterns or, if any tendency did emerge, it was actually to converge to a state closer to the average.

The values corresponding to the ergodic distribution (steady state) are valid *per se*, but can be nicely complemented by providing information on how fast this state is reached. This information, rarely provided in convergence analysis studies, can be obtained via the transition path analysis or asymptotic half-life of convergence. As indicated by Magrini (1999), this refers to the time it takes to cover half the distance from the ergodic distribution; the results from applying Equation (5) are reported in Table 5. A priori, the results might not seem very intuitive, since it takes longer to reach the steady-state during the period leading stronger convergence (2000–2008) than during the second period (2008–2016) of slower convergence. However, it is precisely because the ergodic distribution in Table 4.b is more extreme than in Table 4.c that it actually takes longer to reach it.

Several authors, including Bulli (2001) and Johnson (2000, 2005a), have highlighted the problems of considering a discrete approach in which results partly depend on how the limits among states/classes are chosen. An alternative, which we follow here, is to consider the continuous counterpart to the transition probability matrices in Table 3. The continuous counterparts to the information reported in Table 3 are displayed in Figure 2. Specifically, Figure 2.a reports densities (estimated non-parametrically) for years 2000 (solid line), 2008 (dashed line) and 2016 (dotted line). It clearly indicates that the distribution of per capita income was bimodal in 2000, and remained so in 2016, with the probability mass separating further—i.e., the rich become richer. This would confirm that the strong convergence patterns found for pre-

2000 years have almost vanished, and that the convergence during our sample period is more strongly related to intra-distribution dynamics (changes in the departments' relative positions, or churning).

Will this polarization persist over time? The (discrete) ergodic distributions in Table 3 do not confirm this, since they suggest that probability mass would tend to concentrate in the richer states–regardless of the trends considered (2000–2016, 2000–2008 or 2008–2016). This result is corroborated by the continuous counterpart to the ergodic distributions in Table 3, reported in Figure 6.a, which clearly shows that bimodality will vanish, and departments will tend to converge to levels of higher relative per capita income, since the probability mass will become tighter and above unity. However, the upper tail of the distribution will still be fat, indicating that, in the long run, a number of departments will still enjoy per capita income levels well above the average.

We therefore complement the existing literature on regional convergence in Colombia in several ways, by considering a more recent period, and by applying instruments that make the analysis much more precise—i.e., the mobility indices, transition path analysis, and the continuous approach to the ergodic distributions. Although some of these instruments had previously been considered, this study is the first to contemplate others in this context, such as the continuous version of the ergodic distributions or the asymptotic half-life of convergence. A few studies, such as Birchenall (2001), also considered the analysis of transition probability matrices and even mobility indices but, unfortunately, the period analyzed by this author ended in 1995, and he concluded that convergence was over in the 1990s. Our analysis in the ensuing subsections enriches the study further, by conditioning on several relevant factors.

5.2. Conditioning

5.2.1. Weighted analysis

Results for the GDP- and population-weighted conditioned analysis are reported in Tables 6 and 7, respectively. As for the rest of the analysis (i.e., mobility indices, transition path analysis and continuous counterparts to the probability matrices), results are presented in the same tables and figures as those corresponding to the unweighted analysis.

Regarding the discrete analysis offered by transition probability matrices in Tables 6 and 7, results differ remarkably from those obtained for the unweighted analysis. Regardless of the weighting scheme (either GDP or population), and of the period considered (2000–2016, 2000–2008 or 2008–2016), the intra-distribution mobility leads to ergodic distributions with the probability mass overwhelmingly concentrated in the upper states. In several cases, for instance under 2000–2016 trends, the tendency is particularly extreme, with almost 90% of the probability mass concentrated in states 4 and 5 (Tables 6.a and 7.a). This would suggest that, in the long run, most of the population (in the case of the population-weighted analysis) would escape from poverty.

The mobility indices (Table 4) and, in particular, the transition path analysis (Table 5) complement these results, although interpretation is rather tricky. According to the asymptotic half-life of convergence in Table 5, it would take a much longer period to reach the steady-state when conditioning either by population or by GDP. However, and analogously to what occurred in the unweighted case when comparing the sub-periods, this occurs because the corresponding ergodic distributions are more extreme and, consequently, more difficult to reach.

The continuous counterparts to the discrete analysis offered by transition probability matrices are reported in Figure 2.b, 2.c, and in Figures 6.b and 6.c for ergodic distributions. Results strongly corroborate those tendencies observed when discretizing the normalized per capita income space state, as for all years 2000, 2008 and 2016 bimodality almost disappears (particularly for GDP-weighted, see Figure 2.b). Therefore, comparing years 2000 and 2016 reveals a slight intensification of weighted convergence (either by GDP or population), although the most prominent feature is the existence of much tighter densities, indicating that in terms of either people or GDP, discrepancies are much less marked.

The importance of weighting is even more obvious when we look at Figures 3 and 4, which provide explicit comparisons between unweighted and weighted distributions for 2000, 2008 and 2016. In all cases the importance of our conditioning schemes is apparent, as densities become much tighter (indicative of more convergence) when weighting either by GDP or by size, and regardless of the period considered. Finally, as indicated by the ergodic distributions in Figures 6.b and 6.c, this will ultimately result in strong convergence for people and GDP, with probability mass tightly concentrated above unity, although these (weighted) steady-state distributions will become slightly bimodal, with a cluster of people ending up slightly richer than the rest.

5.3. Conditioning: spatial analysis

The physically contiguous-conditioned (or neighbor-relative) counterparts to the previous analyses—both conditioned and unconditioned—are reported in Table 8 (transitions and ergodic distributions), and in Figures 5 and 6 (densities, static and ergodic, respectively). As in the preceding sections, mobility indices and transition path analysis are also reported (Tables 4 and 5).

Analogously to what was found when comparing Table 3 to Tables 6 and 7, results differ remarkably after conditioning, although several nuances deserve discussion—and are not entirely coincidental as when weighting schemes were introduced. In this case, we observe that intra-distribution mobility differs remarkably for the two sub-periods considered, being higher during 2008–2016 (Table 8.c)—entries in the main diagonal average to 0.67, compared to 0.76 for 2000–2008 (Table 8.b). This finding is corroborated by the mobility indices in Table 4, which also indicate that persistence is lower in the second sub-period ($\mu_1^{2008-2016} = 0.680$ and $\mu_1^{2000-2008} = 0.634$). These levels of persistence are lower than the state-relative series, which average to 0.81 and 0.77 for the first and second sub-periods, respectively (Table 3).

The implications of disparate mobility levels are not innocuous in terms of long-term distribution, as under 2008–2016 trends probability will be more tightly concentrated above the average, yielding an almost bi-modal ergodic distribution (Table 8.c). However, although the results might be partially influenced by the choice of cut-off points,[10] the overall result is that probability mass tends to concentrate more tightly in states containing values closer to the average—i.e., spatial spillovers exist for Colombian departments.

Figure 5 reports the physically-contiguous counterparts to the unweighted densities (state-relative) in Figure 2. All three graphics, corresponding to the three periods, show tighter distributions for physically-contiguous compared to state-relative per capita GDP series. Therefore, regardless of the choice of cut-off points, each department's per capita GDP resembles the average of its surrounding departments much more than the average for Colombia. This implies that, for instance, the GDP per capita in Guaviare is much more similar to the average of Meta, Vichada, Guainía, Vaupés and Caquetá than to departments in the Pacific region (Cauca, Chocó, Nariño and Valle del Cauca), thereby corroborating the existence and importance of spatial spillovers. However, the tendency is more marked during the second sub-period, as shown by a much tighter density (compare the dashed lines in Figure 5.c and Figure 5.b). Therefore, the slightly unconditional convergence process is much more accelerated when spatial interactions among neighbors are factored in. We also interpret this result as evidence supporting the 'people follow jobs' hypothesis (Carlino and Mills, 1987), which has not been evaluated for the Colombian context. Although it is a very different way of testing the hypothesis, it helps to better understand the issue due to how inconclusive this literature is (Hoogstra et al., 2017).

The continuous counterpart (Johnson, 2005a) to the ergodic distribution in Table 8.a is reported in Figure 6.d. It indicates that, under 2000–2016 trends, probability will become tightly concentrated in the vicinity of 1—i.e., departments' per capita GDP will be very much

[10] See Temple (1999).

closer to their neighbors' average than to the nation's average.[11]

When will this physically-contiguous conditioned ergodic (or stationary) distribution actually be achieved? An approximation is provided by the transition path analysis (asymptotic half-life of convergence) reported in the last row of Table 5 for the three periods evaluated. The first emerging pattern indicates that, under 2000–2016 trends, the steady state corresponding to neighbor-conditioned relative GDP series would be achieved faster than under either 2000–2008 or 2008–2016 trends. The second pattern shows that the speed is also faster when controlling for geographic spillovers than when these do not enter the analysis—the speed is lower (more years) for the first three rows in the table. There are two explanations for these apparently puzzling results. On the one hand, spatial spillovers had already played a role by the beginning of the period and, therefore, the ergodic distribution is not too far from the initial distribution, at least when compared to the other scenarios. On the other hand, the ergodic distributions corresponding to the physically-contiguous case are less extreme and, therefore, can be achieved (hypothetically) earlier.

These results, and especially the trend towards the stratification of provinces in different clubs, are of no minor concern to the authorities, and reveal that there is still some room for policies promoting convergence in per capita GDP among Colombian departments, because the natural tendency towards spatial agglomeration seems to be persistent. Thus, in addition to explicit regional policies and other central government policies to re-balance regional development (central investment projects, endowment of infrastructures, credit policy, etc.), other measures are also needed to balance the tendency towards localization of economic activity induced by market forces. Improvements in the accessibility and the role of market mechanisms in the interior are needed, but increasing the role assigned to official interprovincial migrations is probably necessary too.

6. Conclusions

The hypothesis of convergence—which (in its simplest form) states that countries' long-run per capita income levels are independent from initial conditions—has been widely tested over the last thirty years. The issue became particularly important after the emergence of modern growth theory in the mid-1980s, as testing empirically the hypothesis helped to 'unlock' the mechanics of economic growth (Johnson and Papageorgiou, 2019). This critical role of the convergence hypothesis as a test for either validating or refuting alternative growth theories attracted the interest of many renowned economists (Islam, 2003), ultimately leading to a vast

[11] The tendency is even sharper for 2008–2016 trends, but it is not reported for reasons of space.

increase in the related literature—including several surveys (Durlauf and Quah, 1999; Temple, 1999; Sala-i-Martin, 1996b; De la Fuente, 1997; Islam, 2003; Johnson and Papageorgiou, 2019).

In his informative survey, Islam (2003) attempts to systematize this literature by proposing a classification not only of the different methodologies employed to analyze macroeconomic convergence but also the ways in which it is understood. This is particularly interesting because the first distinction he considers is convergence within an economy vs. convergence across economies, since the latter (regional convergence) has become a large area in itself. As Jerzmanowski (2006) states, "growth experiences differ over time within a country almost as much as they differ among countries".

In some contexts, these regional disparities have been of particular concern. This is the case of the European Union, for a variety of reasons, including the implementation of cohesion policies, expansion and further integration initiatives, and even the challenge posed by Brexit, all of which have given rise to a flourishing new body of empirical research. Regional convergence, however, has also been studied in other contexts, including several developing countries. These settings can be even more relevant, as it is now a key global fact that income distribution is more unequal in rapid-growth countries.

In this study we focus on one of these other contexts: Colombia. It has one of the most dynamic and fastest-growing economies in South America, but there is a widespread consensus that it has deficiencies in its distribution of income—including at the regional and departmental levels. Several studies have documented this reality, finding generally either weak or no economic convergence (depending on the period analyzed). The lack of economic convergence in Colombia has become a structural bottleneck, hindering equal opportunities for social and economic development, while simultaneously revealing the poor performance of public policies in providing the right conditions to push regional economies towards a sustainable pattern of economic growth.

We contribute to this literature in several directions. First, our database spans the period 2000 to 2016, enabling us to evaluate the most recently designed and implemented convergence-enhancing public policies. Second, we use the distribution dynamics approach, which has been rarely use in the case of Colombia, and complement it by also considering mobility indices (Shorrocks, 1978), evaluating the asymptotic half-life of convergence (Kremer et al., 2001), and following the continuous space-state approach proposed by Johnson (2005b). Third, we adapt the model to control explicitly for the role of demography and geography, introducing different weighting schemes (population and GDP) as well as comparing different spatially-conditioned GDP series.

Results are multiple and can be assessed from several points of view. The unweighted results indicate that convergence has taken place, but only until 2008, since when the process has stagnated. Although the ergodic distribution is tighter (indicative of convergence), the result is driven entirely by the 2000-2008 trends. These trends, however, differ remarkably when either demographic or geographical conditioning schemes are introduced. For the population-weighted analysis, convergence exists regardless of the sub-period considered, similarly to what occurs when conditioning by GDP. In all cases not only do the ergodic distributions become much tighter, but the bimodality existing in 2000, 2008 and 2016 vanishes almost entirely, implying that large shares of population escape (and will continue to escape) from poverty. When taking spatial spillovers into account, (conditional) convergence also accelerates.

Our results are in line with previous findings in the literature, since the weak convergence process is corroborated, and our update indicates this pattern still holds. However, shifting the analysis to population-weighted comparisons has obvious implications, as the pattern changes completely, indicating that population tends to concentrate in the richest departments—pointing to some possible weaknesses in the cohesion policies. The spatial spillovers, however, were already relevant by the beginning of the analyzed period and their importance will not vanish. Given its importance, some regions' wealth might be jeopardized by their geographical proximity to regions in conflict.

Therefore, although Colombia's rapid growth has helped to narrow the gap with both Latin American peers and high income countries by accelerating the reduction of poverty rates, several challenges remain, some of which relate to the regional and urban-rural disparities. The poverty rate gaps between the richest and poorest departments have not only persisted but widened, and they are actually higher than in Latin America as a whole and in most of the world. Our analysis has shown that the picture is less dismal when both time and population are factored in as, over time, convergence will occur, and it will accelerate when the person is the unit of analysis. However, as suggested by the transition-path analysis, this will not be a fast process. Therefore, more concerted efforts are needed to alter these dynamics—particularly in terms of higher investment in infrastructures, improving access to public services (and their quality), or commitments to the post-conflict agenda.

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Table 1: Descriptive statistics, GDP[a] per capita, levels (Y/N) and annual growth rates ($\dot{y}$)

Region/department	GDP per capita ($y = Y/N$) 2000	2008	2016	GDP per capita annual growth rate, % ($\dot{y}$) 2000–08	2009–16	2000–16
Andean region (*región Andina*)						
Antioquia	9,527,459	11,670,101	14,775,733	2.280	2.656	2.615
Bogotá	15,365,413	18,490,566	22,209,135	2.078	2.057	2.191
Boyacá	8,119,965	11,489,800	16,221,994	3.932	3.907	4.155
Caldas	6,425,773	8,835,265	10,603,601	3.601	2.048	2.990
Cundinamarca	9,257,191	10,974,681	13,500,206	1.909	2.328	2.244
Huila	7,327,728	8,837,738	10,533,620	2.104	1.970	2.158
Norte De Santander	5,370,294	6,991,723	8,647,538	2.975	2.390	2.842
Quindio	7,073,460	7,242,962	9,695,486	0.263	3.293	1.872
Risalarda	6,704,815	8,640,555	11,050,625	2.858	2.771	2.983
Santander	10,961,875	18,961,839	25,113,904	6.278	3.171	4.997
Tolima	6,578,952	8,902,233	10,595,253	3.417	1.953	2.843
Mean	8,428,448	11,003,406	13,904,281	2.882	2.595	2.899
Median	7,327,728	8,902,233	11,050,625	2.858	2.390	2.842
Standard deviation	2,816,588	4,119,461	5,362,993	1.512	0.639	0.928
Coefficient of variation	0.334	0.374	0.386	0.525	0.246	0.320
Caribbean and Insular regions (*regiones Insular y Caribe*)						
Atlántico	7,753,283	9,203,528	11,767,553	1.923	2.768	2.485
Bolívar	6,903,056	10,563,291	13,476,255	4.840	2.743	4.014
Cesar	5,955,472	10,839,303	12,346,045	6.880	1.457	4.382
Córdoba	5,350,309	6,300,707	7,103,318	1.833	1.341	1.681
La Guajira	6,299,663	8,708,442	6,440,889	3.663	-3.296	0.130
Magdalena	4,332,094	5,739,551	7,022,047	3.175	2.266	2.882
San Andrés	8,597,970	10,580,772	13,639,518	2.332	2.862	2.752
Sucre	3,969,552	5,008,283	6,551,388	2.616	3.029	2.991
Mean	6,145,175	8,367,985	9,793,377	3.408	1.646	2.665
Median	6,127,567	8,955,985	9,435,436	2.896	2.505	2.817
Standard deviation	1,598,610	2,363,628	3,282,774	1.719	2.097	1.328
Coefficient of variation	0.260	0.282	0.335	0.505	1.274	0.499
Pacific region (*región del Pacífico*)						
Chocó	2,873,187	3,895,060	5,891,218	3.439	4.705	4.314
Valle del Cauca	10,118,828	12,031,392	14,497,618	1.942	2.093	2.138
Cauca	4,054,367	5,677,214	8,878,017	3.812	5.093	4.718
Nariño	3,821,309	4,844,613	6,364,919	2.671	3.079	3.047
Mean	5,216,923	6,612,069	8,907,943	2.966	3.743	3.554
Median	3,937,838	5,260,913	7,621,468	3.055	3.892	3.680
Standard deviation	3,307,620	3,685,515	3,950,231	0.831	1.404	1.183
Coefficient of variation	0.634	0.557	0.443	0.280	0.375	0.333
Orinoco region (*región de la Orinoquía*)						
Meta	10,186,385	18,702,060	21,175,999	6.984	1.390	4.399
Vichada	4,838,190	5,556,719	5,073,262	1.550	-1.006	0.279
Casanare	45,042,363	30,440,587	24,331,523	-4.260	-2.458	-3.558
Arauca	15,376,749	24,904,445	12,878,117	5.504	-7.066	-1.038
Mean	18,860,922	19,900,953	15,864,725	2.444	-2.285	0.021
Median	12,781,567	21,803,253	17,027,058	3.527	-1.732	-0.379
Standard deviation	17,976,762	10,697,557	8,665,483	5.024	3.560	3.325
Coefficient of Variation	0.953	0.538	0.546	2.055	-1.558	160.442
Amazon region (*región Amazónica*)						
Amazonas	4,602,647	5,055,671	6,387,089	1.049	2.631	1.946
Caquetá	4,144,700	5,051,334	6,871,802	2.222	3.479	3.019
Guainía	4,597,360	4,517,773	5,375,707	-0.194	1.951	0.924
Guaviare	4,743,605	4,779,901	5,216,987	0.085	0.977	0.561
Putumayo	4,573,519	6,308,091	6,761,880	3.637	0.775	2.327
Vaupés	3,441,953	3,196,848	4,204,793	-0.817	3.092	1.185
Mean	4,350,631	4,818,269	5,803,043	0.997	2.151	1.660
Median	4,585,440	4,915,617	5,881,398	0.567	2.291	1.565
Standard deviation	489,203	1,005,089	1,047,206	1.674	1.113	0.932
Coefficient of variation	0.112	0.209	0.180	1.680	0.517	0.562
Full sample (6 natural regions/33 departments)						
Mean	8,008,772	9,786,153	11,066,759	2.624	1.832	2.347
Median	6,425,773	8,708,442	10,533,620	2.616	2.328	2.615
Standard deviation	7,316,501	6,194,563	5,643,370	2.219	2.336	1.742
Coefficient of variation	0.914	0.633	0.510	0.846	1.276	0.742

[a] In constant 2010 Colombian pesos.
Source: National Administrative Department of Statistics (DANE, *Departamento Administrativo Nacional de Estadística*) and the authors.

Table 2: Descriptive statistics for departments and regions, population, levels (N) and annual growth rates ($\dot{N}$)

	Population (N)			Population annual growth rate ($\dot{N}$)		
Region/department	2000	2008	2016	2000–08	2009–16	2000–16
Andean region (*región Andina*)	2000	2008	2016	2000–2008	2009–2016	2000–2016
Antioquia	5,289,912	5,911,399	6,534,857	1.242	1.120	1.251
Bogotá	6,302,881	7,155,052	7,980,001	1.419	1.220	1.398
Boyacá	1,234,550	1,263,252	1,278,107	0.256	0.130	0.204
Caldas	959,483	974,493	989,934	0.173	0.175	0.184
Cundinamarca	2,076,798	2,397,511	2,721,368	1.608	1.418	1.603
Huila	938,244	1,054,423	1,168,869	1.306	1.152	1.301
Norte De Santander	1,189,505	1,275,834	1,367,708	0.782	0.776	0.825
Quindio	519,805	543,579	568,506	0.498	0.499	0.528
Risalarda	869,888	914,171	957,254	0.553	0.513	0.565
Santander	1,905,077	1,989,514	2,071,016	0.483	0.447	0.492
Tolima	1,336,721	1,378,903	1,412,220	0.346	0.266	0.324
Mean	2,056,624	2,259,830	2,459,076	0.788	0.701	0.789
Median	1,234,550	1,275,834	1,367,708	0.553	0.513	0.565
Standard deviation	1,826,045	2,088,672	2,348,044	0.513	0.458	0.514
Coefficient of variation	0.888	0.924	0.955	0.652	0.653	0.652
Caribbean and Insular regions (*regiones Insular y Caribe*)						
Atlántico	2,017,388	2,255,143	2,489,514	1.246	1.105	1.245
Bolívar	1,792,634	1,937,500	2,121,956	0.867	1.016	0.997
Cesar	844,564	941,258	1,041,204	1.212	1.128	1.239
Córdoba	1,361,658	1535,414	1736170	1.343	1.375	1.440
La Guajira	548,879	763,496	985,452	3.735	2.876	3.502
Magdalena	1,118,977	1,180,134	1,272,442	0.593	0.840	0.759
San Andrés	67,672	72,167	77,101	0.717	0.738	0.770
Sucre	734,647	794,914	859,913	0.880	0.877	0.930
Mean	1,060,802	1,185,003	1,322,969	1.324	1.244	1.360
Median	981,771	1,060,696	1,156,823	1.046	1.060	1.118
Standard deviation	606,840	657,829	718,715	1.010	0.689	0.898
Coefficient of variation	0.572	0.555	0.543	0.763	0.554	0.660
Pacific region (*región del Pacífico*)						
Chocó	437,343	467,074	505,016	0.733	0.872	0.850
Valle del Cauca	3,949,031	4,293,541	4,660,741	0.934	0.916	0.979
Cauca	1,215,944	1,297,703	1,391,836	0.726	0.781	0.798
Nariño	1,446,493	1,599,646	1,765,906	1.125	1.105	1.181
Mean	1,762,203	1,914,491	2,080,875	0.879	0.918	0.952
Median	1,331,219	1,448,675	1,578,871	0.834	0.894	0.915
Standard deviation	1,316,771	1,434,787	1,558,286	0.190	0.136	0.170
Coefficient of variation	0.747	0.749	0.749	0.216	0.148	0.179
Orinoco region (*región de la Orinoquía*)						
Meta	697,478	835,526	979,710	2.027	1.785	2.019
Vichada	48,901	60,494	73,702	2.392	2.219	2.442
Casanare	263,956	313,431	362,721	1.927	1.636	1.887
Arauca	215,979	241,446	265,190	1.246	1.048	1.215
Mean	306,579	362,724	420,331	1.898	1.672	1.891
Median	239,968	277,439	313,956	1.977	1.710	1.953
Standard deviation	239,389	288,107	339,280	0.478	0.484	0.509
Coefficient of variation	0.781	0.794	0.807	0.252	0.289	0.269
Amazon region (*región Amazónica*)						
Amazonas	62,065	70,313	77,088	1.396	1.027	1.283
Caquetá	398,736	436,485	483,846	1.010	1.151	1.145
Guainía	31,640	37,084	42,123	1.780	1.426	1.698
Guaviare	89,038	100,208	112,621	1.322	1.306	1.392
Putumayo	293,525	319,390	349,537	0.943	1.007	1.033
Vaupés	36,151	40,649	44,079	1.312	0.904	1.173
Mean	151,859	167,355	184,882	1.294	1.137	1.287
Median	75,552	85,261	94,855	1.317	1.089	1.228
Standard deviation	141,932	154,108	170,067	0.300	0.198	0.236
Coefficient of variation	0.935	0.921	0.920	0.232	0.174	0.183
Full sample (6 natural regions/33 departments)						
Mean	1,221,078	1,347,004	1,477,203	1.155	1.056	1.171
Median	869,888	941,258	989,934	1.125	1.027	1.173
Standard deviation	1,416,049	1,586,376	1,756,952	0.693	0.550	0.654
Coefficient of variation	1.160	1.178	1.189	0.600	0.521	0.558

Source: National Administrative Department of Statistics (DANE, *Departamento Administrativo Nacional de Estadística*) and the authors.

Table 3: Transition probability matrix and ergodic distribution, per capita income (GDP/N), unweighted, 2-year transitions, limits all years

	Upper limit, all years:				
(Number of observations)	0.970	0.988	1.005	1.023	Max.
(105)	0.81	0.19	0.00	0.00	0.00
(92)	0.20	0.68	0.12	0.00	0.00
(103)	0.00	0.10	0.73	0.17	0.00
(99)	0.00	0.00	0.14	0.78	0.08
(96)	0.00	0.00	0.00	0.08	0.92
Initial distribution (2000)	0.18	0.24	0.21	0.15	0.21
Final distribution (2016)	0.15	0.24	0.18	0.21	0.21
Ergodic distribution	0.10	0.10	0.12	0.28	0.41

a) 2000–2016

	Upper limit, all years:				
(Number of observations)	0.970	0.989	1.006	1.024	Max.
(45)	0.89	0.11	0.00	0.00	0.00
(47)	0.18	0.72	0.09	0.00	0.00
(47)	0.00	0.06	0.74	0.20	0.00
(44)	0.00	0.00	0.14	0.78	0.07
(48)	0.00	0.00	0.00	0.06	0.94
Initial distribution (2000)	0.18	0.24	0.21	0.18	0.18
Final distribution (2008)	0.24	0.18	0.18	0.24	0.15
Ergodic distribution	0.04	0.02	0.05	0.14	0.75

b) 2000–2008

	Upper limit, all years:				
(Number of observations)	0.970	0.988	1.004	1.020	Max.
(50)	0.80	0.20	0.00	0.00	0.00
(43)	0.14	0.74	0.12	0.00	0.00
(47)	0.00	0.09	0.74	0.17	0.00
(46)	0.00	0.05	0.10	0.71	0.14
(45)	0.00	0.00	0.00	0.12	0.88
Initial distribution (2008)	0.15	0.24	0.15	0.24	0.21
Final distribution (2016)	0.09	0.33	0.27	0.18	0.12
Ergodic distribution	0.19	0.26	0.18	0.20	0.16

c) 2008–2016

Notes: The variable of analysis is $x_{it} = \ln y_{it}/\ln \bar{y}_t$, where y_{it} is the per capita GDP of the department. The 2-year (or biennial) transition refers to the movement of x_{it} from one of the five states in period t to another (including staying in the same) state in period $t+5$. The transition matrices presented in this Table are estimated by averaging the observed 2-year transitions of *departments* during the periods 2000–2016 (top panel), 2000–2008 (middle panel), and 2008–2016 (bottom panel). The transition matrices and ergodic distributions displayed in each panel are based on five states, whose upper limits (the "grid") are chosen to yield a virtually uniform distribution over the observed sample. In order to facilitate comparisons, these cut-off points were calculated using the entire 2000–2016 sample (totalling 33 departments $\times$ 17 years $=$ 561 observations), i.e., the top panel, and remained unchanged throughout the entire analysis. The numbers in parentheses on the left are the numbers of observations beginning from a particular state. The cells are arranged in ascending order, with the upper left cell in each matrix showing transitions from the poorest to the poorest (persistence). The ergodic distributions are computed following Kremer et al. (2001).

Table 4: Mobility indices (μ_1)[a], 2-year transitions

Transition matrix	2000–2008	2008–2016	2000–2016
Unweighted	0.624	0.624	0.623
GDP-weighted	0.569	0.605	0.548
Population-weighted	0.574	0.606	0.549
Physically contiguous-conditioned	0.634	0.680	0.631

[a] The values refer to the μ_1 index, as defined in Equation (6), which summarises the mobility information in each transition probability matrix in one number so as to facilitate comparisons across them.

Table 5: Transition path analysis (asymptotic half-life of convergence, $H - L$)[a], 2-year transitions

Transition matrix	2000–2008	2008–2016	2000–2016
Unweighted	72.024	31.588	47.874
GDP-weighted	138.502	65.334	45.343
Population-weighted	158.355	65.998	46.854
Physically contiguous-conditioned	24.629	24.068	16.501

[a] The values indicate the speed at which the ergodic or steady-state distribution is approached. Specifically, they refer to the concept of the asymptotic half-life of the chain, $H - L$, which is how long it takes to cover half the distance from the stationary distribution. Since we are using 2-year transitions, these numbers should be multiplied by 2 to convert them into years.

Table 6: Transition probability matrix and ergodic distribution, per capita income (GDP/N), GDP-weighted, 2-year transitions, limits all years

	Upper limit, all years:				
(Share of GDP)	0.970	0.988	1.005	1.023	Max.
(0.03)	0.81	0.19	0.00	0.00	0.00
(0.06)	0.16	0.73	0.11	0.00	0.00
(0.12)	0.00	0.09	0.78	0.13	0.00
(0.28)	0.00	0.00	0.09	0.83	0.08
(0.51)	0.00	0.00	0.00	0.06	0.94
Initial distribution (2000)	0.04	0.06	0.10	0.15	0.50
Final distribution (2016)	0.01	0.07	0.08	0.19	0.52
Ergodic distribution	0.01	0.04	0.07	0.29	0.59

a) 2000–2016

	Upper limit, all years:				
(Share of GDP)	0.970	0.989	1.006	1.024	Max.
(0.03)	0.86	0.14	0.00	0.00	0.00
(0.06)	0.12	0.78	0.10	0.00	0.00
(0.12)	0.00	0.07	0.77	0.17	0.00
(0.20)	0.00	0.00	0.09	0.77	0.13
(0.59)	0.00	0.00	0.00	0.05	0.95
Initial distribution (2000)	0.04	0.06	0.10	0.29	0.36
Final distribution (2008)	0.03	0.07	0.07	0.33	0.36
Ergodic distribution	0.01	0.03	0.11	0.24	0.62

b) 2000–2008

	Upper limit, all years:				
(Share of GDP)	0.970	0.988	1.004	1.020	Max.
(0.03)	0.74	0.26	0.00	0.00	0.00
(0.08)	0.13	0.79	0.07	0.00	0.00
(0.11)	0.00	0.11	0.75	0.14	0.00
(0.29)	0.00	0.01	0.12	0.74	0.14
(0.49)	0.00	0.00	0.00	0.13	0.87
Initial distribution (2008)	0.03	0.05	0.09	0.19	0.50
Final distribution (2016)	0.01	0.07	0.06	0.21	0.52
Ergodic distribution	0.02	0.10	0.11	0.26	0.52

c) 2008–2016

Notes: The notes for Table 3 also apply here with the exception that the transition matrices are estimated by averaging the observed 2-year transitions of *GDP* (i.e., the GDP of each province that moves from one state to another) during the periods 2000–2016 (top panel), 2000–2008 (middle panel), and 2008–2016 (bottom panel). Therefore, the numbers in parentheses on the left are the percentage of GDP beginning from a particular state; these percentages were calculated taking into account the GDP of each province beginning from a particular state, and the sum of the numbers in parentheses in Table 3.a represents 100%.

Table 7: Transition probability matrix and ergodic distribution, per capita income (GDP/N), population-weighted, 2-year transitions, limits all years

	Upper limit, all years:				
(Share of population)	0.970	0.989	1.006	1.024	Max.
(0.07)	0.81	0.19	0.00	0.00	0.00
(0.12)	0.16	0.73	0.11	0.00	0.00
(0.16)	0.00	0.09	0.77	0.13	0.00
(0.28)	0.00	0.00	0.09	0.83	0.08
(0.37)	0.00	0.00	0.00	0.06	0.94
Initial distribution (2000)	0.09	0.11	0.14	0.16	0.38
Final distribution (2016)	0.01	0.14	0.12	0.21	0.41
Ergodic distribution	0.02	0.05	0.08	0.31	0.53

a) 2000–2016

	Upper limit, all years:				
(Share of population)	0.970	0.989	1.006	1.024	Max.
(0.07)	0.86	0.14	0.00	0.00	0.00
(0.10)	0.12	0.78	0.10	0.00	0.00
(0.16)	0.00	0.07	0.77	0.16	0.00
(0.21)	0.00	0.00	0.10	0.77	0.13
(0.45)	0.00	0.00	0.00	0.05	0.95
Initial distribution (2000)	0.09	0.11	0.14	0.30	0.24
Final distribution (2008)	0.06	0.13	0.10	0.35	0.25
Ergodic distribution	0.01	0.03	0.13	0.26	0.57

b) 2000–2008

	Upper limit, all years:				
(Share of population)	0.970	0.988	1.004	1.020	Max.
(0.06)	0.74	0.26	0.00	0.00	0.00
(0.14)	0.14	0.79	0.07	0.00	0.00
(0.15)	0.00	0.11	0.74	0.15	0.00
(0.30)	0.00	0.01	0.12	0.74	0.14
(0.35)	0.00	0.00	0.00	0.13	0.87
Initial distribution (2008)	0.06	0.10	0.13	0.21	0.38
Final distribution (2016)	0.01	0.14	0.10	0.23	0.41
Ergodic distribution	0.03	0.12	0.12	0.27	0.46

c) 2008–2016

Notes: The notes for Table 3 also apply here with the exception that the transition matrices are estimated by averaging the observed 2-year transitions of *people* (i.e., the population of each province that moves from one state to another) during the periods 2000–2016 (top panel), 2000–2008 (middle panel), and 2008–2016 (bottom panel). Therefore, the numbers in parentheses on the left are the percentage of population beginning from a particular state; these percentages were calculated taking into account the population of each province beginning from a particular state, and the sum of the numbers in parentheses in Table 3.a represents 100%.

Table 8: Transition probability matrix and ergodic distribution, per capita income (GDP/N), physically contiguous-conditioned, 2-year transitions, limits all years

	Upper limit, all years:				
(Number of observations)	0.977	0.988	0.999	1.008	Max.
(101)	0.80	0.18	0.01	0.01	0.00
(101)	0.18	0.69	0.13	0.00	0.00
(95)	0.00	0.14	0.65	0.19	0.02
(98)	0.00	0.00	0.17	0.73	0.10
(100)	0.00	0.00	0.01	0.13	0.86
Initial distribution (2000)	0.21	0.18	0.24	0.15	0.21
Final distribution (2016)	0.18	0.15	0.24	0.27	0.15
Ergodic distribution	0.16	0.18	0.20	0.26	0.20

a) 2000–2016

	Upper limit, all years:				
(Number of observations)	0.979	0.989	0.999	1.010	Max.
(46)	0.88	0.10	0.00	0.02	0.00
(46)	0.13	0.73	0.14	0.00	0.00
(50)	0.00	0.12	0.61	0.22	0.05
(43)	0.00	0.00	0.15	0.73	0.11
(46)	0.00	0.00	0.00	0.15	0.85
Initial distribution (2000)	0.24	0.18	0.21	0.18	0.18
Final distribution (2008)	0.24	0.18	0.09	0.27	0.21
Ergodic distribution	0.23	0.11	0.14	0.33	0.18

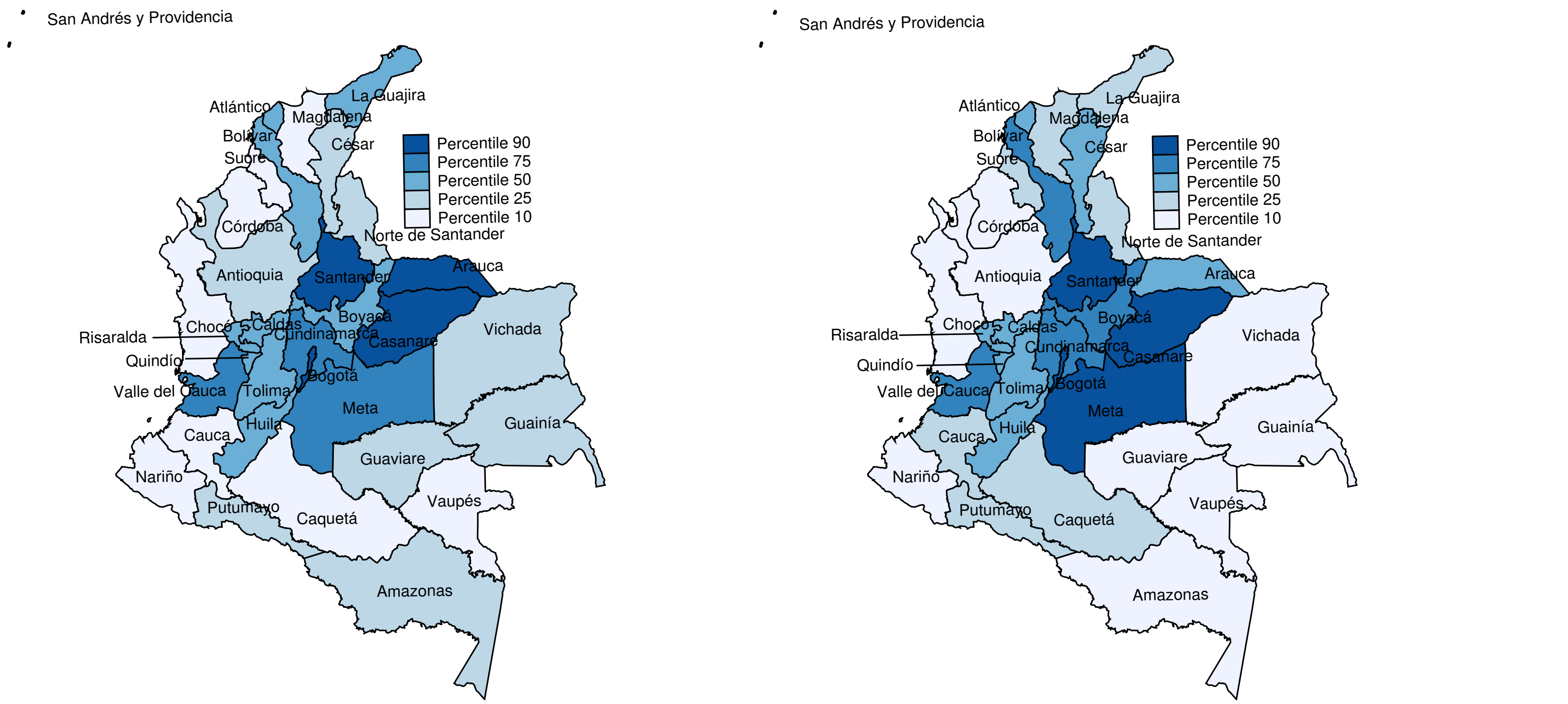
b) 2000–2008

	Upper limit, all years:				
(Number of observations)	0.977	0.987	0.999	1.007	Max.
(73)	0.83	0.17	0.00	0.00	0.00
(18)	0.29	0.38	0.28	0.06	0.00
(23)	0.00	0.17	0.49	0.34	0.00
(32)	0.00	0.06	0.18	0.69	0.06
(85)	0.00	0.00	0.02	0.00	0.98
Initial distribution (2008)	0.18	0.15	0.24	0.24	0.18
Final distribution (2016)	0.18	0.24	0.09	0.24	0.24
Ergodic distribution	0.21	0.09	0.11	0.09	0.50

c) 2008–2016

Notes: The notes for Table 3 also apply here with the exception that the variable of analysis is the neighbour-relative GDP per capita series of province i in period t, x_{it}^{NR}, as defined in Equation (9). The 2-year (or biennial) transition refers to the movement of x_{it}^{NR} from one of the five states in period t to another (including staying in the same) state in period $t+2$. Therefore, the transition matrices presented in this table are estimated by averaging the observed 2-year transitions of *provinces* during the periods of 2000–2016 (top panel), 2000–2008 (middle panel), and 2008–2016 (bottom panel).

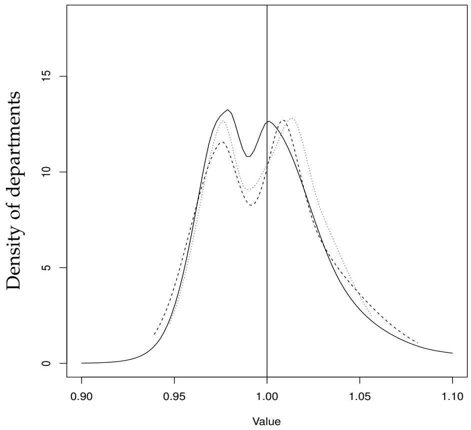
Figure 1: GDP per capita, Colombian departments, 2000 vs. 2016



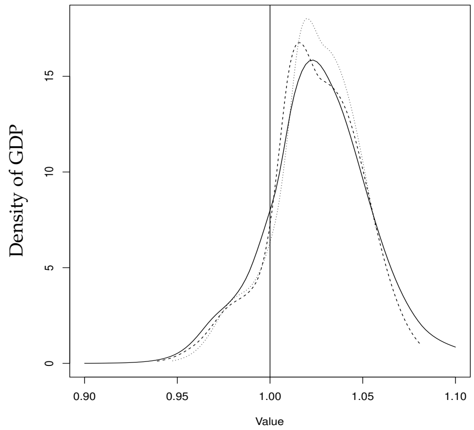
(a) 2000

(b) 2016

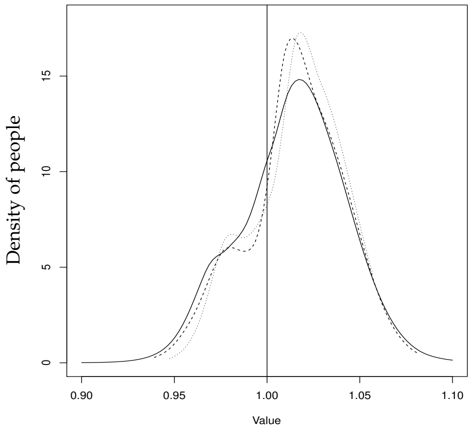
Figure 2: GDP/N, densities, 2000 vs. 2008 vs. 2016



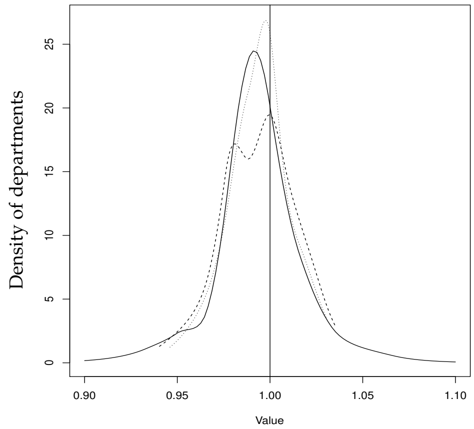
(a) Unweighted



(b) GDP-weighted



(c) Population-weighted

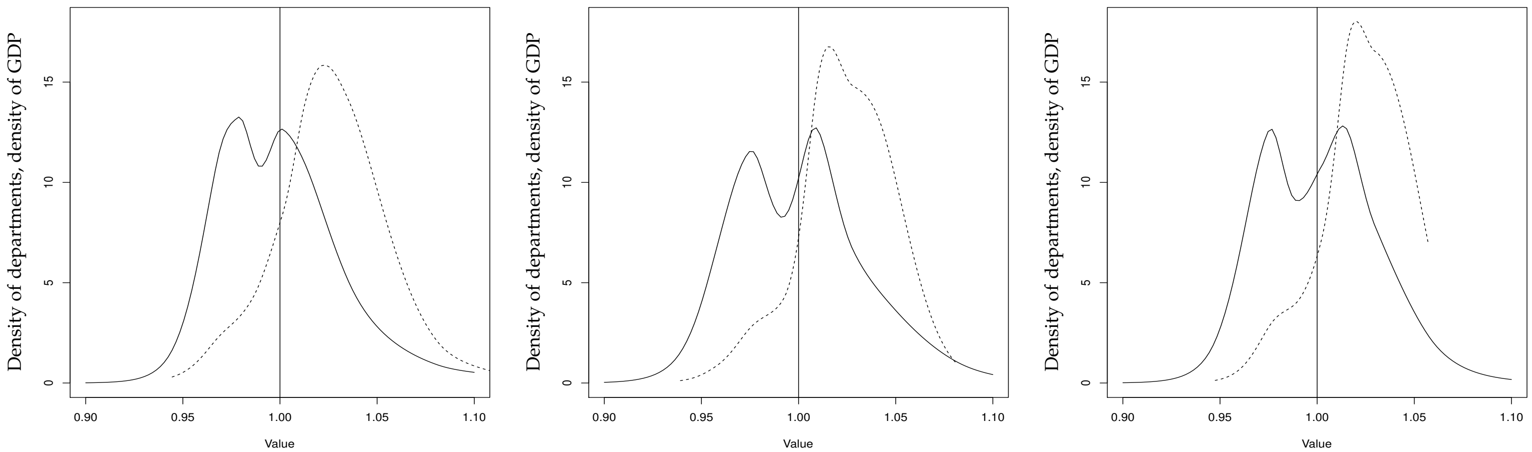


(d) Physically contiguous-conditioned

2000 —— 2008 ------ 2016 · · · · · ·

Notes: All figures contain densities estimated using local likelihood density estimation. The vertical line represents the average, which is the unity because we have normalized the variable of analysis, $x_{it} = \ln y_{it} / \ln \bar{y}_t$, where y_{it} is the per capita GDP of the department.

Figure 3: GDP/N, densities, unweighted vs. GDP-weighted

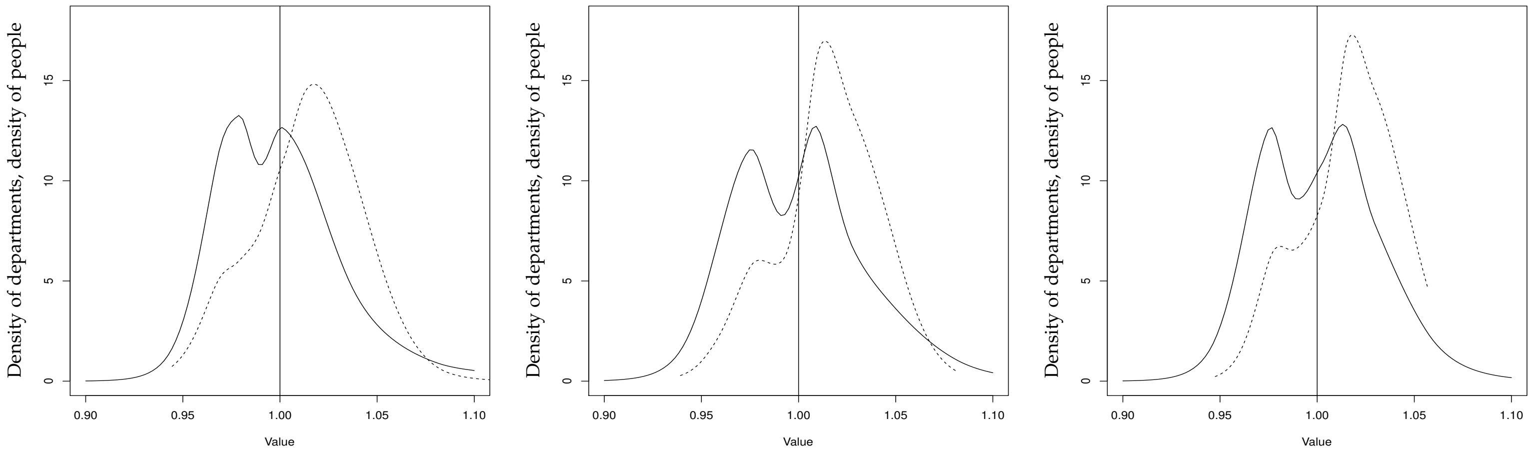


(a) 2000 **(b)** 2008 **(c)** 2016

Unweighted —— GDP-weighted ------

Notes: All figures contain densities estimated using local likelihood density estimation for the years 2000, 2008 and 2016. The vertical line represents the average, which is unity because we have normalized the variable of analysis, $x_{it} = \ln y_{it} / \ln \bar{y}_t$, where y_{it} is the per capita GDP of the department. The solid line is the unweighted density of the x_{it}, whereas the dashed line refers to the GDP-weighted density.

Figure 4: GDP/N, densities, unweighted vs. population-weighted

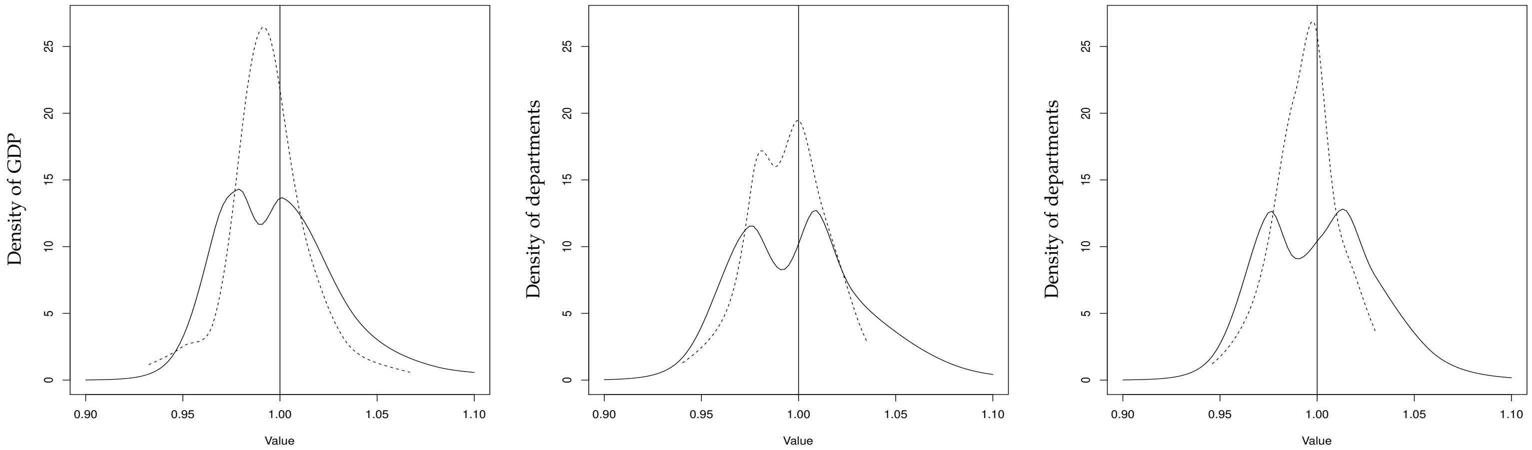


(a) 2000 **(b)** 2008 **(c)** 2016

Unweighted —— Population-weighted ------

Notes: All figures contain densities estimated using local likelihood density estimation for the years 2000, 2008 and 2016. The vertical line represents the average, which is unity because we have normalized the variable of analysis, $x_{it} = \ln y_{it}/\ln \bar{y}_t$, where y_{it} is the per capita GDP of the department. The solid line is the unweighted density of the x_{it}, whereas the dashed line refers to the population-weighted density.

Figure 5: GDP/N, densities, unweighted vs. physically contiguous-conditioned

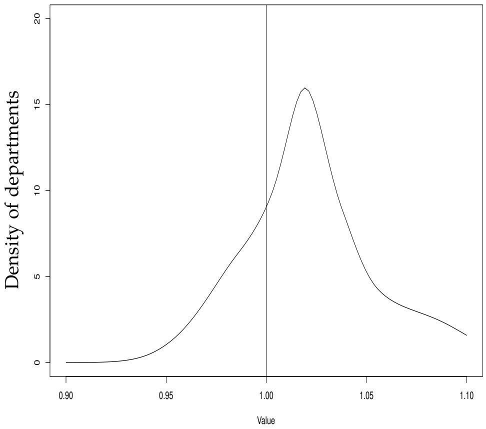


(a) 2000 **(b)** 2008 **(c)** 2016

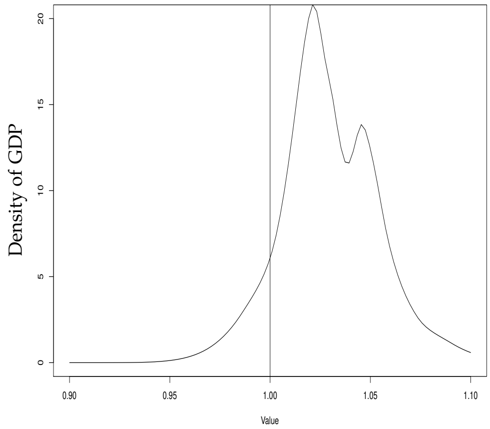
Unweighted —— Physically contiguous-conditioned ------

Notes: All figures contain densities estimated using local likelihood density estimation for the years 2000, 2008 and 2016. The vertical line represents the average, which is unity because we have normalized the variable of analysis, $x_{it} = \ln y_{it} / \ln \bar{y}_t$, where y_{it} is the per capita GDP of the department. The solid line is the unweighted density of the x_{it}, whereas the dashed line refers to the neighbor-relative GDP per capita series of province i in period t, x_{it}^{NR}, as defined in Equation (9).

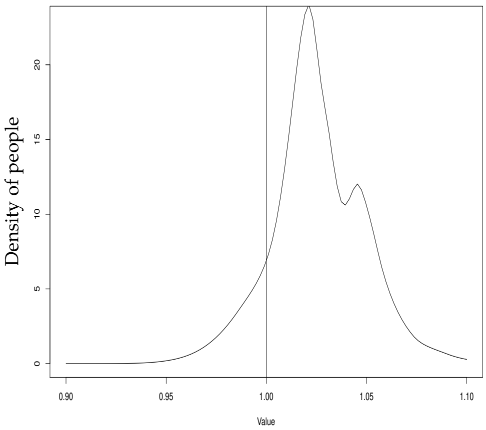
Figure 6: GDP/N, ergodic distributions, 2000–2016, 2-year transitions



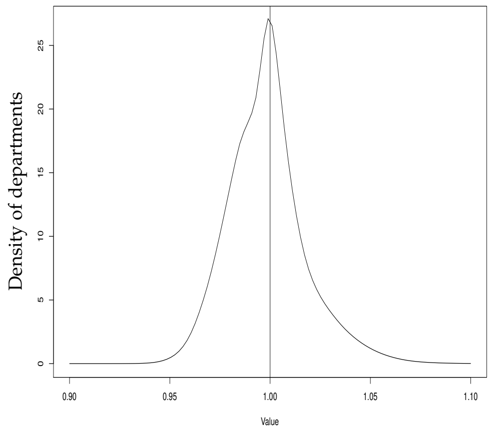
(a) Unweighted



(b) GDP-weighted



(c) Population-weighted



(d) Physically contiguous-conditioned

Notes: All figures contain ergodic densities estimated using local likelihood density estimation. The vertical line represents the average, which is unity because we have normalized the variable of analysis, $x_{it} = \ln y_{it}/\ln \bar{y}_t$, where y_{it} is the per capita GDP of the department. The scale of the vertical axes is not displayed in full in order to facilitate comparison of the densities.