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Regional Convergence, Spatial Scale, and Spatial Dependence: Evidence from Homicides and Personal Injuries in Colombia 2010-2018

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Abstract

This paper studies regional convergence and spatial dependence of homicides and personal injuries in Colombia. In particular, through the lens of both classical and distributional convergence frameworks, two spatial scales are contrasted: municipalities and states. For both homicides and personal injuries, sigma convergence is only found at the state level. In contrast, beta convergence is found at both state and municipal level. The distributional convergence framework highlights further contrasting patterns. For homicides at the state level, four convergence clusters are found, while two clusters are present at the municipal level. For personal injuries, at both spatial scales, two clusters are found. Moreover, significant and robust spatial autocorrelation is found only at the municipal level. Overall, these results re-emphasize the role of spatial disaggregation as well as spatial dependence when evaluating regional convergence and designing regional development policies. Lastly, a discussion of the previous results and their relation to current and future policies is also included.

JEL Codes: O47, O40, O15

Keywords: convergence, distribution dynamics, spatial autocorrelation, homicide rates, social development, Colombia, crime.

1 Introduction

In recent years, a growing number of regional convergence studies have shown that even though there are little signs of convergence of GDP per capita across regions, it is possible for some other social variables to show stronger tendencies towards convergence (Royuela and García, 2015; Mendez, 2018; Kurniawan et al., 2019). In the case of Colombia, for instance, Royuela and García (2015) have reported that literacy rates, life expectancy, income per capita and homicide rates were converging at the state (department[1]) level in different periods up to 2005. Other studies have shown similar results at the state level; where a set of social indicators and disposable income have been shown to converge (Branisa and Cardozo, 2009b,a).

In terms of spatial scale and coverage, most regional convergence studies in Colombia have been limited to social and economic variables at the state (department) level. Among the few municipal-level studies, Galvis-Aponte and Wilfried Hahn-De-Castro (2016) finds no signs of economic convergence; something that few studies have suggested at the state level (Royuela and García, 2015; Galvis-Aponte et al., 2017).

The study of convergence in homicides and injuries is important for the development of Colombia and many other countries in Latin America where high levels of violence are still present. In an influential World Bank report, Ayres (1998) stated that "crime and violence threaten to become the single major obstacle to the realization of the region's long-standing aspirations for sustainable economic and social development ". Further contributions on this topic include Heinemann and Verner (2006) or Bourguignon (2000), where the authors study the correlation of inequality, development and crime.

Lower crime and violence rates are part of the broader and multidimensional definition of development. Therefore, in this paper we study the spatio-temporal dynamics and regional convergence patterns of homicides and personal injuries over the 2010-2018 period. In particular, by using a novel and detailed dataset from the Colombian National Police, we study regional convergence in two spatial scales: municipalities and states (departments). Our results suggests that conclusions regarding regional convergence largely depend on both the selected spatial scale and the methodological framework to study convergence.

Most studies about Colombia have used the classical (beta and sigma) convergence framework of Barro and Sala-i Martin (1991) to evaluate the evolution of regional disparities in both economic and social variables. One important limitation of this framework, however, is that it only describes the behaviour of the average region. As such, it leaves aside important patterns (for instance, polarization, stratification, and local convergence clusters) associated with the evolution of the entire regional distribution. To solve this limitation, some studies have used the distributional convergence of Quah (1997).

From these methodological standpoints, we find sigma convergence at the state level, but not at the municipal level. In contrast, beta convergence is found at both state and municipal level. By evaluating regional dynamics beyond the average region, the distributional convergence framework was able to provide further new insights. For homicides at the state level, four local convergence clusters are found, while two local clusters are found at the municipal level. For personal injuries, at both spatial scales, two convergence clusters are found.

A further contribution of this paper is the study of spatial dependence. As argued by Rey and Montouri (1999), the omission of the spatial dependence and geographic interactions among regions could distort the overall evaluation of regional convergence. Few studies have evaluated the role of spacial dependence in accelerating or retarding the regional convergence process of

[1]Colombia is divided among departments ("departamentos" in Spanish) and municipalities. Throughout this paper departments are referred as states

Colombia. Among them, Barón (2003) reports a random spatial distribution of GDP per capita between 1980 and 2000 at the state level. Consistent with this finding, our results also suggest a lack of robust spatial autocorrelation at the state level. However, at the municipality level, we find strong evidence of spatial autocorrelation. Overall, these results emphasize the role of spatial disaggregation when evaluating spatio-temporal dynamics and regional convergence.

The rest of the paper is organized as follows. Section 2 presents the methods and data. Section 3 shows the results of the classical convergence analysis, the distributional convergence framework and the spatial approach. In addition, section 4 relates the findings of this paper to current and future policy. Lastly, section 5 presents some concluding remarks and suggestions for further research.

2 Methodology and Data

2.1 Classical Convergence Framework

The seminal works of Barro (1991) and Barro and Sala-i Martin (1991, 1992) have stimulated a vast literature which studies the convergence hypothesis. Their approach, today known as the beta convergence approach, stated that the level of economic growth of an economy depended on its initial size. When studying regional data sets, Barro and Sala-i Martin (1995) propose the following equation:

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

Where i is the index for each region, 0 and T represent the initial and final time, y is the economic variables to be studied (in most cases income) β is known as the β coefficient or speed of convergence, α summarizes unobserved parameters such as the steady state and $w_{i,0T}$ represents the error term. If the data adjusts to the model presented in (1) then a second parameter known as the "half-life" can be computed:

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

This alternative measure of convergence indicates the time that it would take the average region to halve the distance between its initial income and its steady state equilibrium.

A complementary analysis of convergence, which is more general in statistical terms, is the so-called $\sigma - convergence$. This approach studies the evolution of the cross-sectional dispersion over time. Different statistical measures of dispersion can be used to analyze $\sigma - convergence$. In this paper, the standard deviation of the natural rates will be computed. Note, that in most papers dealing with income variables the standard deviation of the *Log* of the variables is considered. But given the small changes of the rates studied in this paper and that such rates by construction are bounded variables, the deviation of natural rates is preferred.

2.2 Distribution Dynamics Framework

Classical convergence measures are useful for studying the âaverage behaviorâ in a cross-section of regions. However, these approaches do not shed light on the evolution of the entire distribution, including its intra-distributional dynamics. The approach suggested by (Quah, 1993, 1996, 1997) focuses on these features of the convergence process by using stochastic kernels methods

Figure 1: Distribution dynamics framework, image taken from Mendez-Guerra (2019)

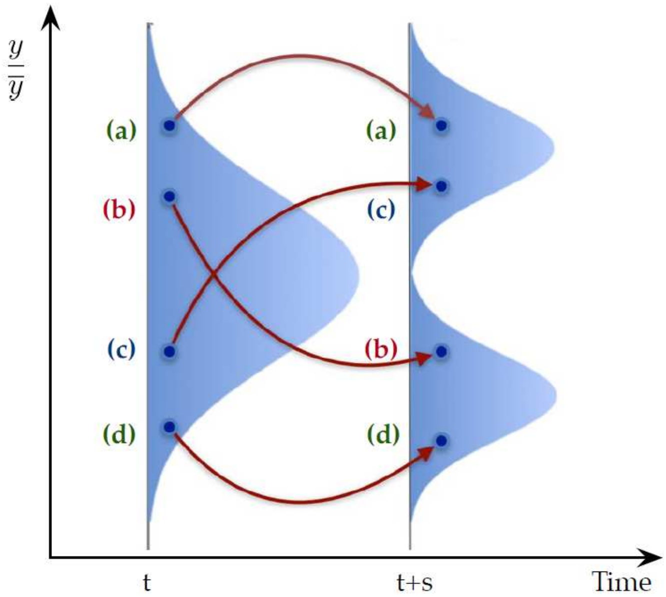


Figure 1 depicts a visual summary of the distributional convergence framework. As shown by the graph, over time there is a process of clustering that takes places within the distribution. This internal polarization (or stratification in a more general sense) is not captured by classical measures of convergence [2]

To formalize the intution of Figure 1, given the crime rates considered in this paper, let us first define $C_t(x)$ as the cross-regional crime rate distribution at time t and $C_{t+s}(y)$ as the distribution at time $t+s$. The dynamics of the distribution can me modeled by a first-order auto-regressive process of a time-homogeneous Markov chain. This is shown in equation (3)

$$\underbrace{C_{t+s}(y)}_{Future\,Distribution} = \int \underbrace{C_{t+s|Z_t=x}(y)}_{Stochastic\,Kernel} \underbrace{C_t(x)}_{Initial\,Distribution} dx \tag{3}$$

The mapping of the initial distribution, $C_t(x)$, into the future distribution, $C_{t+s}(y)$, depends on the stochastic kernel, $C_{t+s|Z_t=x}(y)$; which is a transitional operator commonly estimated as a conditional distribution function. An estimate of the stochastic kernel can be obtained by dividing the joint probability density function $C_{t,t+s}(y,x)$ by the marginal probability density function $C_t(x)$:

$$C_{t+s|Z_t=x}(y) = \frac{C_{t,t+s}(y,x)}{C_t(x)} \tag{4}$$

To estimate and display this stochastic Kernel, we use the conditional density estimator of Hyndman (1996). This estimator is shown to have better asymptotic mean properties and the results can be presented using two new visualization tools. The first one is a three-dimensional density plot in which the conditional densities are shown side-by-side in a perspective plot. The second one is similar to a boxplot, but instead of using the median as indicator of centrality, it uses the mode of each conditional density. This plot will capture the internal polarization (or stratification) of the distribution; convergence clusters will appear as series of modes localized on a horizontal row.

[2]For a more detailed review of the distributional approach see Magrini (2009)

2.3 Spatial Auto-correlation Framework

Studies of classical convergence usually assume spatial independence among observations (countries, states, municipalities, etc.). However, this assumption is likely to bias their results in the sense that spatial neighbors of a region are likely to affect its behavior and performance (Fingleton and López-Bazo, 2006), To start exploring the potential role of spatial dependence, we compute the Moranâs I statistic of spatial autocorrelation as follows:

$$I = \frac{\sum_i \sum_j w_{ij} c_i.c_j}{\sum_i c_i^2} = \frac{\sum_i (c_i \times \sum_j w_{ij} c_j)}{\sum_i c_i^2} \tag{5}$$

Where w_{ij} is the spatial weights matrix and c_i is the crime rate in area i (either a municipality or a state). When inspecting the significance level of the Moranâs I, the bootstrap method, based on 10.000 permutations, is used to generate a pseudo-p value (see Anselin et al. (2006))

Next, we differentiate the crime rates to control for regional fixed effects. That is, the Moranâs I for the variable $C_{i,t} C_{i,t1}$ is reported. Thus, if there is a fixed effect μ_i related to region i, it is possible to present the value of each region at time t as the sum of some intrinsic value and the fixed effect; which is $C_{i,t} = C*_{i,t} + \mu_i$. Differencing the variables removes such fixed effect μ_i. By using this differential approach we can better evaluate the robustness of the commonly used Moranâs I statistic of spatial autocorrelation.

2.4 Data

Two crimes will be considered for the period 2010-2018 in Colombia: the homicide rates and the personal injury rates. The former variable was also considered in previous convergence studies (Royuela and García, 2015) and the latter is an extra variable that we consider important for various reasons.First, homicides are an extreme form of violence while personal injury represent a less extreme form of violent behavior. Taken together, they provide more complete picture of the spatial temporal dynamics of violence. Second, being personal injuries a more common crime, we gain an insight into the crime patterns of many more municipalities.

The total number of homicides in Colombia per year from 2010 until 2018 and personal injuries data for the same years are taken from the Colombian National Police Department [3]. Each observation in these datasets include very specific information about the time and actors involved in each crime. For this study, only the location was considered to generate the counting of crimes per department and municipality

In order to compute crime rates both the number of cases (number of crimes) and the population at risk are needed. Population census and estimates for states and municipalities reported by the Colombian National Bureau of Statistics (DANE) were used. Once a raw rate is found, it has to be mapped into a non-crime rate, which means the ratio of the population that were not "affected" by a given crime. These non-crime rates (NCR) where computed as follows:

$$NCR = 10.000 - raw\ rate * 10.000 \tag{6}$$

Where these rates are provided per 10.000 people. We will consider NCR instead of raw rates, following the standard in the convergence literature (stressed, for example byKenny (2005)) in which the variables are defined positively (the larger the number, the better),

[3]Data for the Archipelago of San Andres, Providencia and Santa Catalina is not considered in this paper, given that spatial autocorrelation is studied with a queen contiguity criterion.

3 Results

On average, the non-murder rate (NMR) and the non-personal injury rates (NPIR) showed different patterns as it can be seen in figure 4. At the state level, for NMR (panel (d)) on average there has been a major improvement. in 2010 the mean NMR was 9996.7 with a standard deviation of $\sigma_{dept,2010} = 1.8$; while in 2018 NMR increased (crime decreased) to 9997.6 and $\sigma_{dept,2018} = 1.3$. Also, the worst performing state in each year has increasingly improved over the 8 year period. These results indicate that $\sigma - convergence$ was present on average for the whole period at this spatial level.

Figure 2: Quantiles distribution for both crime variables at the municipal and state level

(a) Municipal Non Personal Injury Rates

(b) Municipal Non Murder Rates

(c) State Non Personal Injury Rates

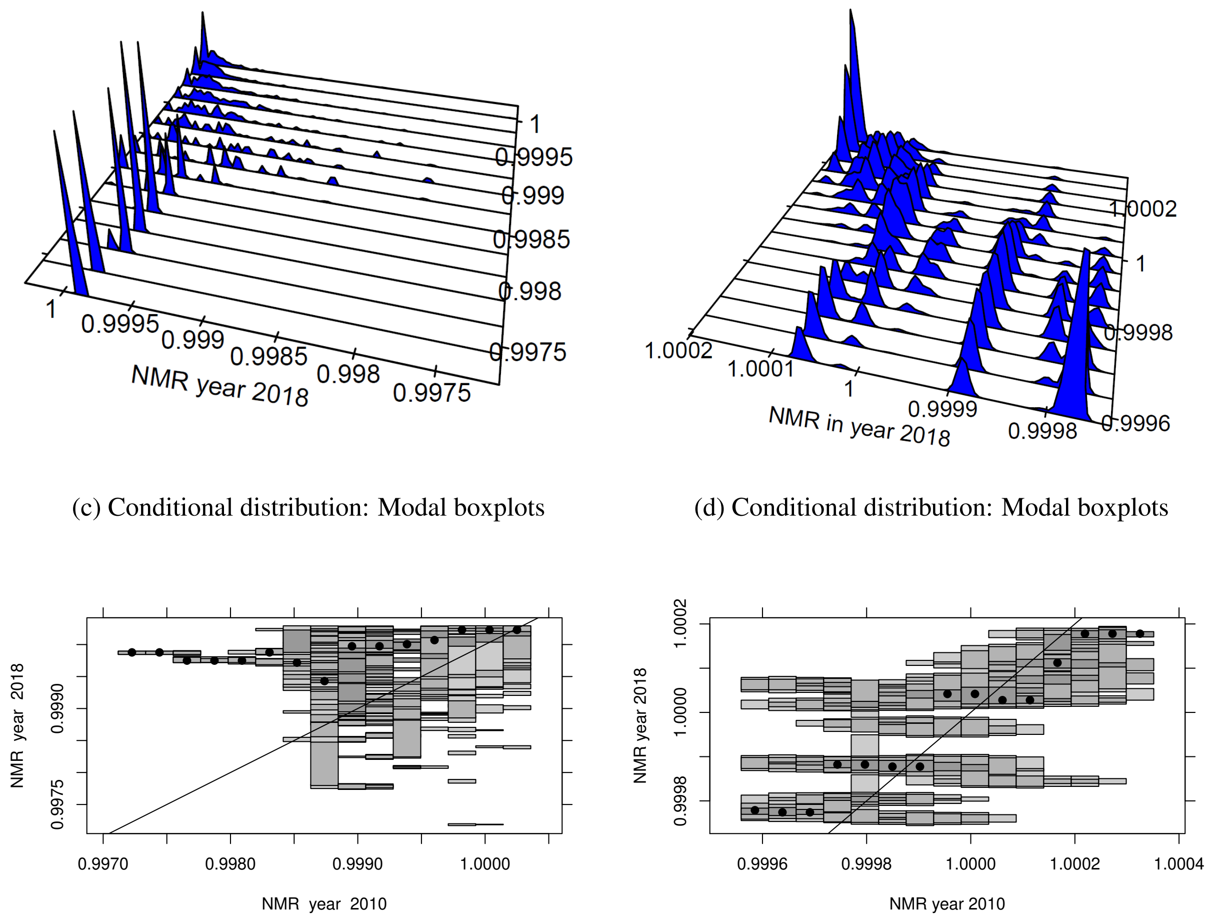
(d) State Non Murder Rates

In contrast, the NPIR (panel (c)) deteriorated during this period given that the average rate in 2018 was 9973.6 while it was 9987.5 on average in 2010. However, the dispersion of the data also decreased suggesting $\sigma - convergence$ for this variable. The values for the standard deviation are $\sigma_{dept,2010} = 9.3$ and $\sigma_{dept,2010} = 8.2$ for these years respectively. Overall, it could be the case that a trade-off between these two variables has been taking place. A reduction in homicides may be related with an increase of lower levels of violence.

In the case of municipalities, the patterns are much more contrasting in panel (a) it is clear that NPIR at the municipal level have worsened, it can be seen that all quantiles curves were closer in the year 2010 and by 2018 they have significantly diverged, suggesting no patterns of Ï-convergence. In addition, for NMR (panel (b)) it seems that there has been a small improvement as the median has slightly increased over the 8-year period. Given that the red curve on the graph representing the 0.2 quintile has also grown over this time period this may suggest that the dispersion of the data has also decreased. However, a detailed calculation of the standard deviation shows that it has slightly increased over this period, see following section.

Overall, from figure 2 the average pattern and a visual approximation of convergence can be observed. However for the sake of precision, an statistical measure of dispersion is needed to state the convergence or divergence of the cross section; this is evaluated in the following subsection.

Figure 3: Distributional convergence and clusters in non-murder rates



(a) Conditional distribution - Municipalities

(b) Conditional distribution - Departments

(c) Conditional distribution: Modal boxplots

(d) Conditional distribution: Modal boxplots

3.1 Classical convergence

Table 1 presents the summary of the results for the classical convergence analysis for both variables and both disaggregation levels. In this table, it can be seen that significant $\beta -$ *convergence* coefficients are found for both aggregation levels (spatial scales) and crime variables.

Table 1. Classical convergence framework summary

crime rate and level	**β - coefficient**	**half-life (years)**	σ_{2010}	σ_{2018}
NMR (dept)	0.08	8.6	1.9	1.3
NMR (mun)	0.10	6.9	3.1	3.3
NPIR (dept)	0.13	5.3	9.3	8.2
NPIR (mun)	0.06	10.2	9.5	15.0

Note: all beta coefficients are highly significant p-value < 0.001

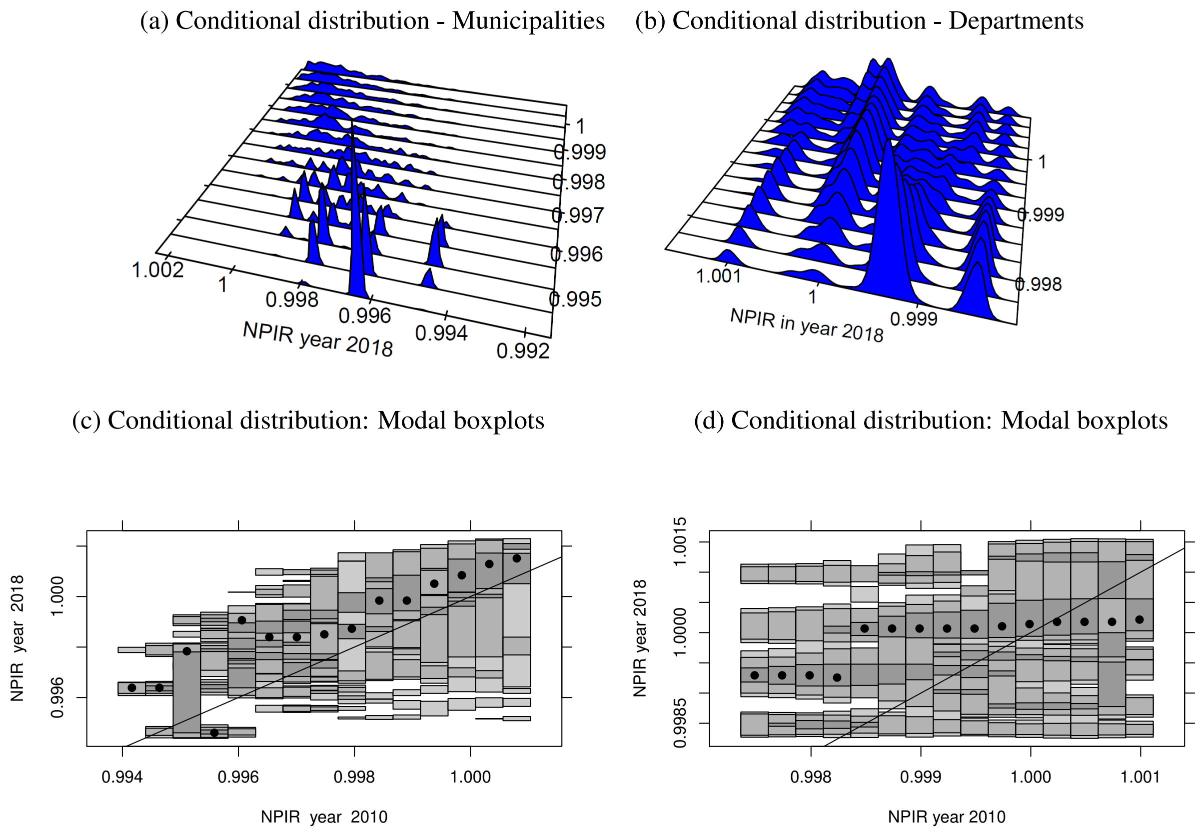
A major result of this classical convergence approach is the fact that at the state level there is evidence of both sigma and beta convergence, while the equivalent is not true for municipalities. Sigma convergence is not found at the municipality level.

Moreover, as far as it is known to the authors of this paper, the present result is the first time in the literature in which robust beta convergence is found for homicides rates in Colombia at the state level. In a previous study Royuela and García (2015) rates were studied from 1990 to 2005, the authors reported that beta convergence even though it was recovered from a linear regression was mostly driven by one region which has a major improvement over this period [4]. In the case of the data of the current paper from 2010 to 2018 the regression is robust and not driven by a single region; it can be said that the improvement of survival rates has been widely shared by many states and in this sense portrays an inclusive social development.

3.2 Distributional Convergence

The results for the study of the variable NMR are presented in Figure 3. It can be seen from the conditional distribution plots (panels (a) and (b)) that at the municipality level there appear to be fewer convergence clubs. These clusters are clearly shown in the modal boxplots (panels (c) and (d)). At the municipality level there seem to be two convergence clubs; conversely the existence of at least four convergence clubs is reported at the state level.

Figure 4: Distributional convergence and clusters in non-personal injury rates



(a) Conditional distribution - Municipalities (b) Conditional distribution - Departments

(c) Conditional distribution: Modal boxplots (d) Conditional distribution: Modal boxplots

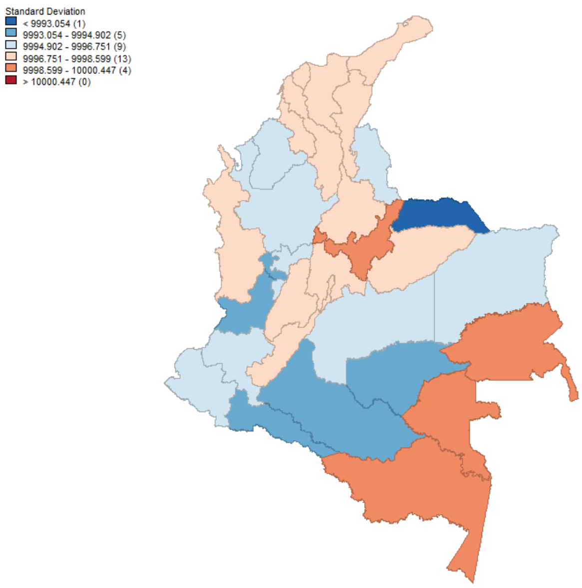
The diagonal lines in the modal boxplots indicate whether a region has improved in rela-

[4]As a matter of fact, using the data of Royuela and García (2015) and removing that region gives a p-value of over 0.45 for the beta regression for survival rates

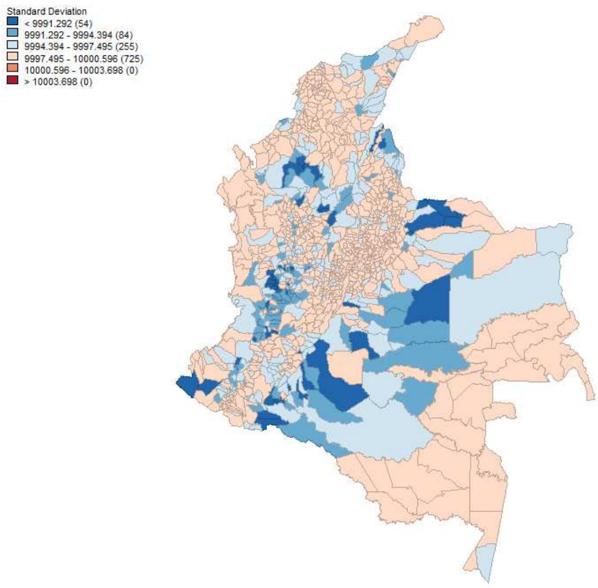
tive terms or not over this time frame. Points located over this line represent regions which improved in relative terms; in contrast point below the line refer to regions which worsen over this period. At the municipality level the modes of the cluster are located in most cases over the diagonal, indicating a general improvement of relative NMR. At the state level, however, the results are more heterogeneous given that most clubs are crossed by the diagonal line, which means that some members of the club improved while others declined in relative magnitude. In general terms, it can be stated that municipal and state levels show different patterns of clustering.

Figure 5: Crime rates in 2010 for both levels

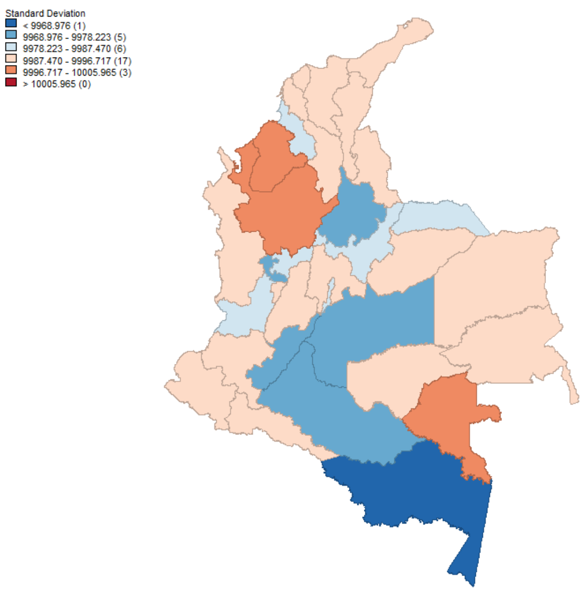
(a) NMR - departmental level



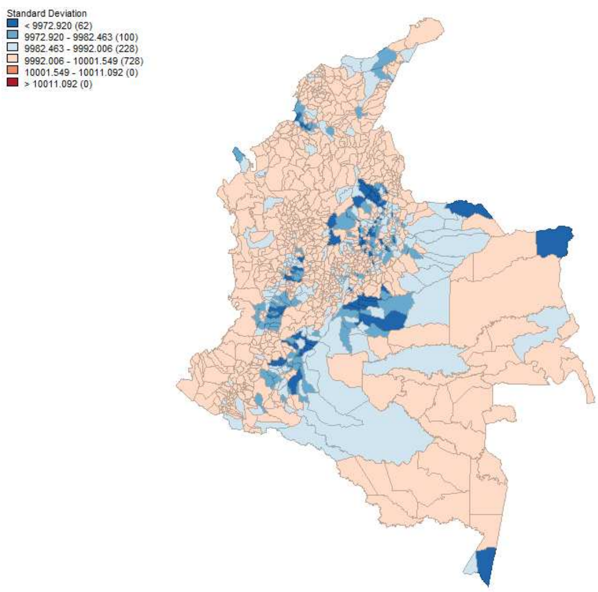
(b) NMR - municipal level



(c) NPIR - departmental level



(d) NPIR - municipal level



In the case of NPIR, the clustering process seem more clearly presented at the departmental level. As shown in panel (d) for this variable there seem to be two different convergence clubs.

At the municipality level, the results seem inconclusive; there might be a lower cluster around 0.996 and a second cluster at 0.998 (relative NPIR in 2018, y axis in the boxplots). For values over 0.998 the data shows a unique pattern in which most regions appear to improve in relative terms (data above the diagonal) but no clear clustering is shown. It should not be forgotten that all variables in the conditional approach are computed in relative terms (divide by the average in that year) in this sense when we refer to "improvement" that means in relative terms. It must be clear by referring to Figure 2(a) that in terms of average magnitudes NPIR worsen over the 8-year period.

3.3 Spatial Autocorrelation

Figure 5 shows four choropleth maps of the regions of Colombia. All maps are standard deviation maps in which the dark blue present the lowest values of non-crime-rates (more crime) and the orange represent the higher values (less crime). Panels (a) and (b) include the non-murder rates in 2010 for municipalities and states, and panels (c) and (d) show the non-personal injury rates at both spatial levels in 2010.

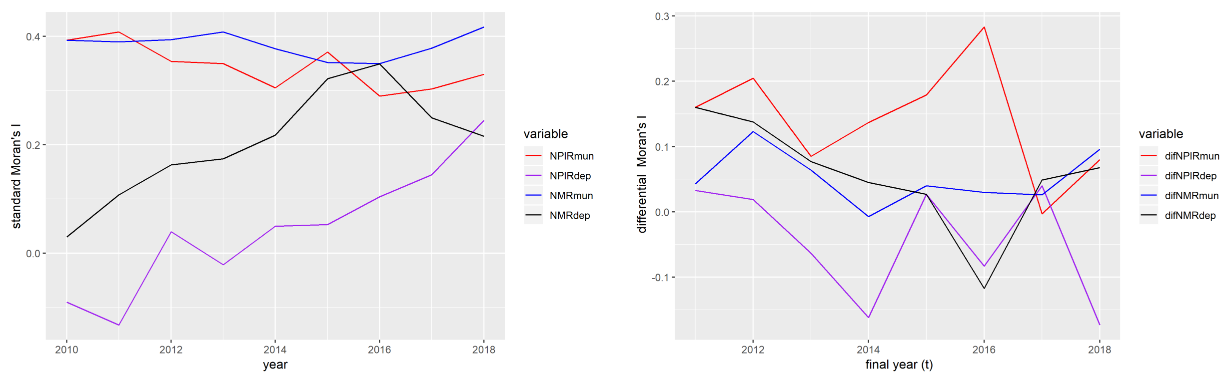
Regional inequality in terms of violence and crime seem evident by looking at Figure 5. In panel (a) is clear that in 2010 there are three layers in terms of murder rates, first there is a core of municipalities with low homicide rates (near the capital Bogota) surrounded by a layer of high crime zones which in part are also surrounded by an extra layer of low crime areas. However, panel (c) indicate the existence of two layers for NPIR a core of high crime rates and a periphery of lower crime rates.

From panels (c) and (d), it is noticeable that the spatial distribution of NPIR differs in both levels. For example, at the departmental level the lowest value is recorded in Amazonas (the furthest south state in dark blue in panel (d)). However, when this state is divided into municipalities, it seems that most of the crime is concentrated in the municipality of Leticia (the furthest south municipality in dark blue in panel (c)). Crime in this municipality seems to be driving up the average for the state which would certainly affect surrounding spatial regions when calculating spatial autocorrelation. Figure 5 may shed some intuition on the fact that spatial autocorrelation is not robust at the state level.

Figure 6: Moran's I for crime rates at both spatial levels

(a) Moran's I for crime rates

(b) Differential Moran's I for crime rates



The standard Moranâs I is calculated using queen contiguity weights. In Figure 6 panel (a), the evolution of this statistic is plotted for both crime variables at both disaggregation levels. In general, the statistics found are significant for most years. In panel (a) it can be seen that spatial autocorrelation, for all years, larger at the municipality level than at the departmental level. Though, larger in magnitude the Moranâs I for NPIR and NMR remains on average stable for municipalities, while it shows a growing tendency for states (purple and black curves in panel(a)).

In order to evaluate the robustness of the data registered in panel (a), the differential Moranâs I was computed for both variables and levels. The results are shown in panel (b). As expected, the magnitude of the spatial autocorrelation decreased when considering differential variables. Also note that the significance of the statistics vastly changed. For the NPIR, at the state level, the autocorrelation was negative in 50% of the cases and in over 85% of the years insignificant; while in over 85% of the years was highly significant at the municipal level.

For the NMR the results are considerably similar. While on average the differential Moranâs I at the state and municipality level have similar magnitudes (blue and black curves in panel (b)), the significance of the statistics are the opposite. In over 85% of the years, the differential Moranâs I is significant at the municipality level, whereas at the departmental level is insignificant in over 85% of the years.

4 Discussion and Policy Implications

An analysis of convergence could be used by policy makers as a framework to systematically evaluate how close or far from a particular region is from a national development target. Although in the short-run this target can vary across regions; in medium and the long run, a convergence target should be prioritized to promote national cohesion and stability

4.1 Vertical policy coordination

Aggregation of regional differences from the municipal to the state level can hide local convergence clusters. The formulation of national and regional policies should carefully consider the risks of information loss due to data aggregation. Thus, it could be more appropriate for the formulation of national development plans to have convergence targets at the state level as well as the municipal level. Policy makers from the central government should continuously monitor the differences in both targets. In the end, the achievement of a unified target largely depends on the vertical coordination among central, state, and municipal governments.

The current Colombian National Development plan includes a specific national homicide rate target of 23,3 per year per 100.000 inhabitants to be achieved by 2022. However, in this plan there is no specific mention to municipal or departmental targets. Given the heterogeneity of the crime rates and the presence of regional clusters, a more specific setting of regional targets may help the optimal use and allocation of resources.

4.2 Horizontal/spatial policy coordination

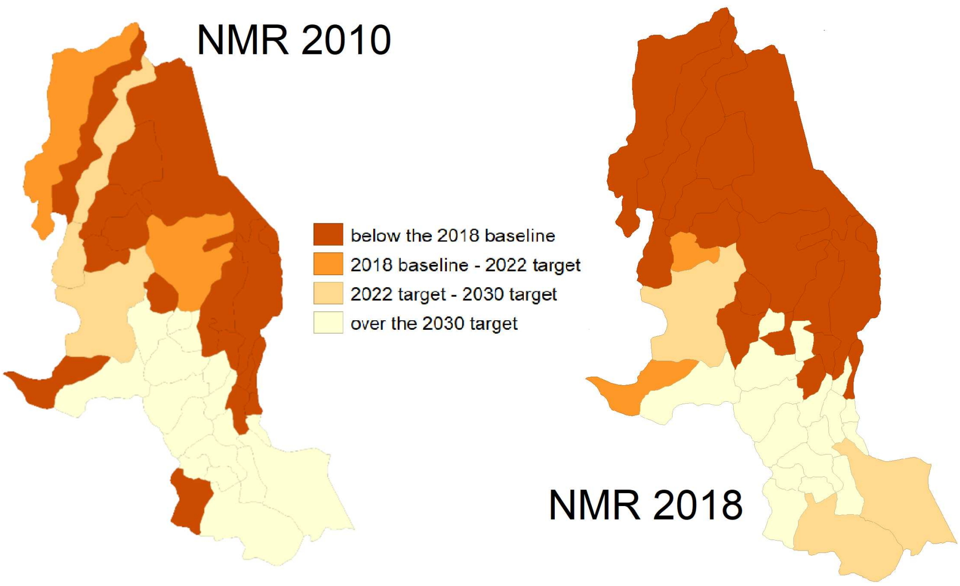
Spatial spillovers from regional neighbors have both positive and negative effects on the convergence path of a region. Regional governments need to further coordinate their policy interventions to jointly maximize (minimize) positive (negative) spillovers. For example, learning from successful policy interventions in neighboring regions is a form of technological transfer that can accelerate the rate of convergence.

Coordination and spillovers can be seen from the experience of the state of "Norte de Santander" over the last 8 years (see Figure 7). The custom breaks in that choropleth map are the values of the 2018 national baseline, the 2022 national target and the 2030 national target in the

Colombian National Development plan . In general terms (see map for the year 2018), over 8 years, the north of the state became a region in which 18 municipalities where under-performing relative to the national average, while 17 municipalities in the south were outperforming it.

In the one hand, the violent spillover of regions in the north at the beginning in 2010 may have spread across all regions in the north by the end of 2018. On the other hand, some positive spillovers can also be seen in the south. Southern municipalities colored red in the years 2010 and 2014 improved considerably by 2018 and all regions in the south reached the 2022 target. This evidence suggests that the coordination of violent forces (negative spillover) in the north and the coordination of non-violent forces (positive spillover) in the south took place over the period 2010-2018. A more detailed inspection of spatial autocorrelation shows that the Moranâs I at the state level at the beginning of the period was not significant in 2010 while it showed a highly significant pattern by 2018.

Figure 7: NMR for years 2010 and 2018 for "Norte de Santander"



4.3 The need for a spatial perspective in current cash transfer programs

Conditional cash transfer programs (CCT) seem to be significantly related with the reduction of a diversity of crimes, specially robbery and theft. However, in the short run, CCT may not be directly related with a decrease in homicide rates, as reported in the study done by Camacho and Mejía (2013). In a longer timeframe, it has been shown that homicides are negatively correlated with the expansion of CCT, as is reported for Brazil and Mexico by Lance (2014). Also, in a longer time-frame, Loureiro (2012) reported a significant effect on property crimes but not on homicides in the case of Brazil.

Given the 8-year scope of this paper, the possibility of finding data for previous years, and the growing interest in a government-led national CCT in Colombia, it may be possible to study the hypothesis of a negative correlation between crime rates and CCT programs in Colombia. Spatial regressions could be used to test this hypothesis (regressions that may be evaluated by using the spatially filtered crime variables or other spatial econometric models). Moreover, such research could contribute to the literature by suggesting a case for spatially focused CCTs. Ultimately, this type of analysis could serve a as tool for combating organized crime in specific locations Ingram and Marchesini da Costa (2017).

5 Concluding Remarks

There are large differences in crime rates across the Colombian regions. Recent studies have highlighted violence and security as variables that are pivotal for understanding the development process of Colombia. Peace is perhaps one of the elusive pieces to trigger a more sustainable development path in Colombia. This country is in its way to recover from the longest internal conflict of the American continent.

In this context, this paper finds no strong signs of convergence at the municipality level in terms of homicides and personal injury rates. These findings contrast those at the state level. At this higher spatial scale, regional convergence is found, at least through the lens of the classical convergence approach of Barro and Sala-i Martin (1991); Barro (1991) Through the lens of the distributional convergence approach of Quah (1997), however, we find multiple convergence clubs and clear patterns of crime fragmentation across space. There are also substantial differences between the convergence dynamics of homicides and personal injuries.

Results from our spatial dependence analysis indicate the presence of spatial autocorrelation at both levels: municipalities and states. However, at the state level, spatial autocorrelation is not robust for most years. This lack of statistical significance at the state level is in sharp contrast with the municipal-level data, where spatial autocorrelation of the differential variables is found to be significant in almost all years. These results (re)emphasize the role spatial scale plays when evaluation spatial processes, and ultimately when evaluating regional convergence.

The results of this paper also point to some milestones for further research. Firstly, robust spatial autocorrelation at the municipal level suggest the possibility of applying spatial filtering models. For example the Getis filter Getis and Ord (2010) is widely used in order to remove the spatial component of variables; as it has been used in several studies such as Cravo and Resende (2013) and Fischer and Stumpner (2008)

The next extension has to do with the determinants of the convergence clubs. An ordered logit model could help us identify how regions could move or "escape" from a lower convergence club. Finally, one could also evaluate the spatial and temporal relationship between homicides and personal injuries. On this relationship, it is worth noticing that homicides appear to show a decreasing tendency while personal injuries appear to show an increasing tendency. Such inverse relation could be studied in more detail and evaluate to what extend there is trade-off between these two variables.

Aknowledgements

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