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 non-parametric 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. The paper concludes with a discussion about the relationship between crime types and their relevance to current and future development policies.

JEL Codes: R11, R12, R58

Keywords: convergence, distribution dynamics, spatial econometrics, crime, homicide rates, sustainable development, Colombia.

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 (departmental[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).

The study of convergence in homicides and personal 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. That is, we consider than being development a multidimensional concept, beyond economic growth, studies of violence and crime can shed light on the development of a regions such as Latin America and in

[1] Colombia is divided among departments ("departamentos" in Spanish) and municipalities. Throughout this paper the terms “departments” and “states” are used interchangeably.

particular of countries with high crime statistics like Colombia. 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 suggest 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 frame- work 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 framework (see for example Quah (1997)).

Based on the current literature and taking advantage of the dataset constructed from the National police department, we aim to answer the following research questions: Beyond states, is there convergence of crime rates at the municipal level for homicides and personal injuries? What are the spatial patterns of crime and how significant is the spatial dependence of crime? Is there any relation between both types of crime? Overall, considering that crime is an important measure of the level of development of a society, are there strong signs of crime convergence in Colombia between 2010 and 2018?

Based on these methodological standpoints and research questions, 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 spatial dependence in accelerating or retarding the regional convergence process of 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 literature review and section 3 the methods and data. Section 4 shows the results of the sigma and beta convergence frameworks, the distributional convergence analysis and the spatial autocorrelation analysis. Moreover, in section 5 the relation between the crime variables is further analysed and in Section 6 the findings of this paper are related to policy interventions.. Lastly, section 7 presents some concluding remarks and suggestions for further research.

2. Literature Review

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).

Moreover, there is an established literature that uses convergence theory for studying crime rates across regions. For example, the Cook and Winfield's study (2013) uses the classical convergence approach to analyse crime at the state level in the USA over the period from 1960 to 2009. Moreover the same authors in 2015 extended their study considering counties and states (Cook, S. and

Winfield, T. (2015)). In Addition, Castro and Valdivia (2013) using a spatial panel regression, tested beta convergence of homicide rates across Mexican municipalities and presented different patterns of convergence depending on the gender of the victims.

In terms of previous studies about regional convergence of crime in Colombia, to the best of our knowledge, the only study that has taken into consideration crime-related variables has been the work of Royuela and García (2015). However, this study is limited to homicides at the state level . In the present paper, we study crime-related variables at both state and municipal levels. Our dataset includes not only a new variable about personal injury rates , but also is based on the most recent data collected by the National Police Department.

There is also a large body of literature that considers the determinants of crime across the world and in Colombia. The seminal work of Becker (1968) proposes a model in which criminals are rational agents that weight the costs and benefits of their actions. Ever since there has been a growing interests in the quantitative study of the determinants of criminal behavior. Some of the most cited papers in the literature are Fajnzylber et al. (1998; 2002). In these papers, cross-country regressions are used to evaluate the determinants of crime incidence.

Literature that deals with crime and development in Colombia, from a quantitative standpoint, has also been growing since the turn of the century. In a highly influential paper, Sanchez and Núñez (2001) test the significance of different socio-economic variables as explanatory variables of crime. The authors found that when working with data for the largest Colombian cities, the increase in homicides in the 80s was largely due to drug traffic. Nevertheless, when studying 700 municipalities, the authors find that poverty and inequality together with the intensity of armed conflict and drug trafficking are significant to explain crime patterns. In contrast, when studying large cities between 1984 and 2006 Cotte Poveda (2012) finds that economic growth, economic development, inequality, poverty and human capital are important variables to explain the level of urban violence.

The relation between inequality and crime in Colombia has been explored in several research paper. Buonanno and Vargas (2019) explore the long run relationship by using proportions of slaves as an instrument of inequality to explore the long-run relationship between economic disparities and crime. They find a positive and significant effect of the Gini coefficient of the value of land on property and violent crimes.

As emphasized by Valencia and Cuartas (2009) crime in Colombia appears to be explained by subjective and objective determinants. That is by the rational decisions of actors based on the profits to be done by criminal actions and also by "objective" determinants such as poverty and inequality. As shown in the literature there are several determinants that are significant to explain crime levels in Colombia, one of those important factor is the population of municipalities. This is one of the determinants that is explored in this paper, though strict causal inferences methodologies are not implemented, it will be shown that the patterns of both crimes highly depend of the number of inhabitants in the municipality.

3. Methodology and Data

3.1 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 both across countries and regions within countries. Their approach, known as the beta convergence approach, is summarized by the negative relationship between the growth rate of a variable and its initial level. When studying regional data sets, Barro and Sala-i Martin (1995) propose the following equation:

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

Where i is the index for each region, 0 and T represent the initial and final time periods, y is the variable under study (per-capita income in most cases), β is the speed of convergence, α summarizes the unobserved parameters associated to the steady state of the economy, and $w_{i,0T}$ represents the random error term. If the data adjusts to the model presented in Equation (1), then a second indicator of convergence, known as the "half-life", can be computed as:

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

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 σ *convergence*. This approach studies the evolution of the cross-sectional dispersion over time. Different statistical measures of dispersion can be used to analyse σ *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.

The standard model expressed by equation (1) assumes the independence (non-interaction) among regions. To overcome this problem, a variety of spatial econometric models have been proposed in the literature in order to account for this spatial interaction. In the cross-section analysis that is considered in this paper (using the data for initial and final years) many plausible models can be used, such as: the spatial lag model, the spatial error model, the spatial cross-regressive model and the spatial Durbin model. In order to draw a comparison with the previous literature on convergence of crime in Colombia (Royuela and García, 2015) we opt to use the same spatial models that the authors used, these are the spatial error and spatial lag models. The implementation of other models is left for further research.

Thus, the models to be estimated are given by the following equations:

The spatial lag model:

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

The Spatial error model:

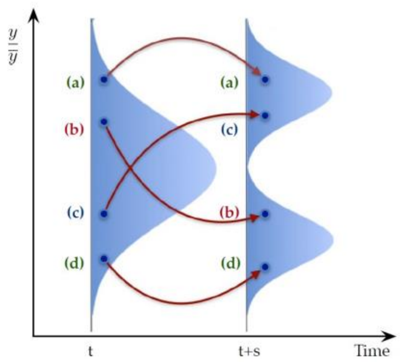
$$log\frac{y_{iT}}{y_{i0}} = \alpha + \beta \cdot log(y_{i0}) + \lambda W \varepsilon_t + u_t \quad (4)$$

3.2 Distributional Convergence Framework

Classical convergence measures are useful for studying the —average trend— 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. Motivated by these limitations Quah (1993b, 1996, 1997) proposed the distributional dynamics framework which focuses on the intra-distribution features of the convergence process, by using stochastic kernels methods

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

Figure 1: Distributional convergence framework



[2] For a more detailed review of the distributional approach See Epstein et al. (2003), Magrini (2004, 2009), Bianco (2016) and Mendez (2018, 2020)

Note: Cross section profile of the distribution of the variable y in relative terms. Adapted from Quah (1997).

To formalize the intuition 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 $t+s$. Then, the dynamics of the distribution can be modelled by a first-order autoregressive process of a time-homogeneous Markov chain:

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

The mapping of the initial distribution, $C_t(x)$, into the future distribution, $C_{t+s}(y)$, depends on the stochastic kernel, $C_{t+s=Zt=x}(x)$; 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 $C_t(x)$

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

To estimate and display this stochastic Kernel, we use the conditional density estimator of Hyndman et. al (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.

3.3 Global and Local Spatial Autocorrelation Frameworks

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 performance (Fingleton and López-Bazo, 2006). To start exploring the potential role of spatial dependence, we compute the Moran's 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 Moran's 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 Moran's I for the variable $C_{i,t} - C_{i,t-1}$ 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 $C_{i,t} = C *_{i,t} + \mu_i$ Taking out the first temporal difference of the variables removes such fixed effect μ_i. By using this differential approach, we can better evaluate the robustness of the commonly used Moran's I statistic of spatial autocorrelation.

Furthermore, it is also possible to study spatial autocorrelation beyond a general standpoint. Local spatial association aims to identify the position spatial clusters and spatial outliers (Anselin et al 2007; Anselin 1995). This local spatial statistic is commonly based on the breaking up of a global statistic of spatial association. In the case of the statistic consider in this paper (the Moran's I statistic) and in the context of regional crime rates evaluation, it potentially classifies regions into four groups. Regions with high survival (no-crime) rates values surrounded by neighbours with high survival rates (that is, a high-high cluster). Regions with low survival rates surrounded by neighbours with low survival rates (that is, a low-low cluster). Regions with high survival rates surrounded by neighbours with high crime rates (that is, a high-low group). And regions with low survival rates surrounded by neighbours with high survival rates (that is, a low-high group). The first two groups (high-high and low-low clusters) identify the location of spatial clusters (also known as hotspots and cold spots). The other two groups (high-low and low-high groups) identify the location of spatial outliers. For a period t, a local Moran's statistic is defined for each state or municipality i as

$$I_{it} = \frac{\sum_i c_i \sum_j w_{ij} \cdot c_j}{\sum_i c_i^2} = \left(\frac{C_i - \bar{C}}{m_0}\right) \sum\nolimits_j w_{ij} \, c_j \tag{6}$$

Where the notation follows that of the previously described global Moran's I (equation (5)). Similarly, as described for the differential definition of the Global Moran's I, equation (6) can also be extended to a time-differential definition.

3.4 Data

Two crime rates will be considered for the period 2010-2018: the homicide rate and the personal injury rate. The former has been considered in previous convergence studies (Royuela and García, 2015) and the latter provides a complementary perspective that we consider important for two reasons. First, homicides are an extreme form of violence while personal injuries represent a less extreme form of violent behaviour. Taken together, they provide a 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; more information about the sources and the description of the data is presented in table 1. 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

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

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. Non-crime rates will be considered instead of raw rates, following the standard in the convergence literature, as stressed by Kenny (2005) and Royuela and García (2015). In this literature variables are defined positively (the larger the number, the better), because convergence towards zero can turn problematic in mathematical terms.

Table 1. Data description

Variable	Description	Source
Homicides count	Number of homicides for each year from 2010 to 2018	Colombian National Police Department (2019)[4]
Personal Injuries count	Number of personal injuries cases for each year from 2010 to 2018	Colombian National Police Department (2019)
Population	Estimates of population of each department for the period 2010-2018	Colombian National Bureau of Statistics (DANE) (2011)[5]
Population	Estimates of population of each municipality for the period 2010-2018	Colombian National Bureau of Statistics (DANE) (2014)[6]

4. Results

3.1 Some Descriptive Facts

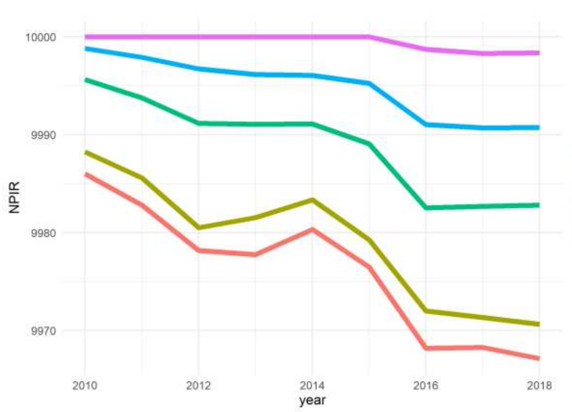
In figure 2, the quantile trend for municipalities and states for the two crimes is plotted over the 2010-2018 period. In the case of municipalities, the patterns of the crimes is contrasting; From panel (a) it is clear that NPIR at the municipal level has worsened, all quantiles curves were closer in the year 2010 and by 2018 they have significantly diverged, suggesting no patterns of $\boldsymbol{\sigma - convergence}$. In contrast, for NMR (panel (b)) it seems that there has been a small improvement as the median has

[4] Dataset available on the website of the Colombian National Police Department in the section of criminal statistics https://www.policia.gov.co/grupo-informaci%C3%B3n-criminalidad/estadistica-delictiva
[5] Dataset available on the website of the Colombian National Bureau of Statistics https://www.dane.gov.co/index.php/estadisticas-por-tema/demografia-y-poblacion/series-de-poblacion
[6] Dataset available on the Colombian government open data website https://www.datos.gov.co/Mapas-Nacionales/PROYECCIONES-POBLACI-N-Caracterizaci-n-poblaci-n/2yih-wg7m

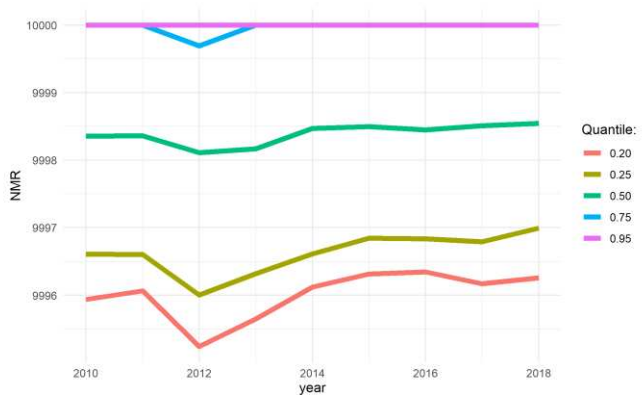
slightly increased over the 8-year period. Given that the red curve on the graph representing the 0.2 quintile has also grown over this time period, this may suggest that the dispersion of the data has also decreased. However, a detailed calculation of the standard deviation shows that it has slightly increased over this period, as it will be shown in the see following subsection.

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

(a) Municipal Non-Personal Injury Rate

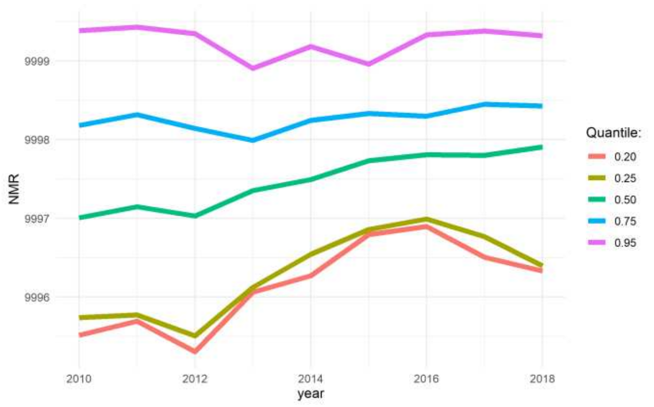


(b) Municipal Non-Murder Rate



(c) State Non-Personal Injury Rate

(d) State Non-Murder Rate



The figure of NPIR at the state level (figure 2, panel (c)) presents a deteriorating trend during the 2010-2018 period; the average rate in 2018 was 9973.6 while it was 9987.5 in 2010. However, the dispersion of the data also decreased suggesting $\sigma - convergence$ for this variable. At the state level for NMR (figure 2, panel (d)) there has been a major improvement. In 2010 the mean NMR was 9996.7 with a standard deviation of 1.8. In 2018, the NMR increased (that is, the crime rate decreased) to

9997.6 with a standard deviation of 1.3. In fact, an overall reduction of 0.9 murders per 10.000 inhabitants means that in a city like Bogota (Colombia's capital) the improvement could be seen as a reduction of 650 homicides per year.

Overall, it has been shown that while murder rates have shrunk, personal injury rates have steadily increased. This suggests that a trade-off between these two variables may have been taking place, this trade-off would be seen if a reduction in homicide rates were correlated with an increase of lower levels of violence. An in-depth analysis of this relation between these crime rates is presented in section 4.

3.2 Sigma and Beta Convergence

Table 1 presents the summary of the results for the sigma convergence analysis for both variables and both disaggregation levels. In table 1 the standard deviation of the non-crime rates for the initial and final years is reported. In a similar manner as it was shown in the tendency of the quantiles in figure 2 there appear to be signs of sigma convergence for both crime variables at the state level. In contrast, at the municipal level the dispersion of the crime rates appears to be increasing over time.

Table 2. Sigma convergence framework summary

Non-crime Rate	σ_{2010}	σ_{2018}
NMR (state)	1.9	1.3
NMR (municipality)	3.1	3.3
NPIR (state)	9.3	8.2
NPIR (municipality)	9.5	15.0

Before presenting the results of the computation of spatial beta regressions, it is necessary to show that the residuals of the simple beta OLS regression are spatially autocorrelated, since this will suggest that the residuals are not independent and the simple OLS is a misspecified model. In the case of states, the residuals of the regressions for NMR and NPIR have global Moran's I statistics of 0.08 and 0.23, respectively, being not significant for NMR while highly significant with a pseudo p-value of 0.01 for NPIR. At the municipal level, the residuals for NMR and NPIR are highly spatially autocorrelated with a Global Moran's I statistic equal to 0.34 and 0.36, both with pseudo p-values lower than 0.01.

In table 2 the cross-sectional estimates of the three beta convergence models (equations (1), (3) and (4)) is shown. First the non-murder rate convergence will be considered. The columns 1 to 3 present the estimates of the three models at the state level, while columns 4 to 6 present the estimates at the municipal level. For all models and for both disaggregation levels the coefficient of the $\log(y_0)$ variable is highly significant. However, the coefficients of ρ in the spatial lag model and λ in the spatial error model are significant only at the municipal level. Similarly, Royuela and García (2015) reported coefficients of ρ and λ which were not significant at the state level over the period 1990 to 2005. Moreover, the authors reported half-lives of 15.3, 11.5 and 15.8 for equations (1), (3) and (4), respectively. Those years are lower in magnitude to the ones reported in table 2, in columns 1 to 3. This evidence suggests that the speed of convergence of homicide rates at the state level has significantly decreased .

In terms of non-murder rates for municipalities, the speeds of convergence are relatively higher for all models, being the highest for the spatial error model. Interestingly the explanatory power of the models varies considerably at the municipal level, being the R^2nearly double for the spatial error model when compared to its value for the ordinary least squares model.

For non-personal injury rates (columns 8 to 13 in table 2) the conclusions drawn from the convergence frameworks need to be taken carefully, as for this social variable we are referring to a convergence to a lower level which means a stationary state with higher crime. For this crime, the three models at both disaggregation present highly significant coefficients for the $\log(y_0)$ variable. At the state level the coefficient ρ is not significant, while λ has a 5% significance level. At the municipal level both of these coefficients become highly significant.

Table 3. Beta convergence: cross-sectional estimates

	Non murder rate at the state level			Non murder rate at the municipal level			Non personal injury rate at the state level			Non personal injury rate at the municipal level		
	Ordinary least squares	Spatial lag model	Spatial error model	Ordinary least squares	Spatial lag model	Spatial error model	Ordinary least squares	Spatial lag model	Spatial error model	Ordinary least squares	Spatial lag model	Spatial error model
$log(y_0)$	-0.476***	-0.463***	-0.502***	-0.551***	-0.512***	-0.715***	-0.649***	-0.677***	-0.687***	-0.418***	-0.296***	-0.367***
Speed of convergence (%)	2.11	2.07	2.21	2.38	2.24	2.93	2.71	2.81	2.84	1.90	1.41	1.70
Half-life (years)	32.8	33.6	31.4	29.1	30.9	23.7	25.5	24.7	24.4	36.5	49.2	40.9
ρ		-0.224			0.446***			0.284			0.575***	
λ			0.185			0.615***			0.434**			0.594***
R^2	0.543	0.560	0.553	0.246	0.365	0.459	0.390	0.425	0.480	0.075	0.323	0.330
Number of observations	32	32	32	1120	1120	1120	32	32	32	1120	1120	1120
Akaike information criterion	-509.4	-508.3	-509.8	-14993.3	-15140.4	-15274.9	-366.585	-365.871	-370.167	-11537.4	-11807.5	-11814.2

Note: asterisks denote different significance levels: *10%; **5%; and***1%.

In terms of speeds of convergence, states appear to be converging at about 50% higher speed levels than those reported for municipalities. At both spatial levels, the spatial error model appears to have the largest explanatory power. Moreover, at the municipal level the R^2 reported for the spatial error model presents a nearly 5-fold increase from the initial value reported for the OLS model.

Overall, it seems the spatial error model is the model more suited to explain the convergence of the non-crime rates as seen by the largest value of the R^2, the significance of the coefficients of λ and the lowest Akaike Information Criterion.

Overall, it has been found that beta convergence appears to be robust for both desegregation levels and both non-crime rates. In terms of spatial dependence, it appears that spatial beta models are needed for municipalities for both crimes, while the appear to be required just when evaluating NPIR at the state level. In terms of sigma convergence, it has been shown that the standard deviation of the cross section is decreasing only at the state level. This result is probably explained by the fact that as spatial aggregation increases (from municipalities to states) it masks the dispersion of individual observations. As municipal data is aggregated into states the crime rates at this larger units moves closer towards the mean, reducing cross sectional dispersion.

This result is in line with the literature in terms of the effects of spatial scale on crime rates. For example, Cook and Winfield's (2015) report strong sings of beta convergence for both states and counties in the US. However, from 2000 to 2010 (the latest available data in their study), they reported sigma convergence for states while divergence for counties. Thus, showing a similar heterogeneity in terms of convergence and spatial scale as it was the case in Colombia during the 2010-2018 period.

Nevertheless, beyond the average results of sigma and beta convergence presented in tables 1 and 2, convergence clubs are also being formed for both crimes and spatial levels as will be explained in the following section.

3.3 Distributional Convergence

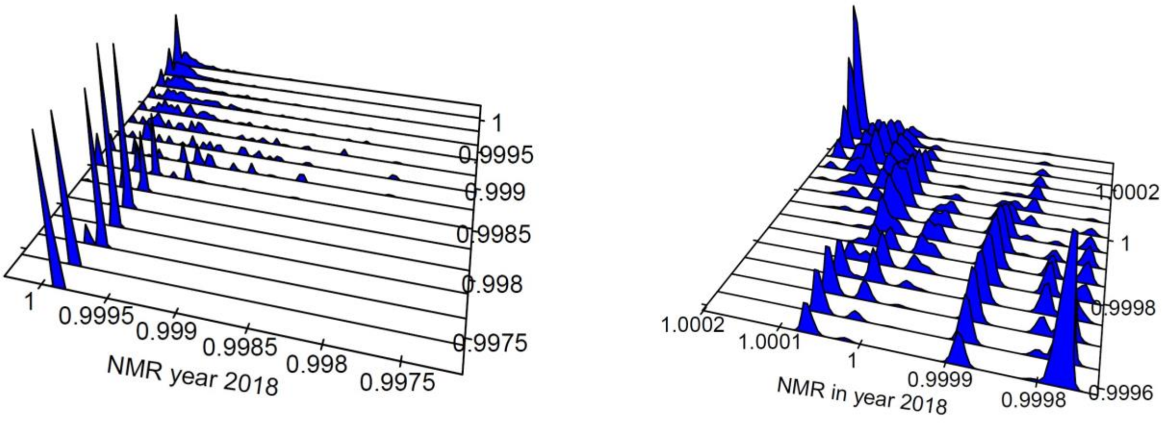
The results for the study of the variable NMR are presented in Figure 3. It can be observed from the conditional distribution plots (panels (a) and (b)) that at the municipal level there appear to be fewer convergence clubs. These clusters are clearly shown in the modal boxplots (panels (c) and (d)). At the municipal level there seem to be two convergence clubs; conversely the existence of at least four convergence clubs is reported at the state level. In this framework, convergence clubs are found when the modes of the distributions (represented by black dots in the model boxplots) are located along a horizontal line, such lines with between three and four modes can be seen in Figure 3 panel (d). In simple terms, they are considered to form a convergence clubs because regions which had different relative crime rates in the initial year (recorded on the x axis in the boxplots) are more likely to have the similar relative crime rates in the final year (y axis)

The diagonal lines in the modal boxplots indicate whether a region has improved in relative terms or not over this time frame. Points located above 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 municipal level the modes of the cluster are located in most cases above 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.

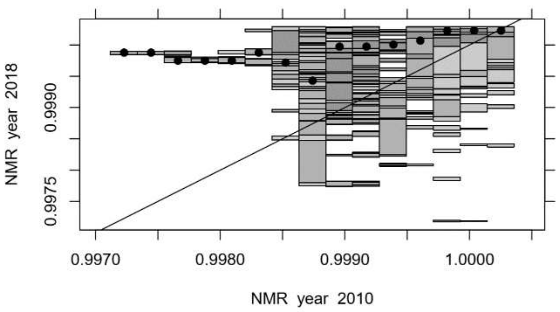
Figure 3: Distributional convergence and clusters in non-murder rates (NMR)

(a) Conditional distribution - Municipalities

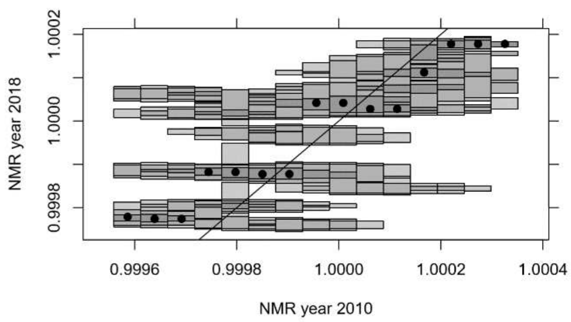
(b) Conditional distribution - States



(c) Modal boxplots: Municipalities



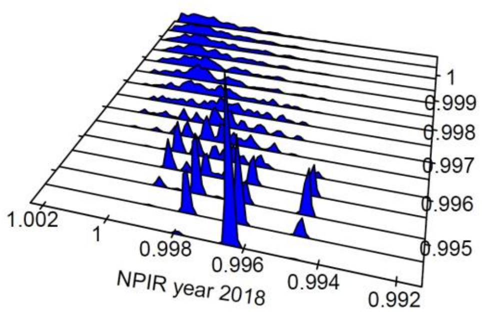
(d) Modal boxplots: States



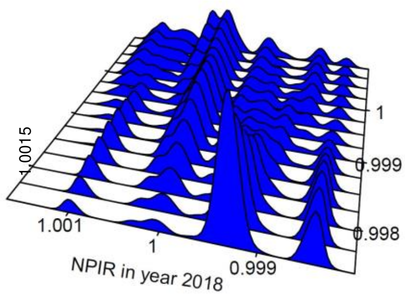
The analysis of the distributional dynamics of non-personal injury rates is shown in Figure 4. Panels (a) and (c) relate to municipalities while (b) and (d) to states. At the municipal level, the results seem inconclusive; there might be a lower cluster around 0.996 and a second cluster at 0.998 (relative NPIR in 2018, y axis in the boxplot in figure 4 panel (c)). 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" this refers to a higher value in relative terms. It seems clear by referring to the quantiles trends in Figure 2 panels (a) and (c), that in terms of average magnitudes NPIR worsened over the 8-year period.

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

(a) Conditional distribution: Municipalities

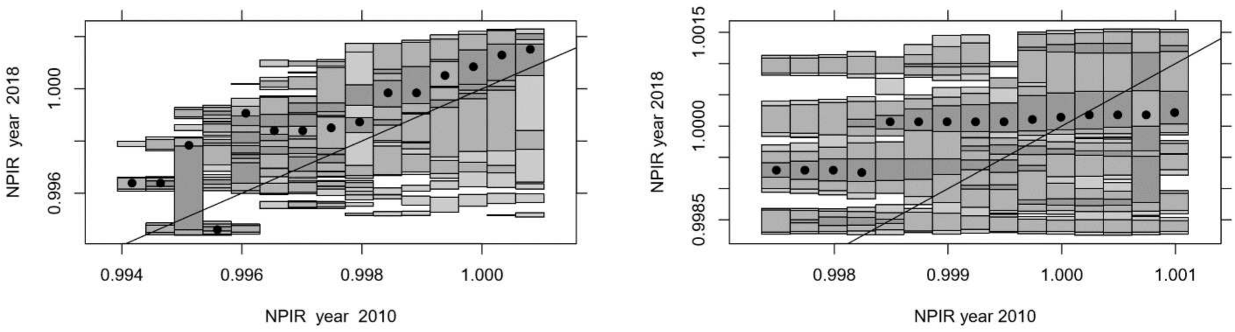


(b) Conditional distribution: States



(c) Modal boxplots: Municipalities

(d) Modal boxplots: States



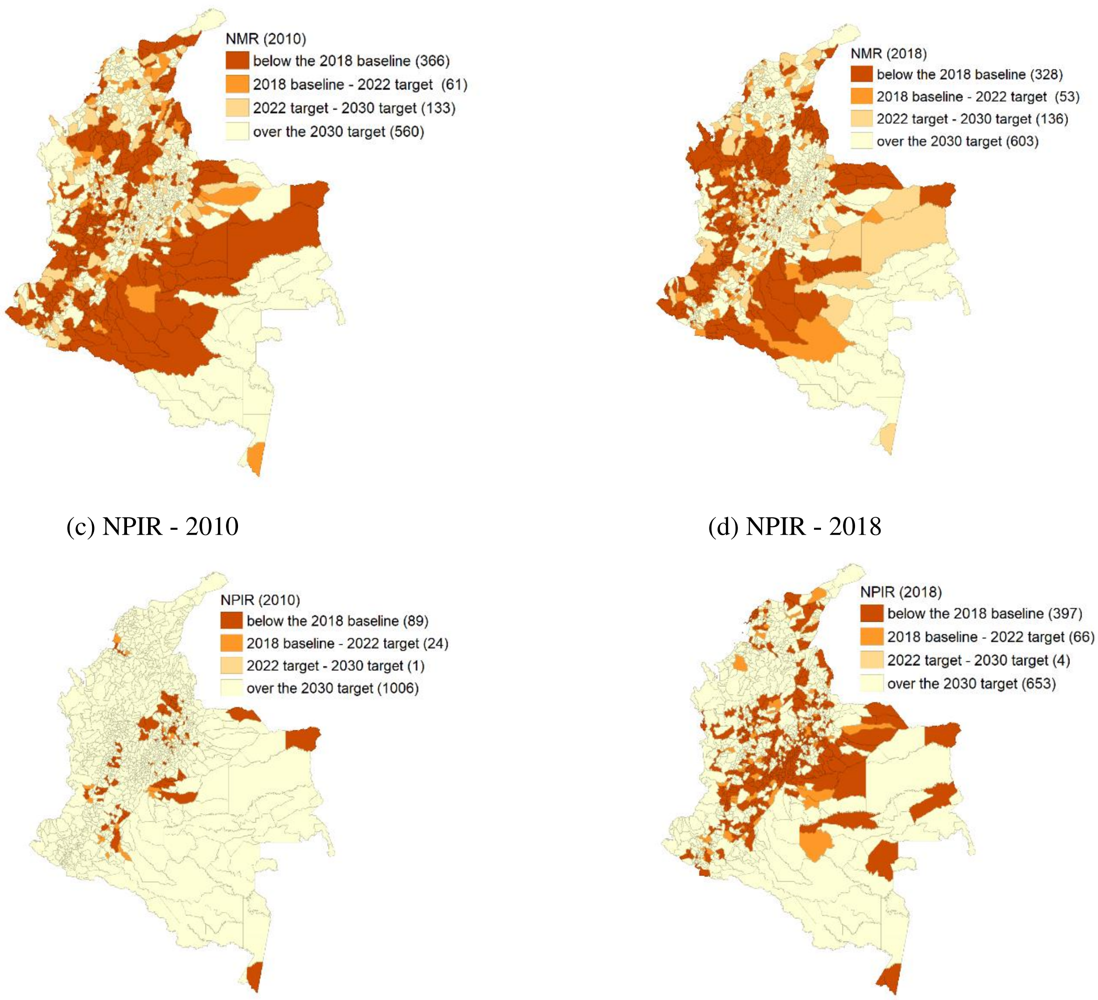
A clustering process seems to be taken place at the departmental level (panels (b) and (d) in Figure 4). The distributions as seen in panel (b) do not represent narrow peaks and they span across a wide area of the plot, while the distributions are narrower for municipal data as seen in (a). In panel (d), as seen by the two horizontal lines formed by the modes, two different convergence clubs have been formed. Overall, the distribution dynamics frameworks show that beyond the sigma and beta convergence reported in the previous section, convergence clubs are being formed at both desegregation levels and for both crime variables.

3.4 ESDA and Global-Local Spatial Autocorrelation

Figure 5 shows four choropleth maps of the municipalities of Colombia. All maps are created according to the baselines and targets found in the Colombian National Development plan; the lowest values of non-crime-rates (more crime) are in red and the lighter yellow bins represent the higher values (less crime).Panels (a) and (b) present the non-murder rates in 2010 and 2018 for municipalities and states, and panels (c) and (d) show the non-personal injury rates in 2010 and 2018.

Figure 5: Crime rates in 2010 for municipalities and states

(a) NMR - 2010 (b) NMR - 2018



(c) NPIR - 2010 (d) NPIR - 2018

Note: The 2018 baselines, the 2022 targets and the 2030 targets are taken from the Colombian National Development plan (Departamento Nacional de Planeación (2019))

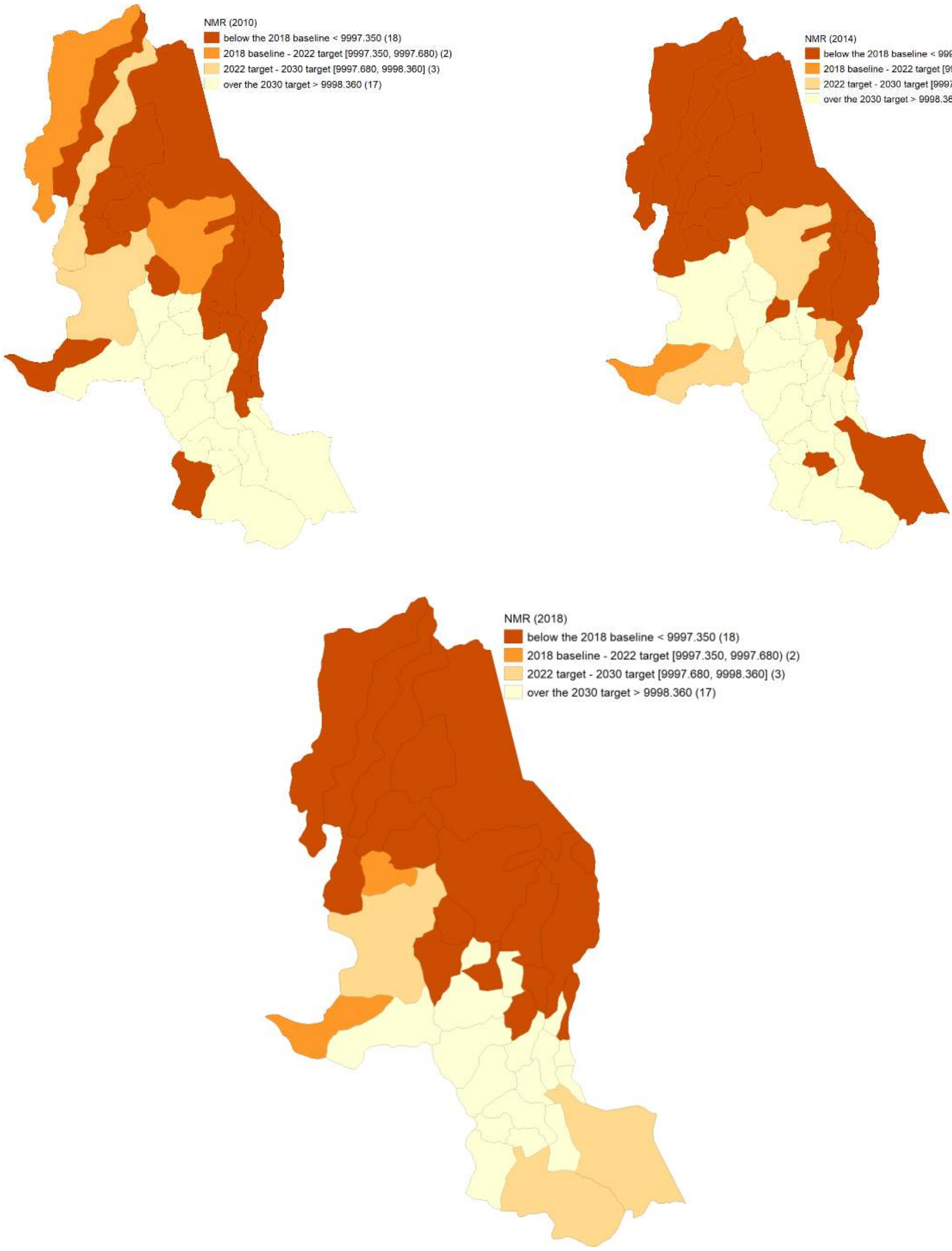
Regional inequality in terms of violence and crime seem evident by looking at Figure 5. In panel (a) is clear that in 2010 there is a core of municipalities with low homicide rates (near the capital Bogota). In the south-eastern part of the country near the amazon there is a cluster of regions which have NMR beyond the 2030 target. Other regions with low crime in 2010 (over the 2030 target) include municipalities near the border with Panama and a core of municipalities in the north that spans to most parts of the states of: Atlántico, Bolívar, Magdalena and Sucre. In 2018 it is shown that the clusters of crimes remain stable. However, major improvements can be observed, as 43 extra municipalities have reached rates beyond the 2030 target.

From panels (c) and (d), it is noticeable that the spatial distribution of NPIR differs greatly in both years. For example, in 2010 around 8% of the municipalities were performing worse than the 2018 baseline, by 2018 that figure increased to 35%. This shows a clear deterioration in the occurrence of this type of crime as presented in previous sections.

A further exploration of the data in Figure 5, can be observed in one of the departments in Colombia that currently has some of the highest crime statistics in the Country. Coordination and spillovers can be seen from the experience of the state of Norte de Santander over the last 8 years (see Figure 6). 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 (Departamento Nacional de Planeación (2019)). 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 underperforming 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 coloured 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 Moran's 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 6: SDGs targets in the 2018-2022 national development plan for different years (2010, 2014, 2018) in the department of Norte de Santander



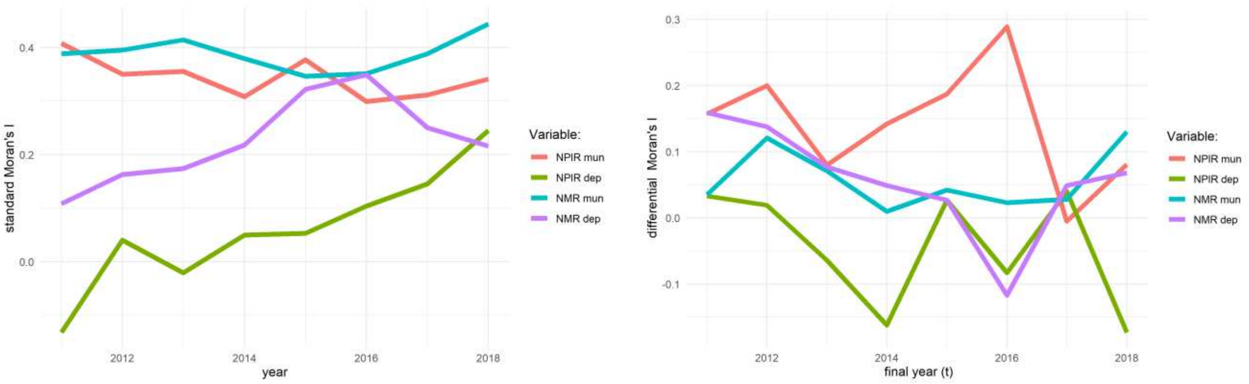
Note: The 2018 baseline, the 2022 target and the 2030 targets are taken from the Colombian National Development plan (Departamento Nacional de Planeación (2019))

To proceed with the global spatial autocorrelation analysis the standard Moran's I was calculated. The spatial weight matrix was constructed using queen contiguity weights; thus, by considering two regions as neighbours if there is a common border even if that border consist of a vertex. In Figure 7 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 is shown that spatial autocorrelation is, for all years, larger at the municipality level than at the departmental level. Though, larger in magnitude the Moran's I for NPIR and NMR appear more stable for municipalities, while it shows a growing tendency for NPIR for states (green curve in panel(a)) and first increasing and then decreasing for NMR (purple curve)

In order to evaluate the robustness of the data registered in panel (a), the 1-year first temporal differential Moran's 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, 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 it was highly significant at the municipality level.*
For the NMR the results are considerably similar. The significance of the Moran's I is contrasting at both spatial levels. *In over 85% of the years, the differential Moran's I is significant at the municipality level, whereas at the departmental level is insignificant in over 85% of the years.*
It appears that overall, spatial autocorrelation is robust only at the municipal level. the reasons for this can be firstly related to the number of observations. In the case of states, the number of regions is only 32 (nearly a minimum for statistical inference from regressions to be valid); while it is robust for municipalities where the number of regions is 1120. Moreover, the masking that is seen in terms of convergence as helping to achieve beta convergence at the state level, may also cause the distribution of non-crime rates for states to be similar to the global mean. Therefore, spatial autocorrelation tests that try to show statistically different values away from the mean (positively or negatively spatially autocorrelated) may become more difficult to test at higher spatial scales.

Figure 7: Moran's I for crime rates at both spatial levels

(a) Moran's I (b) Differential Moran's I

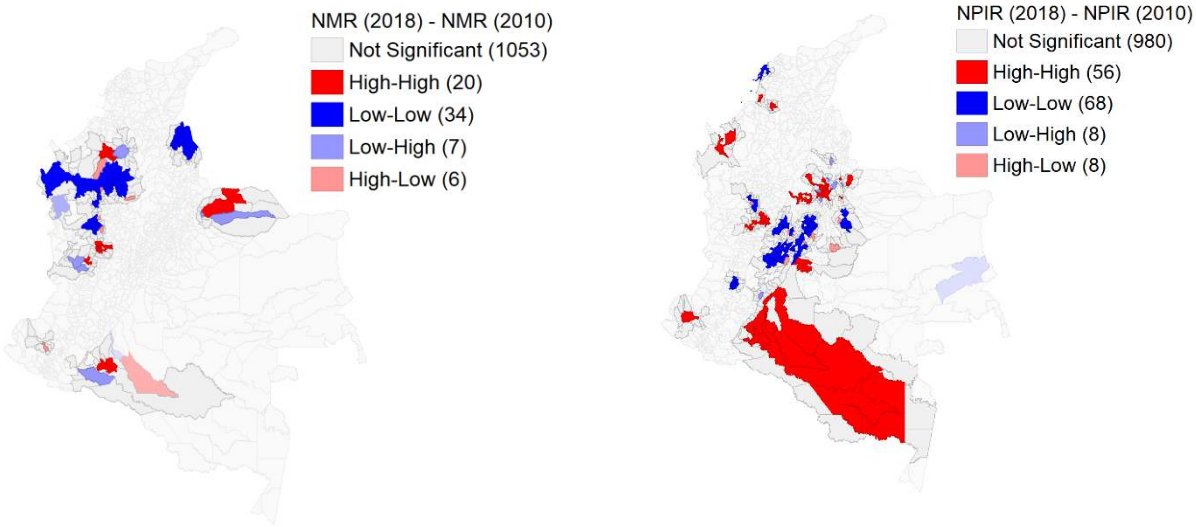


Furthermore, the local spatial autocorrelation computed with the differential Moran's I statistic allows us to find local clusters where cores and neighbours are statistically different from the average. The clusters are shown in Figure 8 using the differential statistic for the years 2010 and 2018. From panel (a) it is noticeable that the north-western low-low cluster for NMR includes most of the state of Antioquia which has endured for years the presence of several guerrillas, paramilitary squads and drug cartels; moreover, the other low-low cluster (high crime) is located in the state of "Norte de Santander" which will be further discussed at the end of the paper and which has in recent years experienced a deterioration of the state control of the territories. It is also possible to see that central regions near the capital are not included in any of the 4 type of clusters.

In addition, in panel (b) the clusters for NPIR are plotted in the choropleth map of Colombian municipalities. In in the central regions of the country for NMR there are no significant clusters; in contrast for NPIR, low-low (high relative crime) clusters are well documented in the central areas, including large parts of the state "Cundinamarca" and also including Colombia's capital Bogota. In terms of high-high clusters (low crime clusters) there is a large concentration of low crime municipalities in the south in parts of the Amazon region and a large fraction of municipalities in Santander in the centre-east (above Bogota) are also part of a high-high (low crime) cluster.

Figure 8: Differential local Moran's I clusters

(a)Non murder rates (b) Non personal injury rates



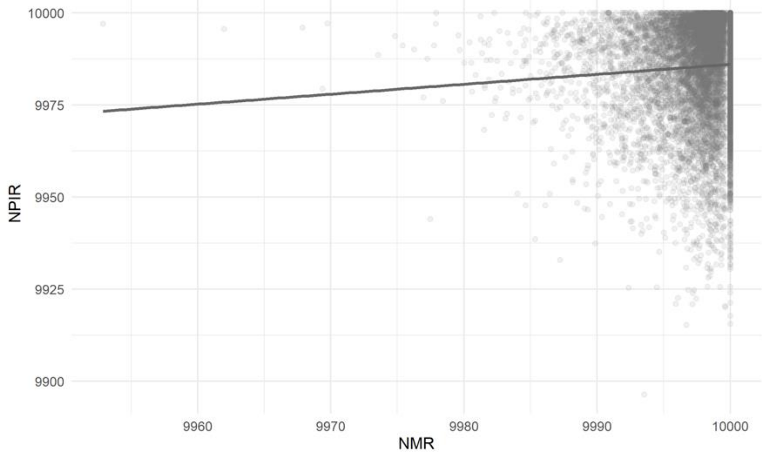
Note: The cores and the neighbours are shown, differential Moran's I for years 2010 and 2019 based on 999 permutations and considering relevance lower than 0.01.

5. The relation between NPIR and NMR at the Municipal Level.

A puzzling fact has been shown throughout this study, it appears that homicide rates have on average steadily decreased, while personal injury rates have grown over the same period for both disaggregation levels. It may be the case that there has been a trade-off between these two types of crimes; a plausible explanation for this trend could be that criminals may have opted to commit "lower intensity" crimes such as personal injuries instead of homicides. A clear causality bond between these variables is beyond the scope of this paper; however, a descriptive study of the correlation of these variables can shed some light onto this puzzle.

In Figure 9, NPIR is plotted as a function of NMR for all municipalities and years. Therefore, each point represents the crime rates for one municipality for a given year in the period 2010-2018. Running a simple linear regression, shown by the grey line in figure 9 it is found that the slope coefficient is highly significant with a value of approximately 0.25. This coefficient means a survival rate increase by 4 is related with surge of non-personal injuries by 1. Here the expected trade-off is not evident, and the opposite appears as the norm. On average, a reduction of one type of crime comes with the improvement of the figures for the other.

Figure 9: NPIR as a function of NMR



Note: the curve represents a simple OLS linear regression of NPIR as a function of NMR, the slope coefficient is highly significant with $p<0.001$

Nevertheless, the relation shown in figure 9, does not hold for all type of municipalities. A common way to categorize municipalities in Colombia can be done by referring to the senate law 617 of the year 2000. In this law, municipalities are divided into 6 categories and an extra special category in terms of their population and revenue. The General Accounting Department, published the list of categories for the year 2020. The list was used to split the sample of municipalities into 7 categories. In table 4, the estimates of the OLS linear regressions of NPIR on NMR for each category is presented together with the population range of each category as defined by the aforementioned law.

Table 4. OLS estimates of NPIR as a function of NMR for each municipal category

Municipality category	Population range	NMR (slope coefficient)	p-value
6	(, 10.000]	0.14	0.01
5	(10.000, 20.000]	-0.10	0.62
4	(20.000, 30.000]	0.25	0.57
3	(30.000, 50.000]	0.94	0.04
2	(50.000, 100.000]	0.23	0.65
1	(100.000, 500.000]	-1.00	0.07
Special	(500.000,)	0.05	0.94

Note: p-values and slope estimates rounded up at 2 decimal digits.

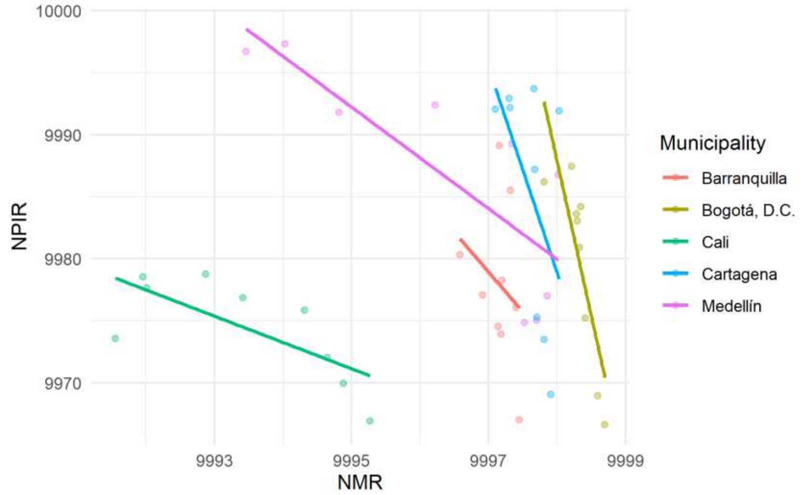
From table 4 it appears that there is no clear evidence of a relation that holds between the rates of these two crimes for all municipal categories, as seen by the different magnitudes and signs of the slope coefficients. In the one hand, in categories 2,3,4, and 6 it appears that there is a positive correlation between both crimes, being statistically significant for categories 6 and 3. On the other hand, the "trade-off" is reported for category 1 and 5, for the former the slope coefficient is large and significant. Moreover, for the municipalities in the special category (the largest cities in the country) the relation is not clear as shown by the significance of the slope (0.94). A closer look at this category can be observed in figure 8.

The group of cities in the special category is extremely important in terms of the relative population of the country and in their predominance as centres of economic activity. In figure 8 the OLS regression for each city and for all years is shown by the curves in different colours. The significance per se is not possible to be estimated given that just 9 observations for each city are collected in the dataset of this paper. However, a general trend is persistent across these cities, which is that as homicide rates decline the personal injury rates worsen. Thus, the "trade-off" appears more evident as municipalities become larger, especially for municipalities with populations over 500.000 people.

The importance of the results shown in the figures 10 and table 4 can be thought in terms of the relative contribution that municipalities in the special and 1st categories have in the total of crimes committed in Colombia in one year. In terms of personal injuries in 2018, 58% of all cases recorded by the police happened in a municipality in the special and 1st categories and 42% of all homicides took place in the municipalities in the same categories. Therefore, taking advantage of the relation among these variables can be helpful for the policymakers of these municipalities and cities for which a "trade-off" appears to take place.

Moreover, as it has been shown in this section, the intensity of crimes and their relationship show high heterogeneity in terms of the population size of municipalities. Most crimes, as mentioned in the previous paragraph, happened in larger municipalities. Therefore, it appears that population and possibly population density are likely to play a major role as determinants of criminal activity in Colombian municipalities. Similar results have been reported by Cotte Poveda (2012), the author studied Colombia's largest cities and highlighted that population size is a highly significant determinant of violent crimes.

Figure 10: NPIR as a function of NMR for municipalities in the special category



Note: curves represent a simple OLS regression of NPIR as a function of NMR for each city.

6. 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.

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 (Departamento Nacional de Planeación (2019)) 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.

Horizontal/spatial policy coordination

Spatial spillovers from regional neighbours 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 neighbouring regions is a form of technological transfer that can accelerate the rate of convergence.

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.

Considering that violence and peace are part of a multidimensional perspective of development, the current paper sheds light onto the development process of Colombia in the 2010s. 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). 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.

Moreover, as this is one of the first evaluations of regional convergence at multiple scales in Colombia, further research that aims to fully integrate these two scales is still needed. For instance, we could evaluate convergence in a multilevel model as in Chasco and Lopez-García (2009). This perspective could provide new insights on how municipal convergence affects stats convergence.

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.

To sum up, the following answers have been found to our original research questions. First, we have found strong patterns of convergence across Departments in Colombia, while only beta convergence across municipalities. Second, we have found that spatial effects are important in explaining the patterns of crime in Colombia, more so for the case of municipalities. In terms of the relations between personal injuries and homicides, however, there appears to be no trade-off when considering all municipalities, it highly depends on the population size of each municipalities. For municipalities with over 100.000 inhabitants, there appears to be a trade-off between homicides and personal injuries: fewer homicides are associated with more personal injuries. Overall, disparities remain high in both types of crime, and further research is need to account for the increase of personal injuries. Nevertheless, in terms of homicides and personal injuries, we find a reduction of regional disparities in both spatial scales: municipalities and states.

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 Griffith, 2002; 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. For example, it was reported in this paper that the relation between bot crimes was highly dependent on the population size of the municipality, thus in a determinants framework it can be tested if population or population density are robust predictors of crime levels. This point is very important as conditioning on population size may help to explain why most of the crimes occurred in the most populated regions of Colombia. 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.

Finally, an evaluation of the role of gender on regional crime dynamics may prove relevant in the context of Latin America in general and Colombia in particular. This type of research, as mentioned in the literature review, has been carried out by Castro and Valdivia (2013) in the Mexican context. Motivated by the encouraging results of this emerging literature, a plausible extension of current paper would evaluate how gender differences affect the process of regional convergence.

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