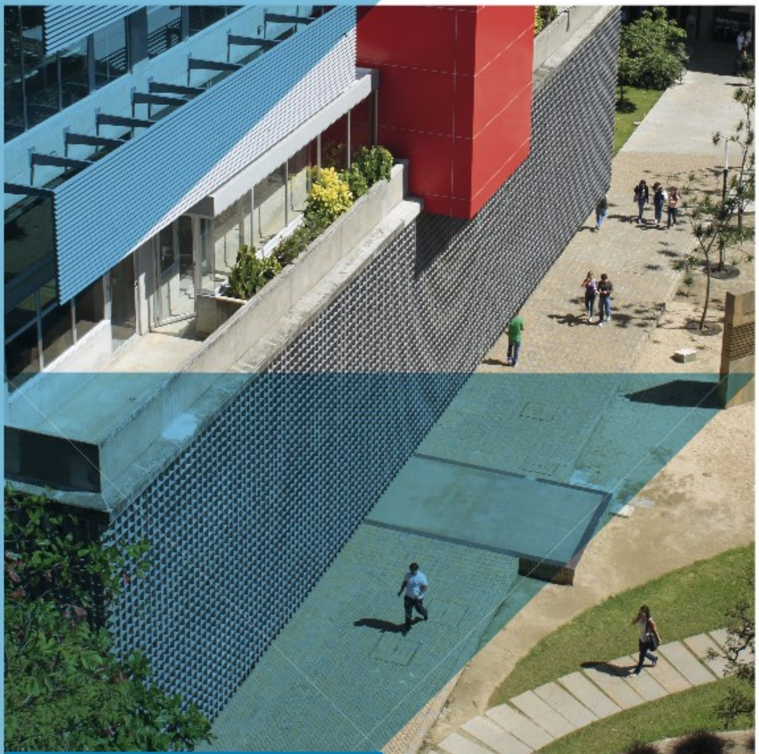

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INTERNAL FORCED DISPLACEMENT AND CRIME: EVIDENCE FROM COLOMBIA

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Abstract

Internal forced displacement, a phenomenon associated to internal conflict, poses important socio-economic challenges for the receiving areas. One of the most relevant aspects is related to crime, since the reception of forced displaced persons might increase inequality and the heterogeneity of population. This paper studies the relationship between internal forced displacement and crime. We use a panel of Colombian municipalities for the period 2003-2016. We include spatial patterns for the study of crime, allowing to capture the dynamics of this relationship across time and space. Our results provide evidence of a spatial correlation between crime and internal forced displacement.

Keywords: Internal Forced Displacement, Internal Migrations, Crime, Spatial Panel.

JEL Code: K42, O15, R23, R59.

I. Introduction

Forced displacement is commonly associated to civil conflicts and high levels of criminal acts of illegal armed groups. This phenomenon has similar effects to other types of migration for receiving

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areas, causing socio-economic alterations such as inequality, poverty, unemployment and crime. The theoretical and empirical approaches generally used for studying the effects of migrations can be applied to forced displacements.

In Colombia, internal migration is mostly caused by forced displacement. It is a consequence of the domestic conflict and of the beginning of a new era dominated by criminal networks (InSight Crime, 2018). It is mostly characterized by the flow of inhabitants from rural to urban areas. This calamity has affected around eight million people in five decades and has created a conspicuous amount of problems and difficulties in all aspects of reception places (Unidad para las Victimas, 2018). Additionally, during the period of time analyzed crime rates have persisted -- and even increased-- in most municipalities, negatively affecting the welfare of the population (Roche-villarreal, 2012).

The main objective of this paper is to study the relationship between internal forced migration and crime. For that purpose, we conduct a study of crime rates in Colombian municipalities for the period 2003-2016, introducing a spatial component for the analysis. Recent theoretical approaches recognize the significance of spatial analysis when studying this relationship.

This article is organized as follows. In Section 2, we conduct a literature review of the most relevant theories and empirical studies exploring the relationship between crime and migrations. Section 3 presents the theoretical framework. Section 4 introduces our empirical strategy for spatial panel data, section 5 our results. Section 6 concludes.

II. Literature Review

Forced displacement is a rapid and unexpected type of migration (Roche-villarreal, 2012), and it is mostly derived from the strategy of territorial control and attacks to civilian population by armed illegal and criminal groups. Their territorial supremacy lead to the appropriation of important resources by insurgents and criminals, causing the loss of welfare and properties for the affected civilian population. Hence, the increased risk of suffering permanent injuries and the loss of lives for the inhabitants of the conflict areas are the most important determinants of forced displacement (Ibáñez, 2009). Host areas of forced migrants face different socioeconomic problems, such as the worsening of labor market conditions, the increase in inequality and worse living conditions (less access to public services and to the educational system). Internal forced displacement also implies a change in the dynamics of the local population in receiving areas, as well as a larger heterogeneity of population; these are similar consequences to the ones of general migration.

Theoretical approaches trying to explain the crime-migration relationship have their foundation in sociological and criminological theory. Three of the main theories are the Social Disorganization Theory, the Cultural Theory and the Strain Theory. The Social Disorganization Theory places special emphasis on the lack of resources, inhabitants' diversity and residential mobility, stating that these are determinants of criminal acts. As a consequence of these factors, communities are unable to build strong relations, increasing social disorganization, which finally leads to higher crime rates (Mears, 2001). Cultural Theory proposes that the causes of crime are related to cultural contradictions, since immigrants face different behavior patterns in host areas, these contradictions promote tensions among the population. Strain Theory proposes that crime is derived from tensions generated by the pressures to succeed and structural barriers in the receiving areas. Therefore, tensions are generated between immigrants and the local population, since each group tries to quickly improve its living conditions (Thomas, 2011). These theories have a particularly characteristic in common, one the main determinants of the crime is the population heterogeneity, due to the differences between migrants and local inhabitants.

The seminal work of Becker (1968) addresses the rationality behind crime: the process of utility maximization of criminals is derived from the evaluation of the cost, benefit and punishment of committing a crime. Ehrlich (1973) explains the relationship between criminal activities and aspects like income, physical elements and other variables.

Migration and its effects on well-being, economic growth, labor market, and security has been widely studied in the literature. Migration can be internal or external. The latter is a phenomenon that occurs more frequently in developed countries, where migration is mostly motivated by economic reasons. On the other hand, internal migration is a local phenomenon that can be explained by different aspects. It can be explained by public order problems in specific regions of the country, and by economic motivations such as labor opportunities, better education offer, or higher wages, among others. These two types of migration imply two different scenarios for the analysis of crime. With regard to international migration, the opportunity cost when committing a crime is much higher, since --depending on the severity-- deportation is very likely. Contrarily, if migration is internal, there are less obstacles to see crime as a viable option for income generation.

Chiswick & Miller (2014) state that if crime can be observed and analyzed as an economic factor, then it is clear how migration comes into play. One of the first determinants of internal migration that has been studied is related to the returns between rural and industrial activities. When rural fertility exceeds urban fertility, the agricultural labor force will grow faster than industrial employment (Herrick, 1965). In principle, this was viewed as beneficial due to the scarce labor supply in the large industrial centers. But today, the migration is being increasingly viewed as the major contributing factor to the phenomenon of urban surplus labor and as a force that continues to exacerbate serious urban unemployment problems, caused by growing economic and structural imbalances between urban and rural areas (Herrick, 1965).[1] As for crime and its economic effects, its increase is negatively related to the welfare of citizens – by the reduction in security perception-, its influence on investment decisions, and the lower public investment in sectors that would generate higher welfare effects, since resources are diverted to investment for the prevention of crime.

In some specific cases, migration could be related to crime. When low-skilled people arrive to areas in which job opportunities are scarce, and in most cases, with few contact networks, this reduces the chance of getting a job and increases the possibility of enrolling in illegal activities. An important factor that increases the participation in illegal activities is the fact that these activities generate high income with little effort.[2] The government's effort to punish crime is a key factor for its reduction, as stated by Ehrlich (1973).

Despite of the general belief claiming that there is a link between migration and crime, empirical research exploring this relationship is sparse (Reid, Weiss, Adelman, & Jaret, 2005). Reid et al. (2005) examine the effects of migration on crime rates in metropolitan areas. After controlling for a host of demographic and economic characteristics, they find that migration does not increase crime rates in the receiving areas, and even some aspects of migration lessen crime in metropolitan areas. A similar approach is the one of Bianchi, Buonanno, & Pinotti (2012), who find that migration only increases the incidence of robberies, while leaving unaffected all other types of crime. One important aspect of these studies is that migration is international, i.e., the opportunity cost of committing a crime is higher for immigrants, as mentioned above. Similarly, Kubrin, Hipp, & Kim (2016) find a decrease of violent crimes in neighborhoods located in the southern part of

[1] In this perspective, for the Colombian case Calderón-Mejía and Ibáñez (2016), find that internal migration substantially reduces wages for urban unskilled workers who compete for jobs with forced migrants.

[2] Psychological and social factors are also important determinants of criminal behavior (see Hirschi; 1969).

California where more immigrants from Northern Africa arrive, but in areas with higher rates of Central American immigrants more violent crimes are committed. In neighborhoods with more East Asian immigrants, lower property crimes were committed.

In the literature, different studies analyze both the positive and negative effects of the relationship between migration and crime. Bell, Fasani, & Machin (2013) find that the reception of a greater number of migrants increases crime rates. They provide evidence of higher crime rates in areas of Wales where asylum seekers are located. Nunziata (2015) presents a low positive correlation for three specifications for the relationship migration-crime in European countries. On the same line of argumentation, Spenkush (2011) finds –for the U.S. case-- that an increase of 10% in the share of migrant population rises the property crime rate by 1.2% , but without any effect on violent crime rates. Wadsworth (2010) states that there was a reduction in homicide and robbery in the U.S. between 1990 and 2000, partially due to the increase in immigration. This is similar to the findings of Ousey & Kubrin (2009) for 159 large U.S. cities in the period 1980-2000.

Internal migrations share some commonalities with international migrations, such as the motivation of migrants to achieve better economic conditions and to escape of violence. This type of migration, though, can also be the result of governmental policies. Should that be the case, a population change will take place and it will interfere with the community's capacity of inhibiting crimes. It will increase the heterogeneity of the population and promote socio-economic disadvantages (Treyger, 2013).

One of the main characteristics of internal migration is that, to a large degree, it corresponds to a movement from rural population to urban areas (Meng & Zhang, 2013). Similarly to the studies conducted for the relationship between international migration and crime, findings for the relationship between internal migrations and crime are ambiguous. For the Canadian case, Andresen (2013) affirms that there is a lack of evidence of the effect of local migration on crime rates. This goes in line with the findings of Meng & Zhang (2013) for rural to urban domestic migrations in China. On the contrary, Treyger (2013) presents an increase of crime rates caused by government relocation of domestic migrants. Schultz (1971) finds that before the internal conflict, interregional migration in Colombia responded to market forces drawing rural labor to the cities from regions where the returns to labor were relatively low and the supply of labor was growing relatively rapidly.

Traditional approaches explain the variation of crime rates based on economic and demographic conditions, but criminal activities present spatial and temporal concentrations. Hence, the analysis of patterns and causes of crime rates requires using an approach that allows the inclusion of the spatial dynamics of the variables (Almeida, Haddad, & Hewings, 2003). The main theoretical perspectives are related to the Routine Activities and Crime Hot Spots approaches. The Routine Activities approach proposes that the place determines favorable or unfavorable conditions for crime acts through two forms: first, physical features influence the social control capacities of crime suppressors. Second, criminal actions are not randomly distributed in space, crime is influenced by routine activities that occur and by characteristics of each place, that means the criminal actions have spatial concentration in areas with characteristic conducive to crime. The Crime Hot Spots approach associates the population conditions and some land uses with the spatial concentration of the crime. Furthermore, physical conditions can show signs of the social control that the community can exercise in the area (Anselin, Cohen, Cook, Gorr, & Tita, 2000).

Consequently, some studies consider the inclusion of spatial effects to explain the relationship between migration and crime. Arnio & Baumer (2012) provide evidence in favor of the presence of spatial heterogeneity effects in Chicago's neighborhoods between 2007-2009, but the concentration of immigrants does not have significant effects on crime. Similarly, Graif & Sampson (2009) suggest the same effect of spatial patterns and migrants for homicide rates across neighborhoods of Chicago between 1990-2000. Using a spatial panel data model for the migration-crime relationship between 2001 and 2011 for Wales and England, Jaitman & Machin (2013) find evidence supporting this linkage. Additionally, Cracolici & Uberti (2009) suggest that the importance of the inclusion of spatial effects for the analysis of crime rates in the Italian provinces and the concentration of foreigners in the previous periods are an important determinants of criminal activities for this region.

As a consequence of the decades-long clash between government forces and antigovernment insurgent groups, internal forced displacement has been the main cause of internal migrations in Colombia. The intensification of the armed internal conflict and the intention of illegal armed groups to expand territory control and asset appropriation, in conjunction with the country's institutional weakness, has induced the mobility of the population to safer areas in other municipalities (Ibáñez, 2009). Important studies about the effects of displacement on poverty, inequality, and the labor market have been conducted. Ibáñez & Vélez (2008) find that welfare losses caused by forced displacement in Colombia represent 37% of the net present value of rural lifetime aggregate consumption. They affirm that a violent environment modifies the net benefits of migration.[3] Additionally, forced displaced persons confront a decrease in labor income, severe conditions in host areas, and severe disruption of risk-sharing mechanisms. The effects of government programs are transitory, and forced migrants are unable to recover the levels of income and welfare that they had before displacement (Ibáñez & Moya, 2010).

Using a structural model of crime and inequality, Bourguignon, Nunez & Sanchez (2017) show that income distribution in Colombia influences aggregate crime and find that many criminals live in households with an income per capita eighty percent below the mean. Furthermore, inflows of forced migrants increase the proportion of low-skilled and informal workers, causing a reduction of informal wages (Calderón-Mejía & Ibáñez, 2016). Consequently, the welfare loss of forced displaced people can determine the incurrence in illegal actions of this population and generate labor market problems. Informal wage reduction and an unequal distribution of income influences the criminal propensity of the entire population.

While internal forced displacement and its effects has been widely studied, its repercussion in terms of crime in receiving areas has not been thoroughly studied and evidence is little and not conclusive. One of the previous works is the one of Roche-Villarreal (2012), who studies the effect of displacement on crime against property for municipalities, but his results do not reflect a relationship (Reid et al.,2005). For the specific case that motivates this study, the Colombian conflict, it persisted for over 50 years and led to 7'849.014 cases of displacement, according to the *Unidad para las Victimas*.

III. Theoretical Framework

Becker (1968) defines criminals as rational agents, being their actions a result of a maximization process that considers costs and punishment of illegal acts. He also presents the number of crimes of an individual as a function of the probability of conviction, the punishment, and a combined variable that captures other influences. Ehrlich (1973) expands this model and presents an

[3] Other studies by Ana Maria Ibañez have been important for the analysis of crime – see Ibáñez, Rodríguez and Zarruk, 2013-, violence and internal migration in Colombia – see Ibáñez and Moya, 2010, Engels and Ibáñez, 2007, Fernandez, Ibáñez and Peña (2014); and labor market effects of migration by internal refugees - Calderón-Mejía and Ibáñez, 2016.

individual crime behavioral function, assuming the number of criminal actions are monotonically related with the probability of arrest (p), marginal cost of the punishment (f), the marginal earning of the illegal (w_c) and legal (w_l) activities, probability of be unemployment (u) and group of variables (π) that may affect the frequency of crimes.

$$q_i = \psi(p, f, w_c, w_l, u, \pi) \tag{1.1}$$

This approach assumes that all individuals are identical, quality that permits to aggregate the individual functions. Therefore, the number of crimes in the society are defined as an aggregate behavioral function.

$$Q = \Psi(P, F, Y_c, Y_l, U, \Pi) \tag{1.2}$$

Where the variables denote the mean of the components of the individual behavioral function. Additionally, Ehrlich (1973) proposes some behavioral implications for this model: The increase in the probability of arrest and the marginal cost of punishment reduce the incentives of participating in illegal activities. Similarly, an increase in the probability of being unemployed and an increase in the earnings derived from illegal activities generate a rise in incentives for committing a crime.

Extensions of the Becker-Ehrlich model allow to include socio-economic, geographic and demographic variables (Cracolici & Uberti, 2009). This theoretical framework is usually used for the analysis of the relationship between all types of migration and crime. For our study, this model allows to consider the reception of forced displaced persons and to take into account the spatial allocation of the variables.

The internal flow of forced displaced persons has indirect effects on crime rates in the receiving areas. Three principal factors of utmost importance for determining the size and scope of the effect are the probability of apprehension, the severity of punishment and the demographic factors. The first two aspects are related to the government's ability (or inability) to maintain the levels of security. Meanwhile, the change in demographic characteristics is a consequence of the variation of the share of young population, average levels of education, the unemployment rate, poverty levels and others socio-economic variables (Roche-villarreal, 2012).

The inclusion of spatial patterns in the analysis of criminal actions is related to the distribution of socio-economic variables across space and the interdependence of geographical areas (Light & Harris, 2012). Specifically, the spatial distribution of crime is determined by the location of the criminals and victims, environmental conditions, and population characteristics. Hence, the geographic concentration of crime is associated with hot spots with particular conditions (Anselin et al., 2000). These patterns require the addition of spatial effects when analyzing crime. The inclusion of spatial effects in econometric modeling is accomplished considering the spatial weight matrix interaction with the variables of the model. The spatial weight matrix describes the spatial allocation of the units of analysis and their spatial relationship (Tita & Radil, 2010).

Consequently with the approaches of Becker (1968) and Ehrlich (1973), this paper presents a supply offences function, where each kind of crime depended of the reception of the forced displaced persons and determinants of the heterogeneity.

$$\left(\frac{Q}{N}\right)_i = \mathrm{A}FDP_i X_i W e^{(\mu_i+\tau_t+\varepsilon_{it})} \tag{1.3}$$

In the equation (1.3), the component $\left(\frac{Q}{N}\right)_i$ represent the number of specific crimes in area i, where N is a population scale factor, A is a constant, FDP_i is the number of reception of forced displaced persons in region i, X_i is a portmanteau of heterogeneity variables of population in i and the probability of apprehension for the same type of crime in the area, W are the spatial effects and u_i summarize the effects of the physic, income and other nonquantifiable variables in the same area. From the linearization of the equation (1.3) is obtainable the econometric specification for the panel model:

$$logC_{it} = \alpha + \beta'_i logFDP_{it} + \beta_i X_{it} + W + \mu_i + \tau_t + \varepsilon_{it} \tag{1.4}$$

Where i denotes municipalities and t denotes time. C_{it} is the crime rate per 100.000 inhabitants of the region i and year t, FDP_{it} is the reception forced displaced persons rate per 100.000 inhabitants, X_{it} is a portmanteau of heterogeneity variables the probability of apprehension for the same type of crime in the area,, μ_i are municipality fixed effects, τ_t are time fixed effects and ε_{it} the error term.

IV. Empirical Strategy

The most common empirical strategy when addressing the relationship between crime and migration is the panel data approach. However, this empirical strategy assumes spatial invariance and therefore, leads to inconsistent results (Graif & Sampson 2009). Other theoretical standpoints recognize the non-stationary and spatial process of crime, integrating the spatial components in the models (Cahill & Mulligan, 2007). It is therefore possible to integrate the spatial components to the theoretical model presented in the previous section and to conduct the estimation of a spatial panel. Hence, the identification of the ideal spatial model specification is an important phase in the incorporation of the spatial effects in the model.

We use four data sources. Crime categories for the municipalities come from the Colombian National Police yearly reports. Internal forced displacement statistics are produced by the *Unidad para las Victimas*. Demographic data is produced by the National Department of Statistics (DANE). We also use data from the Municipal Panel of the *Centro de Estudios para el Desarrollo Económico* (CEDE), at the *Universidad de los Andes*.

Table 1 presents information about central variables included in the analysis and the number of occurrence according to each crime category. Our study considers five types of crime: homicides, kidnapping, personal injuries, automobile theft and residence burglary. We selected these crime categories because they are reported and registered with more frequently. The main explanatory variables is the number of reception forced displacement population in each municipality. Additionally, this research considers significant predictors of crime and determinants of population heterogeneity for use in control variables.

Table 1. Description of variables included in the analysis of forced displacement-crime relation and data source

Variable	***Description***	***Source***
Dependent Variables		
Homicide rates	Logarithm of the number of homicides per 100.000 inhabitants in each municipality	Policia Nacional Colombia
Kidnapping rate	Logarithm of the number of kidnapping per 100.000 inhabitants in each municipality	Policia Nacional Colombia
Personal injuries rate	Logarithm of the number of personal injuries per 100.000 inhabitants in each municipality	Policia Nacional Colombia
Residence burglary rate	Logarithm of the number of residence burglary per 100.000 inhabitants in each municipality	Policia Nacional Colombia
Automobile theft rate	Logarithm of the number of automobile theft per 100.000 inhabitants in each municipality	Policia Nacional Colombia
Reception FDP rate	Logarithm of the number of reception of forced displaced persons per 100.000 inhabitants in each municipality	Unidad para las Victimas
Percentage Male 19-34	Percentage of male population between 15-34 years for each municipality	DANE
Log Population	Logarithm of the total population for each municipality	Panel CEDE
Probability of apprehension	Ratio of the number of arrest for each kind of crime per crime know in each crime category and municipality	Policia Nacional Colombia

We choose our control variables based on previous empirical studies on crime and considering the data availability for Colombian municipalities. Other researches considers a population density an important determinant of criminal acts because with larger population in area provides more opportunities for offending and less social controls for criminals (Reid, Weiss, Adelman & Jaret, 2005). Furthermore, the males are more prone to commit criminal acts (Cheng, Liu & Wang, 2017). The empirical strategy includes proportion of males in total inhabitants to control for these effects. Additionally, the econometric model includes apprehension rate for each kind of crime, because with the higher probability of be arrest reduce individual incentives for commit a crime (Ehrlich, 1973). Table 2 presents the descriptive statistics of the variables included in the analysis.

Table 2. Descriptive statistics of variables

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Homicide rate	15,344	36.08786	60.36675	0	1607.467
Kidnapping rate	15,344	2.048034	8.874547	0	255.4278
Personal injuries rate	15,344	98.94865	132.3395	0	4723.072
Residence burglary rate	15,344	23.03598	44.96272	0	1087.326
Automobile theft	15,344	5.406671	17.69463	0	886.1439
Reception of forced displaced persons rate	15,344	704.9444	1849.586	0	70958.08
Total population	15,344	41197.11	251271.3	837	7980001
Percentage of male 15-34	15,344	32.49694	2.946209	20.74386	68.43639
Probability of capture for homicide	15,344	43.01665	92.91093	0	2900
Probability of capture for kidnapping	15,344	353.6303	2452.473	0	118200
Probability of capture for personal injuries	15,344	7.971155	51.9168	0	2300
Probability of capture for residence burglary	15,344	18.898	82.43693	0	3100
Probability of capture for Automobile theft	15,344	9.572107	50.00202	0	1200

- The criminal and reception of forced displaced persons rates are obtained of by multiplying each crime variable by a factor of 100,000/total population municipality, the probability of apprehension for each kind of crime is determined by the division of the number of captures above the number of crimes committed in the same category.
- The descriptive statistics in table 2, correspond to the information of the variables in levels.

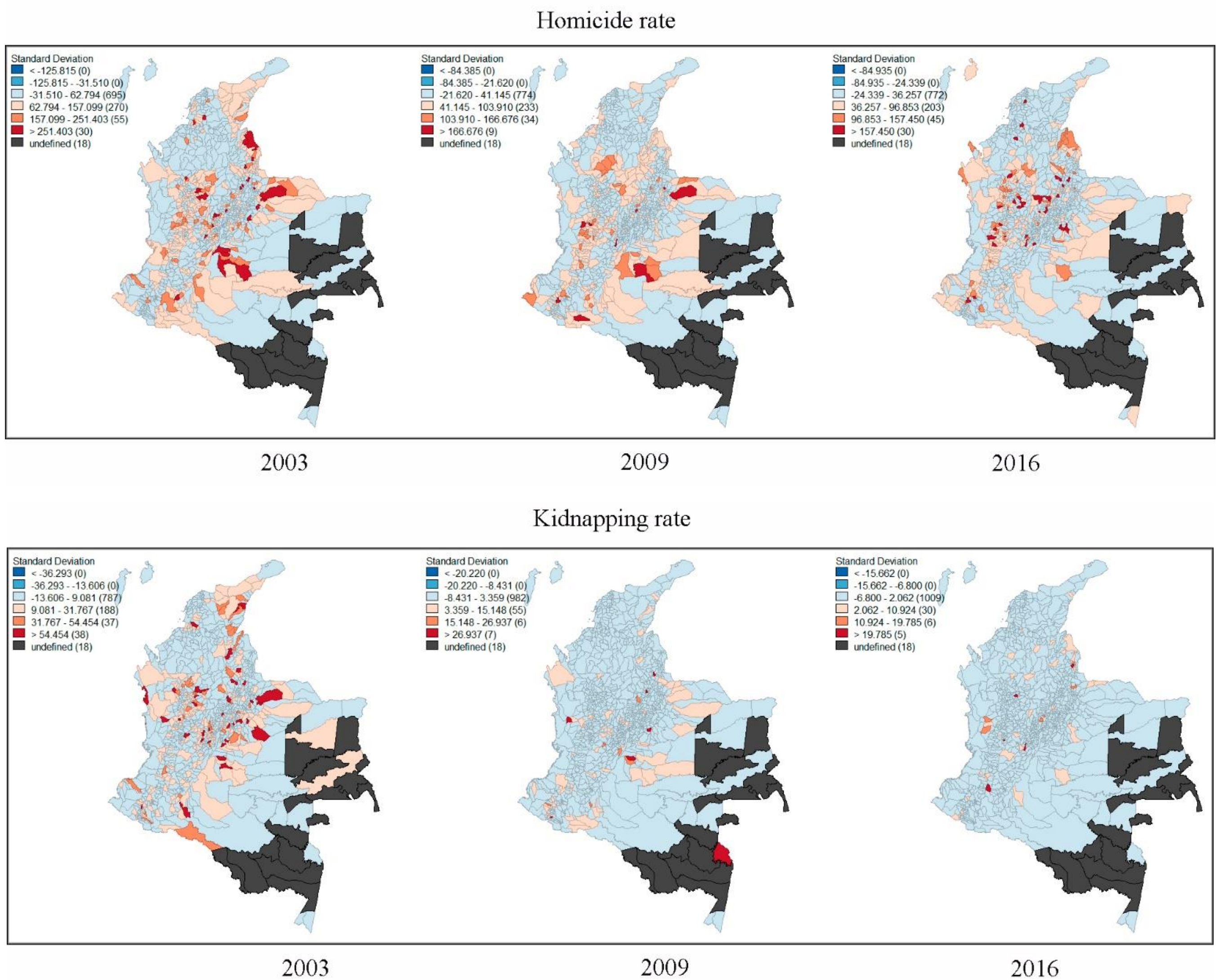
Before estimating the dynamic of spatial patterns, the Explanatory Spatial Data Analysis (ESDA) is a descriptive step for identifying the presence of spatial effects in the area of analysis (Ye & Wu, 2011). In Colombia, the presence of criminal gangs, drug cartels and illegal armed groups across geographical areas is an important determinant of crime. The change in dynamics of these criminal congregations and of governmental actions generate lead to a change in crime rates over time and space. Therefore, our study provides an ESDA of the five categories of crime rates, but –because of space limitations—we only show the analysis for the first, seventh and thirteenth years of the period of time analyzed (2003, 2009 and 2016). This procedure consists of taking a sample of the selected period to see if there are changes in the spatial dynamics of the variables and to verify the inclusion of these effects in the empirical model.

Figure 1 depicts the spatial dynamics of the five categories of crime: homicides, kidnapping, personal injuries, automobile theft and burglary residences. Specifically, municipalities with high homicide rates are concentrated in the following departments:[4] Andean region, Cesar and Guajira (Caribbean region), Valle del Cauca and Choco (Pacific region), Arauca, Meta and Casanare (Orinoquia region), Putumayo and Caqueta (Amazonas region). For the 6^{th} and 13^{th} years, the spatial dynamics change since the number of municipalities with homicide rates above of the mean decrease, particularly in the Pacific region. Kidnapping rates show a similar spatial distribution, but with smaller number of municipalities above the mean than homicide rates. As in the case of homicides, kidnapping rates show a significant reduction in the years 2009 and 2016. For this category, the largest number of municipalities with high rates are located in Arauca, Casanare and Norte de Santander (North-East) and Nariño, Putumayo and Cauca (South-West).

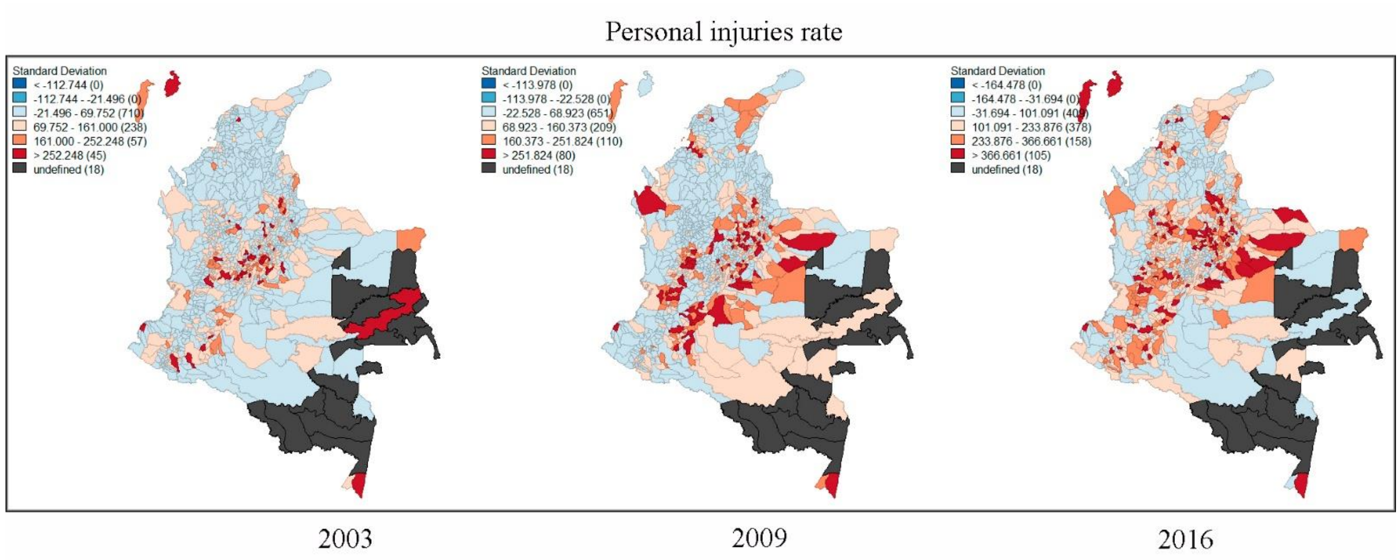
Personal injuries rates show a similar distribution in 2003 and the municipalities with higher rates are located in the east, central and western part of Colombia. As for year 2009, an increase in the number of municipalities with high rates can be observed, especially in the eastern and northern area. In 2016, municipalities with rates above of the mean are concentrated in the Andean region, the north-east and the south-west area. Residences burglary rates show a similar geographic allocation for the three years of analysis, this rate increases each period and presents more municipalities with higher rates in 2016, particularly in the Orinoquia and Andean regions. Automobile theft rates present a constant spatial distribution of the municipalities with the highest figures; these municipalities are located in the center, north-east and south-west areas. Reception rates of forced displaced persons in 2003 are concentrated in bordering areas of the Colombian territory, especially in Choco, Antioquia, Putumayo, Valle del Cauca, Guajira, Cesar and Magdalena. The number of municipalities with forced displaced persons rates below the mean increase in 2009 and in greater proportion in 2016. For the last year, municipalities with higher rates are located in the Pacific Coast.

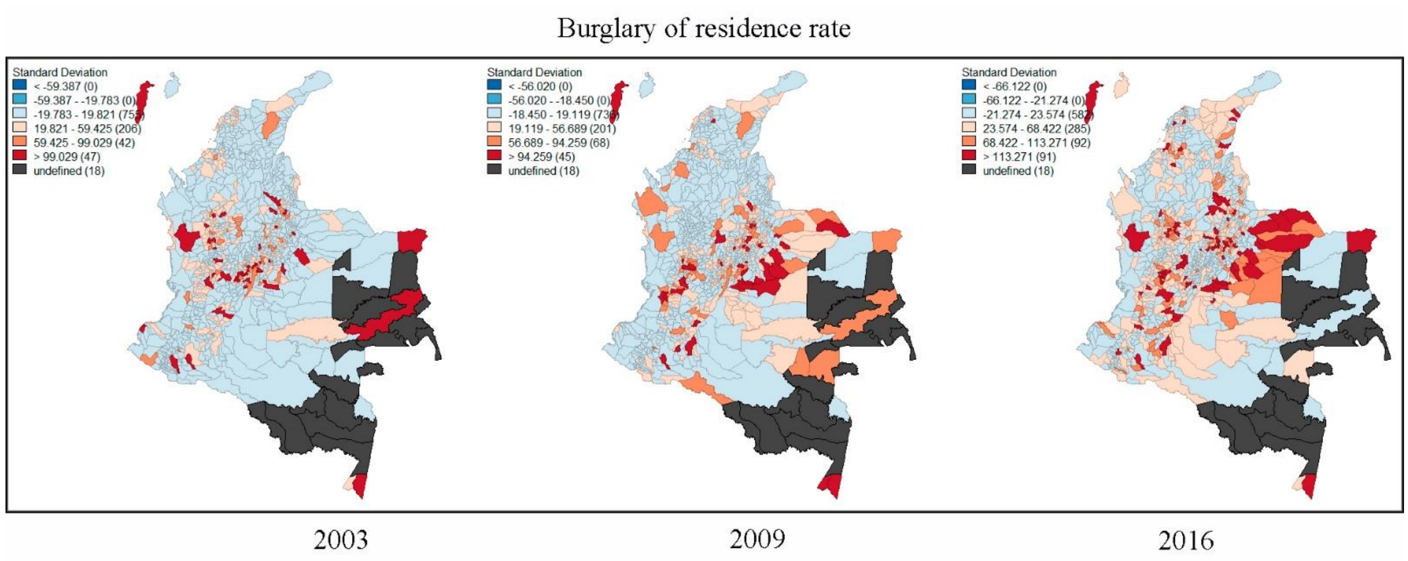
[4] The departments are political units equivalents to states or provinces

Figure 1. Standard Deviation maps



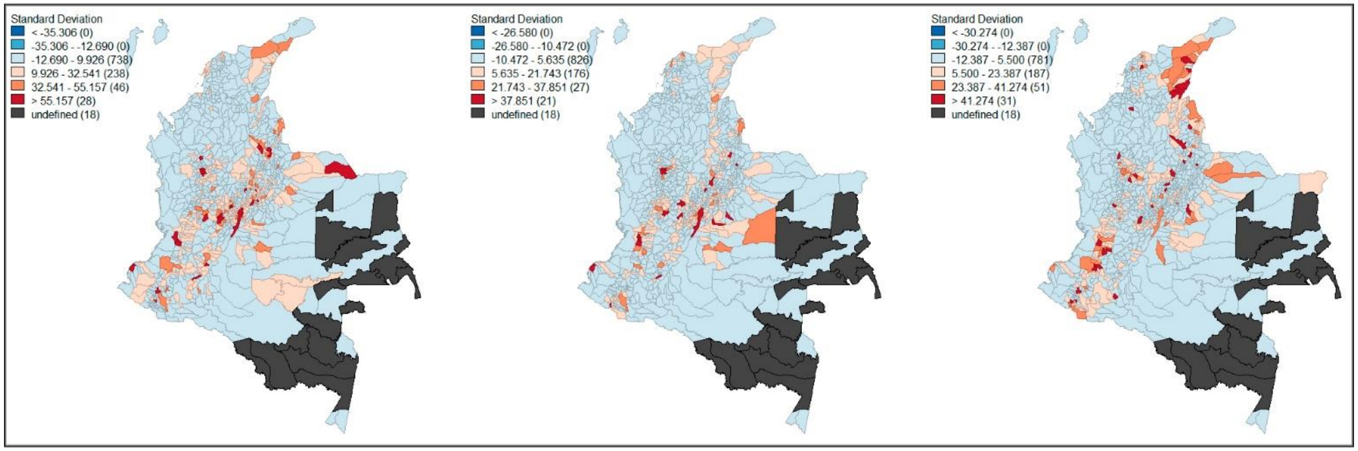
Source: Own elaboration with data of Policia Nacional de Colombia and Panel CEDE and Unidad para las Victima





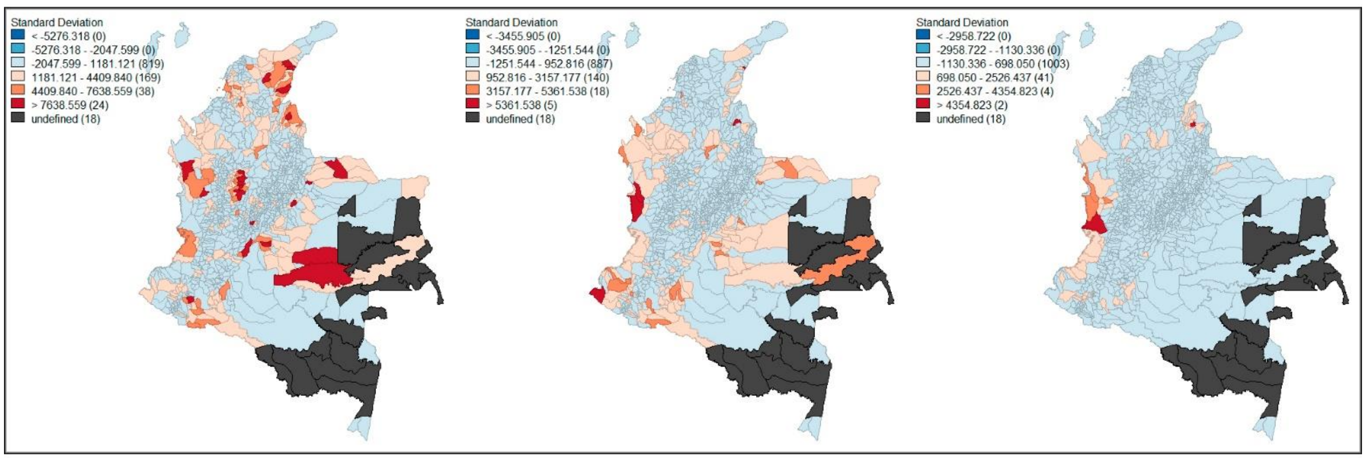
Source: Own elaboration with data of Policia Nacional de Colombia and Panel CEDE and Unidad para las Victimas

Automobile theft rate



2003 2009 2016

Reception of FDP Rate



2003 2009 2016

Source: Own elaboration with data of Policia Nacional de Colombia and Panel CEDE and Unidad para las Victimas

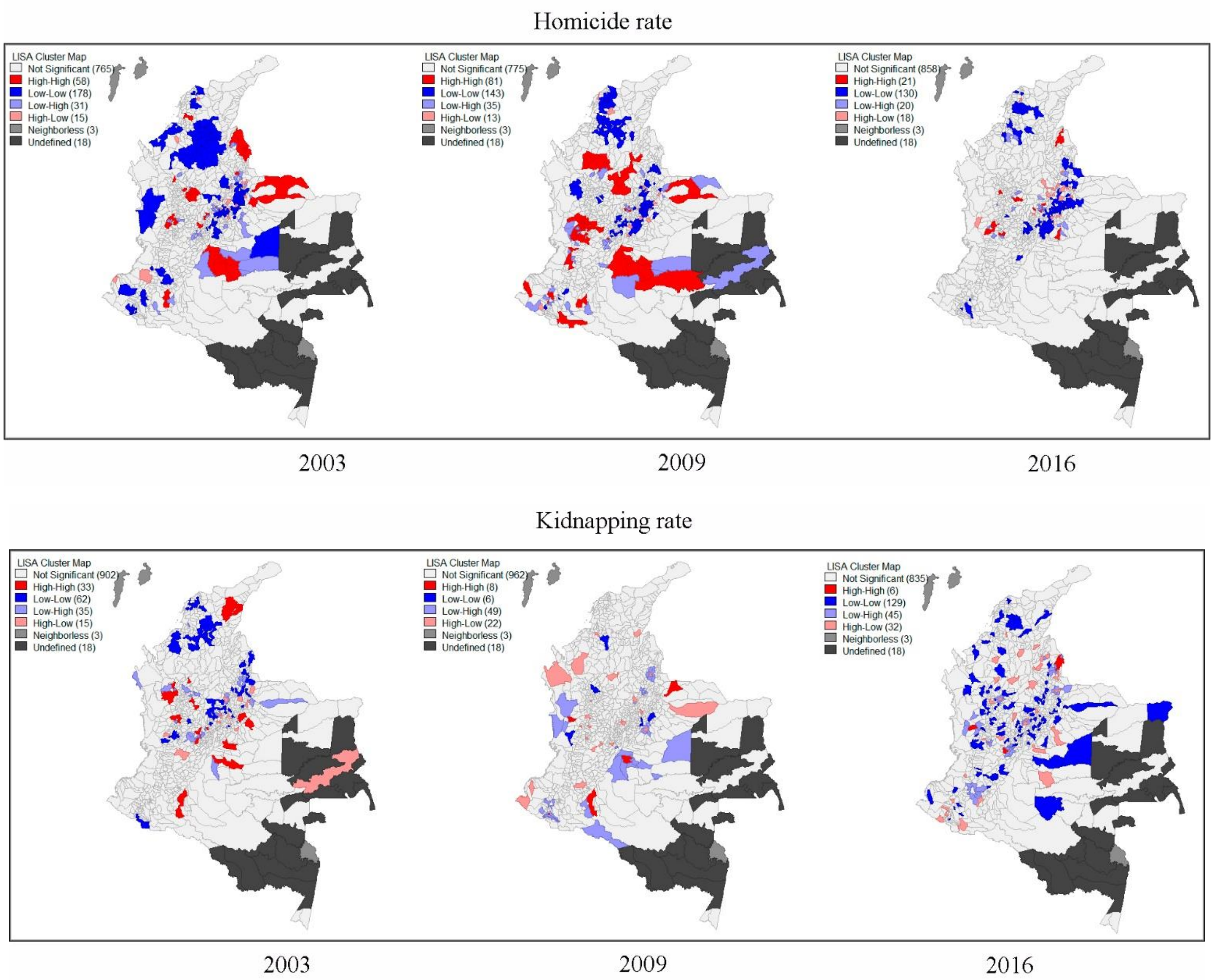
Considering the capacity of the criminal actions for concentration of spatial effects, it is necessary to identify the relationships determined by geographic proximity. Local Indicators of Spatial Association (LISA) maps allow to detect the existence of spatial clusters and the influence of spatial global autocorrelation (Cracolici & Uberti, 2009). Figure 2 includes the LISA maps for the five crime categories and the rates of reception of displaced persons. These maps show important changes from 2003 to 2016, since important differences can be identified for the five crime categories. In some cases, a reduction of cluster is present. In other cases, growth and overdispersion is present, but all LISA maps have spatial clusters in the center and north-west area. High rates municipality neighborhoods are depicted in red and low rates municipality neighborhoods are depicted in blue. The considerable presence of these clusters contribute significantly to a positive spatial autocorrelation.

Additionally, the Moran's I for the cross-section regressions for each year and for each kind of rate describes the presence of spatial autocorrelation; Table 3 presents the tests for the years 2003, 2009 and 2016 for each kind of log crime rate in the basic regression with log reception of forced displaced persons rate. The construction of LISA maps, Moran's I tests and posterior spatial regressions, use a spatial weight matrix of queen contiguity first order and normalized.

Table 3. Moran's I Test for regressions between log crime rate and log reception forced displaced persons rate

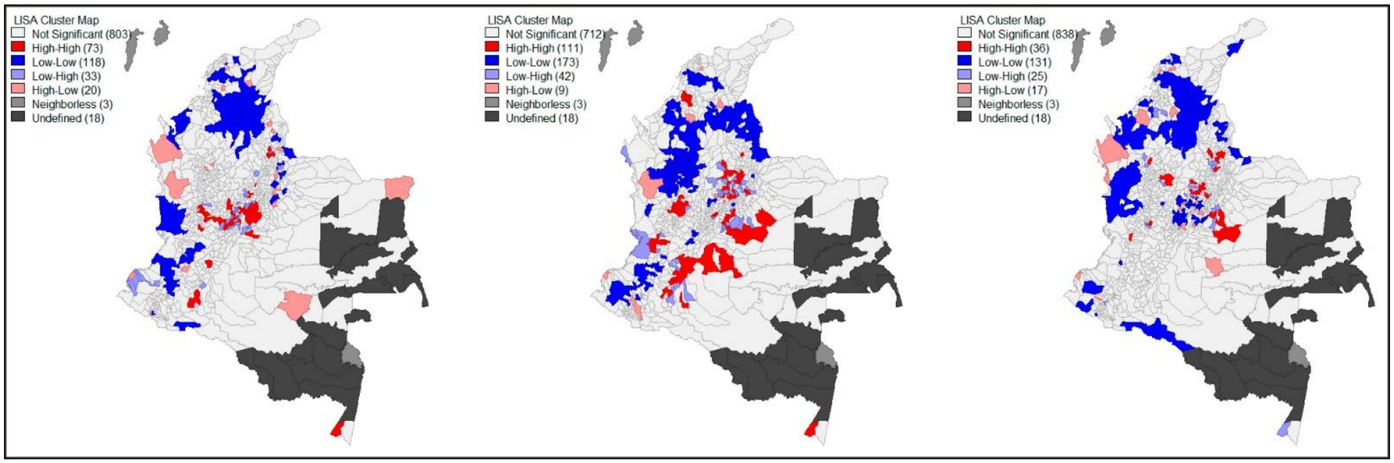
Moran test for spatial dependence				
		2003	**2009**	**2016**
variable	***Test***			
Homicide Rates	χ^2	99.44	64.08	30.58
	Prob. > χ^2	0.000	0.000	0.000
Kidnapping Rate	χ^2	21.87	11.36	2.4
	Prob. > χ^2	0.000	0.000	0.121
Personal Injuries Rate	χ^2	61.95	97.11	80.07
	Prob. > χ^2	0.000	0.000	0.000
Residence Burglary Rate	χ^2	221.32	194.79	62.24
	Prob. > χ^2	0.000	0.000	0.000
Automobile Theft Rate	χ^2	132.39	139.14	226.14
	Prob. > χ^2	0.000	0.000	0.000

Figure 2. LISA maps



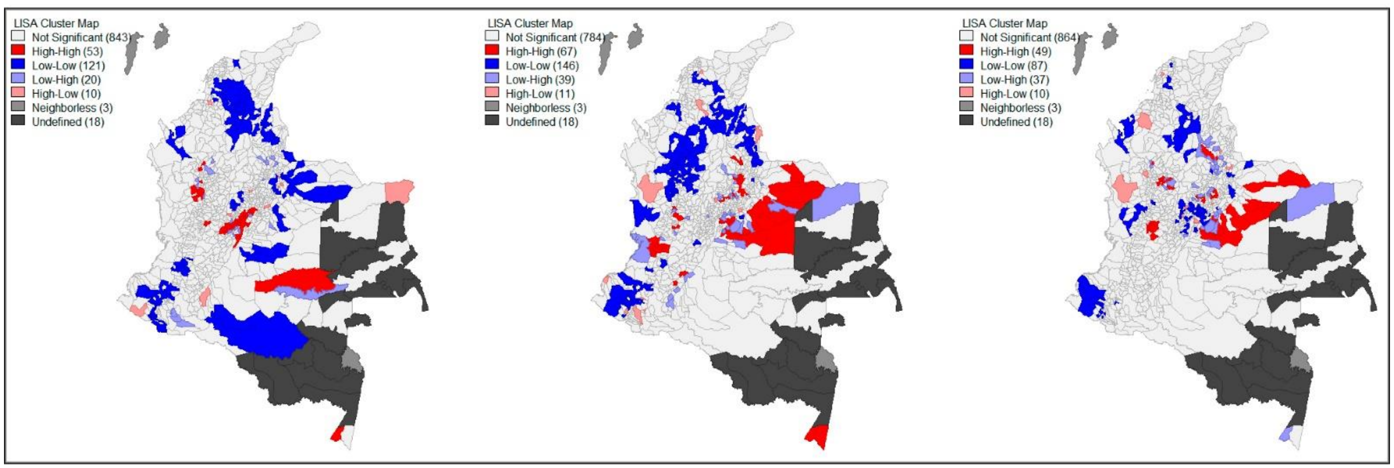
Source: Own elaboration with data of Policia Nacional de Colombia and Panel CEDE and Unidad para las Victimas

Personal injuries rate



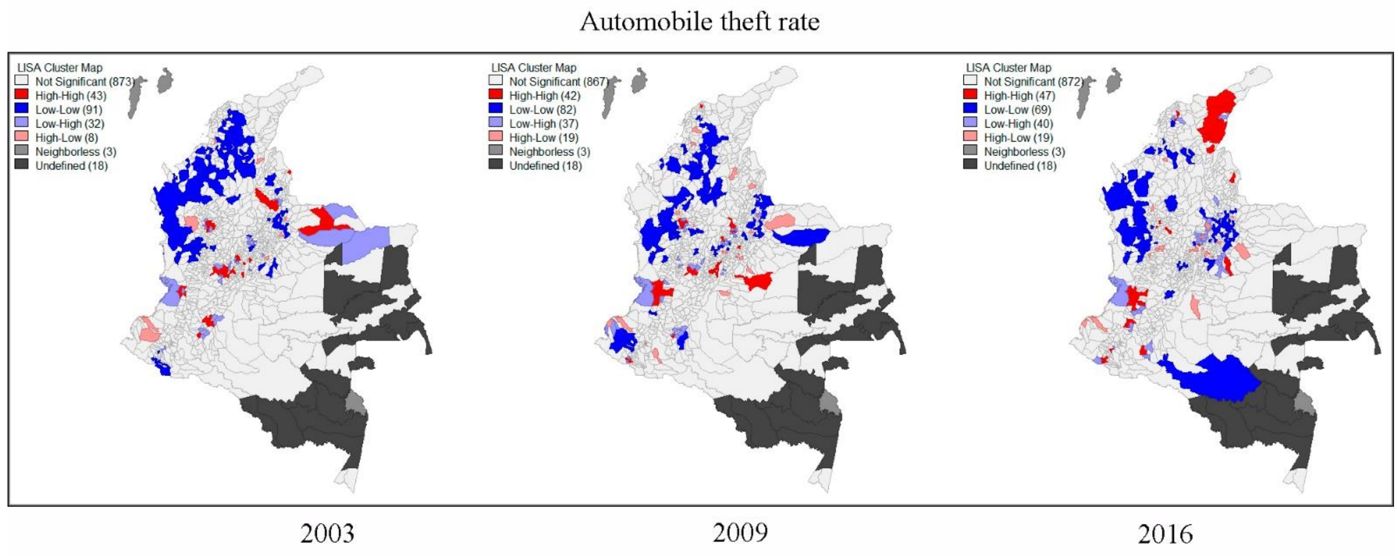
2003 2009 2016

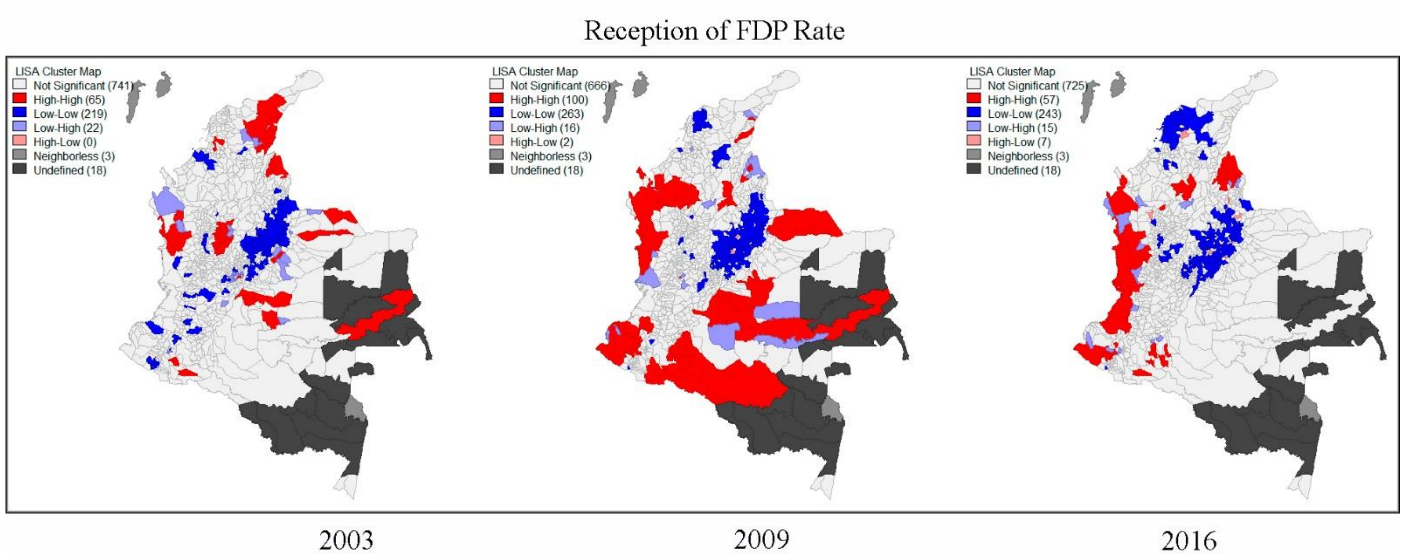
Burglary of residence rate



2003 2009 2016

Source: Own elaboration with data of Policia Nacional de Colombia and Panel CEDE and Unidad para las Victimas





Source: Own elaboration with data of Policia Nacional de Colombia and Panel CEDE and Unidad para las Victimas

Spatial panel models offers technically advantages over traditional approach, such as a less collinearity, increase degrees of freedom and permits to incorporate numerous effects. The procedure for proper identification model consists first in identify the adequate model without spatial effects and choose between the models Pooled, Fixed Effects Panel and Random Effects Panel. The second phase consists in estimating the general model of spatial Durbin model (SDM) and test if is more appropriate than spatial lag model (SAR), spatial error model (SEM), spatial lag of X (SLX), spatial Durbin error model (SDEM), general nesting spatial model (GNS) or spatial autocorrelation model (SAC) (Torres-Preciado, Polanco-Gaytán, & Tinoco-Zermeño, 2017).

The equation (1.4) represents a traditional model without spatial interaction, such as:

$$Y_{it} = \beta X_{it} + \mu_i + \epsilon_{it} \qquad (2.1)$$

Where Y_{it} and X_{it} represents the dependent and explanatories variables respectively, μ_i is the unobserved effects between units in the sample and ϵ_{it} the traditional error term. The matrix of spatial weights (W) describes the spatial arrangement of the geographic areas and their neighborhood links. This matrix defines the intensity of spatial effects and its interaction with terms of traditional model describes the kind of spatial econometric model and for N units of analysis the spatial. Weights spatial matrix is an NxN matrix, where all elements in the diagonal are equal to zero and the other elements in the matrix represent the spatial contiguity between the areas (Cracolici & Uberti, 2009). Usually, the spatial weighs matrix is a binary matrix and their elements characterize if a spatial unity is contiguous to other, when the elements are neighbors the elements takes a value of one. Alternatively, the normalization of this matrix is also used. Additionally, the usual spatial contiguity used for create the spatial weights matrix can be ***Rook*** when units shares a common vertex and ***Queen*** when have a vertex or point in common (Fischer & Getis, 2010).

V. Results

In line with the procedure suggested by Elhorst (2014), this paper initially provides the estimation for pooled, fixed effect and random effect panel models for each kind of crime categories. Table 4 presents the results for each type of crime and the significance of the coefficients of the pooled regressions. Table 5 provides information of the fixed effects panel regression and Table 6 for the random effects panel.

Table 4. Pooled estimations

Variable	***Homicide rate model***	***Kidnapping rate model***	***Personal injuries rate model***	***Burglary residences model***	***Automobile theft rate***
Reception FDP rate	.26382617***	.08912482***	-.03694894***	-0.01608378	-.01268782*
Population	1.2929056***	.71507213***	.94017414***	2.1134704***	2.0668262***
Percentage Male 19-34	-.03089431**	-.08942313***	-.06225877***	-.18865872***	-.08176896***
Probability of apprehension	.00725166***	.000309***	.00044811***	.00718324***	.01816854***
Constant	-12.065457***	-11.699514***	-4.1126869***	-16.040054***	-22.643217***
Observations	15344	15344	15344	15344	15344

Significance: * p<.1; **p<.05; *** p<.01

Table 5. Fixed effect estimations

Variable	***Homicide rate model***	***Kidnapping rate model***	***Personal injuries rate model***	***Burglary residences model***	***Automobile theft rate***
Reception FDP rate	.04603446***	.02752444***	-.05464209***	-0.01313828	0.00004585
Population	2.3354171***	-3.9790224***	-0.0516808	2.6455422***	0.41587503
Percentage Male 19-34	-.30095992***	-.61058417***	.32854318***	.14347018***	-.08167562**
Probability of apprehension	.00920971***	.00030803***	.00131163***	.00639889***	.01292281***
Constant	-12.520778**	50.437407***	-7.2600823	-31.934865***	-6.831111
Observations	15344	15344	15344	15344	15344

Significance: * p<.1; **p<.05; *** p<.01

Table 6. Random effect estimations

Variable	***Homicide rate model***	***Kidnapping rate model***	***Personal injuries rate model***	***Burglary residences model***	***Automobile theft rate***
Reception FDP rate	.12578669***	.07547447***	-.05756337***	-.02345688**	-0.00168746
Population	1.5803721***	.78722408***	.88545233***	2.0553716***	2.0644318***
Percentage Male 19-34	-.08995007***	-.18240844***	.04878316**	-.07868178***	-.0912083***
Probability of apprehension	.0087392***	.00031141***	.00083336**	.00632693***	.01386742***
Constant	-12.432416***	-9.3171962***	-7.1249612***	-19.022246***	-22.314712***
Observations	15344	15344	15344	15344	15344

Significance: * p<.1; **p<.05; *** p<.01

For each type of regressions, the basic model suggests a significant and positive relationship between crime rates and internal forced displacement. Nevertheless, this does not hold for residence burglary and automobile theft rates, where the log of forced displaced persons is not significant for the estimation with controls. Our data includes information for 1096 Colombian municipalities (out of 1122 municipalities); this argument and statistic test (Hausmman and Breusch-Pagan tests, see annex 1) support the fixed effect panel specification. The results of fixed effects models are consistent with the ones of Roche-Villarreal (2012) and present the counterintuitive sign in the coefficients of probability of apprehension and percentage of males between 19-34 years. The probability of apprehension is related to the number of criminals: cities with high crime rates have more criminals and more arrests, but this variable does not represent a deterrence to crime. On the other hand, the negative sign in the percentage of males between 19-34 years is possibly a sign of the change of the criminal population, since age and sex are not a determinant for all types of crime.

In our work, the interactions of the spatial effects are introduced with a spatial weight matrix of queen contiguity normalized and provides the estimation of the seven spatial specifications (SAR, SEM, SLX, SAC, SDM, SDEM, and SGN) for each category of crime. Table 7 shows the results of the spatial general nested model specification. Since it is the most appropriate model, it allows to incorporate the spatial determinants of the allocation of crime, of forced displaced person and heterogeneity population variables and includes in the spatial error term, that contains the omitted spatial variables correlated with crime. Additionally, the selection criteria AIC statistic in SGN models present the lowest values, confirming the empirical relevance of using this spatial model (see annex 2 for SAR, SEM, SLX, SAC, SDM, SDEM). Additionally, Table 8 presents the decomposition of the direct, indirect and total effects of the SGN for the models. The equations (2.3) and (2.4) presents SGN model specification.

$$logC_{it} = \alpha + \delta W logC_{it} + \beta'_i logFD_{it} + \beta_i X_{it} + WZ_{it}\theta + u_{i,t} \qquad (2.2)$$

$$u_{it} = \lambda W u_{it} + \mu_i + \tau_t + \varepsilon_{it} \qquad (2.3)$$

Where i denotes municipalities, j the contiguous municipalities and t denotes time. C_{it} is the crime rate per 100.000 inhabitants of the region i and year t, FDP_{it} is the reception forced displaced persons rate per 100.000 inhabitants, X_{it} is the logarithm of population, percentage of male between 19-34 years and probability of apprehension, Z_{jt} denotes the explanatories variables in the neighbor municipalities, μ_i are municipality fixed effects, τ_t are time fixed effects, ε_{it} the error term and u_{jt} the spatial error term.

Table 7. SGN model estimations

Variable	***Homicide rate model***	***Kidnapping rate model***	***Personal injuries rate model***	***Burglary residences model***	***Automobile theft rate***
Reception FDP rate	0.01316678	-0.00652809	-0.00967941	.02505036**	-0.00315888
Population	0.77446797	1.4951581**	-1.8679576***	-1.9136101**	-1.4537463*
Percentage Male 19-34	-.14188303***	.08094279*	-0.05387527	-.1579991***	0.00008322
Probability of apprehension	.00972359***	.00029993***	.0028585***	.00674314***	.0131025***
Spatial					
Reception FDP rate	.08727466***	.02888089**	-.04871129***	-.05669624***	0.00448081
Dependent variable	.48737893***	.63903087***	.70511169***	.74154561***	.54749953***
Spatial error term	-.41721956***	-.6138512***	-.61182389***	-.66365103***	-.44647918***
Population	2.0101036**	-4.0259587***	1.8067429**	3.5617325***	3.1065565***
Percentage Male 19-34	-0.03477145	-.41431576***	.16682703***	.18749747***	-.10394889*
Probability of apprehension	-.00695238***	-.00016795***	-.0036189***	-.00670266***	-.0092068***
Constant	3.7939097***	3.3064173***	3.2508369***	4.3100933***	3.7598023***
Statistics					
AIC	79508.28	76617.582	76473.867	84879.098	79507.565
Observations	15344	15344	15344	15344	15344

Significance: * p<.1; **p<.05; *** p<.01

The results of the spatial estimations confirm the relevance of spatial effects for the analysis of crime. Most of the coefficients associated to the variables' spatial effects are significant. Additionally, the spatial effects of forced displaced persons show a positive sign for the homicide and kidnapping rates and a negative sign for personal injuries and residence burglary. This explains that forced displaced persons, in some cases, increase the social control for some type of crimes, but increase the occurrence of others.

Table 8. Direct, indirect and total effects

	Homicide estimation	*Kidnapping estimation*	*Personal Injuries estimation*	*Burglary of residence estimation*	*Automobile theft estimation*
Direct					
Reception FDP rate	0.0232179**	-0.0024263	-0.0208834**	0.0164385	-0.0028074
	(0.0098753)	(0.0089129)	(0.0088959)	(0.0119479)	(0.0098511)
Population	1.030601	0.9854459	-1.76918***	-1.429546*	-1.158563
	(0.7120705)	(0.6396915)	(0.6300803)	(0.8455048)	(0.7083523)
Percentage Male 19-34	-0.1530316***	0.0207518	-0.0278831	-0.1421098**	-0.0131904
	(0.04839)	(0.0433241)	(0.0426396)	(0.0570445)	(0.0480333)
Probability of apprehension	0.0094861***	0.0003039***	0.002535***	0.0063586***	0.0128428***
	(0.0004048)	(0.0000149)	(0.0004047)	(0.0008217)	(0.0007222)
Indirect					
Reception FDP rate	0.1722189***	0.0641633**	-0.1766107***	-0.1384776**	0.0057122
	(0.0285913)	(0.0317525)	(0.0378982)	(0.0559216)	(0.0312113)
Population	4.388677***	-7.97329***	1.557049	7.783693***	4.797201***
	(1.36657)	(1.462422)	(1.696799)	(2.491263)	(1.471915)
Percentage Male 19-34	-0.1910237**	-0.941552***	0.4097195***	0.2554987*	-0.2157182**
	(0.0808632)	(0.0849689)	(0.1002854)	(0.1421476)	(0.0863166)
Probability of apprehension	-0.0040684***	0.0000616	-0.0050988***	-0.0061839	-0.0042212
	(0.0012947)	(0.0000544)	(0.0014893)	(0.0044471)	(0.0027006)
Total					
Reception FDP rate	0.1954367***	0.061737*	-0.197494***	-0.1220391**	0.0029047
	(0.0296083)	(0.0329369)	(0.0396816)	(0.0585122)	(0.0326105)
Population	5.419278***	-6.987844***	-0.212131	6.354147**	3.638638***
	(1.226427)	(1.357032)	(1.635095)	(2.425591)	(1.35593)
Percentage Male 19-34	-0.3440553***	-0.9208003***	0.3818364***	0.1133889	-0.2289086***
	(0.0683214)	(0.0756657)	(0.0943737)	(0.1348704)	(0.0756634)
Probability of apprehension	0.0054178***	0.0003654***	-0.0025637*	0.0001746	0.0086216***
	(0.00136)	(0.0000585)	(0.001509)	(0.0046551)	(0.0029184)

Significance: * p<.1; **p<.05; *** p<.01

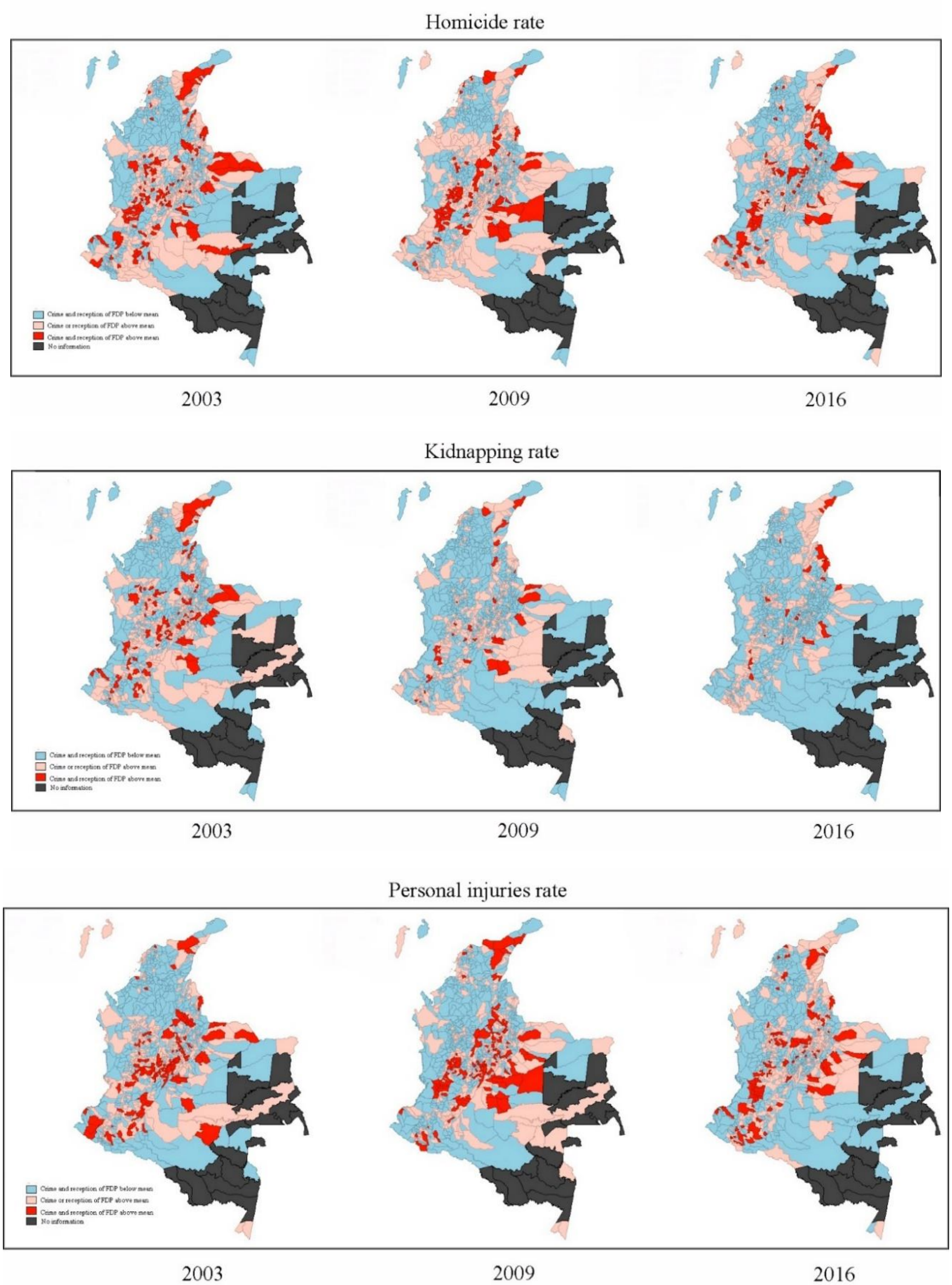
The essential result of our estimations is that each category of crime has different determinants and dynamics, this confirms the differences in the spatial distribution of crime and of the reception of forced displaced persons across the Colombian territory. Due to these differences, it is inappropriate to consolidate a composite crime index. Consequently, the spatial allocation of the population heterogeneity variables are relevant for the explanation of crime levels, which shows that previous estimates present bias error, since they do not consider the spatial patterns of the variables.

The estimation results for homicide, kidnapping, personal injuries and residence burglary rates suggest a significant relationship with the allocation of forced displaced persons in nearest areas. This means that in the case of homicide rates, it is possible to identify a positive effect of the reception of forced displaced persons in nearby areas with an increase in the local homicides, this is similar to the findings for kidnapping rates. These patterns suggest a mobility of criminals to nearby places for committing these types of crimes. The effect of the reception of forced displaced persons on the personal injuries rate presents a contrary sign in the results, this suggest an increase in social control in adjacent places due to the reception of displaced persons, it reduces personal injuries among the population in local areas. Residence burglary presents dual effects: more forced displaced persons cause an increase in this type of crime in the local area, and an increase in forced migrants in nearest places contribute to a reduction of residence burglary. Only the automobile theft rate is unrelated to the reception of forced displaced persons in main and adjacent areas.

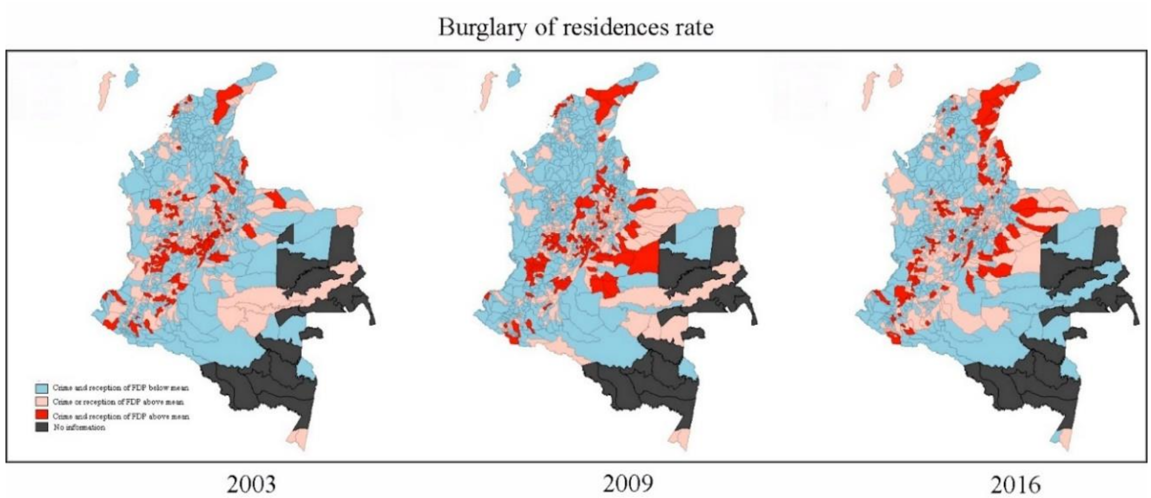
The results of spatial effects about the reception of forced displacement persons, suggest that in just the cases of homicides and personal injuries present direct and significant effects, which means that the increase in 1% of the forced displacements persons cause an increase in homicides and a decline in personal injuries close to 2% for both cases, in the same municipality of reception. Furthermore, the indirect effect of the reception of forced displaced people imply the existence of significant spatial spillovers and suggests that an increase of 1% in neighboring municipalities have positive impact in homicide and kidnapping rates about 17% and 6% respectively and negative impact close to 17% in residence burglary and 13% in personal injuries.

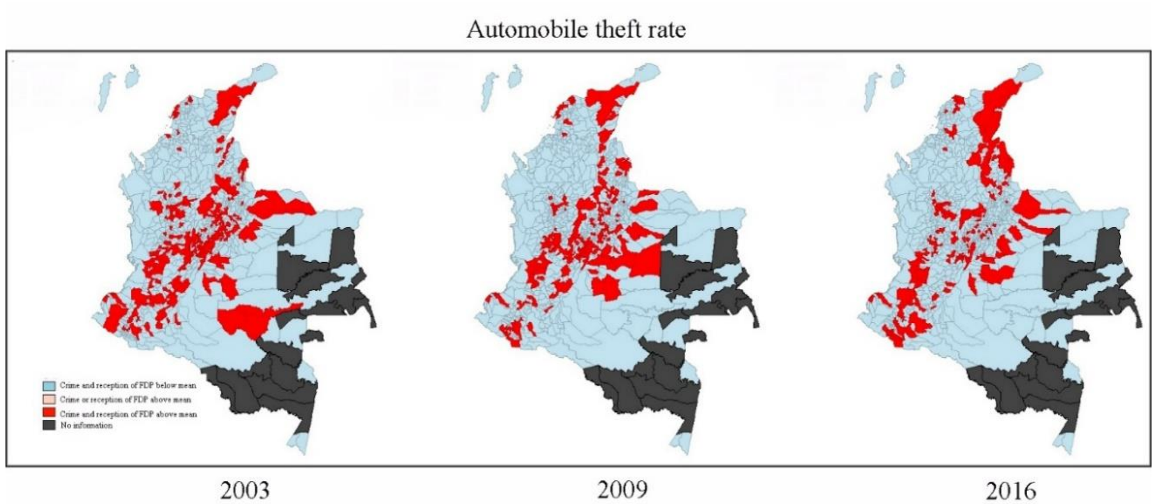
A correlation between the crime categories and the reception of forced displaced people can be suggested, rather than a causality link. The possible reason is related to omitted variables bias. Each crime category has specific dynamics and determinants, accompanied with limited data for the municipalities, these are difficulties that impede the identification of more appropriate specifications. Consequently with these arguments, Figure 3 provides evidence of the correlation. This graphic presents maps for each kind of crime in the years 2003, 2009 and 2016, where the municipalities with high levels for each crime category and of reception of forced displaced persons (above the mean) present a close spatial allocation.

Figure 3. Spatial correlation



Source: Own elaboration with data of Policia Nacional de Colombia and Panel CEDE and Unidad para las Victimas





Source: Own elaboration with data of Policia Nacional de Colombia and Panel CEDE and Unidad para las Victimas

VI. Conclusions

This paper presents theory and empiric arguments of the relationship between the forced displaced persons and the crime rates in reception place. The economic theory suggests that individuals with adverse socio-economics conditions are prone to commit crimes, are that indeed all the forced migration change the conditions of municipalities and affect the crimes rates, because all locations suffer a lack of opportunities and resource. As people who have been used to a certain life style arrive in the reception areas, they start to understand that they can no longer support themselves. The threat of a new place may scare many people and when they do not understand what is going on, they might turn to less than legal solutions. This is explained because most of the displaced people that enter the cities are farmers with no formal education at all; and when there is no legal opportunities to succeed in the cities, the informal market and the local gangs appear as an option where there is much money with a little effort. People arrive after having lost not only their possessions but sometimes their dignity, and they need fast incomes and sadly, the easiest way to attain these are through illegal methods. Once a person is involved in this, it is hard to get out, and therefore, displacement creates an increase in crime. Even though some people may start small, crime is a vicious circle that drags people in constantly and makes them preform crimes that they might sometimes not want to, and as people slowly get involved for money, it becomes harder to get out.

The empirical results provide evidence for some kind of crime the causality between crime and reception of forced displaced persons and the heterogeneity of population, and result suggest a correlation relationship for all crimes of the analysis, because some places have highest rates of crime and forced migrants, additionally these areas presents a nearest spatial allocation in Colombian territory. It is necessary, in the light of these expected results, that the government's effort is to generate opportunities for this vulnerable population, victims of internal conflict in their regions of origin and the few job opportunities in the regions where they arrive. It is then necessary to motivate in these families the qualification of their members according to the needs of the productive sector, and to encourage those firms of activities that are labor intensive, ideally qualified, in order to generate greater economic returns to these households. Therefore, social and economic programs to reduce the adverse conditions of the vulnerable population they must be executed through plans that impact the local population of the municipalities and nearest areas.

VII. References

Almeida, E., Haddad, E., & Hewings, G. (2003). the Spatial Pattern of Crime in Minas Gerais: an Exploratory Analysis. *Economia Aplicada*, *9*(1), 39–55.

Andresen, M. A. (2013). International immigration, internal migration, and homicide in Canadian provinces. *International Journal of Offender Therapy and Comparative Criminology*, *57*(5), 632–657. https://doi.org/10.1177/0306624X12436798

Anselin, L., Cohen, J., Cook, D., Gorr, W., & Tita, G. (2000). Spatial Analyses of Crime. *Measurement and Analysis of Crime and Justice*, *4*.

Arnio, A. N., & Baumer, E. P. (2012). Demography, foreclosure, and crime: Assessing spatial heterogeneity in contemporary models of neighborhood crime rates. *Demographic Research*, *26*, 449–488. https://doi.org/10.4054/DemRes.2012.26.18

Becker, G. S. (1968). Crime and Punishment: An Economic Approach. *Journal of Political Economy*, 169–217.

Bell, B., Fasani, F., & Machin, S. (2013). Crime and Immigration: Evidence from Large Immigrant Waves. *Review of Economics and Statistics*, *95*(4), 1278–1290. https://doi.og/10.1162/REST_a_00337

Bianchi, M., Buonanno, P., & Pinotti, P. (2012). Do Immigrants Cause Crime? *Journal of the European Economic Association*, *10*(6), 1–38. Retrieved from papers2://publication/uuid/593A3AF6-C7F8-417C-9060-803619975027

Bourguignon, F., Nuñez, J., Sanchez, F., May, A., Bourguignon, F., & Sanchez, F. (2017). A Structural Model of Crime and Inequality in Colombia. *Journal of the European Economic Association*, *1*(2), 440–449.

Calderón-Mejía, V., & Ibáñez, A. M. (2016). Labour market effects of migration-related supply shocks: Evidence from internal refugees in Colombia. *Journal of Economic Geography*, *16*(3), 695–713. https://doi.org/10.1093/jeg/lbv030

Cheng, J., Liu, J., & Wang, J. (2017). Domestic migration, home rentals, and crime rates in China. *The Journal of Chinese Sociology*, *4*(1), 8. https://doi.org/10.1186/s40711-017-0056-3

Chiswick, B., & Miller, P. (2014). Handbook of the Economics of International Migration. Burlington: North Holland.

Cracolici, M. F., & Uberti, T. E. (2009). Geographical distribution of crime in Italian provinces: A spatial econometric analysis. *Jahrbuch Fur Regionalwissenschaft*, *29*(1), 1–28. https://doi.org/10.1007/s10037-008-0031-1

Ehrlich, I. (1973). Participation in Illegitimate Activities: A Theoretical and Empirical Investigation. *Journal of Political Economy*. https://doi.org/10.1086/260058

Elhorst, J. P. (2014). *Spatial Econometrics From Cross-Sectional Data to Spatial Panels*. Groningen, Netherlands: Springer. https://doi.org/10.1007/978-3-642-40340-8

Engel, S., & Ibáñez, A. M. (2007). Displacement due to violence in Colombia: A household-level analysis. *Economic Development and Cultural Change*, *55*(2), 335-365.

Fernandez, M., Ibáñez, A. M., & Peña, X. (2014). Adjusting the Labour Supply to Mitigate Violent Shocks: Evidence from Rural Colombia. *The Journal of Development Studies*, *50*(8), 1135-1155.

Fischer, M. M., & Getis, A. (2010). *Handbook of Applied Spatial Analysis*. https://doi.org/10.1007/978-3-642-03647-7

Graif, C., & Sampson, R. J. (2009). Spatial Heterogeneity in the Effects of Immigration and Diversity on Neighborhood Homicide Rates. *Homicide Studies*, *13*(3), 2–20. https://doi.org/10.1177/1088767909336728

Herrick, B. H. (1966). Urban migration and economic development in Chile. *MIT Press Books*, *1*.

Ibáñez, A. M. (2009). Forced displacement in Colombia: magnitude and Causes. *The Economics of Peace and Security Journal*, *4*(1).

Ibáñez, A. M., & Moya, A. (2010). Vulnerability of Victims of Civil Conflicts: Empirical Evidence for the Displaced Population in Colombia. *World Development*, *38*(4), 647–663. https://doi.org/10.1016/j.worlddev.2009.11.015

Ibáñez, A. M., Rodríguez, C., & Zarruk, D. (2013). Crime, punishment, and schooling decisions: evidence from Colombian adolescents.

Ibáñez, A. M., & Vélez, C. E. (2008). Civil Conflict and Forced Migration: The Micro Determinants and Welfare Losses of Displacement in Colombia. *World Development*, *36*(4), 659–676. https://doi.org/10.1016/j.worlddev.2007.04.013

InSight Crime (2017, November) Colombia Profile Retrieved from https://www.insightcrime.org/colombia-organized-crime-news/colombia/#history

Jaitman, L., & Machin, S. (2013). Crime and immigration: new evidence from

England and Wales. *IZA Journal of Migration*, *2*(1). https://doi.org/10.1186/2193-9039-2-19

Kubrin, C. E., Hipp, J. R., & Kim, Y. A. (2016). Different than the Sum of Its Parts: Examining the Unique Impacts of Immigrant Groups on Neighborhood Crime Rates. *Journal of Quantitative Criminology*, 1–36. https://doi.org/10.1007/s10940-016-9320-y

Light, M. T., & Harris, C. T. (2012). Race, Space, and Violence: Exploring Spatial Dependence in Structural Covariates of White and Black Violent Crime in US Counties. *Journal of Quantitative Criminology*, *28*(4), 559–586. https://doi.org/10.1007/s10940-011-9162-6

Mears, D. P. (2001). The Immigration-Crime Nexus: Toward an Analytic Framework for Assessing and Guiding Theory, Research, and Policy. *Sociological Perspectives*, *44*(1), 1–19. https://doi.org/10.1525/sop.2001.44.1.1

Meng, X., & Zhang, D. (2013). The Social Impact of Rural-Urban Migration on Urban ëNativesí.

Nunziata, L. (2015). Immigration and crime: evidence from victimization data. *Journal of Population Economics*, *28*(3), 697–736. https://doi.org/10.1007/s00148-015-0543-2

Ousey, G. C., & Kubrin, C. E. (2009). Exploring the Connection between Immigration and Violent Crime Rates in U . S . Cities, 1980 – 2000. *Social Problems*, *56*(3), 447–473. https://doi.org/10.1525/sp.2009.56.3.447.448

Reid, L. W., Weiss, H. E., Adelman, R. M., & Jaret, C. (2005). The immigration-crime relationship: Evidence across US metropolitan areas. *Social Science Research*, *34*(4), 757–780. https://doi.org/10.1016/j.ssresearch.2005.01.001

Roche-villarreal, L. (2012). *Forced Displacement and Crime in Colombia*.

Schultz, T. P. (1971). Rural-urban migration in Colombia. *The Review of Economics and Statistics*, 157-163.

Spenkush, J. (2011). Understanding The Impact Of Immigration On Crime, (March 2010), 39.

Thomas, P. M. (2011). Theoretical articulation on immigration and crime. *Homicide Studies*, *15*(4), 382–403. https://doi.org/10.1177/1088767911424539

Tita, G. E., & Radil, S. M. (2010). *Spatial Regression Models in Criminology: Modeling Social Processes in the SpatialWeights Matrix*. *Handbook of Quantitative*

Criminology. https://doi.org/10.1007/978-0-387-77650-7

Torres-Preciado, V. H., Polanco-Gaytán, M., & Tinoco-Zermeño, M. A. (2017). Crime and regional economic growth in Mexico: A spatial perspective. *Papers in Regional Science*, *96*(3), 477–494. https://doi.org/10.1111/pirs.12205

Treyger, E. (2013). Migration and Violent Crime: Lessons from the Russian Experience. *Georgetown Immigration Law Journal*, *27*(2), 257–310. https://doi.org/10.1146/annurev.soc.31.041304.122308

Wadsworth, T. (2010). Is immigration responsible for the crime drop? an assessment of the influence of immigration on changes in violent crime between 1990 and 2000*. *Social Science Quarterly*, *91*(2), 531–553. https://doi.org/10.1111/j.1540-6237.2010.00706.x

Ye, X., & Wu, L. (2011). Analyzing the dynamics of homicide patterns in Chicago: ESDA and spatial panel approaches. *Applied Geography*, *31*(2), 800–807. https://doi.org/10.1016/j.apgeog.2010.08.00

ANNEX

Annex 1. Statistics test for fixed effects panel model

Annex 1.1 Hausman test for homicide rate

	Homicide rate *Coefficients*			
	Fixed Effect	***Random Effect***	***Difference***	***S.E.***
Reception FDP rate	0.0460345	0.1257867	-0.0797522	0.0040293
Population	2.335417	1.580372	0.755045	0.5779111
Percentage Male 19-34	-0.3009599	-0.0899501	-0.2110099	0.0268817
Probability of apprehension	0.0092097	0.0087392	0.0004705	0.0000836

Test:	**Coefficient**	**P. Value**
(FE-RE)=0	441.37	0.000

Annex 1.2 Breush-Pagan test for homicide rate

Breusch - Pagan Test		
Component	***Variance***	***S. E.***
Homicide rate	27.64952	5.258281
e	15.80386	3.975408
u	4.561606	2.135792
Test	***Value***	***P. Value***
Var(u)=0	5508.7	0.000

Annex 1.3 Hausman test for kidnapping rate

	Kidnapping rate *Coefficients*			
	Fixed Effect	***Random Effect***	***Difference***	***S.E.***
Reception FDP rate	0.0275244	0.0754745	-0.04795	0.0046888
Population	-3.979022	0.7872241	-4.766246	0.5350277
Percentage Male 19-34	-0.6105842	-0.1824084	-0.4281757	0.0273372
Probability of apprehension	0.000308	0.0003114	-0.00000338	0.00000494

Test:	Coefficient	P. Value
(FE-RE)=0	438.52	0.000

Annex 1.4 Breush-Pagan test for kidnapping rate

Breusch - Pagan Test		
Component	***Variance***	***S. E.***
Kidnapping rate	17.56637	4.191225
e	13.46473	3.669431
u	1.663708	1.289848
Test	***Value***	***P. Value***
Var(u)=0	1140.93	0.000

Annex 1.5 Hausman test for personal injuries rate

	Personal injuries rate *Coefficients* *Fixed Effect*	*Random Effect*	*Difference*	*S.E.*
Reception FDP rate	-0.0546421	-0.0575634	0.0029213	0.0040608
Population	-0.0516808	0.8854523	-0.9371331	0.5363529
Percentage Male 19-34	0.3285432	0.0487832	0.27976	0.0258553
Probability of apprehension	0.0013116	0.0008334	0.0004783	0.0000819

Test:	**Coefficient**	**P. Value**
(FE-RE)=0	134.76	0.000

Annex 1.6 Breush-Pagan test for personal injuries rate

Component	**Breusch - Pagan Test** ***Variance***	***S. E.***
Personal injuries rate	17.95184	4.236961
e	13.57667	3.684654
u	3.325764	1.823668
Test	***Value***	***P. Value***
Var(u)=0	3811.19	0.000

Annex 1.7 Hausman test for residence burglary rate

	Residence burglary rate *Coefficients* *Fixed Effect*	*Random Effect*	*Difference*	*S.E.*
Reception FDP rate	-0.0131383	-0.0234569	0.0103186	0.0052858
Population	2.645542	2.055372	0.5901706	0.7264877
Percentage Male 19-34	0.1434702	-0.0786818	0.222152	0.0339206
Probability of apprehension	0.0063989	0.0063269	0.000072	0.0001692

Test:	**Coefficient**	**P. Value**
(FE-RE)=0	55.74	0.000

Annex 1.8 Breush-Pagan test for residence burglary rate

Breusch - Pagan Test		
Component	***Variance***	***S. E.***
Burglary residence rate	37.291	6.107242
e	24.85036	4.985013
u	7.235115	2.689817
Test	***Value***	***P. Value***
Var(u)=0	5026.35	0.000

Annex 1.9 Hausman test for automobile theft rate

	Automobile theft rate			
	Coefficients			
	Fixed Effect	***Random Effect***	***Difference***	***S.E.***
Reception FDP rate	0.0000459	-0.0016875	0.0017333	0.0036703
Population	0.415875	2.064432	-1.648557	0.5786497
Percentage Male 19-34	-0.0816756	-0.0912083	0.0095327	0.0251465
Probability of apprehension	0.0129228	0.0138674	-0.0009446	0.0001238

Test:	**Coefficient**	**P. Value**
(FE-RE)=0	59.79	0.000

Annex 1.10 Breush-Pagan test for automobile theft rate

Breusch - Pagan Test		
Component	***Variance***	***S. E.***
Automobile theft	29.71991	5.451597
e	15.90869	3.98857
u	7.187335	2.680921
Test	***Value***	***P. Value***
Var(u)=0	9967.1	0.000

Annex 2. Spatial models estimation

Annex 2.1 SAR Models estimation

Variable	***Homicide rate model***	***Kidnapping rate model***	***Personal injuries rate model***	***Burglary residences model***	***Automobile theft rate***
Reception FDP rate	.03928658***	.01875999**	-.0395144***	-0.00218982	-0.00134828
Population	1.9935376***	-2.7813709***	-0.36926941	1.5847831**	0.19830885
Percentage Male 19-34	-.26203474***	-.4400183***	.21677485***	.08100764**	-0.05351436
Probability of apprehension	.00923633***	.00030295***	.00156969***	.00631998***	.01300001***
Spatial					
Dependent variable	.16346578***	.25485003***	.34195674***	.36167261***	.21290555***
Constant	3.9444627***	3.5906023***	3.5436229***	4.7608031***	3.9336012***
Statistics					
AIC	79617.765	77038.73	76805.381	85258.433	79586.996
Observations	15344	15344	15344	15344	15344

Significance: * p<.1; **p<.05; *** p<.01

Annex 2.2 SLX Models estimation

Variable	***Homicide rate model***	***Kidnapping rate model***	***Personal injuries rate model***	***Burglary residences model***	***Automobile theft rate***
Reception FDP rate	.02898481***	0.00514448	-.03273289***	0.00546563	-0.00230181
Population	1.2616546*	0.63531079	-1.7577104***	-0.80987899	-0.87998387
Percentage Male 19-34	-.17428178***	-0.03200999	0.00437306	-.12981466**	-0.01033292
Probability of apprehension	.00942731***	.00030885***	.00243371***	.00683815***	.0128903***
Spatial					
Reception FDP rate	.13775192***	.05994831***	-.13569803***	-.11106698***	0.00447079
Population	3.5868556***	-7.2871409***	1.8455236*	6.7067214***	3.8475209***
Percentage Male 19-34	-.16927997**	-.87423029***	.39876563***	.28681466***	-.19413384***
Probability of apprehension	-.00316192***	0.00003579	-.00365547***	-0.0026884	-.00288404*
Constant	3.9630603***	3.6229821***	3.6626073***	4.9706619***	3.9849507***
Statistics					
AIC	79691.535	77134.901	77444.874	86146.919	79848.503
Observations	15344	15344	15344	15344	15344

Significance: * p<.1; **p<.05; *** p<.01

Annex 2.3 SEM Models estimation

Variable	*Homicide rate model*	*Kidnapping rate model*	*Personal injuries rate model*	*Burglary residences model*	*Automobile theft rate*
Reception FDP rate	.03521429***	.01794219**	-.03324451***	0.00454871	-0.00132783
Population	1.8253695***	-2.8319352***	-0.52333682	1.0963063	-0.13440098
Percentage Male 19-34	-.2763521***	-.45765801***	.21191998***	0.05374717	-0.05342487
Probability of apprehension	.00943298***	.0003017***	.00196801***	.00671644***	.01311403***
Spatial					
Spatial error term	.16868963***	.24557798***	.34326594***	.36410139***	.21723251***
Constant	3.9431657***	3.6021918***	3.5459156***	4.7598794***	3.9317971***
Statistics					
AIC	79612.803	77118.258	76826.326	85257.913	79578.766
Observations	15344	15344	15344	15344	15344

Significance: * p<.1; **p<.05; *** p<.01

Annex 2.4 SAC Models estimation

Variable	*Homicide rate model*	*Kidnapping rate model*	*Personal injuries rate model*	*Burglary residences model*	*Automobile theft rate*
Reception FDP rate	.02308928**	0.01177801	-.03054955***	0.01545757	-0.00156363
Population	1.242563*	-1.6997357***	-0.34742308	-0.53589577	-0.7624258
Percentage Male 19-34	-.25724749***	-.26302599***	.12346633***	-0.06437202	-0.03953111
Probability of apprehension	.00920173***	.00024835***	.00098561***	.00604309***	.01223978***
Spatial					
Dependent variable	-.39214199***	.64997189***	.71479297***	-.67399603***	-.44005112***
Spatial error term	.48341514***	-.61890462***	-.62198616***	.75087711***	.54602716***
Constant	3.81192***	3.3158759***	3.2493182***	4.301082***	3.7642613***
Statistics					
AIC	79578.417	76757.331	76536.746	84903.161	79515.438
Observations	15344	15344	15344	15344	15344

Significance: * p<.1; **p<.05; *** p<.01

Annex 2.5 SDM Models estimation

Variable	***Homicide rate model***	***Kidnapping rate model***	***Personal injuries rate model***	***Burglary residences model***	***Automobile theft rate***
Reception FDP rate	.02545592***	0.00258285	-.02559087***	0.01111807	-0.00302186
Population	1.0316584	0.72543565	-1.820535***	-0.89027083	-1.0325929
Percentage Male 19-34	-.17285591***	-0.01011524	-0.00977169	-.13506638**	-0.00302814
Probability of apprehension	.00951187***	.00030501***	.0025492***	.0068721***	.01297582***
Spatial					
Reception FDP rate	.11549539***	.04446987**	-.08560804***	-.0716386***	0.00494754
Dependent variable	.15906318***	.21832512***	.32920604***	.358109***	.21532861***
Population	3.0328405***	-5.8567427***	1.9191205**	4.38724***	3.411883***
Percentage Male 19-34	-.11301561*	-.68744302***	.27151848***	.24438905***	-.15743907**
Probability of apprehension	-.00425416***	-0.0000259	-.0034893***	-.00540284***	-.00536523***
Constant	3.9348871***	3.5686791***	3.5347548***	4.75317***	3.9296665***
Statistics					
AIC	79552.905	76826.714	76718.099	85213.434	79569.176
Observations	15344	15344	15344	15344	15344

Significance: * p<.1; **p<.05; *** p<.01

Annex 2.6 SDEM Models estimation

Variable	***Homicide rate model***	***Kidnapping rate model***	***Personal injuries rate model***	***Burglary residences model***	***Automobile theft rate***
Reception FDP rate	.0298929***	0.00587309	-.0327803***	0.00583986	-0.00267197
Population	1.1489348	0.32010642	-1.6456728***	-0.3129891	-0.81211668
Percentage Male 19-34	-.18456035***	-0.06336306	0.0325431	-.09830376*	-0.01023238
Probability of apprehension	.00942682***	.00030653***	.00231434***	.00658099***	.0128727***
Spatial					
Reception FDP rate	.12341636***	.04982654**	-.09620986***	-.06545627**	0.00547888
Spatial error term	.15629713***	.21259889***	.3269925***	.35774818***	.21497482***
Population	3.4667442***	-6.7172771***	1.9601676*	4.5267857***	3.4110365***
Percentage Male 19-34	-.15339968**	-.79628353***	.34935521***	.29053479***	-.1771604**
Probability of apprehension	-.00283849***	0.00004188	-.00313151***	-.00428018**	-0.0027971
Constant	3.9360492***	3.5723255***	3.5378558***	4.7549525***	3.9299285***
Statistics					
AIC	79559.112	76849.393	76739.054	85223.387	79570.68
Observations	15344	15344	15344	15344	15344

Significance: * p<.1; **p<.05; *** p<.01