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A Spatial Analysis to Permanent Income as Deterrent of Homicides: the case of Medellin City*

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Abstract

This paper studies the relationship between permanent income and homicides, estimating an income-crime elasticity. We assume that this elasticity varies across geographical areas. We estimate different specifications of Spatial Panel Models using information of urban areas in Medellin (Colombia), areas known as communes. Spatial Models consider the importance of location and the type of neighbors of each commune. We simulate an intervention over permanent income in order to estimate the income elasticity for each commune and the average elasticity of income-crime on the city. We provide evidence about spatial dependence between the homicides per commune and their neighbors, and about a relationship between homicides and neighbor's income. In our case of study, the average estimated impact of 1% increase in permanent income in a specific commune produces a decrease in the homicide rate on average in 0.39%. Finally, permanent income plays a crime deterrent role, but also this effect of income on crime varies across the city, showing that some areas are strategically located to this kind of intervention.

Keywords: Permanent income, Homicides, Spatial panel, Elasticity.

JEL classification: K4, C23, R12, R23.

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1. Introduction

From the classical perspective of the Economic Theory of Crime, the criminal act obeys to a rational decision by the individual which is the result of a comparison between the expected utility of the crime and its cost (Becker, 1968; Ehrlich, 1973; Lochner, 1999). Also, the criminal acts constitute one of cities' major problems. This kind of problem is usually faced by regional level governments (Brooks, 2008).

Studies about crime reduction have focused on the analysis of the discouragement of the availability of the police force and, on the efficiency of the judicial system. Nonetheless few works have studied the dissuasive effect that income may have on crime on a spatial unit.

This article aims to evaluate the effect of average work income in the homicides level, given that the communes are not isolated territorial units and, that it brings the relevance to consider spatial relations. For this purpose, we estimate different spatial panel data models, which use as independent variable the total number of homicides per 10,000 inhabitants. Also, we use the permanent income as our main explanatory variable, joint with variables that represent the spatial relationships across communes.

There is a part of each criminal act that occurs within a territorial unit that should be explained by the characteristics of that same unit. However, the characteristics of those neighbors of the unit can also influence the level of crime. The criminal activity in a particular commune can be a source of externality to nearby communes (such externality can be either positive or negative). This means that being close to a commune with high levels of criminal activity may have an effect on the own crime, disregarding the initial economic conditions. This important relationship between neighbors and their characteristics is what is commonly called as spatial analysis.

In the last four decades Medellin has been one of the Latin American cities with the highest crime levels, mainly caused by drug dealing structures and organized crime (Gaviria & Pagés, 2002).

This city reached the highest homicide level in 1991 with 381 deaths per 100 thousand inhabitants, being cataloged as the most violent city in the world that year. Nevertheless, this situation changed progressively. For example, the homicide rate in 2014 was 26.95 homicides per 100,000 inhabitants.

Our results show that permanent income has a statistically significant effect as a deterrent mechanism to reduce crime in Medellín's communes. Moreover, we find that spatial panel specifications capture a lower marginal effect of an intervention on permanent income in comparison with traditional panels.

This paper contributes to the relationship between homicides and quality of life. Also, it formalizes the impact of the ceasefire agreed between illegal groups and Medellín's local government during years 2005-2008 on the city's homicide level.

The article is divided into six sections including this introduction. On the second section we present the theoretical framework. Then, in the third section we explain our empirical approach. To continue, on the fourth section we describe the data used and contextualize our case study for Medellín (Colombia). In the fifth section, we present the main stylized facts, the results of econometric models, and some robustness tests. Finally, in the last section we conclude our paper by summarizing the main results and giving some advice for public policy.

2. Theoretical framework

Various academic studies have been concerned about understanding and finding ways to reduce and prevent violence levels, in order to assist states to ensure the welfare conditions under which the inhabitants of a country or city live. The economic analysis of crime begins its formalization with Becker (1968), who argues that state investment in police force directly influences the decrease in crime. Becker (1968) exposed that the probability of apprehension and severity in penalties make the individual doubt at the moment of committing a crime.

For his part, Ehrlich (1973) states that the individual has the opportunity to participate in two market activities: one legal and another illegal. This is focused on the efforts and time that somebody has to spend to generate some income. In that sense, it compares the time and resources that the individual invests in legal and illegal activities, showing a clear disadvantage for the latter, given the likelihood of being arrested. For a person to act illegally, it will be sufficient that the expected marginal benefit of the crime exceeds the expected marginal value of punishment.

Studies about the causes of criminal activity, like Levitt (2001) & Spelman (2005), have related homicides with arrests, convictions, prisons and fundamental socio-economic

conditions to explain some determinants of violence. For Bayley (1994), the population's safety does not depend mainly on the police, moreover, many others factors of each area (poverty, inequality, urban habitat, migration, etc.) affect further crime levels.

Related to socio-economic conditions, Hipp (2007, 2011) considered an economic segregation variable in the presence of ethnic segregation. He concluded that economic segregation and inequalities in income raise the crime rates in cities with ethnic heterogeneity. Additionally, poverty lost significance when in the specification is included the income to explain the variations in robberies and homicides. This happens because income can be considered the main factor of deterrence in the criminal reasoning.

South (2005) and Choe (2008) established the income inequalities as a starting point to explain the criminal differences in the units of analysis and found differences between the effects of short and long terms. Dahlberg & Gustavsson (2008) suggested that the research using the total income as an explanatory variable skew the results of the relationship between income and crime. The criminal individuals respond to incentives where one of them is the income in a legal activity, i.e. work. Then, it is the permanent income and not the transitory one which should be considered as a determinant factor for crime.

Dahlberg & Gustavsson (2008) separated the permanent from the transitory income, and they found that increases in the inequality due to differences in permanent income have a positive and significant effect on the total number of crimes (both violent and property) while an increase in the inequality due to difference in transitory income has no significant variation in any type of crime.

In most of the studies previously analyzed, we exposed the importance of the differences in income of the units of analysis, the main effect of economic inequality was positive against crime levels. Chintrakarn & Herzer (2012) found evidence of opposite effects between inequality and crime, which justify the fact that the greater the equality, the more increases the demand for protection of crime, leading to reductions in crime levels.

Menezes et al. (2013), in a study of the Brazilian city Recife, using spatial econometrics, found evidence of spatial dependence and the existence of direct and indirect effects. The investigation concluded that inequality indeed increased the homicide levels by a direct effect, but due to the spatial relationship between neighborhoods, this effect is mitigated by the

indirect one. In addition, the average income has a negative and significant relationship with the homicides, but a not significant positive indirect effect.

This relations show that the economic structure of a country is an important factor in the dynamics of crime, just as variables such as the education levels, migration, urbanization, income and expenditure distribution, poverty and wage levels; all factors in which the education has a particularly significant impact (Tekely & Günsoy, 2013).

Fleisher (1966) related the variables crime, income, and education, and found that low levels of income can influence of juvenile delinquency and that in areas of extremely high crime levels, an income increase of 1% can cause a decrease of 2.5% in the crime rate.

Freeman (1996) and Lochner (1999) showed that criminal acts have a direct relationship with the phenomena of juvenile delinquency and low educational level. However, the education may refer to all levels of it, from preschool to tertiary education. Alcan & Şhahin (2011) showed that illiteracy is one of the characteristics explains criminality and that this can be improved increasing the minimum education level of the population.

Sánchez (2003) in a study for the city of Bogotá, states that public policies referred as “zanahoria” (measured by the unemployment rate and public spending on the social sector) generate a negative impact on homicides and thefts.

Medina et al. (2011) identify some general characteristics of violence in the city of Medellín and the main costs that this phenomenon represents for public policy. Meanwhile, Martin (2012) makes an analysis of the condition of violence, mafia, and crime in the city during 1975-2012. In this research, a period that can be framed in the years 2005-2008 is referenced, in which illegal armed groups under the direction of Diego Fernando Murillo Bejarano, alias “Don Berna”, exercised activities that redounded in an improvement in the security, which some attribute to a guaranteed governance by that leader (“Donbernabilidad”).

These very special conditions of the city during this time arose a secondary hypothesis about the negative impact that the so-called “Donbernabilidad” had on crime. This hypothesis will be driven in this research, what we want to test specifically is if there is any evidence that during the period of 2005-2008 the homicides rate was significantly lower than the trend trajectory of the crime variable. It is noteworthy that this period will also include unobservable factors such as the social efforts of the municipal government to attend the demobilized during

this time. However, we rely on if there is evidence of different trajectory, a considerable part of that difference is given by the “donbernabilidad” effect.

Finally, we identified two articles in which spatial models were implemented to explain the relationship between income and crime levels. The first one is from Menezes et al. (2013), which has been mentioned above. These authors use regression models with spatial lag in violent crime (dependent variable) and in error, using distinctions between direct and indirect effects and including the average income of each neighborhood of Recife. The second article is from Scorzafave & Soares (2009), in which the calculation of the elasticity of inequality by crime is made, mainly of property crime. This study presents, as one of its contributions, the estimation of the elasticity income-crime in a spatial regression, arguing that it should be negative and inelastic. We expect that improvements in permanent income due to some political interventions lead to reductions in crime. However, according to the initial levels of crime and economic conditions, the response could be lower than the impulse given, meaning that the elasticity should be greater than -1 and lower than zero.

3. Methodology

We rely in the following specification to analyze the determinants of the homicide rate in the communes of Medellin during the first decade of this century.

$$Hom\ Rate_{it} = \beta X_{it} + \varepsilon_{it} \quad (1)$$

Where X_{it} is a matrix which contains the predetermined variables (income, male population, coverage of social security, Quality of Life Index and education variables), β is the coefficient's matrix and ε_{it} represent the error term and is equal to $\varepsilon_{it} = \alpha_i + u_{it}$. The parameter α_i represents the individual heterogeneity across communes. However, the objective of this analysis is the approaching of the elasticity between income and homicides. We can then transform the Eq. (1) to a log-log definition. Besides, we know that $\ln(Hom\ Rate_{it}) = \ln(Hom_{it}) - \ln(Population_{it}/100,000)$. That means, if we used the natural logarithm of homicide rate as dependent variable, we will force the coefficient of population equals to one. Rewriting:

$$\ln(Hom_{it}) = \beta X_{it} + \varepsilon_{it} \quad (2)$$

Now X_{it} refers to a new specification using the log of average work income, male's population, social security enrollment and population. Although this model can be estimated using traditional panel strategies like Pool OLS, Fixed Effects and Random Effects Methodology; there is also a relationship that cannot be taken into account using those models. That relationship is driven by the location of the geographical units, known as spatial effects. There is a strong evidence that crime indicators have a spatial relationship between unit's outcomes. That means that the number of homicides in the commune i are particularly related with the homicides in its neighbors. Using the specifications developed by Elhorst (2014) we define the following model, which corresponds to Spatial Panel specification:

$$\ln(Hom_{it}) = \rho W_i \ln(Hom_{it}) + \beta X_{it} + \alpha_i + u_{it} \quad (3)$$

$$u_{it} = \lambda W_i u_{it} + e_{it} \quad (4)$$

This is a broad specification of the Spatial Panel Model. However, a more general one can include spatial lags of predetermined variables, as following:

$$\ln(Hom_{it}) = \rho W_i \ln(Hom_{it}) + \beta X_{it} + \delta W_i \ln(Income_{it}) + \alpha_i + u_{it} \quad (5)$$

$$u_{it} = \lambda W_i u_{it} + e_{it} \quad (6)$$

These last equations are our object of interest. The parameter ρ captures the incidence of the homicides of i 's neighbors on the homicides in the commune i . This parameter gives us the impact of being surrounded by a specific type of communes (high or low crime). Similar to this is the coefficient δ , which represents the spatial relationship between the neighbors communes through the predetermined variable of average work income, i.e. the level of income in the commune i does not only affect the homicides in the commune i , also it affects the number of homicides in the neighbors of i . Finally, the last coefficient is λ , which can be defined as the intensity that an exogenous shock can spread through the geographical units neighbors of the first affected commune. In other words and assuming that W is now a normalize matrix, a λ close to one allows than an external shock in i will affect i 's neighbors in a similar proportion than i . In the opposite case, λ close to zero means that a particular shock in i does not have significant impact on i 's neighbors.

As we have mentioned in the last paragraphs, the Eq. (5) and Eq. (6) are the more general specification of a Spatial Panel Model, we therefore move on to some particular specifications according with different assumptions.

1. Spatial Autoregressive Model (SAR)

$$\delta = \lambda = 0$$

Rewriting the Eq. (5) and Eq. (6):

$$\ln(Hom_{it}) = \rho W_i \ln(Hom_{it}) + \beta X_{it} + \alpha_i + e_{it} \quad (7)$$

This model assumes that the spatial relationship can be captured only through the dependent variable. The geographical relationship between neighbors is driven only by their crime levels.

2. Spatial Error Model (SEM)

$$\rho = \delta = 0$$

Rewriting:

$$\ln(Hom_{it}) = \beta X_{it} + \alpha_i + u_{it} \quad (8)$$

$$u_{it} = \lambda W_i u_{it} + e_{it} \quad (9)$$

The spread of external shocks is the explanation of the geographical relationship between communes. The similarities in the crime behavior are given by the contagious of external shocks more than similar trends in the homicide figures.

3. Spatial Autoregressive Model with Spatial Autoregressive Disturbance (SARAR)

$$\delta = 0$$

Rewriting:

$$\ln(Hom_{it}) = \rho W_i \ln(Hom_{it}) + \beta X_{it} + \alpha_i + u_{it} \quad (10)$$

$$u_{it} = \lambda W_i u_{it} + e_{it} \quad (11)$$

This specification combines the main ideas of the SAR and SEM models. The spatial relation is driven in a direct way through the patterns in homicides between neighbors and on an indirect way through the contagious effect of external shocks.

4. Durbin Model

$$\lambda = 0$$

Replacing in the Eq. (5) and Eq. (6):

$$\ln(Hom_{it}) = \rho W_i \ln(Hom_{it}) + \beta X_{it} + \delta W_i \ln(Income_{it}) + \alpha_i + e_{it} \quad (12)$$

The Durbin Model combines the methodology of the SAR model with a new idea of the contagious process. This specification assumes that the shocks are almost endogenous and they spread through the dependent and predetermined variables. In

our case the predetermined variable that interacts spatially between neighbors is the average work income. We thus assume that an external shock in a commune i spreads through the changes in homicides and the changes in average work income.

Although we estimate each one of these Spatial Panel Data Models, we need to contrast the results between them to then focus on one specific estimation. In order to do that we apply different statistical tests that compare two set of models and allow us to infer which of them better represents the information in our dataset. Two main tests will be done:

1. Test between SAR and Durbin Model

$$H_0: \delta = 0$$

$$H_1: \delta \neq 0$$

Statistic: Wald Lineal Test (F distribution)

Rejection Region: $Prob(Statistic) < \alpha$

Conclusion: under no rejection of H_0 the model that best fit the data is SAR, and under rejection of H_0 the alternative hypothesis suggests that the Durbin model is a better strategy.

2. Test between SEM and Durbin Model

$$H_0: \delta = -\rho\beta$$

$$H_1: \delta \neq -\rho\beta$$

Statistic: Wald No Lineal Test (F distribution)

Rejection Region: $Prob(Statistic) < \alpha$

Conclusion: under no rejection of H_0 the model that best fit the data is the Durbin Model, and under rejection of H_0 the alternative hypothesis suggests that the SEM model should be used (Belotti et al, 2013).

Finally, those specifications allow us to define a way to simulate the effect of an intervention in the average work income or according to the literature, in the permanent income. We want to show that the homicides responds negatively to a positive shocks in permanent income, but this effect is different across geographical units. To corroborate this, we rely on the methodology of Drukker et al. (2013). The authors expose a way to estimate the marginal effect of an intervention in a predetermined variable on the outcome, and also they break down the total marginal effect in the individual and the spatial effect.

4. Case Study: Medellín

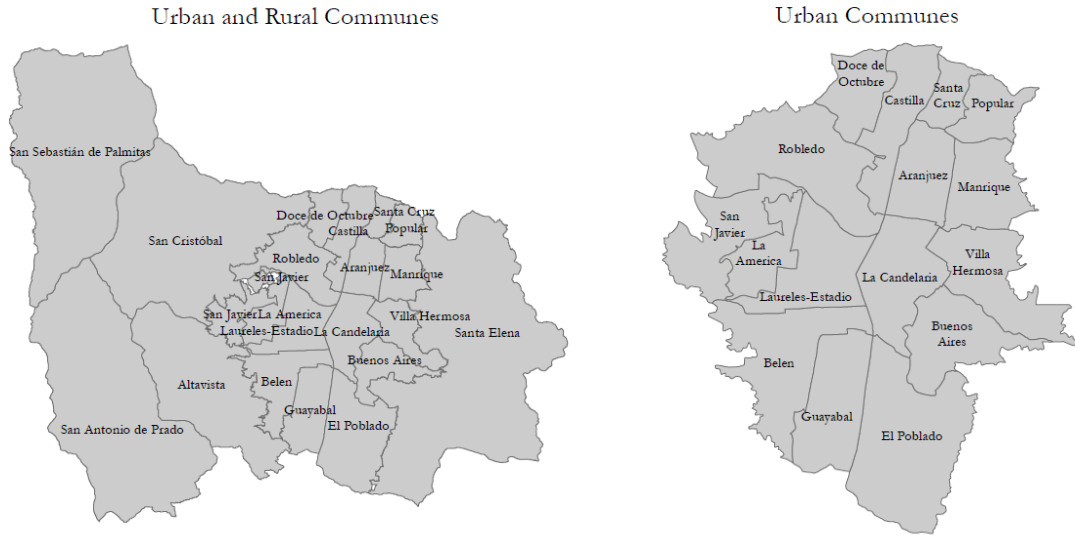
Medellín (Colombia) is a city that in the late twentieth century was characterized by presenting phenomena of violence, which placed it among the cities with the highest crime rates in the world. This phenomenon has been generated by the presence of different actors among which are: delinquency, organized crime, guerrilla, and paramilitaries, who among their strategies to gain power have faced the different statements of the government, either through violence or coercion through perquisites.

The national government, through their representatives in the department and in the city, has designed policies aimed to counter the criminal phenomena generated by different actors. In this case, local governments have made development plans focused on specific objectives critical to the city, which have been an important factor in achieving progress in science and technology, education, and entrepreneurship.

Medellín is divided into 16 communes and 5 townships (Figure 1), where the communes are generally associated with the urban zone of the city while the townships are associated with the rural zone. However, the political division of the communes leads to particular conditions that differ from the city's generality. Having this in mind, we cannot drive analysis without focusing on just a particular conditions. For our research, the criminal dynamic in the urban zone is much more relevant given that is there where almost all the casualties tend to happen. The 5 geographical units corresponding to the townships have more area than those in the urban zone. Also, we can argue that there is a natural barrier that divides the rural and the urban zone. The limit between those spatial units is given by a set of mountains that has not allowed the tendency of many cities of the world, where the urbanization process leads to a proper match between the urban zone and the suburbs and areas in the border of the cities.

The analysis of crime in Medellín should consider the socioeconomic characteristics of each commune, which are fundamental to explain not only the behavior of homicides in the city but also the criminal tendencies. These specific characteristics of violence within the city make it necessary for the research related to crime, its determinants and the impact that this phenomenon has on the political and economic conditions of Medellín, to require a spatial analysis. A spatial analysis that collects relevant information about how the socioeconomic characteristics are distributed and how the different geographical units are related.

Figure 1: Communes (urban) and townships (rural) of Medellin



Source: Author's calculation.

Note: the graph on the left shows all the city of Medellin where in the middle are located the 16 urban communes; and those particularly big units located in the borders correspond to the 5 rural communes or townships. The graph on the right is a zoom of the 16 urban communes.

4.1. Dataset

The dataset used in this analysis contains information from the following institutions: Information System for Security and Coexistence – City of Medellin (SISC, for its acronym in Spanish), National Institute of Legal Medicine (INML, for its acronym in Spanish), Judicial Research Department (Sijin, for its acronym in Spanish), National Police, Survey of Life's Quality, Medellin's Development Plan 2012-2015, and the statistics department of the City of Medellin.

The variables targeted to this analysis are the homicides, household income, male population, Quality of Life Index, Human Development Index, coverage of education levels, and social security enrollment. The units of analysis are the 16 communes of Medellin, during the time period 2004-2013.

4.2. Variables

In Hom_{it} : is the natural logarithm of homicides in the commune i year t .

$\ln(Income_{it})$: natural logarithm of the average monthly household work income in the commune i year t.

$\ln(Population_{it})$: natural logarithm of the total population of the commune i year t.

Dummy: variable which is equal to one during the time period 2005-2008 and zero otherwise. This variable was defined to capture the effect of the period called “donbernabilidad”.

$\ln(Male\ population_{it})$: natural logarithm of male’s population in the commune i year t.

$\ln(Social\ Security_{it})$: natural logarithm of the total population covered by social security in the commune i year t. This variable is used as a proxy of formal employment.

Quality of Life Index_{it}: Quality of Life index in the commune i year t.

Illiterate_{it}: percentage of illiterate population in the commune i year t.

University Students_{it}: percentage of population who are enrolled in an university program in the commune i year t.

$W_i \ln Hom_{it}$: spatial lag of the natural logarithm of homicides, i.e. the natural logarithm of the homicides of the i’s neighbors in year t.

$W_i \ln(Ingreso_{it})$: natural logarithm of the average monthly household work income in the i’s neighbors year t.

$W_i u_{it}$: spatial lag of the error term. This variable guaranties the contagion effect of external shocks as external shocks and not only as a consequence of changes in the homicide of the commune first affected.

ε_{it} : error term.

W: square matrix of order equal to n, where n is the number of communes (16). This matrix was defined following the rule of contiguity spatial matrix of the queen’s type. In other words, we rely in the definition that one commune is neighbor of other if between both of them there is a share limit. This assumption is supported by the idea that the contagious effect between two communes depends on the interconnections between both. We assume that these interconnections are more significant between units who share limits, even more due that we have few geographical units.

$$W = W_{ij} = \begin{cases} 1 & \text{if the commune } i \text{ share a limit with the commune } j, \forall i \neq j \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

5. Results

5.1. Summary Analysis

Medellin was during the 90's labeled as one of the most dangerous cities in the world. For the year 1991, Medellin reached its maximum historic of 381 homicides per 100,000 inhabitants (Figure 2). This rate means that each 10 hours approximately 7 citizens were the victim of homicide. After the death of the infamous drug lord Pablo Escobar, the homicide rate in the city started to decrease reaching 159.6 homicides per 100,000 inhabitants in 2000. Although this rate was high for any government, there was a clear improvement respect to the Medellin in the 90's.

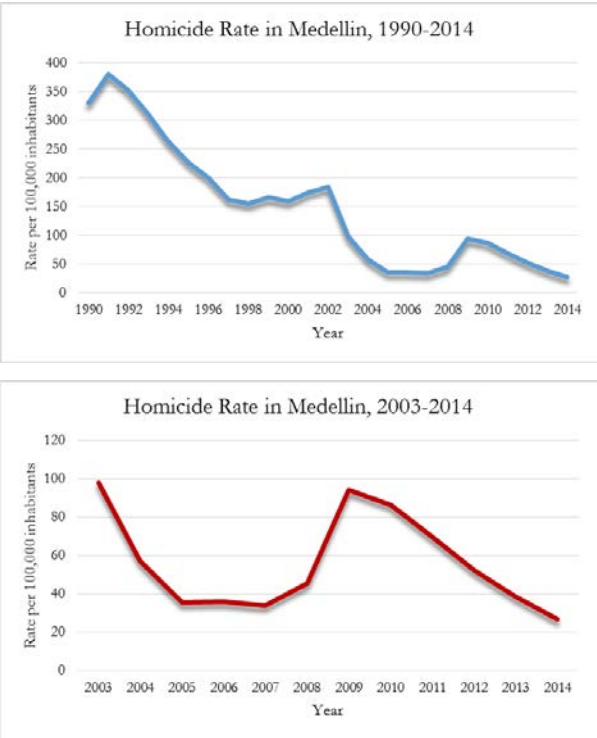
Nevertheless, our analysis is focused on variability inside the city. For that, we have information during the time period 2003-2013, disaggregated by commune. Figure 2 exposes the significant declining in the homicide rate for the last 10 years. In 2003, the homicide rate in the city was 98.2 per 100,000 inhabitants; and in 2014, the rate was 26.95 per 100,000 inhabitants. This reduction of 73% of the homicide rate in 10 years can be categorized in two periods: 2003-2008 and 2009-2014.

The first period of analysis, 2003-2008, is mainly predetermined by an external factor. This factor has its own character: Diego Murillo Bejarano known as "Don Berna". "Don Berna" was the successor of the drug market after Pablo Escobar died. "Don Berna" commanded an illegal armed group known as United Self-Defense of Colombia (AUC, for its acronym in Spanish). In December 2003, the combatants from the group "Cacique Nutibara" belonging to the AUC demobilized in Medellin. During the following years, "Don Berna" was in charge of keeping the order in the city. Although there is evidence of the effects of national programs in demobilization (Pena et al., 2015), the situation in Medellin was more like a peace given by the concentration of power in one man. We called this first period as "Donbernabilidad", and we define this term as a period of relative peace given by "Don Berna".

The following period corresponds to the years 2009 to 2014. Figure 2 shows that after the extradition of "Don Berna" in 2008, the homicides rate per 100,000 inhabitants in 2009 reached closely the homicide rate in 2003 (94.38 in 2009 respect to 98.2 in 2003). The previous paragraph exposed the particular characteristics of the low homicides rates experimented at the beginning of the 2000's. As we mentioned before the trend of the

homicides rate prior 2009 was the result of the interaction between city dynamic levels of crime and an exogenous shock called “Donbernabilidad”. However, after 2009, this shock was no longer present and we can assume that the homicide rate returned to its city dynamic level trajectory.

Figure 2: Homicide Rate in Medellin per 100,000 inhabitants, 1990-2014

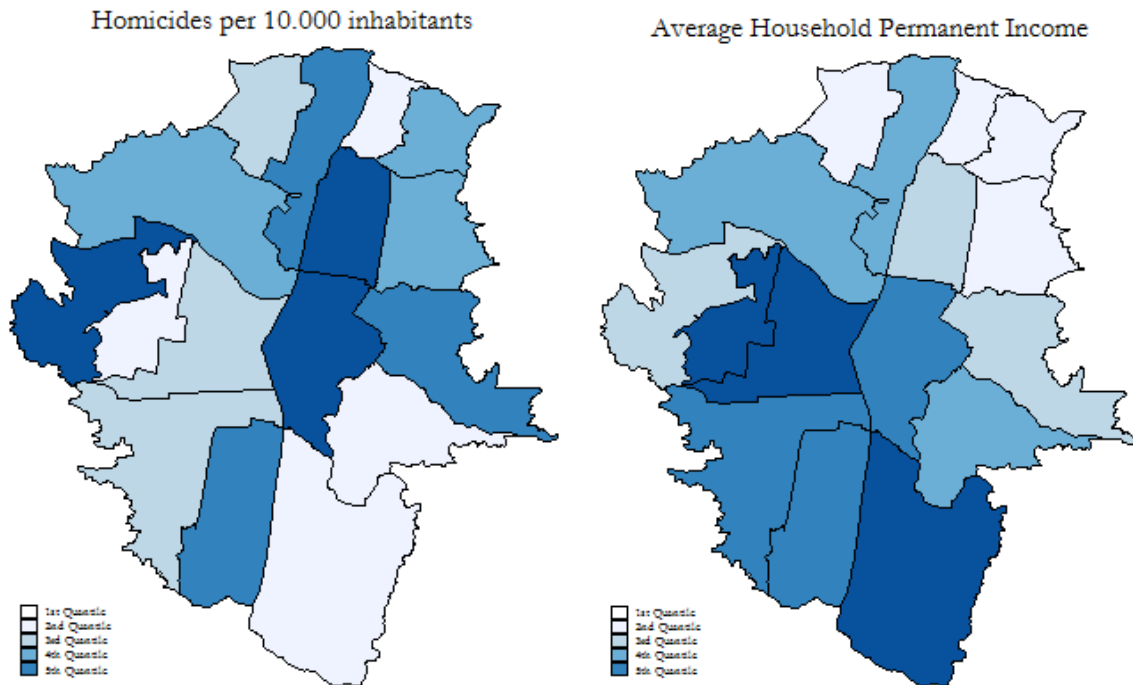


Source: Author’s calculation based on data from Municipality Statistics

Note: the graph on the bottom is a zoom for the years of analysis (2003-2014) of this research of the graph on the top.

This process gave the city public policy some lessons. Crime issues cannot be managed for those who commit crimes, structural changes were needed to change the crime trend of the city, and security investments are not enough to improve security. The investment on social capital and development are crucial to overpass the high crime history.

Figure 3: Homicides Rate per 10,000 inhabitants and Average Household Permanent Income by urban communes, average 2004-2013



Source: Author’s calculation based on data from SISC and Survey of Life’s Quality

Note: Intense blue refers to greater values of the variable, i.e. dark blue corresponds to the highest homicide rates for the graph on the left and highest permanent income for the graph on the right.

These lessons seem to be learned by the municipality government. There has been a continuously decreasing of the homicide rate since 2009, reaching 26.95 homicides per 100,000 inhabitants in 2014. Compared to the behavior of the crime in the first period, there is a structural difference between both. While during the first period the rate decreased dramatically at the first year, the following years it remained at similar rates. Instead, the second period is characterized for a slightly decrease year by year during the whole period. Figure 3 shows the geographical distribution of the average homicide rates and the permanent income, measured as monthly average household work income, for the complete time period of analysis 2004-2013. Using those maps we can identify the communes where the homicide rates behave relatively more problematic. San Javier, La Candelaria and Aranjuez are the communes with the highest average homicides rate during the period 2004-2013. Besides,

they are in the second quintile of the income distribution (except La Candelaria who belongs to the fourth quintile¹), setting a starting point in the link between homicides and income.

In addition, we have thus identified the communes which have had the fewer homicide rates, on average during the period of analysis. Those are El Poblado, La America, Buenos Aires and Santa Cruz. The first two communes belong to the highest group of income distribution, the third one is located in the third quartile and only the last one belongs to the lowest income group. This distribution of the average income during the whole period plus the unchanged distribution of these variables through the time (see annex 1) also support the importance of analyzing these issues using spatial approaches to characterize the crime patterns in a disaggregated level (Choe, 2008; Hipp, 2011).

Using a naïve approach, we would like to put this difference in income distribution into perspective. The average labor income in the commune El Poblado was 6.5 times the average income of the commune Popular during 2013 while in 2004 this figure was 5.5. This let us expose that the income inequality perceived between communes can be increased during the last decade. We refer to this statement as a naïve approach because there is an eventually spatial self-distribution of income. People who start to earn more can move to other places. This will thus maintain the difference in income, however, it cannot totally explain the gap's increase.

Indeed, this also explains what we can see in annex 1. Focusing on the distribution of the Quality of Life Index and Human Development Index between 2004 and 2013, it seems unaltered. The communes in the top quintile are concentrated in the south zone, likely related to income concentration. Worries arise about how this immobility in life's quality distribution can explain the spatial concentration of other factors, or in another way, those set of factors have been leading this life's quality immobility. In one way or another, these facts expose the spatial correlation in the distribution of some main variables across the city, a correlation that can help us to find the best place to allocate some policies to intervene and reduce crime.

Another factor that may contrast this spatial correlation across communes is the link between the distribution of the percentage of university students and the distribution of the percentage of illiterate population. Although the percentage university students are highly correlated with

¹ La Candelaria corresponds to the downtown of the city. The majority of the economic activity and the commercial trade happen in this zone. That is the main reason why the average income is relatively higher.

the location of the universities, its distribution shows a particular opposite behavior with respect to the illiterate population distribution. The communes to the north of the city have been in the top distribution of illiterate population, and also the bottom in university students. This brings up the vicious circle that less educated parents raise less educated sons, compared with those with more educated parents. That in conjunction with lower labor income, let some communes be more vulnerable to others with respect to crime victimization.

5.2. Spatial Panel Data Models

Using the methodology exposed in the third section, we estimated the four different specifications of spatial panels. We also defined a contiguity matrix type “Queen”, that means that we consider neighbors of the commune i , those communes that share a border with i . Although there are a lot of possible definitions of the contiguity matrix, we rely on this broadly used matrix to capture the spillover effect of being surrounded by neighbors with high or low homicide rate.

The result obtained from the four specifications can be found in Table 1. Notice that the spatial panel’s coefficients cannot be interpreted as a traditional beta, because the spatial lags play a multiplier role of a traditional marginal impact. However, these coefficients allow us to understand the direction of the marginal direct effect and also how significant they are.

Some main remarks arise from Table 1. One of them is the relevance of the university students. This variable can be labeled as a protective factor of homicides, more population studying tertiary education leads to lower homicide rates. Another significant variable that plays the role of a protective factor is the index of Quality of Life. It has a negative and significant coefficient, which means that improvements in the quality of life in a commune leads on reducing crime in that commune. The corresponding dummy of “Donbernabilidad” let us infer that indeed during the years of 2005 to 2008 the reduction and stability of the homicides rate had been driven by one significant external factor, that according to what we exposed in previous sections, can be attributed to the control under one person of the main illegal gangs in the city.

Table 1: Spatial Panel Models

	SAR	SEM	SARAR	Durbin
Ln(Income)	-0.29744 (0.19757)	-0.43468* (0.25905)	-0.33181 (0.22400)	-0.56124** (0.28141)
Ln(Population)	-7.65300*** (2.69105)	-7.07781 (4.50167)	-2.47884 (4.74364)	-4.13329 (2.57024)
Dummy	-0.32476*** (0.05619)	-0.61115*** (0.13680)	-0.81678*** (0.30648)	-0.23751*** (0.06500)
Ln(Male population)	6.79444* (3.62885)	6.65348 (4.76506)	2.54032 (4.59140)	3.51006 (3.57755)
Ln(Social security)	0.06764 (0.12368)	0.01351 (0.11248)	0.01635 (0.09708)	0.07431 (0.12236)
Quality of Life Index	-0.08830* (0.04986)	-0.10308** (0.04415)	-0.08153** (0.04030)	-0.09840** (0.04592)
% Illiterate population	1.39994 (2.85114)	-0.46676 (3.92084)	-0.58508 (3.47348)	0.67243 (2.74392)
% University students	-0.98813** (0.48405)	-1.41855*** (0.42747)	-1.02651*** (0.27765)	-1.03724** (0.47817)
rho	0.56871*** (0.06678)		-0.59648*** (0.10766)	0.60415*** (0.06407)
lambda		0.62563*** (0.05519)	0.85091*** (0.03596)	
W*Ln(Income)				0.54800** (0.21855)

Source: Author's calculation.

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. % means percentage values over the total population of each commune. Rho (ρ) and Lambda (λ) are the spatial coefficients associated with the number of homicides and error term, respectively (see Eq. (3) and Eq. (4)).

It is relevant to mention that for all the models the spatial lags are significant to a level of confidence of 99%. Both, spatial lag of the \ln (homicides) and the spatial lag of the error term, expose the relevance of the geographical interaction between units of analysis especially when we are analyzing the patterns of crime variables. Finally, our main variable of interest, \ln (Income), is just statistically significant at 95% level of confidence for the Durbin Model and the coefficient is negative, meaning that increases in permanent income in a commune i leads in a decrease of homicides in the same commune. Although this result is not consistent with the rest of the spatial panels we have to take into account that the Durbin Model includes a spatial lag of the \ln (Income). This specification allows us to infer that income just becomes relevant when we consider their spatial correlation across units.

In order to corroborate this last statement, Table 2 presents some results for statistical test which contrast the different specifications of spatial panel. This table is helpful in the way that it gives us the individual information of each test, nevertheless, we want to focus on the last column that presents the conclusion of each test. According to this, the Durbin Model is a good option to identify the data generation process. Having this in mind, Table 3 separates the total marginal effect of each variable in Durbin's estimation in its direct and indirect effect.

Table 2: Tests between Spatial Panel Models

Test	Method	Statistic	P-value	Result
SAR	Lineal Wald	6.29	0.0122	Durbin is not represented by SAR
SEM	No-lineal Wald	2.43	0.1189	Durbin is not represented by SEM

Source: Author's calculation.

Note: More details can be found in the methodology section; and for more references see (Belotti et al, 2013).

First of all, we have to mention that the direct effect measures the impact that each variable has on the dependent variable for the same unit of analysis: changes in x_i leads in changes in y_i , while the indirect effect refers to the impact that each variable has on the dependent variable given the spatial interaction across units, in a broad approach that means: changes in

x_j leads in changes in y_i through changes in y_j ($j \neq i$, and i and j considered as neighbors). It is also relevant to mention that given this approach we should not expect significance in the indirect effect of the variable of $\ln(\text{Income})$. That is because the Durbin Model specified the indirect effect as a direct impact including the variable of $W*\ln(\text{Income})$, so we are allowing that the income in commune j directly affects homicides in commune i without first impacts homicides in commune j .

Table 3: Marginal effects of Durbin's model broken by direct and indirect component

	Direct	Indirect	Total
Ln(Income)	-0.51889** (0.24201)	0.48972 (0.35354)	-0.02917 (0.46030)
Ln(Population)	-4.5154 (3.30093)	-6.02503 (4.89595)	-10.54044 (8.09356)
Dummy	-0.26395*** (0.08021)	-0.33406*** (0.12278)	-0.59801*** (0.19107)
Ln(Male population)	3.78342 (4.43867)	5.16472 (6.25181)	8.94814 (10.60245)
Ln(Social security)	0.10891 (0.14157)	0.13164 (0.18125)	0.24056 (0.32036)
Quality of Life Index	-0.10884** (0.05173)	-0.13666* (0.07222)	-0.24550** (0.12048)
% Illiterate population	0.19824 (3.50195)	0.07914 (4.44038)	0.27739 (7.90103)
% University students	-1.28118** (0.54485)	-1.67269* (0.87519)	-2.95387** (1.38431)

Source: Author's calculation.

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. % means percentage values over the total population of each commune. The total impact is the sum of the indirect and direct component.

Table 3 shows the significance of the direct and indirect impact of the dummy variable 2005 to 2008, Quality of Life Index and percentage of university students. All of these variables are acting as a protective factor against crime, however, the most impressive results are that the magnitude of the indirect effect overtakes the direct impact. This also supports the relevance of the specification, showing the important role of the spatial interactions across units of analysis. Focusing then on public policy, this gives us the idea of a better possible design of political interventions, interventions that take into account that those indirect effects can be more resource efficient.

Although in Table 3 we identified the specific relevance of some variables and also their direct and indirect impact on homicides, we are more interested in how this can help us in designing public policy interventions. It is worldwide considered that some public policies should be specific oriented, i.e. some public policies should be localized in those specific places where the social problem is more intensified. However, in this sense, we will take into account also those places where the spatial effect (or indirect effect on neighbors) is more beneficial. In other words, we want to take advantage of this spatial impact to make some interventions more efficient and also targeted the right key players.

In order to do that, we rely on the methodology of Drukker et al. (2013). This methodology simulates the impact of one intervention across the units of analysis. So this process allows different levels of impact depending on the specific characteristics of unit i and its neighbors. We extend the Drukker et al. methodology to apply on spatial panel data.

Table 4 presents the results of an intervention that increased the permanent income of each commune in 1%. Furthermore, the impact of this intervention is divided by commune of intervention and by individual and spatial effect. The individual effect refers to the impact on homicides in the intervened commune and the spatial effect to the impact on neighbors' homicides. As one of the main conclusions, the spatial impact has an opposite sign with respect to the individual one, i.e., increases in permanent income of commune i , keeping the rest of the variables and communes' characteristics unaffected, leads to increases in homicides in i 's neighbors. This result supports the studies of Menezes et al (2013) and Scorzafave & Soares (2009) in Brazil. The mechanism by which this can be explained is based on a context of inequality presence, based on the existence of inequality across units of analysis, an

increase in the income of one of them can attract some potential offenders from neighbor's units and cause an increase in violence.

Table 4: Individual and Spatial Effects of a 1% increase in the Permanent Income in each commune.

Commune	Individual Effect	Spatial Effect	Total Effect	Decreasing Marginal Rate
Aranjuez	-0.477	0.047	-0.430	-0.005
San Javier	-0.473	0.053	-0.420	-0.006
Buenos Aires	-0.470	0.058	-0.411	-0.006
Castilla	-0.470	0.059	-0.411	-0.007
Guayabal	-0.469	0.060	-0.408	-0.007
Doce de Octubre	-0.468	0.062	-0.406	-0.007
Popular	-0.465	0.066	-0.399	-0.007
Santa Cruz	-0.465	0.066	-0.399	-0.007
Robledo	-0.462	0.072	-0.390	-0.008
El Poblado	-0.461	0.072	-0.389	-0.008
La América	-0.460	0.075	-0.385	-0.008
Laureles Estadio	-0.460	0.075	-0.384	-0.008
Manrique	-0.456	0.081	-0.375	-0.009
Belén	-0.456	0.082	-0.374	-0.009
La Candelaria	-0.455	0.083	-0.372	-0.009
Villa Hermosa	-0.452	0.088	-0.364	-0.010

Source: Author's calculation.

Note: Each row corresponds to the result of the 1% increase in the permanent income for the commune *i*, and all the other variables and communes remaining constant. The individual effect refers to the variation of homicides in the commune *i*, while the spatial effect represents the average variation in the homicides of *i*'s neighbors. The total effect corresponds to the individual plus the spatial effect. Finally, the decreasing marginal rate is the rate in which the spatial effect is dismissing each year, i.e. the spatial effect represents the impact of *i* on *i*'s neighbors; and this effect is weakened by the decreasing marginal rate each year.

The results of the income simulation have some influence in the design of public policy for crime deterrence. Table 4 shows how different is the impact of the intervention depending on the commune intervened. Although both, individual and spatial effect, are fairly close across units, each minimum difference leads to different total impacts of the income intervention. As an example, an increase in the permanent income of Aranjuez in 1% implies a reduction in the homicides in Aranjuez in nearly 0.48% and an increase of the homicides in Aranjuez's neighbors in 0.05%. If the same intervention is done in the commune Villa Hermosa, the decrease in homicides is 0.45% and the increase on its neighbors in on average nearly to 0.09%. Then, in a context where increases of 1% of permanent income in Aranjuez cost as much as in Villa Hermosa, the intervention of the first one seems to be more efficient than in the second one. However, these results have to be considered carefully, because as we mentioned before they depend on the cost of intervention and also on their strategical location in the city, i.e. the spatial impact can be huge in low homicide zone while in high homicide zone the spatial impact could be lower; in real terms, an increase of 0.05% in a high homicide area can mean more homicides than an increase of 0.1% in low homicides zone.

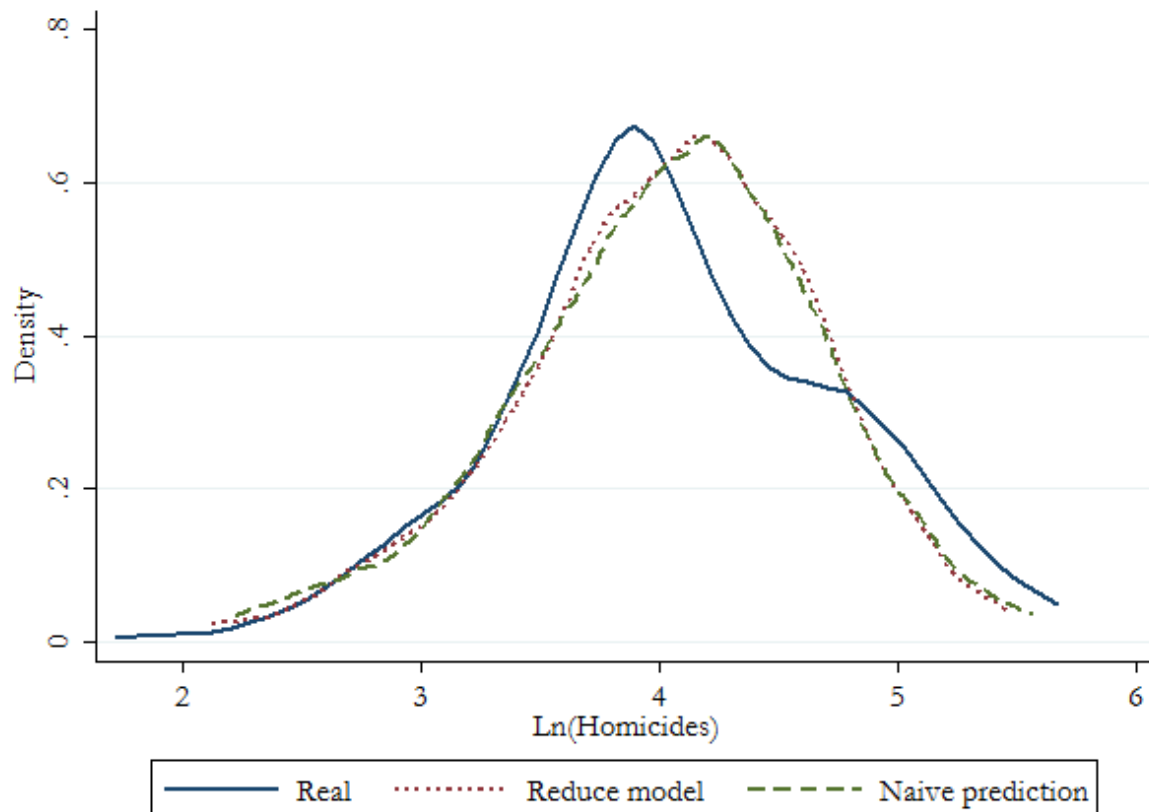
Besides, there is an extra column in Table 4 that shows the Decreasing Marginal Rate of the spatial effect. This value represents the rate at which the spatial effect is vanishing each year. This means that the spatial effect is not permanent, and according to this simulation, it lasts approximately 10 years. As it is expected, the communes where the spatial impact is greater tend to be the same with the high decreasing marginal rate. This behavior can be explained in a general way by the fact that the direct and indirect effect have opposite signs, this should be seen as a positive pattern meaning that the increases in neighbor's homicides under a particular intervention do not tend to be constant across time.

Finally, if we average the total effect of an intervention that increases the permanent income in 1% of each commune we obtain the average elasticity of income on homicides for the whole city. So an increase in 1% in permanent income leads on average to a decrease of 0.39% of the homicides in the city. This is an inelastic response which is in accordance with previous investigations. However, it is important to mention that the impact varies across communes with Aranjuez being the leader (reduction of 0.43%) and Villa Hermosa in the bottom of the magnitude of the impact (reduction of 0.36%).

5.3. Robustness

Two main approaches have been employed to check the robustness of the principal results. On one hand, we compare the Kernel Distribution Function of the real $\ln(\text{Homicides})$ with the prediction of the Spatial Panel Data. On the other hand, we would like to check whether the main results change when we modified the Durbin model, adding or dropping some regressors or including their spatial lags.

Figure 4: Kernel Density Function for observed and predicted $\ln(\text{Homicides})$



Source: Author's calculation

Note: the dotted lines came from the Durbin specification model. Although there is not an overlapping of the real and predicted series for those high values of homicides, broadly speaking the behavior of the distribution is similar.

Figure 4 compares the Kernel Density Distribution Function of the real $\ln(\text{Homicides})$ and two other variables obtained from the Spatial Panel Data Model, the reduced form and the

“naïve” approach. The reduced form refers to the predicted $\ln(\text{Homicides})$ using the characteristic information matrix of the Spatial Model.² The “naïve” approach is commonly named so because it is based on a linear common prediction, but just adding the spatial component.³ Broadly speaking, the distribution between the real and the predicted series is not so different, keeping in mind that all these spatial models establish a particular distribution a priori. However, one specific remark is that the model is overestimating the mode of the distribution, which implies that around the mode in particular, and in the center of the distribution in general, the reduction impact of any intervention can be overestimated. Taking this into account, better policies may be designed.

The second robustness check is presented in Annex 2. It contains four different specifications of the main Durbin model. Those specifications include the spatial lags of other regressors, as $\ln(\text{Male population})$ and the Percentage of University students. These variations do not lead to significant changes of our results, the $\ln(\text{Income})$, the Quality of Life Index, the Dummy variable, and the Percentage of University students are still significant and considered as protective factor of homicides.

6. Conclusions

This paper presents an unusual approach used in emerging economies. The crime analysis by spatial models allows the identification of elements that traditional models do not consider, such as spatial unit and the relationships with its neighbors. In this case, the homicides can be explained by individual characteristics of each commune of the city, as well as the characteristics and crime levels in the neighbors of the same.

One of the goals of this work was to quantify the elasticity of permanent income against crime. Spatial panels found that the elasticity is -0.39 and it differs from any other traditional panel estimation given that this exercise included the spatial relationship patterns typical of studies about crime and for urban analysis. It should be noted that this elasticity is an average between the responses of the different communes to an increment of 1% in the income level of each

² The reduced form equation is $\ln(\text{Homicides})_{it} = (I - \rho W_i)^{-1}(X_{it}\beta + \alpha_i)$, where α_i refers to the individual fixed heterogeneity component of a Durbin Model with Fixed Effects and I corresponds to the identity matrix.

³ The equation referred in this approach is $\ln(\text{Homicides})_{it} = \rho W_i \ln(\text{Homicides})_{it} + X_{it}\beta + \alpha_i$.

commune keeping the rest of the values constant. Thus, if the intervention happens in the commune of Aranjuez the level of homicides can decrease to about 0.43% while if the intervention happens in the commune of Villa Hermosa the impact will be 0.364%.

It is due to these results that we can suggest that the behavior of public investment and the government intervention should not be based only on what the commune is expected to improve if intervened, but also in how much contribution will have the commune in the development of its neighbors. Public policies must be formulated, with a focus on investments that obey better individual and spatial responds, rather than simply seeking the mitigation of a problem that can be transitory.

In this sense, the “policy makers” must act on what the priority of social development should be in the city, improve living conditions or reduce the disparities between communes. It is clear then that for “policy makers” it is much more convenient to structure development policies that seek to increase the general conditions of the population, rather than the ones that seek to reduce disparities. This is because the fundamental policies in spatial analysis, which take into account the differences in the distribution of variables, involve not only acting on vulnerable sectors but do it in a controlled manner and in multiple dimensions. So, there must be taken into account not only the criminal conditions but also the existing relationship between this variable and the socioeconomic characteristics of each commune.

Concerning these variables of individual characteristics, this study found that the quality of life in the communes is primordial in overcoming crime, as referenced in the literature on the case. The quality of life includes several dimensions, where two of the primary are health and education. Although this research shows that basic education itself is not sufficient to face the crime problem, education still is one of the best ways to deter crime. The crime patterns in the city are now responding to the population enrolled in postsecondary education. We found a particular large indirect effect of the percentage population in universities, not only explained for the tradeoff of the young population between crime and study but also for the externalities caused from the knowledge generation (innovation, entrepreneurship, city integration and availability of human capital).

Another contribution that this work has to offer is the formalized demonstration of the “Donbernabilidad” effect, referenced by Martin (2012). Events in the years 2005-2008, in which illegal groups structured governance strategies outside the legal institutions at the same

time that the mayor's office conducted some institutional efforts, becomes the clearest example of an intervention that worked as an exogenous shock to reduce the level of homicides over those years. However, we have to be aware that this type of facts is not long-run interventions. Medellin has faced these two ways of crime improvements: one strongly dependent on an external factor (2005-2008) and other as a result of multiple socioeconomic and security policies (2011-2014). This experience had given us some learnings, one of them the relevance of socioeconomic intervention to reach long-run objectives.

As one of the general advice that we want to expose is that all political interventions should be done in a controlled manner and in multiple dimensions in order to achieve satisfactory results. As is proven in this research, interventions have often side effects. Effects that should be discussed and try to quantify before the intervention. This can help not only to focus resources and identify the most vulnerable population but to complement with other interventions that can face the negative side effects that can arise.

This paper concludes by recognizing the need for accurate, reliable, and available information from the responsible institutions. If theories on the economics of crime are revisited, the deterrence would not only depend on interventions of socioeconomic variables, but also in matters related to police force and security investment. That is why this work wants to leave, on the research agenda, the need for additional exercise where variables of institutional force (police and justice) will be included, when there is certainty that such information exists and is reliable.

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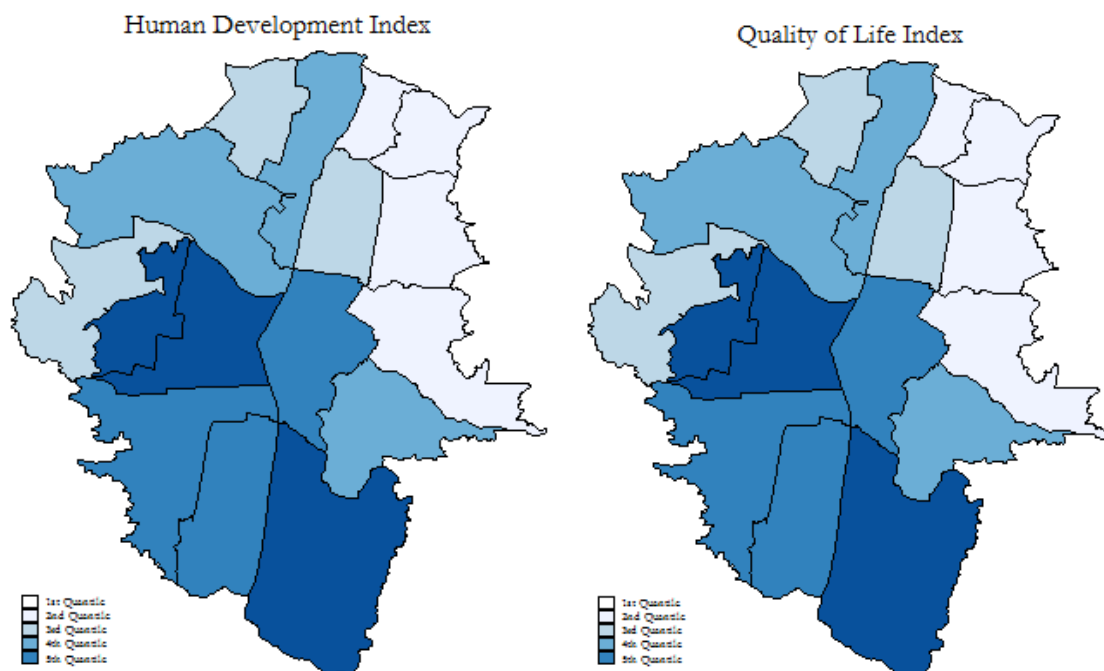
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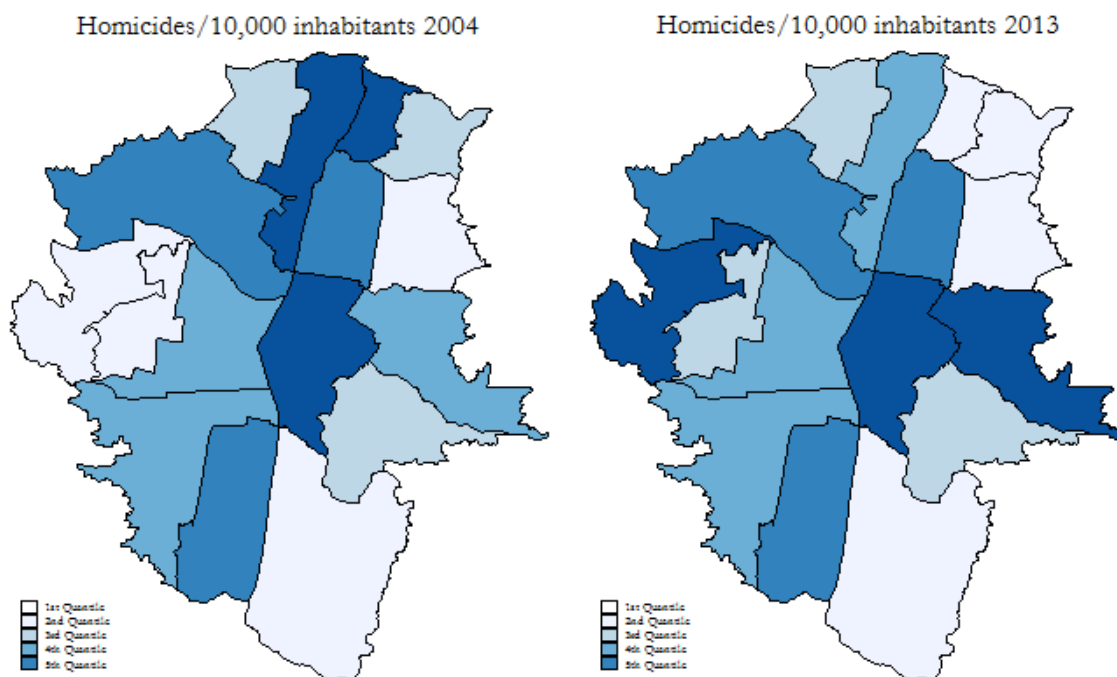
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Annex 1:

Human Development Index⁴ and Quality of Life Index, average 2004-2013.

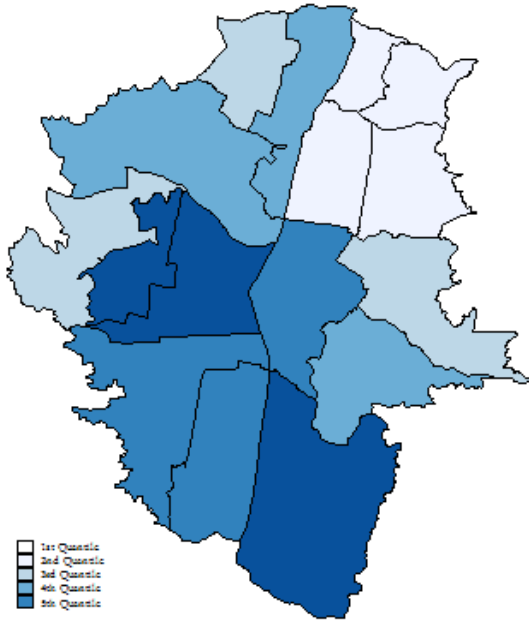


Geographical distribution of the principal variables, first year of analysis (2004) and last year of analysis (2013).

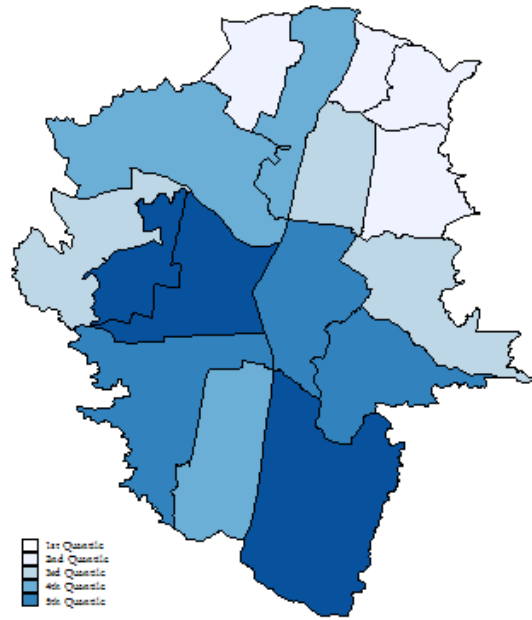


⁴ The average calculated for Human Development Index correspond to the time period 2004-2011.

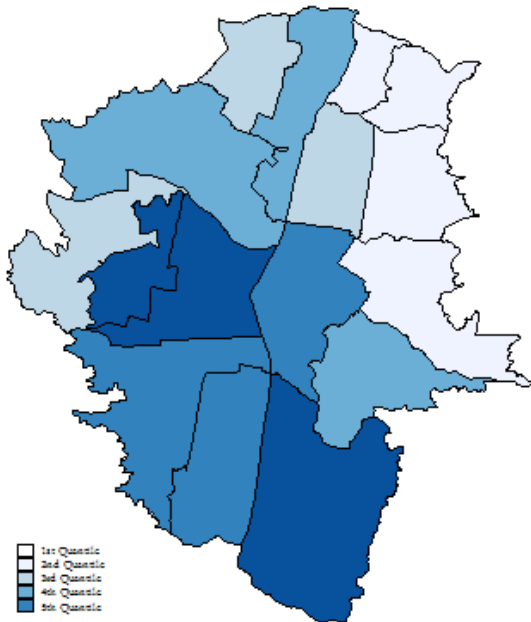
Household Permanent Income 2004



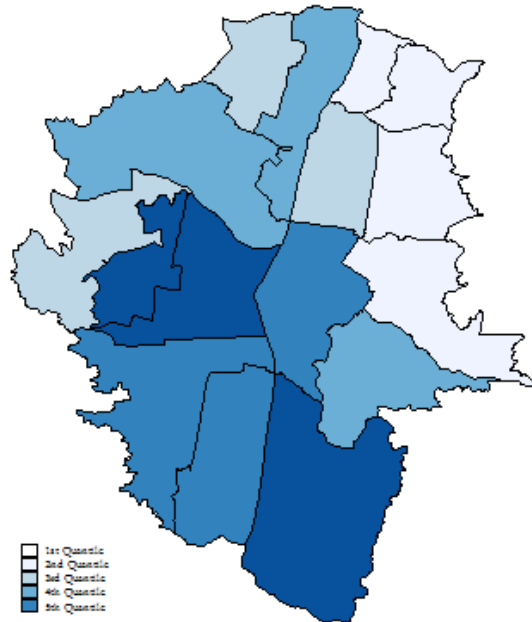
Household Permanent Income 2013

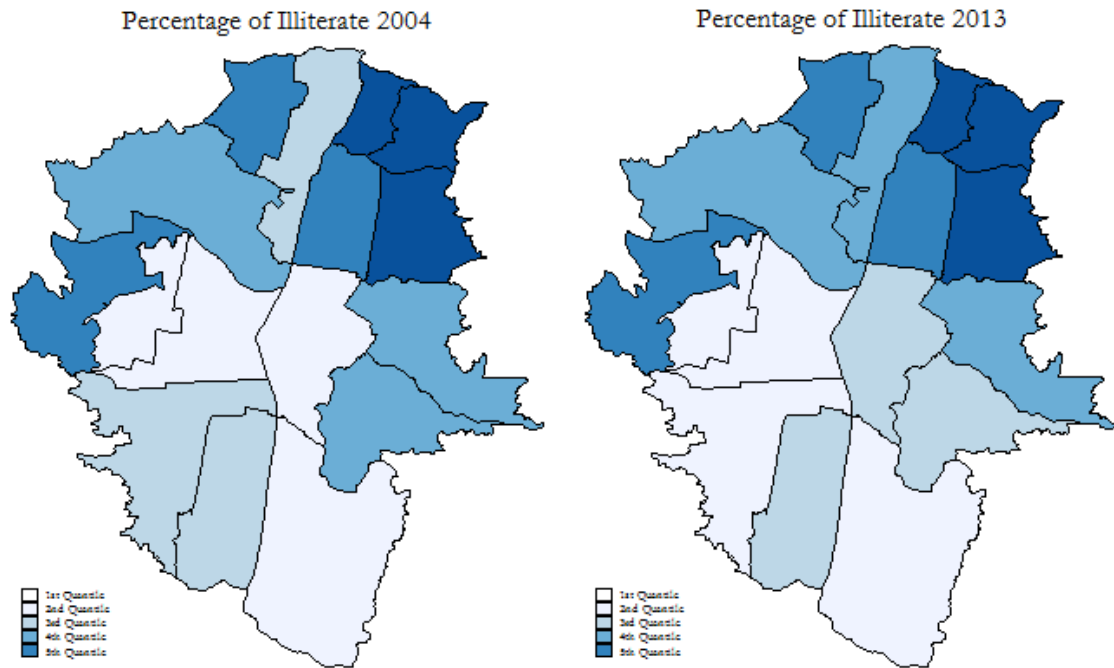


Quality of Life Index 2004

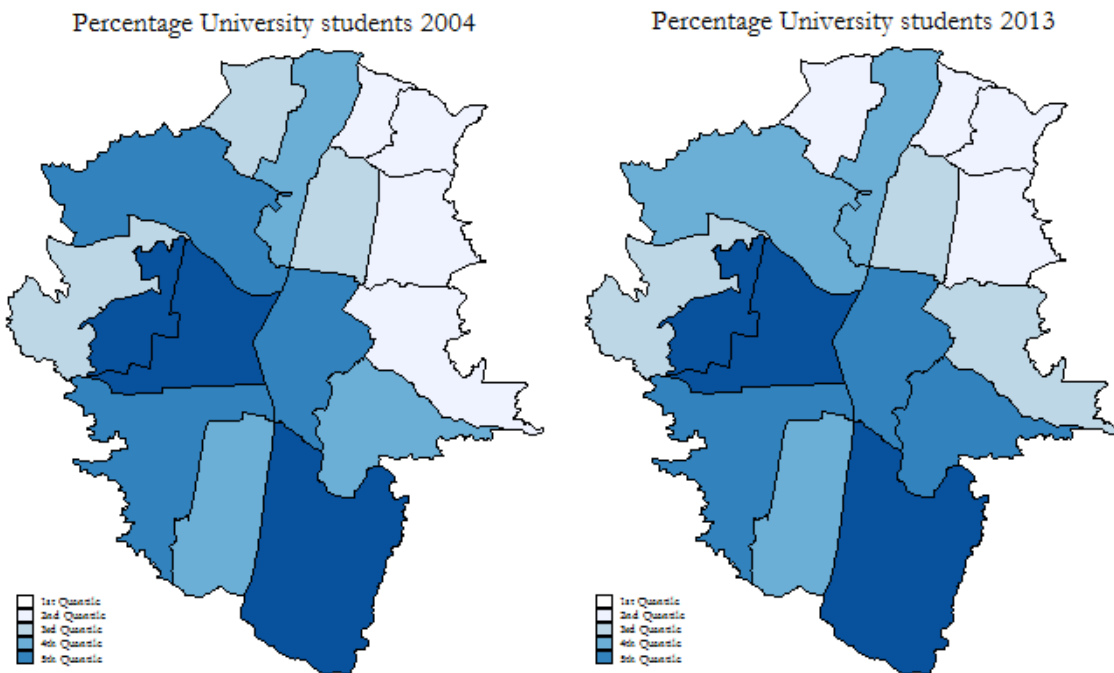


Quality of Life Index 2013





1



Source: Author's calculation based on data from INML, Sijin, National Police, Survey of Quality of Life and Medellín's Municipality.

Note: Intense blue refers to greater values of the variable, i.e. dark blue corresponds to the highest values for each variable mapped.

Annex 2

	Option 1	Option 2	Option 3	Option 4
Ln(Income)	-0.55193** (0.27580)	-0.50272* (0.26576)	-0.53485* (0.28327)	-0.47596* (0.26495)
Ln(Population)	-3.99714 (2.62507)	-4.64866* (2.50810)	-4.80846* (2.52903)	-5.33257** (2.44795)
Dummy	-0.23305*** (0.06140)	-0.33283*** (0.07915)	-0.27453*** (0.06745)	-0.37057*** (0.07136)
Ln(Male population)	3.38918 (3.63606)	3.42206 (3.70029)	4.2378 (3.48984)	4.15596 (3.62354)
Ln(Social security)	0.07575 (0.12167)	0.07601 (0.11898)	0.05891 (0.12644)	0.06057 (0.12253)
Quality of Life Index	-0.09838** (0.04581)	-0.08690* (0.04581)	-0.08827* (0.04615)	-0.07673* (0.04519)
% Illiterate population		0.23934 (2.66840)	1.48764 (2.97638)	1.05504 (2.89310)
% University students	-1.06681** (0.45659)	-1.07690** (0.51607)	-1.13853** (0.48481)	-1.17825** (0.52626)
rho	0.60315*** (0.06432)	0.58707*** (0.06354)	0.59259*** (0.06168)	0.57498*** (0.05970)
W*Ln(Income)	0.55368** (0.21969)	0.63617*** (0.24682)	0.2591 (0.27083)	0.34596 (0.27010)
W*Ln(Male population)		-3.51377** (1.68214)		-3.52426** (1.68867)
W*University students			1.52405** (0.71878)	1.53029** (0.65353)

Source: Author's calculation.

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. % means percentage values over the total population of each commune. Rho (ρ) and Lambda (λ) are the spatial coefficients associated with the number of homicides and error term, respectively (see Eq. (3) and Eq. (4)).