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The Effect of Adult Criminalsô Spillovers On the Likelihood of Youths Becoming Criminals ♣

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Abstract

We use a unique data set at the individual level to estimate an empirical model explaining the probability of young individuals to become criminals as a function of the presence of adult criminals in their neighborhoods, an a complete set of control variables, including census sector fixed effects. We use the census of criminals captured in Medellín between 2000 and 2010 to construct our peerôs variables, and find a strong and robust positive effect of the presence of adult criminal neighbors on the probability of becoming criminal. The result is robust across different specifications of the presence of criminals, and with respect to the probability of committing different types of crimes, even controlling for contextual and group effects. Both modeling peer effects as the sum of friendsô efforts and modeling them as deviations from the means, affect the likelihood to become criminal, although with differential importance by type of crime.

Key words: Crime, Social Interactions

JEL codes: C31, K40, K42

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Introduction

The study of social interactions have become of great interest in the economics field. Of particular interest has been the study of the relationship between neighborhood or peers effects, and crime. Notable work on this topic is that by Ballester et al. (2010), Calvó-Armengol and Zenou (2004), Glaeser et al. (1996), Glaeser et al. (2002), OʼFlaherty and Sethi (2007a, b), Patacchini and Zenou (2008), etc. Nonetheless, most of the very insightful theoretical contributions have required huge efforts in creativity on the part of the empirics, who have so far provided very interesting evidence, but only at the aggregate level, rather than with individual data, and thus, there is still an important set of concepts waiting to be empirically tested.

In this article we use a unique data set at the individual level that allow us to identify between 2002 and 2010, the census of captured criminals in Medellín, a city with one of the highest crime rates in the world. We couple that information with the 2002 Sisben dataset, a survey used to target public social expending to the poorest population of the country, to construct for each individual in the dataset, criminal neighborsʼ effects variables based on the identities of individuals who become criminals later on. Since we focus our analysis for the sample of individuals 5 to 16 in 2002 to 13 to 24 in 2010, and we are also able to get baseline socioeconomic variables in 2002, we use this information before individuals become adults to partially control for household location.

We use a slightly modified version of a theoretical model proposed by Calvó-Armengol and Zenou (2004) to propose and interpret the coefficients of an empirical model explaining the probability of individuals 5 to 16 in 2002 becoming criminals as a function of the presence of adult criminal neighbors, an a complete set of control variables, and very importantly, we control for contextual effects, and are also able to control for group fixed effects, partly following the specifications suggested by Lee (2007), Lee, Liu and Lin (2010), Liu and Lee (2010), and Bramoullé, Djebbari and Fortin (2009), among others.

We find a strong and robust positive effect of the presence of adult criminal neighbors on the probability of youths becoming criminal. The result holds for most of our specifications, and we find that the network of adult criminals involved in soft crimes (injuries, street fight, and harassment, among others) is the only one that does not affect the likelihood of someone deciding to commit hard crimes (weapons, homicides) later on.

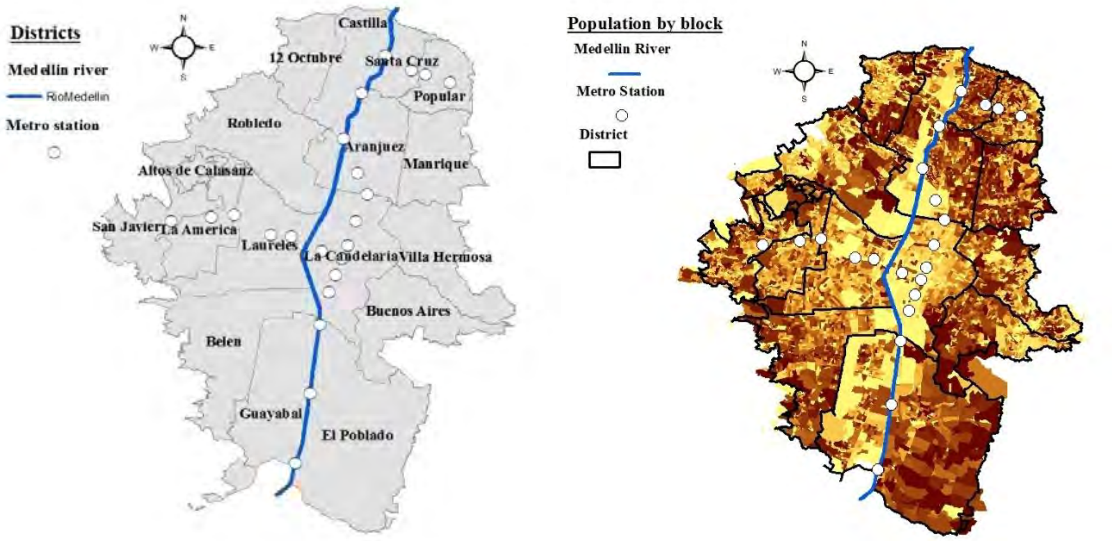
We begin describing the socioeconomic structure of Medellín and providing a brief review of the literature, and then proceed to present the theoretical and empirical models, describe our data and present the results. We finally offer some conclusions.

I. Medellin City of Contrast: Polarization, Public Goods and Crime.

a. Socioeconomic Patterns

Medellin is a city of Colombia located in the department (State) of Antioquia, in the North-West of the country. Medellin is the second main city after Bogotá and it has a very strong economy in several industrial sectors and financial markets. Nonetheless, Medellin is a city full of contrast for many reasons, where the most important is that although this city has excellent offer of public goods and many economic resources, it is one of the most unequal cities in Colombia in both income and security. In particularly, the city has two considerable results with significant lags that need special attention: spatial inequality and security.

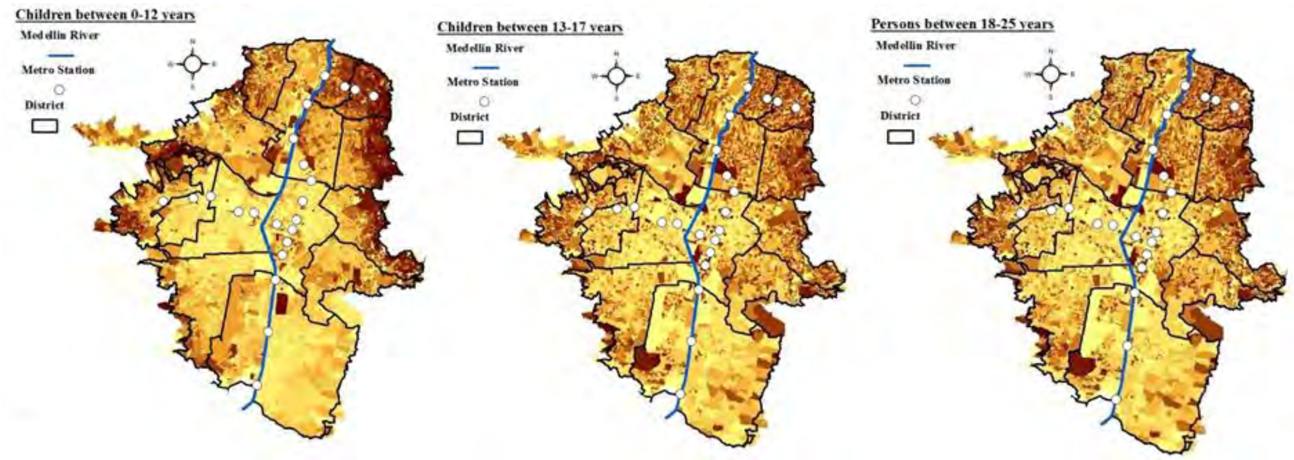
Map 1. Medellin Districts and Population by blocks



According to CENSUS 2005 the city has 2.219.041 people (approximately 5.5% of Colombian population); distributed into 16 districts and 249 neighborhoods (see map 1[1]). The places with the most concentration of people are located in the south and north of the city, especially in ñPobladoò and ñBelenò on the south and ñManriqueò, ñPopularò, ñSanta Cruzò on the north (see map 1). Nonetheless, the young people, especially the kids are concentrated in the poor part of the town. The Map 2 shows that the children (0-12 years) are concentrated especially in neighborhoods in the north of the city, while the distribution of young people is a little smoother on the space, except in the down town (center of the city). These characteristics are very important for the policy makers, because the future of the city depends largely on the kids and this population has a huge concentration in districts with a lot of crimes like drug traffic, robbers and homicide.

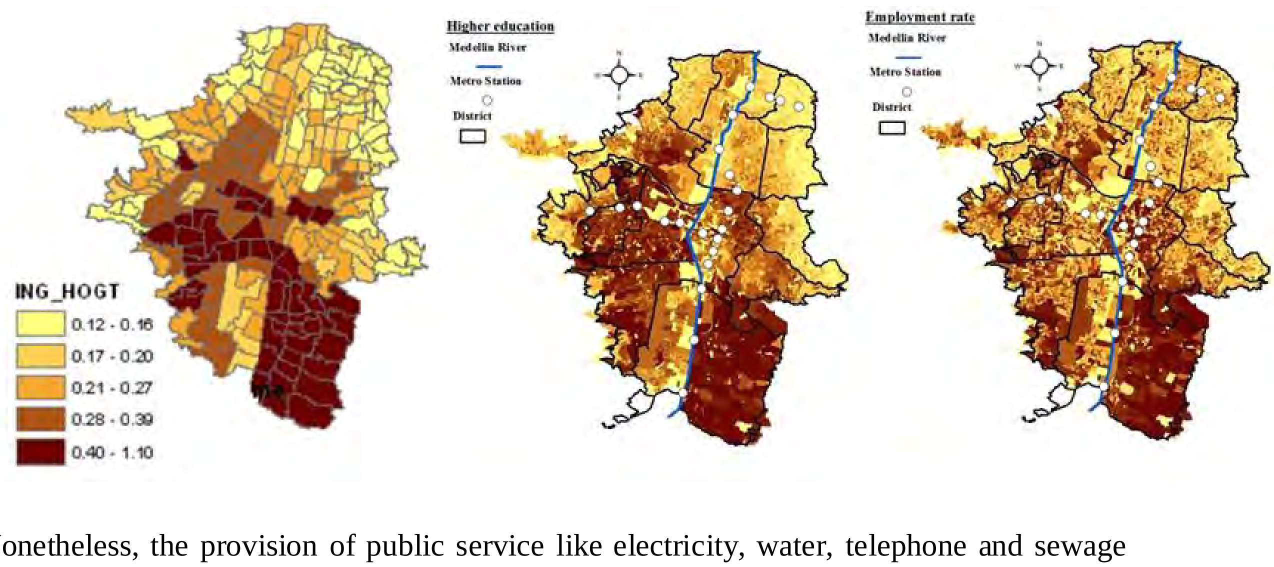
[1] When the color is darker means more intensity of the variable.

Map 2. Distribution by groups of age



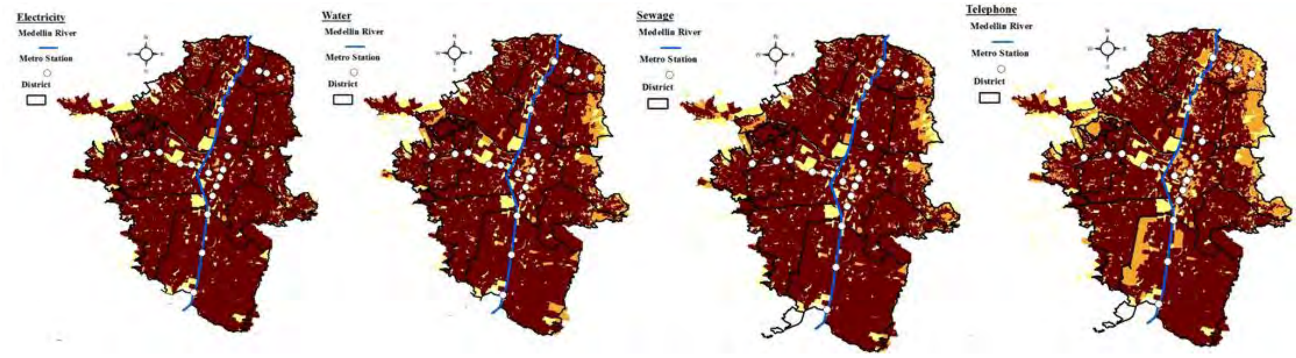
Medellin also has a great spatial polarization in key economic outcomes such as income, employment and higher education. The map 3 represents the spatial distribution of income, the share of people with higher education and share of the employment rate (for every block of the city). In this case, it is clear that Medellin has two different cities within itself. People from the southeast of the city reach very high socio-economic outcomes, while people from the north of the city have the opposite situation. This pattern creates a particular polarization within the city, especially between northern and southern suburbs, that causes a significant inequality between people.

Map 3. Social-economic outcomes



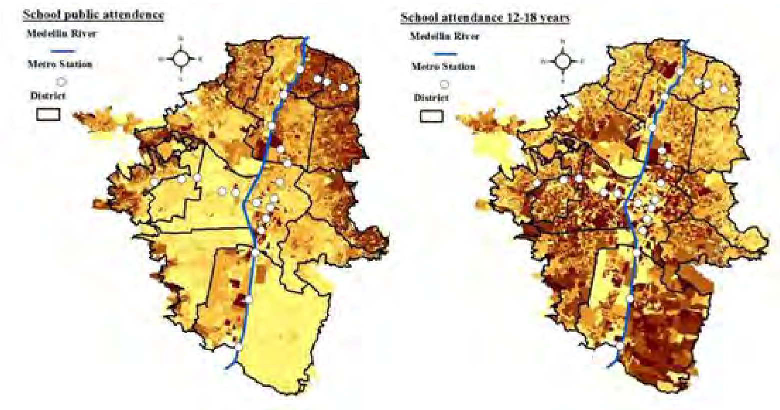
Nonetheless, the provision of public service like electricity, water, telephone and sewage are homogeneous across the city. The map 4 shows the share of access in every block of the city to the most important public services. In this map is clear that the offer of public service covers most of the population.

Map 4. Public service delivery



Additionally, public education has an excellent targeting in the city. The map 5 shows that public education is concentrated in the north and east of the city, the poorest zones of Medellin. However, school attendance of children between 12 and 18 years, teenagers, is very low if we compare with the school attendance of teen living in the south and west of the city.

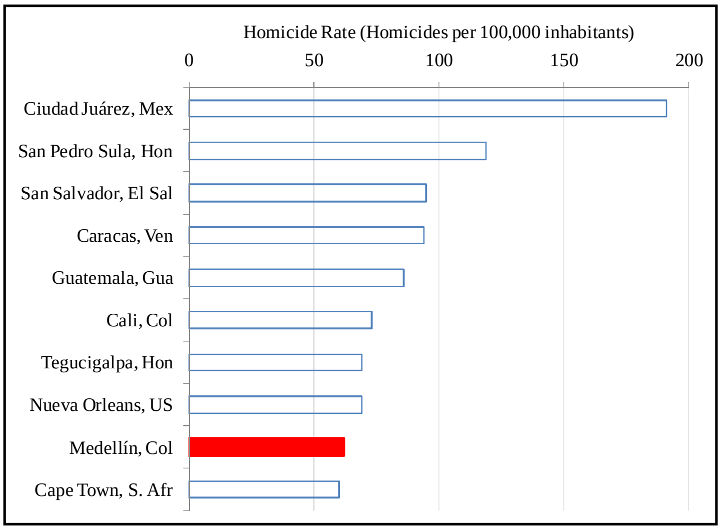
Map 5. Public school attendance and school attendance



b) Crime Patterns

Medellín has been during the last three decades one of the most violent cities of the world, and at times, it has had the highest homicide rate. Even though current homicide rates are much lower than the ones observed during the early 1990s, Medellín was still recently ranked among the 10 most violent cities of the world, as it can be observed in Figure 1, where it was ranked 9th by a study published by two Mexican nongovernmental organizations. Now days (2010), the homicide rate is nearly 100 per 100,000 inhabitants.

Figure 1. Cities with the Highest Homicide Rates of the World, 2009.



Source: CCSPJP and Movimiento Blanco

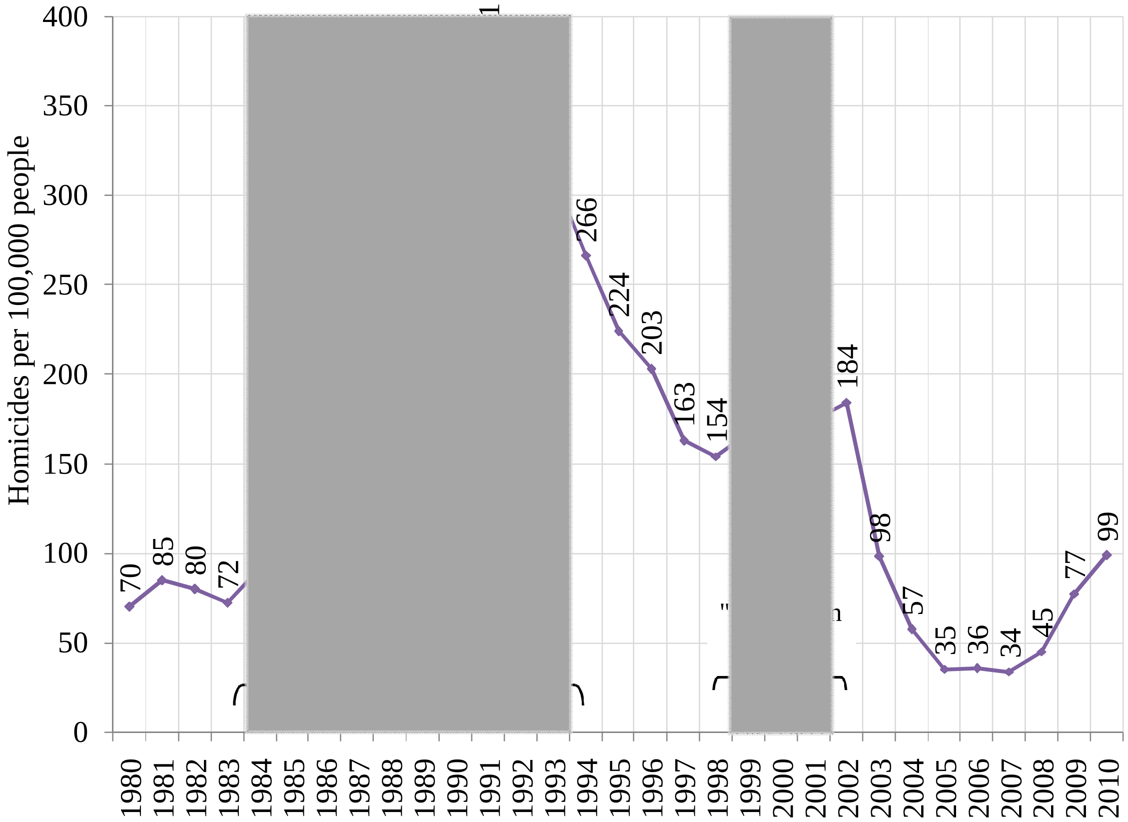
Although, Colombian violence has been traditionally high due to existence of guerrilla groups, drug business took off in the late 1970s and early 1980s, fueled initially the emergence of organized crime to support the business, guerrilla and paramilitary groups, to care for both the entire business chain.

Figure 2 shows the evolution of the homicide rate in Medellin over the period 1987-2009. As it is stressed by Gaviria et al. (2010) and Medina and Tamayo (2012), we can divide the history of homicides in Medellin in three periods: in the first one, from mid 1980s to early 1990s, the homicide rate began to rise and continued increasing until the early 1990s, when the homicide rate reached its highest level and began a persistent decline reaching levels not seeing since late seventies. Gaviria et al. (2010) stressed that the peak of the homicide rate observed in the early 1990s was due to the ñboom of the Medellin drug cartel, and itôs declaration of war to the government and other illegal groupsò (Gaviria et al., 2010).

In the second period that goes from October 2002 to November 2003, there are two episodes highlighted by Medina, Posso and Tamayo (2012); with the ôhot-spotö, called *Operación Orion*, perpetuated by military forces against the urban militias, which took place in the thirteen commune, *San Javier*, the homicide rate presents a severe decline. This was followed by the paramilitary demobilization process that took place in November 2003. ñThese operations had a huge impact in the reduction of the homicides in the cityò (Medina, Posso and Tamayo, 2012)[2].

[2] See Desmond et al. (2009), Giraldo (2008) Sánchez and Betancur (2000) for the effects the *Operación Orion*.

Figure 2. Homicide rate in Medellin



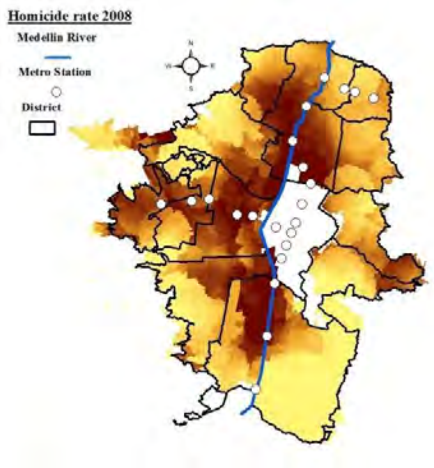
Source: Medina, Posso and Tamayo (2011)

The homicide rate has a very interesting pattern, which is shown on the map 6 and 7. The map 7 represents the homicide rate for the years 1999, 2002, 2006 and 2008; and shows that this rate has a spatial concentration in the north and west of Medellin, especially in districts *12 de Octubre*, *Aranjuez*, *Castilla* and *San Javier*.

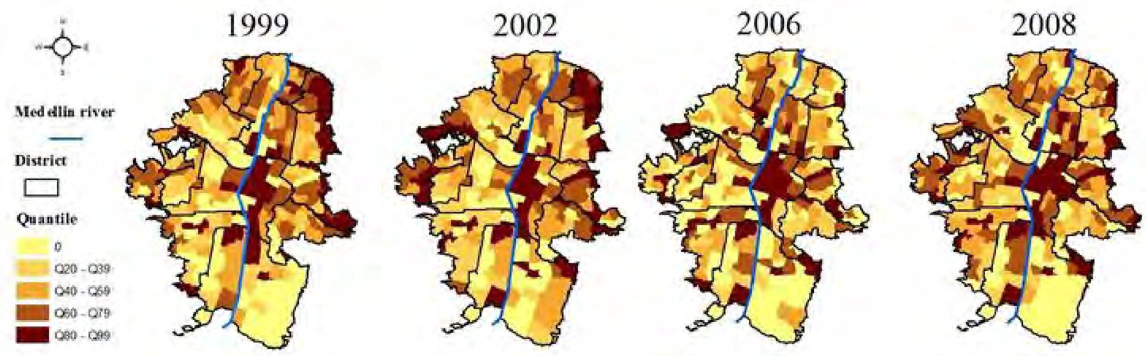
Third, mid 2008-nowdays, with the extradition of the paramilitary leaders in 2008, homicide rate begin to increased

Map 6 and seven presents the homicide rate for 2009 and the years 1999, 2002, 2006 and 2008, respectively. As for the homicide rate in 2009 as the homicide rate for 1999, 2002, 2006 and 2008, it can be appreciate a spatial concentration of the homicides in the north and west of Medellin, especially in districts *12 de Octubre*, *Aranjuez*, *Castilla* and *San Javier*, among these ten years. This very interesting pattern of crime, homicides are committed in the same places, which have been stressed by Gaviria et al. (2010) and Llorente and Rivas (2005), for the case of Bogota.

Map 6. Spatial distribution of Homicide rate 2009 by blocks[3]



Map 7. Spatial distribution of Homicide rate by neighborhoods 1999, 2002, 2006 and 2008



The spatial concentration of homicide rate and crime in general, has important impacts over the quality life of people. Nonetheless, this effect is not unique, the spatial concentration of the crime can have influence over the dynamic of neighborhoods because the persistence can produce externalities over the people who live in these suburbs in many ways, for example, it can create a low social capital. The social capital, like human capital, has important impacts over the futures outcomes of the people. For example, in Benabou (1993) the social capital can reduce the cost of education for the people who live in the neighborhood. For the case of Medellin, we can think that the social capital play a negative role, essentially because it is produced in criminals environments. In the same way that

[3] This map excludes the down town of the city; specifically it excludes ñLa Candelariaò (district 10). We do this because the dynamic of homicide is very different between neighborhoods and downtown, in the first the homicides are very related with the territory, while in the downtown is related with common crimes.

Benabou (1993) obtained, we can expect that the cost of being a criminal could be lower and the likelihood of being a criminal would increase.[4]

Another point of view about the problem that has been mentioned is expressed by Roland Fryer (2006). He proposed the following example: ñif a minority of children wants to go to the school and improve their social status, first, they have to avoid the social sanction of the group, in our case a criminal group. These sanctions have many forms in Medellin, and sometimes include threats and constraint.

This paper shows some evidence which confirm in some way these hypothesis. We try to identify the effect (externalities) of a negative social capital, in this case neighborhoods offenders, over the likelihood of being a criminal. Basically, we think that if a kid grew up in a neighborhood criminal the probability of being a criminal today will be higher.

II. Literature Review

Though, every city has some special characteristics, there are some common things and phenomena among them. In this sense, Plato used to say that ñ*Any city however small, is in fact divided into two, one the city of the poor, the other of the rich*ò (The Republic). Medellin is not an exception. The city has a strong socio-economic polarization that is represented in the two following zones: the city of the ñpoorò (at the north, and its frontiers on the west and the east) and the city of the ñrichò (south-east, *El Poblado*). This strong polarization also occurs in the case of crime phenomenon. Then, when a city like Medellin has these segregation patterns, new mechanisms could appear and reinforce the initial inequality between the two parts of the town. We now proceed to describe some mechanisms we consider that are behind the causal relation that goes from neighborhoods environment and criminal incidence.

In general, in the literature is clear that patterns of segregation through long periods may trap a city in basin of attraction of segregated equilibrium (see Sethi and Somanathan, 2004; Bowles, Loury and Sethi, 2010). Also, Sethi and Somanathan (2004) argue that segregation over the social outcomes can come in many ways, but, in general, the lower inequality is consistent with extreme levels of segregation in cities in which the minority population is large. Nonetheless, if the minority group is small the lower inequality is untenable. Also, Bowles, Loury and Sethi (2010) present evidence that if segregation is sufficiently extreme the inequality group can persist with no group differences in ability, and no discrimination.

In addition to the channel segregation, there are other mechanisms that reinforce initial inequities between groups and are usually associated with the endowments of family, peers

[4] In fact, Medina and Tamayo (2012) find a negative effect of the homicide rate on life satisfaction for the subsample of individuals living in their current houses for at least 10 years or more, who had moved to that place at some point in the past.

group, characteristics of the neighborhood and social networks of the individual (Benabou,1993; Cutler and Glaeser, 1997; Glaeser, Sacerdote y Scheinkman, 1996; Krug et al., 2002; Sethi and Somanathan, 2004; Bowles, Loury and Sethi, 2010; Morales, 2011, and others). However, although household endowments play a central role in the production of the future outcomes of individuals, the environment in which these individuals grow could have a significant explanatory power, in particular when the goal is to analyze crime and other social outcomes, which in the end affect the economic development of the city.

For example, Benabou (1993) shows that when a city has a huge socioeconomic polarization, inequality in educational opportunities often arises, which in turn produce more inequality in the future. But, this result not only has impacts over educational opportunities; in the long term these inequalities have negative repercussions on the standard of living of both the high and low skilled communities.

Also, Benabou (1993) argues that the extent to which a city ñworksò may be inversely related to the feasibility of segregation, in at least two ways: first, the distribution of abilities in the population is important to explain the local community composition and the macroeconomic productivity and growth. Second, the characteristics of young people, the new ñworkers of the cityò, reflect the distribution of skills acquired by their parents and neighbors. In conclusion, Benabou shows how the local externalities produce segregation and this result influences the way in which a city works (productivity).

Another example of the harmful effects of segregation is the work of Cutler and Glaeser (1997). They present evidence that black people are doing significantly worse in segregated environments, but when the segregation disappear the results are close to those of white people. Their empirical results suggest that a one standard deviation reduction in the rate of segregation would eliminate 30 percent of the gap between whites and blacks in outcomes like earnings, becoming a single mother and high school graduation rate.

In the particular case of crime, OôFlaherty, Brendan and Sethi (2010) show that a greater segregation raises both murder rates and victimization rates among black people, although it is not the case for white people. Additionally, larger black share in the population raises murder and victimization rates in both black and white people. Also, OôFlaherty and Sethi (2007) have shown that geographic differences in robbery rates can result in racial segregation in neighborhoods.

In addition to spatial segregation, the neighborhood environment where individuals grow plays a key role. For example, Glaeser, Sacerdote y Scheinkman (1996) argue that social interactions create enough variability between individuals to explain the high cross-city variance of crime rates. According to their analytical model, the amount of social interaction is inversely related to the importance of crime. Thus, social interactions are higher in minor crimes and lower in murder. Patacchini and Zenou (2008) found similar evidence, but using weak and strong ties between adolescents in United States[5]. On the other hand, Falk and Fischbacher (2002) show evidence that individual who behave

[5] Patacchini and Zenou (2008) assume that a weak ties are acquaintances and strong ties are close friends.

conditionally on their social environment is most likely to be criminal in a neighborhood with high crime rate that in other with low rate.

Another literature has emphasized in an indirect way the potential risk of people to become a criminal. For example, Hunt (2003), using individual-level victimization, found that an increase in the share of young people birthed by a teen mother increases the assault rate. Also, children of poor teenage mothers are less likely to have been able to invest in education and in consequence that would trigger low probabilities of obtaining well paid jobs, increasing the probability to become a criminal.

Krug et al. (2002) mention similar arguments and add two additional aspects: poor attachment between parents and children and parental conflict in early childhood, since, teenage mothers are likely to be characterized by a family environment that includes these factors. Krug et al. (2002) mentioned a very important fact that is in connection with this work, and is the role played by social interactions developed in the neighborhood where teenage mothers lived, since they are more likely to live in neighborhood with high levels of crime.

Additionally, based on a survey that was conducted by the IDB, Cohen and Rubio (2007) present some of the principal problems of ñcrime and violenceò for some Latin-American countries. Their conclusions on crime and violence are: Latin America countries have high incidence of crime, high variance of homicide and violence rates, problem of youth gangs and violence and most crime and violence in Latin America are committed by young men. They conclude that poverty is not the most significant factor to determine crime neither it is a necessary condition for gang membership. Dropping out of school seems to be a stronger risk factor.

In the same line Buvinic, Morrison and Orlando (2005) set out five reasons that explain high youth criminality in Latin America: (1) drop out of high school or low school performance, (2) weak law enforcement and poor efficacy of the judicial system on adolescent and early middle-age criminals, (3) access to alcohol and drugs, (4) high unemployment rates among formative years, and (5) the availability and easy access to a fire gun.

In the particular case of Colombia and Medellin, there is a growing literature regarding the problem of peer effects and social interaction over social outcomes like adolescent fertility, quality live and crime. For example, for the case of Medellin, Morales (2011) found that social interaction have a significant predictive power over the adolescent reproductive decisions. Basically, the author argues that young mothers decide to have her first child faster when in the presence of strong social forces or peer effects.

On the other hand, Gaviria, Medina and Tamayo (2010) studied the link between adolescent fertility rates, school attendance and the persistence of Crime in Medellin. In fact, they find ñthat actually neighborhoods with (i) high effective adolescent fertility rates, (ii) low secondary enrollment, and (iii) high crime rates at the moment the children of their teen mothers become teenagers, are more likely to have higher homicide rates in the future, when those children reach their peak crime ages, estimated to be between 18 to 26 years old in violent cities of Colombia.ò

Medina and Tamayo (2012), who exploit the large variation in the homicide rates between neighborhoods in Medellin, find a negative effect of the homicide rate over the quality life of people living in their current houses for at least 5 years or more and over the perception of security in the households.

III. Model and Empirical Strategy

We motivate our empirical model by setting a theoretical framework similar to the one in Calvó and Zenou (2004), CZ, who explain the decision to become a criminal by a rational model. In their model, there is a network N composed of a finite set of agents, that is, $N =$ $\{1,$é $,n\}$, and each individual i is connected to another j if $g_{ij} = 1$, and he is not connected if $g_{ij} = 0$. Individuals choose to become criminals or participate in the labor market. If the individual becomes criminal gets a payoff $V_i = y_i$ ï $p_i f$, where y_i is his reward as a criminal, p_i is the probability of being caught and f is the fine. On the other hand, if he becomes employed earns a wage w. If individuals become criminals, they also decide how much effort e_i to exert, where $e = (e_1,$é $,e_n)$ is the population crime effort profile, and e_{-i} is the crime effort profile of all individuals but i.

We express the key effects we are going to address empirically by a slight modification of Calvó and Zenouôs model in which the individualôs payoff as criminal (i) increases with own effort e_i even as it increases the probability of being caught, (ii) falls with the aggregate effort of his network, $\bar{e}_j$ as a result of the competition for crime rewards in a commonsô tragedy style, (iii) increases with the aggregate effort of those in his network with whom he is connected ($\Sigma_{j\in N}\, g_{ij}\, e_j$) by means of the positive spillovers of learning to become a criminal, and reducing his probability of being caught; and finally, and complementing CZôs framework, (iv) the individualôs payoff as criminal is sensible to his networkôs payoff, which we express as a function of its mean effort relative to the mean effort in the population, $\Phi\left(\sum_{j\in N} g_{ij}e_j, \bar{e}_{-i}\right)$. This term aims to represent the information revealed by his network regardless of how much he is connected to it, and beyond what he can learn from it. An example of what can be used in this term is the rate of arrests of criminals in individual ***i*ôs** neighborhood, which will reveal information beyond what he could have learned by simple observing or having being lectured by the members of his network; information that also reveals the strength of law enforcement in his neighborhood. To represent what individual i could learn from observing the arrests rate of his neighborhood, we assume that $\Phi_1\left(\sum_{j\in N} g_{ij}e_j, \bar{e}_{-i}\right) < 0$ and $\Phi_2\left(\sum_{j\in N} g_{ij}e_j, \bar{e}_{-i}\right) > 0$, that is, we assume that arrests fall with the effort exerted by the members of $i$ôs network keeping constant the average effort of the whole population, and increases with the average effort of its complement, keeping constant the average effort of *i*ôs neighborhood. We define the criminalôs payoff as

$$V_i = e_i \left(1 - \sum_{j \in N} e_j \right) - \phi e_i \left[\theta \Phi \left(\sum_{j \in N} g_{ij} e_j , \bar{e}_{-i} \right) - \sum_{j \in N} g_{ij} e_j \right] \tag{1}$$

In this case, a strategic complementary, defined as the increase in individual *i*ôs marginal payoff to his effort whenever any individual of *i*ôs network with whom he is connected, increases his effort, happens if $\partial^2 V_i / \partial e_i \partial e_j = \phi [g_{ij} - \theta(\Phi_1 + \Phi_2)] \geq 0$.

Our empirical model expresses the decision to become criminal as a function of the main effects included in equation (1). We estimate

$$C_{iN} = \alpha_0 + \gamma \phi \left(g_{ijN} \bar{e}_j \right) + \tilde{\theta} \Phi_{\bar{e}_j, \bar{e}} + \alpha \bar{e}_j + X_{iN} \beta + l_N \beta_N + \varepsilon_{iN} \tag{2}$$

Equation (2) defines the binomial decision to become a criminal, C_{iN}, which is equal to one if the individual became a criminal at some point between 2002 and 2010, and includes a peer group effect seek to capture the positive spillover due to learning from criminals with which individual *i* is connected, $g_{ijN} \bar{e}_j$, which for simplicity we will express as $\bar{e}_{ij}$. We estimate both the number and the rate of individuals that became criminals in that period who lived in 2002 within 100 meters of each individual included in the regression, using a kernel estimation explained in detail in Appendix A1, and which we denote in equation (2) as $\phi(\bar{e}_{ij})$. We also control for the spillover due to the payoff of *i*ôs peers, for which we use the rate of individuals captured for having committed homicide, defined as the number of murderers captured divided by the number of homicides committed, $\Phi_{\bar{e}_j, \bar{e}}$, and to capture the effect of *i*ôs network regardless of how many of its individuals he interacts with, we use for $\bar{e}_j$ the homicide rate of *i*ôs neighborhood. Finally, we include a set of individual *i*ôs characteristics to control for the opportunity cost he has of getting involved in crime, and neighborhood fixed effects, l_N.

Following the recommendations of the literature included in the articles by Lee (2007), Lee, Liu and Lin (2010), Liu and Lee (2010), and Bramoullé, Djebbari and Fortin (2009) among others, who propose several approaches in response to the challenges faced when trying to identify peer effects previously pointed at by Manski (1993), and in particular, in order to control for contextual effects that could prevent us from disentangling the effects explained by the action of each individualôs adult criminal neighbors from that of their adult criminal neighborsô mean characteristics, we also estimate an extended equation that includes a kernel regression on the *X* variables, estimated in the same way it was estimated the peers variable, and which we denote as $\phi(X_{iN})$:

$$C_{iN} = \alpha_0 + \gamma\phi\left(g_{ijN}\bar{e}_j\right) + \tilde{\theta}\Phi_{\bar{e}_j,\bar{e}} + \alpha\bar{e}_j + X_{iN}\beta + \phi\left(X_{iN}\right)\tilde{\beta} + l_N\beta_N + \varepsilon_{iN} \quad (3)$$

Bear in mind that although our model does estimate endogenous effects, defined as those arising from other individualsô actions, in our case, the group of individuals that are included in the peers variable are different to those included in the regression. In particular, they belong to a different age cohort. Model (3) allows us to estimate the endogenous effects, γ, that individuals from older age cohort had on youths in 2002, controlling for contextual effects, measured as the mean characteristics of youths in 2002, and controlling for group effects through the neighborhoodøs fixed effects (See Bramoullé, Djebbari and Fortin, 2009). Although we do not model correlated effects, their omission is likely to have minor effects in the estimated coefficients based on the results found by Medina, Tamayo and Torres (2012), who estimate a similar model with correlated effects and find their inclusion redundant.[6]

According to the intuition behind equation (1), we would expect $\phi > 0$, $\tilde{\theta} < 0$, and $\alpha < 0$. Regretfully, although we can build detailed indicators of criminals with whom individuals could potentially interact, we can only construct by neighborhood the captures rate for homicides, and the homicide rates, we cannot construct other crime or capture rates (robbery, weapons, etc.).

IV. Data

In this section we describe the main sources of information. We use mainly three sources: Population Census 2005 provided by the Administrative Department of National Statistics (*DANE*, by its acronym in Spanish), SIJIN and Police data for crime variables, and the Sisben survey of 2002[7].

First, we use the Population Census of 2005 to characterize the most important socioeconomic patterns at the block level for Medellin. Second, we use information of homicides (*National Police Department*) and individuals captured during 2002 and 2010 for different types of crime (*Judicial Police Sectional of the National Police Department*). We georeference all of the homicides committed between 1998 and 2002 at the block level and constructed the homicide rates at the block level using the kernel procedure described in appendix A1.[8]

We match individuals captured between 2002 and 2010 with the information of the *Sisben* survey for 2002 in order to identify the place where criminal live in 2002, at block level.[9]

[6] The model estimated by Medina, Tamayo and Torres (2012), contrary to ours, uses individuals in the same age cohort to construct their peer variable.
[7] This survey was collected by the Municipality of Medellin between 2000 and 2002, and includes nearly a million individuals, which basically accounts for the census of people in the poorest socioeconomic strata. It contains a wide range of socioeconomic variables, including the address of the house.
[8] We use a spatial bandwidth of 100 meters, and a temporal bandwidth of the years between 1998 and 2002.
[9] We use names, last names, age, and document to match the data. We match names with typos using the Levenshtein edit distance.

To identify the effect of the neighborhood environment on the probability that an individual becomes a criminal later on, we focus our analysis on youths 5 to 16 years old in 2002. The idea is to have baseline information of a sample of children and youths who at that time were not contaminated by the crime industry, and were at the most beginning to be affected by the presence of adult criminals surrounding them. These children were old enough to be likely to have committed a crime by 2010, and young enough to have not been sensibly affected by crime by 2002. We could have used a lower age cutoff to make sure the later goal was fulfilled; nonetheless, we increased it up to 16 years old to have enough observations to obtain our empirical estimates. Still, since the mean age in our target sample is around 11 years old, most of our population had not enrolled in crime activities by 2002.

Since we can observe the census of people captured in Medellín by any crime between 2002 and 2010, we can identify who among that population became criminals later on, and did not, which we use to construct our dependent variable.

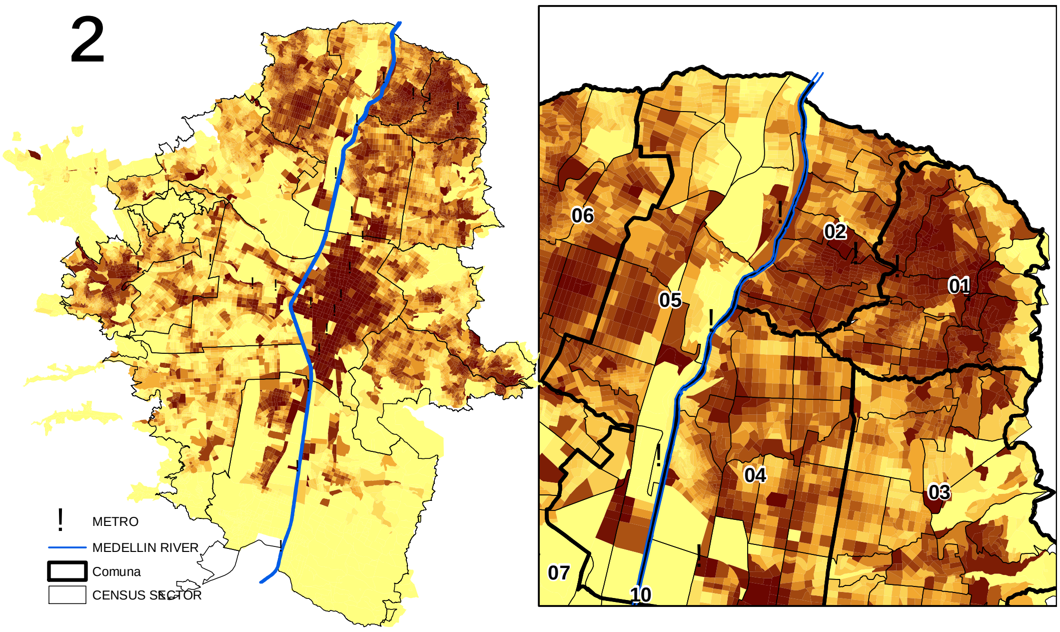
This leaves us with a sample of 282,439 individuals that satisfy the conditions previously stressed, from which 21,178 were captured for having committed a crime, which means that 7,5 % of the total individuals were captured between 2002 and 2010. At a first look, this could be a very high rate of captured people, but there are several aspects that have to be taken in account: first, Sisben survey interviews households mostly in the lower socioeconomic strata. In fact, 95% of total households are located in that survey stratum 1 and 2. Second, most of the crimes are committed by criminals between 15 an 30 years old (75%), but only the 30% of the individuals in Medellin have this age range. Table 1 presents the frequencies of individuals who decided to become criminals by type of crime.

We are interesting to know how the environment where these children and youths grew up affected the likelihood they become criminals. Thus, following a similar procedure used to construct the homicide rate at the block level, we construct our environment variables, which are defined as the number of criminals captured by different types of crimes who live at a radius of 100 meters from the centroid of the block, and which at 2002 were at least 20 years old. We repeat this procedure for four types of crimes which we define as ñHard Crimesò (crimes involving the use of firearms, traffic and carry of drugs, extortion and kidnapping), ñMedium Crimesò (robbery -this includes cars, offices, etc-, vandalism, etc), ñSoft Crimesò (injuries, street fight, harassment, among others), ñWeapons and Homicidesò, which are the most serious violence crimes perpetuated by gang members and it is defined based on individuals captured for committing crimes involving the use of firearms, extortion and kidnapping; and ñDrugsò.

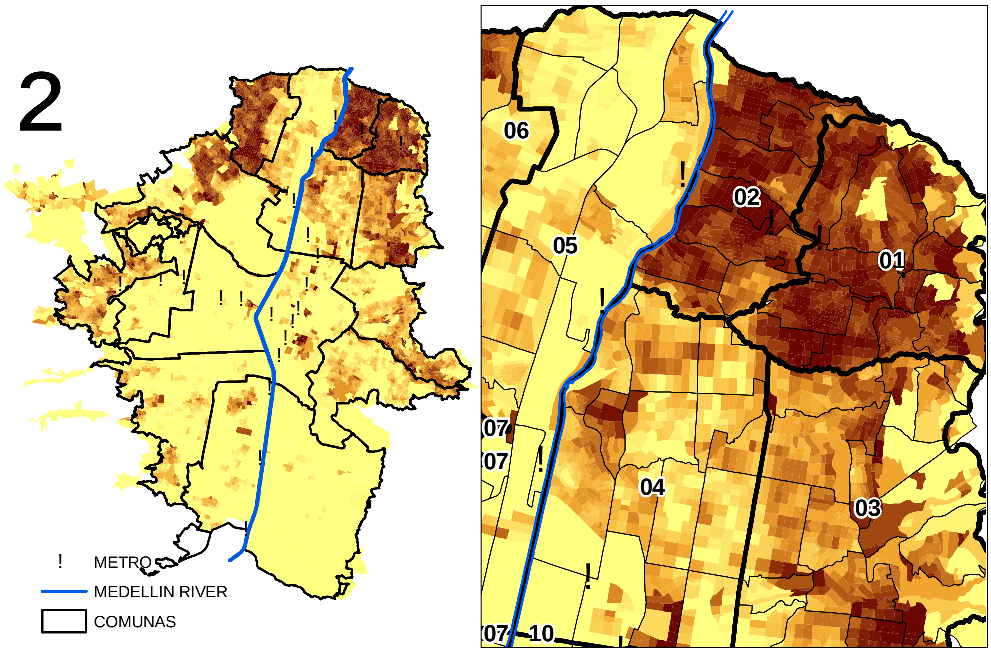
Note that individuals used to construct our variables for adult criminal neighbors are brought from a mutually exclusive population set to the one we use to determine the effects on the decision to become a criminal, composed merely by youths in 2002. Thus, we are assuming that individuals who were captured for any crime between 2002 and 2010, had been committing crimes for a period of time long enough to either have affected the environment of the members of our target population at some point between 2002 and the moment he was captured, or signal contextual information that might have affected them.

Map 8 and 9 show the homicides and criminal rates in the environment of the children of study, respectively. As we already said, in this article the environment or the network variable refer to the rate of criminals living at a radius of 100 meters from the centroid of the block where the children in our sample (treatment and control group) live.

Map 8. Homicide Rate by Block, 2002.



Map 9. Criminal rate by block for 100 meter radius.



What is novel in this article is that we can find variation across the blocks inside the census sector (which for the case of Medellin is similar to the neighborhood), and therefore this allows us to control for neighborhood (fixed) effects in our regressions. We use the homicides committed between 1998 and 2002 to construct the homicide rate by block to use it as control variable to help identify the effect of the criminal environment where the children grew up (control and treatment group).

Table 1 Frequency of Individuals Who Decided to Commit Crimes by Type

CRIME	**No**	**%**
Homicide	266	1.26
Drugs traffic and carry	12,390	58.5
Fire arms	2,213	10.45
Kidanpping and terrorism	132	0.62
Extortion	220	1.04
Conspiracy	48	0.23
Robbery	3,433	16.21
Personal injury	404	1.91
Domestic violence	349	1.65
Harrasment	46	0.22
Vandalism	341	1.61
others	1,336	6.31

V. Results

Tables 2, 3 and 4 present the main results of our empirical estimations. Tables 2 and 3 do not include variables controlling for contextual effects, while Table 4 does. Table 2 defines the presence of adult criminal neighbors as the number of criminals 20 years old or more in 2002 who lived in the environment of each child 5 to 16 in 2002. We know these individuals became criminals at some point between 2002 and 2010 because in that period of time they were captured for having committed some crime (hard crime, drugs, homicides, soft crime and medium crime). Table 3 uses as criminal neighbor variables the previous figures divided by the population of each personôs environment. That is, in that table the variable is constructed in rates.

Conceptually, we can read the results based on the ñpresence of adult criminal neighborsò variable in levels the same way Liu, Patacchini and Zenou (2011) do. They define that as the local-aggregate model, and suggest that in that case, it is the sum of friendsô efforts that affects the response of each individual. They also define the model that uses the peer variable constructed in rates, as the local-average model, and suggest that in that case, it becomes costly for individuals to deviate from the average effort of friends.

Each panel of Table 2 contains the effect of each of our variables related to the presence of adult criminal neighbors, on the decision of individuals 5 to 16 years old in 2002 to become criminals, by type of crime. The panel on the left includes only our adult criminal neighbor variable, the one in the middle also includes the homicide rates and the one in the right adds the capture rates.

The most notable result of both tables is the robust, positive and significant effect of our adult criminal neighbor variable, on the likelihood of children 5 to 16 in 2002 to become criminals. In addition, the magnitude of the coefficients barely change once we include in the estimation the homicide rates, or the rates of captures by homicides, even in the cases where any of those or both of those variables are statistically significant, as it is the case of their effect on the likelihood to commit robbery. In that case, regardless of whether we construct our adult criminal neighbor variable as the number of adult criminals in the individualsô network, or the rate of adult criminals in his network, the capture rates affect negatively the likelihood to commit robbery, as it is predicted by the theoretical model. Nonetheless, the coefficients of the homicide rates are slightly positive, in contrast with the modelôs prediction. This might have to do with the fact that we can only construct the homicide rates and not the robbery rates, neither the capture rates due to robbery but only those due to homicides. In addition, since the sample of criminals we are using to construct our adult criminal neighbor variables is of individuals older than those on which we are studying its effect, the generational gap implies that to a large extent these two population were not perfectly comparable competitors, but rather those conforming the adult criminal neighbors would perform as the teacher of the children in 2002, and thus, the concept of rivalry for the crime rewards does not fully applies in this case.

The only case in which our adult criminal neighbor variable did not affect the likelihood of children 5 to 16 in 2002 becoming criminals was in that of weapons and homicides. That is, the network of individuals involved in committing soft crimes does not affect the likelihood of someone becoming weapons trafficker or murderer, which makes sense to the extent that the technology required to perform soft crimes might not suffice to excel the performance of hard crimes, and to that extent, it is not likely to sensibly affect the likelihood of people exposed to it to become criminal of hard crimes.

It is also important to highlight again that all regressions included in Tables 2 and 3 control for all the variables included in Table 5, and additionally, they control for census sector fixed effects. The effect of the presence of adult criminals in the neighborhood seem very robust taking into account that individuals in our sample live in more than 200 different census sectors.

Table 4 includes the results of both equations (2) and (3). The table has two panels: panel (i) includes the results obtained when the presence of adult criminals was constructed in levels, and panel (ii) when it was constructed in rates. Each panel has results not controlling for contextual effects (A), and controlling for them (B). The table shows that once we control for contextual effects we still find robust positive effects of the presence of adult criminals on the likelihood of individuals becoming criminals of any type or committing robbery, and less robust results on their likelihood of becoming involved in carrying weapons or committing homicides, and drug carrying or trafficking. In particular, the effects on the likelihood of carrying weapons or committing homicides is only significant when the individualsô adult criminal neighbors were involved in homicides or medium crime, in the specific case in which the neighbors variable is constructed in rates (panel ii.B). In the case of the likelihood of individuals getting involved in drug carrying or trafficking, the results in levels are still significant, although when the neighbors variable is constructed in rates (panel i.B), it is only significant when the individualsô neighbors were involved in drug carrying or trafficking (panel ii.B).

To illustrate the intuition behind the other control variables included in our estimations we present in Table 5 the full set of result of the likelihood of children becoming criminals of hard crimes. The higher the socioeconomic strata where the individuals lived in 2002, or its Sisben score, the lower the likelihood he would become a criminal later on, although those coefficients are not statistically significant. Having being enrolled in 2002, or having had a higher educational attainment (primary or secondary versus no education), reduces the likelihood of becoming criminal, as it would be expected by a household who promotes the enrollment of its children anticipating higher returns from future wages that those that might potentially be obtained from other activities like crime.[10]

When the children has private health insurance (social security) he is less likely to become criminal, nonetheless, when his household head has it, he is more likely. That might be signaling the fact that to have private health insurance, the household head is likely to have been working at that time in a formal activity and thus, staying less time in the house with his children than other household heads without private health insurance. This result is consistent with that obtained for household head working (positive although not significant) or unemployed (positive and significant).

It is also interesting to note that there is a nonlinear relationship between the education of the household head and the likelihood of becoming a criminal. Household heads with primary, secondary or higher education are more likely to have children who become criminals than those with no education, or with graduate education.

Other variables signaling the vulnerability of the household at the baseline are positively related to the likelihood of children becoming criminals, like households headed by a woman, the number of children under 6, and the number of children 12 to 25 years old.

[10] Professional and postsecondary education have the correct sign but are not significant presumably by the small number of individuals that age in those education levels in 2002.

Whether the household lives in a rented or owned house does not seem to affect the likelihood its children become criminals, but the age of the children (at a decreasing rate) and that of the household head, both affect it positively.

It is worth to highlight to additional results. First, children in 2002 who were the oldest children of their household, and those who had an older brother who later on became captured for having committed any crime, are significantly more likely to become criminals. Actually, a one standard deviation increase in the share of eldest sons, in the sample would increase the likelihood of individuals becoming criminals in 0.05 of a standard deviation. In the case of children with a brother who became captured later on, an increase in the share of them by one standard deviation would increase the likelihood of them becoming criminals in 0.024 standard deviations.

VI. Conclusions

In this article we use a unique data set at the individual level that allow us to identify between 2002 and 2010, the census of captured criminals in Medellín, a city with one of the highest crime rates in the world. We couple that information with the 2002 Sisben dataset, a survey used to target public social expending to the poorest population of the country, to construct for each individual in the dataset, variables indicating the presence of adult criminal neighbors, based on the identities of individuals who become criminals later on. Since we focus our analysis for the sample of individuals 5 to 16 in 2002 to 13 to 24 in 2010, and we are also able to get baseline socioeconomic variables in 2002, we use this information before individuals become adults to partially control for household location.

We use a slightly modified version of a theoretical model proposed by Calvó-Armengol and Zenou (2004) to propose and interpret the coefficients of an empirical model explaining the probability of individuals 5 to 16 in 2002 becoming criminals as a function of our criminal neighbors effects, an a complete set of control variables, and very importantly, we are able to control for census sector fixed effects.

We find a strong and robust positive effect of the presence of adult criminals in individualsô neighborhood, on the probability of becoming criminal by type of crime. Once we control for contextual effects in our estimations, that is, for the mean characteristics of the individualsô neighbors, we find that only when we consider adult criminal neighbors who commit homicides, and when the model defines the adult criminal neighbor variable in rates, we find a positive effect of the presence of adult criminals in individualsô neighborhood, on the likelihood of individuals getting involved in carrying or trafficking weapons, or committing homicides. On the contrary, although in the case of drug carrying or trafficking, we also found a similar result when we use the adult criminal neighbor variable in rates, in that case, the most robust results are found when that variable is in levels.

Altogether, the results show that both models in which what matters is the sum of friendsô efforts in some activity, as well as models in which it is costly to deviate from the average effort of friends, we find robust effects of the presence of adult criminals in individualsô neighborhood on the likelihood of their getting involved in a criminal activity of any type, or in robbery; that it is the number of friends what matters the most in the likelihood of individuals getting involved in drugs-related activities, and deviations from the average effort of adult criminal neighbors what matters the most in the likelihood of individuals getting involved in weapons-related activities or in homicides.

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Appendix A1

We use a bi-variated kernel density estimator to construct the variables used in our estimations (homicide rate, distance to crime, and arrest rates), and the maps. We use two variables: the distance, in meters, from the centroid of each block to the place where the homicide was committed, and numbers of months elapsed between the date of each homicide and the date the survey was carried out. Given random *r*-vectors X_1,X_2,***é*** ,X_n the multivariate kernel density estimator is defined,

$$\hat{f}_H(x) = \frac{1}{n|H|}\sum_{i=1}^{n} K\left(H^{-1}(x - X_i)\right), \quad x \in \Re^r$$

Where H is an ıı ı ıı nonsingular matrix that generalizes the window width and *K* is a multivariate function with mean 0 an integrates to 1. We tried with Bartlett Epanechnikov kernel, since it is the one with the minimal asymptotic integral squared error, and Gaussian kernel. We use *Rule-of-Thump Method* and Likelihood Cross-Validation to the window width

Table 2. Estimates of Peer Effects By Type of Crime. Peer Variables in Levels

Variable	Criminal of Any Type	Weapons, Homicides	Drugs	Robbery	Criminal of Any Type	Weapons, Homicides	Drugs	Robbery	Criminal of Any Type	Weapons, Homicides	Drugs	Robbery
Hard Crime	**0.0025**	**0.0003**	**0.0018**	**0.0003**	**0.0025**	**0.0003**	**0.0018**	**0.0003**	**0.0028**	**0.0004**	**0.0018**	**0.0005**
(Kernel of Number of Criminals[*])	*7.22*	*2.44*	*6.51*	*2.17*	*7.24*	*2.46*	*6.45*	*2.25*	*7.71*	*2.87*	*6.29*	*3.31*
Capture Rate									-0.0008	0.0000	0.0002	**-0.0009**
(Murderers Captured by Homicide[**])									*-1.33*	*-0.02*	*0.43*	*-3.41*
Homicide Rate					0.00002	0.00001	-0.00001	**0.00001**	0.00002	0.00001	-0.00001	**0.00001**
(Homicides per 100,000 Inhabitants[***])					*1.16*	*1.16*	*-0.91*	*2.11*	*1.26*	*1.46*	*-0.60*	*1.72*
Drugs	**0.0034**	**0.0004**	**0.0025**	**0.0005**	**0.0034**	**0.0004**	**0.0024**	**0.0006**	**0.0038**	**0.0005**	**0.0025**	**0.0008**
(Kernel of Number of Criminals[*])	*7.41*	*2.20*	*6.69*	*2.65*	*7.43*	*2.23*	*6.62*	*2.74*	*7.86*	*2.67*	*6.51*	*3.60*
Capture Rate									-0.0005	0.0000	0.0003	**-0.0008**
(Murderers Captured by Homicide[**])									*-0.95*	*0.17*	*0.74*	*-3.31*
Homicide Rate					0.00002	0.00001	-0.00001	**0.00001**	0.00002	0.00001	-0.00001	**0.00001**
(Homicides per 100,000 Inhabitants[***])					*1.21*	*1.17*	*-0.87*	*2.14*	*1.36*	*1.49*	*-0.51*	*1.77*
Homicides	**0.0056**	**0.0010**	**0.0041**	**0.0003**	**0.0057**	**0.0010**	**0.0041**	0.0003	**0.0064**	**0.0011**	**0.0040**	**0.0009**
(Kernel of Number of Criminals[*])	*5.28*	*2.50*	*4.85*	*0.56*	*5.29*	*2.52*	*4.80*	*0.62*	*5.63*	*2.71*	*4.43*	*1.84*
Capture Rate									-0.00074	-0.00004	0.00023	**-0.00081**
(Murderers Captured by Homicide[**])									*-1.26*	*-0.17*	*0.50*	*-3.17*
Homicide Rate					0.00001	0.00001	-0.00001	**0.00001**	0.00001	0.00001	-0.00001	**0.00001**
(Homicides per 100,000 Inhabitants[***])					*1.02*	*1.13*	*-1.04*	*2.04*	*1.06*	*1.38*	*-0.76*	*1.64*
Soft Crime	**0.0042**	0.0005	**0.0028**	**0.0007**	**0.0042**	**0.0005**	**0.0028**	**0.0007**	**0.0047**	**0.0006**	**0.0028**	**0.0010**
(Kernel of Number of Criminals[*])	*5.32*	*1.69*	*4.45*	*2.10*	*5.31*	*1.68*	*4.41*	*2.13*	*5.78*	*2.04*	*4.38*	*2.94*
Capture Rate									-0.00032	0.00006	0.00051	**-0.00079**
(Murderers Captured by Homicide[**])									*-0.57*	*0.29*	*1.12*	*-3.18*
Homicide Rate					0.00001	0.00001	-0.00001	**0.00001**	0.00002	0.00001	-0.00001	**0.00001**
(Homicides per 100,000 Inhabitants[***])					*0.97*	*1.10*	*-1.09*	*2.06*	*1.13*	*1.41*	*-0.71*	*1.66*
Medium Crime	**0.0035**	**0.0008**	**0.0019**	**0.0005**	**0.0035**	**0.0008**	**0.0019**	**0.0005**	**0.0038**	**0.0009**	**0.0019**	**0.0007**
(Kernel of Number of Criminals[*])	*6.34*	*3.80*	*4.37*	*2.19*	*6.36*	*3.81*	*4.33*	*2.23*	*6.65*	*4.13*	*4.12*	*3.01*
Capture Rate									-0.00038	0.00000	0.00053	**-0.00079**
(Murderers Captured by Homicide[**])									*-0.67*	*-0.01*	*1.18*	*-3.18*
Homicide Rate					0.00001	0.00001	-0.00001	**0.00001**	0.00002	0.00001	-0.00001	**0.00001**
(Homicides per 100,000 Inhabitants[***])					*1.02*	*1.15*	*-1.06*	*2.07*	*1.18*	*1.45*	*-0.68*	*1.69*

[*] Kernel in a space (100 m Ratio)-time (2002-2008) Bandwidth of Number Criminals. [**] Kernel in a space (100 m Ratio)-time (2002-2008) Bandwidth of Number of Murderes by Homicide. [***] Kernel in a space (100 m Ratio)-time (1998-2002) Bandwidth of Number of Homicides per 100,000 Inhabitants. *t*-Statistics in Italics.

Table 3. Estimates of Peer Effects By Type of Crime. Peer Variables in Rates

Variable	Criminal of Any Type	Weapons, Homicides	Drugs	Robbery	Criminal of Any Type	Weapons, Homicides	Drugs	Robbery
Hard Crime	**0.00013**	**0.00002**	**0.00007**	**0.00003**	**0.00014**	**0.00002**	**0.00007**	**0.00004**
(Kernel of Number of Criminals*)	*7.01*	*2.44*	*4.54*	*3.37*	*7.34*	*2.39*	*4.31*	*4.59*
Capture Rate					-0.0009	0.0000	0.0003	**-0.0010**
(Murderers Captured by Homicide**)					*-1.59*	*-0.03*	*0.64*	*-3.86*
Homicide Rate	-0.000014	0.000002	**-0.00003**	0.000007	-0.000017	0.000003	**-0.000024**	0.000001
(Homicides per 100,000 Inhabitants***)	*-1.00*	*0.38*	*-2.32*	*1.06*	*-1.17*	*0.62*	*-1.99*	*0.18*
Drugs	**0.00016**	**0.00002**	**0.00008**	**0.00004**	**0.00018**	**0.00002**	**0.00009**	**0.00005**
(Kernel of Number of Criminals*)	*6.89*	*1.84*	*4.50*	*4.02*	*7.22*	*1.99*	*4.36*	*4.92*
Capture Rate					-0.00062	0.00004	0.00043	**-0.00092**
(Murderers Captured by Homicide**)					*-1.09*	*0.21*	*0.93*	*-3.67*
Homicide Rate	-0.000013	0.000003	**-0.00003**	0.000006	-0.00001	0.00000	**-0.00002**	0.00000
(Homicides per 100,000 Inhabitants***)	*-0.95*	*0.55*	*-2.29*	*0.90*	*-1.01*	*0.78*	*-1.95*	*0.17*
Homicides	**0.00031**	**0.00007**	**0.00018**	**0.00001**	**0.00036**	**0.00007**	**0.00016**	**0.00006**
(Kernel of Number of Criminals*)	*5.39*	*3.33*	*3.79*	*0.58*	*5.56*	*2.76*	*3.20*	*2.22*
Capture Rate					-0.00092	-0.00008	0.00030	**-0.00087**
(Murderers Captured by Homicide**)					*-1.55*	*-0.35*	*0.64*	*-3.35*
Homicide Rate	0.00000	0.00000	**-0.00002**	**0.00001**	0.00000	0.00000	-0.00002	0.00001
(Homicides per 100,000 Inhabitants***)	*-0.06*	*0.48*	*-1.79*	*1.90*	*-0.19*	*0.74*	*-1.43*	*1.10*
Soft Crime	**0.00021**	**0.00002**	**0.00010**	**0.00005**	**0.00024**	0.00002	**0.00010**	**0.00008**
(Kernel of Number of Criminals*)	*4.87*	*1.02*	*2.92*	*2.81*	*5.24*	*0.91*	*2.72*	*3.89*
Capture Rate					-0.00039	0.00009	0.00057	**-0.00086**
(Murderers Captured by Homicide**)					*-0.69*	*0.43*	*1.26*	*-3.46*
Homicide Rate	0.00000	0.00000	**-0.00002**	0.00001	0.00000	0.00001	-0.00002	0.00000
(Homicides per 100,000 Inhabitants***)	*-0.22*	*0.82*	*-1.78*	*1.35*	*-0.22*	*1.14*	*-1.38*	*0.64*
Medium Crime	**0.00015**	**0.00003**	**0.00007**	**0.00003**	**0.00016**	**0.00003**	**0.00006**	**0.00005**
(Kernel of Number of Criminals*)	*5.55*	*2.98*	*3.06*	*2.88*	*5.65*	*2.92*	*2.71*	*3.71*
Capture Rate					-0.0003	0.0000	0.0006	**-0.0008**
(Murderers Captured by Homicide**)					*-0.58*	*0.13*	*1.36*	*-3.32*
Homicide Rate	-0.00001	0.00000	**-0.00002**	0.00001	0.00000	0.00000	-0.00002	0.00000
(Homicides per 100,000 Inhabitants***)	*-0.43*	*0.34*	*-1.84*	*1.30*	*-0.32*	*0.64*	*-1.37*	*0.68*

* Kernel in a space (100 m Ratio)-time (2002-2008) Bandwidth of Number Criminals per Capita. ** Kernel in a space (100 m Ratio)-time (2002-2008) Bandwidth of Number of Murderes by Homicide. *** Kernel in a space (100 m Ratio)-time (1998-2002) Bandwidth of Number of Homicides per 100,000 Inhabitants. *t* -Statistics in Italics.

Table 4. Estimates of Peer Effects by Type of Crime Controlling for Contextual Effects. Peer Variables in Levels and Rates

(i) Levels

	A. Not Controlling for Contextual Effect				B. Controlling for Contextual Effect			
	Criminal of Any Type	Weapons, Homicides	Drugs	Robbery	Criminal of Any Type	Weapons, Homicides	Drugs	Robbery
Hard Crime	**0.0028**	**0.0004**	**0.0018**	**0.0005**	**0.0016**	0.0002	**0.0011**	**0.0004**
(Kernel of Number of Criminals*)	*7.71*	*2.87*	*6.29*	*3.31*	*4.00*	*1.44*	*3.35*	*1.97*
Capture Rate	-0.0008	0.0000	0.0002	**-0.0009**	**-0.0014**	-0.0001	-0.0002	**-0.0009**
(Murderers Captured by Homicide)	*-1.33*	*-0.02*	*0.43*	*-3.41*	*-2.38*	*-0.38*	*-0.48*	*-4.42*
Homicide Rate	0.00002	0.00001	-0.00001	**0.00001**	0.00002	0.00001	0.00000	**0.00001**
(Homicides per 100,000 Inhab)	*1.26*	*1.46*	*-0.60*	*1.72*	*1.58*	*1.39*	*-0.42*	*1.95*
Drugs	**0.0038**	**0.0005**	**0.0025**	**0.0008**	**0.0022**	0.0002	**0.0016**	**0.0005**
(Kernel of Number of Criminals*)	*7.86*	*2.67*	*6.51*	*3.60*	*4.10*	*1.23*	*3.53*	*2.22*
Capture Rate	-0.0005	0.0000	0.0003	**-0.0008**	**-0.0013**	-0.0001	-0.0002	**-0.0009**
(Murderers Captured by Homicide)	*-0.95*	*0.17*	*0.74*	*-3.31*	*-2.19*	*-0.27*	*-0.33*	*-4.36*
Homicide Rate	0.00002	0.00001	-0.00001	**0.00001**	**0.0000**	0.0000	0.0000	**0.0000**
(Homicides per 100,000 Inhab)	*1.36*	*1.49*	*-0.51*	*1.77*	*1.65*	*1.41*	*-0.35*	*2.00*
Homicides	**0.0064**	**0.0011**	**0.0040**	**0.0009**	**0.0037**	0.0008	**0.0024**	0.0005
(Kernel of Number of Criminals*)	*5.63*	*2.71*	*4.43*	*1.84*	*2.94*	*1.61*	*2.32*	*0.92*
Capture Rate	-0.00074	-0.00004	0.00023	**-0.00081**	**-0.0014**	-0.0001	-0.0002	**-0.0009**
(Murderers Captured by Homicide)	*-1.26*	*-0.17*	*0.50*	*-3.17*	*-2.33*	*-0.54*	*-0.43*	*-4.16*
Homicide Rate	0.00001	0.00001	-0.00001	**0.00001**	0.0000	0.0000	0.0000	**0.0000**
(Homicides per 100,000 Inhab)	*1.06*	*1.38*	*-0.76*	*1.64*	*1.43*	*1.33*	*-0.55*	*1.88*
Soft Crime	**0.0047**	**0.0006**	**0.0028**	**0.0010**	**0.0026**	0.0003	**0.0016**	**0.0007**
(Kernel of Number of Criminals*)	*5.78*	*2.04*	*4.38*	*2.94*	*2.85*	*0.92*	*2.11*	*1.80*
Capture Rate	-0.00032	0.00006	0.00051	**-0.00079**	**-0.0012**	0.0000	0.0000	**-0.0009**
(Murderers Captured by Homicide)	*-0.57*	*0.29*	*1.12*	*-3.18*	*-1.97*	*-0.21*	*-0.09*	*-4.27*
Homicide Rate	0.00002	0.00001	-0.00001	**0.00001**	0.0000	0.0000	0.0000	**0.0000**
(Homicides per 100,000 Inhab)	*1.13*	*1.41*	*-0.71*	*1.66*	*1.48*	*1.35*	*-0.51*	*1.91*
Medium Crime	**0.0038**	**0.0009**	**0.0019**	**0.0007**	**0.0021**	**0.0006**	0.0008	**0.0005**
(Kernel of Number of Criminals*)	*6.65*	*4.13*	*4.12*	*3.01*	*3.27*	*2.64*	*1.60*	*1.78*
Capture Rate	-0.00038	0.00000	0.00053	**-0.00079**	**-0.0012**	-0.0001	0.0000	**-0.0009**
(Murderers Captured by Homicide)	*-0.67*	*-0.01*	*1.18*	*-3.18*	*-2.02*	*-0.48*	*-0.01*	*-4.26*
Homicide Rate	0.00002	0.00001	-0.00001	**0.00001**	0.0000	0.0000	0.0000	**0.0000**
(Homicides per 100,000 Inhab)	*1.18*	*1.45*	*-0.68*	*1.69*	*1.52*	*1.40*	*-0.50*	*1.93*

(ii) Rates

	A. Not Controlling for Contextual Effect				B. Controlling for Contextual Effect			
	Criminal of Any Type	Weapons, Homicides	Drugs	Robbery	Criminal of Any Type	Weapons, Homicides	Drugs	Robbery
Hard Crime	**0.00014**	**0.00002**	**0.00007**	**0.00004**	**0.00008**	0.00001	0.00002	**0.00003**
(Kernel of Number of Criminals*)	*7.34*	*2.39*	*4.31*	*4.59*	*3.69*	*1.16*	*1.48*	*3.22*
Capture Rate	-0.0009	0.0000	0.0003	**-0.0010**	**-0.00147**	-0.00008	-0.00007	**-0.00102**
(Murderers Captured by Homicide)	*-1.59*	*-0.03*	*0.64*	*-3.86*	*-2.45*	*-0.36*	*-0.15*	*-4.93*
Homicide Rate	-0.000017	0.000003	**-0.000024**	0.000001	0.00000	0.00000	-0.00001	0.00000
(Homicides per 100,000 Inhab)	*-1.17*	*0.62*	*-1.99*	*0.18*	*0.10*	*0.84*	*-1.04*	*0.60*
Drugs	**0.00018**	**0.00002**	**0.00009**	**0.00005**	**0.00010**	0.00001	**0.00004**	**0.00004**
(Kernel of Number of Criminals*)	*7.22*	*1.99*	*4.36*	*4.92*	*3.85*	*0.86*	*1.73*	*3.60*
Capture Rate	-0.00062	0.00004	0.00043	**-0.00092**	**-0.00133**	-0.00005	-0.00004	**-0.00098**
(Murderers Captured by Homicide)	*-1.09*	*0.21*	*0.93*	*-3.67*	*-2.25*	*-0.23*	*-0.09*	*-4.81*
Homicide Rate	-0.00001	0.00000	**-0.00002**	0.00000	0.00000	0.00001	-0.00001	0.00000
(Homicides per 100,000 Inhab)	*-1.01*	*0.78*	*-1.95*	*0.17*	*0.14*	*0.98*	*-1.08*	*0.53*
Homicides	**0.00036**	**0.00007**	**0.00016**	**0.00006**	**0.00019**	**0.00004**	0.00006	0.00004
(Kernel of Number of Criminals*)	*5.56*	*2.76*	*3.20*	*2.22*	*2.67*	*1.69*	*1.01*	*1.23*
Capture Rate	-0.00092	-0.00008	0.00030	**-0.00087**	**-0.00145**	-0.00014	-0.00006	**-0.00091**
(Murderers Captured by Homicide)	*-1.55*	*-0.35*	*0.64*	*-3.35*	*-2.36*	*-0.65*	*-0.12*	*-4.29*
Homicide Rate	0.00000	0.00000	-0.00002	0.00001	0.00001	0.00000	-0.00001	0.00001
(Homicides per 100,000 Inhab)	*-0.19*	*0.74*	*-1.43*	*1.10*	*0.72*	*0.83*	*-0.80*	*1.52*
Soft Crime	**0.00024**	0.00002	**0.00010**	**0.00008**	**0.00012**	0.00000	0.00002	**0.00006**
(Kernel of Number of Criminals*)	*5.24*	*0.91*	*2.72*	*3.89*	*2.38*	*0.01*	*0.54*	*2.73*
Capture Rate	-0.00039	0.00009	0.00057	**-0.00086**	**-0.00117**	-0.00001	0.00006	**-0.00094**
(Murderers Captured by Homicide)	*-0.69*	*0.43*	*1.26*	*-3.46*	*-1.98*	*-0.06*	*0.12*	*-4.57*
Homicide Rate	0.00000	0.00001	-0.00002	0.00000	0.00001	0.00001	-0.00001	0.00001
(Homicides per 100,000 Inhab)	*-0.22*	*1.14*	*-1.38*	*0.64*	*0.73*	*1.30*	*-0.68*	*1.01*
Medium Crime	**0.00016**	**0.00003**	**0.00006**	**0.00005**	**0.00008**	**0.00002**	0.00001	**0.00003**
(Kernel of Number of Criminals*)	*5.65*	*2.92*	*2.71*	*3.71*	*2.58*	*1.94*	*0.36*	*2.58*
Capture Rate	-0.0003	0.0000	0.0006	**-0.0008**	**-0.00113**	-0.00008	0.00009	**-0.00090**
(Murderers Captured by Homicide)	*-0.58*	*0.13*	*1.36*	*-3.32*	*-1.92*	*-0.37*	*0.17*	*-4.44*
Homicide Rate	0.00000	0.00000	-0.00002	0.00000	0.00001	0.00000	-0.00001	0.00001
(Homicides per 100,000 Inhab)	*-0.32*	*0.64*	*-1.37*	*0.68*	*0.68*	*0.70*	*-0.62*	*1.05*

* Kernel in a space (100 m Ratio)-time (2002-2008) Bandwidth of Number Criminals.

** Kernel in a space (100 m Ratio)-time (2002-2008) Bandwidth of Number of Murderes by Homicide.

** Kernel in a space (100 m Ratio)-time (1998-2002) Bandwidth of Number of Homicides per 100,000 Inhabitants.

Table 5. Peer and Control Estimates By Type of Crime. Peer Variables in Rates

Variable	*coef*	*se*	*Beta*	*coef*	*se*	*Beta*	*coef*	*se*	*Beta*	*coef*	*se*	*Beta*	*coef*	*se*	*Beta*
Peer: Hard Crimes	0.00002***	0.00001***	0.0069												
Peer: Medium Crimes				0.00003***	0.00001***	0.0079									
Peer: Soft Crimes							0.00002	0.00002	0.00240						
Peer: Drugs										0.00002***	0.00001***	0.0056			
Peer: Homicide.													0.00007***	0.00002***	0.0075
Capture Rate	-0.00001	0.00021	-0.0001	0.00003	0.00021	0.0003	0.00009	0.00021	0.0010	0.00004	0.00021	0.0005	-0.00008	0.00022	-0.0009
Homicide Rate (2002)*	0.000003	0.00001	0.0018	0.000004	0.00001	0.0018	0.00001	0.00001	0.0031	0.000004	0.00001	0.0022	0.000004	0.00001	0.0020
Socioeconomic stratum 2	-0.000	0.001	-0.0021	-0.000	0.001	-0.0020	-0.000	0.001	-0.0021	-0.000	0.001	-0.0020	-0.000	0.001	-0.0022
Socioeconomic stratum 3	-0.001	0.001	-0.0027	-0.001	0.001	-0.0028	-0.001	0.001	-0.0029	-0.001	0.001	-0.0028	-0.001	0.001	-0.0028
Sisben Score	0.000	0.000	0.0002	0.000	0.000	0.0002	0.000	0.000	0.0003	0.000	0.000	0.0003	0.000	0.000	0.0003
School Enrollment	-0.005***	0.001	-0.0200	-0.005***	0.001	-0.0200	-0.005***	0.001	-0.0200	-0.005***	0.001	-0.0200	-0.005***	0.001	-0.0200
Primary education	-0.002***	0.001	-0.0091	-0.002***	0.001	-0.0090	-0.002***	0.001	-0.0090	-0.002***	0.001	-0.0091	-0.002***	0.001	-0.0091
Secondary education	-0.002***	0.001	-0.0092	-0.002***	0.001	-0.0092	-0.002***	0.001	-0.0091	-0.002***	0.001	-0.0091	-0.002***	0.001	-0.0092
Professional education	-0.028	0.028	-0.0019	-0.028	0.028	-0.0019	-0.028	0.028	-0.0019	-0.028	0.028	-0.0019	-0.028	0.028	-0.0019
Post-professional education	-0.015	0.066	-0.0004	-0.015	0.066	-0.0004	-0.015	0.066	-0.0004	-0.015	0.066	-0.0004	-0.014	0.066	-0.0004
Social security	-0.002***	0.001	-0.0098	-0.002***	0.001	-0.0098	-0.002***	0.001	-0.0098	-0.002***	0.001	-0.0098	-0.002***	0.001	-0.0098
Employed	0.013***	0.003	0.0083	0.013***	0.003	0.0083	0.013***	0.003	0.0083	0.013***	0.003	0.0083	0.013***	0.003	0.0083
TheHousehold head has primary education	0.001*	0.001	0.0068	0.001*	0.001	0.0068	0.001*	0.001	0.0068	0.001*	0.001	0.0068	0.001*	0.001	0.0067
The household head has secondary education	0.002**	0.001	0.0084	0.002**	0.001	0.0084	0.002**	0.001	0.0085	0.002**	0.001	0.0084	0.002**	0.001	0.0083
The household head has professional education	0.004**	0.002	0.0037	0.004**	0.002	0.0037	0.004**	0.002	0.0037	0.004**	0.002	0.0037	0.004**	0.002	0.0037
The household head has post-professional education	-0.008	0.009	-0.0017	-0.008	0.009	-0.0017	-0.008	0.009	-0.0017	-0.008	0.009	-0.0017	-0.008	0.009	-0.0017
Female Household Head	0.001**	0.000	0.0040	0.001**	0.000	0.0041	0.001**	0.000	0.0041	0.001**	0.000	0.0040	0.001**	0.000	0.0041
The household head is employed	0.000	0.001	0.0002	0.000	0.001	0.0002	0.000	0.001	0.0003	0.000	0.001	0.0002	0.000	0.001	0.0003
The household head is unemployed	0.001*	0.000	0.0035	0.001*	0.000	0.0035	0.001*	0.000	0.0035	0.001*	0.000	0.0035	0.001*	0.000	0.0035
Number of children under 6 years old in the household	0.003***	0.000	0.0259	0.003***	0.000	0.0259	0.003***	0.000	0.0260	0.003***	0.000	0.0259	0.003***	0.000	0.0259
Number of children between 12 and 25 years old in the household	0.000***	0.000	0.0065	0.000***	0.000	0.0065	0.000***	0.000	0.0065	0.000***	0.000	0.0065	0.000***	0.000	0.0065
The household head has social security	0.003***	0.001	0.0143	0.003***	0.001	0.0143	0.003***	0.001	0.0143	0.003***	0.001	0.0143	0.003***	0.001	0.0143
House Ownership	0.001	0.000	0.0035	0.001	0.000	0.0035	0.001	0.000	0.0035	0.001	0.000	0.0035	0.001	0.000	0.0035
Rent house	0.001	0.000	0.0029	0.001	0.000	0.0029	0.001	0.000	0.0029	0.001	0.000	0.0029	0.001	0.000	0.0029
Age difference between the son and the household head	0.000***	0.000	0.0061	0.000***	0.000	0.0061	0.000***	0.000	0.0062	0.000***	0.000	0.0061	0.000***	0.000	0.0061
Son of the Household Head	0.006***	0.001	0.0152	0.006***	0.001	0.0151	0.007***	0.001	0.0152	0.006***	0.001	0.0152	0.007***	0.001	0.0152
The individual is the eldest son	0.009***	0.000	0.0472	0.009***	0.000	0.0472	0.009***	0.000	0.0473	0.009***	0.000	0.0473	0.009***	0.000	0.0472
The individual's elder relative has been captured	0.005***	0.000	0.0235	0.005***	0.000	0.0235	0.005***	0.000	0.0236	0.005***	0.000	0.0235	0.005***	0.000	0.0235
Age	0.006***	0.000	0.2053	0.006***	0.000	0.2053	0.006***	0.000	0.2054	0.006***	0.000	0.2053	0.006***	0.000	0.2055
Age Square	-0.000***	0.000	-0.1274	-0.000***	0.000	-0.1273	-0.000***	0.000	-0.1274	-0.000***	0.000	-0.1273	-0.000***	0.000	-0.1275
Constant	-0.037***	0.003		-0.037***	0.003		-0.037***	0.003		-0.037***	0.003		-0.037***	0.003	
Number of Observations	270,232			270,232			270,232			270,232			270,232		
R2	0.011			0.011			0.011			0.011			0.011		
Log-Likelihood	257,569.59			257,571.00			257,567.18			257,568.73			257,570.62		

note: *** p<0.05, ** p<0.1, * p<0.15