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EFFECTS OF ECONOMIC AND EDUCATIONAL CONDITIONS ON CRIME RATES

Kaio Torres Dias
FGV EPGE
Valdemar Pinho Neto
FGV EPGE

This paper investigates which factors influence the decision to commit different types of crimes – thefts, robberies, and violent crimes – and the choice of location for these infractions. For this purpose, educational and socioeconomic data were used for over 100 neighborhoods in the city of Rio de Janeiro from 2013 to 2018, in addition to microdata regarding crime reports and arrests made in such city and period. Furthermore, spatial regressions at the neighborhood level and logistic regressions at the individual level were used to identify how educational and economic conditions in a neighborhood and its surroundings affect crime. Thus, the analyzes reveal that commercial districts tend to attract different types of crime – in particular, theft and violent crime – while high levels of poverty contribute to the emergence of robbers but reduce the occurrence of this type of crime in the location. Furthermore, the rise in burglary in the vicinity of a neighborhood significantly increases its own burglary rate.

Keywords: crime, poverty, education.

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Kaio Torres Dias: kaio.anime@gmail.com
Valdemar Pinho Neto: valdemar.pinho@fgv.br
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1. Introduction

The crime problem in Rio de Janeiro is an old and internationally known issue. From criminal groups that have more influence than the State in certain parts of the city to worrying rates of street crimes, such as robberies and thefts, crime in Rio de Janeiro is a complex social phenomenon that is difficult to analyze and has received significant attention from both the government and the media. On the State's side, only in the 2010s, it can be mentioned can the creation of the UPPs (Police Pacification Units), the Segurança Presente program, and the 2018 Federal Intervention as examples of the various public policies carried out in attempts to mitigate the problem in Rio de Janeiro. As for the media industry, several channels report daily the infractions in the city, both in morning and evening news.

Several historical, cultural, and demographic aspects of the region influence this reality, but some of the most critical factors in explaining this phenomenon – especially concerning financially motivated crimes, such as thefts and robberies – are of an economic and educational nature. In this sense, on the one hand, the decision to engage in illicit activities to obtain wealth is conditional on the legal options for earning income that one has, and these, in turn, are affected by the state of the economy and of the educational system in the individual's location. On the other hand, in addition to the decision to become a criminal, the offender must choose his place of action. This choice is also affected by the economic conditions of the place since these can influence both the expected gain from the offense and the chance of it being successful. Thus, analyzing the effects of socioeconomic and educational variables on crime is vital to understanding this problematic aspect of Rio de Janeiro's reality.

In this context, the study of criminality by economic science is a relatively recent field that has been explored, mainly in Theoretical and Empirical Microeconomics. In the theoretical field, the first works were written in the 60s to explain criminal behavior from the perspective of a model of choice under uncertainty in which the agent needs to decide between dedicating himself to a legitimate job with sure return and getting involved in criminal activities at the risk of being caught and punished (Becker, 1968). This model has been modified and expanded in different ways in recent decades to introduce new elements that could make it more credible and adaptable to various scenarios – like intertemporal choice and division of the agent's time between work and crime (Chalfin & McCrary, 2017). Empirically, some of the first surveys were carried out in the 1970s and 1980s, and most of them used data from different periods for a region or a single moment for a set of locations – practices that were later heavily criticized due to the problems they caused to the verification of causal relationships. Thus, the following

generations of researchers began to adopt more sophisticated techniques – such as difference-in-differences and instrumental variables – and broader databases – with observations varying both in space and in time –, which improved the quality and precision of the empirical articles in the field (Levitt & Miles, 2006).

In this context, the works on crime currently produced with econometric techniques can be divided using two criteria: the variables that influence the crime and the location of the analysis. Within the first category, there are studies focused both on characteristics of the population itself – like income, education, and gender – as well as elements related to the capture and punishment of criminals – policing, penal law, and penitentiary conditions – the last type of variables being the most common due to the greater ease of finding natural experiments related to it. Within the second category are studies carried out worldwide – at national, state, municipal, or more segregated levels – but many of the studies that became a reference in the area focused on regions of the United States.

Considering such classifications, it is possible to place the present work among the empirical articles that analyze the effects of education and economic conditions on crime levels and among those that study crime in the context of the city of Rio de Janeiro in Brazil. Research in the first group has often found that education has a strong negative effect on crime (Lochner & Moretti, 2004). Some indicate that credit conditions and dismissals also influence the practice of illegal activities (Khana et al., 2021). In addition, recent studies carried out in Brazil have found a positive impact of job loss on the tendency to commit crimes and a mitigating effect of unemployment insurance on this impact (Britto et al., 2022), and correlations between poverty rates and violence in the vicinity of a neighborhood with the occurrence of homicides (Carvalho et al., 2019). As for the works done in Rio de Janeiro, most focus 2 on aspects related to policing, organized crime, and the punishment of criminals – an understandable trend given the atypical size of parallel power in the region (Tealde, 2019; Montolio & Oliveira, 2020; Bruce et al., 2021). Therefore, a survey in Rio de Janeiro focused on the effects of both socioeconomic and educational conditions on crime is a rare and essential contribution to the area.

Thus, the methods chosen to perform such analysis were spatial regression with panel data and logistic regression with individual data. The first methodology uses information on the criminal, economic, and educational conditions of several neighborhoods in Rio de Janeiro from 2013 to 2018 in a regression with fixed effects by neighborhood and by year to explain how variations in these aspects affect both the occurrence of infractions in the region and the choice of turning to criminality on the part of its inhabitants. The second uses data from apprehended criminals and the neighborhoods where they could have acted in a

logistic regression model to discover which characteristics of a location increase or decrease the chance of an offender choosing it as a place to act. Moreover, both methods separate the infractions according to the type of crime carried out – thefts, robberies, or violent crimes (rape, bodily harm, and homicides) – to better understand how the studied variables influence different types of illicit actions.

Such choices of econometric methodologies and levels of segregation of bases have advantages that make rare analyzes in the literature of Economics of Crime viable. Firstly, using neighborhoods for data segregation allows separating the criminal's place of origin from his place of activity – which would be difficult in a municipal or more aggregated separation – allowing the separation of the decision to commit the crime and the choice of the place of action. Second, the proximity of the territorial units and the constant transition of people between them allows the spatial regression to verify not only the effects of the conditions of a neighborhood on its crime but also the effects of the conditions of the nearby locations. Third, separating the analysis into different types of crimes allows the study of the heterogeneity of the impacts of socioeconomic and educational variables since different offenses may require different equipment and skills, in addition to being committed by offenders with different motivations and profiles.

In this sense, firstly, it appears that the rise in poverty increases the number of 3 inhabitants who commit robberies but reduces the number of infractions that occur in the place. The reduction in the occurrence of robberies and the origination of robbers in nearby places decreases the presence of infractions and offenders in the analyzed neighborhood. Second, the number of thefts in a locality increases when poverty in the neighborhood decreases or when the number of jobs per inhabitant increases – with an identified variation of 13 to 22 thefts per thousand inhabitants in the year for each job per resident added. Third, violent crimes tend to occur in neighborhoods with high commercial activity and in the vicinity of other places where violent crimes are common. Their offenders tend to live in areas with less poverty. Finally, there is a slight increase in the conversion of neighborhood residents to all types of crime – most notably, robbery – when the high school dropout rate goes up or the daily class hours go down. Such findings reveal that there is a significant variation in the effects of the socioeconomic and educational conditions of a neighborhood both in terms of which crime is analyzed and which parameter of criminality is studied – occurrence of the infraction or adherence of the residents to the crime – which reinforces the importance of the chosen empirical strategies.

Thus, the article is divided into five parts besides this introduction. The first section explains the composition of the databases used in the different analyses – highlighting their limitations and advantages. The second details the different

empirical methods used in the study of crime in Rio de Janeiro while clarifying some of the methodological decisions made in designing the chosen strategy. The third displays the main results of the regressions performed for the article and highlights the interpretations considered most appropriate for them. The fourth shows some robustness tests used to increase the reliability of the results published in the article. Finally, the fifth concludes the work and makes the final observations of the paper.

2. Databases

Since this article explores the effects of different aspects of Rio de Janeiro city on crime – income, education, and commercial activity, to name a few – several databases from different sources were used to obtain the results found in the work. Furthermore, the variety of these bases and the decision to use neighborhoods as the data segregation 4 level led to the need to employ different data aggregation methods to produce the variables chosen for the regressions. Thus, it is necessary to analyze separately each data source used and the information obtained from them.

First, the source for data related to crime in the city was the Public Security Institute (ISP), the public institution responsible for producing and disseminating information regarding public security in the state of Rio de Janeiro. However, because the data made available by the ISP to the public is aggregated at the level of municipality and of Integrated Circumscription of Public Security (CISP) – a district administrative division used to organize policing – and because these only include information regarding reports of crimes and not arrests made, it was necessary to request microdata for both reports and arrests for the period analyzed especially for the preparation of this article. Thus, the ISP provided two databases referring to criminal activities carried out in the city of Rio de Janeiro.

The first database contains data on reports/victims of crimes carried out in the city studied for the period from 2013 to 2018, while the second provides information on arrests and seizures carried out in the same location between 2016 and 2018 – the shorter time interval of the last base is due to the ISP making arrest data available only from 2016 onwards. The data made available in the first include the date of execution, the neighborhood of the occurrence, and the classification of the reported crime, and, in the second, in addition to these data, there is information regarding the criminal arrested – age, the neighborhood of origin, formal education, profession, and genre. However, although the locations at CISP and municipality levels are standardized and well-defined, the neighborhood where the crime occurred was sometimes absent, and its notation needed to be standardized in all databases. Thus, it was necessary to manually associate the

names used in the databases with numerical codes representative of the Rio neighborhoods – due to the impossibility of identifying the neighborhoods for some notations used or due to the mere absence of the neighborhood of occurrence, it was not possible to include all the crimes in the analysis, but at least 90% of reports and arrests were accounted for.

Furthermore, in addition to statistics on reported crimes and arrests made by neighborhood, statistics on the number of criminals originating in each neighborhood were constructed. This variable was built based on the neighborhoods of origin of the offenders registered in the ISP prison database, but it has limitations worthy of being highlighted. First, because the data refer only to arrested criminals, offenders who were not caught are absent from this statistic. Second, a relevant number of captured offenders do not have information that allows identifying their neighborhoods of origin or reside outside the city of Rio de Janeiro – about 40% of arrests fit into one of these cases. Thus, it is possible to assume that the lack of information about the neighborhood of origin is unrelated to the neighborhood's characteristics or the criminal's. However, such a hypothesis is not reasonable for excluding uncaught offenders – criminals with certain traits or coming from specific neighborhoods may be more challenging to capture, for example – which is a limitation worthy of consideration when interpreting the results.

In addition, it was decided to select three categories of crimes for analysis: theft, – illegal removal of property without the use of violence or threat – robberies – illegal removal of property using violence or threat – and violent crimes – bodily injury, homicide, and rape. This division was carried out because different types of crimes have different methods of execution and objectives, which means that a socioeconomic or educational variable can have a positive effect on a particular category of crime and a negative one on another – populous environments facilitate theft, but not armed robberies, for example. Therefore, this division made it possible to identify the number of apprehended criminals, reported crimes, the ratio between these values – arrest rate per reported crime – and the number of criminals originated for each type of crime each year and in each neighborhood.

Secondly, the source of data referring to the economic conditions of the neighborhoods was Data.Rio – a virtual portal designed by the Pereira Passos Institute to provide various information about the city of Rio de Janeiro. Such data, in turn, originates from the Annual Social Information Report (RAIS) – a public instrument for collecting data related to work in Brazil – and contains information regarding the remuneration and workplace of people formally allocated to jobs in Rio de Janeiro between 2013 and 2018. These data made it possible to identify the average salary and the number of workers each year and in each city neighborhood. That said, it should be noted that Rio de Janeiro is a large

city in which commuting to different neighborhoods to work and the presence of informal jobs are expected, which means 6 that the number of employees is an excellent metric to identify whether a location is a commercial center – throughout this work, a place with many jobs per inhabitant will be called a commercial center and one with few, residential –, but not for unemployment, and that the average salary is indicative of the income of people who transit by the place, but not necessarily of those who live there. These observations are necessary for a better interpretation of the effects of these variables on crime.

In addition, Data.Rio was also the source of data regarding the population and the spatial location of the neighborhoods. Population data were used in the construction of criminal, socioeconomic, and educational variables related to the size of the local population – for example, the number of jobs per inhabitant – and spatial location data were used to measure distances between neighborhoods – information used to weight the effects of outer neighborhoods on the spatial regression described in the next section. However, it should be noted that the government carried out the last census in 2010, so to estimate the population by neighborhood from 2013 to 2018, it was assumed, by hypothesis, that the division of the Rio population between neighborhoods did not vary significantly. Thus, the proportion of the city's total population in the neighborhood in 2010 was multiplied by the estimated value of the total inhabitants each year to obtain the updated values of the location's number of residents.

Third, information regarding the local poverty level was obtained through the Cadastro Unico for Social Programs (CadUnico) database – an instrument for collecting data on low-income Brazilian families. This base provided the number of people registered in CadUnico each year and in each neighborhood, which was used as a metric to identify the number of people considered poor who live in each region of the city. This information complements the RAIS data in the constitution of the socioeconomic scenario of the neighborhoods, as it refers to the financial conditions of the residents of the neighborhoods and not their workers. However, as in the case of the prison database, the CadUnico records obtained are restricted to the period from 2016 to 2018.

Finally, in fourth place, the source for the education data was the National Institute of Educational Studies and Research Anísio Teixeira (Inep) – a public institution dedicated to creating and disseminating studies and data on the Brazilian educational 7 system. The institution provided data regarding school dropout rates and daily class hours at schools in Rio de Janeiro for high school from 2013 to 2018. These metrics were chosen because they indicate how much young people in the neighborhood are dedicating themselves to school activities, thus, making it possible to isolate the effect that dedication can have in reducing crime. The choice

to restrict the school phase to high school was due to this being a period in which school dropout is frequent and in which most crimes committed by young people occur – according to the prison database used, about 95% of arrests of under-18s refer to offenders aged 14 or over. That said, it is relevant to point out that some small neighborhoods – about a fifth of the total sample – do not have high schools, and, therefore, applying the chosen education metrics to them was impossible.

Such databases were used to produce the variables present in the regressions that participate in the analyzes present in this work and detailed in the next section. Tables 1 and 2 below provide, respectively, brief descriptions of such variables and their descriptive statistics for the period from 2016 to 2018, excluding neighborhoods without information on local secondary education – the restriction in the database was made so that observations from all variables referred to the same locations and years. Additionally, choropleth maps with 2018 data have been included in the appendix to visually illustrate Rio's neighborhoods' different criminal, socioeconomic, and economic conditions.

TABLE 1

VARIABLES' DESCRIPTIONS

Variable	Description
Reported offenses	Number of offenses reported in the neighborhood during the year per 1,000 inhabitants.
Prison rate	Number of prisons for crimes reported in the neighborhood divided by the number of reported offenses in the neighborhood in percentage.
Originated offenders	Number of criminals arrested that were residents of the neighborhood per 100,000 inhabitants.
Reported jobs	Number of formal jobs registered in RAIS in firms in the neighborhood per inhabitant.
Log (Income)	Natural logarithm of the mean income of the formal jobs registered in RAIS.
Daily-class hours	Mean value of the number of daily-class hours of the high school classes in the neighborhood's schools.
Dropout rate	Mean value of the dropout rate of the high school classes in the neighborhood's schools.
CadUnico participation	Number of people registered in the Cadastro Unico resident of the neighborhood per inhabitant.

TABLE 2

DESCRIPTIVE STATISTICS

Statistic	N	Mean	St. Dev.	Min	Max
Reported offenses (Robbery)	354	19.054	20.133	0.144	146.491
Reported offenses (Theft)	354	14.802	22.977	0.168	258.845
Reported offenses (Violent crimes)	354	5.201	3.726	0.433	29.278
Prison rate (Robbery)	354	3.064	3.007	0.000	21.918
Prison rate (Theft)	354	1.908	1.628	0.000	11.111
Prison rate (Violent crimes)	354	3.365	2.531	0.000	20.000
Originated offenders (Robbery)	354	40.486	58.528	0.000	475.460
Originated offenders (Theft)	354	28.866	59.173	0.000	686.492
Originated offenders (Violent crimes)	354	11.953	14.652	0.000	171.623
Reported jobs	354	0.472	1.237	0.000	11.386
Log (Income)	351	7.760	0.392	7.111	9.315
Daily-class hours	354	5.452	0.698	4.200	9.000
Dropout rate	354	6.022	6.324	0.000	37.900
CadUnico participation	354	0.213	0.202	0.005	1.381

3. EMPIRIC STRATEGY

3.1. *Spatial regression by neighborhood*

The first method used to analyze crime in Rio de Janeiro was a spatial linear regression with year and neighborhood fixed effects with different databases in the 2013 to 2018 period. This regression uses panel data to verify the effect of socioeconomic and educational conditions on the crime levels of neighborhoods and the number of criminals originating from them while controlling for unobservable factors for each year and each neighborhood. Such conditions refer both to those of the analyzed neighborhood and to those of the nearby locations since the spatial nature of the method is in the presence of the representation of variables from the places spatially close to the unit studied in the regression – the effects of the variables of the vicinity of the neighborhood will be called an external effect, for simplicity.

This representation can be carried out in several ways, the most common being the average value of the places in the direct vicinity of the analyzed place and the weighted average value of all the locations outside the analyzed one. In the present article, the second form was chosen because, given the significant variance in the sizes of the neighborhoods – the area of the largest neighborhood, Guaratiba, is more than 800 times that of the smallest, Zumbi – it is reasonable to assume that,

in some cases, neighborhoods neighbors are so far from most of the region that their socioeconomic and educational conditions have little effect on it while, in others, even neighborhoods that do not border may be close enough to influence the analyzed region. Thus, the effects of the external regions are given by the weighted average of the conditions of the neighborhoods, with the weights given by the inverse of the exponentials of the distances between the spatial centers of the analyzed region and the other locations $e^{-d_{i,j}}$) – other weighting methods are displayed in the Robustness Tests section. Thus, one can represent the external effect of a variable x on neighborhood i in year t ($X_{-i,t}$) – considering a database with neighborhoods identified from 1 to n – in the following way:

$$x_{-i,t} = \frac{\sum_j^{n/\{i\}} e^{-d_{i,j}} x_{j,t}}{\sum_j^{n/\{i\}} e^{-d_{i,j}}}$$

Using a matrix representation, it is possible to illustrate the composition of all external effects to which neighborhood i is exposed ($Z_{i,t}$) by multiplying the vector of weights referring to this neighborhood (W_i), in which each element consists of the weight of the variables from a neighborhood j to a neighborhood i – being 0 if $i = j$ and $\frac{e^{-d_{i,j}}}{\sum_j^{n/\{i\}} e^{-d_{i,j}}}$ otherwise -, with the matrix of variables of neighborhoods outside i in year t ($X_{\mathrm{i,t}}^{\mathrm{ext}}$), in which each column represents an explanatory variable and each line a neighborhood:

$$Z_{i,t} = W_i^{\,T} X_{\mathrm{i,t}}^{\mathrm{ext}}$$

Thus, this empiric strategy's complete representative equation can be written in the following way:

$$Y_{i,t} = \beta_{int} X_{i,t} + \beta_{ext} Z_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

The strategy is used in two different ways: the first takes as the dependent variable ($Y_{i,t}$) the number of complaints per thousand inhabitants of the selected type of crime (thefts, robberies, or violent crimes) made during the year t in the neighborhood i and the second uses for this function the number of perpetrators of crimes committed in the year t originating in neighborhood i. These models complement each other because the first illustrates what factors lead crime to occur in a neighborhood, and the second shows what conditions lead the inhabitant of a neighborhood to become a criminal. Concerning the independent variables, firstly, the vector $X_{-i,t}$ represents the socioeconomic and educational indicators used in the regression, and the vector β_{int} associated with it represents the effects of these variables on the level of crime in that location and year. Second, $Z_{-i,t}$ represents the weighted average of the previously defined external variables,

and β_{ext} determines the effects of such variables on the dependent variable of neighborhood i. Third, α_i and γ_t illustrate neighborhood and year fixed effects, respectively. Finally, $\epsilon_{i,t}$ represents the equation error.

Due to some of the database limitations detailed in the previous section, several regressions with both dependent variables were performed. In this sense, the most relevant restrictions were the limited number of years present for the database of prisons and CadUnico – which is restricted to the period from 2016 to 2018, while the bases of crime reports and other socioeconomic and educational data are available at least since 2013 – and the cases of neighborhoods without records of secondary education institutions, which prevents the construction of educational statistics for them. Thus, it was decided to carry out six regressions with different databases to analyze reports by neighborhood and four to study the number of offenders originated by neighborhood. In the first case, the first regression includes observations from all neighborhoods in the sample for the period from 2013 to 2018 but excludes data referring to the educational conditions of the place, CadUnico, its prisons, and criminals; the second excludes observations from neighborhoods without educational statistics but includes such variables in the regression; the third and fourth resemble the first and second, respectively, but exclude observations from the years 2013 to 2015 to include data referring to prisons and CadUnico; finally, the fifth and sixth regressions add the number of criminals originated by neighborhood to the analyzes of the third and fourth, respectively. In the second case, the first and second regressions do not include external effects; the first includes neighborhoods without educational statistics but excludes these variables from the regression, while the second excludes these neighborhoods and adds the variables to the analysis; the third and fourth are equivalent to the first and second, respectively, but include external effects in the analyses.

3.2. *Logistic regression by criminal*

To understand how criminals choose the neighborhood in which they will act, what factors affect this decision, and how, it was chosen a binary logistic regression with data from arrested criminals and the conditions of the neighborhoods in which they could have acted in addition to fixed time effect. The dependent variable of this method has a value of 1 for the neighborhood in which the offender committed his crime and 0 for all other neighborhoods; that is, for each crime, there is a number of observations equal to the number of neighborhoods in the sample – 148 in the complete database and 117 in the base that excludes neighborhoods without record of educational variables. The independent variables for each observation consist of socioeconomic and educational conditions in the neighborhood, a

dummy variable 12 representing a trait of the criminal, and interactions between the dummy variable and neighborhood conditions. Thus, the logistic regression equation can be represented as follows:

$$P\left(Y_{i,c,t} = 1 \middle| X_{i,t}, Z_c, \gamma_t\right) = \mathrm{F}(\beta_0 X_{i,t} + \beta_1 Z_c + \beta_2 X_{i,t} Z'_c + \beta_3 d_{c,i} + \gamma_t)$$

$$F(x) = \frac{1}{1 + e^{-x}}$$

In this case, the probability of the criminal c choosing the neighborhood i to commit his crime during the year t ($P\left(Y_{i,c,t} = 1 \middle| X_{i,t}, Z_c, \gamma_t\right)$ is given as a function of the conditions of the neighborhood in that year ($X_{i,t}$), the binary variable that represents an individual characteristic of the offender (Z_c), the interaction between this variable and the conditions ($X_{i,t} Z'_c$), the distance between the criminal's place of origin and the chosen neighborhood ($d_{c,i}$) and the fixed effect of the year (γ_t). Such a representation of the offender's choice allows one to verify both which characteristics of a neighborhood make it more or less attractive for a crime and how the effects of these factors change when applied to the decision of offenders with specific characteristics, revealing the heterogeneity of the impacts of the neighborhood conditions.

The choice of the logistic regression model over the traditional linear regression was due to the option of using a binary variable to represent the offender's decision regarding his place of action. Such a model allows the construction of a plausible function that relates the conditions of the neighborhoods and the criminal to the probability of him choosing a neighborhood to act in and uses the maximum likelihood method to obtain the representative coefficients of the effects of the variables. However, the model and databases have limitations that need to be acknowledged. First, the sample is restricted to crimes registered in the prison database, as only this database has information about offenders, which restricts the set of criminals to those who were captured. This selection clearly cannot be considered random – offenders who are arrested may be less competent or more likely to take risks, for example – so this restriction must be considered when interpreting the results. Second, information that could be relevant, such as the influence of criminal groups on specific neighborhoods, is not included in the model, which can bias the regression estimators. Finally, as in the case of spatial regression, database limitations led to the execution of six regressions with different data. The first uses data from all prisons in the sample but does not include educational variables, distance from the criminal's place of origin to neighborhoods, or individual characteristics. The second adds educational variables to the analysis but excludes observations from neighborhoods without high school statistics. The third adds the distance from the place of origin to that of the crime,

excludes neighborhoods without educational data, and only contains observations referring to crimes in which the offender has an identified neighborhood of origin in Rio de Janeiro. Finally, the fourth, fifth, and sixth regressions are equivalent to the first, second, and third, respectively, but a characteristic of the criminal is added – if he is young, that is, under 18 years old – and the interactions of this characteristic with the other variables.

4. Results

The different empirical strategies and crimes investigated in the analyzes generated several relevant results that can help the understanding of how the economy and the educational system of a neighborhood can affect the occurrence of infractions in it and the conversion of its inhabitants to crime. Thus, the results of each type of crime were analyzed separately, and comparisons were made between the econometric models that have complementary roles in explaining the phenomenon of criminality. In this sense, because the models have different formats and dependent variables, the interpretations of the variables will differ between them.

First, the regressions referring to robberies – detailed in tables 3, 4, and 5 below – indicate that some of the significant main effects are related to changes in the neighborhood's poverty level and external criminal levels. The first variable – measured through the number of people registered in the CadUnico per inhabitant – has a negative effect on the occurrence of crime in all spatial regression models with statistics on schools or offenders originating in the neighborhood – according to the models with educational variables, there is a reduction of about 0.3 robberies per thousand inhabitants when the percentage of the population registered in CadUnico increases by 10% –, evidence reinforced by logistic regression at the individual level, especially for young criminals. However, its effect is inverse in the spatial regression with educational statistics that analyzes the factors that determine the number of criminals coming from the neighborhood: the number of offenders increases when poverty increases – a 1% increase in the percentage of registered in CadUnico causes an increase of about 2 offenders per 100,000 inhabitants, in this case.

This apparently ambiguous result is explained from an economic point of view by focusing on the effects of poverty on the expected returns of legal and illegal activities in the neighborhood. In this sense, on the one hand, robberies in poorer regions should have a lower expected return, as potential victims carry less valuable goods than those in neighborhoods with greater purchasing power, which would discourage robbers from acting in these places. On the other hand,

inhabitants of poor neighborhoods have a low expected income from work, which makes the illegal alternative comparatively more attractive, encouraging citizens to turn to crime. Finally, the substantial repulsive effect of poverty on young criminals identified in the logistic regression may be due to a more risk-loving behavior on their part – that is, a greater appreciation of the expected return to the detriment of the risk of being caught –, which can be caused both by particular psychological traits of young people and by the milder legal punishments imposed on them in case of capture.

The effect of external criminal statistics is consistently positive and significant for all spatial regression models, both in the occurrence of robberies and the number of offenders. That is, neighborhoods close to areas with many robberies tend to suffer more robberies, and neighborhoods close to places that form many robbers also originate more criminals of this type – which reveals a robust spatial relationship between the crime levels in nearby regions. This relationship is explained by the fact that, in general, there is not an abrupt separation between neighborhoods in a way that a criminal can quickly move between near neighborhoods and in a way that residents on one side of a border between neighborhoods live in conditions very similar to those on the other side of the border.

TABLE 3

ROBBERY – REPORTED OFFENSES

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	-11.75***	-13.08***	5.09*	-3.71	1.74	-4.93
	(1.52)	(1.59)	(2.82)	(3.25)	(2.71)	(3.26)
Log(Income)	2.74	0.83	0.19	0.41	1.07	0.32
	(2.66)	(2.07)	(2.92)	(2.49)	(2.76)	(2.45)
Daily-class hours		-0.05		0.91		1.02
		(1.07)		(1.62)		(1.60)
Dropout rate		0.05		-0.02		-0.03
		(0.06)		(0.06)		(0.06)
CadUnico participation			23.84*	-29.95**	-7.25	-32.03**
			(13.85)	(14.86)	(14.04)	(15.08)
Prison rate (Robbery)			-0.12	-0.04	-0.09	-0.07
			(0.09)	(0.12)	(0.08)	(0.11)
Originated offenders (Robbery)					-0.03**	0.03**
					(0.00)	(0.01)
Reported offenses (Robbery) – Ext	0.24***	0.27***	0.21**	0.20***	0.20**	0.20***
	(0.07)	(0.05)	(0.08)	(0.07)	(0.08)	(0.07)
Reported jobs – Ext	4.73	7.91**	-13.28**	-6.48	-10.72*	-5.94
	(3.55)	(3.23)	(6.43)	(6.53)	(6.12)	(6.50)
Log(Income) Ext	0.86	0.42	0.30	-0.07	0.22	-0.13
	(0.97)	(0.68)	(0.68)	(0.58)	(0.65)	(0.57)
Daily-class hours – Ext	-0.82	-0.60		-0.68		-0.72
	(0.89)	(0.64)		(0.74)		(0.73)
Dropout rate – Ext	0.02	0.17		-0.06		-0.02
	(0.18)	(0.15)		(0.14)		(0.14)
CadUnico participation – Ext			-2.28	13.92	24.92	20.06
			(38.05)	(33.72)	(36.15)	(33.29)
Prison rate (Robbery) – Ext			0.22	0.15	0.17	0.11
			(0.19)	(0.19)	(0.18)	(0.19)
Originated offenders (Robbery) – Ext					-0.00	-0.05 ***
					(0.01)	(0.02)
R2	0.10	0.16	0.08	0.12	0.19	0.15
Adj. R2	-0.10	-0.04	-0.43	-0.41	-0.27	-0.37
Num. obs.	888	702	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 4

ROBBERY – ORIGINATED OFFENDERS

	(1)	(2)	(3)	(4)
Reported jobs	-88.88***	27.77*	-117.18***	45.13***
	(32.28)	(15.26)	(34.38)	(16.32)
Log(Income)	22.20	1.28	36.81	1.60
	(35.35)	(13.17)	(35.62)	(12.49)
Daily-class hours		-14.64*		-10.13
		(8.60)		(8.12)
Dropout rate		0.54*		0.50*
		(0.30)		(0.28)
CadUnico participation	-1077.17***	230.07 ***	-1135.31***	215.52***
	(170.02)	(78.25)	(169.59)	(75.27)
Prison rate (Robbery)	0.95	0.71	1.20	0.63
	(1.02)	(0.61)	(1.07)	(0.58)
Originated offenders (Robbery) – Ext			0.42**	0.51***
			(0.19)	(0.09)
Reported jobs – Ext			110.35	-56.37*
			(79.46)	(32.75)
Log(Income) – Ext			-4.30	4.85*
			(8.15)	(2.82)
Daily-class hours – Ext			-0.41	0.12
			(10.75)	(3.72)
Dropout rate Ext			1.17	0.18
			(1.90)	(0.71)
CadUnico participation – Ext			903.18*	-176.91
			(470.94)	(168.96)
Prison rate (Robbery) – Ext			-1.86	0.04
			(2.30)	(0.94)
R2	0.17	0.10	0.22	0.24
Adj. R2	-0.26	-0.40	-0.22	-0.21
Num. obs.	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 5

ROBBERY – INDIVIDUAL

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	0.11***	0.25***	0.24***	0.13***	0.29***	0.26***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
CadUnico participation	-0.59***	-0.28**	-0.67***	-0.59***	0.16	0.05
	(0.10)	(0.11)	(0.16)	(0.10)	(0.15)	(0.18)
Log(Income)	0.22***	-0.30***	-0.13*	0.22***	-0.23**	-0.34***
	(0.05)	(0.06)	(0.08)	(0.05)	(0.09)	(0.12)
Prison rate (Robbery)	0.05***	0.13***	0.16***	0.05***	0.12***	0.13***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Dropout rate		-0.03***	-0.03***		-0.02***	-0.03***
		(0.00)	(0.01)		(0.01)	(0.01)
Daily-class hours		-0.17***	-0.11**		-0.13**	-0.09
		(0.04)	(0.05)		(0.06)	(0.07)
Distance			-0.18***			-0.13***
			(0.00)			(0.01)
Young				0.07*	1.54	1.49
				(0.04)	(0.96)	(1.26)
Reported jobs – Young				-0.03***	-0.06***	-0.06***
				(0.01)	(0.02)	(0.02)
CadUnico participation – Young					-0.82***	-0.64**
					(0.22)	(0.26)
Log(Income) – Young					-0.11	-0.09
					(0.12)	(0.15)
Prison rate (Robbery) – Young					0.02*	0.03**
					(0.01)	(0.01)
Dropout rate – Young					-0.01	-0.01
					(0.01)	(0.01)
Daily-class hours – Young					-0.08	-0.06
					(0.07)	(0.09)
Distance – Young						-0.03***
						(0.01)
Log Likelihood	-18564.86	-16250.67	-9481.49	-18559.11	-16412.22	-10004.92
Deviance	37129.72	32501.34	18962.98	37118.21	32824.44	20009.84
Num. obs.	474270	354858	232645	474716	378420	249662

*** p<0.01; ** p<0.05; * p<0.1

Second, analyzes of theft occurrences indicate that the number of jobs in a region and its poverty level are essential factors in determining the execution of this crime – which is shown in tables 6, 7, and 8. The first variable – representative of commercial activity in the neighborhood – has a positive and significant effect on all spatial regression models for the number of thefts carried out – indicating that the addition of one job per inhabitant can generate 13 to 22 additional thefts per thousand inhabitants in the year – and for the individual logistic regression. This effect can be explained by the fact that places with high commercial activity tend to have many commercial establishments and passersby carrying valuable goods, representing, from the criminal's point of view, a broad group of potential victims. The reason for this effect not being consistently perceived in the spatial regression of robberies may be the difference in the execution of crimes: while robberies are actions carried out quickly and often without attracting attention, robberies can more easily cause commotion and violence, which makes the first type of infraction more viable in crowded, closed, or guarded places.

The effect of poverty on the occurrence of theft is consistently negative across all spatial regression models with crime realizations and individual regression, even though it is significant only in the latter case. The probable explanation for this impact is the same as that described in the analysis of robberies: ceteris paribus, poorer regions will have passersby and commercial establishments with less valuable goods than the richer ones, which reduces the expected gain from stealing from them. This hypothesis is reinforced by the strengthening of this effect in the case of young criminals – similar to the case of robberies – and by the immensely positive, albeit not significant, effects of poverty levels in nearby regions, which would indicate a substitution effect between neighborhoods: having a poorer vicinity would attract more thefts to the neighborhood because it has a high expected return on crime compared to the close locations.

TABLE 6

THEFT – REPORTED OFFENSES

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	13.41***	15.54***	15.84***	21.58***	15.69***	21.22***
	(3.44)	(1.55)	(3.16)	(4.52)	(3.16)	(4.55)
Log(Income)	7.08	0.08	0.24	-1.32	0.20	-1.34
	(5.98)	(2.01)	(3.25)	(3.42)	(3.25)	(3.43)
Daily-class hours		1.73*		1.48		1.57
		(1.04)		(2.28)		(2.28)
Dropout rate		-0.00		-0.14*		-0.14*
		(0.06)		(0.08)		(0.08)
CadUnico participation			-26.65*	-13.91	-23.01	-15.35
			(15.69)	(20.75)	(15.89)	(20.96)
Prison rate (Theft)			-0.16	-0.37	-0.18	-0.40
			(0.21)	(0.26)	(0.21)	(0.26)
Originated offenders (Theft)					0.01	0.01
					(0.01)	(0.01)
Reported offenses (Theft) – Ext	0.01	0.01	0.05	0.05	0.05	0.05
	(0.04)	(0.01)	(0.07)	(0.07)	(0.07)	(0.07)
Reported jobs – Ext	-0.86	-6.54**	-5.41	-9.86	-5.58	-9.78
	(7.62)	(3.03)	(7.27)	(9.10)	(7.28)	(9.17)
Log(Income) – Ext	0.30	0.52	0.76	1.27	0.76	1.20
	(2.20)	(0.67)	(1.28)	(1.33)	(1.29)	(1.34)
Daily-class hours – Ext	-0.12	0.57		0.31		0.31
	(2.02)	(0.63)		(1.15)		(1.15)
Dropout rate – Ext	-0.29	-0.14		-0.26		-0.27
	(0.41)	(0.14)		(0.20)		(0.20)
CadUnico participation – Ext			48.30	44.07	46.24	42.29
			(43.01)	(47.02)	(43.98)	(47.85)
Prison rate (Theft) – Ext			0.21	0.33	0.21	0.35
			(0.47)	(0.59)	(0.47)	(0.60)
Originated offenders (Theft) – Ext					-0.01	0.01
					(0.03)	(0.03)
R2	0.02	0.17	0.10	0.13	0.11	0.13
Adj. R2	-0.19	-0.03	-0.40	-0.39	-0.40	-0.40
Num. obs.	888	702	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 7

THEFT – ORIGINATED OFFENDERS

	(1)	(2)	(3)	(4)
Reported jobs	20.25	35.57	10.87	38.43
	(19.21)	(25.26)	(20.71)	(29.27)
Log(Income)	5.46	-1.44	6.14	-1.94
	(21.08)	(21.87)	(21.23)	(22.13)
Daily-class hours		-8.34		-9.18
		(14.40)		(14.75)
Dropout rate		0.13		0.13
		(0.49)		(0.51)
CadUnico participation	-259.46**	89.30	-285.46***	78.29
	(101.53)	(130.15)	(103.18)	(135.29)
Prison rate (Theft)	2.34*	1.79	1.99	1.41
	(1.36)	(1.64)	(1.38)	(1.69)
Originated offenders (Theft) – Ext			0.24	0.28
			(0.18)	(0.22)
Reported jobs Ext			14.07	-29.37
			(47.79)	(59.34)
Log(Income) – Ext			-1.72	0.61
			(4.82)	(4.87)
Daily-class hours – Ext			0.63	-1.19
			(7.20)	(7.45)
Dropout rate Ext			1.19	1.09
			(1.17)	(1.29)
CadUnico participation – Ext			293.20	-34.36
			(290.07)	(309.77)
Prison rate (Theft) – Ext			0.19	-3.16
			(3.47)	(3.87)
R2	0.03	0.02	0.05	0.04
Adj. R2	-0.48	-0.51	-0.48	-0.54
Num. obs.	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 8

THEFT – INDIVIDUAL

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	0.10***	0.25***	0.24***	0.09***	0.24***	0.21***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
CadUnico participation	-3.08***	-1.31***	-1.86***	-3.07***	-0.93***	-0.82***
	(0.16)	(0.17)	(0.25)	(0.16)	(0.19)	(0.23)
Log(Income)	0.50***	-0.06	-0.01	0.50***	-0.01	-0.20**
	(0.05)	(0.06)	(0.08)	(0.05)	(0.07)	(0.10)
Prison rate (Theft)	0.38***	0.46***	0.49***	0.38***	0.44***	0.43***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Dropout rate		-0.04***	-0.04***		-0.04***	-0.05***
		(0.00)	(0.01)		(0.01)	(0.01)
Daily-class hours		0.06*	0.03		0.02	-0.03
		(0.04)	(0.05)		(0.04)	(0.06)
Distance			-0.14***			-0.10***
			(0.00)			(0.01)
Young				-0.04	0.23	-2.49**
				(0.05)	(0.98)	(1.26)
Reported jobs – Young				0.02**	0.03*	0.02
				(0.01)	(0.02)	(0.02)
CadUnico participation – Young					-1.50***	-0.94*
					(0.42)	(0.48)
Log(Income) – Young					-0.15	0.05
					(0.13)	(0.16)
Prison rate (Theft) – Young					0.06**	0.03
					(0.02)	(0.03)
Dropout rate – Young					0.02	0.02
					(0.01)	(0.01)
Daily-class hours – Young					0.14*	0.27***
					(0.08)	(0.10)
Distance – Young						0.04***
						(0.01)
Log Likelihood	-14415.24	-12697.70	-7060.17	-14414.78	-12795.68	-7406.80
Deviance	28830.47	25395.39	14120.34	28829.56	25591.37	14813.60
Num. obs.	398956	304402	181594	399254	318325	189924

*** p<0.01; ** p<0.05; * p<0.1

Third, the occurrence of violent crimes increases with the rise in the number of jobs in a neighborhood and with the occurrence of these crimes in nearby neighborhoods; besides that, the number of perpetrators of these offenses becomes greater in neighborhoods with less poverty – as represented by tables 9, 10 and 11 below. Considering that this category of crimes – homicides, rapes, and bodily injuries – often has more emotional motivations than financial ones, it becomes difficult to explain the effects of socioeconomic variables on these events. That said, it is possible to justify the findings not by direct causality between crime and economic conditions but by the correlation of these conditions with aspects of the neighborhoods that can explain the occurrence of violent crimes.

In this sense, demographic characteristics associated with the number of jobs can explain this finding: young men and adults are among the most common passersby in these locations and are also the most frequent perpetrators of violent crimes, which may mean that the statistic captures the effect of the neighborhood's demography. The positive impact of violent crime in the vicinity, in turn, may reflect the similarities in several unobserved aspects – cultural, for example – that neighboring neighborhoods tend to have. Finally, the increase in criminals originating in neighborhoods with less poverty may be due not to an increase in the number of perpetrators of violent crimes but to a greater frequency with which victims denounce them in these places.

TABLE 9

VIOLENT CRIMES – REPORTED OFFENSES

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	3.90***	4.37***	3.07***	2.32**	3.05***	2.46***
	(0.87)	(0.47)	(0.86)	(0.92)	(0.87)	(0.90)
Log(Income)	1.86	-0.05	2.33***	1.17*	2.31***	1.05
	(1.51)	(0.61)	(0.88)	(0.69)	(0.89)	(0.68)
Daily-class hours		-0.17		-0.27		-0.18
		(0.32)		(0.46)		(0.45)
Dropout rate		-0.04**		-0.01		-0.02
		(0.02)		(0.02)		(0.02)
CadUnico participation			1.38	7.29*	1.28	11.45***
			(4.28)	(4.21)	(4.34)	(4.37)
Prison rate (Violent crimes)			-0.00	-0.04	-0.01	-0.05
			(0.03)	(0.03)	(0.03)	(0.03)
Originated offenders (Violent crimes)					0.00	0.02***
					(0.01)	(0.01)
Reported offenses (Violent crimes) – Ext	0.01	0.10*	0.17*	0.17**	0.17*	0.17**
	(0.12)	(0.06)	(0.09)	(0.07)	(0.09)	(0.07)
Reported jobs – Ext	2.29	0.75	1.64	3.18*	1.43	2.89
	(2.05)	(0.97)	(2.04)	(1.92)	(2.06)	(1.89)
Log(Income) – Ext	-0.27	-0.09	-0.30	-0.30*	-0.31	-0.36**
	(0.56)	(0.20)	(0.20)	(0.15)	(0.20)	(0.15)
Daily-class hours – Ext	0.20	0.37*		0.01		0.01
	(0.51)	(0.19)		(0.21)		(0.21)
Dropout rate Ext	-0.12	-0.10**		0.04		0.03
	(0.10)	(0.04)		(0.04)		(0.04)
CadUnico participation – Ext			-4.24	-4.52	-1.58	-3.74
			(11.76)	(9.60)	(12.17)	(9.82)
Prison rate (Violent crimes) – Ext			-0.03	-0.08	-0.05	-0.10
			(0.08)	(0.08)	(0.08)	(0.08)
Originated offenders (Violent crimes) – Ext					0.02	0.01
					(0.02)	(0.02)
R2	0.04	0.21	0.10	0.16	0.11	0.20
Adj. R2	-0.17	0.03	-0.39	-0.34	-0.40	-0.29
Num. obs.	888	702	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 10

VIOLENT CRIMES – ORIGINATED OFFENDERS

	(1)	(2)	(3)	(4)
Reported jobs	12.14*	-3.29	11.87*	-6.89
	(6.59)	(7.92)	(7.08)	(9.11)
Log(Income)	2.77	6.29	1.51	5.40
	(7.21)	(6.83)	(7.24)	(6.87)
Daily-class hours		-3.23		-3.96
		(4.49)		(4.54)
Dropout rate		0.37**		0.32**
		(0.15)		(0.16)
CadUnico participation	-92.49***	-208.16***	-84.84**	-210.63***
	(34.76)	(40.84)	(35.17)	(41.85)
Prison rate (Violent crimes)	0.42**	0.19	0.56**	0.19
	(0.21)	(0.26)	(0.23)	(0.28)
Originated offenders (Violent crimes) – Ext			-0.16	-0.04
			(0.16)	(0.16)
Reported jobs – Ext			-2.55	7.31
			(16.41)	(18.79)
Log(Income) Ext			3.72**	2.74*
			(1.65)	(1.53)
Daily-class hours – Ext			-0.37	-0.19
			(2.24)	(2.09)
Dropout rate – Ext			-0.48	0.23
			(0.43)	(0.44)
CadUnico participation – Ext			48.28	67.35
			(101.10)	(99.12)
Prison rate (Violent crimes) – Ext			0.96	0.35
			(0.68)	(0.76)
R2	0.04	0.13	0.07	0.16
Adj. R2	-0.46	-0.35	-0.46	-0.35
Num. obs.	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 11

VIOLENT CRIMES – INDIVIDUAL

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	0.06***	0.16***	0.19***	0.07***	0.17***	0.16***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
CadUnico participation	0.01	0.20	-0.09	0.01	0.07	0.08
	(0.11)	(0.13)	(0.19)	(0.11)	(0.15)	(0.17)
Log(Income)	-0.05	-0.32***	-0.25**	-0.05	-0.34***	-0.79***
	(0.07)	(0.08)	(0.11)	(0.07)	(0.09)	(0.12)
Prison rate (Violent crimes)	0.08***	0.13***	0.11***	0.08***	0.12***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dropout rate		-0.03***	-0.03***		-0.03***	-0.04***
		(0.01)	(0.01)		(0.01)	(0.01)
Daily-class hours		-0.01	-0.03		-0.01	0.03
		(0.04)	(0.06)		(0.05)	(0.06)
Distance			-0.36***			-0.37***
			(0.01)			(0.01)
Young				0.01	-0.82	-1.50
				(0.06)	(1.39)	(1.95)
Reported jobs – Young				-0.02	-0.07*	-0.14**
				(0.02)	(0.04)	(0.07)
CadUnico participation – Young					0.57**	0.50
					(0.29)	(0.33)
Log(Income) – Young					0.06	0.18
					(0.18)	(0.24)
Prison rate (Violent crimes) – Young					0.03**	0.04
					(0.02)	(0.02)
Dropout rate – Young					0.02	0.01
					(0.01)	(0.01)
Daily-class hours – Young					-0.01	-0.09
					(0.10)	(0.14)
Distance – Young						0.07***
						(0.02)
Log Likelihood	-10104.30	-8862.59	-4344.40	-10110.88	-8990.11	-4766.93
Deviance	20208.59	17725.19	8688.79	20221.75	17980.21	9533.87
Num. obs.	254178	186592	132447	255220	203371	144228

*** p<0.01; ** p<0.05; * p<0.1

Additionally, concerning educational variables, it was expected that they would affect the decision to become the author of a crime, but not the choice of location for the offense – since they have little effect on the return and the risk of illegal activity. In this sense, it is verified in all spatial regression models for the number of offenders per inhabitant that the increase in the high school dropout rate increases the conversion for all crimes and that the increase in daily class hours in this period reduces all forms of conversion to crime. However, these effects are often low and not significant at the 5% level – the most prominent effects would be on the practice of robbery, with an extra hour of class reducing the number of burglars per 100,000 inhabitants by 10 to 15 and a 2% reduction in the school dropout rate, reducing by 1 the number of perpetrators of robberies per 100,000 inhabitants. As indicated by the statistics at the end of the Appendix, such a timid result may derive from the fact that most captured criminals have not completed elementary school, so they would not be affected by the conditions of secondary education.

Finally, logistic regression indicates that increasing the distance between the place of the offense and the criminal's home reduces the probability of crime in that location for all categories of crime. Such an impact can originate from several factors: the higher cost of time and money for locomotion, the greater risk of being caught carrying illegal or stolen material in transit between places, and the simple expenditure of energy to cover the distance, to mention some.

5. Robustness Tests

Bearing that the choice of how to weigh the conditions of the outer neighborhoods based on distance is a decision that inevitably contains some degree of arbitrariness, alternative definitions were tested to increase the robustness of the results obtained in the spatial regressions. These tests show that the article's main findings are verified similarly when different strategies are used to aggregate the effects of criminal, economic, and educational statistics of the outer neighborhoods. Thus, we chose to experiment with two techniques as alternatives to weighing with the inverse of the distance's exponential: a weighting with the inverse of the distance root and a binary one based on a maximum distance.

In the first alternative – whose results are exhibited in tables 12 to 17 in the Appendix –, the external effect of a variable x in the year t on the neighborhood i would be given by the following equation:

$$x_{-i,t} = \frac{\sum_j^{n/\{i\}} \frac{x_{j,t}}{\sqrt{d_{i,j}}}}{\sum_j^{n/\{i\}} \frac{1}{\sqrt{d_{i,j}}}}$$

This format differs from the initial choice of weighting in the analysis by giving greater weight to neighborhoods far from the analyzed one. Such an effect is verified because the inverse of an exponential function decays much faster than the inverse of a square root as the distance increases. This difference suggests that the exponential model is adequate if the hypothesis that the influence of distant neighborhoods on crime in a neighborhood is meager is adopted and that the model that uses the square root should be used if it is considered that even remote locations can significantly affect a neighborhood's crime. Naturally, the adequacy of a model can be greater or lesser depending on several municipal factors, including urban ones – it is reasonable to assume that in a city with a more extensive railway and road network, more distant regions would be more relevant, for example.

When testing this alternative format, the nature of the effect identified in the main results and the significance of these impacts remains the same. There were no notable changes in the main results of the effects of the internal variables of the neighborhoods other than minor changes in the absolute value of the impacts – in general, changes in value below 10% of the original level. However, in the case of external variables, even though the significance and nature of the effect were not changed, the absolute value of the impact increased significantly – becoming more than five times greater than the original number in some cases – while the average value of the observations of these variables changed little. This indicates that the impacts of distant neighborhoods are relevant and raises the importance of external effects on crime in a neighborhood.

In the second alternative – presented in tables 18 to 23 –, the external effect of a variable is given by the following equations:

$$w_{i,j} = \begin{cases} 1, d_{i,j} < 10 \\ 0, d_{i,j} \geq 10 \end{cases}$$

$$x_{-i,t} = \frac{\sum_{j}^{n/\{i\}} w_{i,j} x_{j,t}}{\sum_{j}^{n/\{i\}} w_{i,j}}$$

That is, the value of an external variable consists of the simple average of the variable's values of all neighborhoods whose geometric centers are less than 10 kilometers away from the center of the analyzed location. This weighting format is similar to the option often used in the literature of considering the effect only of neighboring locations to the analyzed one, but bearing in mind that the significant variance in the size of neighborhoods and the fact that the boundaries between locations, in general, do not characterize discontinuities in the values of social statistics, it was considered more appropriate to use the distance between centers to

determine the vicinity of the neighborhood. Such a strategy reinforces the valuation of nearby locations over further ones characteristic of the original weighting by considering only the statistical values of the places in the defined vicinity and completely excluding distant places from the analysis of the studied neighborhood.

Again, the external variables concentrate the relevant changes from the original regression. On the one hand, the neighborhood's internal variables remain with effects of the same nature and significance while their absolute value varies, both increasing and decreasing, more significantly than in the case of the previous alternative – in some cases reaching a growth of 20 % against the original value. On the other hand, even if the effects of external variables, in general, do not change direction – positive impacts remain positive and negative ones remain negative – the absolute values of such effects vary, increasing or decreasing, and they may cease to be significant to the level of 5% level in some cases.

6. Conclusion

Therefore, the analyzes carried out indicate that educational and, mainly, economic variables have significant effects on criminality and that both the intensity and the nature of these impacts can vary according to the type of offense, the analyzed phenomenon – occurrence of the infraction or conversion to crime – and the profile of the criminal. Furthermore, such effects are robust to different definitions of external effects and the use of different empirical methodologies for the analysis. Thus, it can be identified with reasonable reliability that the increase in poverty encourages the inhabitants of a neighborhood to commit robberies and thefts – even though these infractions tend to become more common in places with a reduction in poverty – that the increase in commercial activity attracts thefts, and that the growth in crime in nearby locations can increase the amount of crime and offenders in a neighborhood.

Such results are useful both for the academic goal of explaining the social phenomenon of crime and for constructing and evaluating public policies based on data. For example, the identified effects indicate that poverty reduction policies can reduce criminals originating in the benefited neighborhoods but increase the number of robberies and thefts that occur in them, which could demand a preventive change in policing in the region. Thus, the present article not only provides a valuable contribution to the literature on Economics of Crime both methodologically – by including the effects of external variables on crime and separating the issues of the criminal's place of action and the decision to carry out the offense – and in terms of results – by providing evidence of the effects of economic variables on crime – as well as providing academic material that can contribute to reducing crime in the future.

References

BECKER, G. S. Crime and punishment: an economic approach. *Journal of Political Economy,* v. 76, n. 2, 1968, p. 169–217. Available at: http://www.jstor.org/stable/1830482.

BRITTO, D.; PINOTTI, P.; SAMPAIO, B. The effect of job loss and unemployment insurance on crime in Brazil. *Econometrica*, v. 90, n. 4, 2022.

BRUCE, R.; CAVGIAS, A.; MELONI, L. Policy enforcement in the presence of organized crime: evidence from Rio de Janeiro. *Journal of Development Economics,* v. 162, 2023.

CARVALHO, J. R.; MEDEIROS, C. N.; OLIVEIRA, V.H. Violence and local development in Fortaleza, Brazil: a spatial regression analysis. *Appl. Spatial Analysis*, v. 12, 2019, p. 147-166. Available at: https://doi.org/10.1007/s12061-017-9236-4

CHALFIN, A.; MCCRARY, J. Criminal deterrence: a review of the literature. *Journal of Economic Literature*, v. 55, n. 1, 2017, p. 5-48.

DRACA, M.; MACHIN, S. Crime and economic incentives. *Annu. Rev. Econ.,* v. 7, 2015, p.389-408.

FREEMAN, R. *The economics of crime*. Handbook of Labor Economics, v. 3c. Amsterdam, Netherlands: North Holland Publishers, 1999.

JAITMAN, L. Frontiers in the economics of crime: lessons for Latin America and the Caribbean. *Latin America Economic Review*, v. 28, n. 19, 2019.KAPLOW, L.; SHAVELL, S. Economic analysis of law. Harvard Law School, John M. Olin Center for Law, Economics and Business. *Discussion Paper,* n. 251, 1999.

KATZ, L.; LEVITT, S.; SHUSTOROVICH, E. Prison conditions, capital punishment, and deterrence. *American Law and Economics Review*, v. 5, n. 2, 2003.

KHANNA, G. et al. Job loss, credit and crime in Colombia. *American Economic Review: Insights*, v. 3, n. 1, 2021, p. 97-114.

LEVITT, S. Alternative strategies for identifying the link between unemployment and crime. *Journal of Quantitative Criminology,* v. 17, n. 4, december 2001.

LEVITT, S. Economic contributions to the understanding of crime. *Annu. Rev. Law Soc. Sci.*, v. 2, 2006, p. 147-164.

LEVITT, S. Incentive compatibility constraints as an explanation for the use of prison sentences. *International Review of Law and Economics,* v. 17, 1997, p. 179-192.

MONTOLIO, D.; OLIVEIRA, C. Law incentives for juvenile recruiting by drug trafficking gangs: empirical evidence from Rio de Janeiro. *IEB Working Paper*, n. 10, 2020.

RUTTENAUER, T. Spatial regression models: a systematic comparison of different model specifications using Monte Carlo experiments. *Sociological Methods and Research*, 2019

TEALDE, E. The impact of police presence on drug-trade-related violence. *Economa,* v. 20, n. 1, Fall 2019, p. 61-82.

8. Apendices

8.1. *Tables for the robustness tests' regressions*

8.1.1. *Weighting with the inverse of the square root of the distance*

Table 12

Robbery – Reported offenses (Weighting with the inverse of the square root of the distance)

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	-11.73***	-12.64***	5.37*	-2.50	1.95	-3.32
	(1.49)	(1.48)	(2.74)	(3.01)	(2.64)	(3.01)
Log(Income)	2.43	0.08	0.62	0.37	1.41	0.40
	(2.66)	(2.03)	(2.84)	(2.39)	(2.68)	(2.36)
Daily-class hours		-0.43		1.22		1.55
		(1.05)		(1.57)		(1.56)
Dropout rate		0.06		-0.01		-0.02
		(0.06)		(0.06)		(0.06)
CadUnico participation			22.91*	-28.20*	-7.51	-29.23**
			(13.69)	(14.38)	(13.90)	(14.69)
Prison rate (Robbery)			-0.11	-0.07	-0.09	-0.11
			(0.08)	(0.11)	(0.08)	(0.11)
Originated offenders (Robbery)					-0.03***	0.03**
					(0.00)	(0.01)
Reported offenses (Robbery) – Ext	1.19***	1.62***	1.20**	1.59***	1.28***	1.50***
	(0.32)	(0.26)	(0.47)	(0.45)	(0.44)	(0.44)
Reported jobs – Ext	18.79	31.87***	-51.36**	-36.68	-40.70*	-33.54
	(11.61)	(9.88)	(24.31)	(25.42)	(23.00)	(25.22)
Log(Income) – Ext	10.17	2.32	-2.27	-3.90	-1.78	-3.85
	(8.42)	(5.96)	(6.11)	(5.23)	(5.85)	(5.20)
Daily-class hours – Ext	-6.92	-8.48		-5.70		-9.65
	(7.09)	(5.88)		(6.38)		(6.66)
Dropout rate – Ext	0.54	1.91**		-0.43		-0.32
	(0.90)	(0.78)		(0.89)		(0.90)
CadUnico participation – Ext			-16.47	198.25	124.76	263.95
			(192.85)	(196.55)	(183.37)	(195.61)
Prison rate (Robbery) – Ext			1.67*	0.58	1.16	0.05
			(0.95)	(0.90)	(0.91)	(0.93)
Originated offenders (Robbery) – Ext					0.03	-0.16**
					(0.06)	(0.07)
R2	0.11	0.19	0.10	0.17	0.21	0.20
Adj. R2	-0.09	0.01	-0.39	-0.33	-0.24	-0.29
Num. obs.	888	702	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 13

THEFT – REPORTED OFFENSES (WEIGHTING WITH THE INVERSE OF THE SQUARE ROOT OF THE DISTANCE)

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	13.18***	14.86***	15.28***	21.67***	15.20***	21.27***
	(3.38)	(1.48)	(3.10)	(4.29)	(3.10)	(4.30)
Log(Income)	6.80	0.31	-0.15	-1.40	-0.28	-1.44
	(5.98)	(2.02)	(3.23)	(3.40)	(3.24)	(3.40)
Daily-class hours		1.77*		1.79		1.88
		(1.06)		(2.26)		(2.26)
Dropout rate		-0.01		-0.17**		-0.17**
		(0.06)		(0.08)		(0.08)
CadUnico participation			-25.17	-13.70	-22.12	-16.51
			(15.64)	(20.66)	(15.85)	(20.82)
Prison rate (Theft)			-0.14	-0.36	-0.17	-0.40
			(0.21)	(0.25)	(0.21)	(0.26)
Originated offenders (Theft)					0.01	0.01
					(0.01)	(0.01)
Reported offenses (Theft) – Ext	-0.69*	0.06	-0.18	-0.17	-0.21	-0.22
	(0.40)	(0.13)	(0.54)	(0.57)	(0.54)	(0.57)
Reported jobs – Ext	8.32	-16.70*	-38.06	-35.81	-39.17	-36.73
	(25.20)	(9.62)	(26.09)	(32.95)	(26.28)	(33.24)
Log(Income) – Ext	5.61	4.11	-1.94	1.31	-3.00	-0.18
	(18.84)	(5.88)	(8.16)	(8.64)	(8.35)	(8.80)
Daily-class hours – Ext	-1.69	4.27		8.32		8.92
	(16.06)	(5.89)		(10.05)		(10.10)
Dropout rate – Ext	-2.04	-0.46		-2.84**		-3.06**
	(2.04)	(0.78)		(1.33)		(1.34)
CadUnico participation – Ext			444.39**	360.05	413.45*	331.82
			(218.14)	(274.14)	(220.66)	(276.51)
Prison rate (Theft) – Ext			1.95	3.63	2.05	3.97
			(2.24)	(3.07)	(2.27)	(3.16)
Originated offenders (Theft) – Ext					0.02	0.06
					(0.10)	(0.12)
R2	0.03	0.16	0.11	0.14	0.12	0.15
Adj. R2	-0.18	-0.03	-0.39	-0.37	-0.38	-0.37
Num. obs.	888	702	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 14

VIOLENT CRIMES – REPORTED OFFENSES (WEIGHTING WITH THE INVERSE OF THE SQUARE ROOT OF THE DISTANCE)

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	4.05***	4.59***	3.30***	2.57***	3.30***	2.78***
	(0.85)	(0.45)	(0.86)	(0.89)	(0.86)	(0.87)
Log(Income)	1.86	0.08	2.18**	1.00	2.09**	0.86
	(1.51)	(0.61)	(0.89)	(0.70)	(0.89)	(0.69)
Daily-class hours		-0.06		-0.36		-0.26
		(0.32)		(0.46)		(0.45)
Dropout rate		-0.04**		-0.01		-0.02
		(0.02)		(0.02)		(0.02)
CadUnico participation			1.31	6.62	1.43	10.80**
			(4.31)	(4.24)	(4.36)	(4.41)
Prison rate (Violent crimes)			-0.01	-0.06*	-0.01	-0.06*
			(0.03)	(0.03)	(0.03)	(0.03)
Originated offenders (Violent crimes)					0.00	0.02***
					(0.01)	(0.01)
Reported offenses (Violent crimes) – Ext	-1.14*	0.46	0.45	0.65	0.11	0.29
	(0.61)	(0.28)	(0.61)	(0.51)	(0.66)	(0.53)
Reported jobs – Ext	14.22*	-2.74	2.25	9.18	1.93	9.25
	(7.39)	(3.38)	(7.59)	(7.37)	(7.60)	(7.26)
Log(Income) – Ext	-2.30	-1.34	-1.92	-1.78	-2.55	-2.60*
	(4.75)	(1.77)	(1.76)	(1.39)	(1.83)	(1.41)
Daily-class hours – Ext	2.18	3.35*		-1.09		-0.87
	(4.04)	(1.76)		(1.83)		(1.80)
Dropout rate – Ext	– 1.14**	-0.57**		0.38		0.22
	(0.54)	(0.25)		(0.29)		(0.29)
CadUnico participation – Ext			4.61	-19.02	19.21	-13.05
			(59.01)	(56.67)	(59.98)	(56.92)
Prison rate (Violent crimes) – Ext			-0.24	-0.65*	-0.31	-0.60
			(0.38)	(0.38)	(0.39)	(0.37)
Originated offenders (Violent crimes) – Ext					0.15	0.11
					(0.11)	(0.10)
R2	0.05	0.21	0.09	0.15	0.10	0.19
Adj. R2	-0.16	0.03	-0.41	-0.36	-0.41	-0.31
Num. obs.	888	702	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 15

ROBBERY – ORIGINATED OFFENDERS (WEIGHTING WITH THE INVERSE OF THE SQUARE ROOT OF THE DISTANCE)

	(1)	(2)	(3)	(4)
Reported jobs	-88.88**	27.77*	-125.15***	35.26 **
	(32.28)	(15.26)	(33.99)	(15.60)
Log(Income)	22.20	1.28	26.92	0.42
	(35.35)	(13.17)	(35.17)	(12.36)
Daily-class hours		-14.64*		-13.03
		(8.60)		(8.11)
Dropout rate		0.54*		0.59**
		(0.30)		(0.29)
CadUnico participation	-1077.17***	230.07***	-1102.47***	188.28**
	(170.02)	(78.25)	(171.16)	(75.87)
Prison rate (Robbery)	0.95	0.71	0.86	0.90
	(1.02)	(0.61)	(1.04)	(0.58)
Originated offenders (Robbery) – Ext			1.06	1.81***
			(0.85)	(0.37)
Reported jobs – Ext			290.16	-176.05
			(299.62)	(124.04)
Log(Income) – Ext			1.64	23.69
			(77.00)	(26.80)
Daily-class hours – Ext			-44.38	20.41
			(83.09)	(34.16)
Dropout rate – Ext			7.80	5.36
			(11.70)	(4.60)
CadUnico participation – Ext			5152.05**	-1481.11
			(2533.67)	(1011.51)
Prison rate (Robbery) – Ext			-16.49	5.25
			(11.70)	(4.64)
R2	0.17	0.10	0.22	0.25
Adj. R2	-0.26	-0.40	-0.23	-0.21
Num. obs.	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 16

THEFT – ORIGINATED OFFENDERS (WEIGHTING WITH THE INVERSE OF THE SQUARE ROOT OF THE DISTANCE)

	(1)	(2)	(3)	(4)
Reported jobs	20.25	35.57	4.92	27.74
	(19.21)	(25.26)	(20.41)	(27.67)
Log(Income)	5.46	-1.44	4.98	-1.01
	(21.08)	(21.87)	(21.11)	(21.86)
Daily-class hours		-8.34		-11.53
		(14.40)		(14.55)
Dropout rate		0.13		0.31
		(0.49)		(0.52)
CadUnico participation	-259.46**	89.30	-261.95**	121.71
	(101.53)	(130.15)	(103.22)	(134.14)
Prison rate (Theft)	2.34*	1.79	2.03	1.59
	(1.36)	(1.64)	(1.38)	(1.66)
Originated offenders (Theft) – Ext			0.27	0.57
			(0.65)	(0.77)
Reported jobs – Ext			-6.95	-107.88
			(177.21)	(214.42)
Log(Income) – Ext			25.52	24.78
			(43.02)	(43.47)
Daily-class hours – Ext			-31.16	-71.83
			(54.10)	(65.00)
Dropout rate – Ext			10.20	15.71*
			(7.09)	(8.55)
CadUnico participation – Ext			1982.79	799.60
			(1492.74)	(1764.44)
Prison rate (Theft) – Ext			-16.13	-48.18**
			(16.47)	(20.08)
R2	0.03	0.02	0.06	0.06
Adj. R2	-0.48	-0.51	-0.47	-0.50
Num. obs.	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 17

VIOLENT CRIMES – ORIGINATED OFFENDERS (WEIGHTING WITH THE INVERSE OF THE SQUARE ROOT OF THE DISTANCE)

	(1)	(2)	(3)	(4)
Reported jobs	12.14*	-3.29	10.44	-8.50
	(6.59)	(7.92)	(6.90)	(8.60)
Log(Income)	2.77	6.29	2.95	5.12
	(7.21)	(6.83)	(7.11)	(6.78)
Daily-class hours		-3.23		-4.06
		(4.49)		(4.48)
Dropout rate		0.37**		0.43**
		(0.15)		(0.17)
CadUnico participation	-92.49***	-208.16 ***	-86.58**	-206.97***
	(34.76)	(40.84)	(34.77)	(41.34)
Prison rate (Violent crimes)	0.42**	0.19	0.51**	0.06
	(0.21)	(0.26)	(0.24)	(0.31)
Originated offenders (Violent crimes) – Ext			-2.67***	-1.64*
			(0.86)	(0.91)
Reported jobs – Ext			10.16	27.28
			(60.72)	(68.90)
Log(Income) – Ext			41.78***	30.09**
			(14.67)	(13.74)
Daily-class hours – Ext			1.01	-7.51
			(16.64)	(17.72)
Dropout rate – Ext			2.32	5.05*
			(2.59)	(2.82)
CadUnico participation – Ext			-196.66	131.08
			(513.78)	(563.22)
Prison rate (Violent crimes) – Ext			2.00	-2.39
			(3.40)	(3.67)
R2	0.04	0.13	0.09	0.18
Adj. R2	-0.46	-0.35	-0.42	-0.32
Num. obs.	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

8.1.2. *Binary weighting based on the distance*

TABLE 18

ROBBERY – REPORTED OFFENSES (BINARY WEIGHTING BASED ON THE DISTANCE)

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	-11.59***	-11.99***	3.12	-4.66	0.64	-4.79
	(1.44)	(1.42)	(2.69)	(2.93)	(2.57)	(2.94)
Log(Income)	3.07	1.41	1.41	0.53	1.90	0.73
	(2.66)	(2.08)	(2.92)	(2.49)	(2.74)	(2.46)
Daily-class hours		-0.25		0.62		1.13
		(1.08)		(1.64)		(1.64)
Dropout rate		0.06		-0.04		-0.06
		(0.06)		(0.06)		(0.06)
CadUnico participation			17.67	-32.66**	-13.42	-40.25***
			(14.07)	(14.82)	(14.23)	(14.98)
Prison rate (Robbery)			-0.10	-0.10	-0.08	-0.14
			(0.09)	(0.12)	(0.08)	(0.12)
Originated offenders (Robbery)					-0.03***	0.03*
					(0.00)	(0.01)
Reported offenses (Robbery) – Ext	0.47***	0.50***	0.20	0.19	0.16	0.10
	(0.14)	(0.10)	(0.19)	(0.16)	(0.19)	(0.17)
Reported jobs – Ext	8.99	5.14	-28.83**	-31.24**	-19.25	-31.79**
	(6.60)	(5.56)	(14.30)	(14.04)	(13.68)	(14.12)
Log(Income) Ext	1.68	1.14	0.05	0.59	0.36	0.76
	(2.68)	(1.91)	(1.96)	(1.62)	(1.84)	(1.61)
Daily-class hours – Ext	-1.23	-1.07		-2.60		-3.49*
	(2.06)	(1.48)		(1.98)		(2.00)
Dropout rate – Ext	0.05	-0.08		-0.19		-0.29
	(0.54)	(0.44)		(0.45)		(0.44)
CadUnico participation – Ext			12.08	32.91	-23.17	10.79
			(82.88)	(77.73)	(84.77)	(81.20)
Prison rate (Robbery) – Ext			0.62	0.68	0.34	0.75*
			(0.49)	(0.44)	(0.47)	(0.45)
Originated offenders (Robbery) – Ext					-0.01	-0.04*
					(0.03)	(0.03)
R2	0.10	0.15	0.05	0.10	0.17	0.13
Adj. R2	-0.10	-0.04	-0.48	-0.44	-0.31	-0.41
Num. obs.	888	702	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 19

THEFT – REPORTED OFFENSES (BINARY WEIGHTING BASED ON THE DISTANCE)

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	12.52***	13.64***	15.11***	18.75***	14.90***	18.50***
	(3.26)	(1.39)	(2.97)	(4.08)	(2.98)	(4.11)
Log(Income)	6.15	-0.16	-0.19	-1.59	-0.26	-1.58
	(6.01)	(2.02)	(3.22)	(3.40)	(3.23)	(3.41)
Daily-class hours		1.67		1.24		1.28
		(1.05)		(2.25)		(2.27)
Dropout rate		-0.01		-0.14*		-0.14*
		(0.06)		(0.08)		(0.08)
CadUnico participation			-25.44	-15.51	-22.33	-16.38
			(15.54)	(20.34)	(15.70)	(20.42)
Prison rate (Theft)			-0.15	-0.39	-0.18	-0.40
			(0.21)	(0.26)	(0.22)	(0.26)
Originated offenders (Theft)					0.01	0.01
					(0.01)	(0.01)
Reported offenses (Theft) – Ext	-0.04	0.04	-0.12	-0.00	-0.17	-0.05
	(0.09)	(0.03)	(0.33)	(0.37)	(0.34)	(0.38)
Reported jobs – Ext	21.38	3.58	7.89	22.51	6.22	20.79
	(14.88)	(5.36)	(14.74)	(17.03)	(15.51)	(18.09)
Log(Income) Ext	-0.05	0.72	-1.34	0.08	-2.35	-0.98
	(6.06)	(1.86)	(6.24)	(6.90)	(6.41)	(7.13)
Daily-class hours – Ext	0.17	0.80		1.21		1.06
	(4.65)	(1.44)		(3.32)		(3.34)
Dropout rate – Ext	-0.51	-0.29		-0.75		-0.73
	(1.22)	(0.43)		(0.60)		(0.61)
CadUnico participation – Ext			105.37	101.77	101.61	96.81
			(92.78)	(99.49)	(92.93)	(100.50)
Prison rate (Theft) – Ext			1.38	0.68	1.29	0.57
			(1.36)	(1.79)	(1.38)	(1.81)
Originated offenders (Theft) – Ext					0.01	0.01
					(0.06)	(0.07)
R2	0.03	0.16	0.11	0.14	0.11	0.14
Adj. R2	-0.18	-0.03	-0.39	-0.38	-0.39	-0.39
Num. obs.	888	702	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 20

VIOLENT CRIMES – REPORTED OFFENSES (BINARY WEIGHTING BASED ON THE DISTANCE)

	(1)	(2)	(3)	(4)	(5)	(6)
Reported jobs	4.05***	4.42***	3.40***	3.12***	3.41***	3.21***
	(0.82)	(0.42)	(0.81)	(0.82)	(0.82)	(0.81)
Log(Income)	1.60	-0.12	2.00**	0.82	1.97**	0.72
	(1.51)	(0.61)	(0.88)	(0.70)	(0.88)	(0.69)
Daily-class hours		-0.20		-0.35		-0.28
		(0.31)		(0.46)		(0.45)
Dropout rate		-0.03*		-0.01		-0.02
		(0.02)		(0.02)		(0.02)
CadUnico participation			2.04	9.34**	1.80	13.05***
			(4.28)	(4.20)	(4.33)	(4.38)
Prison rate (Violent crimes)			-0.00	-0.03	-0.00	-0.03
			(0.03)	(0.03)	(0.03)	(0.03)
Originated offenders (Violent crimes)					0.00	0.02***
					(0.01)	(0.01)
Reported offenses (Violent crimes) – Ext	-0.29	0.05	0.32	0.41**	0.30	0.36**
	(0.22)	(0.09)	(0.21)	(0.16)	(0.21)	(0.16)
Reported jobs – Ext	11.47***	4.23**	-1.29	1.77	-2.60	1.41
	(4.44)	(1.90)	(4.09)	(3.69)	(4.18)	(3.73)
Log(Income) – Ext	-1.80	-1.12**	-0.27	-0.42	-0.68	-0.75*
	(1.54)	(0.57)	(0.53)	(0.41)	(0.60)	(0.45)
Daily-class hours – Ext	0.46	0.68		-0.06		0.02
	(1.18)	(0.43)		(0.57)		(0.56)
Dropout rate – Ext	-0.32	-0.10		0.02		0.03
	(0.32)	(0.13)		(0.13)		(0.12)
CadUnico participation – Ext			-15.60	-0.99	-11.50	0.77
			(25.21)	(21.76)	(25.33)	(21.50)
Prison rate (Violent crimes) – Ext			0.10	-0.08	0.01	-0.13
			(0.21)	(0.18)	(0.21)	(0.19)
Originated offenders (Violent crimes) – Ext					0.07	0.03
					(0.05)	(0.04)
R2	0.05	0.21	0.10	0.15	0.11	0.19
Adj. R2	-0.16	0.04	-0.40	-0.36	-0.40	-0.31
Num. obs.	888	702	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 21

ROBBERY – ORIGINATED OFFENDERS (BINARY WEIGHTING BASED ON THE DISTANCE)

	(1)	(2)	(3)	(4)
Reported jobs	-88.88***	27.77*	-84.78**	26.13*
	(32.28)	(15.26)	(33.00)	(15.47)
Log(Income)	22.20	1.28	15.62	0.86
	(35.35)	(13.17)	(35.48)	(13.01)
Daily-class hours		-14.64*		-18.79**
		(8.60)		(8.58)
Dropout rate		0.54*		0.54*
		(0.30)		(0.30)
CadUnico participation	-1077.17***	230.07***	-1072.89***	213.20***
	(170.02)	(78.25)	(171.78)	(77.68)
Prison rate (Robbery)	0.95	0.71	0.65	0.77
	(1.02)	(0.61)	(1.07)	(0.61)
Originated offenders (Robbery) – Ext			-0.37	0.04
			(0.32)	(0.13)
Reported jobs – Ext			356.20**	137.46*
			(180.66)	(73.84)
Log(Income) – Ext			14.40	1.11
			(23.21)	(8.28)
Daily-class hours – Ext			-1.55	9.80
			(29.53)	(10.56)
Dropout rate – Ext			-2.75	1.99
			(5.85)	(2.32)
CadUnico participation – Ext			-912.48	-824.00**
			(999.67)	(371.68)
Prison rate (Robbery) – Ext			-10.99*	-6.09***
			(6.00)	(2.28)
R2	0.17	0.10	0.19	0.16
Adj. R2	-0.26	-0.40	-0.26	-0.35
Num. obs.	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 22

THEFT – ORIGINATED OFFENDERS (BINARY WEIGHTING BASED ON THE DISTANCE)

	(1)	(2)	(3)	(4)
Reported jobs	20.25	35.57	15.72	29.36
	(19.21)	(25.26)	(19.68)	(26.44)
Log(Income)	5.46	-1.44	4.85	-2.02
	(21.08)	(21.87)	(21.29)	(22.22)
Daily-class hours		-8.34		-8.27
		(14.40)		(14.75)
Dropout rate		0.13		0.11
		(0.49)		(0.51)
CadUnico participation	-259.46**	89.30	-255.30**	86.18
	(101.53)	(130.15)	(102.65)	(132.80)
Prison rate (Theft)	2.34*	1.79	2.50*	1.80
	(1.36)	(1.64)	(1.40)	(1.69)
Originated offenders (Theft) – Ext			-0.22	-0.03
			(0.39)	(0.43)
Reported jobs – Ext			51.28	24.94
			(101.65)	(115.41)
Log(Income) Ext			9.87	7.43
			(13.11)	(13.22)
Daily-class hours – Ext			24.70	19.66
			(21.07)	(21.59)
Dropout rate Ext			0.51	0.25
			(3.46)	(3.94)
CadUnico participation – Ext			258.22	278.64
			(620.06)	(653.88)
Prison rate (Theft) – Ext			15.39	11.80
			(10.74)	(11.43)
R2	0.03	0.02	0.05	0.03
Adj. R2	-0.48	-0.51	-0.49	-0.55
Num. obs.	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

TABLE 23

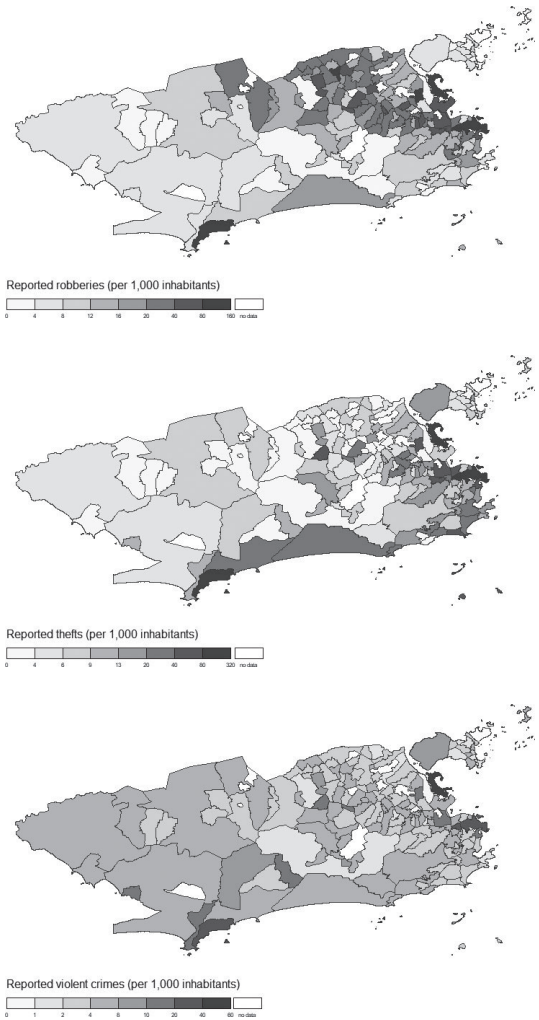
VIOLENT CRIMES – ORIGINATED OFFENDERS (BINARY WEIGHTING BASED ON THE DISTANCE)

	(1)	(2)	(3)	(4)
Reported jobs	12.14*	-3.29	12.23*	-3.83
	(6.59)	(7.92)	(6.68)	(8.12)
Log(Income)	2.77	6.29	2.32	5.08
	(7.21)	(6.83)	(7.25)	(6.88)
Daily-class hours		-3.23		-3.48
		(4.49)		(4.55)
Dropout rate		0.37**		0.33**
		(0.15)		(0.16)
CadUnico participation	-92.49***	-208.16 ***	-90.58**	-210.26***
	(34.76)	(40.84)	(35.08)	(41.64)
Prison rate (Violent crimes)	0.42**	0.19	0.45**	0.22
	(0.21)	(0.26)	(0.21)	(0.27)
Originated offenders (Violent crimes) – Ext			-0.56	-0.18
			(0.38)	(0.35)
Reported jobs – Ext			14.34	1.44
			(33.32)	(35.12)
Log(Income) – Ext			9.33*	8.68*
			(4.90)	(4.49)
Daily-class hours – Ext			-2.09	-4.02
			(5.98)	(5.59)
Dropout rate – Ext			-1.09	-0.34
			(1.22)	(1.25)
CadUnico participation – Ext			1.28	-119.29
			(205.55)	(196.45)
Prison rate (Violent crimes) – Ext			0.71	0.97
			(1.85)	(1.86)
R2	0.04	0.13	0.06	0.15
Adj. R2	-0.46	-0.35	-0.47	-0.36
Num. obs.	444	351	444	351

*** p<0.01; ** p<0.05; * p<0.1

8.2. *Data Maps*[1]

Figure 1 – Crime reports



[1] The data illustrated in the images refer to 2018 for the database used in the last column of the regressions with panel data - the ones with all the variables included. Neighborhoods without data for high school variables are excluded from the sample.

Figure 2 – Prison rates by crime

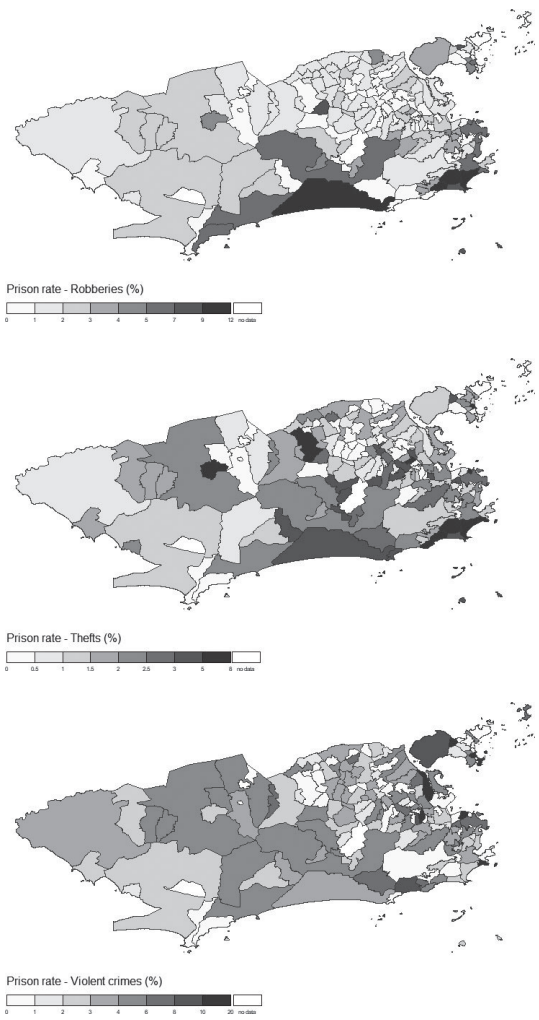


Figure 3 – Originated offenders in the neighborhood by crime

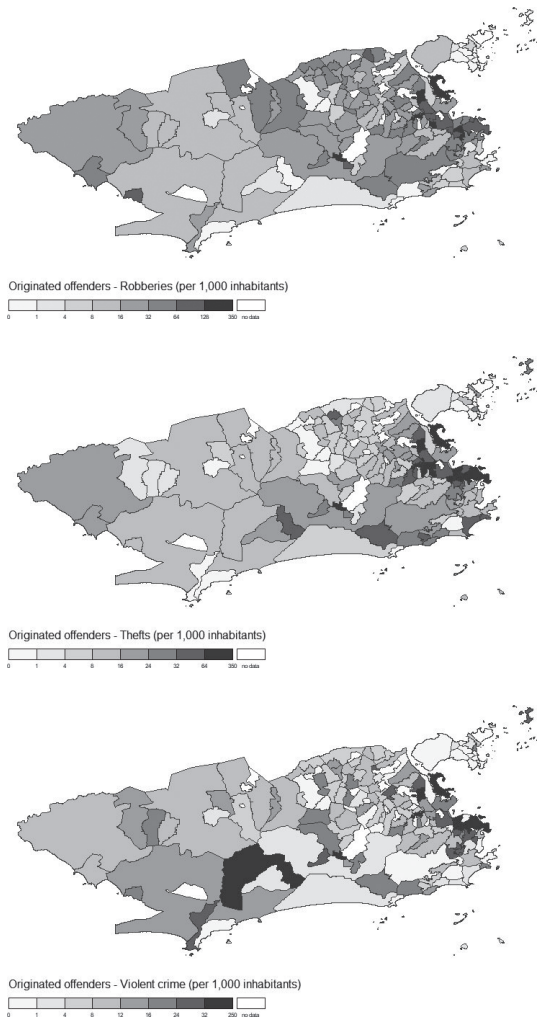
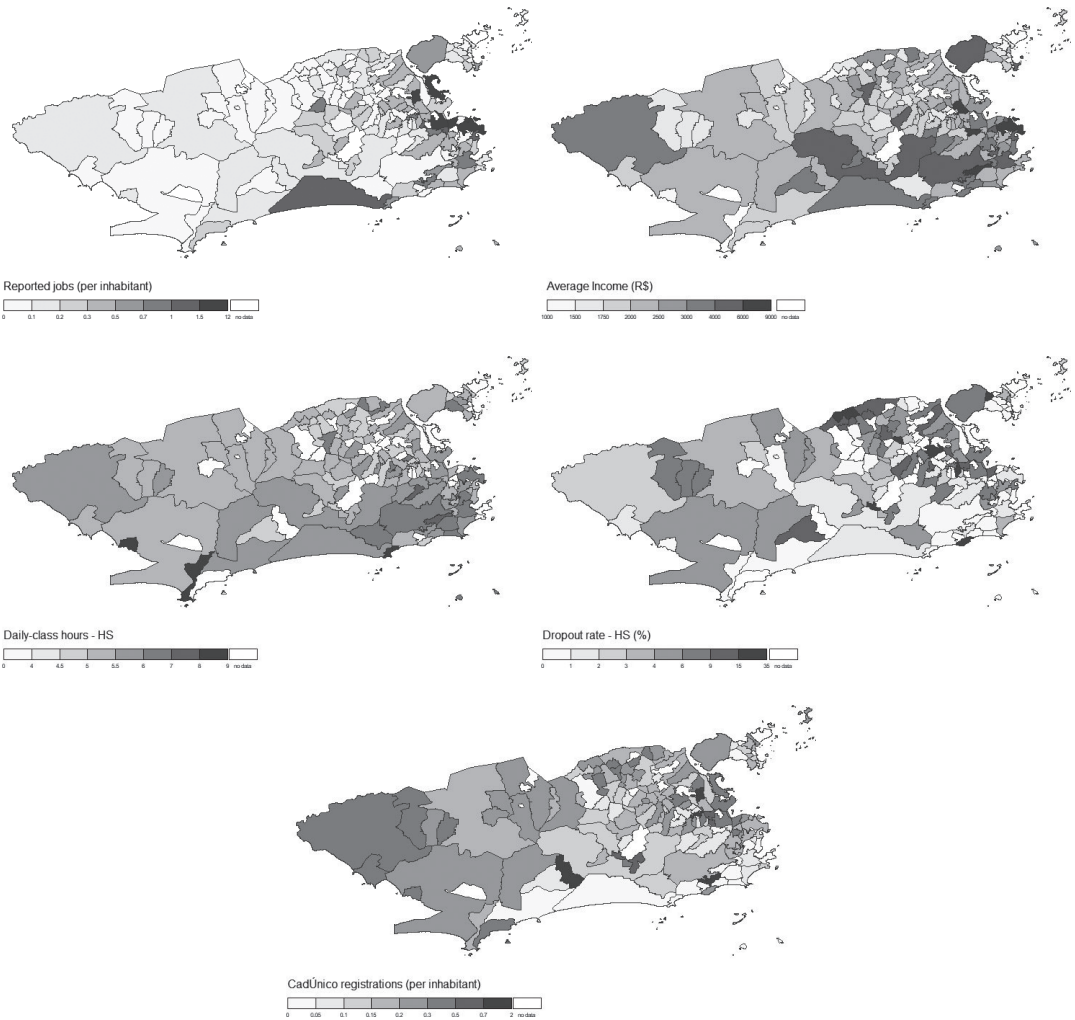


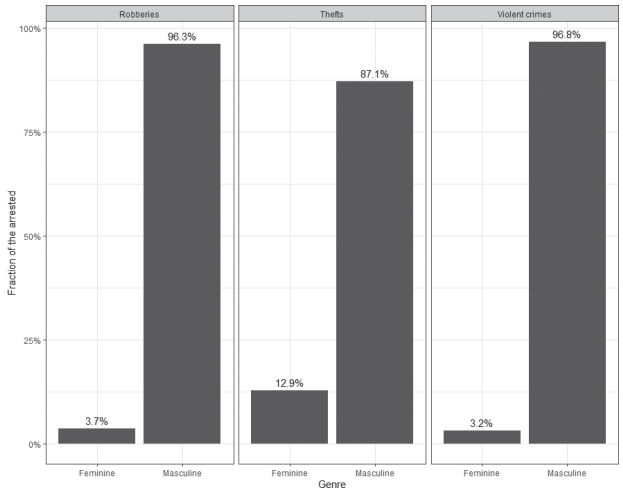
Figure 4 – Socioeconomic and educational conditions



8.3. *Statistics from arrested criminals*

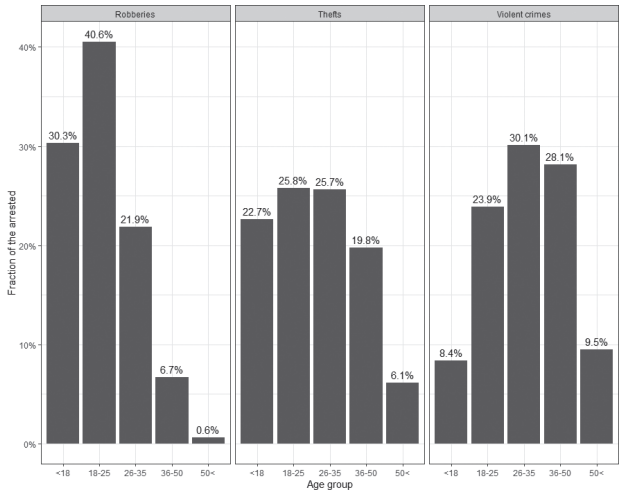
8.3.1. *Statistics referring to all the arrested criminals*[2]

Figure 5 – Genre distribution among arrested criminals



8.3.2. *Statistics referring to arrested criminals over 18 years old*

Figure 6 – Age distribution among arrested criminals



[2] Data referring to criminals arrested for crimes in Rio de Janeiro between 2016 and 2018 with known age, gender, education, and profession.

Figure 7 – Employment distribution among arrested criminals

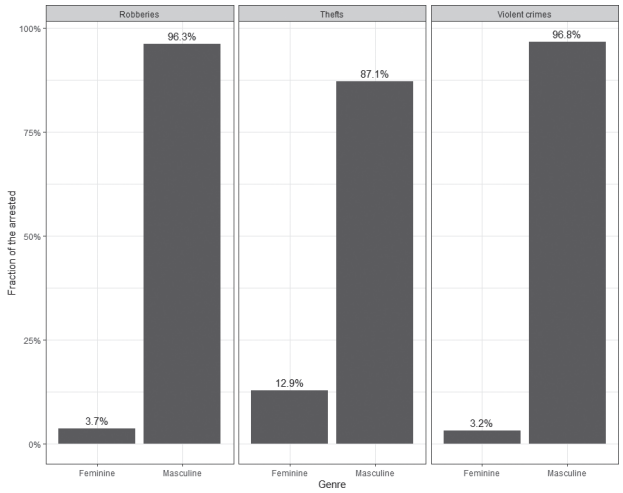
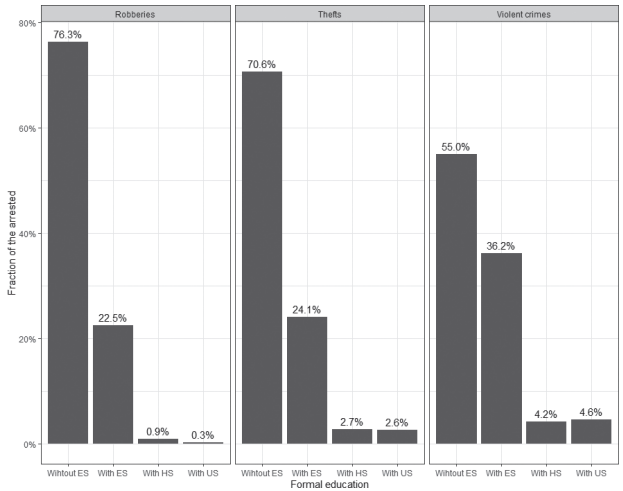


Figure 8 – Schooling distribution among arrested criminals[3]



[3] ES = Elementary Schooling, HS = High Schooling e US = University Schooling