

# **ARTIGO**

# THE SOCIOECONOMIC DETERMINANTS OF CRIME IN BRAZIL: THE ROLE OF SPATIAL SPILLOVERS AND HETEROGENEITY

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## ABSTRACT

This paper aims to examine the determinants of crime in Brazil's 5,565 municipalities, considering the presence of possible spatial spillovers and heterogeneity. We confirmed the existence of both effects and, to control them, we estimated spatial models with regimes for the five macro-regions of Brazil: North (N), Northeast (NE), Southeast (SE), South (S) and Central-West (CW). Among our results, we found that population size is important for explaining crime in all regions, while population density is significant only in the NE and CW. The Economic-Educational (EE) and Social Disorganization (SD) Factors, constructed using factorial analysis, are also significant for all regions, except the EE factor in the N and the SD factor in the NE. We emphasize the fact that the EE factor coefficients had different signs and magnitudes depending on the region, while social disorganization induces crime in all regions. Social inequality leads to criminality only in the South and the spatial coefficient  $\rho$  (Rho) is significant and positive for all regions, indicating that homicides in nearby municipalities increases the likelihood of violent crime locally due to spatial spillovers. Therefore, a spatial approach that considers geographic patterns, spatial spillovers and heterogeneity can help with the design of better public security policies that focus on each local reality. **Keywords**: Crime; Homicide; Spatial Spillover; Heterogeneity.

### RESUMO

### OS DETERMINANTES SOCIOECONÔMICOS DA CRIMINALIDADE NO BRASIL: O PAPEL DAS EXTERNALIDADES E HETEROGENEIDADES ESPACIAIS

O presente artigo objetivou perscrutar os determinantes do crime nos 5.565 municípios do Brasil, considerando possíveis presenças de transbordamentos e heterogeneidade espaciais. Confirmou-se a presença de ambos os efeitos e, para controlá-los, foram utilizados modelos espaciais com regimes para as macro regiões do Brasil: Norte (NO), Nordeste (NE), Sudeste (SE), Sul (SU) e Centro-Oeste (CO). Dentre os resultados, o tamanho da população é importante para explicar o crime em todos os regimes enquanto a densidade demográfica é significativa apenas para o NE e CO. O Fator Econômico e Educacional (EE) e de Desorganização Social (DS), construídos com análise fatorial, também foram significativos para todas as regiões, com exceção do EE no todo e DS no NE. O Fator EE apresentou coeficientes com sinais e magnitudes diferentes a depender da região enquanto a desorganização social é indutora de criminalidade em todas as localidades. A desigualdade social é significante apenas no Sul do país e o coeficiente espacial p (Rho) é significante e positivo para todas as regiões, indicando que homicídios em municípios vizinhos aumenta a probabilidade de crime violento localmente devido a presença de transbordamentos espaciais. Portanto, a abordagem espacial adotada, ao considerar padrões geográficos, transbordamentos e heterogeneidade espacial, pode auxiliar no desenho de melhores políticas de segurança pública focalizadas para cada realidade local. **Palavras-chave:** Criminalidade; Homicídio; Transbordamentos Espaciais; Heterogeneidade.

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# **1. INTRODUCTION**

The homicide rate in Brazil has been increasing in recent decades and has become an obstacle to the social and economic development of the country, due to the high costs it imposes on society. According to the *Relatório de Conjuntura Nº 4* (2018)<sup>1</sup> the cost of crime in Brazil grew sharply between 1996 and 2015 from about R\$113 billion to R\$285 billion, an average increment of 4.5% per year, and representing 4.38% of the national income. According to Murray *et al.* (2013), the economic cost of crime in Brazil has a profound impact on people's quality of life and is associated with many of the country's social costs, such as healthcare, security, prisons, loss of human capital, personal losses, etc.

Brazil witnessed 13,910 homicides in 1980, a relatively small number when compared with the 49,932 homicides of 2010, according to the *Mapa da Violência* (2012). This represents an increase of approximately 260% in the period, a growth rate of 4.4% per year. Reports from the *Fórum Brasileiro de Segurança Pública* (FBSP) point out that in 2016, 61,283 murders were recorded, a rate of 30.5 deaths per 100,000 inhabitants; this is the largest number of violent deaths recorded in Brazilian history. These numbers make Brazil one of the most violent countries in the world. The World Health Organization (WHO) ranked the country as having the ninth highest homicide rate in the world and the fifth in the Americas, behind only Colombia (48.8), Venezuela (51.7), El Salvador (63.2) and Honduras (85.7).

The data above suggest a failure in the public security mechanisms of the Brazilian State, which is unable to manage and promote effective public policies for increasing the population's quality of life. In this paper we have compiled a brief review of the literature on the Economic Theory of Rational Choice and the Social Disorganization Theory. These theories are important for understanding the factors that have an influence on individuals and lead them to crime. We then undertook an empirical investigation into the crime rate in Brazilian municipalities, using the number of homicides per 100,000 inhabitants as a proxy, following the suggestion of Murray *et al.* (2013) that Brazil's homicide statistics are its most reliable data on local violence, as well as being highly correlated to other types of crime. The main purpose is to search for the determinants of criminal activity in Brazil and compare them with current theories on the subject. We only identified four papers that encompassed all Brazil's municipalities (5,565) in an empirical investigation, namely those by: Oliveira (2005), Ingram and Costa (2016), Peres and Nivette (2017) and Barros *et al.* (2019).

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The paper also aims to adopt a spatial approach to characterizing the distribution of homicides at the municipal level. We specifically look for the presence of spatial dependence and heterogeneity, as well as the formation of significant clusters throughout Brazil, since violence in one place may spread to nearby municipalities and have different determinants and diffusion factors across regions. Some of the papers identified the importance of the spatial and heterogeneity components for explaining the determinants of crime and its distribution in some of the regions (ALMEIDA *et al.*, 2005; OLIVEIRA, 2008; ALMEIDA AND GUANZIROLI, 2013; PLASSA AND PARRÉ, 2015; ANJOS JÚNIOR *et al.*, 2016) and in Brazil as a whole (INGRAM AND COSTA, 2016; BARROS *et al.*, 2018). To achieve our proposed objective, we use Exploratory Spatial Data Analysis (ESDA) and Spatial Econometrics as tools for identifying and measuring these spatial effects.

Waiselfisz (2010), Murray *et al.* (2013), and Andrade and Diniz (2013) argue that there are important regional differences in homicide rates and trends in Brazil. According to these authors, violent crimes were spatially concentrated in state capitals and metropolitan regions until the late 1990s, but recently there has been a persistent upturn in the incidence of such crimes in rural areas. Considering the relative shortage of empirical work at the municipal level for the country as a whole, the Brazilian federal entities could use these results as instruments for their public security planning, with the aim of implementing effective public policies for promoting safety in the country. This idea is reinforced by the fact that, because of its explicitly spatial approach, our research highlights the geographical patterns, spatial spillovers and heterogeneity that have an influence on violence in Brazil, which can help with the design of effective public policies aimed at inhibiting crime.

In addition to this introduction, this paper is structured in four other sections. In the second, we present the theoretical framework of the Economic Theory of Rational Choice and the Social Disorganization Theory, which enabled us to choose the right variables for the required statistical and econometric modelling. In the third section, we detail the methodology and database used in the paper. The results and our analysis of them are set out in the fourth section, while the fifth section presents our final considerations.

# 2. THEORETICAL FRAMEWORK

### 2.1 ECONOMIC THEORY OF RATIONAL CHOICE

This theory was developed by Gary Becker (1968) and seeks to understand crime from the viewpoint of the rational choice of individuals as they attempt to maximize utility. Becker (1968) functionally formalized this relationship as follows:

### $\theta_{i} = \theta_{i} \left( \rho_{i} f_{i}, u_{i} \right)$

where  $\theta_j$  is the number of crimes committed by individual *j*, which is a function of the probability of being convicted  $\rho_j$  and the punishment when found guilty  $f_j$ . Finally,  $u_j$  is a variable that represents other possible influences on decision-making, such as education and expected income from legal activities.

According to Becker (1968), an increase in  $\rho_j$  or  $f_j$  is responsible for the decrease in the number of crimes committed, because it raises the opportunity cost of the individual without a counterpart in an increase in benefits. This relationship becomes evident when we consider the expected utility function of individual *j* (*EU*<sub>*i*</sub>):

$$EU_{j} = \rho_{j} U_{j} (Y_{j} - f_{j}) + (1 - \rho_{j}) U_{j} (Y_{j})$$
<sup>(2)</sup>

which is an increasing function of the benefit resulting from offense,  $Y_{j}$ . There have also been several theoretical and empirical advances based on the theory in question. In this paper, we present the work of Ehrlich (1973), Block and Heinecke (1975) and Zhang (1997), which will be analyzed for the purpose of serving as a theoretical basis.

Among other points, Ehrlich's research (1973) added to Becker's by indicating the optimal allocation of time t to the formal/lawful l (safe) or illicit i (risky) market. Like Becker (1968), Ehrlich (1973) assumes that the individual behaves to maximize their expected utility, but now with s possible states of nature, which results in

$$U_{s}=U(X_{s}t_{c}) \tag{3}$$

where  $X_s$  denotes an abstract good of the economy (including returns from legitimate and illegitimate activities) in state *s*;  $t_c$  is the time devoted to consumption (or activities not related to markets). We can represent the expected utility in a general way as:

$$EU(X_{s}t_{c}) = \sum_{(s=a)}^{n} \pi_{s}U(X_{s}t_{c})$$
(4)

where  $\pi_s$  is the probability of the occurrence of state *s*.

Based on Becker (1968) and Ehrlich (1973), Block and Heinecke (1975) state that the problem of offense supply was formulated in terms of a structure of multifactorial preferences, given the ethical and psychological differences involved in the decision-making process, which took into account aspects other than just income. The authors demonstrated that the results of Becker (1968) and Ehrlich (1973) are valid only if legal and illegal activities are monetarily equivalent, and if they are independent of the level of wealth, as in the utility function:

$$U=U(L,T,W) \tag{5}$$

where *L* indicates the time devoted to legal activities, while *T* refers to the time devoted to illicit activities; *W* is the level of wealth of the individual; and *U* is a Neumann-Morgenstern utility indicator. The author also assumes that  $\partial U \partial W > 0$ ,  $\partial U \partial L < 0$  and  $\partial U \partial T < 0$ , so an increase in wealth raises the utility of the agent, while the increase in the time devoted to legal and illegal activities decreases. According to Block and Heinecke (1975), the explicit inclusion of the variables *L* and *T* is intended to clarify the role of morality and ethics in the decision-making process. The function of spending time on legal and illegal activities is determined by:

$$\max_{L,T} \int U[L,T,W^0 + rL + (V - aF)\theta] f(a) da$$
(6)

where *r* is the rate of return on legal activities and *V* is the return on illegal ones; *a* is a real stochastic rate of failure, apprehension and being condemned for engaging in illegal activities, restricted to  $0 \le a \le 1$ ; and *F* is the penalty for a committed crime.  $\theta$  is the number of crimes, which is related to the time dedicated to illicit activities,  $\theta = \theta(T)$ , with  $\theta^{\wedge}$ ; *(T)*>0. Unlike Becker (1968) and Ehrlich (1973), Block and Heinecke (1975) emphasize the role of the relationship between marginal preference in legal activities  $U_t$  when compared

with illegal activities  $U_r$ . If  $U_L - U_r > 0$ , Block and Heinecke (1975) claim that the individual has a *preference* for honesty, which would induce them to practice fewer crimes.

Zhang (1997) developed a formal model that included the existence of social programs that would enable the individual to access a minimum level of wellbeing. The author's main proposal was to verify the impact of these transfers on the comparative time the individual allocates to legal and illegal activities. The initial hypothesis is:  $t_i$  is the time devoted to illegal activities, with two possible scenarios, 1) *b* the likelihood of being apprehended, and 2) *1-b* the probability of being successful. In Scenario 2), the individual will have an income of  $I_2=A+W+G(t_i)$ , where *A* represents the initial income, *W* is the amount received from the transfer program and  $G(t_i)$  is the net income obtained from the illicit activity. In Scenario 1), the individual will have an income of  $I_1=A+G(t_i)-F(t_i)$ , in which  $F(t_i)$  represents the punishment when apprehended, which also results in the loss of the benefit from the transfer program, *W*. Zhang (1997) assumes a Von Neumann-Morgenstern utility:

 $EU = (1-b)U(I_{1}) + bU(I_{2}) = (1-b)U[A + W + G(t_{i})] + bU[A + G(t_{i}) - F(t_{i})]$ (7)

where the objective is to maximize  $t_i$  subject to  $0 \le t_i \le N$ , with N being the total amount of time available. The first order condition is:

 $D_{1} = (1-b)U'(I_{1})G'(t_{i}) + bU'(I_{2})[G(t_{i}) - F(t_{i})]$ (8)

which would be satisfied if  $U^{*}<0$ . If the individual is risk averse,  $U^{*}<0$ , the time spent on illegal activities is reduced because of the increased income provided by the transfer policy. According to Zhang (1997) this occurs because the income obtained from the transfer decreases the marginal utility obtained from illicit activities. However, the author does not discard the possibility of the transfer leading to an increase in the level of crime, because if the individual is a risk-lover  $U^{*}>0$ , the extra income can make them devote less time to legal activities (with a lower return) as they seek more risky, crime-related activities (with a greater return).

### 2.2 SOCIAL DISORGANIZATION THEORY

Shaw and Mckay's (1942) Social Disorganization Theory states that socioeconomic factors are important for explaining crime, which is mainly caused by the effects of demographic collapse due to the process of uncontrolled urbanization. This scenario culminates in a negative socioeconomic environment for the population, such as poor housing conditions, an inappropriate family environment (domestic violence, or the absence of a paternal figure, etc.), unemployment, among others. Therefore, population growth associated with the increase in urbanization and demographic density is often one of the initial drivers of social disorganization. According to Peres and Nivette (2017), this context leads to a weakening of the community's capacity to hold common beliefs and exert social control. The authors argue that some structural social conditions, such as poverty, ethnic heterogeneity and family disruption caused by the absence of a paternal figure, for example, weaken society's ability to maintain social ties and norms, thereby increasing the likelihood of crime. In this context, according to the authors, neighborhoods rely mostly on illegal and violent forms of conflict resolution.

Glaeser and Sacerdote (1999) also claim that the degree of urbanization and demographic density are relevant factors for understanding crime. The authors argue that high demographic density results in anonymity among individuals, making it difficult to identify criminals, which makes the likelihood of

successfully committing a crime exceed the chances of being detained, thus encouraging illegal activities. According to Peres and Nivette (2017), the Social Disorganization Theory is a theoretical perspective that helps explain the spatial concentration of crime in densely populated urban centers. In fact, Uchôa and Menezes (2012), Resende and Andrade (2011), and Becker and Kassouf (2017) provide empirical evidence that supports the contention that urbanization is important for explaining crime in Brazilian states.

It is important to note that the problem of social disorganization does not affect the whole of the population equally. According to Araújo Jr and Fajnzylber (2001), young people are most susceptible to socioeconomic problems in Brazil, and the group that is most likely to commit murder. Loureiro and Carvalho Junior (2007) found evidence showing that individuals between 15 and 24 years old play a decisive role when it comes to explaining crime in Brazil, because it is the group that suffers most and commits most of the homicides. Scorzafave and Soares (2009), and Becker and Kassouf (2017) also confirmed the relevance of unemployment for explaining crime in the country, especially among the young.

According to Suliano and Oliveira (2013), education acts as an inhibitor of crime, especially in young people. Better qualifications enable the individual to earn higher wages and have more opportunities in the legal employment market, thereby reducing their wish to take part in illegal activities. Kume (2004) argues that the homicide rate reduces by approximately 6% in the short term and 12% in the long term for every extra year's schooling. Becker and Kassouf (2017) found evidence to show that a 1% increase in spending on education can reduce homicide rates in the country by 0.1%. Finally, Barros *et al.* (2018) argue that socioeconomic development and education are important for reducing crime in Brazil.

In practice, the theoretical frameworks of the Economic Theory of Rational Choice and the Social Disorganization Theory helped us choose the variables used in the statistical and econometric modelling employed in this paper. In other words, these theories supported our efforts to outline potential influences on violent crime in Brazil.

### 3. METHODOLOGY AND DATABASE

This paper adopted the basic model proposed by Kelly (2000), which is defined as follows: Suppose that the total population in a municipality is N, then individuals could be the victims of a criminal act, which is an exponential function  $\delta$  of demographic density d, such that  $(\partial \delta(d))\partial d > 0$ . According to Kelly (2000), a high population density provides criminals with a large number of potential victims while reducing the risk of being caught. Only a fraction of the population, X, however, is willing to commit a criminal act, which is a function of several factors that are related to social disorganization and exclusion.

According to Kelly (2000), social inequality is also an important determinant of crime. With regard to Brazil, Mendonça *et al.* (2003) analyzed all the states in the country for the 1987-1995 period and found that inequality is, in fact, an important factor for inducing crime. The authors argue that consumption has a benchmark that is imposed by society's standards, which may result in individual dissatisfaction when it is not satisfied because of impossible economic conditions, which are especially evident in unequal societies. Loureiro and Carvalho Junior (2007), Scorzafave and Soares (2009), Resende and Andrade (2011) and Becker and Kassouf (2017) confirmed the importance of social inequality for understanding violence in Brazil. Kelly (2000) also argues that poverty, unemployment, family instability, etc., are also important for explaining crime, which is represented in the model by a vector *x*.

Kelly (2000) also argues that there are situations in which an individual who is predisposed to commit crime meets a potential victim, which occurs at an exponential rate of  $X\delta N$ . In other words, the larger the population, demographic density and proportion of the population prone to committing crime, the greater the rate. Not all criminal opportunities, in fact, result in a crime, because a certain fraction (1- $\pi$ ) of these opportunities is judged to be too risky in terms of subsequent capture and punishment, so only the n fraction actually leads to a crime being committed. This is a function of the institutional conditions of the country and its regions. Finally, Kelly (2000) proposes a model that represents the number of crimes as a Poisson process, with an expected value

 $\lambda = \pi X \delta N \tag{9}$ 

For the estimation, a log-linear relationship is assumed to exist between the variables, as:

 $log(\lambda_m) = \beta_0 \ log(d_m) + \beta_1 \ log(N_m) + \beta_2 \ log(Gini_m) + \beta_3 \ log(X_m)$ (10)

where  $\lambda_m$  is the number of crimes committed;  $d_m$  is demographic density;  $N_m$  is the size of the population;  $Gini_m$  is the inequality represented by the Gini index;  $X_m$  is a vector of variables related to socioeconomic conditions; and subscript *m* refers to the 5,565 Brazilian municipalities. According to Kelly (2000), however, the model tends to suffer from multicollinearity, due to the large correlation between the variables that are included, especially those linked to vector *X*. To solve the multicollinearity problem, Peres and Nivette (2017) conducted a principle-component factor analysis to reduce the dimensions of the variables, and then combined the social-structural disadvantage effects into the aggregated indicators that are linearly independent.

This paper seeks to resolve the multicollinearity problem by using aggregated indicators that are constructed using factorial analysis, according to Peres and Nivette (2017). This technique makes it possible to include a large number of variables that can explain crime in Brazil, thus avoiding the poor specification bias of the model, while dealing with the multicollinearity. The first step is to check the suitability of the sample, which is performed by way of the *Kaiser-Meyer-Olkin* (KMO) test and the Bartlett sphericity test. The second step is to extract the factors from the dataset using the Principal Component Method. Factorial analysis relates the  $Z_i$  variables and the k common factors linearly, which are extracted as:

$$Z_{i} = l_{i1} F_{i} + \dots + l_{ik} F_{k} + \varepsilon_{i}$$
  

$$\vdots \qquad \vdots \qquad \vdots$$
  

$$Z_{p} = l_{p1} F_{p} + \dots + l_{pk} F_{k} + \varepsilon_{p}$$
  
(11)

or in a matrix by

 $D(X-\mu) = LF + \varepsilon \tag{12}$ 

*F* being a random vector containing *k* factors, which seek to summarize the *p* variables ;  $\varepsilon$  is a random error vector, which contains that part of *Z<sub>i</sub>* that is not explained by the *F<sub>j</sub>* factors, with *j*=1,2,...,*k*  $\in$  N; *L* is a matrix of the *I<sub>ij</sub>* (loadings) parameters to be estimated, which represent the degree of linear relationship between *Z<sub>i</sub>* and *F<sub>j</sub>*. The variability coming from the random error is called uniqueness, while the variability of the parameter matrix is called commonality.

Peres and Nivette (2017) argue that there are many exogenous sources of social disorganization. Among them, the authors highlight socioeconomic status (per capita income, absolute poverty, infant mortality rate, unemployment and education), ethnic heterogeneity (measured by the percentage of the population that is not white), family disruption (measured by the number of households headed by women) and the percentage of young people in the population. The variables used in the factorial analysis to represent the vector X of social and economic characteristics in the model, based on Peres and Nivette (2017), are shown in Chart 1, and all refer to the year 2010.

### CHART 1

Variables used in the factorial analysis model and their respective sources.							
	Variables	Source					
HDI	HDI – Human Development Index	ATLAS <sup>2</sup>					
Higher_education	Population with higher education (%)	IBGE <sup>3</sup>					
Income_pc	Average per capita income	ATLAS					
Illiterate_pop	Illiterate population (%)	IBGE					
Extremely_poor	Proportion of extremely poor people	ATLAS					
Primary_school	Population without primary school education (%)	ATLAS					
Unemployed_pop	Unemployed population (%)	IBGE					
Women_heads	Women as family heads (%)	ATLAS					
Non-white_pop	Non-white resident population (%)	IBGE					
Population_15-24	Population between 15 and 24 years old (%)	IBGE					
		Source: research data					

Source: research data.

In the econometric model, the dependent variable is the homicide rate per 100,000 inhabitants, which is available in SIM-DATASUS, and is a proxy that is widely used to represent the crime level of a particular region (SANTOS AND SANTOS FILHO, 2011; UCHÔA AND MENEZES, 2012; MURRAY et al., 2013). We also used an arithmetic mean of the years 2009, 2010 and 2011to represent 2010, in order to minimize the impact of random shocks. Finally, the explicit explanatory variables in the econometric estimation are: a) demographic density, defined as the total number of people in the population divided by the area of the municipality; b) the total population of the municipality; c) the per capita value of the Bolsa Família program for the municipality; and d) the Gini Index. Variables a), b) and c) are taken from the IBGE while d) comes from the Atlas of Human Development.

### 3.1 EXPLORATORY SPATIAL DATA ANALYSIS (ESDA) AND SPATIAL ECONOMETRICS

ESDA is a technique used to capture the effects of spatial dependence and spatial heterogeneity in the data used. ESDA is also able to capture spatial clusters, indicate how the data are distributed, show the occurrence of different spatial regimes or other forms of spatial instability (non-stationarity), and identify outliers (ALMEIDA, 2012). Moran's I is a statistic that seeks to capture the degree of spatial correlation between variables across regions; mathematically this statistic can be represented by:

$$I_t = \left(\frac{n}{S_0}\right) \left(\frac{z_t' W z_t}{z_t' z_t}\right) \ t = 1, \dots n$$
(13)

)

Atlas of Human Development (2013).

<sup>3</sup> Demoaraphic Census (2010).

where n is the number of regions,  $S_o$  is a value equal to the sum of all elements of matrix W, z is the normalized value of the variable of interest, and Wz is the mean value of the normalized variable of interest in neighboring regions according to a weighting matrix W.

According to Almeida (2012), the LISA (Local Indicator of Spatial Association) statistic has two characteristics: (i) for each observation it should be possible to indicate the existence of spatial clusters that are significant; and ii) the sum of local indicators in all places should be proportional to the global spatial autocorrelation indicator. The local Moran I statistic (LISA) is:

$$I_{i} = z_{i} \sum_{j=1}^{J} w_{ij} z_{j}$$
(14)

where  $z_i$  represents the variable of interest of the standardized region *i*,  $w_{ij}$  is the spatial weighting matrix element (*W*) and  $z_j$  is the value of the variable of interest in standardized region *j*. The spatial component is incorporated into the econometric model essentially with spatially lagged variables. This model is represented mathematically as follows:

$$y = \rho W y + X \beta + \xi$$
(15)  
$$\xi = \lambda W \xi + \varepsilon$$

where X is the matrix of explanatory variables;  $\beta$  is the  $k \times 1$  vector of the regression coefficients; and  $\varepsilon$  is the error term. The Spatial Autoregressive Model (SAR) is obtained by imposing the following constraints on the model (12):  $\rho \neq 0$ ,  $\tau=0$  e  $\lambda=0$ . However, the model will suffer from the endogeneity problem of the lagged variable. Therefore, it must estimate it with instrumental variables, normally using the explanatory variables (WX). The Spatial Error Model (SEM) emerges if  $\rho=0$ ,  $\tau=0$  and  $\lambda\neq 0$ , that is, when spatial dependence manifests itself in the error term. According to Kelejian and Prucha (1999), the model should be estimated with maximum likelihood (MV), or by GMM.

In an analysis covering all 5,562 Brazilian municipalities, Ingram and Costa (2016) observed that violence in neighboring regions has a positive effect on local violence (spatial spillover) and that there is considerable heterogeneity in homicides throughout Brazilian municipalities. According to Almeida (2012), the use of spatial econometric models, together with spatial regimes, is capable of simultaneously controlling spatial dependence and heterogeneity. Here, therefore, we will use five spatial regimes, one for each of the major regions as defined by the IBGE: I) North; II) Northeast; III) Southeast; IV) South; V) Central-West. The model with <sup>4</sup> spatial regimes is:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_g \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \dots & 0 \\ 0 & \ddots & 0 & \vdots \\ \vdots & 0 & \ddots & 0 \\ 0 & \dots & 0 & X_g \end{bmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_g \end{bmatrix} + \begin{bmatrix} \xi_1 \\ \vdots \\ \xi_1 \end{bmatrix} \qquad \xi \sim Normal \ (0, \Omega)$$
 (16)

Spatial regimes should not be used in econometric models if they do not contribute to the adequacy of the model when compared to the global model. Therefore, a test needs to be performed to verify if the regimes are adequate; this is known as the Spatial Chow test:

$$C = \left\{ \frac{(e'_r e_r - e_{IR}' e_{IR})/k}{(n-2k)} \right\}$$
(17)

where  $e_r$  is the error of the restricted model as estimated by MQO; and  $e_{IR}$  is the error for the unrestricted form for the whole sample. The null and alternative hypotheses are respectively:

$$H_0: y = X\beta + \varepsilon \qquad H_1: y = \begin{bmatrix} X_1 & 0 & \dots & 0 \\ 0 & \ddots & 0 & \vdots \\ \vdots & 0 & \ddots & 0 \\ 0 & \cdots & 0 & X_m \end{bmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \vdots \\ \beta_m \end{bmatrix} + \varepsilon \qquad (18)$$

The test follows an *F* distribution with *k* and (n-mk) degrees of freedom. In the case of spatial structural stability, we shall have  $H_0: \beta_1 = \ldots = \beta_m$ , so the coefficients for each spatial regime will be similar, resulting in similarity with the global model. If not, the coefficients will be different and capture the heterogeneity contained in the sample, thus inducing non-acceptance of the null hypothesis.

### 4. SPATIAL DISTRIBUTION AND THE SOCIOECONOMIC DETERMINANTS OF CRIME IN THE BRAZILIAN MUNICIPALITIES

The application of factorial analysis to the ten socio-economic variables linked to social disorganization, which were described in the previous section, enabled two factors to be extracted that have characteristic roots greater than one ( $\lambda_{i\geq 1}$ ). Table 1 shows the factors obtained, with their respective characteristic roots, explained variance and cumulative variance. The two factors were able to explain approximately 76.54% of the variance in the variables. Therefore, the two factors are able to summarize the variables relatively well, especially considering they are social variables.

The Kaiser-Meyer-Olkin (KMO) test of the sample's suitability for the factorial analysis model presented a value of 0866, indicating that the set of variables has a sufficiently high correlation for the method use. Bartlett's sphericity test is also statistically significant<sup>4</sup>, thus rejecting the null hypothesis that the correlation matrix is equal to the identity matrix. Therefore, from both tests, the sample is suitable for the factorial analysis method.

Characteristic root, variance explained by factor and cumulative variance.								
Characteristic root	Variance explained by factor (%)	Cumulative variance						
5,21625	52,16	52,16						
2,43753	24,38	76,54						
	Characteristic root 5,21625	Characteristic rootVariance explained by factor (%)5,2162552,16						

### TABLE 1

Source: research data.

Finally, we performed orthogonal rotation of the factors using the Varimax method; the results are shown in Table 2, which presents the factorial loads of each factor, as well as the uniqueness of each variable. The variables are considered according to their contribution to the factor, and the absolute value of

4 Chi-square: 56715,548; Degrees of freedom: 45; p-valor: 0,000

the factorial loads, which are highlighted in bold. Factor 1 is related to six of the ten variables used and presents a positive relationship with three and a negative relationship with the remaining one. Among the positives, we have: HDI, Human Development Index; Higher Education, population with higher education (%); and Income\_pc, average per capita income. These variables are associated with the economic and educational development of the municipalities. The higher the values for these variables, the more the municipality is characterized as being a place that provides good social conditions.

### TABLE 2

Factorial loadings and commonality							
Factorial							
F1	F2	Uniqueness					
0.9536	-0.1997	0.0508					
0.8919	-0.0098	0.2045					
0.8884	-0.2254	0.1600					
-0.8852	0.3347	0.1044					
-0.8575	0.3023	0.1734					
-0.8537	-0.0295	0.2703					
-0.1140	0.8439	0.2747					
0.0909	0.7770	0.3880					
-0.5116	0.7062	0.2396					
-0.4377	0.5725	0.4806					
	Factorial           F1           0.9536           0.8919           0.8884           -0.8852           -0.8575           -0.8537           -0.1140           0.0909           -0.5116	Factorial loadings           F1         F2           0.9536         -0.1997           0.8919         -0.0098           0.8884         -0.2254           -0.8852         0.3347           -0.8575         0.3023           -0.8537         -0.0295           -0.1140         0.8439           0.0909         0.7770           -0.5116         0.7062					

Source: research data.

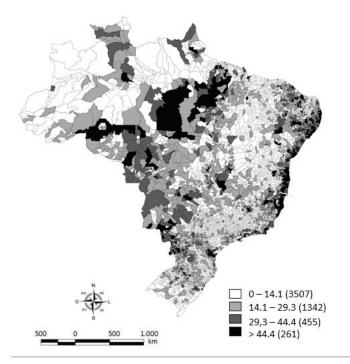
The negatives, on the other hand, are: Illiterate\_pop, illiterate population (%); Extremely\_poor, proportion of extremely poor people; and Primary\_school, population (over 18 years old) without a primary school education. High values (in absolute terms) for the variables are related to low economic and educational development, thus justifying the inverse impact of the variables cited in the previous paragraph. Because Factor 1 captures these characteristics, it is called the *Economic and Educational Factor* of Brazilian municipalities.

Factor 2 is related to four of the ten variables, all with a positive impact: Unemployed\_pop, unemployment (%); Women\_heads, women who are heads of the family (%); Non-white\_pop, non-white resident population (%); and Population\_15-24, population between 15 and 24 years old (%). We called Factor 2 the *Social Disorganization Factor*, since it is linked to social and individual characteristics (BURSIK, 1998; LOUREIRO AND CARVALHO JUNIOR, 2007; PERES AND NIVETTE, 2017).

To better understand how crime is distributed throughout the country, Figure 1 shows the homicide rate (per 100,000 inhabitants) in Brazilian municipalities. We can observe that the homicide rate is essentially concentrated in three regions: i) Coastal areas with a large population concentration; ii) the agricultural frontier, located especially in Pará, Mato Grosso and Rondônia; iii) border regions in Paraná and Mato Grosso do Sul that have high flows of people. This is in line with the empirical evidence found by Waiselfisz (2011), Andrade *et al.* (2013), Steeves *et al.* (2015), Ceccato and Ceccato (2017), who also identified high crime rates in regions i), ii) and iii). These authors also indicate that ii) and iii) are mainly responsible for the "Interiorization of crime" hypothesis in Brazil. Santos and Santos Filho (2011), Steeves *et al.* (2015), Ceccato and Ceccato (2017), which is raditionally violent places, like most state capitals and metropolitan regions, crimes rates have stabilized or declined.

### **FIGURE 1**

Homicide rate distribution per 100,000 inhabitants in Brazilian municipalities.



Source: research data.

The spatial concentration of the homicide rate in municipalities is visible in the country (Figure 1). Moran's I coefficients, shown in Table 3, confirm this hypothesis, since the values are positive and statistically significant at 1%, regardless of the convention matrix applied. Thus, municipalities with a high homicide rate tend to be surrounded by those that also have high crime rates.

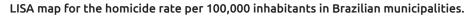
### TABLE 3

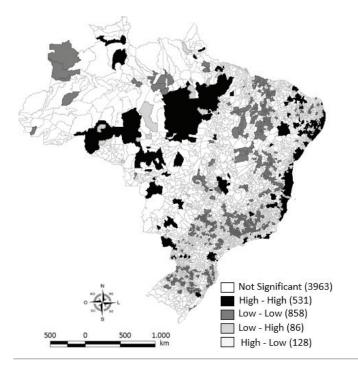
Moran's I for the homicide rate. 2010.		Weight	s Matrix	
	Three neighbors	2	Seven neighbors	Ten neighbors
Homicide rate per 100,000 inhabitants	0.48*	0.46*	0.45*	0.43*
				Source: research data. r: * Significance at 1%.

On the other hand, the LISA map in Figure 2 identified spatial clusters for the homicide rate. The positive spatial concentrations (High-High and Low-Low) are generally similar to those in Figure 1 (not considering spatial clusters). There is a large spatial concentration of homicides along the Amazon agricultural frontier as there is on the Brazilian coastline, especially in the Northeast. Some cities, such as Curitiba and Rio de Janeiro, also have a similarly high crime rate spatial association. According to Andrade *et al.* (2013), Plassa and Parré (2015), Anjos Junior *et al.* (2016), the Curitiba metropolitan region has the largest concentration of municipalities with a high crime rate in the South. A police force is the best policy for reducing crime in the region, since poverty and socioeconomic conditions do not explain the homicides in this metropolitan region of Curitiba.

Cerqueira (2010) claims that in the city of Rio de Janeiro alone, the annual cost of crime is as much as 5% of the city's GDP. Ceccato and Ceccato (2017) stress the fact that the Brazilian coastline has historically high crime rates that are due, among other influences, to "predatory tourism" with a considerable number of tourists being attracted to the city, especially in the summer, which can have an influence on its homicide rates. Chimeli and Soares (2017) found evidence for Pará State showing that illegal logging is an important driver of crime in the state, while Andrade *et al.* (2013), Ceccato and Ceccato (2017) and Waiselfisz (2016) emphasize the role of conflicts involving the use of land in states on the agricultural frontier.

### **FIGURE 2**





Source: research data.

The OLS regressions performed as a first attempt to model the determinants of crime in Brazilian municipalities are shown in Table 5; there are two components. The first component corresponds to the coefficients and their respective standard deviations, t-statistics and the p-value. The Jarque-Bera and Koenker-Basset tests are presented in the second component. We also check for possible correlations between the variables used (Appendix A) in order to avoid multicollinearity problems, since this is a current problem in model estimation, as Kelly (2000) suggests. We find no extremely high correlations that might compromise the estimation of the model, with the exception of the *Bolsa Família* and the Economic and Educational Factor that are correlated negatively. In other words, the *Bolsa Família* per capita value destined for the municipality is related to the region's economic and educational characteristics. To avoid the multicollinearity problem, therefore, we estimated the following models using only the Economic and Educational Factor, since it is indirectly linked to the *Bolsa Família* program.

TA	B	LE	5
	-		-

OLS Regression.									
Coefficient	Standard deviation	<b>T-statistics</b>	P-value						
-0.7841**	0.1170	-6.7033	0.0000						
-0.0520**	0.0081	-6.4561	0.0000						
0.0592**	0.0092	6.4322	0.0000						
0.0163	0.0141	1.1544	0.2484						
0.4339*	0.1749	2.4800	0.0132						
0.4363***	0.0214	20.3788	0.0000						
119.733**			0.0000						
537.527**			0.0000						
	-0.7841** -0.0520** 0.0592** 0.0163 0.4339* 0.4363*** 119.733**	-0.7841**0.1170-0.0520**0.00810.0592**0.00920.01630.01410.4339*0.17490.4363***0.0214119.733**	-0.7841**0.1170-6.7033-0.0520**0.0081-6.45610.0592**0.00926.43220.01630.01411.15440.4339*0.17492.48000.4363***0.021420.3788119.733**						

Source: research data.

Note: \*\* Significant at 1%; \* Significant at 5%.

In Table 5, only the demographic density variable is not sufficiently statistically significant to explain crime in Brazilian municipalities. Moreover, due to the log-linear relationship between the model's variables, the results are presented in terms of elasticity, that is, in percentage terms. However, the Jarque-Bera test is statistically significant at 1%, so it is possible to reject the null hypothesis of residual normality. With regard to variance, the Koenker-Bassett test rejected the homoscedasticity hypothesis, also at 1% significance, indicating the presence of non-constant variance in the residuals, a fact that can invalidate statistical inference. According to Almeida (2012), the spatial heterogeneity present in the data, as noted in Figures 1 and 2, can also lead to structural instability in the regression parameters. In this context, methods need to be adopted for controlling these problems in order to obtain consistent results. Almeida (2012) stresses that spatial regimes are suitable for this purpose, since they can control spatial heterogeneity. The structural stability diagnosis for the OLS model is shown in Table 6.

### **TABLE 6**

Structural stability for heterogeneity and tests for spatial dependence.								
Individual Stability	Coefficient	P-value						
Constant	29.7210**	0.0000						
Economic and Educational Factor	87.0250**	0.0000						
Social Disorganization Factor	13.3110**	0.0099						
Demographic Density	147.0090**	0.0000						
Gini Index	35.0310**	0.0000						
Population	28.2420**	0.0000						
Spatial Chow Test	732.5770**	0.0000						
ML ρ (lag)	893.3310**	0.0000						
MLR ρ (robust lag)	75.4310**	0.0000						
ML λ (error)	886.9930**	0.0000						
MLR λ (robust error)	69.0930**	0.0000						

Source: research data. Note: \*\* Significant at 1%; \* Significant at 5%.

The spatial Chow test, which is required for checking the adequacy of the model for spatial regimes, proved to be significant at 1%. Therefore, the global OLS model in Table 5 may not be adequate due to the instability of the regression parameters, which makes the global coefficients inadequate. We also applied the test to all coefficients individually and all variables are statistically significant, highlighting the

presence of structural instability for the coefficients, which varies according to the region in the country. On the other hand, the Lagrange multiplier (LM) and the robust Lagrange multiplier (rLM) tests capture spatial autocorrelation in the model residual. The LM tests suggest that both the lag of the dependent variable and the error term should be adopted with a statistical significance of 1%. Using the rLM tests, both the lag ( $W_Y$ ) and error term ( $W\xi_p$ ) remained statistically significant at 1%, but due to the greater value for the  $\rho$  (lag), this is the pattern that best captures the spatial dependence in the residuals.

In this context, we should adopt the Spatial Autoregressive Model (SAR) with spatial regimes. Moreover, due to the non-normality and heteroscedasticity of the residuals, we used Kelejian and Prucha's (1999) Generalized Method of Moments, together with the robust error of White (1980), to estimate the SAR spatial regime model. In summary, the SAR spatial regime approach was able to control spatial autocorrelation in the residuals, since the Anselin-Kelejian test rejected the hypothesis of remaining spatial dependence in the error (Appendix B). It is worth mentioning that we chose the spatial lag matrix that generated the lowest coefficient for the Anselin-Kelejian test for each regime (Appendix B) to estimate the spatial models in Table 7, opting to use the five neighbors' matrix in the N, NE and SE regimes; three neighbors for the South; and seven neighbors for the Central-West. Therefore, we estimated the SAR model with spatial regimes for the I) North; II) Northeast; III) Southeast; IV) South; and V) Central-West. We note that the coefficients differ in terms of their statistical significance and magnitude for each spatial regime, thus corroborating the structural instability indicated by the spatial Chow test.

Mariahlar	Spatial Regimes							
Variables	(N)	(NE)	(SE)	(S)	(CW)			
Constant	-0.7605**	-1.2652**	-1.1113**	-0.4186	-1.6838**			
Economic and Educational Factor	0.1398**	-0.0101	-0.1173**	-0.1871**	-0.0989*			
Social Disorganization Factor	-0.0181	0.0604*	0.0613**	0.0928**	0.0997*			
Demographic Density	-0.0272	0.1958**	-0.0145	0.0419	-0.2081**			
Gini Index	-0.6978	-0.3559	0.3057	1.0343**	-0.2241			
Population	0.2950**	0.3510**	0.4483**	0.3979**	0.6178**			
Crime Spillover (p)	0.4949**	0.3623**	0.2982**	0.1965*	0.3525**			
Anselin-Kelejian test	0.0490	3.725	0.425	0.672	0.619			

### TABLE 7

Source: research data. Note: \*\* Significant at 1%; \* Significant at 5%.

Population size stands out in these results due to its 1% significance and its positive coefficient in all regions, indicating that an increase in municipal populations is one of the main factors explaining crime in Brazil. The results corroborate Kelly (2000), who argues that population size is an important inducer of crime. According to Glaeser and Sacerdote (1999) and Kelly (2000), a large population enables criminals to reduce their probability of being apprehended because they avoid recognition after the offense. Therefore, the results obtained here confirm the importance of population size for explaining crime in Brazil.

The Economic and Educational Factor is significant for explaining homicides for all regions, except for the NE, although it has coefficients with diverse signs and magnitudes in each case. In the North region, an increase in educational and economic levels results in an increase in homicides. One possible explanation for this empirical evidence is the way in which socioeconomic development has been evolving in this

region. Its development is linked to expansion of the agricultural frontier in the legally-defined Brazilian Amazon region5, which is often associated with social conflict, illegal activities and land grabbing. Chimeli and Soares (2017) argue that illegal logging is an important inducer of crime in the region, while Andrade *et al.* (2013), Ceccato and Ceccato (2017) and Waiselfisz (2016) emphasize the role of conflict related to the use of land, which leads to violent crime.

In the SE, S and CW, the economic and educational development effect occurs as expected, with an increase in education and wealth resulting in a reduction in crime. Therefore, growth in education and economic well-being implies a decrease in the benefits obtained from criminal activities, since its opportunity cost (a salary paid in the formal employment market, for example) would be superior to the proceeds of crime. This dissuades individuals from practicing illegal activities, which is in line with Becker's (1968) Economic Theory of Rational Choice propositions and their developments by Ehrlich (1973), Block and Heinecke (1975).

Demographic density, in its turn, is significant only in the NE and CW regions, both at 1%. However, the coefficient signs are different, with an increase in demographic density causing an increase in the crime rate in the NE, while in the CW it has an inverse relationship. In the NE region, the relationship is in line with Glaeser and Sacerdote (1999) and Kelly (2000), who argue that an increase in the demographic level makes social anonymity more possible, thus reducing the probability of being caught. This is also consistent with Becker's Rational Choice Theory (1968), since a lower probability of being caught reduces the individual's opportunity cost of committing a crime. In the CW region, on the other hand, the increase in demographic density leads to a reduction in homicides. This empirical evidence contradicts the literature on the subject and the reasons for this scenario require specific research.

The Gini Index, a proxy for socioeconomic inequality in the municipalities, was statistically significant only in the South region. It is the variable with the highest coefficient in absolute terms, indicating that it has the most relevant impact on crime in the region. This evidence contrasts with Mendonça *et al.* (2003), Loureiro and Carvalho Junior (2007), and Becker and Kassouf (2017), who analyzed all Brazilian states and found that inequality is an important factor for inducing crime in Brazil. This difference may relate to the geographical unit used by the authors, which can hide important information that eventually emerges at the municipal level. Neither did the authors consider the heterogeneity of crime in Brazil, a fact that can invalidate the global coefficients obtained. In short, by analyzing crime at the municipal level and observing spatial heterogeneity, the results presented in this paper can contribute to the literature on the determinants of crime in Brazil by revealing possible local patterns of social inequality that have an effect on violence.

The Social Disorganization Factor was statistically significant for the NE, SE, S and CW, with a positive coefficient for all regions. This result indicates that when there is greater social disorganization in the municipalities, there is a higher rate of homicides in those localities. Therefore, the results are coherent with the Social Disorganization Theory proposed by Shaw and Mckay (1942). In this theory, many social problems, like unemployment, domestic violence, the absence of a father figure, ethical heterogeneity, etc., can lead to disorganization in society, in its values and in the ties between individuals, leading to marginalization and, consequently, to crime.

The spatial coefficient  $\rho$  (Rho) is significant at 1% and positive for all regions, indicating that there are crime spillovers between municipalities. The results corroborate the empirical evidence of Ingram and

<sup>5</sup> All Northern states are part of the legally-defined Brazilian Amazon region.

Costa (2016) and Barros *et al.* (2018), suggesting that homicides in nearby municipalities increases the likelihood of homicides locally. We also note that the spatial spillover coefficient  $\rho$  (Rho) differs significantly between regions, from 0.19 in the South to 0.49 in the North. When using the SAR model, it is worth mentioning that, according to Lesage and Pace (2009), the explanatory variable effects are not fully provided by their respective coefficients  $\beta_k$ . This occurs because of the spatial interactions that exist between municipalities, which induces an indirect marginal effect spillover. The total impact must also consider these indirect effects, which are calculated with the equation:  $(1-\rho)^{-1} \beta_k$ , which we calculated for each regime in Appendix C.

In summary, the empirical evidence provided by this paper presented meaningful differences due to the regions' heterogeneity, especially after considering the spatial interactions between municipalities. This fact has several implications for policy design and future research, since it can significantly affect its results and consistency.

# **5. FINAL CONSIDERATIONS**

This paper sought to analyze crime determinants in Brazil, by adopting the empirical approach proposed by Kelly (2000). Due to multicollinearity between the socioeconomic variables chosen to capture important elements that could inhibit or induce crime, we adopted factorial analysis, following Peres and Nivette (2017), which resulted in two factors that synthesized the selected variables. The first captured economic and educational dimensions, while the second has many of the aspects of the Social Disorganization Theory. By including them in the econometric estimation, therefore, we avoided the multicollinearity problem while maintaining important dimensions of the inducers of crime. This is an important methodological contribution of this paper to the specialized literature, especially for those who are looking to adopt the Kelly (2000) approach.

We confirmed the existence of a positive spatial dependence for homicide, and the existence of significant spatial clusters throughout the country. In other words, municipalities with a high crime rate tend to have neighbors with similar features. We also identified the presence of structural instability in the crime rate in Brazil, caused by spatial heterogeneity. In this context, we estimated spatial model regimes considering the North (N), Northeast (NE), Southeast (SE), South (S) and Central-West (CW) regions of the country. The aim of this procedure was to treat both of the spatial effects, dependence and heterogeneity.

Among the econometric results, population size proved to be highly significant and gave a positive coefficient for all regimes, highlighting that population size is important for explaining violent crime in Brazil. In other words, considering the literature on the subject, a large population reduces a criminal's probability of being apprehended by reducing the chances of them being recognized. Demographic density, in turn, was significant only in the NE and CW regions, although with mixed results. A high demographic density leads to crime in the NE, which is in line with the literature, while in the CW we have an inverse relationship.

The Social Disorganization Factor proved to be statistically significant for all regions in the country, except in the North. For the other regions, besides showing how important this factor is for explaining crime, it resulted in a positive sign for all coefficients, indicating that greater social disorganization is linked to higher homicide rates. Therefore, social problems, like unemployment, domestic violence, the absence of a father figure, ethical heterogeneity, etc., cause disorganization in society, leading to marginalization and, consequently, to crime.

The Economic and Educational Factor, on the other hand, is not only significant in the NE region, although it is different in terms of its sign and magnitude to others that are significant. In the North, for example, there was a positive impact, while in the Southeast, South and Central-West it was negative. Therefore, for the North region, an increase in educational and economic standards results in a higher homicide rate. One possible reason is linked to the expansion of the agricultural frontier, which is associated with socioeconomic development, but also with land use conflicts and illegal activities. In the Southeast, South and Central-West, we had a negative effect as expected, with the increase in economic and educational standards resulting in a reduction in crime, which can be explained by an increase in opportunity cost (salary paid in the formal employment market, for example) that dissuades individuals from practicing illegal activities.

Another important result refers to the Gini Index, a proxy of the inequality found in the municipalities. Many theories and several empirical papers have claimed that this variable is one of the main causes of delinquency in Brazil. By considering spatial interactions and heterogeneity this paper, however, demonstrated that delinquency is only significant in the South region. In other words, the structural instability consideration for crime avoids inconsistent and biased coefficients, since it can hide important information that eventually emerges at the municipal level. Furthermore, the literature has not normally considered crime heterogeneity in Brazil, a fact that can invalidate the global coefficients obtained. In this context, this paper contributes to the literature by revealing possible local patterns of the social inequality effect on violence.

The spatial coefficient p (Rho) is also significant at 1% and positive for all regions, indicating that homicide in nearby municipalities increases the likelihood of violent crime locally due to spatial spillovers. In this context, we considered the presence of an indirect marginal spillover effect, providing the total effect for each explanatory variable, which contributes to a better quantification of the determinants of crime.

Finally, the approach adopted in this paper helped to identify the determinants of crime in Brazil better by controlling spatial interactions and heterogeneity with the multicollinearity problem, which avoided bias and inconsistency in the results. Since there are only a few empirical papers that consider all the municipalities in Brazil, our results can serve as a useful instrument for designing better public security policies. This fact is reinforced by the explicit spatial approach we adopted, which considered the geographical patterns, spatial spillovers and heterogeneity that have an influence on violence in Brazil, which can help by considering existing regional differences for designing policies that focus on the reality encountered in each locality.

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# **APPENDIX**

### **APPENDIX A**

Correlation of the variables used in the econometric estimation.

	Homic	Demo.Dens	Gini.Ind	BolsaFam	Econ.Factor	Econ.Factor Social.Factor		
Homicide	1.0000							
Demo.Density	0.2060	1.0000						
Gini Index	0.2215	-0.2062	1.0000					
BolsaFamilia	0.1178	-0.2500	0.4802	1.0000				
Econ.Educ.Factor	0.0032	0.3834	-0.3575	-0.8007	1.0000			
Social.Dis.Factor	0.3308	0.2071	0.3272	0.3477	0.0000	1.0000		
Population	0.4555	0.5230	0.2671	-0.0835	0.2680	0.5021	1.0000	

Source: research results.

### **APPENDIX B**

Anselin-Kelejian test - convention matrix decision.

	Spatial Regimes								
Weight Matrix	(NO)	(NE)	(SE)	(SO)	(CW)				
Three neighbors	0.945	6.262	1.085	0.672	0.708				
Five neighbors	0.049	3.725	0.425	1.403	1.067				
Seven neighbors	0.839	4.621	1.709	1.153	0.619				
Ten neighbors	1.052	5.033	5.439	1.304	0.995				

Source: research results.

### **APPENDIX C**

Indirect and total marginal effect provided by the spatial interactions in each regime.

	5						-			
Variables	Indirect Effect					Total Effect				
Valiables	(NO)	(NE)	(SE)	(SO)	(CW)	(NO)	(NE)	(SE)	(SO)	(CW)
Constant	-1,5054	-1,9839	-1,5835	-0,5210	-2,6004	-2,2659	-3,2491	-2,6947	-0,9396	-4,2841
Economic and Educational Factor	0,2767	-0,0158	-0,1671	-0,2329	-0,1528	0,4165	-0,0258	-0,2844	-0,4200	-0,2517
Social Disorganization Factor	-0,0358	0,0947	0,0873	0,1155	0,1539	-0,0539	0,1551	0,1485	0,2083	0,2536
Demographic Density	-0,0538	0,3070	-0,0206	0,0521	-0,3214	-0,0809	0,5027	-0,0351	0,0940	-0,5295
Gini Index	-1,3814	-0,5581	0,4355	1,2872	-0,3460	-2,0792	-0,9141	0,7412	2,3215	-0,5701
Population	0,5840	0,5503	0,6388	0,4952	0,9541	0,8790	0,9013	1,0871	0,8932	1,5719
Source: research results.										

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