




Criminal Spillovers in Brasilia's Integrated Development Region: An analysis of violent crime (2010-2017)

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ABSTRACT

The objective of this article is to understand the spatial distribution of crime in Brasilia's Integrated Development Region. It concludes that the crime rates in this region are not randomly distributed spatially, because an exploratory analysis of spatial data indicates the existence of spatial dependence. This means that the municipalities that border the Federal District are responsible for more than 80% of the crimes carried out in the period under examination. The main victims are young people, mainly black men shot by firearms, and the proportion of young people between 15 and 19 years of age was a determining factor in this positive correlation, among other significant conditions obtained by using estimates of spatial regressions using Spatial Durbin Models – SDM and data panels for the years 2010 to 2017. We detected a 51% incidence of spillovers for fatal crimes.

KEYWORDS

Brasilia's Integrated Development Region, Crime, Spillover

Spillovers espaciais de criminalidade na Região Integrada de Desenvolvimento do Distrito Federal: Uma análise de crimes contra a pessoa (2010-2017)

RESUMO

O objetivo deste artigo foi compreender a distribuição espacial da criminalidade na Rede Integrada para o Desenvolvimento do Distrito Federal (RIDE/DF). Concluiu-se que as taxas de crimes na RIDE/DF não estavam distribuídas aleatoriamente no espaço pois, por meio de uma análise exploratória de dados espaciais, foi detectada a existência de dependência espacial, em que os municípios limítrofes e mais próximos do DF concentram as maiores taxas de crimes, sendo esses responsáveis por mais de 80% dos registros de crimes realizados no período em análise. As principais vítimas são jovens, homens negros atingidos por armas de fogo, sendo que a proporção de população jovem entre 15 e 19 anos de idade foi um fator determinante de correlação positiva, dentre outros condicionantes significativos obtidos por estimações de modelos de regressão espacial do tipo Spatial Durbin Model – SDM, para os anos de 2010 a 2017, utilizando painel de dados. Na análise dos efeitos, notou-se que nos crimes contra a vida houve uma presença expressiva de spillovers, em torno de 51% dos efeitos totais.

PALAVRAS-CHAVE

Rede Integrada para o Desenvolvimento do Distrito Federal, Crime, *Spillover*

CLASSIFICAÇÃO JEL

P48, R10, R15

1. Introduction

Criminality and violence have been discussed and investigated through many studies, especially because they can be related to countless variables and social statistics. Notably, issues like inequality and income concentration, poverty, unemployment, social security, health, crime, and violence draw the attention in scientific studies and governmental platforms aiming to elaborate and coordinate public policies.

At the beginning of this century, Brazil managed to reduce poverty enough to roughly comply with the millennium development objectives of the United Nations. Even so, some challenges remain to effectively consolidate democracy, good citizenship, and the law commitment. According to a report from UNODC (2011), Brazil presented an average of 25 homicides per 100,000 inhabitants between 2000 and 2010. This rate is unequally distributed between distinct areas in cities and metropolitan regions, ranging from low levels in middle- and upper-class neighborhoods to alarming proportions in marginalized areas. Similar results were found by the 2017 Atlas of Violence (Cerqueira et al., 2017).

Based on these assumptions, this article seeks to answer the following propositions: what was the configuration of criminality in Brasilia's Integrated Development Region interpreted through the spatial analysis of violent crimes from 2010 to 2017? Can this criminality be explained by socio-spatial variables and phenomena? Were there spillovers from the Federal District into the neighboring municipalities during our period of analysis?

This discussion is justified by the importance and breadth of this study. It is fundamental to think of crime and violence beyond a social perspective, aiming their definition and study methods for variables, also taking into account that situations of violence, and crime result from human actions given space or territory population on a regional scale. The analyzed period from 2010 to 2017 was motivated due to its violent crime increasing and the volume of data available, that sustains the initial hypotheses of clusters¹ of violent crime formation. Therefore, it was first inferred that crime rates in Greater Brasilia were not randomly distributed evidencing spatial dependency.

The digital meshes used to capture and demonstrate the spatial attributes of the variables were provided by Costa and Marguti (2015) and Cerqueira et al. (2019), through the software: ArcGis, GeoDa, GeoDaSpace, and Stata. Concerning for the objectives, this study is divided into four sections in addition to this introduction. The first section presents a review of the literature. The second offers a brief characterization of Brasilia's Integrated Development Region. The third section presents the econometric analysis we propose in this work followed by a discussion of the results. The last present the study conclusions.

¹Groupings of homogeneous characteristics in space.

2. Review of the literature

Various studies have analyzed crime from the point of view of behavior, decisions, and choices. Becker (1968) argues that the propensity to commit a crime is defined by the benefits and costs that it offers. To the author, various factors influence individuals in their decisions about whether to commit crimes. They can compare the returns from crime and legal markets over time and make their decisions in terms of the more profitable activity and the one which guarantees the best well-being.

According to Sah (1990), the perception and propensity of the individual to commit a crime can be the result of variables such as income and education. To this author, individuals who are less favored economically have a greater propensity to commit crimes, given that their low incomes are related to low levels of human capital, such as education, which makes the legal activity less attractive when compared to criminal activities. In addition, crime rates can be reflected by levels of salaries, employment, and production, given that to the extent that income decreases, the returns provided by the legal market diminish, while the relative returns of illegal activities increase.

Opting for criminal activity can also be influenced by societal pressures on individuals to achieve their socially determined objectives. This becomes greater when individuals are far from reaching their objectives and do not have the means to achieve them. In this way, the pressure exerted on individuals can lead them to seek illegal means to achieve their objectives when the legal market does not offer real chances of attaining them. That being so when material success represents the great ambition of these individuals, respect in society requires high-salaried jobs in keeping with these objectives. When they are scarce, criminal activities become an alternative path to achieving material success (Sah, 1990)

The socio-economic approach to criminality is based on the incentive theory for individuals elaborated by Becker (1968), which investigates the determinants of criminality searching for a rational economic explanation that induces individuals to commit a crime. Since Becker (1968), various authors have dealt with this subject based on the rational school perspective in which criminal behavior is conditioned on variables such as salary, individual resources, punishment, and the efficiency of the judicial system. A variety of socio-economic variables have been tested in empirical investigations of violent crime, including income, the unemployment rate, education, family composition, poverty, marital status, income inequality, gender, ethnicity, and urbanization.

However, according to Gutierrez et al. (2004), many of these variables present ambiguous results, or in other words, they can vary according to the type of crime they are being related to. Social thinking believes that the environment exerts a strong influence on the propensity of the individual to commit a crime. However, even though the environment can have an influence, the current crime rate would be lower if the number of arrests and punishments were greater and more efficient in the past. Crime

rates are affected by economic parameters, given that changes in parameters such as income distribution modify the information available to individuals.

Ehrlich (1973) states in his study that criminals even when they are convicted and punished, tend to continue in the illegal market. Given the opportunities and preferences of the criminal, the optimal choice will always be to commit crimes and repeat these crimes if their opportunities continue unaltered. Part of this is because criminals lose space in the legal market and have few opportunities compared to the illegal market once they have a criminal record and having served prison time affects their abilities and opportunities to work.

An increase in police force spending and cuts in the judicial system tend to increase the proportion of criminals imprisoned and criminal punishment. However, during periods of increased criminality, the productivity of these resources tends to be smaller, given that there is an increase in the number of criminals who are arrested, judged, and convicted. Thus, given the costs of enforcing the law, crime rates and the probability of punishment should be negatively related, however, the causality occurs in the opposite direction since the probability of being arrested is reduced when there is an increase in crime, given the excess of work for the police force (Ehrlich, 1973).

The size of the population and its density are negatively related to the probability of punishment, because in an area with a denser population, criminals can avoid the police more easily. In analyzing the crime rate in the United States, Ehrlich (1973) evaluates the effect of the probability and severity of punishment (through the ratio between the number of criminals and crimes registered), income, inequality, (measured as a percentage of families with below average income), and the ethnic composition of crime indices. As expected, crime rates vary inversely with the probability of arrest and punishment. Crimes against property such as robbery, theft, and assault are positively related to the percentage of families with incomes below-average salaries.

In terms of ethnicity, crimes vary positively with the percentage of non-white citizens in the population. Ehrlich (1973) also considers the effectiveness of the law in indices of criminality and observes that the probability of arrest and punishment is directly related to current spending on the police force and inversely related to crime rates. In the same way, the effectiveness of the application of the law is negatively affected by the size and density of the population and positively affected by measures of relative poverty, levels of education, and the proportion of non-white citizens.

The positive relationship between crime and income inequality demonstrates the need for social incentives to equalize education and training and increase opportunities for the low-income population. Thus, a reduction in criminality should be related not only to an increase in public safety spending and the effectiveness of the law but also to a reduction in the profits from crime (Ehrlich, 1973).

Among the empirical works which address the relationship between crime and socio-economic variables, we highlight Schaefer and Shikida (2001), Engel and Shikida

(2003), Borilli and Shikida (2003), and Borilli (2005), who analyze the economics of crime through interviews with prisoners who have been judged and convicted for lucrative crimes. Among their principal results were the motives that these individuals gave for entering the world of crime, which were rational decisions, the influence of friends, the need to help their family, and "easy money". The association between a low level of education and crime was confirmed. The main measures to combat criminality, according to the interviewees, would be investments in education and employment.

Araújo Júnior and Fajnzylber (2001) meanwhile, employ econometric techniques to explore panel data that addresses the economic and demographic determinants of the murder rate in Brazil from 1981 to 1996. The source for the mortality data was the Ministry of Health and the socio-economic variables were provided by the National Household Survey conducted by IBGE.

The variables utilized by Araújo Júnior and Fajnzylber (2001) as basic determinants of variations in crime rates were average family income per capita, unemployment rates, income inequality indicators, female-led families as a measure of social disorganization, and the number of military police per 100 thousand inhabitants, which were tabulated per state, period, and age. They concluded that the young had higher murder rates than the old. In most states, the crime curve has an "inverted U" shape.

The evidence of this study indicates that criminality is more accentuated in youths and there are strong effects due to social and economic variables, such as income and unemployment. They suggest that to contain crime, leaders need to offer better opportunities for legal work, restrict the arrest of individuals in marginal sectors, and pay more attention to youths. (Araújo Júnior and Fajnzylber, 2001).

Various works explore spatial data in an analysis of areas, bearing in mind that they do not provide data that makes it possible to identify specific points where crime occurs, and most works, such as Araujo and Vieira (2017) and Almeida and Guanzirol (2013), adopt the Exploratory Analysis of Spatial Data to identify geographic patterns of crime in examined areas, in which they verify whether there is spatial dependence between areas, or in other words, whether there is positive spatial autocorrelation that can explain the effects of the dependent variables generated by their neighboring relationships.

After confirming the existence of spatial dependence and determining the variables which are conditioned by crime and spillovers from neighboring areas, usually spatial regression models and estimated cross-sections are used for Spatial Autoregressive (SAR) and Spatial Error Models (SEM) among others. Only the study of Uchôa and Menezes (2012), using an estimation of panel data, captures spatial autocorrelation through lagged dependent variables or residuals, and their influence on crime in Brazil.

The works of Gomes et al. (2017), Gaulez et al. (2015), and Carrets et al. (2018) analyze crimes against property as an issue that can be explained using the theft rate as a dependent variable, provided by state data on public safety. The explanatory or control variables in most of these works were supplied by local research institutions and the IBGE.

Amin et al. (2009) characterize the demographic and socioeconomic environment in which an individual decides to commit a crime or not in the municipalities of Rio Grande do Sul. For this purpose, cross-section and panel data estimations were used to verify the relationship between crime, development, and economic growth. As a result, they found that the GDP growth rate and per capita income were not conclusive with crime, as they change according to the type of crime. Already MHD indicators show an increase in crime when this indicator increases. Poverty and schooling also showed contradictory signs in the violence and homicide model. Thus, the authors showed that there is a controversial relationship between crime and economic growth and economic development. Pereira and Menezes (2009) discuss how income will impact crime in Brazilian municipalities, in addition to using climate change. From econometric models, the authors concluded that GDP per capita negatively affects crime. UNODC (2019) found, using global data, a positive relationship between the proportion of people between 30 and 49 years old and the homicide rate; while the age group from 50 to 69 years old, showed a negative relationship with fatal crimes.

Considering these results, among others, we would like to emphasize the existence of a positive correlation between crimes against property and GDP per capita, population density, the Gini coefficient, and the FIRJAN index (Garcia Neto et al., 2017). The proportion of non-resident establishments compared to all neighborhood establishments has a positive relationship with criminality, and the concentration of residential homes is associated with lower homicide rates Cruz et al. (2011), and the degree of urbanization positively affect criminality. Crimes against property occur where the expected return is greater. Thus, we can make a preliminary affirmation that criminality is greater in more urbanized regions with denser populations and greater income (Gaulez et al., 2015).

Given the discussions raised by our review of the literature related to the spatial relationships of crime, we may note that there is a lack of analyses that address what conditions crime in developing regions or regions where it is hoped that better governance can resolve the possible effects of the growth of large urban centers circling polarized cities which have centralized public and private services.

Unlike the authors cited above, this article takes a predominantly regional approach considering Brasilia's Integrated Development Region, which encompasses the Federal District and the surrounding municipalities, examining it from the point of view of urban violence which may be caused by socio-economic discrepancies between the region's center and its periphery, which may hypothetically be related to variables which demonstrate socio-spatial segregation and high levels of inequality, as well as

their disconnection from initial assumptions made concerning this integrated region of development.

3. Spatial analysis of fatal crimes between 2010 and 2017

3.1 Spatial analysis of the data: a brief methodological review

The murder rate is the statistic that is most often used to represent criminality in comparisons between municipalities, states, regions, and countries. Homicides affect various social indicators including life expectancy and spending on security, education, leisure, etc. The costs of crime can be further described by the number of victims receiving attention, prison occupancy, the judicial system, life quality declining, and how safe individuals feel, among other measures.

Concerning the Integrated Development Region of the Federal District, created by Complementary Law No. 94 (1998), and it is regulated by Decree No. 7,469 (2011), and Complementary Law No. 163 (2018). The region arose through collective action of the states of Goiás, Minas Gerais, and the Federal District. However, urbanization, city gatherings and region development set up challenges that surpass the complexity and specialization of urban functions. Paviani (2010), relates them to the contradictions within the cities and regions, heterogeneous by nature, as well as the characteristics of highly unequal assets regarding use and consumption. Both arrangements differ from each other, according to IBGE (2019) since their boundaries result from specific laws that define a functional structure and the interests of their political-administrative units.

This Exploratory Analysis of Spatial Data is designed to confirm the existence of spatial effects on the behavior of crime and other explanatory variables within Brasilia's Integrated Development Region. According to Almeida et al. (2005), the first step is to discover whether the spatial data is distributed randomly, to define global autocorrelation statistics. Since we are dealing with spatial dependence which is defined by the distance between the interaction relationships, it is common to use matrices with special weightings (W).

One of the most often used coefficients to measure spatial autocorrelation is Moran's coefficient (1948) which recommends using the cross-product, which is termed Moran I (Anselin, 1999). Generally, the Moran index is used to test the null hypothesis of spatial independence. Moran I presents a statistic that varies from -1 to 1, which provides a general measure of the linear spatial association. According to Almeida (2012), since this is a statistic with a cross-product, it should be interpreted in the following manner: positive spatial autocorrelation reveals that there is a similarity between an attribute and its spatial location, or in other words, high values for a variable of interest tend to be circled by high values in neighboring regions and vice-versa (Tobler's Law) and negative autocorrelation reveals that the values are dissimilar for the attribute being examined, that is, high values of a variable may be circled by low

values in neighboring regions and vice-versa (the opposite of Tobler's Law)². In cases in which there is an absence of spatial autocorrelation in which Moran I is close to zero, this means that there is no spatial dependence, and as a result, the analyzed attributes are independent of their location, or in other words, space does not matter³.

Global autocorrelation spatial statistics are designed to give an aggregate view of data. However, one has to make a local analysis of the observed units, or in other words, an analysis per municipality which is the object of this study. Global patterns may be in line with local patterns, but this is not always the case, and this is why it is important to have a local view of the observed units (Almeida, 2012). Thus, a local analysis is justified when there are two scenarios: the first is when the absence of global autocorrelation occults local patterns, and the second is when a strong indication of global autocorrelation hides other local patterns of association, such as clusters and spatial outliers.

Given this, Anselin (1995) proposes a local indicator that is capable of capturing local patterns of spatial autocorrelation which are termed the Local Indicator of Spatial Association. For it to be appropriate for the proposed indicator, it has to satisfy two criteria: it can signal spatial clusters, and the sum of the local indicators has to be proportional to the global indicator.

In terms of the analysis of the socio-spatial determinants of crime in Brasilia's Integrated Development Region, the goal is to understand the association between crime rates and other socio-economic variables, as well as spillover effects through estimations that utilize spatial econometrics with global and local emphases on spatial autocorrelation.

In this manner, given that the objective of this article is to analyze crime spillovers, we tested and utilized models which capture the spillover effect using lagged explanatory variables. The model which emphasizes spatially lagged variables is the Spatial Durbin Model (SDM), in which the global reach is given by the spatial multiplier which comes from the presence of the spatially lagged dependent variable and the local reach effect arises through the spatial lags of the explanatory variables. The SDM can be represented in the following manner:

²To estimate the significance of the index, we need to associate a statistical distribution with it, with it being more usual to relate the statistical test to a normal distribution. However, to avoid assumptions related to distribution, the most common approach is a test of pseudo-significance. It generates various permutations of attribute values associated with municipalities. Each permutation produces a new spatial arrangement, where the values are redistributed among the areas. Since just one of the arrangements corresponds to the observed situation, we can construct an empirical distribution of Moran I (Druck et al., 2004). In this thesis, we have made countless permutations with the values of crime rates, attributing them randomly to various cities and calculating the Moran Index for each one of these random permutations. We did this 99,999 times and therefore obtained 99,999 positive values for the Moran Index constructed from the observed data. If the value of the originally measured I index corresponds to an "extreme" of the simulated distribution, this is a value of statistical significance.

³In this case, in which space does not matter, one option to assess patterns, measure correlations and identify groups would be through multivariate techniques such as Factor Analysis, Cluster Analysis, Discriminant Analysis, and Non-Spatial Multiple Linear Regression, among others. See Hair et al. (2009).

$$y = \alpha + \pi_1 Wy + \pi_2 X + \pi_3 WX + \epsilon \quad (1)$$

The lag for independent variables is given by WX and the lag for the dependent variable is given by Wy . The central idea of the model is that direct neighbors are affected by the explanatory variables, given that there is only local spillover between municipalities, for example, while the entire region will be affected globally when there is spillover from the dependent variable.

In SDMs, it has been verified that there is a possible trade-off between the biases and efficiency of the estimators, because this model takes into account all of the explanatory variables which have spatial dependence to avoid the bias of the omitted variable, and this makes it possible for irrelevant variables to be introduced into the model, which causes the problem of inefficiency. However, the inefficiency problem of the estimators is preferable to the inconsistency caused by the omission of relevant variables.

In the initial diagnosis of the regression, the results consist of three traditional measures: the condition of multicollinearity, the absence of normality test, and the three diagnoses of heteroskedasticity (Breusch-Pagan, Koenker-Bassett, and White).

Another important point is specifying the autocorrelation which cannot be the target of the error measurement. The tests used are the Lagrange Multiplier (LM) with the intuition of identifying the spatial lag (LM_ρ), the spatial dependence of the error term (LM_λ), or both of the spatial dependencies ($LM_\rho + LM_\lambda$). The LM_ρ test is the test utilized to detect spatial lags of the dependent variable. It is based on the vector score and the information matrix under a null hypothesis that there is no spatial autocorrelation. For this to be true, we initially assume that the errors are not spatially correlated. The LM_λ test is performed with the spatial autocorrelation in the form of a SEM. The test follows a chi-squared distribution⁴ with one degree of freedom Almeida (2012).

However, according to Almeida (2012), during LM tests for spatial lags as well as when the spatial error term does not present significant explanatory power, we must keep in mind that the statistic for the LM_λ and LM_ρ tests follows a chi-squared distribution with one degree of freedom. If $\rho = 0$, and in the cases in which the tests are poorly specified, $\rho \neq 0$, the LM tests transform themselves into a non-centered chi-squared, which makes these tests reject the null hypothesis with great frequency.

In this way, according to Florax et al. (2003), robust LM tests are proposed which resemble traditional tests, however, they include a correction factor that takes into consideration the poor specification and nullifies the problem of a lack of centrality for the chi-squared distribution. In small samples, Anselin and Rey (1991) demonstrate

⁴Distribution of the probabilities obtained by the addition of the squares of the normal standard independent random variables. The number of the terms in the sum is equal to the number of degrees of freedom in the distribution.

that the robust LM test for spatial lags is more powerful than the error term, given that ignoring the spatial lag autocorrelation is more serious than the error because it involves bias and inconsistency in the estimation, while the error just provokes inefficiency in the estimates.

After the specification of the models, we should pay attention to the quality of the fit of the data generation processes as the decisive form of choice for the model that we are adopting. According to Almeida (2012), the estimators and the traditional regression diagnostics do not take spatial effects into account, and because of this, the models can contain autocorrelation or heteroskedasticity errors, and in these cases, the R-squared determination coefficient⁵ of the regression is no longer considered the best indicator of the fit. That being so when estimating the best fit, it is recommended to use the value of the verisimilitude function (LIK)⁶, weighted by the difference between the number of estimated parameters and based on the assumption that the larger the value of the function the better the model. In addition, we suggest the adoption of Information Criteria such as Akaike (AIC) and Schwarz's criteria (BIC), as strategies to define the preferred model, where the evaluation of the fit is penalized by a function of the number of parameters. The Akaike (AIC) criteria and Schwarz's criteria (BIC) use the value of the verisimilitude function (LIK) in their calculations in the form of a logarithm.

In our analysis of the regression results, besides verifying the signs and values of the variable coefficients, we also observed the impacts which translated into direct effects (DE), indirect effects (IE), and total effects (TE). According to Elhorst (2011), growing attention is being given to direct and indirect effects and the spillover of the variables, which apply to the panel data models, with a transversal and spatial sample. The direct effects are caused by the explanatory variables on the dependent variable in the local environment, or in other words, among municipalities, for example.

Meanwhile, indirect effects or spillovers, are global and affect the dependent variable on a regional level. The total effect is the sum of these two effects.

The measurement of the effects is based on the relation and compositions of the spatial variable matrix and changing calculation method depending on the type of spatial model determined. Through the model estimated by OLS, spillovers are not indicated, since they do not include the spatial lag operator.

Through the SDM, on the other hand, the partial derivatives of the variables are estimated in a non-diagonal matrix that is the product of the two others as well, and the DE, IE, and TE effects are generated by multiplying these matrix Golgher (2015).

In a specification with the dependent variable and spatially lagged explanatory variables, we have the Spatial Durbin Model with random effects given by:

⁵Indicates the proportion of the total sample variation of the dependent variable which is explained by the independent variables.

⁶The natural logarithm of the verisimilitude function.

$$Y_t = \rho W y_t + X_t \beta + W X_t \tau + \xi \quad (2)$$

$$\xi_t = \alpha + \epsilon_t \quad (3)$$

According to Elhorst (2011), specific effects should be fixed in cases such as those examined in this article, because each spatial unit represents itself and is not the product of a randomly generated sample. However, it is possible to test statistically whether the model is a better fit for the estimation of unobservable spatial heterogeneity, and a recommended test is Hausman's Hausman (1978). Hausman's test follows an asymptotic distribution of chi-squared with k degrees of freedom under the null hypothesis that the estimator of random effects is correct.

After defining the model, we should estimate it without spatial dependence to check the basic assumptions and then the residuals to see if there is spatial autocorrelation. If the answer is negative, we can stay with the classic model, and if there is spatial dependence, we can estimate with spatial models. In this case, we should choose the model which has the fewest information criteria.

3.2 Exploratory analysis of the spatial data for fatal crimes in Brasilia's Integrated Development Region from 2010 to 2017

The spatial matrix was defined based on the Baumont (2004) procedures, which define the decisive criterion for choosing the matrix as the one which has the highest Moran Index value⁷ or Moran I. Through this indicator, it is possible to infer the global spatial autocorrelation to determine the presence of spatial dependence in the data and then infer the local spatial autocorrelation to detect whether spatial patterns and outliers exist between the municipalities of the Integrated Development Region for the homicide data from 2010 to 2017.

In the case of homicides, the matrix with the highest Moran I, or in other words, the highest significance was the distance matrix with 4 neighbors, which we preferred to use with the distance in kilometers. The spatial weighting matrix considering 4 close neighbors was most frequently used in the analyses of the period from 2010 to 2017, and it was also significant when analyzing the average homicide rates in the municipalities of the Integrated Development Region during the cited period. The W spatial weighting matrix presented a higher global value for Moran I than the other matrices. The value was 0.450 and it was statistically significant, indicating positive global autocorrelation because it exceeded its expected value which was -0.0303 – robust values with 99,999 permutations.

Thus, we may conclude that the municipalities in the Integrated Development Re-

⁷See Moran (1948).

gion which presented higher mean homicide rates per 100 thousand inhabitants from 2010 to 2017 were circled by other municipalities that also presented high homicide rates, that is, a similarity was noted between the values of certain municipalities in the region and their neighbors.

Given that this data was significant, it was possible to construct 3 clusters using the Moran Dispersion Diagram based on the mean homicide rates from 2010 to 2017, with the Moran I presenting a value equal to 0.450 confirming the presence of spatial dependency and a median value of positive local spatial autocorrelation.

Based on an analysis of Figure 1, we may note that the Moran Dispersion Diagram presents 5 municipalities from Goiás (Cidade Ocidental, Luziânia, Novo Gama, Santo Antônio do Descoberto, and Valparaíso de Goiás) with High-High characteristics.

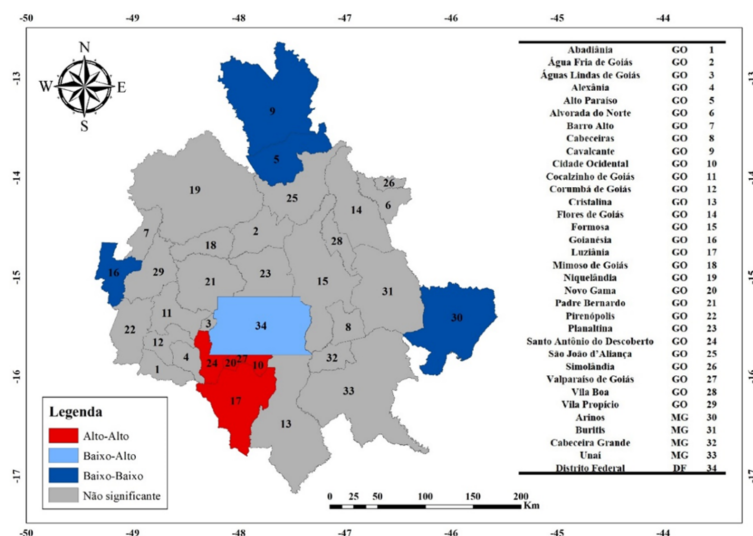
In other words, these municipalities presented high mean homicide rates and are near municipalities which also present high rates when compared to the average data for the Integrated Development Region. The Federal District was classified as Low-High due to its low mean homicide rate and the high mean rates of the cities surrounding it.

The third and last cluster was formed by the municipalities of Alto Paraíso (GO), Cavalcante (GO), Goianésia (GO), and Arinos (MG) which presented a Low-Low type of pattern with low mean homicide rates in consonance with their neighbors which also presented low values compared to the region's average. No High-Low type of grouping was formed, and it was not possible to infer any pattern of statistical significance in the other municipalities.

The Low-Low and Low-High groupings oscillated in composition with the passage of the years, with municipalities in northern and eastern Goiás appearing in greater proportions and those from northern Minas Gerais appearing sporadically. We also observed some spatial outliers in municipalities that were close to the the state of Bahia border, where during some years between 2010 to 2017 were characterized by high homicide rates when compared to neighboring municipalities as Alvorada do Norte and Simolândia in Goiás which.

Both of the them during 2016 and 2017, inferred through matrices of k neighbors of order 4, presented high mean homicide rates per 100 thousand inhabitants and were surrounded by other municipalities which also presented high murder rates.

Figure 1. Local Spatial Analysis for mean homicide rates per 100 thousand inhabitants in municipalities in Brasilia's Integrated Development Region from 2010 to 2017



Source: Elaborated by the Authors based on data from the Ministry of Health SIM/DATASUS (2019) and IPEA (2019), using the GeoDa and ArcGis software.

The outcomes obtained through spatial autocorrelation show positive associations among the values of the crime rates in the municipalities of the region, which demonstrated the existence of spatial dependence in terms of homicide rates for the analyzed period. Through spatial autocorrelation diagnoses of these crime rates, it was possible to infer the force and direction of the associations among the municipal values as well as observe their patterns and spatial outliers.

However, in addition to spatial associations, which were positive in our analyses of crime among the region's municipalities, we also had to identify whether there was any spillover between these cities through these crime indicators or other variables which can affect and/or determine the variations in the levels of criminality in the communities that make up Brasilia's Integrated Development Region.

3.3 Socio-spatial conditioners of fatal crime in Brasilia's Integrated Development Region from 2010 to 2017

In this subsection, fatal crimes are assessed by the homicide rate per 100 thousand inhabitants in this region from 2010 to 2017. The utilization of spatial regression models was motivated by the problem that this article has sought to explain, namely what are the socio-spatial conditioners of crime, in addition to verifying possible spatial spillovers of crime in the region. For fatal crimes, we used spatial models with panel data referring to the 34 municipalities of the Integrated Development Region of Brasilia from 2010 to 2017 based on data supplied by the Ministry of Health's DATASUS (2019).

The explanatory variables of the spatial regression models described in Table 1

were selected per the theoretical and empirical works discussed in the previous sections as well as the characteristics of the creation and formation of the Integrated Development Region. The data on a municipal scale was obtained from secondary sources ceded by government and research bodies such as the Minas Gerais Index of Social Responsibility published by the João Pinheiro Foundation; the municipal statistics of Goiás published by the Mauro Borges Institute; the data for links and remuneration in the formal job market from the Annual Report of Social Information and other data published by the Secretariat of Work and the Ministry of the Economy and; other demographic, economic and social data supplied by the Brazilian Institute of Geography and Statistics (IBGE), the Secretariat of the Treasury, and IPEADATA (IPEA's database of macroeconomic, regional and social indicators).

Considering the variables in Table 1, crimes are presented in terms of their incidence per 100 thousand inhabitants which is the form recommended by the literature. The populational rates for age groups were related to analyzing the age profiles most related to crime in this region, given that the data from Cerqueira et al. (2017); Cerqueira et al. (2019); UNODC (2011) and UNODC (2019) show a greater association with the 15 to 29 age group, which is also true of Brazil and worldwide.

In addition, some theoreticians from the Chicago school, such as Shaw and McKay (1942) in their studies also identified a greater frequency of crime in areas populated by youths and those living under low socioeconomic conditions. This being so, we also included variables related to occupations and income, the data for which is restricted to the formal job market, and various explanatory variables were included to analyze possible relationships between employment, income, and rates of criminality.

The explanatory spatial model for murders in Greater Brasilia from 2010 to 2017 was estimated by following the procedures stipulated by Belotti et al. (2017), which initiates the estimation process for relationships between crimes and their conditioners based on a robust SDM with fixed effects, given that these are most often recommended in the literature ⁸. The model ⁹ was described in the following manner:

⁸See LeSage and Pace (2009) and Elhorst (2010).

⁹The model features variables given in natural logarithms.

Table 1. Description of the variables utilized in the estimated spatial regression for the dependent variables of crimes in Brasilia's Integrated Development Region from 2010 to 2017

Variable	Description
HR	Homicide rate per 100 thousand inhabitants per year. The total number of deaths classified as homicides is divided by the municipal population and multiplied by 100,000. In 2010 the census data was used, and the other years used estimates from the IBGE.
Prop1519ag	The number of individuals within the 15 to 19 age group is divided by the total population and multiplied by 100. In 2010 the census data was used, and the other years used estimates from the IBGE.
Prop2029ag	The number of individuals within the 20 to 29 age group is divided by the total population and multiplied by 100. In 2010 the census data was used, and the other years used estimates from the IBGE.
Prop3049ag	The number of individuals within the 30 to 49 age group is divided by the total population and multiplied by 100. In 2010 the census data was used, and the other years used estimates from the IBGE.
Prop5069ag	The number of individuals within the 50 to 69 age group is divided by the total population and multiplied by 100. In 2010 the census data was used, and the other years used estimates from the IBGE.
ORfs	Occupation rate in the formal sector. The number of those employed in the formal sector per year on December 31 was divided by the population in the 15 to 59 age group as a percentage. In 2010 the census data was used, and the other years used estimates from the IBGE.
MEslcp	Municipal expenses per capita for sports and leisure. Municipal expenses for sports and leisure per year are divided by the population. In 2010 the census data was used, and the other years used estimates from the IBGE. The values have been converted to 2017 reais based on the Broad Consumer Price Index (IPCA).
GDPcp	Gross Domestic Product in current prices per year divided by the population. In 2010 the census data was used, and the other years used estimates from the IBGE. GDP was converted to 2017 reais based on the Broad Consumer Price Index (IPCA).

Source: Elaborated by the Authors based on the Ministry of Health data of DATASUS (2019), IBGE (2019), IMB (2019), FJP (2019), ME (2019), SEJUSP (2019), SSP/DF (2019) and SSP/GO (2019).

$$\begin{aligned}
 nlHR_{it} = & \beta_{0t} + \beta_1 nlProp1519ag_{it} + \beta_2 nlProp2029ag_{it} + \beta_3 nlProp3049ag_{it} + \\
 & \beta_4 nlProp5069ag_{it} + \beta_5 nlORfs_{it} + \beta_6 nlMEslcp_{it} + \beta_7 nlGDPcp_{it} + \\
 & \rho \sum_{j \neq i}^N w_{ij} y_{jt} + \tau_1 \sum_{j \neq i}^N w_{ij} nlProp1519ag_{jt} + \\
 & \tau_2 \sum_{j \neq i}^N w_{ij} nlProp2029ag_{jt} + \tau_3 \sum_{j \neq i}^N w_{ij} nlProp3049ag_{jt} + \tau_4 \sum_{j \neq i}^N w_{ij} nlProp5059ag_{jt} + \\
 & \tau_5 \sum_{j \neq i}^N w_{ij} nlORFs_{jt} + \tau_6 \sum_{j \neq i}^N w_{ij} nlMEslcp_{jt} + \\
 & \tau_7 \sum_{j \neq i}^N w_{ij} nlGDPcp_{jt} + \epsilon_{it}
 \end{aligned}
 \tag{4}$$

in which: the first term is the model constant, and the seven following terms specified with the β coefficient refer to the variables for each municipality. The coefficient which measures the spatial dependence of the dependent variable is ρ , and W_{ij} is the matrix of spatial weights. The other coefficients represented by τ refer to the estimations of the explanatory variables of the neighbors, and ϵ_{it} is the error term.

The estimated results for the model presented in Equation 4 are displayed in Ta-

ble 2, in which the Hausman test is significant for fixed effects. The estimation considered 2,176 observations and eight variables for the 34 (thirty-four) municipalities in the Integrated Development Region over eight years (2010 to 2017). The spatial dependence was measured based on the matrix of k neighbors of order 4.

Table 2. The results of the estimation of the spatial regression model with fixed effects with panel data of a Spatial Durbin Model – for homicide data and other socio-spatial data for the Integrated Development Region from 2010 to 2017

Variables	Coefficients	Standard Error	Z Value	$P > z $
nlProp1519ag	14.374	6.825	2.11	0.035**
nlProp2029ag	4.710	5.849	-0.81	421
nlProp3049ag	13.661	5.684	2.40	0.016***
nlProp5069ag	-15.262	2.748	-5.55	0.000***
nlORfs	1.119	1.430	0.78	434
nlMEslcp	-94	347	-0.27	786
nlGDPcp	-2.226	1.335	-1.67	0.095*
wnlProp1519ag	31.835	16.931	1.88	0.060*
wnlProp2029ag	10.680	17.444	0.61	540
wnlProp3049ag	-25.262	16.224	-1.56	119
wnlProp5069ag	2.119	7.987	0.27	791
WnlORfs	4.860	3.734	1.30	193
WnlMEslcp	1.037	764	1.36	175
WnlGDPcp	-5.232	2.812	-1.86	0.063*
ρ	-2.194	929	-2.36	0.018***
Hausman's Test	AIC	BIC		LIK
40.41 (0.000)*	4.171.569	4.748.497	0.2390943 (0.000)*	-1.925.784

Source: Elaborated by the Authors using the Stata and GeoDa softwares. Regression diagnostics: multicollinearity condition number value 265.311569, Jarque-Bera value 0.3601. Diagnostics for heteroskedasticity: Breusch-Pagan test value 15.0003***, Koenker-Bassett test value 17.2508***, White test value 34. Diagnostics for spatial dependence for weight matrix (Knn=4): Moran's I (error) value 2.7946***, Lagrange Multiplier (lag) value 4.7951***, Robust LM (lag) value 0.9523, Lagrange Multiplier (error) value 4.1897***, Robust LM (error) value 0.3469, Lagrange Multiplier (SARMA) value 5.1420**. Level of Statistical Significance: *** = 1%; ** = 5%; * = 10%..

In Table 2, the seven first variables represent the model's explanatory variables, while the seven following variables are spatially lagged, that is, they are estimates based on the neighbors' explanatory variables. Considering the results in the previous table, we may note that just six variables were statistically significant to explain the homicide rate: the proportions for the 15 to 19 age group, the 30 to 49 age group, and the 50 to 69 age group, GDP per capita, the proportion for the 15 to 19 age group for the neighboring municipalities, and the GDP per capita of the neighboring municipalities.

The ρ coefficient is significant and negative, conditioning greater homicide rates in neighboring municipalities which implies lower values of this indicator for a given municipality in the Integrated Development Region, and this also implies that crime is dispersed in this region and presents indications of spillover. According to Uchôa and Menezes (2012), this fact is linked to the type of aggregation of the data used. When

more disaggregated data is used, we observe islands of safety formed, for example, by individuals with much higher income which can be captured in the disaggregated data for the municipalities. In more aggregated cases, such as an analysis of the states, the association tends to be positive because it occurs between neighbors within the same region, so that regionally criminality remains high or low.

In terms of the explanatory variables related to the age groups, it was possible to note the presence of a positive relationship between the proportion of the 15 to 19 age group and the homicide rate in the municipalities, and this relationship was also present in spillovers, or in other words, the values of this indicator in neighboring municipalities also positively influenced the homicide rates in other municipalities. This result is in line with the findings of Gomes et al. (2017) who, using an estimation with an SDM, found that the proportion of the 15 to 24 age group presented a positive relationship with the homicide rate in the municipalities of the state of Paraná. Uchôa and Menezes (2012), through a spatial model with panel data for crimes in Brazilian states, also obtained the same result, and report that a larger proportion of youths indicates a larger proportion of individuals of that age who are active in criminal activity.

In addition, it is these youths who most suffer from homicides in the Integrated Development Region. Considering that many of these individuals are involved in drug trafficking, they become a portion of the population that is at once a cause and effect of criminality, which explains the large impact that this portion of the population exercises on criminality.

The proportion for the 30 to 49 age group also presented a positive coefficient, indicating that greater homicide rates in municipalities are related to municipalities with greater numbers of individuals in this age group. This fact coincides with a study by UNODC (2019) which, using world data, shows a positive relationship between the proportion of people between 30 and 49 and the murder rate, therefore this age group is more often seen as a cause of violence rather than being a victim of it. The rate for the 50 to 69 age group presented a negative relationship with fatal crimes and, in this sense, we inferred that the age of active criminal activity ends more or less at 49 years of age, because from that age on, greater proportions of people with ages above this age lead to lower murder rates.

Among the socio-economic variables, GDP per capita was the only one that demonstrated statistical significance in the causal relationships for fatal crimes. GDP per capita serves as a measure of economic activity in a given society and generally, it is used as an indicator of its degree of economic development, however, Amin et al. (2009) emphasize that the relationship between GDP and criminality does not present a defined pattern in the literature, because there are ambiguous relationships which change according to the types of data and types of crimes.

In the Integrated Development Region, GDP per capita presented a negative rela-

tionship with the crimes analyzed concerning the explanatory rates as well as the lags. This signifies that municipalities with low levels of economic activity, as well as those which of the same level as their neighbors, present higher murder rates. These results are similar to the findings of Pereira and Menezes (2009) who observed a high negative relationship between GDP and murder rates for 5,561 Brazilian municipalities using data for the year 2012, with the relationships remaining strong when we consider the spatiality of the deaths.

In the SDM estimation, a change in the explanatory variables in one location had an indirect impact on the other municipalities. According to Elhorst (2011), one of the strong points of Spatial Durbin Models is that they do not impose restrictions on the magnitude of indirect effects. These indirect effects, also known as spatial spillovers, generally are the main focus of empirical studies which use spatial econometric techniques.

Direct effects measure the impact of altering one given explanatory variable of the model on the dependent variable in a spatial unit. Meanwhile, the indirect effects measure the impact of a change in an explanatory variable in a given location on the dependent variable in all of the other units. This is why indirect effects indicate or do not indicate the existence of significant spatial spillovers. Therefore, the direct, indirect, and total effects of the explanatory variables for the murder rate are displayed in Table 3, as in the SDM presented above.

Based on Table 3, the direct effects generated by the model indicate that: *i*) an increase of 1% in the proportion of the 15 to 19 age group in a municipality increases its murder rate by 1.34%; *ii*) an increase of 1% in the proportion of the 30 to 49 age group in a municipality increases its murder rate by 1.51%, and *iii*) an increase of 1% in the proportion of the 50 to 69 age group in a municipality decreases its murder rate by 1.34%. Based on an analysis of indirect impacts or spillovers, it may be concluded that: *i*) an increase of 1% in the proportion of the 15 to 19 age group in neighboring municipalities increases the murder rate of the given municipality by 2.39%; *ii*) an increase of 1% in the proportion of the 30 to 49 age group in neighboring municipalities diminishes the murder rate of the given municipality by 2.46%, and *iii*) an increase of 1% in the GDP per capita of neighboring municipalities diminishes the murder rate in the given municipality by 0.41%.

Table 3. Breakdown of the fixed effects model's total spatial effects. Spatial Durbin Model was estimated using panel data for homicides and other socio-economic variables in the Integrated Development Region from 2010 to 2017

Variables	Direct Effect	Indirect Effect	Total Effect
nlProp1519ag	1.347888**	2.393762**	3.741651***
nlProp2029ag	-0.5548802	1.132.884	0.5780034
nlProp3049ag	1.518236***	-2.465808*	-0.9475726
nlProp5069ag	-1.575717***	0.4674029	-1.108314*
nlORfs	0.0982647	0.4076082	0.505873
nlMEslcp	-0.0116515	0.088045	0.0763935
nlGDPcp	-0.2036576	-0.4159924*	-0.61965***

Source: Elaborated by the Authors using the Stata software. Level of Statistical Significance: *** = 1%; ** = 5%; * = 10%.

The total effects imply that: *i*) an increase of 1% in the proportion within the 15 to 19 age group in a municipality and its neighboring municipalities increases the homicide rate in the given municipality by 3.74%; *ii*) an increase of 1% in the proportion within the 50 to 69 age group in a municipality and its neighboring municipalities decreases the homicide rate in the given municipality by 1.1%, and *iii*) an increase of 1% in GDP per capita in a municipality and its neighboring municipalities diminishes the homicide rate in the given municipality by 0.61%.

Taking into account the significant results for total effects, we have found that spillovers are superior to direct effects, representing around 51% of the total effect. This indicates that changes in the variables of the proportion of the 15 to 19 age group and the proportion of the 50 to 69 age group and GDP per capita in neighboring municipalities can lead to greater or roughly equal changes in the homicide rate of a given municipality when comparing changes in their variables. These proportions diverge from those obtained by Uchôa and Menezes (2012) in Brazilian states in which the indirect effects were just responsible for 25% of the total effects. However, our findings are similar to Pereira and Menezes (2009) who, on a municipal scale, observed significant negative spillovers for GDP per capita in fatal crimes, and this implies that a policy that supports income for humble residents in neighboring municipalities will generate positive effects in controlling the advance of criminality. In addition, this indicates that leaving policies that guarantee the generation of income for the humbler population aside will lead to a situation requiring the temporary repression of criminal activity which will not have a permanent effect.

4. Conclusion

Studying socio-spatial phenomena is a huge challenge given all of the nuances in these debates and various currents of research. The Integrated Development Region was created based on centralizing policy decisions that present problems still today in terms of its definition as a region of development, governance, funding, the mapping

of local flows and demands, and the active participation of federal and civil society entities, etc.

In the Exploratory Analysis of Spatial Data, we detected a spatial autocorrelation which showed positive associations among the crime rates for this region's municipalities, or in other words, this indicated the existence of spatial dependence among the murder rates in these municipalities for the analyzed period.

Through diagnoses of spatial autocorrelation for crime rates, it has been possible to infer the levels of force and direction of the associations of these values among municipalities. For the homicide rates, we verified that most of the highest observations about the region's average were concentrated among the municipalities along the southern border of the Federal District, even though Brasilia had lower rates than the regional average. Values below the region's average which presented significant similarities with neighboring municipalities were observed in northern and eastern Goiás.

In determining the variables which spatially condition these crime rates through the use of spatial regression models like SDM, we observed positive relationships between the proportion of youths in the population and negative relationships between the proportion of more elderly residents in the population. The GDP per capita also presented a negative relationship as did per capita spending on sports and leisure. In analyzing the total effects, we noted that spillovers were greater than direct effects representing roughly 51% of the total effect, and there were indications that changes in the proportion of the 15 to 19 age group, the proportion of the 50 to 69 age group, and GDP per capita in neighboring municipalities can indicate greater or similar changes in the murder rate in a given city when compared to changes in its variables.

Given our objective and initial hypotheses, we conclude that criminality in the Federal District has proven to be high among young men and includes the use of firearms. The worst murder rates occurred in the micro-region on the southern border of the Federal District.

As for violent crimes, more than 80% of the incidents of the Integrated Development Region occurs within the Federal District and five neighboring municipalities. In our Exploratory Analysis of Spatial Data, it was possible to detect the presence of High-High spatial patterns in these locations. Regarding fatal crimes, we observed conditioning factors related to the youth population, inactivity, and GDP, with the expressive presence of spillovers.

Our findings are sufficient to answer our objective, which allows us to understand the spatial configuration of criminality in the Integrated Development Region, through an analysis of the spatialization of violent crimes from 2010 to 2017. The spillovers noted among the region studied evidence the criminality arisen, when one consider their socio-spatial variables and phenomena during the period under examination.

In sum, our results confirm our initial hypothesis that the crime rates in the region are not distributed randomly in space, and spatial dependence was detected, with the municipalities bordering the Federal District being those with the highest crime rates. In addition, the same locations were created or reorganized to meet the problems of populational spillover from the Federal District resulting from uncontrolled urbanization, precarious urban infrastructure, segregation in land ownership, and the search for lower costs of living.

During this study, we have encountered several limitations related to the availability of data for municipal socio-economic data, inconsistencies and a lack of standardization in crime data generated by state and district public safety bodies, as well as difficulties in accessing criminal and socio-economic data for the Federal District by Administrative Region.

In this sense, the results obtained here could be used for many other agendas in terms of the spatialization of crime in the Integrated Development Region, such as studies that further explore variables that condition criminality in spatial econometric models, as well as those which can demonstrate new socio-spatial determinants of crime. In addition, future research can try to identify spatial heterogeneity in the crime data for this region which could help make the mapping, monitoring, and evaluation of crime-fighting policies more effective.

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