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Spatial correlation between homicide rates and inequality: Evidence from urban neighborhoods[☆]

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HIGHLIGHTS

- We analyzed the impact of socioeconomic and neighborhood characteristics on homicide rates.
- We caught the neighborhood impact on homicide rates.
- Areas with low criminality are surrounded by neighborhoods with high murder rates.
- A reduction in the Gini coefficient implies a decrease in the neighborhood homicide rate (total effect).
- A reduction in the Gini coefficient implies an increase in the homicide rates in surroundings neighborhoods (indirect effect).

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ABSTRACT

Working with a unique neighborhood homicide dataset from 2008 to 2010, this paper makes two contributions. First, we capture the importance of the spatial dependence on homicide rates within large urban center neighborhoods. Second, we measure the influence of spatial dependence more precisely by calculating the total, direct, and indirect effects of neighborhood characteristics on homicides. The results show that areas with low homicides rates are surrounded by neighborhoods with high murder rates, and that, despite the significant positive effect of inequality on criminality, this influence is mitigated by the nature of the spatial dependence of criminality among the neighbors.

1. Introduction

Different perspectives have contributed to an understanding of the topic: violent crimes that occur in the biggest cities of the worlds.

According to Becker (1968), violent crime is caused by three factors: moral cost, law enforcement, and the economic incentives faced by individuals. From this perspective, income inequality may be viewed as a proxy for the disparity between ill-gotten and legal gains. In recent years, several works have examined income inequality and criminality. For example, Kelly (2000), Brush (2007), and Choe (2008) have found significant and positive effects from the Gini coefficient on crime rates.

Glaeser and Sacerdote's (1996) work goes further and demonstrates a positive relationship between big cities and crime. They suggested that three factors caused this relationship: (1) increased demand for ill-gotten gains implies high profitability; (2) anonymity reduces the moral cost; and (3) anonymity also decreases the likelihood of getting arrested. Recently, some papers (e.g., Cork, 1999, Messner and Anselin, 2004, Cohen and Tita, 1999, and Scorzafave and Soares, 2009) have tested the relationship between geography and crime. These articles suggest that the number of murders follows a pattern (i.e., the cluster of homicide rates

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between cities and States). Moreover, these articles also suggest that it is possible to show that the problems occur with greater frequency in areas that are experiencing problems with urbanization.

This article also identifies the impact of socioeconomic variables on crime and space. However, it differs from other studies for two reasons. First, we are working with a unique neighborhood homicide dataset from Recife, one of the largest cities in Brazil, from 2008 to 2010. This dataset enables us to capture more accurately the importance of the spatial dependence on homicide rates, because the neighborhoods are located within a large urban center, and it is natural to expect that the crime rates in one neighborhood will affect the crime rates in nearby neighborhoods. Second, we also measure the influence of spatial dependence more precisely, by calculating the total, direct, and indirect effects (LeSage and Pace, 2009; Elhorst, 2011) of neighborhood characteristics on homicides. As stated by LeSage and Pace (2009), in the presence of spatial dependence, the estimated coefficients of spatial econometric models can be an imprecise measure of the influence of variables on the dependent variable.

2. Data and empirical strategy

All of the variables in this study are measured at the neighborhood level by using the Brazilian official division of homogeneous areas into specific urban neighborhoods. Recife is the central city of the fifth largest metropolitan area in Brazil, and is one of the five capitals with the highest homicide rates during the years studied. We used a unique dataset to determine the homicide locations, which were registered by a GPS[1] and mapped in a shape file to allow for microanalysis based on census sectors as well as other data aggregations, including specific neighborhoods.[2]

The dependent variable in this study is the average male homicide rate per 100,000 inhabitants from 2008 to 2010. We defined homicide as an intentional violent injury followed by death. The homicide rate was calculated based on the number of murders that occurred over the three-year period and the population data from 2010. The tested explanatory variables were available in the Brazilian Demographic Census from the IBGE (Brazilian Bureau of Statistics). To avoid endogeneity, we used lagged variables from 2000.

Following authors such as Cook (2009), Kelly (2000), and Scorzafave and Soares (2009), we considered inequality, socioeconomic, and environmental variables in the regression. The socioeconomic conditions help explain the patterns of violence and are the preeminent candidates for intervention.

To estimate the impact of the variables on the homicide rate while considering the spatial dependence of this phenomenon, we first estimated the following spatial model:

$$\begin{aligned} &\textit{homicide rate} = \rho W \textit{homicide rate} + X\beta + u \\ &u = \lambda W u + e \qquad (1) \\ &e \sim N(0, \sigma^2 I), \end{aligned}$$

where X encompasses the independent variables of Table 1 and W is a spatial weight matrix. If $\lambda = 0$, we obtain the spatial autoregressive (SAR) model in the notation of LeSage and Pace (2009). If $\rho = 0$, we obtain the spatial error model (SEM). We construct a normalized spatial weight matrix such that the spatial influence decays nonlinearly with distance across municipalities.

Table 1
Determinants of the homicide rate in Recife—dependent variable: homicide rate.

	OLS	Lag	Error
Neighborhood population in 2000	0.504**	0.544**	0.459**
Demographic density in 2000 (km^2)	−0.028	0.046	0.179
Population growth 2000–2010	1.941**	1.712**	1.161**
Gini index	3.692**	4.206**	4.611**
% female as household head	−1.000	−1.623*	−1.376
% young population (15–18 years)	−3.177**	−3.884**	−4.037**
Average per capita income	−0.647	−0.609**	−0.468*
% household head with college degree	−0.300	−0.334*	−0.304
d_downtown	1.417	1.759*	2.332**
Constant	16.741**	22.861**	17.961
Rho		−0.722**	
Lambda			−4.700**
Moran-I	−0.064*		
RLM (Lag)	3482		
RLM (Error)	0.013		
Wald test		12.09**	22.12**
LM test		6.92**	3.45*
LL		−144.69	−144.42
R2	0.46		
Obs.	94	94	94

Note: all variables are in logarithms. The variable d_downtown is a dummy equal to 1 for three downtown areas (*Recife Antigo, São Jose, and Santo Antonio*). RML stands for the robust Lagrange multiplier.
* P-value ≤ 0.10.
** P-value ≤ 0.05.

Therefore, the elements w^* of the matrix are

$$w^*_{ij} = \frac{w_i j}{\sum_j w_{ij}} \quad \text{if } i \neq j, \text{ and 0 otherwise,}$$

where $w_{ij} = 1/d^2_{ij}$ and d_{ij} is the distance between neighborhoods i and j. After testing some bands,[3] we chose the matrix that gave the most robust Moran-I and the most significant robust Lagrange multiplier (RLM).

3. Results and discussion

In Table 1, we present three estimated models. The estimated parameters are stable for all specifications. In the first column, we present the results for an ordinary least squares (OLS) regression without considering the spatial effects or correcting for potential underreporting of criminal data. The explanatory variables are presented in Table 1. In the second column, we present the results for SAR model, and, in the third column, we present the results from the SEM. Both are estimated by the maximum likelihood method. The robust Moran-I and the RLM tests are significant, which indicates that a spatial correlation is present and shows that the OLS models are misspecified. Using the RLM as the decision criterion, the SAR model (model II) is the better specification.

The population, the rate of density growth, income, and the Gini coefficient show the anticipated outcome: homicide rates increased in the heavily populated areas that had greater inequality and in those areas that experienced the greatest increase in population density during the three-year period. However, the proportion of women as heads of household, income, and the proportion of heads of household with college degrees are statistically insignificant. The variable regarding the proportion of young people shows a result opposite than the expected. Actually, neighborhoods where there is a higher proportion of young people as household heads are also those where the Gini

[1] GPS—Global Positioning System.

[2] For the present article, the Intentional Violent Lethal Crimes records was used, which correspond to criminal modalities such as homicide, robbery followed by death and injury followed by death. The National Information System used for criminal data is Datasus. However, in 2013, the Brazilian Forum of Public Safety classified the criminal data system produced by the State of Pernambuco (Infopol) as being a high-quality criminal information system within Brazil (Fórum Brasileiro de Segurança Pública, 2013). Infopol and Datasus records are very close, and occasionally the criminal records of Infopol outweigh Datasus (Sauret, 2012).

[3] To construct the W matrix, we use the centroids with $0 < d \leq 5000$.

Table 2
Direct, indirect, and total effects of the variables on homicide rates.

	Direct effect	Indirect effect	Total effect
Neighborhood population in 2000	0.558**	−0.242	0.316**
Demographic density in 2000 (km^2)	0.047	−0.020	0.027
Population growth 2000–2010	1.754**	−0.760	0.994**
Gini index	4.311**	−1.867	2.443**
% female as household head	−1.663	0.721	−0.943**
% young population (15–18 years)	−3.980**	1.724	−2.256**
Average per capita income	−0.624	0.270	−0.354
% household head with college degree	−0.342	0.148	−0.194
d_downtown	1.802*	−0.781	1.022*

Obs.: values calculated by the authors from equation. *P*-values based on 5000 draws of MCMC sampling procedure.
* *P*-value $\leq$ 0.10.
** *P*-value $\leq$ 0.005.

coefficient is high, and those having low per capita income and low proportion of householder heads with a college degree. Therefore, this unexpected result could be the outcome from the multicollinearity.

After controlling for socioeconomic characteristics and inequality, we find that an increased population density shows a significant positive signal (Glaeser and Sacerdote, 1996). The 1% increase in neighborhood population and density growth rate were associated with 0.6% and 2% increases in homicide rate, respectively.

According to LeSage and Pace (2009) and Elhorst (2011), once the model has a spatial autoregressive structure, it is necessary to consider both the direct and indirect effects to obtain the effective impacts of the variables on the homicide rates from the coefficients estimated above. Given that the direct impact of each variable also affects the neighbors' dependent variable, the direct effect results from the effects the variables have on the dependent variable. The indirect effect arises because of the influence of each variable on the neighbors' dependent variable. As a result, the spatial dependence of the model is a dependent variable of the spatial unity. These results are presented in Table 2 along with the estimated coefficients of the SAR model from Table 1.

Although the Gini coefficient is 4.2, the total impact of a 1% Gini increase on the homicide rate is 2.4%. These interesting results may be explained by the negative lag spatial rho estimated coefficient presented in Table 2. This coefficient also highlights the importance of our model in accounting for the actual influence of the variables on homicide rates in the city of Recife. Just as the homicide rates of the spatial unities are negatively associated with their lag spatial homicide rates (neighbors' homicide rates), the indirect effects are always negative because of the variables that cause positive (negative) effects on neighbors' homicide rates and that have a negative (positive) influence on the homicide rate of a specific spatial unity.

Another interesting result is that the elasticity of crime inequality between neighborhoods should be greater than between municipalities. The international literature that focuses on municipalities suggests that a 1% reduction of the Gini coefficient would reduce the crime rates by 0.68% (Choe, 2008), i.e., much lower than what was evidenced in our data.

From this perspective, we now also realize that the effective impact of per capita income and the percentage of heads of households with college degrees do not significantly reduce the homicide rates of Recife's neighbors because the direct and indirect effects cancel each other out (Table 2).

4. Conclusions

Because the distance between neighborhoods is smaller than the distance between municipalities in terms of the number of roads, means of transport linking areas within cities, and physical proximity, it is far from obvious that the same causal pattern would apply on a smaller scale. Nonetheless, the results show that the characteristics that determine homicides rates in cities are also found to operate in neighboring areas. Furthermore, we showed that to measure the influence of spatial dependence adequately, we cannot rely only on estimated coefficients. Rather, we also need to calculate the direct and indirect effects of the variables.

An interesting result is the negative slope of the spatial correlation. Thus, it can be seen that the areas with low crime rates are surrounded by neighborhoods with high murder rates. One possible conclusion is that the process of urbanization may have led to the formation of islands of safety inhabited by people with higher levels of education and greater per capita income. After controlling for the other variables, we noted that inequality has a significant positive effect on criminality. However, this influence is mitigated by the nature of the spatial dependence of criminality among the neighbors. This finding indicates that we cannot use an estimated coefficient of inequality to measure its influence on criminality.

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