THE SPATIAL PATTERN OF CRIME IN MINAS GERAIS: AN EXPLORATORY ANALYSIS*

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RESUMO

Este artigo procura examinar o padrão espacial do crime no Estado de Minas Gerais. Em termos metodológicos, o artigo usa a análise exploratória de dados espaciais (AEDE) para estudar a distribuição das taxas de crime em mais de 750 municípios deste Estado para 1995. Os resultados revelam que as taxas de crime não são distribuídas aleatoriamente, sugerindo autocorrelação espacial positiva. Além disso, a heterogeneidade espacial, representada tanto pela associação espacial local positiva (regimes espaciais com municípios AA e BB) como pela associação espacial local negativa (regimes espaciais com municípios AB e BA), é identificada. Somente um *outlier* espacial do tipo AA é detectado, porém não tem qualquer influência no nível da autocorrelação espacial, medido pelo I de Moran. Ademais, um modelo simples de regimes espaciais com efeitos inerciais, mas sem qualquer covariada causal, tem um poder explicativo de aproximadamente 70% da variação nos dados de crime. A esse respeito, o efeito inercial é um aspecto muito relevante do crime em Minas Gerais. O padrão da distribuição espacial revelado por meio do AEDE fornece um embasamento empírico e sólido para a posterior especificação econométrica de modelos multivariados.

Palavras-chave: análise exploratória de dados espaciais (AEDE), taxas de crime, regimes espaciais, efeitos inerciais, autocorrelação espacial.

ABSTRACT

This paper is aimed at examining spatial pattern of crime in the state of *Minas Gerais*, Brazil. In methodological terms, this paper uses exploratory spatial data analysis (ESDA) to study the distribution of crime rates in more than 750 municipalities of this state for 1995. The findings reveal that crime rates are distributed non-randomly, suggesting positive spatial autocorrelation. Moreover, spatial heterogeneity represented by both the positive local spatial association (spatial regimes of HH and LL municipalities) and the negative local spatial association (spatial regimes of HL and LH municipalities) is identified. Only one spatial outlier of HH type is detected, but it does not have any influential impact on the level of spatial autocorrelation, measured by the Moran's *I*. Furthermore, a simple spatial regimes model with inertial effects, but without any causal covariates, has an explanatory power of about 70% of the variation in the crime data. In this regard, the inertial effect is a very relevant aspect of the crime in *Minas Gerais*. The pattern of spatial distribution revealed through ESDA provides an empirical and solid foundation for the further econometric specification of multivariate models.

Key words: exploratory spatial data analysis (ESDA), crime rates, spatial regimes, inertial effects, spatial autocorrelation.

JEL classification: C21.

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1 Introduction

More than three decades have passed since Gary Becker, a Nobel Prize winner, published a path-breaking article upon economic theory of crime. (Becker, 1968). Once the crime is a socio-economic phenomenon that has multiples causes, there have been many studies examining various aspects of the crime over the years. For instance, Glaezer, Sacerdote and Scheinkmann (1995) have focused the relationship between crime and social capital (or, in other words, sense of community). Lewitt (1996; 1997; 1998) has studied the effects of deterrence (police activities and system of justice) upon crime levels. Kelly (2000) and Fajnzylber *et al* (2001) have analyzed the role played by social inequalities as determinants of criminal behavior. Lochner and Moretti (2001) have examined the effect of education on crime. Witte and Tauchen (1994) have investigated work and crime. Ehrlich (1973) has concentrated his efforts in finding out the role of deterrence on crime.[1]

According Messner *et al.* (1999), it is important to study crime in order to understand where it happens as well as to whom and by whom. In other words, the authors mean the space deserves to be investigated as a relevant aspect of the crime. Most applications considering the relationship between space and crime in the literature adopt spatial econometric models as the preferred methodological tool.

Spatial econometrics is an emerging field in quantitative methods applied for regional science. The difference of spatial econometrics from the standard econometrics refers to characteristics of the socio-economic interaction among agents in a system and the structure of this system across space. These interactions and structures generate spatial effects in various socio-economic processes. These effects are made up of the **spatial heterogeneity** and the **spatial autocorrelation**. The spatial autocorrelation refers to socio-economic interactions among agents, whereas the spatial heterogeneity regards to aspects of the socio-economic structure over space. (Anselin, 1988; Anselin e Bera, 1998).

In space the interaction has a multidirectional nature, generating spatial effects that violate a vital assumption of the classic linear regression model, to wit, the spherical errors assumption. Furthermore, since the heteroskedasticity is resilient to several standard procedures to correct it, it is very likely that its source comes from intricate relationship to the spatial autocorrelation. In spatial processes, it is common that heteroskedasticity generates spatial dependence and, in turn, spatial dependence also induces heteroskedasticity. (Anselin e Bera, 1998).

These characteristics provoke serious difficulties for identifying proper spatial econometric models. Consequently, the identification task may become very time demanding and cumbersome; or worst, lead to estimate wrong spatial econometric models.

An appropriate exploratory spatial data analysis (ESDA) can help to overcome such an identification problem, furnishing clear guesses and indications about the existence of spatial regimes, preliminary spatial autocorrelation, potential regressors, spatial trends, the influence of spatial outliers, etc. Hence, some ESDA work precedes a good spatial econometric modeling.

ESDA is a collection of techniques for the statistical analysis of geographic information, intended to discover spatial patterns in the data and to suggest hypotheses, by imposing as little prior structure as possible. The reason for this approach stems from the drawbacks of the conventional methods such as visual inspection and standard multivariate regression analysis that *"are potentially flawed and may therefore suggest spurious relationships."* By the same token, "*human perception is not sufficiently rigorous to assess 'significant' clusters and indeed tends to be biased toward finding patterns, even in spatially random data.*" (Messner *et al.*, 1999, p. 426-427). Accordingly, it is necessary

1 For a complete survey of crime studies, see Freeman (1999).

to use formal tests and quantitative tools to analyze these spatial patterns to avoid misinterpretations.

ESDA, like its forerunner Exploratory Data Analysis introduced by Tukey (1977), is not aimed at testing theories or hypothesis, hence it "*may be considered as data-driven analysis.*" (Anselin, 1996, p. 113). One of its roles is to shed light on future possibilities in modeling and theorizing; the primary objective is let the data speak for themselves. As an aftermath, the ESDA can be regarded as the first step in the econometric modeling of the crime. This paper illustrates the ESDA approach, applying for Brazilian crime data.

Nowadays crime is one of most relevant socio-economic phenomena over the world. Crime imposes immense social costs, representing pernicious effects on economic activity and quality of life. In the United States, crime costs represent more than 5 percent of the US gross domestic product (GDP). Similar estimations point out that crime-related cost in Latin America is also around 5 percent of GDP. In Mexico, the social losses related to crimes amount about 5 percent, whereas in El Salvador and Colombia these costs are about 9 percent and a little more than 11 percent, respectively. In Brazil, crime costs around 3 percent of GDP. (Fajnzylber *et al.*, 2000, p. 223-224).

However, crime is not a random activity: prior research has suggested significant spatial and temporal concentrations. A national or state average may be misleading since it reveals nothing about variability within the country or state. If crime is indeed spatially concentrated, then analysis of patterns and causes will require a different approach than in the case where it is most evenly distributed. This paper will explore where crime happens, controlling for spatial effects. To this end, the exploration of the patterns of crime in Minas Gerais will consider spatial interaction among the locations to understand their heterogeneity and dependence.

In the literature, there are some studies relating, explicit or implicitly, space and crime. We begin here with a very brief overview of the literature on the role of the geographic space in the study of crime.[2] Place-based theories of crime seek to explain the relationship between place and crime. According to Anselin *et al.* (2000, p. 216), "*routine activities that bring together potential offenders and criminal opportunities are specially effective in explaining the role of place in encouraging or inhibiting crime. The resulting crime locales often take the form of facilities – places that people frequent for a specific purpose – that are attractive to offenders or conducive to offending. Facilities might provide an abundance of criminal opportunities (...). Or they might be the sites of licit behaviors that are associated with increased risk of crime (...).*"

Ecological theories seek, in turn, to explain variations in crime rates through the differing incentives, pressures and deterrents that individuals face in different environments (different locations). The most famous ecological theory is the economic theory of crime developed by Becker (1968) and Ehrlich (1973). This theory asserts "*individuals allocate time between market and criminal activity by comparing the expected return from each, and taking account of the likelihood and severity of punishment.*" (Kelly, 2000, p. 530). Ecological theory highlights the economic factors within an individual cost-benefit analysis of the criminal activity.

Glaezer and Sacerdote (1996) furnish another theory of crime, linked implicitly to space. They investigate why crime rates are much larger in large cities than in small cities and rural areas. Their findings indicate that city size and urbanization rates are important variables to consider in crime studies.

Using an ESDA approach, similar to the one developed in this paper, we found studies analyzing homicide rates in Saint Louis metropolitan area. (Messner *et al.*, 1999; Messner and Anselin,

2 For a more detailed review of literature on space and crime, see Messner *et al.* (2000), Messner and Anselin (2001) and Anselin *et al.* (2000).

2001). The authors found that there is the presence of potential diffusion processes in criminal activity.

In the Brazilian literature, there is no study investigating the spatial patterns of crime, adopting this set of spatial statistical tools.[3] Consequently, this paper is pioneer in doing this kind of investigation, using a vast collection of exploratory spatial statistics methods in order to extract information from Brazilian crime data.

The rest of the paper is divided as follows. Section 2 discusses the data used in the spatial analysis. Section 3 presents the results of the application of the ESDA approach. The conclusions and final remarks are shown in section 4.

2 The data

The crime data for this paper come from the *Secretaria de Segurança Pública do Estado de Minas Gerais* (Public Security Secretariat of the State of *Minas Gerais*). The data consist of the distribution of crime rates in 754 "*municípios*" (municipalities) of the state of *Minas Gerais* for 1995. The crime rate used here is aggregated by municipality of residence and expressed as a rate of homicides and homicide attempt per 100,000 people.

As the crime data come from an official source, there is potentially a problem of underreporting. That is to say, only a fraction of all crimes makes its way to official statistics. However, the use of homicides and homicide attempts as a crime rate shows the property of precision: underreporting is low for this kind of data, unlike crime as theft or rape (Fajnzylber *et al.*, 2000). Besides, the incidence of homicide is regarded as a proxy for crime rate in most studies.

Minas Gerais is an interesting case to be examined from the 27 Brazilian states with respect to socio-economic phenomena like crime. This is because *Minas Gerais* state is Brazil's third richest state, the country's second most populous state and Brazil's fourth largest state but also because there is strong regional inequalities within its territory (see Table 1). It is noteworthy observing that the regions *Triângulo Mineiro/Alto Paranaíba*, *RMBH* and *Sul/Sudoeste* possess just 31 percent of *Minas Gerais*' territory, but they host 53 percent of *Minas Gerais*' population and 67 percent of the state's production. The regions *Noroeste*, *Norte de Minas*, *Vale do Jequitinhonha* and *Vale do Mucuri* possess almost half of the state's territory, but they contain just 17 percent of *Minas Gerais*' population and about 18 percent of the state's production.

Map 1 shows the demographic density across regions in *Minas Gerais* for 1995. There exists some variation in the level of demographic density among regions of *Minas Gerais*. First, *RMBH* is the densest region in the State. Second, the southern part of the State hosts the location of the denser regions, such as *Oeste*, *Sul/Sudoeste*, *Campos das Vertentes*, *Juiz de Fora* and *Vale do Rio Doce* (besides *RMBH*), symbolized in Map 1 with darker shading. Third, the northern part of the State is compounded by less dense regions, represented with lighter colors in Map 1. The observation of map 1 reveals that, for *Minas Gerais*, levels of demographic density are not distributed equally across its territory.

3 Sartoris Neto (2000) has applied a STARMA model to investigate crime in *São Paulo* city.

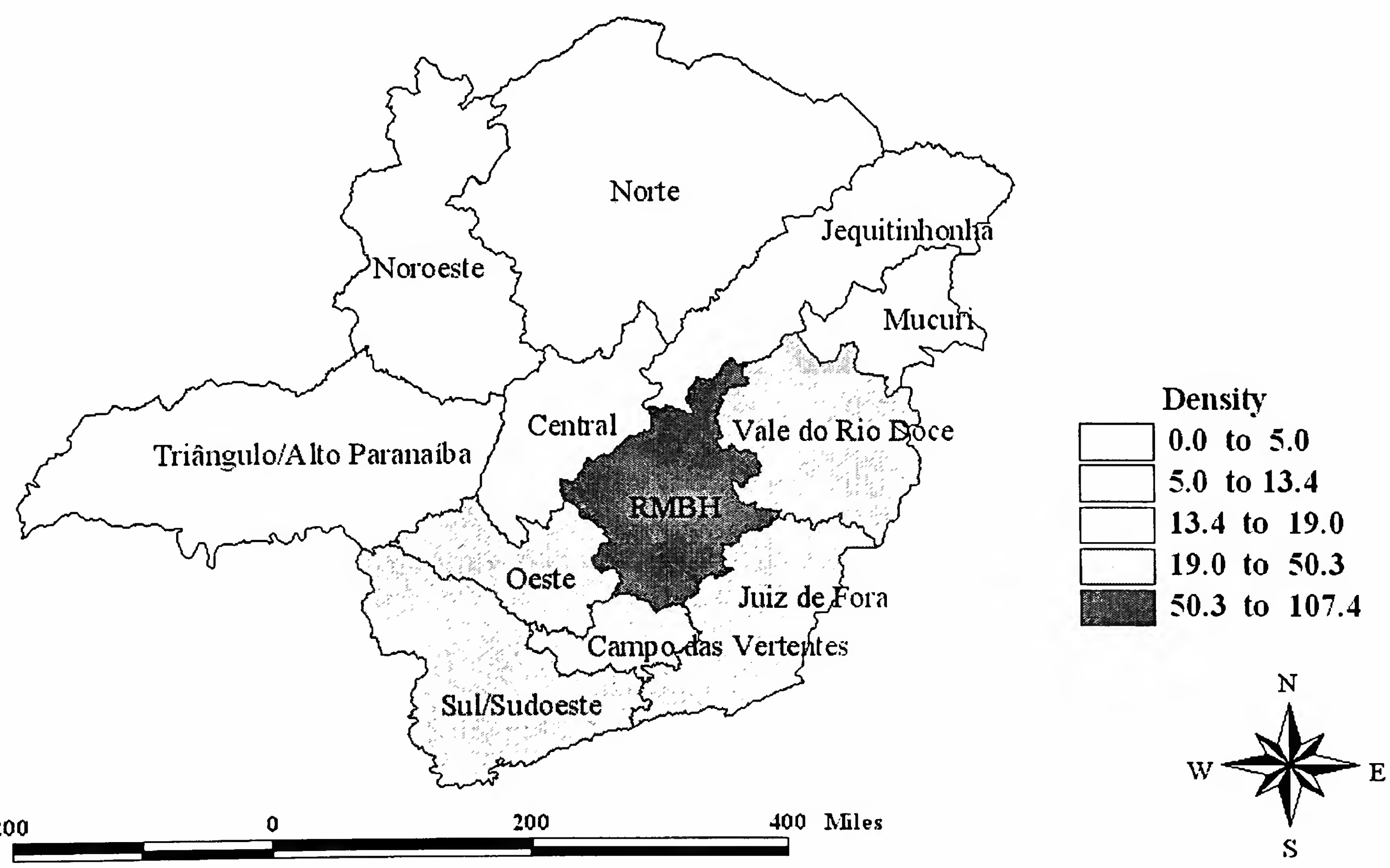
Table 1 - Area, population and production in *Minas Gerais* (1996)

Region	Area	Population	Production
Noroeste	10,7	1,9	1,6
Norte	21,7	8,7	4,4
Jequitinhonha	8,6	4,1	1,1
Vale do Mucuri	3,4	2,4	1,0
Triângulo/Alto Paranaíba	15,5	10,2	11,7
Central	5,4	2,2	1,6
RMBH	6,7	29,9	44,6
Vale do Rio Doce	7,2	9,0	9,1
Oeste	4,1	4,6	3,8
Sul/Sudoeste	8,5	12,5	10,9
Campo das Vertentes	2,1	2,9	1,9
Zona da Mata	6,1	11,6	8,3

Note: *Empirical pseudo-significance based on 999 random permutations.

Source: IBGE.

Map 1 – Demographic density of *Minas Gerais*

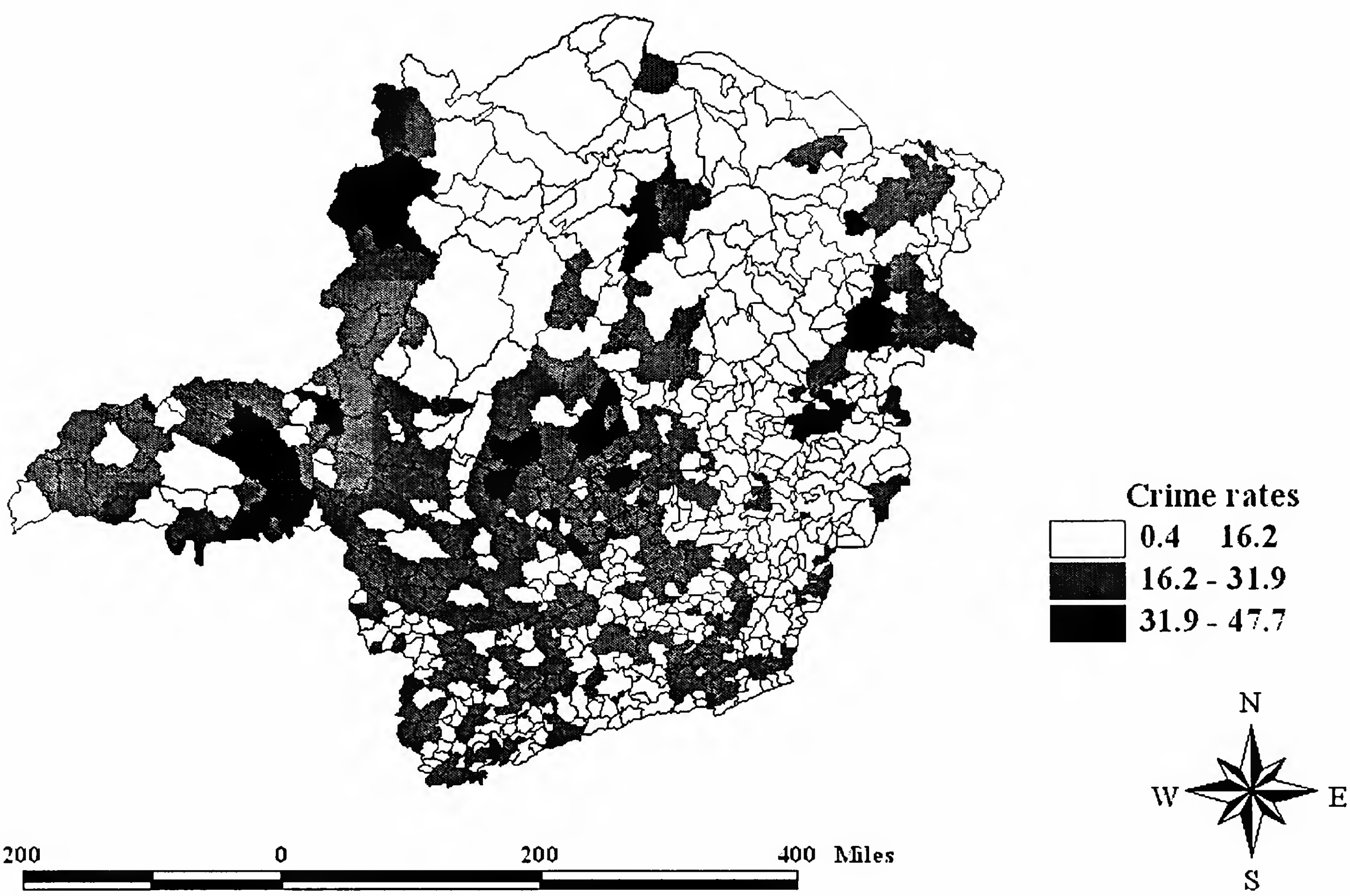


3 Empirical results of ESDA[4]

3.1 Tests for global spatial autocorrelation

We begin the analysis with the choropleth map of the data crime. Map 2 shows the data for 1995. The spatial pattern of the crime rates is illustrated in this map, with the darkest shade corresponding to the highest rate range. The suggestion of spatial clustering of similar values that follows from the visual inspection of this map needs to be confirmed by formal tests.

Map 2 Crime rates in *Minas Gerais* in 1995



The first step in a study of ESDA is to test this hypothesis: are the spatial data randomly distributed? To do that, it is necessary to use global autocorrelation statistics.

The spatial correlation coefficient Moran's I was proposed in 1948.[5] The underlying hypothesis is spatial randomness, that is, there is the absence of spatial dependence in the data. Intuitively, spatial randomness can be expressed as follows: values of an attribute at a location do not depend on values of an attribute at neighboring locations.

4 Most results of this section were obtained through SpaceStat™ extension for ArcView™ (see Anselin, 1999b). Other results were generated in the ArcGIS™ and in the CrimeStat (see Levine, 2002).

5 Formally, this statistics is given by:

$$I = \frac{n}{\sum\sum w_{ij}} \frac{\sum\sum w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum (y_i - \bar{y})^2}$$

where n is the number of locations, y_i is the data value of attribute in analysis (in our case, crime rate), w_{ij} is a spatial weight for the pair of locations i and j.

Moran's I has an expected value of $-[1/(n-1)]$, that is, the value that would be obtained if there was no spatial pattern in the data.[6] The calculated value of I should be equal to this expectation, within the limits of statistical significance, if the y_i is independent of the values of y_j, $j \in J$ (and J is the set of neighboring locations). Values of I that exceed $-[1/(n-1)]$ indicate positive spatial autocorrelation. Values of I below the expectation indicate negative spatial autocorrelation. As the number of locations increases, this expectation approaches zero, which is the expectation for an ordinary correlation coefficient.

There are many possible spatial weights matrices, depending on the choice of the nonzero elements for pairs of correlated observations. For the analysis of the crime rates in *Minas Gerais*, we used the criterion of binary neighborhood, namely, if two locations are neighbors (that is, they have a boundary in common of non-zero length), a value of 1 is taken on; otherwise, a value of zero is assigned. There are two conventions used in the construction of a binary spatial weights matrix: rook and queen conventions. In the rook convention, only common boundaries are considered in the computation of spatial weights matrix, while, in the queen convention, both common boundaries and common nodes are considered.[7]

Table 2 reports the global Moran's I statistics for all municipalities of *Minas Gerais* in 1995. The statistical evidence in Table 2 casts doubt on the assumption of spatial randomness of the crime data for *Minas Gerais*. In fact, since the computed value of I exceeds its theoretical value, we can reject the hypothesis of no spatial autocorrelation at 0.1% significance level for 1995. These results are invariant with regards to convention of binary neighborhood used for the construction of the spatial weights (queen or rook). In addition, Moran's I provides clear indication that the spatial autocorrelation for crime rate in *Minas Gerais* is positive. That is, municipalities with a high crime rate are also adjacent to municipalities with a high crime rate. In an analogous manner, municipalities with a low crime rate are adjacent to municipalities with a low crime rate as well. That is the intuitive meaning of positive spatial autocorrelation.

Table 2 – Global Moran's *I* statistics for crime rates in *Minas Gerais*

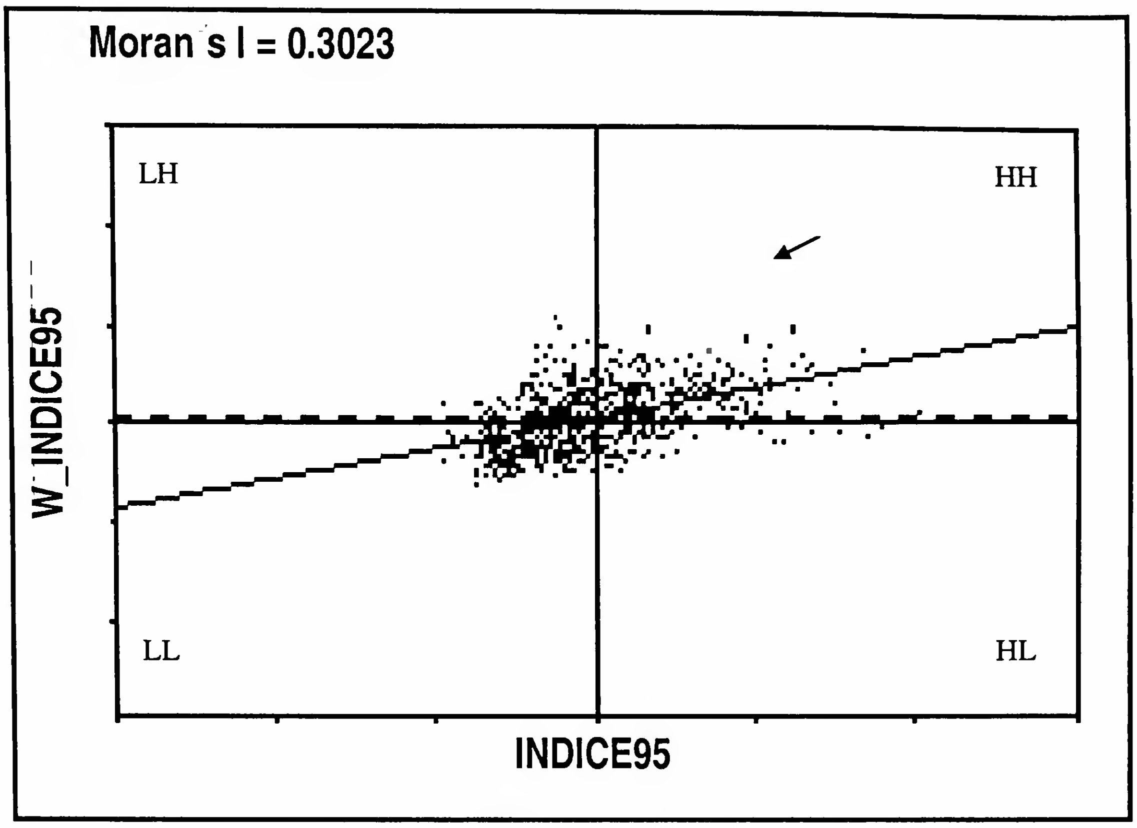
Convention	I statistics	Probability level
Queen	0,302	0,001
Rook	0,303	0,001

An alternative approach to visualize spatial association is based on the concept of a Moran Scatterplot, which shows the spatial lag (i.e. the average of the attribute for the neighbors) on the vertical axis and the value at each location on the horizontal axis (see Figure 1). Note that the variables are expressed in standardized form with mean zero and standard deviation equal to one. (Anselin, 1999a, p. 261).

6 It is noteworthy perceiving that most correlation measures have an expected value of zero.

7 For more details on the concept of binary neighborhood, see Anselin (1988).

Figure 1 – Moran scatterplot for crime in 1995



Thus, Moran's I (the slope of the line in Figure 1) provides a formal indication of the degree of linear association between a vector of observed values y (crime rates) and a weighted average of the neighboring values, or spatial lag, Wy. When the spatial weights matrix is row-standardized such that the elements in each row sum to 1, the Moran's I is interpreted as a coefficient in a regression of Wy on y (but not of y on Wy). As the slope is positive in the Moran scatterplot (see Figure 1), once again we corroborate, diagrammatically, the existence of positive global spatial association.

While the overall tendency depicted in the Moran scatterplot is one of positive spatial association, there are many municipalities that show the opposite, that is, low values surrounded by high values (low-high negative association), portrayed in the upper left quadrant. In addition, there are many municipalities that represent high values surrounded by low values (high-low negative association), portrayed in the lower right quadrant.

In an interactive ESDA setting, it is important to identify outliers or high leverage points that spuriously influence the global spatial association measure. Outliers are observations that do not follow the same process of spatial dependence as the majority of the data. The Moran scatterplot can be very helpful to do this. In fact, the Moran scatterplot is able to identify four types of spatial outliers, namely, HH, LL, HL and LH depending on the quadrant where the outlier lies in.

Spatial outliers are defined in terms of their neighboring observations. An outlier HH is an observation whose value is extremely high in comparison with its neighboring values, which are high as well. An outlier LL is an observation whose value is extremely low with reference to its neighboring values, which are also low. An outlier HL is an observation whose value is extremely high with regards to its neighboring values, which are low. Finally, an outlier LH is an observation whose value is extremely low concerning its neighboring values, which are high.

The fundamental questions are the following: how high is necessary to be detected as an outlier? And how do the detected outliers influence the Moran's I?

To detect spatial outliers, it is necessary to use again the Moran scatterplot with the help of the lines drawn at two standard deviations along both axes. It is worthy noting that any observation that lies outside the two standard deviation range for the horizontal axis and the two standard deviation range for the vertical axis in figure 1 can have influential and pernicious effect on the position of the line indicating diagrammatically the Moran's *I*. The only observation that falls outside these two standard deviation ranges is the "*município*" called *Água Comprida*. This outlier can be classified as being HH, because it lies in the upper right quadrant (look at the arrow in Figure 1).

Is the Moran's *I* sensitive to this outlier HH detected? In order to assess the degree of sensitiveness, we calculate the new Moran's *I*, excluding this outlier detected. Doing this, the regression line (Moran's *I*) is pulled a bit downwards, and the new value of Moran's *I* is 0.2960, indicating yet a positive spatial autocorrelation (corrected to the influence of outliers). In this case, our conclusion is that the outlier HH detected does not exert influence in the computation of the global spatial correlation measure.

3.2 Spatial clustering analysis

The indication of global patterns of spatial association may correspond to the local analysis, although this is not necessarily the case. In fact, there are two cases involved. The first case occurs when no global autocorrelation hides several significant local clusters. The opposite case is when "*a strong and significant indication of global spatial association may hide totally random subsets, particularly in large dataset.*" (Anselin, 1995, p. 97).

The global indicators of spatial association are not capable of identifying local patterns of spatial association, such as clusters or spatial outliers in the data that are statistically significant. To overcome this obstacle, it is necessary to implement a spatial clustering analysis.

Anselin (1995) suggested a new kind of indicator for capturing spatial clusters, known as a local indicator of spatial association (LISA). The intuitive interpretation is that LISA provides for each observation an indication of the extent of significant spatial clustering of similar values around that observation.

LISA (like local Moran) can be used as the basis for testing the null hypothesis of local randomness, that is, no local spatial association. (Anselin, 1995, p. 95). LISA statistics have two basic functions. First, it is relevant for the identification of significant local spatial clusters. Second, it is important as a diagnostic of local instability (spatial outliers) in measures of global spatial association. (Anselin, 1995, p. 102). Map 3 shows the significance of the local Moran statistics.[8]

There are various LISA statistics in the spatial analysis literature.[9] We adopted here the local version of Moran's *I*, because it allows for the decomposition of the pattern of spatial association into four categories, corresponding to the four quadrants in the Moran scatterplot (see Figure 1). Map 3 combines the information of the Moran scatterplot and the LISA statistics. It illustrates the classification into four categories of spatial association that are statistically significant in terms of the LISA concept.[10]

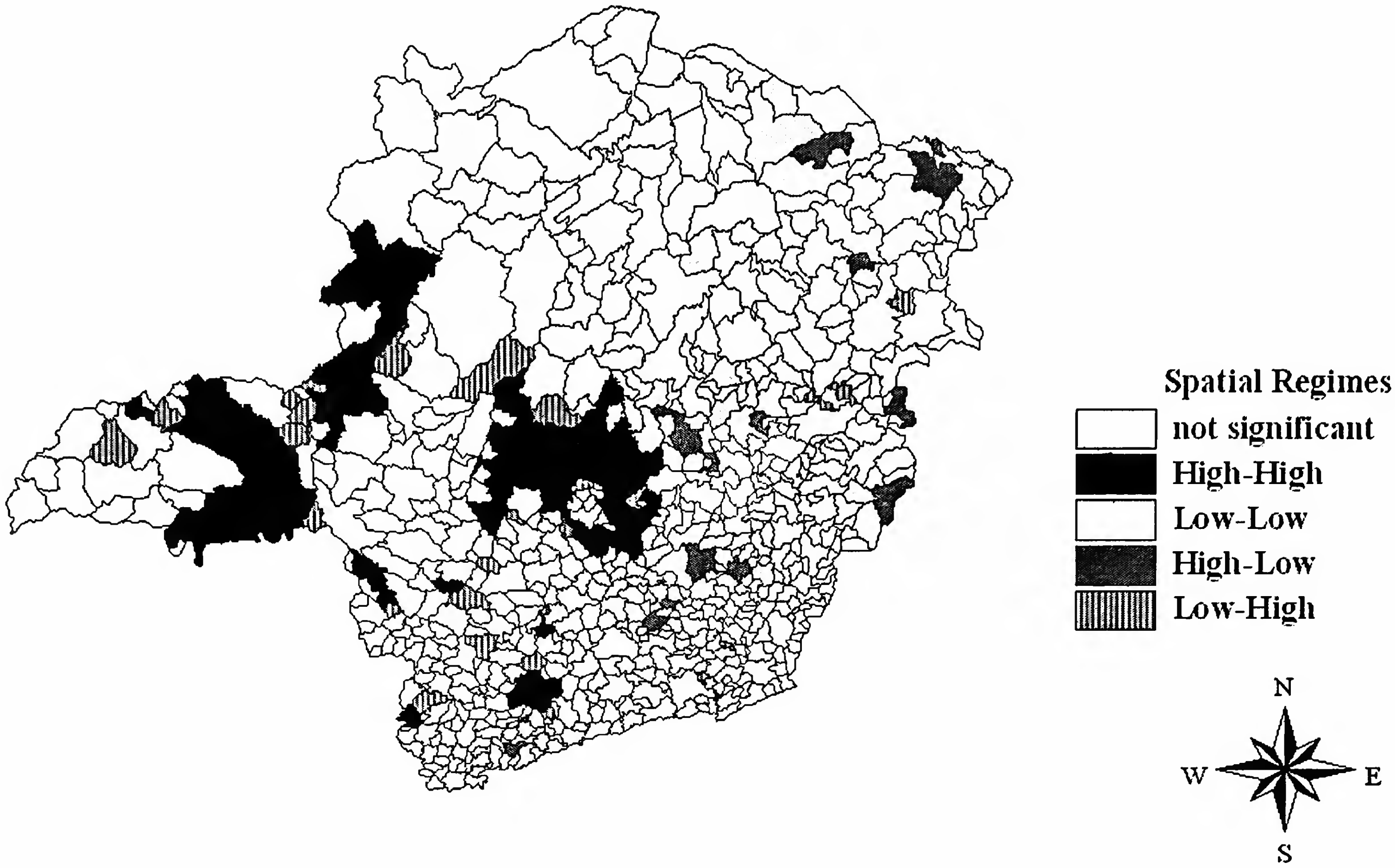
8 Following Anselin (1995), local Moran statistic for an observation i can be stated as

$$I_i = z_i \sum_j w_{ij} z_j$$

where the observation z_i, z_j are in deviation from the mean, and the summation over j is such that only neighboring values $i \in J_i$ are included, where J_i is set of neighbors of i.

9 For more details on examples of LISA statistics, see Anselin (1995).

Map 3 - Moran significance map for crime rates



Beginning with the Moran significance map for crime (Map 3), we find evidence of spatial grouping. Overall, there are some clusters of municipalities with high crime rates, as well as neighbors with high crime rates in the *Triângulo/Alto Paranaíba* and the Central region (mainly in *RM-BH*), besides the South-Southwestern *Minas Gerais* and the Northwestern Minas. The reason for this kind of cluster is because the crime is a contagious phenomenon, spreading over space and time. There are also some municipalities in these regions that are LH: municipalities with a low crime rate surrounded by municipalities with a high crime rate. In general terms, it seems that there are groupings of crime around the larger cities of *Minas Gerais* (or population agglomerations with a high urbanization rate).

To find more evidences about clusters, we implement the spatial ANOVA to test significant difference in means of crime rates between each spatial regime. In this context, spatial regimes are regarded as treatment indicators. The basic model consists of a regression of crime rates on a constant term and the treatment indicator representing each spatial regime. For example, this indicator for HH municipalities takes on a value of 1 when the "municipality" is located in the high-high spatial regime, and a value of zero otherwise. It is worthy noting that there are two underlying assumptions about ANOVA analysis, namely, the homoskedasticity and the absence of autocorrelation in the regression model. If these assumptions are not met, the ANOVA results may be misleading.

10 The LISA statistics (specifically, the local Moran) was chosen in detriment of the Gettis-Ord statistics, because the former conveys more information about the local spatial association. Indeed, the local Moran can identify four categories of spatial association, namely, high-high, low-low, high-low and low-high associations, whereas the Gettis-Ord statistics can detect just two categories: the high-high and the low-low associations.

Table 3 – Spatial ANOVA results

Variables	Regressions			
	1	2	3	4
Constant	14,423	16,496	15,390	15,588
	(51.905)	(56.479)	(52.929)	(53.277)
	[0.000]	[0.000]	[0.000]	[0.000]
HH	10,738			
	(11.941)			
	[0.000]			
LL		-7,742		
		(-9.749)		
		[0.000]		
HL			2,942	
			(1.427)	
			[0.154]	
LH				-3,743
				(-2.465)
				[0.014]
Adj. R-squared	0,158	0,111	0,001	0,007

Notes: t-values are in parenthesis, whereas probability levels are in brackets.

Table 3 shows the regression results. Four ANOVA regressions were estimated. The first regression uses spatial regime formed by HH municipalities as the treatment indicator. The second one adopts the spatial regime of LL municipalities like treatment indicator, whereas the third and fourth ones use the spatial regimes formed by HL and LH municipalities, respectively.

Table 4 – Diagnostics of spatial ANOVA results

Tests	Regressions			
	1	2	3	4
Condition number	1,376	1,471	1,153	1,215
Jarque-Bera	178,642	117,767	125,759	110,246
	[0.000]	[0.000]	[0.000]	[0.000]
Koenker-Basset	0.123	0.000	1,332	1,324
	[0.726]	[0.989]	[0.248]	[0.250]
Moran's I	-1,076	0.528	-0.261	-0.331
	[0.282]	[0.597]	[0.794]	[0.740]
Lagrange Multiplier (error)	1,284	0.216	0.101	0.153
	[0.257]	[0.642]	[0.750]	[0.696]
Robust LM (error)	1,279	2,799	0.026	0.159
	[0.258]	[0.094]	[0.871]	[0.690]
Lagrande Multiplier (lag)	0.691	0.006	0.098	0.133
	[0.405]	[0.939]	[0.755]	[0.716]
Robust LM (lag)	0.687	2,588	0.022	0.140
	[0.407]	[0.108]	[0.881]	[0.709]

Notes: Condition number, Jarque-Bera and Koenker-Basset check for multicollinearity, normality and homoskedasticity in the residuals, respectively. Moran's I, LM(error), Robust LM(error), LM(lag) and Robust LM(lag) verify spatial autocorrelation. Probability levels are in brackets.

The positive and highly significant value at one percent for the coefficient indicates that there is a considerable discrepancy between the mean of crime in the spatial regime of HH municipalities and the overall mean represented by the constant, which is also highly significant. As the signal of the categorical variable is positive, this indicates that the crime in HH municipalities is higher in about 11 points than the overall mean.[11] In relative terms, this represents that the crime in HH municipalities is almost 75 percent higher than the mean crime rate. The diagnostics of this regression, reported in Table 4, do not signal problems in terms of spatial autocorrelation or heteroskedasticity, although indicate problems of non-normality.

Regarding the spatial regime of LL municipalities, the negative and highly significant value of its coefficient (-7.742) reveals a substantial difference between the mean crime rates and the LL municipalities. In other words, as theoretically expected, the crime in spatial regime formed by LL municipalities is lower in almost 8 points than the overall mean. Once again, the diagnostics indicate problems of non-normality. However, there are no problems of spatial autocorrelation and heteroskedasticity, testifying that the ANOVA results are valid.

11 It is worth noting that the adjusted R^2 is low, because no explanatory variable is included into this regression.

Concerning the spatial regime of HL municipalities, the ANOVA analysis shows no statistical significance about the discrepancy between the overall mean and the crime in the high-low municipalities.

As to the spatial regime formed by LH municipalities, its coefficient is negative (-3.743) and significant at the 5 percent level. Fortunately, the residuals of the regression are homoskedastic and spatially non-correlated. In despite of this, the errors are non-normal.

Next let us estimate a regression by OLS that incorporates, besides the spatial regimes, the inertial effects on crime data. This is because, over the years, inertial effects in crime have been verified in the literature. (Andrade and Lisboa, 2001). The criminal inertia can be grasped from the following idea: there is crime at present, because there was crime at past. This kind of inertia occurs due to the criminal re-incidence and social interactions (for instance, involvement of relatives and friends which reduces the costs of crime and provides an infrastructure for supporting criminal activities). So, it is frequent to insert a lagged crime rate by one period in the right side of the equation to capture these effects.

Our objective is to investigate crime in exploratory terms. So, it is not intention to include covariates that represent causal determinants. Indeed, in rigorous terms, it is not correct consider inertial effects as a "determinant"; but this variable shows the extent of how the inertia operates.

The spatial regimes model with inertial effect is estimated below (see Table 5). First of all, it is noteworthy pointing out that the adjusted R-squared is 0.707. This means such a simple model without causal determinants (like income level, inequality index, unemployment rate, etc.) can explain more than 70 percent of the variation of the crime data! The majority of this explanatory power arises from the inertial effect, controlled by spatial heterogeneity in the form of spatial regimes.

Table 5 – Spatial regimes model results

Variables	Coefficient	t-value	Probability level
Const_NS	3,937	9,744	0,000
$Crime_{t-1}$_NS	0,879	32,258	0,000
Const_HH	8,870	5,230	0,000
$Crime_{t-1}$_HH	0,718	10,061	0,000
Const_LL	3,388	3,389	0,000
$Crime_{t-1}$_LL	0,677	5,926	0,001
Const_HL	14,111	3,413	0,001
$Crime_{t-1}$_HL	0,294	1,060	0,290
Const_LH	9,722	4,096	0,000
$Crime_{t-1}$_LH	0,190	0,952	0,342
Adj. R-squared	0,707		

As expected theoretically, the coefficients for the criminal inertia are all positive. These coefficients for the HH municipalities, the LL municipalities and the NS municipalities (that is, municipalities that cannot be classified in any statistically significant spatial regime) are highly significant at the 0.1 percent level. In despite of this, the inertial effects are not significant in the HL and LH municipalities.

Observe that in the HH spatial regime almost 72 percent of the crime rate at the previous period is conveyed to the present period, while in the spatial regime formed by LL "*municípios*" this effect amounts to 68 percent. In the municipalities that cannot be classified in any statistically significant spatial regime, the inertial effect is about 88 percent.

The regression diagnostics are listed in Table 6. The errors are not normal. There are no evidences of spatial autocorrelation in the regression residuals. The assumption of homoskedasticity is not marginally rejected at the 1 percent level.

Table 6 – Diagnostics of spatial regimes model results

Tests	
Condition number	7,343
Jarque-Bera	838,182
	[0.000]
Koenker-Basset	12,839
	[0.012]
Moran's I	-0,758
	[0.448]
Lagrange Multiplier (error)	0,672
	[0.412]
Robust LM (error)	0,734
	[0.392]
Lagrande Multiplier (lag)	0,072
	[0.788]
Robust LM (lag)	0,134
	[0.714]

Note: Probability levels are in brackets.

Table 7 presents the test for structural instability. The Chow test verifies the joint stability of the regression coefficients over the regimes. The null is that the coefficients (the constant and the lagged crime rate) are the same in all regimes. The null is rejected at the 1 percent level. So, there is statistical evidence of the existence of the spatial regimes.

It is possible to check for structural stability on the individual coefficients (in our case, the constant or the lagged crime rate), using again the Chow test. As can be observed in Table 7, there is a statistically significant difference in the relation between the criminal inertia and the crime in each of the regimes defined previously by the precedent analysis. The same happens to the instability of the constant over the spatial regimes.

Table 7 – Test for structural stability

Tests	
1. Test on overall coefficients	
Chow	7,740
	[0.000]
2. Test on individual coefficients	
Constant	4,937
	[0.001]
$Crime_{t-1}$	5,330
	[0.000]

Note: Probability levels are in brackets.

4 CONCLUSIONS AND FINAL REMARKS

Our application of ESDA to crime rates in *Minas Gerais* leads to various substantively important conclusions. First of all, the hypothesis of spatial randomness is clearly rejected. Statistically significant spatial clusters are observed for crime data in 1995. The conclusion is that there is positive spatial autocorrelation. In other words, crime is not distributed evenly and randomly over space in *Minas Gerais*.

Secondly, we could identify considerable spatial heterogeneity in the form of spatial regimes. The intuitive idea about spatial heterogeneity is that crime provides different responses, depending where it occurs. This manner, some of the observed local patterns of spatial association reveal clustering both positive autocorrelation (spatial regimes of HH and LL municipalities) and negative autocorrelation (spatial regimes of HL and LH municipalities). The spatial ANOVA analysis reinforces the evidence of the existence of these spatial regimes. Overall, we perceived that spatial pattern of crime in *Minas Gerais* has a tendency to concentrate around larger population agglomerations. Therefore, there seems to be a possible association between the crime rate and the urbanization or density rate.

Thirdly, a simple spatial regimes model with inertial effects is able to explain about 70 percent of the variation in the crime data. This result sheds lights on the extraordinary power of the ESDA tools in terms of extracting useful information from the crime data.

Fourthly, as Andrade and Lisboa (2001) have already found evidences of the role of inertial effects for the Brazilian case, the criminal inertia is a very important factor in the understanding of the crime phenomenon for *Minas Gerais* as well. The inertial effect is capable of transmitting until 88 percent of the past crime to the present period.

The criminal inertia poses effectively a challenge for the public security policy makers: in practice, crime level is hard to be curbed. Effective police activities may delay to yield palpable results. Consequently, some policy persistence is necessary before enjoying the reduction of the crime level.

Fifthly, as we showed evidences that crime in *Minas Gerais* is displayed spatially in the form spatial regimes, the policy intervention in terms of crime fight must be the responsibility of the State government, which has, on the one hand, power of establishing state police and, the other, coordinating the municipal efforts to fight criminal activities that spillover the municipal borders.

Finally, the procedure for identifying clusters, outliers and spatial dependence discussed in this paper are only initial steps in the understanding of the patterns of crime. Richer econometric models need to be considered to find out the determinants of the crime within a spatial setting. Consequently, the next step would be to insert covariates to explain the crime in *Minas Gerais*, using spatial econometric models. Notwithstanding, the ESDA results provide an empirical and solid foundation for the further econometric task.

In sum, the main conclusion of this paper can be stated in a unique phrase: space matters in the study of crime in *Minas Gerais*. So, it would be good that we begin to acknowledge this fact in our models.

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