CENTRE D'ÉTUDES
ET DE RECHERCHES
SUR LE DÉVELOPPEMENT
INTERNATIONAL

Document de travail de la série
Etudes et Documents
E 2005.24

HOW DO CRIMINALS LOCATE?
CRIME AND SPATIAL DEPENDENCE IN MINAS GERAIS

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October 2005
14p.

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1 Introduction

In Minas Gerais, in 2000, violent crime rate ranged from 0 in some rural municipalities to 1244 per 100 000 inhabitants in the capital, Belo Horizonte. Carneiro (2000) reports that some areas in the suburbs of Rio de Janeiro and São Paulo experience homicide rates comparable as those experienced by a country in war.

The question of the spatial location of criminals has for a long time interested social scientists. Blau and Blau (1982) study crime rates in American metropolitan regions and explain higher rates in urban areas by the difference in social structure. More recently, Glaeser and Sacerdote (1999) used a decomposition analysis to explain why there are more crime in cities, concluding in the existence of scale economies for crime. At a theoretical level, spatial location of crime has been associated with the existence of local interactions between criminals, making their localization not random (see Sah 1991, Glaeser et al. 1996).

There is also a large literature on the empirics of spatial location of crime, reviewed by Anselin et al. (2000), with a particular focus on the process of spatial diffusion of homicide (for example Cohen and Tita 1999, Messner et al. 1999, Baller et al. 2001, Messner and Anselin forthcoming). These works suggest a strong evidence of clustering of homicide around crime centers, emphasizing the emergence of homicide "hot spots". However, these works focus only on homicide and do not provide any evidence concerning the spatial diffusion of violent crime against property.

The aim of this paper is to investigate the existence of a spatial dependence of municipal crime rates in Minas Gerais, one of the 26 Brazilian states. By using spatial econometric techniques of testing and estimations, we explore the amount and structure of spatial diffusion of crime among a cross-section of 723 municipalities of Minas Gerais in 2000. The intuition is that it may exist a kind of geographical criminal inertia, already emphasized theoretically by Sah (1991). Moreover, the database allows a decomposition between violent crime against property and against persons, which enables to see if these two kinds of crime follow the same spatial process or not.

The choice of working at the municipal level has been motivated by the fact that it seems to be the most appropriated in the current context of security policy in Brazil. The national plan of public safety proposed by the new Brazilian government plans to give more prerogatives to municipalities, like formulating safety plans and creating municipal polices (see Secretaria Nacional da Segurança Publica 2003). Moreover, the new Country Assistance Strategy report of the World Bank for Brazil recalls that "*experience in Latin America and elsewhere suggests that the municipal level is one of the most effective entry points for crime and violence prevention*"[1].

The remainder of the paper is as follows. Section 2 briefly reviews recent works dealing

[1] World Bank (2003), p. 9.

with social interactions and their connection with crime at a micro-level, and discusses the link between local interactions and spatial autocorrelation. Section 3 presents the database and preliminary tests of spatial autocorrelation among violent crime rates. Results of regressions using a spatial estimator are presented in Section 4. Section 5 concludes.

2 Conceptual framework

Introducing a spatial variable in crime regressions comes from both theoretical motivations, mainly linked to the concept of social interactions, and from econometric requirements, not taking spatial aspect of crime into account involving biased results.

The concept of social interactions has been renewed during the 1990's, essentially in the field of urban economics, in an attempt, as it is recalled by Akerlof (1997), to go beyond the traditional model of individual behavior. The underlying hypothesis is the fact that individuals do not make their choices independently, their decisions are also the consequences of their social environment (family, friends, neighbors, ethnic and/or religious group, etc.). In other words, these social interactions can lead individuals to a collective behavior, even without formal coordination: individual decisions and social environment are now endogenous. According to Borjas (1995) and Akerlof (1997), social interactions increase with social proximity, essentially due to ethnicity and/or neighborhood. Durlauf (1994) and Borjas (1995) also consider intergenerational transmission of human capital and income stratification. Social interactions are then considered as a vector of *diffusion* of values and knowledge.

This process of diffusion is also present in the explanation of crime. Cohen and Tita (1999) consider two types of crime diffusion. The first one, contagious diffusion refers to the process of disease spreading and underlies a direct contact between the first criminal and his followers (the building of gangs typically follows this process). Contagion itself follows two schemes. Relocation diffusion suggests that criminals move from a point to another, the first one not being a crime center anymore. On the opposite, in the case of expansion diffusion, both former crime center and new crime place experience violence. The second kind of crime diffusion is hierarchical. Unlike contagion, it does not underlies direct contact between criminals but rather the existence of spontaneous innovation or imitation.

Theoretically, Sah (1991) considers a model where individual's decision to commit a crime depends on his perceived probability of punishment (which is endogenous) but not on the actual probability. The perceived probability depends on the individual's environment and particularly on the actual probability of punishment of other criminals. In other words, since the number of arrests by the police is limited, the more the criminals, the less the (perceived and actual) probability of punishment. This work inspired the one of Glaeser et al. (1996) who explain the high crime variance across time and space by differences in social interactions. They find that, for United States, the role played by differences in social interactions in the explanation of differences in crime rates is high for delinquency (such as larceny, theft, car theft), moderate for serious crime (such as robbery, burglary and assault) and small for murder and rape. This result suggests that "learning by seeing" is relevant concerning economic crime but not for interpersonal violence, which is rather conform to intuition.

However, does controlling for spatial autocorrelation in crime rates regressions means measuring the role of social interactions? Anselin et al. (2000) recall that one must be careful with the interpretation of spatial dependence because the scale where crime data are collected (such as states, regions, counties or municipalities) is almost arbitrary and does not reflect the "true" scale of crime (which is individual). Hence, there can be artificial spatial dependence in a variable, due to an inadequate spatial scale. This also requires a specific econometric treatment but such an estimate does not have any economic sense.

Moreover, even in the case where spatial dependence across crime rates corresponds to a "true" spatial process involving the presence of social interactions among criminals at micro-level, controlling for spatial autocorrelation does not "explain" anything. It only measures the amount and strength of the spatial dependence. However, Conley and Topa (2003) suggest that using data in which location information is correct but imprecise (which is typically the case when using postal codes or any administrative level) preserves the identification of parameters. In other words, if there are really social interactions among criminals, involving spatial dependence at a more macro-level, controlling for this spatial dependence keeps the model correct even if it does not inform about the structure of local interactions *per se*.

To sum up, microeconomic theory suggests the existence of local interactions among criminals but available data, which are collected at a more macro-level, do not allow to measure and describe these interactions. On the other side, crime data generally suggest the existence of spatial dependence among crime rates. In order to know whether this dependence is due to a true spatial process or only to a "noise" involved by the imprecision of data, one needs to follow a specific procedure of testing and estimation.

3 Spatial autocorrelation of crime rates in Minas Gerais

3.1 The data

Crime data used in this paper are issued from a database constructed by the *Fundação João Pinheiro* and the Federal University of Minas Gerais from police data. It contains, for

723 municipalities of Minas Gerais[2], the number of occurrences and the gross crime rate per 100.000 habitants. In this paper, we distinguish violent crime against property from that against persons. Violent crime against property is the sum of robbery and armed robbery. Violent crime against persons is the sum of homicide, tentative of homicide and assault. This decomposition enables us to test whether crime against property and persons have the same determinants or, in other words, to see if there is *a* violence or *some* violences.

Though it contains data from 1986 through 2002, we only use in this paper a cross-section of the municipalities for the year 2000. This choice has been conditioned by data availability: 2000 was the year of the last census in Brazil, which provides the best economic and social data at municipal level. During the census, about 25% of the population is surveyed, both at household and individual level. Moreover, it contains household and individual weights, allowing to extend the results of the survey to the hole population. Socio-economic variables used in this paper are issued from census data: we aggregated weighted individual observations by municipality and then divided it by the population, in order to get municipal averages.

Our crime database has the advantage to give data as disaggregated as possible, municipality being the smallest administrative unit in Brazil. Moreover, though Minas Gerais is not the biggest nor the most inhabited state of Brazil, it is the state with the most municipalities, a sign of the willingness of decentralization of this state (and also a sign of the disaggregation of our data). This database is, to the best of our knowledge, the only one of that kind (i.e. to provide municipal-level crime data) for Brazil. However, it suffers from the common weakness of all police-issued crime databases, namely a measurement error. Police data records only reported crimes, not all crimes committed in the area. As a consequence, official crime rates undermine real crime rates. Results presented here are thus to be interpreted with caution.

3.2 Testing for spatial autocorrelation

The first task when working in spatial econometrics is to define what we consider as "neighbor" by constructing a spatial weight matrix. In this paper, we follow most of the preceding works and consider contiguity (that is two observations having a common border) as making neighborhood. We then construct a binary contiguity matrix ("1" for neighbors, "0" else). By construction, this matrix is squared and symmetric. In order to make easier the interpretation of coefficients, the matrix is row-standardized to one (the sum of coefficients for each line, i.e. each municipality, is fixed at one). Hence, the spatial lag of crime rate corresponds to the average crime rate of neighbors.

[2]Minas Gerais now has 853 municipalities but the database was constructed while there were only 723. Crime committed in new municipalities are thus added to the municipality they formerly belonged to.

We first take a look at spatial features of crime rates. Figures 1 and 2 display the Moran scatter plot for the logarithm of each crime rate used. It shows, on the horizontal axis, values of crime rate for each municipality and on the vertical axis the spatial lag, or in other words the neighbors' mean crime rate and thus displays local spatial autocorrelation. The scatter plot is centered on the mean so that the position of each point makes sense. Points located in the lower left and the upper right quadrants suggest positive spatial autocorrelation while upper left and lower rights quadrants suggest a negative one. Moreover, the slope of the linear regression line is the Moran's I-statistic, which corresponds to the global spatial autocorrelation coefficient among all municipal crime rates.

Figures 1 and 2 show a general tendency to positive spatial autocorrelation among crime rates, which is confirmed by the positive value of the Moran's I. This statistic suggests that roughly 35% of municipal crime rates is correlated with neighbors' crime rates. However, these figures also show an extreme heterogeneity in the sample, which unfortunately weakens the results.

We then run OLS regressions of crime rates and test for the presence of spatial autocorrelation (Table 3.2, columns (1) and (2)). We follow Fajnzylber et al. (2002) and consider income inequality, level of development and income growth as the "core" determinants of crime. Since development and crime are likely to be endogenous, we use the lagged value of the Human Development Index (i.e. its value for 1991, year of the preceding census) as a measure of development. We also introduce in the regression a set of usual control variables, well-known to be crime-enhancing: population density, the share of female-headed households[3], the share of male 15-24 years-old and an index of racial polarization constructed following the methodology proposed by Montalvo and Reynal-Querol (2003). Data are issued from the 2000 census and from the Atlas of Human Development in Brazil[4].

We present tests of Lagrange Multiplier for the presence of a spatial lag (LM_{LAG}) or spatial autocorrelation in the error term (LM_{ERR}) along with their version robust to a local misspecification of the model (i.e. presence of a spatial lag when testing for autocorrelation in the error term and inversely), RLM_{LAG} and RLM_{ERR} (see Anselin et al. 1996). We also present the Moran test (which is different from the Moran statistic showed in the preceding figures) for the spatial autocorrelation of the residuals of the OLS regression. These tests suggest the presence of spatial autocorrelation for both crime rate and the error term, the former being more significant than the latter. However, these tests can also be interpreted as specification tests, particularly if there are omitted variables (see

[3] Glaeser and Sacerdote (1999) found that crime are higher in cities partly because of their higher share of female-headed households, which is actually a sign of the weakness of social links and social capital.

[4] *Atlas do Desenvolvimento Humano no Brasil*, UNDP (2003), freely available to download at www.undp.org.br

Table 1: OLS regressions of violent crime rates

	(1)	(2)	(3)	(4)
	Violent crime against Property	Violent crime against Persons	Violent crime against Property	Violent crime against Persons
HDI 1991	13.802	-2.964	14.046	-1.082
	(11.00)	(2.53)	(8.78)	(0.72)
Income Gini	4.485	3.845	4.137	3.671
	(6.41)	(5.88)	(5.79)	(5.49)
Income growth	-0.146	-0.091	0.039	0.046
	(0.68)	(0.46)	(0.17)	(0.22)
Population density	0.000	0.000	0.000	0.000
	(1.95)	(1.46)	(1.81)	(1.40)
Female-headed households	0.002	0.046	0.005	0.047
	(0.07)	(1.36)	(0.13)	(1.36)
Male 15-24 years-old	35.776	28.199	31.471	26.082
	(4.96)	(4.19)	(4.28)	(3.79)
Racial polarization	1.011	1.597	0.935	0.408
	(2.67)	(4.51)	(1.98)	(0.92)
Intercept	-13.485	-1.915	-12.253	-1.344
	(10.64)	(1.62)	(8.72)	(1.02)
Meso-region fixed effect	No	No	Yes	Yes
Observations	723	723	723	723
R-squared	0.31	0.19	0.36	0.25
Moran's I	4.523	2.489	2.986	0.452
(p-values)	(0.000)	(0.013)	(0.003)	(0.651)
LM_{LAG}	33.225	14.556	11.241	0.699
(p-values)	(0.000)	(0.000)	(0.001)	(0.403)
RLM_{LAG}	17.405	25.633	8.796	16.830
(p-values)	(0.000)	(0.000)	(0.003)	(0.000)
LM_{ERR}	18.246	5.115	4.843	0.063
(p-values)	(0.000)	(0.024)	(0.028)	(0.802)
RLM_{ERR}	2.426	16.191	2.397	16.194
(p-values)	(0.119)	(0.000)	(0.122)	(0.000)

Absolute value of z statistics in parentheses.
Crime rates are expressed in logarithms.

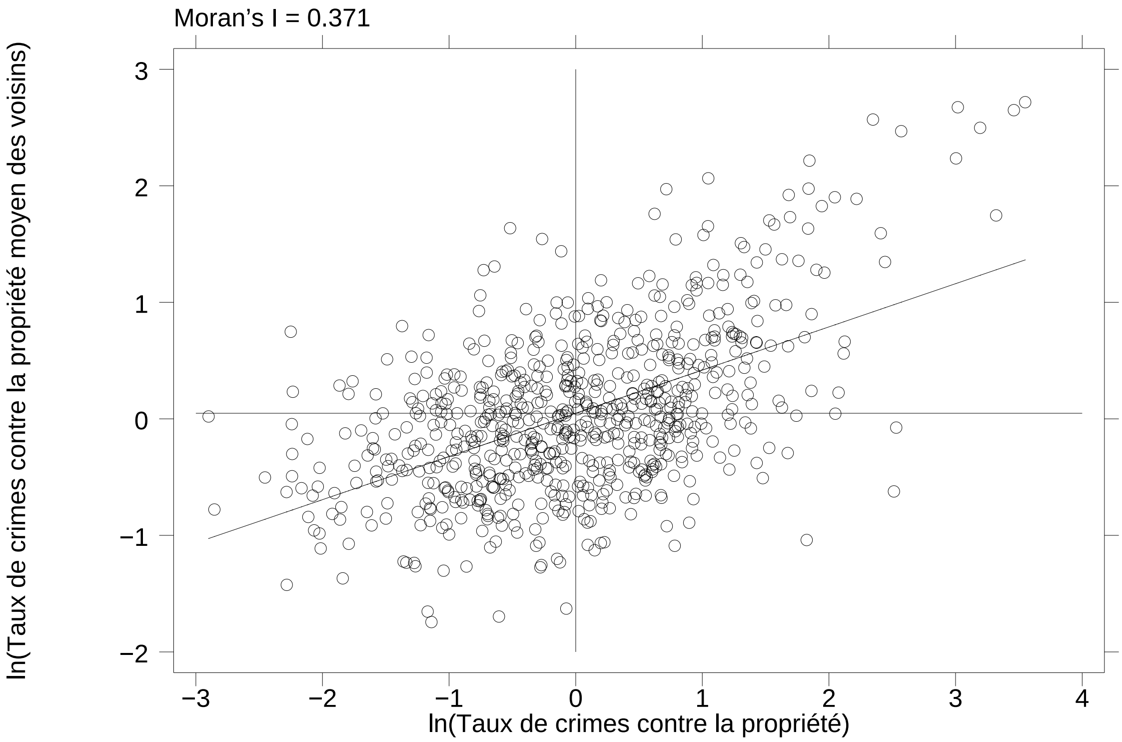

Figure 1: Moran scatterplot for violent crimes against property

Le Gallo 2000). A possible misspecification, since we work upon local correlation among crime rates, is to forget a possible regional effect. Columns (3) and (4) of Table 3.2 display the same OLS regressions as in column (1) and (2) respectively, with the introduction of a meso-region fixed effect (there are 12 meso-regions in Minas Gerais). The only test to be always significant is the robust test for the presence of a spatial lag (RLM_{LAG}). Moreover, tests for the presence of autocorrelation in the error term are always less significant than these for the presence of spatial dependence in the variable. All of this suggests that OLS estimates are likely to be biased and that spatial autocorrelation requires a specific econometric treatment.

4 A spatial econometric model of crime

The model to be estimated is then the following:

$$y = \rho.Wy + X\beta + \epsilon \tag{1}$$

where X is the matrix of independent variables, β the associated vector of coefficients, W the spatial weights matrix, ρ the spatial autocorrelation coefficient and ϵ the error term. In this paper, W is a so-called row-standardized contiguity matrix. In other words, ρ is

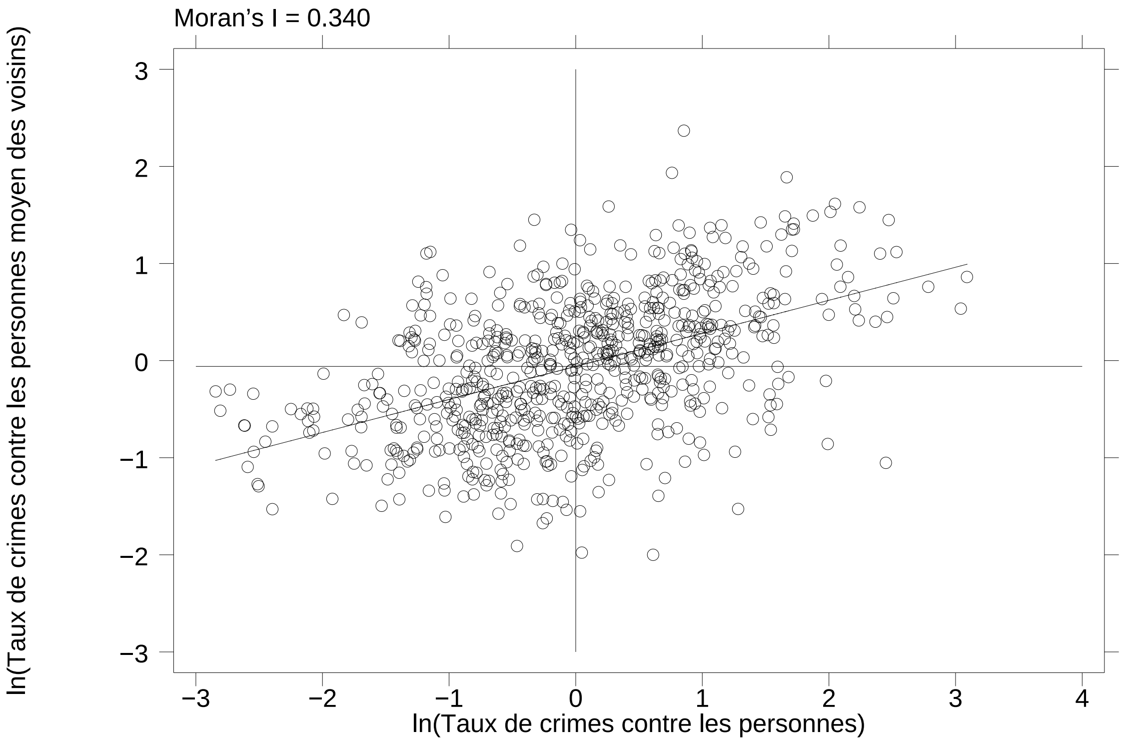

Figure 2: Moran scatterplot for violent crime against persons

the coefficient associated with the effect of the average crime rate of neighbor municipalities upon the crime rate of each municipality. This model cannot be estimated by OLS since spatial autocorrelation biases the estimator, and requires Maximum Likelihood (ML) estimates[5]. Results are presented in Table 4, following the same scheme as in Table 3.2: the first two columns present results for estimates without meso-region fixed effects while the last two columns display results with regional fixed effects. For each regression, Table 2 displays three usual specification tests for the significance of spatial autocorrelation. Though these three tests are asymptotically convergent, they are all displayed in Table 4 because the spatial estimator is not identical to the other ML estimators (see Anselin 2001) and hence has not the same properties.

Comparing results with and without fixed effects gives some information concerning the amount and structure of the dependence between municipal crime rates. As the Moran's I-statistic suggested it in the preceding section, columns (1) and (2) of Table 4 display a positive autocorrelation among crime rates of about 0.2-0.3, this correlation being strongly significant. However, the spatial feature of crime seems to depend on the type of crime considered. Columns (1) and (3) suggest a large spatial diffusion of property crime: even

[5]See Anselin (2001) for a discussion on the OLS bias and on the spatial Maximum Likelihood estimator.

Table 2: Spatial regressions of violent crime rates

	(1)	(2)	(3)	(4)
	Violent crime against Property	Violent crime against Persons	Violent crime against Property	Violent crime against Persons
HDI 1991	11.736	-2.139	13.011	-0.978
	(9.25)	(1.83)	(8.17)	(0.66)
Gini coefficient	4.598	3.668	4.224	3.643
	(6.79)	(5.71)	(6.04)	(5.52)
Income growth	-0.044	-0.052	0.081	0.046
	(0.21)	(0.26)	(0.37)	(0.22)
Population density	0.000	0.000	0.000	0.000
	(1.38)	(1.19)	(1.44)	(1.34)
Female-headed households	0.020	0.042	0.013	0.046
	(0.55)	(1.24)	(0.36)	(1.34)
Male 15-24 years-old	32.487	24.856	29.990	25.432
	(4.64)	(3.73)	(4.17)	(3.73)
Racial polarization	0.764	1.302	0.818	0.398
	(2.07)	(3.66)	(1.76)	(0.91)
Intercept	-12.622	-2.399	-12.112	-1.516
	(10.21)	(2.05)	(8.82)	(1.16)
Meso-region fixed effect	No	No	Yes	Yes
rho (spatial correlation)	0.263	0.204	0.168	0.051
	(5.62)	(3.81)	(3.33)	(0.86)
Observations	723	723	723	723
Log likelihood	-1297.052	-1255.378	-1278.154	-1234.439
Wald test of $rho = 0$	31.549	14.499	11.077	0.733
(p-values)	(0.000)	(0.000)	(0.001)	(0.392)
LR test of $rho = 0$	29.716	13.924	10.769	0.729
(p-values)	(0.000)	(0.000)	(0.001)	(0.393)
LM test of $rho = 0$	33.225	14.556	11.241	0.699
(p-values)	(0.000)	(0.000)	(0.001)	(0.403)

Absolute value of z statistics in parentheses.
Crime rates are expressed in logarithms.

after clustering municipalities by meso-region, spatial dependence is still high (roughly 0.17) and significant. In other words, total autocorrelation (0.263) can be decomposed between a correlation within each meso-region (of about 0.10) and the remaining global spatial dependence. Following the classification proposed by Cohen and Tita (1999), it suggests a *hierarchical* diffusion of violent crime against property, which does not requires any direct contact between criminals.

On the opposite, violent crime against persons appears to be a much more localized phenomenon. Columns (2) and (4) of Table 4 show that, after introducing a regional fixed effect, spatial autocorrelation is small and no longer significant. Spatial correlation among interpersonal violence rates (of about 0.20) is thus almost due to correlation within meso-regions. In other words, it suggests a process of "clustering" around big crime centers like Belo Horizonte, the capital, or the other big cities of the state, places located faraway from these centers not being "infected". Hence, this kind of crime seems to follow a process of *contagious* diffusion, involved by proximity and direct contact between criminals. It should be interpreted, not like a "learning by seeing" process, but rather like a sign of a strong violence inertia, which is conform to the findings of Sah (1991).

These two results are consistent with some preceding works. Glaeser et al. (1996) found a significant impact of social interactions upon property crime (particularly "small" crime like robbery and theft, which corresponds to crime studied in this paper) but not upon serious crime (homicide, rape). Even if we do not work with micro-data and are thus unable to state anything about the impact and amount of social interactions, our results suggest that property crime spreads much more than interpersonal violence, underlying a bigger role of interactions between criminals for the former than for the latter. Moreover, most of preceding works dealing with spatial diffusion of homicide (e.g. Cohen and Tita 1999, Messner et al. 1999, Baller et al. 2001, Messner and Anselin forthcoming) also found a contagious-type diffusion and clustering for that kind of crime.

5 Concluding remarks and policy implications

The aim of this paper was to investigate the existence of a spatial dependence of crime rates at local level. We explored if and how crime rates are correlated using a cross-section of 723 municipalities of Minas Gerais, a Brazilian state, for 2000. Results suggests a significantly positive spatial autocorrelation among crime rates. However, property crime and interpersonal violence do not follow the same scheme. Property crime spreads much more than crime against persons, which itself appears, as a consequence, to be a localized and concentrated phenomenon.

These spatial features of crime should deserve a particular attention from policy-makers. First, in order to limit diffusion of property crime, anti-crime policies (repression but also social policies like employment or housing programs) should concern suburbs as well as crime centers. Fighting crime only in centers do not prevent diffusion of violent crime against property, which does not need direct contact between criminals to spread. If we consider that property crime in hot spots cannot be eradicated totally, priority should even be given to limit its diffusion and hence to fight crime in peripheries. Second, anti-crime policies should also take into account the fact that property crime and interpersonal violence do not share the same spatial features and thus require a specific treatment. Since violent crime against persons seems to not naturally spread so much, efforts should be concentrated to reduce it in high-violence places (essentially poor neighborhoods of cities), all the more if we consider, like our results suggest it, that “pure” violence experiments a strong inertia.

However, it is impossible, as long as data are aggregated, to determine the sources of this inertia, as well as the sources of spatial diffusion of crime in general. There is a real need for micro-level data of crime, in order to really estimate the link between social interactions and crime. Moreover, it would be useful to have more data, particularly for the other Brazilian states. Since criminals do not stop at municipal borders, there are no reasons to assume that they limit their activities to only one state, particularly in the high-crime Southeastern region of Brazil (states of Rio de Janeiro, São Paulo, Minas Gerais and Espirito Santo). Such a mapping of crime activities would be particularly useful for security and social policies.

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