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Murder, Nonnegligent Manslaughter, and Spatial Autocorrelation in Mid-South Counties*

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In this paper we explore to what extent county murder and nonnegligent manslaughter rates in the midsouth are spatially autocorrelated, using a variety of spatial autocorrelation tests. The data are 3-year averages of UCR murder and nonnegligent manslaughter rates from the 383 midsouth counties. Moran's I statistics show a statistically significant amount of spatial autocorrelation in the murder and nonnegligent manslaughter rates among the 383 midsouth counties. G statistics, however, fail to detect a global pattern in this region. We also compute G_i statistics and local Moran's I statistics with these data and detect some patterns of localized spatial autocorrelation. We estimated and compared an MLE spatial lag model and an OLS model with constructs informed by social disorganization theory. The regression analysis failed to detect any significant spatial effects for the midsouth counties.

KEY WORDS: murder; nonnegligent manslaughter; spatial autocorrelation; midsouth counties.

1. INTRODUCTION

In this paper we test for spatial autocorrelation in county murder and nonnegligent manslaughter (NNM) rates in five southern states (Alabama, Arkansas, Louisiana, Mississippi, Tennessee). Over the last 20 years the importance of spatial autocorrelation in models which utilize geographical units of analysis has been increasingly recognized in the social sciences (Odland, 1988; Doreian, 1981; Anselin, 1988; Land and Deane, 1992). Spatial autocorrelation is of particular interest to criminologists, who maintain

*The views expressed in this article are those of the authors and should not be viewed as the opinion of the Federal Bureau of Investigation or the Department of Justice.

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that local crime rates at different levels of geography (neighborhoods, census tracks, counties and urbanized areas) are, in part, a function of place well-being (or the state of local disorganization). There are a number of studies which examine crime measures at the county level (Petee and Kowalski, 1993; Kposowa and Breault, 1993; Kposowa *et al*., 1995; Kowalski and Duffield, 1990; Lee, 1996; Guthrie, 1995; Wilkinson, 1984; for a summary of homicide studies see Land *et al*. 1990). Furthermore, research shows that many of the predictors of county violent crime and homicide rates, such as household poverty, income inequality, urbanization, and population dynamics, are spatially autocorrelated at various levels of geographical analysis, including counties (see Anselin, 1988; Mencken, 1998; Doreian, 1981; Morenoff and Sampson, 1997; Lyson and Tolbert, 1996). If the theoretical determinants of violent crime and homicide are spatially autocorrelated at the county level, it stands to reason that county level crime rates may also be spatially autocorrelated. Failure to address spatial autocorrelation has implications for statistical analysis.

2. SPATIAL AUTOCORRELATION

Spatial autocorrelation represents more geographical clustering of observation values than would be expected in a random distribution of values across geographical units (Anselin, 1998; Odland, 1988). Spatial autocorrelation is present when a value for variable X at location j is dependent upon the value of variable X at location i. For example, the poverty rate in one county is not likely to be independent of poverty and economic circumstances in an adjacent county (Lyson and Tolbert, 1996; Odland, 1988; Mencken, 1998). Spatial autocorrelation is particularly problematic for dependent variables in OLS regression analysis (for a good example, see Land and Deane, 1992). The extent to which this spatial autocorrelation in the dependent variable is not addressed creates statistical problems. Uncorrected spatial autocorrelation can create inflated standard error terms and a Type II statistical error. In other circumstances uncorrected spatial autocorrelation creates model misspecification through the omission of a relevant variable (the coefficient which corrects for spatial autocorrelation) and biased regression coefficients (see Land and Deane, 1992; Anselin, 1988; Doreian, 1981). Odland (1988) maintains that autocorrelation among error terms can create underestimated standard errors and an increased chance for a Type I statistical error.

3. MEASURES OF SPATIAL AUTOCORRELATION

Moran's (1948) I is one of the best-known and most accessible tests for spatial autocorrelation (Odland, 1988; Getis and Ord, 1992). Moran's I has an interpretation similar to a zero-order correlation coefficient; the larger the value, the greater the spatial autocorrelation and the greater the clustering of values by geographical unit. Unlike zero-order correlation coefficients, the mean of Moran's I is not 0, but $-1/N-1$, which approaches 0 as N increases:

$$I = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \mu)(x_j - \mu) / \sum_{i=1}^{n} (x_i - \mu)^2$$

for a row standardized spatial weights matrix w_{ij}.

Getis and Ord (1992; p. 198) point out several limitations of Moran's I. When the measure is computed across all geographical areas in question (i.e., all 383 counties in the midsouth states), localized pockets of important clustering may not be detected. In addition, Moran's I is based on covariation between county values on some variable (e.g., murder/NNM rates) within a specified distance. A positive statistically significant global Moran's I statistic can result from clustering of high murder/NNM rates among nearby counties within a given distance, clustering of low murder/NNM values among nearby counties within a given distance, or a combination of both high and low value clustering within respective distance bands across a global region. Getis and Ord (1992) present alternatives to Moran's I. The G statistic differentiates global spatial autocorrelation so that the patterns detected are better identified as high value clustering or low value clustering.[4] In the equation, d is a distance band, w_{ij} is a binary matrix of ones and zeros, where ones indicate counties within the

$$G = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(d) x_i x_j \Big/ \sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j$$

distance band, and x_i and x_j are values of variable x at locations i and j.

However, both Moran's I and the G statistic may fail to identify local important clusters of positive and negative spatial autocorrelation in a global region. The G_i statistic developed by Getis and Ord (1992, p. 190) is a computation of local clustering of values in a global region. The statistic is formally defined as

$$G_i = \sum_{j=1}^{n} w_{ij}(d) x_j \Big/ \sum_{j=1}^{n} x_j \qquad \text{for} \qquad i \neq j$$

where w_{ij} is a zero/one binary spatial weights matrix, with ones for all county links within the defined area by distance d for a given i and zeros

[4]Getis and Ord (1992, p. 198) point out that with the G statistic, negative Z scores result from clusters of low values and positive Z scores from clusters of high values.

otherwise. The distance d refers to a distance band surrounding each observation, as stipulated in the construction of the weights matrix. Positive Z-score values for each observation indicate clusters of high values (murder/NMM) among counties within d. The G_i statistic allows for the identification of localized spatial clusters, even when other global measures (i.e., Moran's I or the G statistic) do not suggest global patterns.

However, the G series has limitations. These statistics require that data are positive and assumes that the variable under investigation follows a normal distribution. With murder/NNM this may or may not be a sound assumption. These series also do not detect negative spatial autocorrelation very well. We use the permutation approach to test the significance of Moran values [SpaceStat allows 999 random permutations (for details see Anselin, 1998)].

Messner *et al*. (1999) show the utility of local Moran's I statistics in exploring and identifying clusters of counties with high murder/NNM rates, clusters of counties with low murder/NNM rates, and negative spatial autocorrelation. Moran's scatterplot differentiates observations (counties) into four types (four quadrants): (1) high murder/NNM rate and neighbor(s) high murder/NNM rates—county has above-average murder/NNM rates and neighbors have above-average murder/NNM rates; (2) low murder/NNM rates and neighbor(s) low murder/NNM rates—county has below-average murder/NNM rates and neighbors have below-average murder/NNM rates; (3) high murder/NNM rates and neighbor(s) low murder/NNM rates—county has an above-average murder/NNM rate and neighbors have below-average murder/NNM rates; and (4) low murder/NNM rates and neighbor(s) high murder/NNM rates—county has low murder/NNM rates and neighbors have above-average murder/NNM rates (Anselin, 1998, 1996). The first two scenarios represent positive spatial autocorrelation, while the last two represent negative spatial autocorrelation.

4. DATA AND ANALYSIS

In the analysis we examine the spatial autocorrelation in murder/NNM rates (incidents per 100,000 population) in midsouth counties, averaged between 1989 and 1991. We chose the region for several reasons. First, there is general substantive interest in southern violence (Ellison, 1991; Parker, 1989; Huff-Corzine *et al*., 1991). Second, this region contains urban areas with relatively high murder and violent crime rates (New Orleans, LA; Shreveport, LA; Mobile, AL; Memphis, TN). This provides an opportunity to test the extent to which the murder/NNM rates in surrounding counties are spatially autocorrelated with these urban places. Third, this is a region of the nation that is relatively rural. According to the 1990 Census, 75% of midsouth counties were non-MSA, and the urbanization rate for the region was 59%, substantially lower than the 75% urbanization rate for the United States in 1990. This provides an opportunity to explore the extent to which murder/NNM rates in nonmetropolitan counties are spatially autocorrelated with the higher rates in nearby urban areas (Fischer, 1980).

We created a global arc distance weights matrix using county latitude and longitude centroid points as coordinates for the 383 county region. From this general matrix we created a symmetrical 0,1 binary contiguity matrix based on the furthest nearest first neighbor principal.[5]

The average murder/NNM rates for 1989–1991 are taken from the FBI Uniform Crime Reports.[6] The mean of the years 1989–1991 were used to control for variations in reporting from year to year. While criticisms of the UCR data are well documented (see recently Shihadeh and Ousey, 1998), for the most part, the data are considered to be representative of reported crime to law enforcement of a particular area. For comparison, we examine spatial autocorrelation in theoretically relevant predictors of violent crime (Land *et al.*, 1990). These variables include county population density (1990), percentage of county population black (1990), percentage of county households female headed (1990), percentage of county families living in poverty (1990), county unemployment rate (1990), and percentage of population age 16–21 (1990). These measures are taken from the Census of Population and Housing and USA Counties 1996 (U.S. Bureau of the Census, 1991, 1996). The analysis is performed with SpaceStat (Anselin, 1995).

5. RESULTS

Table I presents Moran's I and G statistics for the 1989–91 average murder/NNM rates and the predictors of crime. Figure 1 shows the geographical distribution of murder/NNM rates throughout the region. The analysis shows contradictory results. The Moran's I statistic shows a significant spatial autocorrelation for murder/NNM ($i = .137$, $p = .001$). However, the G statistic shows no significant global spatial autocorrelation for this measure ($G = .02$, $Z = .34$). Figure 1 shows clustering of low murder/NNM rates (0–3 per 100,000) throughout the midsouth, as well as high murder/NNM rate

[5]Getis and Ord (1992) set distance bands equal to the farthest first nearest-neighbor county of any county in the region. We follow their example, and in our analysis the distance is approximately 35 mi.

[6]Some agencies did not report county crime data to the FBI for some years. We performed mean substitutions for those instances based on state and geographic level mean rates. For example, if a nonmetropolitan parish in Louisiana did not report a murder/NNM rate for a given year, we substituted the mean murder/NNM rate for all nonmetropolitan counties in Louisiana for that year.

Table I. Moran's *I* and *G* Statistical Tests for Spatial Autocorrelation for Murder and Nonnegligent Manslaughter Rates and Predictors of Violent Crime in Midsouth Counties[a]

	G			Moran's *I*		
Variable	*G*	Mean	*Z* value	*I*	Mean	*p* value
Murder/NNM (1989–1991 avg.)	0.020	0.019	0.341	0.13722	–0.011	0.001
Percentage black, 1990	0.024	0.019	6.518***	0.72263	–0.005	0.001
% families in poverty, 1990	0.020	0.019	0.278	0.1	–0.009	0.012
Unemployment rate, 1990	0.020	0.019	0.300	0.33698	–0.007	0.001
% female-headed households, 1990	0.020	0.019	2.719***	0.63911	–0.007	0.001
Percentage 16–21, 1990	0.019	0.019	–0.010	0.63235	–0.004	0.001
Population density, 1990	0.027	0.019	2.932***	0.19852	–0.006	0.001

[a]Distance based on farthest nearest-neighbor county.
***$p < .001$.

clusters (12–60 per 100,000). Getis and Ord (1992, p. 198) show that a positive global Moran's *I* value can be computed from clusters of high value and/or clusters of low values. The *G* statistic, on the other hand, computes positive values for concentration of high values within a given distance and negative values for clusters of low values. The patterns of high and low murder/NNM rates in the region may explain why the *G* statistic measure of spatial autocorrelation is not significant, and Moran's *I* is significant.

Neither Moran's *I* nor the *G* statistic will detect local patterns of spatial autocorrelation in global settings. To locate the areas of high and low value within the region, we also calculated the G_i spatial statistic developed by Getis and Ord (1992) for all 383 counties in the analysis and map the *Z* scores from this analysis. Figure 2 presents the geographical distribution of *Z* scores from the G_i analysis, while Table II presents the midsouth counties with statistically significant *Z* scores ($Z \geq 1.96$, $Z \leq -1.96$).

In general, the map shows a trend toward low murder/NNM rate clustering in the Tennessee counties and high murder/NNM clustering in Louisiana. In Louisiana, there are two prominent patterns. Jefferson Parish, LA, and Plaquemines Parish, LA, are among the top 10 G_i scores. These are parishes that border Orleans Parish, LA, and the city of New Orleans and are both part of the greater New Orleans MSA. However, the results are somewhat suspect. Plaquemines Parish has a relatively low murder/NNM rate (5.4) in comparison with Jefferson Parish (12.5). The other pattern in Louisiana is among nonmetro parishes in the center of the state (Grant, La Salle, Natchitoches, Sabine). Grant and Natchitoches parishes have very similar murder/NNM rates (11.4 and 14, respectively), but La Salle Parish has a murder/NNM rate of 4.1. The low-value G_i counties in Table II also show some inconsistencies. For example, Giles Co., TN and

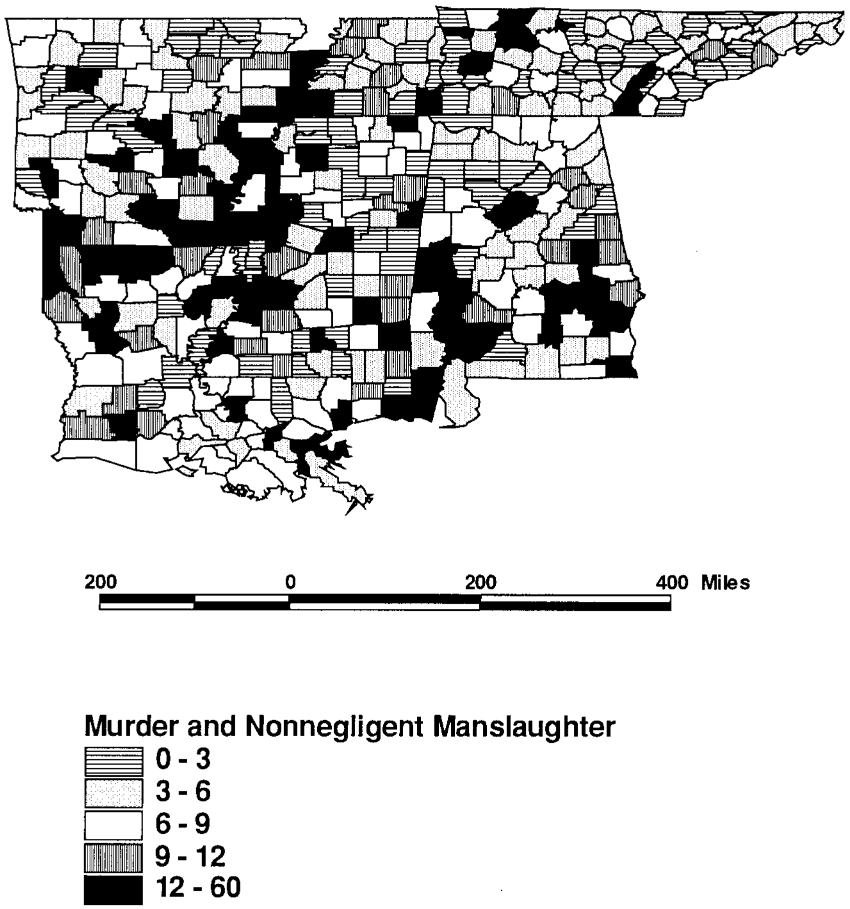

Fig. 1. 1989–1991 average murder and nonnegligent manslaughter rates, midsouth counties (FBI uniform crime reports).

Dyer Co., TN both have relatively high murder/NNM rates (10.4 and 12, respectively).[7]

The G_i analysis shows inconsistent trends and a lack of clear cluster pattern among counties with high and low murder/NNM rates. These inconsistencies may result from violating the expectation of a normally distributed variable. We examined a local Moran scatterplot in order to explain better the spatial autocorrelation pattern detected by Moran's I (Table I). For all counties with statistically significant local Moran's I statistics, we

[7]We also analyzed these data with the G_i^* statistics, which allows for the observation under consideration to be included (i.e., $i=j$). The results were very similar to those found with G_i.

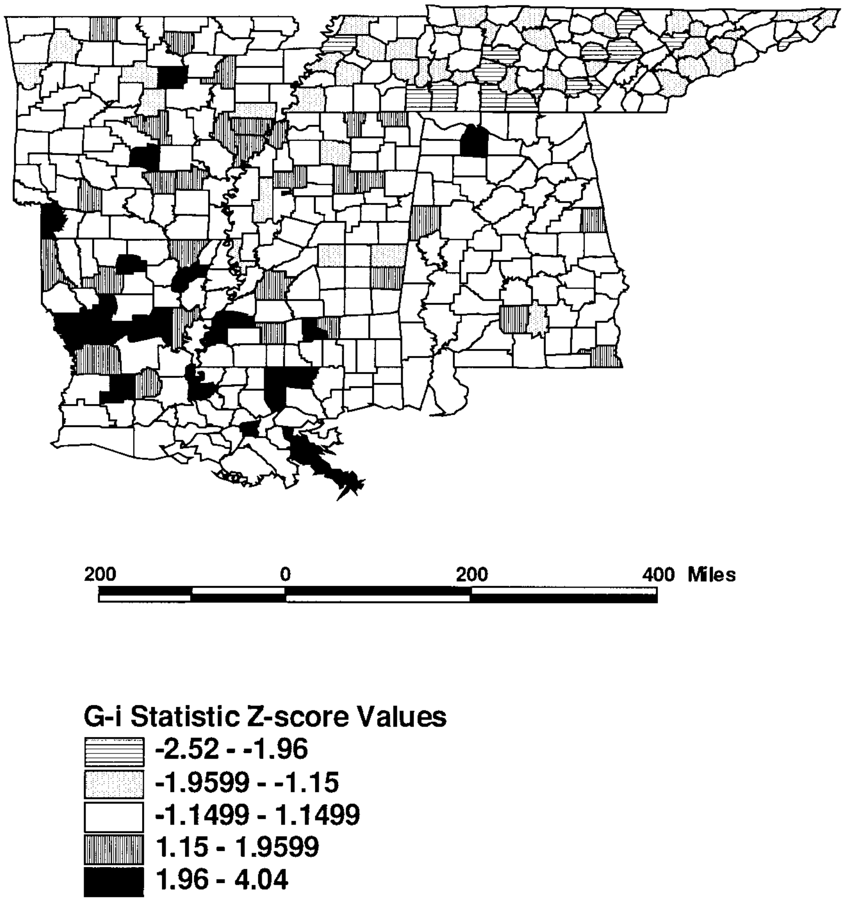

Fig. 2. *Z* scores for G_1 statistics, 1989–1991 murder and nonnegligent manslaughter rates.

classified them by scatterplot quadrant: (a) *high-rate autocorrelation*—high murder/NNM rate and neighbors high murder/NNM rate; (b) *low-rate autocorrelation*—low murder/NNM rate and neighbors low murder/NNM rate; and (c) *negative autocorrelation*—high murder/NNM rate and neighbors low rate, or low murder/NNM rate and neighbors high rate. For counties that did not have a significant local Moran statistic, we classified them in the *not significant* category. Figure 3 presents these categories, while Table III presents the statistically significant high murder/NNM counties and the low murder/NNM counties (based on local Moran's *I* statistics). The map shows visible patterns of significant low murder/NNM rate clustering in Tennessee, northwest Alabama, and northern Arkansas. The murder/NNM rates presented in Table III also shows clusters of low murder/

Table II. Statistics and Significant *Z* Scores for Local Spatial Autocorrelation in Murder and Nonnegligent Manslaughter Rates Among Midsouth Counties

County	G_i	Z	Murder
High murder/NNM rate clusters			
Jefferson, LA	0.043	4.04	12.5
Lincoln, LA	0.042	3.78	13
Jefferson, MS	0.042	3.76	8
St. James, LA	0.027	3.60	8.9
Plaquemines, LA	0.035	3.28	5.2
Sabine, LA	0.038	3.13	8.9
Richland, LA	0.038	3.11	8.9
Jefferson Davis, MS	0.049	3.06	18.7
Miller, AR	0.036	2.91	14.5
Pointe Coupee, LA	0.035	2.69	8.9
La Salle, LA	0.041	2.52	4.1
Lawrence, AL	0.037	2.36	5.4
Adams, MS	0.029	2.34	16.7
Allen, LA	0.008	2.29	16.1
Grant, AR	0.025	2.19	7.1
Cleburne, AR	0.021	2.15	0
Tangipahoa, LA	0.038	2.05	0
Grant, LA	0.031	2.04	11.4
Natchitoches, LA	0.041	2.00	14
Washington, LA	0.031	1.99	4.6
Low murder/NNM rate clusters			
Fentress, TN	0.009	–2.52	4.3
Grundy, TN	0.012	–2.45	3.4
Hardin, TN	0.005	–2.41	13
Giles, TN	0.014	–2.36	10.4
Williamson, TN	0.009	–2.31	4.2
Cumberland, TN	0.009	–2.30	0
Anderson, TN	0.004	–2.28	3.1
Sequatchie, TN	0.006	–2.24	6.7
Maury, TN	0.010	–2.20	7.9
Moore, TN	0.008	–2.16	3.4
Wayne, TN	0.003	–2.14	0
Dyer, TN	0.007	–2.08	12
Lincoln, TN	0.013	–2.01	5.8
White, TN	0.008	–2.01	0
Unicoi, TN	0.008	–1.97	2

NNM rates. Moreover, the murder/NNM rates presented for these statistically significant counties in Table III suggest that the local Moran's analysis is more consistent than the G_i analysis. What we do not see in Table III is the presence of low murder/NNM rates among the counties in the high

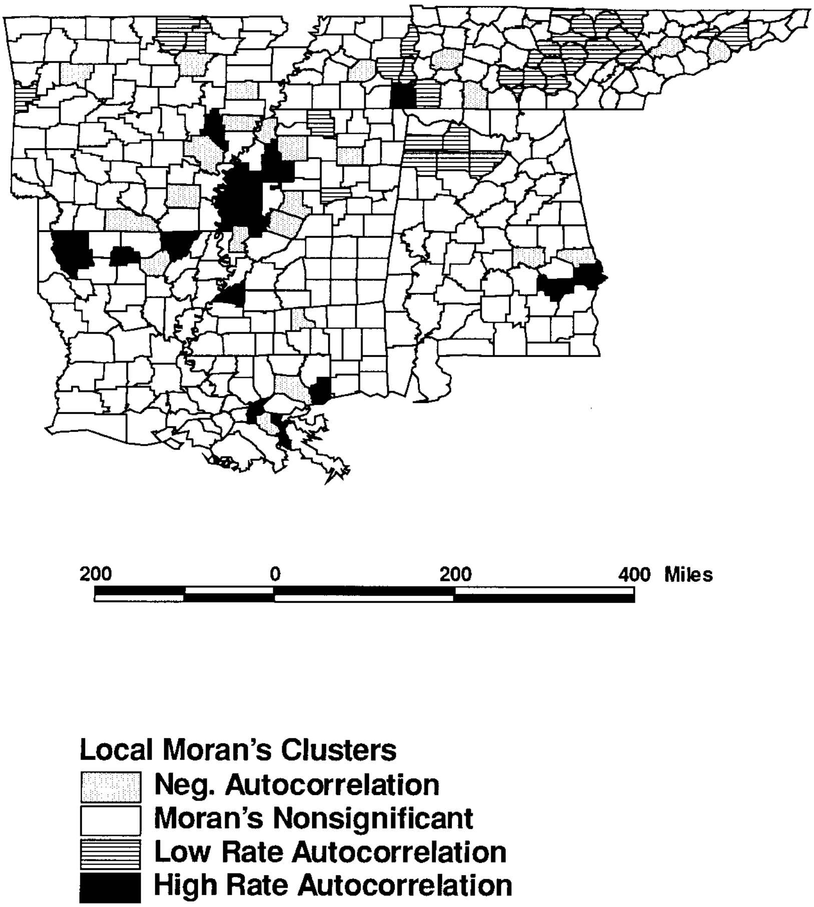

Fig. 3. Local Moran's clusters for midsouth county murder and nonnegligent manslaughter rates (1989–1991).

murder/NNM quadrant. This is not the case in the G_i analysis presented in Table II.

There are also several high murder/NNM rate clusters. One links Bossier and Webster parishes in Louisiana, near the Bossier City/Shreveport area. There is a distinct pattern in northwest Mississippi, but three of these counties (Bolivar, Quitman and Tallahatchie) did not report data during this period and mean substitution was used to construct these rates. This cluster pattern should be interpreted with this in mind.[8] Bullock and Butler counties in Alabama also have relatively high murder/NNM rates.

[8]We examined to what counties with unreported data were present in this table and found only these three counties.

Table III. Local Moran Scatterplot Analysis for Murder and Nonnegligent Manslaughter Rates in Midsouth Counties (Counties with a Significant Local Moran's *I* Statistic)

County	Murder
County high rate/neighbors high	
Bullock, AL	16.7
Butler, AL	10.4
Monroe, AR	17.3
Bossier, LA	9.1
Jefferson, LA	12.5
Lincoln, LA	13
Morehouse, LA	9.3
St. John Baptist, LA	17.3
Webster, LA	12.6
Bolivar, LA	8
Claiborne, MS	13.6
Hancock, MS	12.6
Humphreys, MS	31.3
Quitman, MS	8
Pike, MS	20.1
Tallahatchie, MS	8
Washington, MS	26.8
Hardin, TN	13
County low rate/neighbors low	
Cullman, AL	1
Franklin, AL	4.7
Lawrence, AL	5.4
Marion, AL	1.2
Winston, AL	0
Fulton, AR	0
Izard, AR	0
Sebastian, AR	5.6
Sharp, AR	0
Marshall, MS	2.7
Webster, MS	6.6
Bedford, TN	7
Benton, TN	4.6
Cannon, TN	0
Clay, TN	4.6
Coffee, TN	0
Cumberland, TN	0
Decatur, TN	0
DeKalb, TN	4.6
Fentress, TN	4.3
Greene, TN	4.2
Grundy, TN	3.4
Hamblin, TN	5.9
Henderson, TN	3.1
Moore, TN	3.4
Morgan, TN	0
Overton, TN	7.5
Putnam, TN	4.9
Roane, TN	6.9
Scott, TN	4.6
Van Buren, TN	0
Warren, TN	2
Wayne, TN	0
White, TN	0

One of the goals of our research is to inform those analyses of county level crime measures as to the existence and consequences of spatial autocorrelation. Since much crime research involves some form of regression analysis, we compare a model that corrects for spatial autocorrelation to one that does not. Table IV presents the results of the comparison between an MLE spatial lag regression and an OLS model (without a spatial effects variable) which predict the murder/NNM rates for this region. The analysis in Table IV shows that, at least for murder/NNM in the midsouth, the spatial effects variable has no significant effect. Moreover, comparison of the other coefficients across models shows that they are very similar (e.g., population density coefficient = 0.01149, spatial lag model; population density coefficient = 0.0115, OLS model). We also estimated this model for the overall violent crime rate as the dependent variable and found similar results, and transformed the murder/NNM rates into natural logs and reestimated these models and found similar results (available upon request). We estimated the spatial lag murder/NNM rate model with different distance matrices and failed to produce a significant effect.[9]

6. CONCLUSION

The purpose of this analysis was to examine to what extent murder/NNM rates are spatially autocorrelated at the county level in the midsouth. Past research in population studies, rural sociology, and regional science has shown that many of the predictors of murder and violent crime are spatially autocorrelated (see Anselin, 1988; Land and Deane, 1992; Mencken, 1998; Lyson and Tolbert, 1996). Therefore, it stands to reason that the product (crime, murder) of these social processes may be spatially autocorrelated as well. The Moran's I analysis detects positive global spatial autocorrelation in the midsouth region. The local Moran scatterplot analysis suggests that this positive autocorrelation comes primarily from clustering of low murder/NNM rates throughout the region (at least the patterns are identifiable). What we fail to see in these data, however, are clear patterns of spatial autocorrelation suggesting diffusion of murder/NNM rates from high crime centers to nearby places. The exception to this may be the greater Shreveport/Bossier City region. The G_i analysis suggests some possible patterns in the New Orleans area. However, we examined overal murder/NNM rates. One of the reviewers of this article pointed out that a

[9]We estimated the spatial lag model with a simple contiguity matrix, the distance matrix based on the farthest nearest-neighbor county distance (binary contiguity matrix), and a squared inverse distance matrix. None of these efforts produced a significant statistical effect in the MLE model.

Table IV. Comparison of Spatial Lag and OLS Regression Analysis for Midsouth Counties ($N = 383$): Dependent Variable, County Average Murder and Nonnegligent Manslaughter Rates 1989–1991

Independent variables	Spatial lag model			OLS model		
	Coefficient	*Z* value	Prob.	Coefficient	*t* value	Prob.
Spatial effect	0.052521	0.67764	0.73562	n/a	n/a	n/a
Sustenace diversity, 1990	0.033879	1.77879	0.07528	0.034818	1.80991	0.07111
Population change, 1980–90	−13.8747	−3.0977	0.00195	−14.274	−3.15937	0.00171
Percentage urban	3.07686	1.78989	0.07347	3.01427	1.73498	0.08357
Population density	0.011494	6.53865	0.00001	0.011504	6.47815	0.00001
% 25 and older w/o high school diploma	−6.31005	−0.86632	0.38632	−7.10629	−0.97084	0.33225
Unemployment rate, 1990	−0.187466	−1.03457	0.30087	−0.18117	−0.98891	0.32334
Social Disorganization Index[a]	0.496948	5.98164	0.00001	0.505606	6.14647	0.00001
Constant	8.36703	3.23126	0.00044	8.94592	3.6183	0.00034
		Pseudo R^2 0.327			Adj. R^2 0.3116	

[a] The Index of Social Disorganization is a factor-analyzed summary measure based on family poverty rates, percentage female-headed households, percentage of population black, and percentage of population 16–21. These variables are very highly correlated in the midsouth.

significant increase in youth homicides began in the mid 1980s and peaked in 1993. Perhaps age and possibly race specific homicide rates should be analyzed for spatial autocorrelation, as opposed to overall rates in order to detect diffusion trends in the midsouth region. In order to identify diffusion patterns, an extended time period should be examined.

Additionally, much of the past research on crime using counties as the unit of analysis did not address the issue of spatial autocorrelation (Wilkinson, 1984; Kowalski and Duffield, 1990; Lee, 1996; Guthrie, 1995). Had there been spatial autocorrelation present in the regression models presented in this analysis, then any conclusions drawn from the OLS regression results would be potentially biased and inaccurate (the same can be said for the articles cited above). Our analysis fails to detect spatial autocorrelation in the midsouth regression analysis. However, our analysis should not be cited as a reason not to explore spatial autocorrelation in crime analysis. Our analysis is bounded by time and space. Emerging homicide research on other regions and for other time periods suggests that global spatial autocorrelation may create problems for regression analysis in other spatial and temporal contexts (Messner *et al.*, 1999). Moreover, the lack of spatial effects in the regression models does not negate the importance of detecting and correcting spatial autocorrelation in all statistical analysis. Odland (1988) points out that spatial autocorrelation can create similar problems (risks of both Type I and Type II error) in descriptive and bivariate analysis. The tests to explore spatial autocorrelation are accessible and software are readily available. We urge others who do county-level analysis to explore spatial autocorrelation with a variety of tests.

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