STRUCTURAL COVARIATES OF U.S. COUNTY HOMICIDE RATES: INCORPORATING SPATIAL EFFECTS*

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Spatial analysis is statistically and substantively important for macrolevel criminological inquiry. Using county-level data for the decennial years in the 1960 to 1990 time period, we reexamine the impact of conventional structural covariates on homicide rates and explicitly model spatial effects. Important findings are: (1) homicide is strongly clustered in space; (2) this clustering cannot be completely explained by common measures of the structural similarity of neighboring counties; (3) noteworthy regional differences are observed in the effects of structural covariates on homicide rates; and (4) evidence consistent with a diffusion process for homicide is observed in the South throughout the 1960–1990 period.

One of the more important developments in quantitative criminological research over the course of recent decades has been the application of

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multivariate statistical techniques to explain macrolevel variation in homicide rates. Informed by influential sociological theories of crime, especially anomie/strain theory, social disorganization theory, and opportunity theory, researchers have modeled the effects of a wide range of indicators of structural conditions on homicide rates for varying types of territorial units. The results of this research have sometimes been contradictory. However, in a widely cited article that has become a classic, Land et al. (1990) argue that much of the apparent inconsistency in the literature can be accounted for by the problem of multicollinearity (see also Parker et al., 1999). Commonly used indicators of structural conditions are often highly intercorrelated, which makes statistical estimation unreliable and renders inferences about independent effects susceptible to the "partialing fallacy." To avoid these problems, Land et al. combine correlated structural variables into composite measures and report that in properly specified models, the structural covariates of homicide are reasonably "invariant" across time and space. The most robust structural predictors to emerge in Land et al.'s analyses are measures of resource deprivation/affluence, population structure (size/density), and family disruption (divorce rates).

Since the publication of the path-breaking work by Land et al., criminologists have devoted growing attention to the *spatial distribution* of homicide and criminal violence more generally (Anselin et al., 2000). Spatial analyses are important for both statistical and substantive reasons. Statistically, if spatial processes operate and are not accounted for, inference will be inaccurate and estimates of the effects of independent variables may be biased. Explicit modeling of spatial effects is thus important in any effort to assess "invariance" in the structural covariates of homicide.

In addition, spatial patterns can be of considerable substantive importance. Causal processes do not necessarily operate identically in all places, and spatial analysis can reveal subareas of geography in which the effects of predictor variables differ. In addition, spatial effects can be suggestive of "diffusion" associated with the phenomenon under investigation. Research has revealed that a wide range of social behavior can be understood with reference to diffusion processes, such as lynchings, fertility, and church attendance (Deane et al., 1998; Land and Deane, 1992; Land et al., 1991; Tolnay, 1995; Tolnay et al., 1996). Moreover, the theoretical possibility that *criminal violence* may spread via a diffusion process has long been recognized in the public health literature (Hollinger et al., 1987; Kellerman, 1996), and recent empirical work on homicide has offered evidence generally supportive of the diffusion perspective (Cohen and Tita, 1999; Cork, 1999; Messner et al., 1999).

The purpose of the present paper is to apply recently developed techniques of spatial analysis to explain intercounty variation in homicide rates at four time points in a comparative statics fashion—the decennial years in the 1960–1990 period. Using the Land et al. specification as our baseline model, we reassess the robustness of the structural covariates of homicide with rigorous controls for spatial processes. In doing so, we estimate models of spatial patterning that are consistent with potential diffusion processes.

We begin by explaining important concepts and theoretical processes relevant to structural invariance. Then, after describing data sources and methods, we conduct an Exploratory Spatial Data Analysis (ESDA) (Anselin, 1999a). ESDA is a critical first step for visualizing patterns in the data, identifying spatial clusters and spatial outliers, and diagnosing possible misspecification in analytic models. The results of the ESDA inform our multivariate analyses, wherein we assess the effects of structural variables and formally model spatial processes.

CONCEPTUAL AND THEORETICAL FRAMEWORK FOR SPATIAL ANALYSIS

The first step in a spatial analysis is to test the null hypothesis of spatial randomness against the alternative of spatial autocorrelation. Spatial autocorrelation refers to a situation in which values on a variable of interest are systematically related to geographic location. We illustrate such a situation in Figure 1 by the graph labeled "Univariate Spatial Autocorrelation." This model depicts two adjacent counties, where y_i and y_j indicate the homicide rate of each. In the graph, a two-headed arrow is used to reflect the "simultaneity" inherent in spatial autocorrelation. This is unlike serial correlation in the time domain, in which the underlying process is sequential.[1] In this model, an association between homicide rates is represented without any inference about a causal process generating the association. Formally, we have

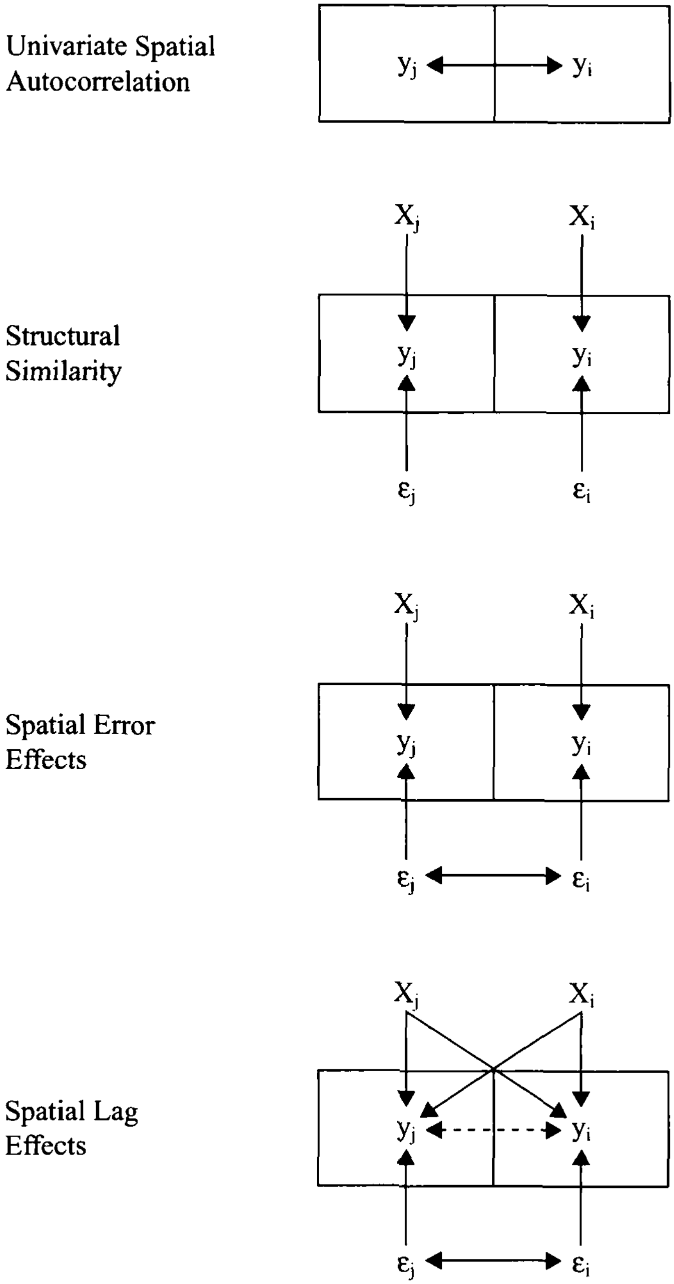
$$\mathrm{Cov}[y_i,y_j] \neq 0, \tag{1}$$

for neighboring i, j. Based on the findings in Messner et al. (1999), our initial hypothesis is that county-level homicide rates will exhibit statistically significant and positive spatial autocorrelation, suggesting that similar homicide rates cluster in space.

Assuming that spatial randomness is rejected, the next question to be

1. In this approach, geographically proximate homicide rates are reciprocally related. The estimation of such effects is analogous to that of nonrecursive models (Land and Deane, 1992). An alternative to simultaneous estimation is the conditional approach, in which the observations at neighboring locations are given. This is more appropriate when the main goal is spatial interpolation. The differences between the simultaneous model and the conditional model are discussed in detail in Cressie (1993).

Figure 1 Spatial Processes



addressed concerns the processes generating the observed spatial clustering. We begin by specifying a regression model of the homicide rates y_i on structural factors observed at location i and a stochastic error term ε_i, or,

$$y_i = \Sigma_k x_{ki}\beta_k + \varepsilon_i, \tag{2}$$

where each x_{ki} is an element in a $1 \times K$ matrix row vector of covariates and β_k is the corresponding element in a $K \times 1$ vector of regression coefficients. As noted, the covariates for our baseline model are the structural variables included in the Land et al. specification.

If homicide rates are determined solely by the structural factors included in the model (the x_k in Equation 2), there should be no spatial patterning of homicide beyond that created by sociodemographic similarities of geographically proximate counties. A purely structural interpretation thus implies the absence of residual spatial autocorrelation (assuming a well-specified model of structural determinants). In other words, no remaining spatial dependence should be found once the structural similarity of neighboring counties has been explicitly controlled for, or, $E[\varepsilon_i.\varepsilon_j] = 0$ for neighboring i, j. This situation is illustrated in the graph labeled "Structural Similarity" in Figure 1. This model suggests that the spatial relationship between y_j and y_i will become nonsignificant once x_k are included in the model.

In practice, the adequacy of the "pure" structural model is assessed by means of specification tests for spatial autocorrelation based on the least-squares residuals. In an analysis of county-level homicide rates for 1980 using a model similar to the Land et al. baseline, Kposowa and Breault (1993) find no evidence of residual spatial autocorrelation based on Moran's I test statistic. However, from their paper, it is not possible to detect how the test was applied and, specifically, what alternative was employed for the neighbor structure (spatial weights) in the tests (see the methods section below). Also, this contrasts with our previous findings of strong spatial effects noted above. We accordingly hypothesize that the structural model will be insufficient to explain the spatial pattern or, in other words, that there will be statistically significant residual spatial autocorrelation.

Assuming that residual spatial autocorrelation is observed, the next task is to select the proper alternative specification. Different approaches to modeling spatial dependence have been proposed in past research. In the early sociological literature, Doreian (1980, 1982) introduces the distinction between a spatial "effect" and a spatial "disturbance" model (see also Land and Deane, 1992). In the former, spatial dependence is introduced as an additional covariate in the model, a so-called spatial lag, or a weighted average of values for the dependent variable in "neighboring" locations. In a spatial "disturbance" model, the spatial dependence is incorporated in the regression error term. Spatial dependence in the form of spatial "effects" is suggestive of a possible diffusion process—events in one place predict an increased likelihood of similar events in neighboring places, net of the effect of structural covariates, whereas spatial dependence in the form of spatial "disturbance" is indicative of omitted (spatially correlated) covariates that if left unattended would affect inference. Although methods for distinguishing between these two sources of dependence have long been available (Anselin, 1988; Doreian, 1980, 1982), they have been almost universally ignored in substantive applications in sociological and criminological research. Instead, spatial dependence emerging from either source has typically been identified with a spatial "effect" model.

In this paper, we preserve the important distinction between the sources of spatial dependence, but we use slightly different terminology. Following Anselin (1988), "spatial dependence" is used as a general term to refer to either a spatial "lag" model (the spatial "effect" model discussed above) or a spatial "error" model (the spatial "disturbance" model from above).

In addition to dependence, we also consider "spatial heterogeneity" as a spatial effect. Spatial heterogeneity refers to a situation in which coefficients or error patterns vary systematically across geographic areas. From a practical standpoint, it is difficult to distinguish spatial dependence from spatial heterogeneity based on regression residuals because all diagnostics have power against both forms of misspecification (Anselin and Florax, 1995). It is therefore important to consider both as potential alternative models and to carry out a specification search that controls for spatial heterogeneity while testing for spatial dependence, and vice versa.

Relating the issue of spatial heterogeneity more directly to the substantive purpose at hand, the Land et al. baseline model, similar to other commonly used models in homicide research, includes an indicator variable for the South.[2] A significant coefficient for this variable suggests a "level" shift in homicide rates across regions. The analysis of spatial heterogeneity considered in this paper extends this notion to allow for a possible structural difference in the regression relationship between geographic regions.[3]

If spatial dependence persists even in the presence of controls for spatial

2. The theoretical rationale for including a variable for the South in regression models of homicide rates derives from the thesis of a Southern "culture of violence." See Hawley and Messner (1989) for a general review and Nisbett and Cohen (1996) for a recent formulation.

3. In recent, nonspatial OLS analyses, Parker and Pruitt (2000) report differences in the structural determinants of city homicide rates across Southern, Western, and other regions. A formal assessment of this form of spatial heterogeneity is an important task for future research.

heterogeneity, the next step is to contrast a spatial error model and a spatial lag model. The spatial error model evaluates the extent to which the clustering of homicide rates not explained by measured independent variables can be accounted for with reference to the clustering of error terms. In this sense, it captures the spatial influence of unmeasured independent variables. This situation is represented in the graph labeled "Spatial Error Effects" in Figure 1. A satisfactory spatial error model implies that it is unnecessary to posit distinctive effects of the lagged dependent variable. The observed spatial clustering in homicide rates is accounted for simply by the geographic patterning of measured and unmeasured independent variables.

The spatial lag model, in contrast, incorporates the spatial influence of unmeasured independent variables but also stipulates an additional effect of neighbors' homicide rates, i.e., the lagged dependent variable. This is the model most compatible with common notions of diffusion processes because it implies an influence of neighbors' homicide rates that is not simply an artifact of measured or unmeasured independent variables. Rather, homicide events in one place actually increase the likelihood of homicides in nearby locales. This situation is depicted in the "Spatial Lag Effects" graph in Figure 1. The influence of homicide in neighboring counties is represented by a dashed arrow in the graph for technical reasons explained in the "Methods" section.

It is important to recognize that these models for spatial lag and spatial error processes are designed to yield indirect evidence of diffusion in cross-sectional data. However, any diffusion process ultimately requires "vectors of transmission," i.e., identifiable mechanisms through which events in a given place at a given time influence events in another place at a later time. The spatial lag model, as such, is not able to discover these mechanisms.[4] Rather, it depicts a spatial imprint at a given instant of time that would be expected to emerge if the phenomenon under investigation were to be characterized by a diffusion process. The observation of spatial effects thus indicates that further inquiry into diffusion is warranted, whereas the failure to observe such effects implies that such inquiry is likely to be unfruitful.

In sum, our spatial analyses begin with an examination of the spatial

4. Theorizing about the precise nature of diffusion mechanisms is beyond the scope of the present paper. Loftin (1986) offers a provocative discussion of how serious assaultive violence may be usefully viewed as a "contagious social process" spread through subcultural dynamics. See also Cohen and Tita (1999) for insightful distinctions between different kinds of diffusion mechanisms that may be applicable to homicide, and Blumstein (1995) for an analysis of the potential role of weapons in the diffusion of criminal violence.

clustering of county-level homicide rates and a search for distinctive spatial regimes in the data. This exploratory analysis paves the way for multivariate modeling. In our multivariate models, we estimate the effects on homicide rates of structural variables with adjustments for spatial dependence and spatial heterogeneity. We then assess the extent to which any observed spatial dependence is best described with reference to the effects of unmeasured predictor variables (the spatial error model) or with reference to the influence of homicides in neighboring counties (the spatial lag model). Evidence consistent with the latter would be suggestive of possible diffusion processes in the generation of homicide rates.

DATA

The data for the homicide rates are constructed from the National Center for Health Statistics (NCHS) mortality files (various years) and the Centers for Disease Control and Prevention (CDC) WONDER system. To avoid extreme heterogeneity, the rates are smoothed by taking a three-year average of the county homicide count centered on each decennial census year of the 1960–1990 period (e.g., 1959–1961). These averages are divided by the single-year census population figure (e.g., 1960). Homicide counts are obtained by aggregating individual homicides to the decedent's county of residence. County groups were generated following the Horan and Hargis (1995) county template so that geographic boundaries are consistent throughout the time period.

The independent variables are county analogues of the measures used by Land et al. (1990). As with Land et al. (1990), resource deprivation and population structure are represented by principal components indexes. The resource deprivation component consists of percent black, median family income (logged), a Gini index of family income inequality, percent of families below poverty, and the percent of families that are female headed. The population structure component comprises population size (logged) and population density (logged). The models also include median age, the unemployment rate, percent divorced, and a Southern dummy variable based on census definitions (16 states and the District of Columbia).[5] These variables come from the USA Counties 1996 CD-ROM and the County and City Data Book Consolidated File, 1947–1977.

We recognize that counties are arbitrary units of analysis, which raises a form of the ecological fallacy problem (King, 1997). The selection of a

5. Data availability requires minor modifications in model specification. For 1960, the variable for family poverty is the percent of families who earn less than $3,000, and the variable for family structure is the percent of families that are single parent. Median age is substituted for percent ages 15–29 as the indicator of age structure for all years.

spatial scale of analysis has important ramifications for the treatment of spatial effects. Counties may be too large an areal unit for analysis, especially for detecting the diffusion of homicide, and the unobserved heterogeneity may create an ecological fallacy. The problem of scale could also work in the opposite direction. If homicide is really a regional phenomenon, slicing the regions of the United States into counties will produce spatial autocorrelation, not because of spatial interaction, but because counties in the same region experience a common regional cause of homicide. In this case, counties are too small an areal unit.

The selection of the unit of analysis should ideally be determined by theoretical considerations, but in practice, data availability imposes severe constraints. We use counties in the present research for a number of reasons. Foremost among these is that the sample size is greatly augmented, relative to using states or MSAs.[6] Also, the county is the smallest spatial unit of analysis for which the necessary data for estimating our models are available for the entire time period under investigation. Furthermore, a county-level analysis can encompass the entire contiguous U.S., thus including not only urban areas, but also rural communities. Finally, we are able to build on precedents in the literature that used counties as units of analysis in the study of homicide and explicitly assess the role of spatial effects (DeFronzo and Hannon, 1998; Kposowa and Breault, 1993; Kposowa et al., 1995; U.S. Department of Health and Human Services, 1997).[7]

METHODOLOGY

As noted, the methodology employed in this paper uses a combination of exploratory spatial data analysis and spatial econometric techniques. In earlier work, Messner et al. (1999) report evidence of strong positive spatial autocorrelation of homicide rates for a subset of U.S. counties, as well as evidence indicating that some of the relations between homicide and its covariates are not stable across space. These findings suggest that the application of techniques of ESDA is useful in the search for spatial regimes (Anselin, 1999a; Cook et al., 1996). Insights gained in this exploratory phase are incorporated in the spatial structure of the model, where

6. Although Land et al. limit their study to state-, metropolitan area-, and city-level ecological aggregation, they acknowledge that a general theory of how structural covariates affect homicide rates should be applicable at other ecological levels, including counties (see Land et al., 1990: fn.13).

7. Previous studies did not include spatial effects or found that they were not warranted.

spatial dependence is explicitly taken into account by applying specification tests and estimation methods from spatial econometrics and spatial statistics (Anselin, 1988; Anselin and Bera, 1998; Cressie, 1993).

Thus, the first step in our assessment of structural invariance consists of exploratory spatial data analysis of the global and local patterns of spatial autocorrelation in the homicide rates. Global autocorrelation is assessed by means of Moran's I statistic (see Appendix 1). A positive and significant Moran's I indicates clustering in space of similar homicide rates.

Local spatial autocorrelation is assessed by means of a local Moran statistic, which indicates for each location the extent to which the pattern of the value at that location and the values at neighboring locations is compatible with spatial randomness. Rejection of this null hypothesis indicates local clustering of high (high surrounded by high) or low (low surrounded by low) values, or local spatial outliers in the form of high values surrounded by low neighbors or low values surrounded by high neighbors (see Appendix 1).

The exploratory phase in the analysis is followed by an ordinary least-squares (OLS) regression of county-level homicide rates on the structural predictors. The results of OLS regressions are scrutinized for the existence of spatial patterns by means of a battery of diagnostics. Spatial heterogeneity is accounted for in a number of ways. First, in the initial (nonspatial) specification, we allow the error variance to be different in different geographic subgroups of the data (groupwise heteroscedasticity following spatial regimes) to assess the sensitivity of the coefficient estimates and specification tests against spatial dependence. In addition, we apply a spatial regime regression, which allows the coefficients to be different in each regime. This yields a "spatial Chow" test on the stability of these coefficients across regimes (Anselin, 1990). Formally, this is similar to switching regressions, but where the different coefficient values are based on spatial regimes. This is useful for two reasons. First, it allows us to explicitly test the spatial structural invariance of regression coefficients. This can reveal different social mechanisms by region or different relative significance of the covariates in the model. Second, if regional stability is rejected, the modeling allows for varying spatial processes to be considered in each region.

Assuming that spatial dependence is observed with controls for spatial heterogeneity, we contrast the spatial error and spatial lag models. A spatial error model is implemented by specifying a spatial stochastic process for the error term, which in turn yields the nonzero correlation for the neighboring ε_i. Formally, a spatial autoregressive error process for the error terms is

$$\varepsilon_i = \lambda \Sigma_j w_{ij}.\varepsilon_j + u_i, \tag{3}$$

where the w_{ij} are row elements in a spatial weights matrix, λ is a spatial autoregressive coefficient, and u_i are i.i.d. errors. The weights matrix reflects the potential interaction between neighboring locations and zeros out pairs of locations for which spatial correlation is ruled out a priori (Anselin, 1988).

To facilitate comparison of the spatial effects model with the spatial lag model, it is instructive to consider the spatial error process from (3) in matrix form:

$$\varepsilon = \lambda W\varepsilon + u, \tag{4}$$

where the symbols have the same meaning as before, but now represent vectors of dimension $n \times 1$ for all observations jointly, and W is an $n \times n$ spatial weights matrix. Solving this for ε and substituting into the regression equation yields (in matrix form)

$$y = X\beta + (I - \lambda W)^{-1}u. \tag{5}$$

The essence of this expression is that the value of the dependent variable for each location is affected by the stochastic errors at all locations through the spatial multiplier $(I - \lambda W)^{-1}$.[8]

As explained above, the spatial lag model differs from the spatial error model in that it allows for an influence of the dependent variable (homicides) of neighboring counties above and beyond that reflected in error terms. Formally, the spatial lag model is (in matrix notation)

$$y = \rho Wy + X\beta + u, \tag{6}$$

with ρ as the spatial autoregressive parameter and the other notation as before. The corresponding "reduced form" of equation (6) is

$$y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1}u \tag{7}$$

This reduced form illustrates two important points. First, the spatial error model (5) is subsumed by the spatial lag model, although in nonnested form.[9] Second, the value of y at each location is not only determined by x_i at that location, but also by the x_j at all other locations, through the spatial multiplier $(I - \rho W)^{-1}$. This is very different from a "lag" model in the time domain, which complicates both estimation and testing (Anselin and Bera, 1998).

In the graph of the spatial lag effects in Figure 1, we depict this difference in two ways. First, we have a dashed arrow between the y's, indicating the inclusion of y_j in the explanation of y_i, based on the structural

8. This only affects the precision of the estimation, because "on average," the stochastic errors disappear. For an extensive discussion, see Anselin and Bera (1998).

9. This is the case in the sense that Equation 5 cannot be obtained from Equation 7 by imposing simple zero restrictions on the coefficients.

relation in Equation 6. We also illustrate the reduced form (7) by including the arrows between the error terms at neighboring locations. In addition, we depict the influence of a covariate x_j at neighboring locations upon y_i.

A crucial concept in these methods is that of a spatial weights matrix (W in Equations 4–7), which incorporates the prior structure of dependence between spatial units. This is necessary due to insufficient information to specify a full matrix of interaction ($n \times n$) from observations in a single cross section (n observations). Each row of a spatial weights matrix has nonzero elements for the columns that correspond to neighboring units.[10] By convention, the diagonal elements are set to zero, and for ease of interpretation, the elements of each row are standardized such that they sum to one.

It is important to keep in mind that all analyses are conditional on the choice of the spatial weights. In our study, we base the weights on a nearest neighbor criterion, using both 5 and 10 nearest neighbors, calculated from the distance between county centroids.[11]

Technically, an instrumental variables approach is used to estimate the spatial lag model, because it properly accounts for the endogeneity of the Wy term (Anselin, 1988; Land and Deane, 1992). We follow Kelejian and Robinson (1993) in using the spatially lagged explanatory variables (WX) as instruments. The spatial error model is estimated by means of the recently suggested generalized moments (GM) method of Kelejian and Prucha (1999).

Note that in contrast to the IV procedure for the spatial lag model, the GM approach does not provide inference for the spatial autoregressive parameter. Hence, this method should only be applied after specification tests (on the residuals of an OLS regression) have clearly established that the spatial error is the proper alternative. In practice, specification tests against a spatial error or spatial lag alternative are based on the Lagrange

10. The notion of neighbor is perfectly general, and it can be based on geographic considerations, such as common boundary or being within a critical distance band, or on economic or social distance. For a general discussion of spatial weights, see Anselin (1988), Anselin and Bera (1998), Cliff and Ord (1981), and Upton and Fingleton (1985). Economic weights are introduced in Case et al. (1993).

11. To the extent that the results of diagnostic tests depend on the spatial weights, it is possible that Kposowa and Breault's (1993) finding of a lack of significant spatial autocorrelation is due to the choice of different weights. In what follows, we report the results for 10 nearest neighbors and indicate where qualitative differences are found for 5 nearest neighbors. In the United States, counties have on average 5 to 6 contiguous neighbors, so that our selection of 10 yields a ring around each county of roughly the first- and second-order contiguous counties. By choosing a fixed number of nearest neighbors, we avoid some methodological problems that may result when the number of neighbors is allowed to vary.

Multiplier principle (see Appendix 2). All computations are carried out by means of the SpaceStat software package (Anselin, 1999b).

RESULTS

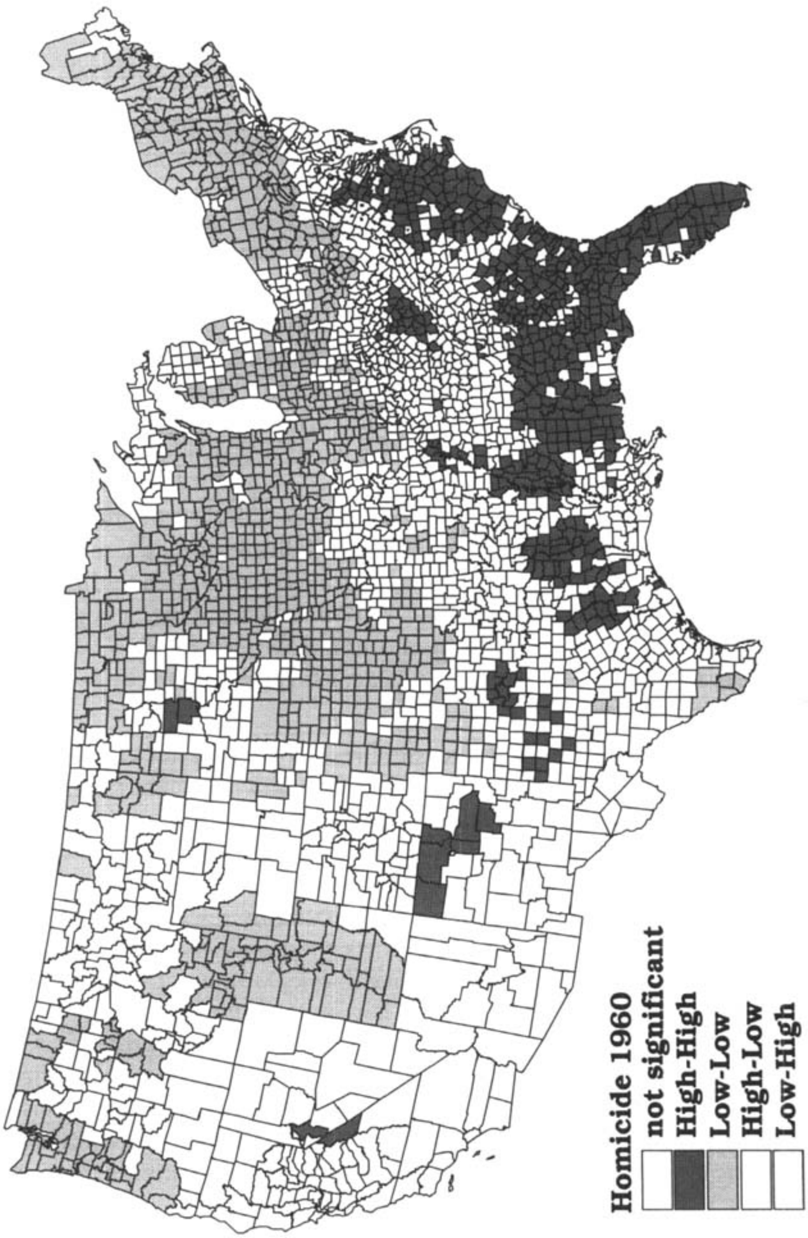
We begin by examining the Global Moran's I statistics for homicide rates in 1960, 1970, 1980, and 1990. The coefficients are .363, .420, .371, and .372, respectively; all of which are statistically significant at the .001 level.[12] These results show that as expected, the null hypothesis of spatial randomness is rejected for all years under study and provide strong evidence of a significant spatial pattern.

Maps 1 to 4 are modified Moran scatterplot maps of the homicide rates for 1960, 1970, 1980, and 1990. There is a slight modification in format relative to the usual approach, necessitated by the use of black-and-white maps. Instead of highlighting four categories, the "High-Low" and "Low-High" categories are whited out. The clustering of high homicide rates is mostly in the South (as indicated by darker gray shading and the label "High-High"). The clustering of low rates is found throughout the Northeast, Midwest, and parts of the West (as indicated by lighter gray shading and the label "Low-Low"). From these maps, we conclude that consistent with the prior literature, the two most important spatial regimes in the United States are the Southern and non-Southern regions. These spatial regimes will be incorporated into the multivariate analyses that adjust for spatial heterogeneity.

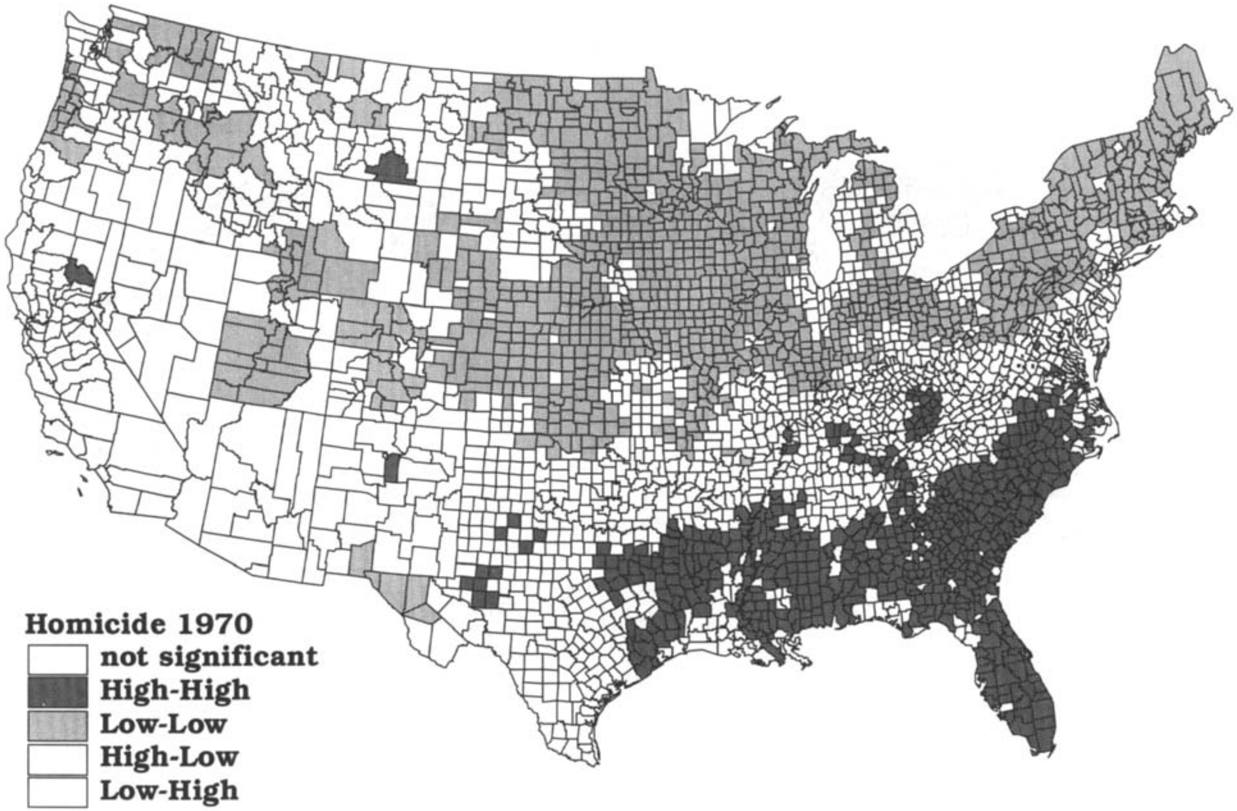
Table 1 presents OLS regression results for the baseline model that includes the structural predictors of U.S. county homicide rates for each of the four periods under consideration. We find consistent effects for all variables, with the exception of percent unemployed. Similar to the findings in Land et al., resource deprivation, population structure, divorce, and Southern location are positively and consistently related to homicide. The negative effect of median age supports the notion that it is counties with younger populations that have higher homicide rates. The negative coefficient for the percent unemployed is counterintuitive but consistent with the results of Land et al. (1990). Land et al. (1990) suggest that unemployment indicates reduced opportunity for violence (less social activity) once resource deprivation is controlled for (see also Cantor and Land, 1985; Land et al., 1995). In general, these non-spatial results for counties mirror those found in empirical studies for other common macrounits of analysis (cities, MSAs, and states).

12. We assess significance based on a permutation approach with 999 random permutations.

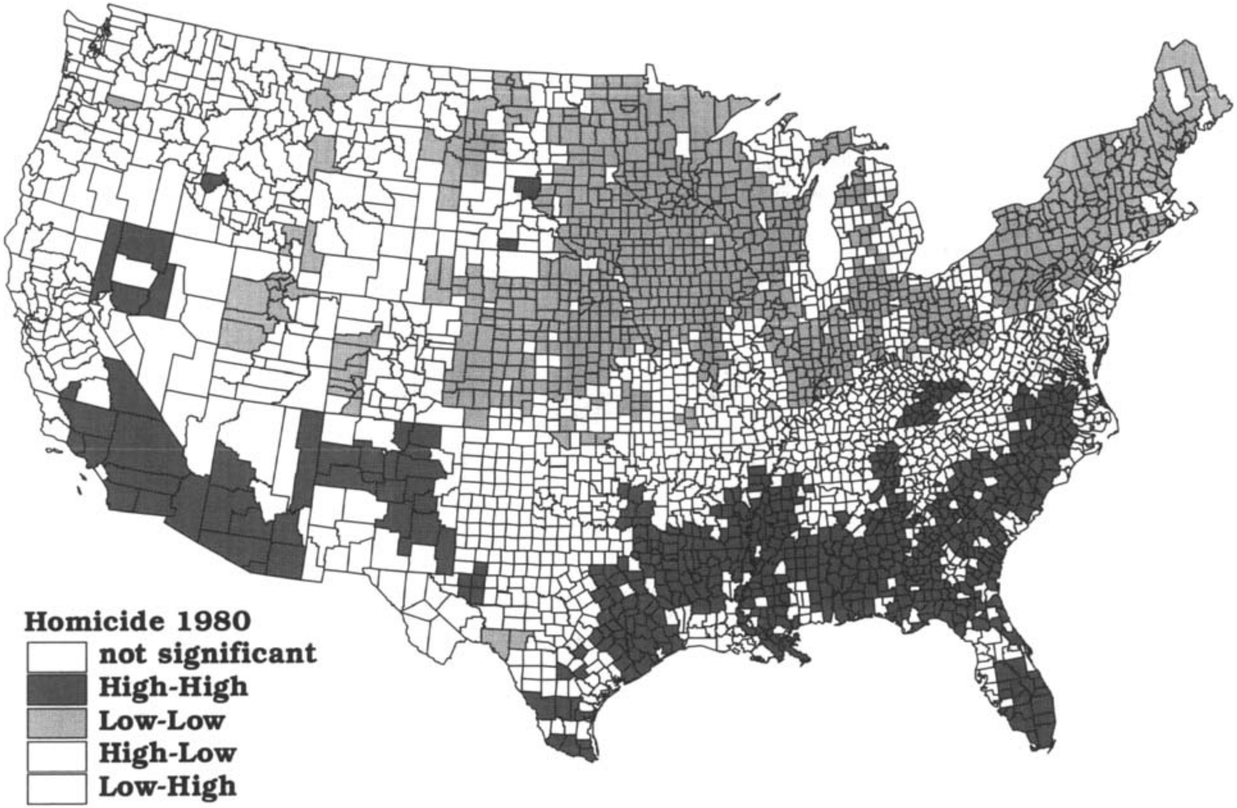
Map 1. Moran Scatterplot Map 1960 Homicide Rate (W = 10 Nearest Neighbors)



Map 2. Moran Scatterplot Map 1970 Homicide Rate (W = 10 Nearest Neighbors)



Map 3. Moran Scatterplot Map 1980 Homicide Rate (W = 10 Nearest Neighbors)



Map 4. Moran Scatterplot Map 1990 Homicide Rate (W = 10 Nearest Neighbors)

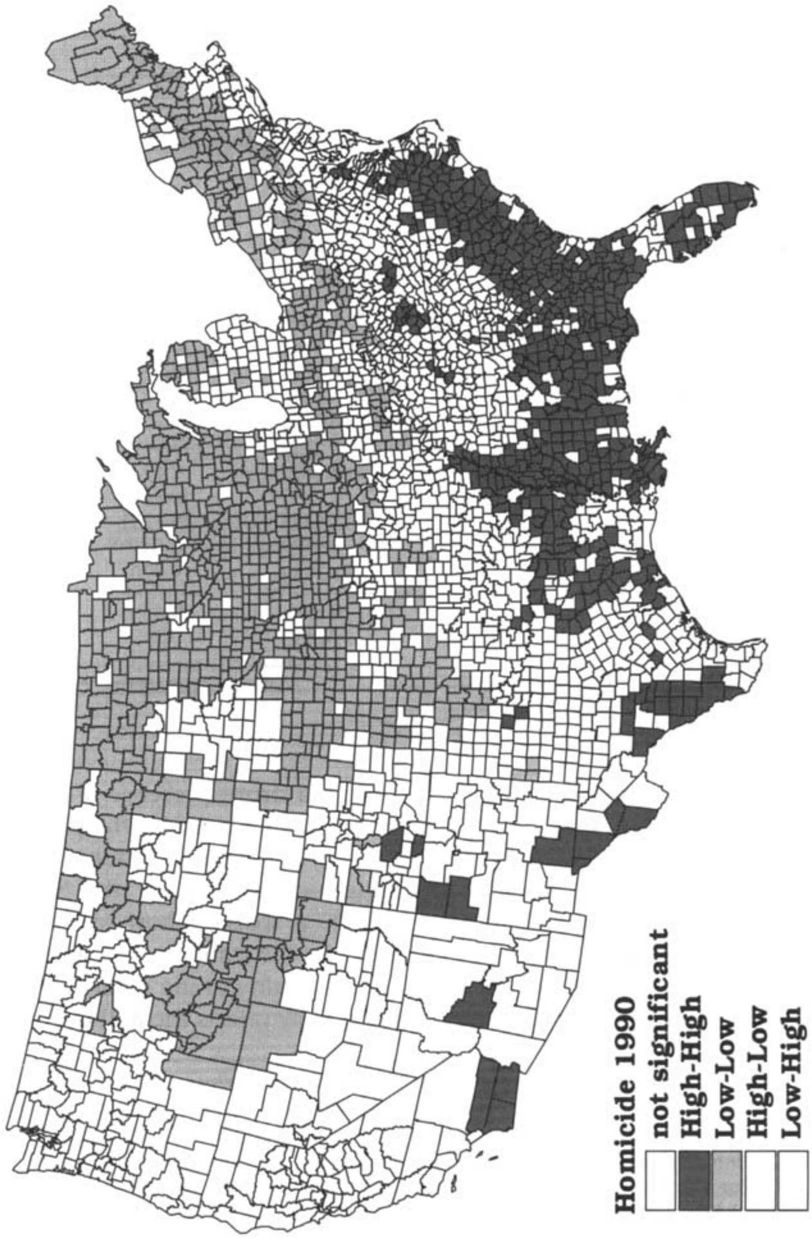


Table 1. Ordinary Least-Squares Regression of County Homicide Rates 1960–1990[a]

Independent Variables	1960	1970	1980	1990
Resource	1.798**	2.913**	3.412**	3.872**
Dep./Aff. Comp.	[0.318]	[0.396]	[0.500]	[0.583]
	(14.571)	(19.511)	(28.268)	(27.133)
Pop. Struct.	0.359**	0.812**	0.747**	1.353**
Comp.	[0.064]	[0.111]	[0.109]	[0.204]
	(3.892)	(6.959)	(7.315)	(13.491)
Median Age	−0.231**	−0.191**	−0.242**	−0.101**
	[−0.192]	[−0.130]	[−0.137]	[−0.055]
	(−11.931)	(−8.394)	(−9.671)	(−3.691)
Divorce	1.160**	1.264**	1.250**	0.583**
	[0.205]	[0.184]	[0.266]	[0.152]
	(12.233)	(12.109)	(18.586)	(10.690)
Unemployment	−0.062	−0.278**	−0.122**	−0.306**
	[−0.028]	[−0.087]	[−0.059]	[−0.141]
	(−1.762)	(−5.562)	(−3.965)	(−7.472)
South	2.639**	3.589**	2.113**	2.194**
	[0.233]	[0.243]	[0.154]	[0.165]
	(11.312)	(12.557)	(9.129)	(9.952)
Intercept	8.126**	8.653**	8.541**	6.517**
	(12.804)	(11.275)	(9.720)	(6.364)
Adj. R-Squared	0.295	0.360	0.431	0.435
N	3085	3085	3085	3085

[a] Unstandardized regression coefficients, standardized regression coefficients in brackets, and t-ratios in parentheses.
* $p \leq .05$; ** $p \leq .01$ (two-tailed tests).

Regression diagnostics, however, reveal a strong presence of both heteroskedasticity and spatial dependence.[13] We first consider the potential for spatial regimes more closely. Table 2 presents the results for an examination of coefficient variation and heteroscedasticity for the South/non-South spatial regimes. The tests include a spatial Chow test on overall coefficient stability across regimes, tests for the stability of individual coefficients, and tests for heteroscedasticity (equality of the error variances by spatial regime). The spatial Chow test clearly rejects the null hypothesis of

13. Heteroscedasticity is indicated by a significant White statistic. All LM statistics for spatial autocorrelation are highly significant. The use of robust forms of these statistics allows for a clear discrimination between alternative models (see Appendix 2 for technical details). Specifically, the robust LME statistics are 3.50, 8.81, 67.90, and 28.05 for the respective years, with the latter three being significant at $p < .01$. The robust LML statistics amount to 15.81, 30.78, 0.37, and 4.05, significant with $p < .01$ for the first two years and marginally ($p < .05$) for the last year. Comparison of these test statistics suggests a spatial lag alternative in 1960 and 1970 and a spatial error alternative in 1980 and 1990. However, this does not account for the potentially confounding effect of spatial heterogeneity, which is examined next.

Table 2. Stability of Regression Coefficients by Spatial Regime—County Homicide Rates 1960–1990

	1960	1970	1980	1990
I. Spatial Chow Test on Overall Stability[a]:				
	150.527**	227.468**	162.712**	168.438**
II. Stability of Individual Coefficients (non-South versus South)[b]:				
Resource Dep. Comp.	0.135	0.868	7.303**	36.065**
Pop. Struct Comp.	0.118	0.286	32.490**	18.758**
Median Age	3.480	0.036	7.352**	0.982
Divorce	0.057	11.088**	15.822**	0.641
Unemployment	24.849**	45.870**	12.922**	28.150**
III. Heteroscedastic Coefficients:				
Non-south	9.776	16.016	21.750	16.209
South	36.930	54.544	30.451	34.204
IV. Test on Heteroscedasticity[b]:				
	360.392**	328.375**	40.296**	164.284**
N (*N* of South)	3085 (1412)	3085 (1412)	3085 (1412)	3085 (1412)

[a] distributed as χ^2 with 6 degrees of freedom.
[b] distributed as χ^2 with 1 degree of freedom.
* $p \leq .05$; ** $p \leq .01$ (two-tailed tests).

coefficient stability. Furthermore, the estimates for the heteroscedastic coefficients indicate a larger variance in the Southern counties. Substantively, this implies that the baseline model fits less well in the South.

A closer examination of the individual tests on coefficient stability across regimes suggests that several of the structural characteristics exert significantly different effects across regions. Moreover, these patterns vary over time. This suggests that the "invariance" of the Land et al. (1990) baseline model of homicide has been overstated. In addition, these results highlight the inadequacy of reducing spatial heterogeneity to a dummy variable for the South and the need to model regional variation in the effects of covariates explicitly.

Given the strong evidence of distinct spatial regimes in the South and non-South, we pursue a disaggregated modeling strategy in the remainder of the empirical investigation. Separate models are estimated for each of the regions and again scrutinized for the presence of spatial dependence. Examination of the residuals in an OLS estimation for the South suggests the need for a spatial lag specification in each of the years considered. In contrast, the results for the non-South suggest a lag model in 1960, but a spatial error model in the subsequent years.[14] Tables 3 and 4 present

14. The OLS results are not reported here, but are available from the authors. Both LME and LML statistics are highly significant in all years, suggesting the need to use the robust forms of the statistics (see Appendix 2). For the South, the robust LME yielded .34, 1.03, 6.11, and 5.76, respectively, and the robust LML 17.06, 38.35, 17.02,

Table 3. Spatial Lag Models of Southern Homicide Rates 1960–1990[a]

Independent Variables	1960	1970	1980	1990
Resource Dep./Aff. Comp.	0.832**	1.792**	3.026**	4.028**
	[0.121]	[0.218]	[0.478]	[0.602]
	(3.386)	(5.820)	(13.994)	(14.814)
Pop. Struct. Comp.	–0.057	0.401	1.551**	1.747**
	[–0.007]	[0.041]	[0.198]	[0.209]
	(–0.265)	(1.497)	(7.637)	(8.247)
Median Age	–0.129**	–0.060	–0.150**	–0.018
	[–0.099]	[–0.039]	[–0.093]	[–0.009]
	(–2.942)	(–1.378)	(–3.736)	(–0.368)
Divorce	0.786**	0.642**	0.775**	0.482**
	[0.092]	[0.075]	[0.149]	[0.097]
	(3.241)	(3.060)	(6.302)	(4.251)
Unemployment	–0.070	–0.353**	–0.244**	–0.438**
	[–0.026]	[–0.092]	[–0.108]	[–0.191]
	(–0.897)	(–3.023)	(–4.145)	(–5.928)
Spatial Lag (ρ)	0.713**	0.651**	0.182*	0.230**
	[0.379]	[0.359]	[0.100]	[0.125]
	(6.005)	(6.905)	(2.431)	(3.261)
Intercept	4.108*	4.153*	9.101**	5.249*
	(2.207)	(2.042)	(5.364)	(2.513)
Sq. Corr.	0.178	0.239	0.311	0.333
N	1412	1412	1412	1412

[a] Unstandardized regression coefficients, standardized regression coefficients in brackets, and t-ratios in parentheses.
* $p \leq .05$; ** $p \leq .01$ (two-tailed tests).

results for these spatial models for the Southern and non-Southern counties, respectively. Table 3 presents spatial lag models for the Southern counties for all time points, whereas Table 4 presents a spatial lag model for the 1960 non-Southern sample and spatial error models for 1970, 1980, and 1990.

Beginning with the results for the South (Table 3), the signs of the coefficients for structural covariates are generally consistent with those observed in nonspatial analyses for the full sample of counties. However, there are interesting changes in magnitudes (and significance) over time. The resource deprivation component is positively related to homicide rates throughout the period, but the strength of the effect steadily

and 7.69, in each year, clearly indicating a lag alternative (although less so in 1990). For the non-South, the corresponding robust LME statistics were 0, 3.48, 40.54, and 11.14, and robust LML was 3.92, .67, 4.39, and .25. In year 1960, a lag is suggested, whereas for the other years, an error process is the suggested alternative.

Table 4. Spatial Regression Models of Non-Southern Homicide Rates, 1960–1990[a]

Independent Variables	1960	1970	1980	1990
Resource Dep./Aff. Comp.	1.571**	3.007**	4.143**	2.875**
	[0.275]	[0.389]	[0.467]	[0.405]
	(9.395)	(14.626)	(19.837)	(13.435)
Pop. Struct. Comp.	0.386**	0.859**	0.290*	0.962**
	[0.126]	[0.211]	[0.056]	[0.229]
	(5.011)	(7.795)	(2.132)	(8.299)
Median Age	−0.156**	−0.157**	−0.304**	−0.066*
	[−0.191]	[−0.163]	[−0.197]	[−0.050]
	(−7.336)	(−6.452)	(−8.607)	(−2.034)
Divorce	0.833**	1.403**	1.318**	0.572**
	[0.276]	[0.359]	[0.366]	[0.239]
	(8.552)	(13.980)	(14.560)	(9.156)
Unemployment	0.079**	−0.024	0.008	−0.045
	[0.061]	[−0.013]	[0.005]	[−0.029]
	(2.622)	(−0.502)	(0.196)	(−0.888)
Spatial Lag (ρ)	0.415**	NI	NI	NI
	[.197]			
	(4.645)			
Spatial Error (λ)	NI	0.243	0.329	0.268
Intercept	4.832**	6.164**	9.622**	3.261**
	(6.544)	(7.309)	(7.588)	(2.621)
Sq. Corr.	0.199	0.234	0.348	0.258
N	1673	1673	1673	1673

[a] Unstandardized regression coefficients, standardized regression coefficients in brackets, and t-ratios in parentheses.
* $p \leq .05$; ** $p \leq .01$ (two-tailed tests).

increases over time. The population structure variable exhibits nonsignificant effects in 1960 and 1970. It is only in the latter years (1980 and 1990) that the expected positive effects emerge. Divorce rates are significantly related to Southern homicide rates throughout the period, but the effect is noticeably weaker in 1990. Unemployment is negatively related to homicide rates in all years except 1960, whereas median age exhibits significantly negative effects sporadically.

Table 3 also indicates that the effects of the Southern spatial lags of homicide are positive and statistically significant in all time periods.[15] These findings support the claim that homicides in Southern counties influence homicides in other counties, consistent with a diffusion interpretation. Note also, however, that the effects of the spatial lags generally weaken over time. An examination of the betas indicates that the spatial

15. The spatial lag for the 1980 model in Table 3 is not significant when a 5 nearest neighbor weights matrix is used instead of a 10 nearest neighbor spatial weights matrix.

lags are the strongest predictors of Southern homicide in 1960 and 1970 but are eclipsed by the structural predictors in 1980 and 1990.

Turning to the non-South (Table 4), the results for the structural covariates are similar to those for all counties in the nonspatial analyses, with the exception of the unemployment variable. Resource deprivation, divorce, and population structure exhibit significantly positive effects on homicide rates, whereas median age yields significantly negative effects. The only significant effect for unemployment is in 1960, and it is positive, contrary to the general pattern.

The results of the spatial analyses are different for the non-South in comparison with the South. In every year except 1960, the spatial error model provides a better fit than does the spatial lag model. Substantively, this implies that for the most part, the residual spatial autocorrelation in the non-South can be adequately accounted for in terms of unmeasured predictor variables. A diffusion process thus seems unlikely in non-Southern counties over recent decades.

SUMMARY AND DISCUSSION

Our analyses yield several noteworthy findings. First, as expected, homicide is not randomly distributed in space. Throughout the 1960–1990 period, county-level homicide rates exhibit appreciable positive spatial autocorrelation. Furthermore, our ESDA reveals a distinctive regional imprint for this spatial autocorrelation. It is mostly in the South that counties have higher than average homicide rates that form statistically significant clusters. These findings suggest that the South and the non-South constitute two distinct spatial regimes in the geographic clustering of homicide.

Second, spatial clustering persists even after controlling for the widely recognized structural predictors of homicide. Residual spatial autocorrelation is highly significant for all time points under investigation. These findings suggest that homicide rates are not generated solely by the internal structural factors represented in the baseline regression model.

Third, in addition to the regional differences in the spatial clustering of homicide rates, there are also significant regional differences in the effects of structural predictors. Scholars have long speculated on reasons for the relatively high homicide rates observed in the South, leading to lively debates over the alleged Southern "culture of violence" (Hawley and Messner, 1989; Nisbett and Cohen, 1996). However, much less attention has been given to the possibility that aspects of Southern culture may condition the effects of structural determinants of homicide (for an exception, see Messner, 1983). An important task for future research is to formulate and test theoretical explanations for why the structural processes underlying homicide rates may differ in varying regional contexts.

In addition, future studies could explore the implications of using varying definitions of regions. Previous research indicates that dividing the South into subregions defined with reference to cultural areas yields important variation in levels of homicide that is concealed in more highly aggregated analyses (Corzine et al., 1999; see also Parker and Pruitt, 2000). Structural effects and spatial processes may also vary across these more refined geographic areas. In any event, our finding of differences in the effects of structural variables across regions broadly defined has a key methodological implication: Coefficients obtained in macrolevel studies of homicide based on samples of units encompassing different regions are likely to yield misleading results unless regional interactions are explicitly taken into account.

Finally, after disaggregating the sample into Southern and non-Southern counties, we observe enduring spatial dependence. In the South, a spatial lag model fits the data well for all decades under investigation. These results are consistent with homicide diffusion. We stress, however, that much more evidence is required to enhance the credibility of such an interpretation. It would be useful, for example, in future research to introduce an explicit temporal dimension into the analysis and examine the extent to which changes over time in homicide rates in the South also follow a pattern consistent with contagion (cf. Cohen and Tita, 1999). Ultimately, of course, demonstration of diffusion processes for homicide will require the identification and measurement of the precise mechanisms involved. Our analyses nevertheless lend credibility to the claim that diffusion processes have operated within the South over the latter decades of the twentieth century.

In the non-South, in contrast, the spatial patterning of homicide rates is more consistent with a spatial error model (at least in the last three decades). This implies that homicide rates cluster because of the clustering of unmeasured variables. Note that if the Land et al. baseline model effectively captures the structural determinants of homicide, the unmeasured variables may reflect cultural factors. This leads to the somewhat ironic suggestion that variation in homicide rates outside of the South may partially reflect a non-Southern culture of nonviolence![16]

16. We deliberately use very guarded language in proposing a possible cultural interpretation for the results in the non-South because the unmeasured variables reflected in the spatial error model could include structural factors not captured in the Land et al. specification. Note, however, that this specification is predicated upon an extensive body of empirical literature, and it incorporates a large number of structural dimensions through the construction of composite indexes.

In sum, our analyses demonstrate striking, substantively meaningful spatial patterns of homicide at the macrolevel. Homicide researchers should attend to these patterns for at least two reasons: Spatial dependence needs to be modeled properly to estimate the effects of nonspatial variables, and spatial dependence directs attention to potential sites for substantively interesting processes, such as diffusion. The application of recently developed techniques of spatial econometrics thus offers promising opportunities for extending our understanding of the social forces contributing to interpersonal violence.

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Appendix 1. Spatial Autocorrelation Statistics

The most commonly used univariate statistic against the null hypothesis of spatial randomness is Moran's I (Cliff and Ord, 1981). A significant and positive value of this statistic indicates spatial clustering (contagion, spillovers, externalities), whereas a significant and negative value suggests a checkerboard pattern of values (competition, repulsion). Formally, Moran's I is $I = \Sigma_i\Sigma_j\, w_{ij}(y_i-\mu)(y_j-\mu) \,/\, \Sigma_i(y_i-\mu)^2$, where w_{ij} is an element of a row-standardized spatial weights matrix, y is the homicide rate, and μ is the average homicide rate in the sample. Inference for Moran's I is based on a normalized z-value, obtained by subtracting the expected value and dividing by the standard error (for technical details, see Cliff and Ord, 1981). It should be noted that for Moran's I to be appropriate, the underlying random variable should have a constant variance. Because homicide rates are intrinsically heteroscedastic (due to the different population base), indication of spatial autocorrelation that ignores this aspect may be spurious (Cressie, 1993; Cressie and Chan, 1989). In our analyses, we carried out Moran's I for the original variates and for a variance-stabilizing transformation, but found no qualitative difference between the results.

Moran's I can be visualized by means of a so-called Moran scatterplot (Anselin, 1996, 1999b), which has Wz on the y-axis and z on the x-axis, where z are standardized variates and W is a row-standardized spatial weights matrix. The slope of the linear smoother in this plot corresponds to the value of Moran's I. This device allows for the categorization of spatial association into four groups, corresponding to the quadrants in the graph: high surrounded by high, low surrounded by low (both positive spatial autocorrelation), and high surrounded by low, low surrounded by high (both negative spatial autocorrelation).

Although Moran's I is a "global" measure of spatial autocorrelation, meaning that it pertains to the complete data set, in exploratory analysis, so-called "local" statistics of spatial association may yield more specific insights into the presence of clusters and spatial outliers. Introduced in Anselin (1995), the Local Moran I statistic is $I_i = (z_i \,/\, \Sigma_i\, z_i^2)\, \Sigma_j\, w_{ij}\, z_j$, where, z refers to the homicide rate in mean-deviation form. Inference is based on a conditional randomization approach (Anselin, 1995). As for the global Moran's I, variance instability must be accounted for when applying this diagnostic to proportions such as homicide rates.

A combination of the information in a Moran scatterplot and the significance of the LISA statistic is a so-called Moran scatterplot map, which shows the locations with significant LISA and indicates by a color code the quadrant in the Moran scatterplot to which that location belongs (Anselin and Bao, 1997). These maps visualize the location of significant clusters and thereby suggest potential multivariate associations and facilitate the initial identification of spatial regimes.

Appendix 2. Regression Diagnostics For Spatial Autocorrelation

Regression diagnostics for spatial autocorrelation are based on the application of the Lagrange Multiplier principle or Rao's Score principle. These tests have the advantage that they are based on estimates obtained from the model under the null hypothesis, which in our case is a standard regression model estimated by OLS. The regression residuals are used to test for the presence of spatial autocorrelation. The LM statistics for the two alternatives of interest (spatial error and spatial lag) are different; this offers the opportunity to exploit the values of these statistics to suggest the likely alternative (the basic results are presented in Anselin, 1988).

Formally, the LM statistic against spatial error autocorrelation takes the form $LME = [e'We/s^2]^2 / T$, with e as a vector of OLS residuals, s^2 as its estimated standard error, $T = [tr(W + W')W]$, and tr as the matrix trace operator. This statistic is asymptotically distributed as $\chi^2(1)$ under the null. Although the LM form is based on an assumption of normality, Anselin and Kelejian (1997) show that this is not required and asymptotically the test is equivalent to a Moran's test (appropriately adjusted for the use of residuals e).

The LM statistics for spatial lag dependence are slightly more complex: $LML = [e'Wy/s^2]^2 / [(WXb)'M(WXb)/s^2 + T]$, with $M = I - X(X'X)^{-1}X'$, b as the OLS estimate, and T as before. This statistic is also asymptotically distributed as $\chi^2(1)$ under the null (see Anselin, 1988 for derivations). Extensive simulation studies in Anselin and Rey (1991) and Anselin and Florax (1995) illustrate the relative power of these tests and demonstrate their attractive properties for applied empirical work.

In some instances, both LME and LML statistics turn out to be highly significant, making it difficult to decide which is the proper alternative. For such circumstances, Anselin et al. (1996) developed a robust form of the LM statistics in the sense that each test is robust to the presence of local deviations from the null hypothesis in the form of the other alternative. In other words, the robust LME is robust to the presence of spatial lag, and vice versa. The robust tests perform well in a wide range of simulations and form the basis of a practical specification search, as illustrated in Anselin and Florax (1995) and Anselin et al. (1996). All tests are implemented in the SpaceStat software package (Anselin, 1999b).