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Spatial (Dis)Advantage and Homicide in Chicago Neighborhoods

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For some time now, research in the ecological tradition has demonstrated the concentration of interpersonal violence in certain neighborhoods, especially those areas characterized by poverty, the racial segregation of minority groups, and single-parent families. Still, fundamental questions remain about what it is about these communities that might explain the link between structural features of neighborhood environments and rates of violent crime. The traditional or perhaps idyllic notion of local communities as "urban villages" characterized by dense networks of personal social ties continues to pervade many theoretical perspectives on neighborhood crime. Yet such ideal typical neighborhoods bear little resemblance to contemporary cities, where weak ties prevail over strong ties and social interaction among residents is characterized by increasing instrumentality. The urban village model is also premised on the notion that networks of personal ties and associations map neatly onto the geographic boundaries of spatially defined neighborhoods, such that neighborhoods can be analyzed as independent social entities. Modern neighborhoods are often less distinctly defined, with permeable borders. Social networks in this setting are likely to traverse traditional ecological boundaries, implying a spatial interdependence among social processes.

This chapter builds on recent criminological research to integrate key dimensions of neighborhood-level structure, social processes, and spatial embeddedness to address the question of crime's ecological concentration. In particular, we examine the extra-local processes related to the spatial dynamics of violent crime, along with more local institutional processes related to voluntary associations and neighborhood organizations. We interpret these dimensions of the urban landscape with a theoretical framework highlighting the role of social control and cohesion—or what we have termed collective efficacy—and neighborhood structural inequality. Our focus on inequality centers on the extreme concentration of socioeconomic resources at both the upper and lower tails of the distribution and on spatial inequality in social processes.

Spatial Dynamics

Contrary to the common assumption in ecological criminology of analytic independence, we argue that neighborhoods are *inter*dependent and characterized by a functional relationship between what happens at one point in space and what happens elsewhere. Spatial interdependence is theoretically motivated on three grounds. First, we expect it to arise as a result of the inexact correspondence between the neighborhood boundaries imposed by census geography and the ecological properties that shape social interaction. One of the biggest criticisms of neighborhood-level research to date concerns the artificiality of boundaries; for example, two families living across the street from one another may be arbitrarily assigned to live in different "neighborhoods" even though they share social ties. From the standpoint of systemic theory, it is important to account for the social and institutional ties that link residents of urban communities to other neighborhoods, particularly those that are more spatially proximate to their own neighborhood. Spatial models address this problem by recognizing the interwoven dependence among (artificial) neighborhood units. The idea of spatial dependence thus challenges the urban village model, which implicitly assumes that geographically defined neighborhoods represent intact social systems that function as islands unto themselves, isolated from the wider sociodemographic dynamics of the city.

Second, spatial dependence is implicated by the fact that homicide offenders are disproportionately involved in acts of violence near their homes (Block 1977; Reiss and Roth 1993). From a routine activities perspective, it follows that a neighborhood's "exposure" to homicide risk is heightened by geographical proximity to places where known offenders live (see also Cohen et al. 1981). Moreover, to the extent that the risk of becoming a homicide offender is influenced by contextual factors such as concentrated poverty, concentrated affluence, and collective efficacy, spatial proximity to such conditions is also likely to influence the risk of homicide victimization in a focal neighborhood.

A third motivation for studying spatial dependence relates to the notion that interpersonal crimes such as homicide are based on social interaction and thus, subject to diffusion processes (Cohen and Tita 1999; Messner et al. 1999; Morenoff and Sampson 1997; Rosenfeld et al. 1999; Smith et al. 2000). Acts of violence may themselves instigate a sequence of events that leads to further violence in a spatially channeled way. For example, many homicides, not just gang-related, are retaliatory in nature (Black 1983; Block 1977). Thus, a homicide in one neighborhood may provide the spark that eventually leads to a retaliatory killing in a nearby neighborhood. In addition, most homicides occur among persons known to one another (Reiss and Roth 1993), usually involving networks of association that follow geographical vectors.

There is, then, reason to believe that spatial dependence arises from processes related to both diffusion and exposure, such that the characteristics of surrounding neighborhoods are, at least in theory, crucial to understanding violence in any given neighborhood. The diffusion perspective focuses on the consequences of crime itself as they are played out over time and space—crime in one neighborhood may be the cause of future crime in another neighborhood. The concept of exposure focuses on the antecedent conditions that foster crime, which are also spatially and temporally ordered. Although both concepts provide strong justification for analyzing spatial dependence, criminological research has been surprisingly slow to adapt tools of spatial analysis, especially in a regression framework that accounts for a competing explanation of clustering—selection effects based on population composition (see also Rosenfeld et al. 1999; Smith et al. 2000). In this chapter, we therefore focus on the independent effect of spatial proximity on the likelihood of homicide, accounting for key structural and social characteristics of life within the boundaries of focal neighborhoods.

Informal and Institutional Processes

Our second major goal is to integrate the study of neighborhood mechanisms with regard to informal and institutional social processes. Neighborhood-level social processes are not easy to study, of course, because the socio-demographic characteristics drawn from census data and other government statistics typically do not provide information on the collective properties of administrative units. Of those studies that have focused on social processes, most have focused on social ties and interaction to the exclusion of organizations (see Peterson et al. 2000). For example, Sampson et al.'s (1997) test of collective efficacy highlighted cohesion and mutual expectations among residents for control. But as alluded to earlier, communities can exhibit intense private ties (e.g., among friends, kin), and perhaps even shared expectations for control, yet still lack the institutional capacity to achieve social control. The institutional component of social capital is the resource stock of neighborhood organizations and their linkages with other organizations. Bursik and Grasmick (1993a) also highlight the importance of public control, defined as the capacity of community organizations to obtain extra-local resources (e.g., police protection, block grants, health services) that help sustain neighborhood stability and control. It may be that high levels of collective efficacy come about because of such controls, such as a strong institutional presence and intensity of voluntary associations. Or it may be that the presence of institutions directly accounts for lower rates of crime. Relatively few studies have examined voluntary associations, and almost none a community's organizational base (for a review see Sampson et al. 2002). In addition to incorporating the systemic dimensions of collective efficacy and social ties, we therefore address this gap by simultaneously examining institutional density and the intensity of local voluntary associations.

In short, this chapter presents a substantive and methodological framework for studying the spatial dynamics of violence in neighborhood contexts. Criminal events require the intersection in time and space of three elements—motivated offenders, suitable targets, and the absence of capable guardians (Cohen and Felson 1979). As such, crime can be ecologically concentrated because of the presence of targets and/or the absence of guardianship (e.g., collective efficacy), even if the pool of motivated offenders is more evenly distributed across the city. We are thus interested in how neighborhoods fare as units of guardianship and collective efficacy; the outcome is the rate of homicide and robbery victimization. Applying this framework, we highlight two neglected dimensions of neighborhood context: (1) spatial dynamics arising from neighborhood interdependence, and (2) social-institutional processes.

Data Sources

The data on neighborhood social processes stem from the Community Survey of the Project on Human Development in Chicago Neighborhoods (PHDCN). The extensive social-class, racial, and ethnic diversity of the population was a major reason Chicago was selected for the study. Chicago's 865 census tracts were combined to create 343 "Neighborhood Clusters" (NCs) composed of geographically contiguous and socially similar census tracts. NCs are smaller than Chicago's 77 community areas (average size = 40,000) but large enough to approximate local neighborhoods, averaging around 8,000 people. Major geographic boundaries (e.g., railroad tracks, parks, freeways), knowledge of Chicago's local neighborhoods, and cluster analyses of census data were used to guide the construction of relatively homogeneous NCs with respect to distributions of racial-ethnic mix, socio-economic status (SES), housing density, and family structure. The Community Survey (CS) of the PHDCN was conducted in 1995, when 8,782 Chicago residents representing all 343 NCs were personally interviewed in their homes.[1] The basic design for the CS had three stages: at stage 1, city blocks were sampled within each NC; at stage 2, dwelling units were sampled within blocks, and at stage 3, one adult resident (18 or older) was sampled within each selected dwelling unit. Abt Associates carried out the screening and data collection in cooperation with PHDCN, achieving an overall response rate of 75 percent.

To assess collective efficacy we replicated Sampson et al. (1997) and combined two related scales. The first is a five-item Likert-type scale of *shared expectations for social control.* Residents were asked about the likelihood that their neighbors could be counted on to take action if: children were skipping school and hanging out on a street corner, children were spray-painting graffiti on a local building, children were showing disrespect to an adult, a fight broke out in front of their house, and the fire station closest to home was threatened with budget cuts. *Social cohesion/trust* was measured by asking respondents how strongly they agreed that "People around here are willing to help their neighbors"; "This is a close-knit neighborhood"; "People in this neighborhood can be trusted"; "People in this neighborhood generally don't get along with each other" (reverse coded); and "People in this neighborhood do not share the same values" (reverse coded). Social cohesion and informal social control were strongly related across neighborhood clusters (r = .80), and following Sampson et al. (1997), were combined into a summary measure of the higher-order construct, "collective efficacy." The aggregate-level or "ecometric" reliability (see Raudenbush and Sampson 1999) of collective efficacy was .85.[2]

In addition to the cohesion and control scales that define collective efficacy, our analysis takes into account institutional neighborhood processes and social networks. *Organizations* is an index of the number of survey-reported organizations and programs in the neighborhood—the presence of community newspaper, block group or tenant association, crime prevention program, alcohol/drug treatment program, mental health center, or family health service. *Voluntary associations* taps the "social capital" involvement by residents in (1) local religious organizations, (2) neighborhood watch programs, (3) block group, tenant associations, or community council, (4) business or civic groups, (5) ethnic or nationality clubs, and (6) local political organizations. The measure of *social ties/networks* is based on the combined average of two measures capturing the number of friends and relatives living in the neighborhood.

Unlike the full-count census measures described below, our community survey measures of social process are based on only about 25 respondents per neighborhood cluster. Moreover, there are differential missing data by items in the scales. To account for measurement error and missing data we employ the empirical Bayes (EB) residuals of the key survey-based predictors—collective efficacy, social ties, organizations, and voluntary associations. EB residuals are defined as the least squares residuals regressed toward zero by a factor proportional to their unreliability (Bryk and Raudenbush 1992, 42). Using EB residuals as explanatory variables corrects for bias in regression coefficients resulting from measurement error (Whittemore 1989).

Structural Characteristics

Based on the 1990 census and our theoretical framework, we examine five neighborhood structural characteristics. All scales are based on the summation of equally weighted z-scores divided by the number of items; factor-weighted scales yielded the same results. *Concentrated disadvantage* represents economic disadvantage in racially segregated urban neighborhoods. It is defined by the percentage of families below the poverty line, percentage of families receiving public assistance, percentage of unemployed individuals in the civilian labor force, percentage of families with children that are female-headed, and percentage of residents who are black. These variables are highly interrelated and load on a single factor using either principal components or alpha-scoring factor analysis with an oblique rotation (see also Sampson et al. 1997, 920). This result makes sense ecologically, reflecting neighborhood segregation mechanisms that concentrate the poor, African-Americans, and single-parent families with children (Bursik and Grasmick 1993b; Land et al. 1990; Massey and Denton 1993; Wilson 1987).

In such a segregated context, it is problematic at best to try and separate empirically the influence of percent black from the other components of the disadvantage scale, for there are in fact no white neighborhoods that map onto the distribution of extreme disadvantage that black neighborhoods experience (Krivo and Peterson 2000; Sampson and Wilson 1995). For example, if one divides Chicago into thirds on concentrated poverty, there are no white neighborhoods in Chicago that fall into the high category (Sampson et al. 1997). Even though traditional in criminology, regression models that enter both percent black and disadvantage thus assume a reality counter to fact. We address this race issue in two ways. First, we assess whether the structural, social, and spatial processes specified in our models vary across regimes defined by racial composition. In other words, although we cannot reliably disentangle the direct effects of race and disadvantage, we address the possibility that racial composition interacts with other variables. Second, we test the robustness of main results, other than disadvantage, to traditional controls for percent black.

Focusing on the pernicious effects of concentrated disadvantage, while obviously important, may obscure the potential *protective* effects of affluent neighborhoods. After all, concentrated affluence may be more than just the absence of disadvantage. Recent years have seen the increasing separation of affluent residents from middle class areas (Massey 1996), a phenomenon not captured by traditional measures of poverty. Moreover, Brooks-Gunn et al. (1993) argue that concentrated affluence generates a separate set of protective mechanisms based on access to social and institutional resources. The resources that affluent neighborhoods can mobilize are theoretically relevant to understanding the activation of social control, regardless of dense social ties and other elements of social capital that might be present. In support of this notion, recent work has demonstrated the importance of measuring the upper tail of the SES distribution when analyzing structural characteristics and youth outcomes (Brooks-Gunn et al. 1993; Sampson et al. 1999). We thus extend our focus by introducing a measure that captures the concentration of both poverty and affluence. The index of concentration at the extremes (ICE) (Massey 2001) is defined for a given neighborhood by the following formula: [(number of affluent families − number of poor families) / total number of families], where "affluent" is defined as families with income above $50,000, and "poor" is defined as families below the poverty line. The ICE index ranges from a theoretical value of −1 (which represents extreme poverty, namely that all families are poor) to +1 (which signals extreme affluence, namely that all families are affluent). A value of zero indicates that there is an equal share of poor and affluent families living in the neighborhood. ICE is therefore an inequality measure that taps both ends of the income distribution, or as Massey (2001, 44) argues, the *proportional* imbalance between affluence and poverty within a neighborhood.

Other structural covariates include the relative presence of *adults per child* (ratio of adults 18+ to children under 18) and *population density* (number of persons per square kilometer). We also build on Sampson et al. (1997) by examining two additional structural characteristics long noted in the ecological literature. *Residential stability* is defined as the percentage of residents five years old and older who lived in the same house five years earlier, and the percentage of homes that are owner-occupied. The second scale captures areas of *concentrated Latino immigration*, defined by the percentage of Latino residents (in Chicago approximately 70 percent of Latinos are Mexican-American) and percentage of persons foreign born.

Violence Measures

To eliminate method-induced associations between outcomes and predictors, we examine two independent measures of homicide relative to our survey-based approach to measuring social process and census-based approach to measuring structural covariates. We analyze homicide as an indicator of neighborhood violence, both because of its indisputable centrality to debates about crime, and because it is widely considered to be the most accurately recorded of all crimes. Our principal data source comes from reports of homicide incidents to the Chicago Police Department. These data consist of aggregate homicide counts that have been geo-coded to match the neighborhood cluster in which the events occurred. We use the homicide count data from two time periods, the years 1991 to 1993 and the years 1996 to 1998.[3] Because homicide is a rare event, we construct rates based on three-year counts for both periods to reduce measurement error and stabilize rates. We replicate the main analysis on a person-based measure of homicide victimization in 1996 derived from vital statistics rather than police records.[4] The original source here was death-record information found in the coroner's report and recorded in vital statistics data for Chicago, which were geocoded based on the home address of the victim.[5] To the extent that basic patterns are similar across recording systems with obviously different error structures, we can place increased confidence in the results of independently measured predictors. Nevertheless, we privilege the incident-based homicide measure from police statistics as our primary outcome, because our theoretical perspective, grounded in the social control of routine activities, places its analytic focus on the neighborhood factors that might suppress the occurrence of homicide events within its boundaries.

Sampson et al. (1997) analyzed violence measured at the same time (1995) as the survey of collective efficacy, meaning that the outcome could have influenced the alleged explanatory factors. By contrast, we assess the ability of our model to predict future variations in violence. Specifically, the census-based factors (1990) and survey-based processes (1995) were measured temporally prior to the event counts of homicide in 1996–1998. Moreover, we address the potential endogeneity of collective efficacy with respect to past violence by explicitly controlling for the rate of violent events in 1992–1993. It may be that neighborhood social trust and residents' sense of control are undermined by experiences with crime, most notably interpersonal crimes of violence and those committed in public by strangers (Bellair 2000; Liska and Bellair 1995; Skogan 1990). Ours is a strict test, because the strong temporal dependence in violence (e.g., the correlation between 1991–1993 and 1996-1998 is .79 for incidence rates) may yield unduly conservative estimates of any of the predictors. This procedure also gives us some purchase on controlling for prior sources of crime not captured in our measured variables.[6]

Statistical Models and Spatial Framework

There are three major features of our approach and data that must be represented in our statistical model: the conception of the outcome as a count of rare events (homicides); the likely unexplained variation between neighborhoods in the underlying latent event rates; and the spatial embeddedness of neighborhood processes. Our model views the homicide count Y_i for a given neighborhood as sampled from an over-dispersed Poisson distribution with mean $n_i \lambda_i$, where n_i is the population size in 100,000s of neighborhood i, and λ_i is the latent or "true" homicide rate for neighborhood i per 100,000 people. We view the log-event rates as normally distributed across neighborhoods. However, we conceive of these log-event rates as spatially auto-correlated. More specifically, using a hierarchical generalized linear model approach (McCullagh and Nelder 1989), we set the natural log link $\eta_i = \log(\lambda_i)$ equal to a mixed linear model that includes relevant neighborhood covariates, a random effect for each neighborhood, plus a spatial autocorrelation term. Thus, our model for the neighborhood log homicide rate conforms to an over-dispersed Poisson distribution (see Raudenbush and Bryk 2002).

The advantage of this approach is three-fold. First, it sensibly incorporates the skewed nature of the homicide outcome, which has many values of zero, while at the same time creating a metric that defines meaningful effect size. Namely, exponentiating the regression coefficient in such a model and multiplying the result times 100 produces the useful interpretation of "the percent increase in the homicide rate associated with a one unit increase in the predictor." Second, the approach represents unique unobserved differences between neighborhoods via random effects. To the extent that neighborhoods have unique features that affect homicide rates, these random effects are important in accounting for variation not explainable by the structural model. Third, the approach incorporates the spatial dependence of neighborhood homicide rates.

Unfortunately, software that can simultaneously handle over dispersed Poisson variates, random effects of neighborhoods, and spatial dependence is not currently available. We therefore employed a two-step approximation. First, we used a hierarchical generalized linear model without spatial dependence to compute posterior modes η_j^* of neighborhood-specific log-homicide rates given the data, the grand mean estimate for Chicago, and the estimated between-neighborhood variance in the true log-rates.[7] Next, we imported these posterior modes into software dedicated to estimating regression models with spatial dependence (SpaceStat). Using this integrated approach, regression coefficients and coefficients of spatial dependence have the desirable interpretation of the ideal model described above.

We estimate spatial dependence by constructing "spatially lagged" versions of our measures of violence. We define y_i as the homicide rate of NC_i, and w_{ij} as element i, j of a spatial weights matrix that expresses the geographical proximity of NC_i to NC_j (Anselin 1988, 11). For a given observation i, a spatial lag $\sum_j w_{ij} y_j$ is the weighted average of homicide in neighboring locations.[8] The weights matrix is expressed as first-order contiguity, which defines neighbors as those NCs that share a common border (referred to as the rook criterion).[9] Thus, $w_{ij} = 1$ if i and j are contiguous, 0 if not. We then test formally for the independent role of spatial dependence in a multivariate model by introducing the spatial lag as an explanatory variable. The spatial lag regression model is defined as

$$y = \rho W y + X\beta + \varepsilon, \tag{1}$$

where y is an N by 1 vector of observations on the dependent variable; Wy is an N by 1 vector composed of elements $\sum_j w_{ij} y_j$, the spatial lags for the dependent variable; ρ is the spatial autoregressive coefficient; X is an N by K matrix of exogenous explanatory variables with an associated K by 1 vector of regression coefficients β; and ε is an N by 1 vector of normally distributed random error terms, with means 0 and constant (homoskedastic) variances.[10]

The most straightforward interpretation of ρ is that, for a given neighborhood, i, it represents the effect of a one-unit change in the average homicide rate of i's first-order neighbors on the homicide rate of i. This interpretation would seem to suggest a diffusion process, whereby a high homicide rate in one neighborhood diffuses outward and affects homicide rates in surrounding neighborhoods. However, the notion of diffusion implies a process that occurs over time, while the spatial autocorrelation process modeled in Equation (1) is entirely cross-sectional—homicide rates are spatially interrelated across neighborhoods but simultaneously determined. Moreover, the interpretation of ρ as a pure diffusion (or feedback) mechanism—the effect of a one-unit change in Wy on y—does not capture the complexity of the spatial process specified in Equation (1). By extending the logic of Equation (1), we can demonstrate that the spatial lag model also incorporates the idea of "exposure" to the values of the measured X variables and the ε term (i.e., unmeasured characteristics) in spatially proximate neighborhoods. According to Equation (1), the value of y at location i depends on the values of X and ε at location i and on values of y in i's first-order neighbors. In turn, the first-order neighbors' values of y are functions of X and ε in i's first-order neighbors and y in i's second-order neighbors, and so on. This process continues in a step-like fashion, incorporating the neighborhood characteristics of successively higher-order neighbors of i (see also Tolnay et al. 1996). This process can be expressed mathematically by rewriting Equation (1) as follows:

$$\begin{aligned} y = {} & X\beta + \rho W X\beta + \rho^2 W^2 X\beta + \dots \\ & + \rho^m W^m X\beta + \varepsilon + \rho W\varepsilon + \rho^2 W^2\varepsilon + \dots + \rho^m W^m\varepsilon, \end{aligned} \tag{2}$$

where $m \rightarrow \infty$. Equation (2) is also known as the "spatial multiplier" process, because it shows that the spatial regression model treats spatial dependence as a ripple effect, through which a change in X or ε at location i influences not only the value of y at location i but also (indirectly) at all other locations in Chicago.

Equation (2) also shows that the spatial effect can be decomposed into two parts: the effect of proximity to the measured X variables, and the effect of proximity to unmeasured characteristics, ε. The first component (the spatial process in the X variables) directly addresses the "proximity hypothesis" discussed above—it estimates the extent to which homicide rates are related to values of the measured X variables in spatially proximate neighborhoods.[11] The second component of Equation (2) (the spatial process in ε) is more ambiguous and depends on the model specification. In part, this component taps the effect of spatial proximity to unmeasured features in nearby neighborhoods that are associated with homicide. For example, the homicide rate of the focal neighborhood might be related to rates in surrounding areas because of overlapping social networks across arbitrary neighborhood boundaries. Another possibility is a spillover effect such that the homicide rate in the focal neighborhood is affected by the homicide rate in nearby neighborhoods directly. Therefore, the ρ coefficient from the spatial lag model captures spatial exposure to the observed X variables, spatial exposure to unobserved predictors, and endogenous feedback effects in y.

Exploratory Spatial Data Analysis

We begin our analysis by examining the geographic distributions of homicide and collective efficacy across Chicago neighborhoods in an exploratory spatial data analysis

(Anselin 1988). Consistent with much past research, homicide events are not randomly distributed with respect to geography. In fact, supplementary tabulations reveal that 70 percent of all the homicides in Chicago between 1996 and 1998 occurred in only 32 percent of the neighborhood clusters, according to the Police data. We thus examined the geographic correspondence between the distribution of neighborhood homicide rates and that of collective efficacy, a key social processes from our theoretical perspective. To facilitate such a comparison, we employ a typology of spatial association, referred to as a Moran scatterplot, which classifies each neighborhood based on its value for a given variable, y, and the weighted average of y in contiguous neighborhoods, as captured by the spatial lag term, Wy. For simplicity, neighborhoods that are above the mean on y are considered to have "high" values of y, while neighborhoods below the mean are classified as "low." The same distinction is made with respect to values of Wy for each neighborhood, resulting in a four-fold classification with the following categories: (1) low-low, for neighborhoods that have low levels of efficacy and are also proximate to neighborhoods with low levels of efficacy; (2) low-high, for neighborhoods that have low levels of efficacy but are proximate to high levels; (3) high-low, for neighborhoods that have high levels of efficacy but are proximate to low levels; and (4) high-high, for areas with high levels of efficacy that are also proximate to high levels of efficacy.

Figure 8.1 displays the results of the spatial typology for two variables: collective efficacy and the 1996–1998 EB homicide rates, constructed from the incident-based Police data.[12] This map conveys two pieces of information for each neighborhood. First, each neighborhood's value for the spatial typology of collective efficacy is denoted by a different fill pattern: light gray for low-low; dots for low-high; diagonal stripes for high-low; and dark gray for high-high.[13] Second, the symbols on the map represent values of the spatial typology of EB homicide rates, constructed from the 1996–1998 police data: black stars indicate significant high-high values (i.e., homicide "hot spots"), and gray crosses indicate significant low-low values (i.e., homicide "cold spots").

We draw two general conclusions from Figure 8.1. First, the map shows that there is a high degree of overlap between the spatial distributions of collective efficacy and homicide. For example, 67 of the 93 neighborhoods that have spatial clustering of high levels of collective efficacy (72 percent) also experience statistically significant clustering of low homicide. Most of the clustering of low homicide coupled with high collective efficacy occurs in neighborhoods located on the western boundaries of Chicago, particularly on the far northwest and southwest sides. Similarly, there is a strong correspondence between the spatial clustering of high homicide rates and low levels of collective efficacy. Of the 103 homicide hot spots, 77 (or 75 percent) also have spatial clustering of low levels of collective efficacy. Second, despite the strong association between the geographic distribution of collective efficacy and homicide, there are many observations where the two typologies are at variance with one another. For example, 14 of the 93 homicide cold spots (15 percent) appear in neighborhoods with low levels of collective efficacy that are surrounded by high levels. Moreover, 15 of 103 homicide hot spots (15 percent) are in neighborhoods that have high levels of collective efficacy but are surrounded by neighborhoods with low levels. Neighborhoods where the level

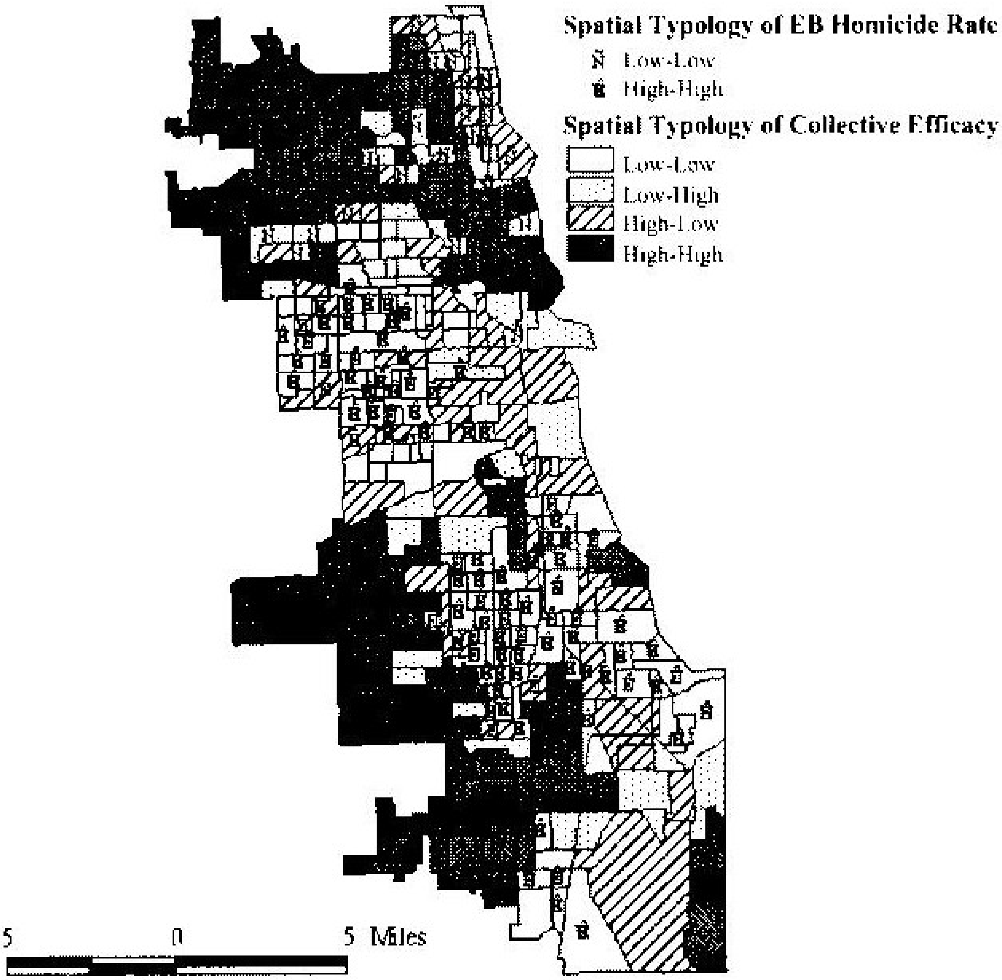

Figure 8.1. Spatial typology of collective efficacy with homicide "Hot" Spots and "Cold" Spots.

of collective efficacy is at variance with surrounding neighborhoods are important theoretically, because they reveal concrete but often neglected forms of spatial advantage and disadvantage (Sampson et al. 1999).

The role of spatial proximity to collective efficacy is further explored in Figure 8.2, which graphs the mean homicide rate for the four categories of the collective efficacy spatial typology.[14] Figure 8.2 reveals that regardless of the level of collective efficacy in the focal neighborhood, mean homicide rates are lower among neighborhoods that are spatially proximate to high levels of collective efficacy (as indicated by the dark gray bars) than they are among neighborhoods that are spatially proximate to low levels of collective efficacy (as indicated by the dotted bars). It is therefore clear that a neighborhood's spatial proximity to collective efficacy conditions its homicide rate, independent of its own level of collective efficacy. In other words, knowing the local level of social organization is not enough, a proposition we now test further in a multivariate spatial analysis of homicide rates with additional covariates.

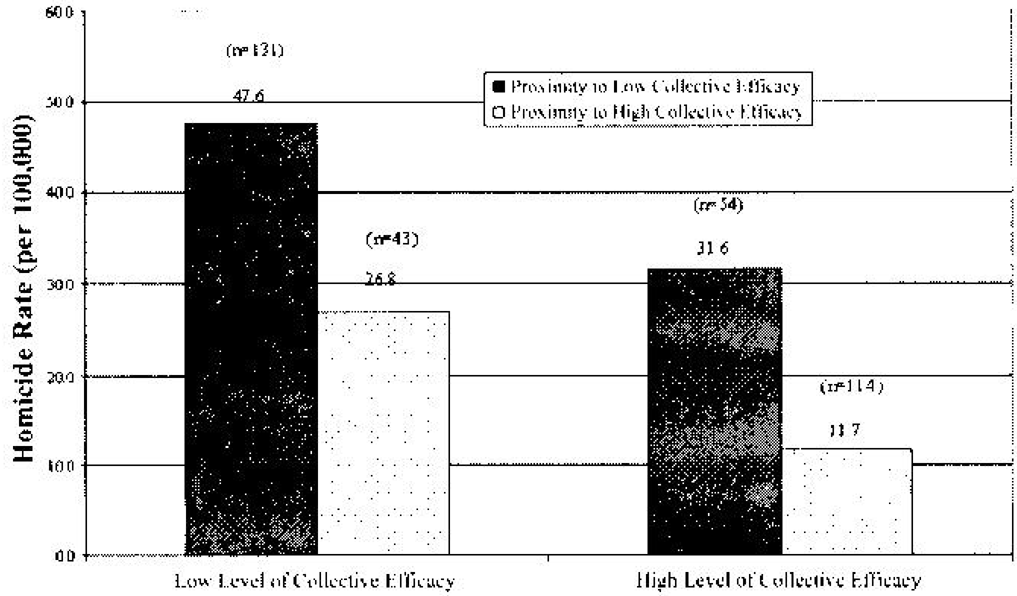

Figure 8.2. Mean homicide rate by level and spatial proximity to collective efficacy.

Multivariate Analysis

We turn to a regression framework to investigate three substantive issues in the analysis of neighborhood homicide rates: the role of multiple social processes as neighborhood mechanisms, the spatial dynamics of homicide, and the endogeneity of collective efficacy. Table 8.1 presents the results of regression models for EB homicide rates using the Chicago Police Data. The first model includes only the structural covariates. The natural log of the concentrated disadvantage index is used, because scatterplots revealed a nonlinear relationship between disadvantage and homicide. The log-transformation effectively linearizes this association.[15] The results show that all of the coefficients in this model are significant, with the exception of the ratio of adults to children. When social and institutional processes are added to the regression, in Model 2, only the effects of disadvantage (positive), residential stability (positive), and density (negative) remain significant.[16] More importantly, Model 2 also reveals that collective efficacy is negatively related to homicide rates, as anticipated by the theoretical discussion. Somewhat unexpectedly, none of the other social or institutional process variables in Model 2 are significantly related to homicide.

Models 3 and 4 represent spatial lag regressions estimated via maximum likelihood. Model 3 introduces the spatial lag term, which is positively related to homicide rates and strongly significant. The introduction of the spatial lag term in Model 3 eliminates the significance of residential stability and diminishes the effects of concentrated disadvantage (by 30 percent), population density (by 20 percent), and collective efficacy (by 16.5 percent). Model 4 adds a control for the prior neighborhood homicide rate (1991–1993) in order to address the possibility that the association between collective efficacy

Table 8.1. Coefficients from the regression of incident-based 1996–1998 empirical Bayes Poisson homicide rate on neighborhood predictors.

	OLS		*Maximum Likelihood*			
Variables	(1)	(2)	(3)	(4)	(5)	(6)
LN concentrated disadvantage	1.30**	1.14**	0.80**	0.54**		
	(0.07)	(0.09)	(0.10)	(0.13)		
ICE index					−1.12**	−0.68**
					(0.18)	(0.19)
Concentrated immigration	0.10**	0.06	0.03	0.04	0.14**	−0.04
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Residential stability	0.05*	0.05*	0.03	0.03	0.03	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Adults per child*	0.01	0.06	0.02	0.12	0.07	0.16
	(0.33)	(0.33)	(0.30)	(0.30)	(0.32)	(0.32)
Population density**	0.27**	0.33**	0.27**	0.24**	−0.20**	0.20**
	(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)
Collective efficacy		−0.65**	−0.54**	−0.47**	−0.67**	−0.47**
		(0.20)	(0.18)	(0.18)	(0.18)	(0.18)
Voluntary associations		0.18	0.15	0.13	0.15	0.14
		(0.10)	(0.09)	(0.09)	(0.09)	(0.09)
Organizations		−0.05	−0.05	−0.03	−0.02	−0.01
		(0.07)	(0.06)	(0.06)	(0.07)	(0.06)
Kin/friendship ties		0.02	0.02	0.05	0.10	−0.13
		(0.16)	(0.15)	(0.15)	(0.16)	(0.16)
Spatial proximity			0.34**	0.31**	0.48**	0.30**
			(0.05)	(0.05)	(0.05)	(0.05)
Prior homicide rate (1991–1993)				0.21**		0.37**
				(0.06)		(0.05)
Constant	2.91**	6.01**	4.62**	3.87**	5.14**	3.81**
	(0.08)	(0.92)	(0.87)	(0.89)	(0.87)	(0.89)
R^2	0.68	0.70	0.72	0.73	0.69	0.73

(Standard Errors in Parentheses)

*Adults per child multiplied by 100

**Population density multiplied by 10,000

$^{**}p < .01$; $^{*}p < .05$

Sources: 1990–1998 Chicago Police Data; 1995 PHDCN Survey; and 1990 Census.

in 1995 and 1996–1998 homicide rates is really a reflection of the downward spiral of neighborhoods caused by prior violence.[17] The control for prior homicide reduces the magnitude of the collective efficacy coefficient (by 13 percent), but it still maintains significance. The control for prior homicide reduces the disadvantage coefficient more substantially (by 33 percent), but because 1991–1993 homicide rates and the logged disadvantage index are so highly correlated (r = .90), it is difficult to disentangle their independent effects on 1996–1998 homicide rates. More important from the standpoint of our theoretical discussion above is that collective efficacy and the spatial term maintain significant and strong associations with variations in future homicide unaccounted for by the stable patterns of violence as reflected in prior homicide.

The remaining models in Table 8.1, Models 5 and 6, offer an alternative specification of the spatial autocorrelation model with and without the control for prior homicide. What is unique about Models 5 and 6 is the substitution of the ICE index for the disadvantage index. The ICE index captures the degree of concentrated affluence relative to the concentration of poverty in a neighborhood (Massey 2001). The coefficients for collective efficacy remain statistically significant in Models 5 and 6 after controlling for prior homicide. Significant spatial dependence also remains in each of the models. Thus, even though they are conceptually distinct, substituting ICE for the disadvantage index does not alter the main findings. The larger message appears to be that concentrated inequality in socioeconomic resources is directly related to homicide.

To assess robustness, Table 8.2 replicates the same set of models using victim-based homicide rates for 1996 from the Chicago Vital Statistics data. The results are similar to those from Table 8.1 for the variables of main theoretical interest: concentrated disadvantage, collective efficacy, spatial proximity, and the ICE index. In Model 1, concentrated disadvantage is the only structural variable that has a statistical association with homicide. Unlike the results for the incident-based homicide measure, density does not have a direct relationship with victim-based homicide. This makes sense from a routine activities perspective, because it is a factor that is theoretically related to the point of the event's occurrence, not the residence of the victim.

When the social process variables are added in Model 2, we again find a significant association between homicide rates and collective efficacy, but not for social ties or any of the institutional measures. The spatial lag term, introduced in Model 3, is significant and positively related to homicide rates. The control for prior homicide is not significant in Model 4,[18] but the coefficients for disadvantage, collective efficacy, and spatial dependence maintain their significance. The effects associated with collective efficacy and spatial dependence also remain significant after the substitution of the ICE index for the disadvantage index in Models 5 and 6.

In sum, we find a fairly robust set of results across independently collected sources of homicide data: the Chicago Police Statistics and Chicago Vital Statistics. Concentrated disadvantage, collective efficacy, and the ICE index are consistently related to homicide. In particular, strong spatial effects are also evident in both data sets; these spatial effects remain after controlling for the strong stability in homicide risk over time. We believe this finding is important, for one of the biggest problems in spatially-based social research is ensuring that ρ is not spurious due to a failure to fully specify the causal processes in a focal community. The strength of our model is that the temporally lagged homicide rate essentially serves as a proxy for all such unmeasured variables. Thus, to the extent that prior homicide adjusts for the unobserved heterogeneity of causal processes, the continued strength of the ρ coefficient increases our confidence in the robustness of the effect of spatial proximity on homicide.

Although we consider homicide to be our best measure of violence, to test the robustness of our main patterns we also replicated the spatial models on a different predatory crime—robbery. Table 8.3 presents the basic models and empirical results. Overall, the same pattern obtains. The spatial proximity coefficient is significant in all models, including those that control for prior robbery. In this case, prior robbery and concurrent robbery are correlated at more than $r = .90$, meaning that there is very little residual variance left to explain. It is not clear whether a reduction in magnitude for the

Table 8.2. Coefficients from the regression of victim-based 1996 empirical Bayes Poisson homicide rate on neighborhood predictors.

	OLS		*Maximum Likelihood*			
Variables	(1)	(2)	(3)	(4)	(5)	(6)
LN concentrated disadvantage	0.66**	0.56**	0.44**	0.35**		
	(0.05)	(0.07)	(0.08)	(0.10)		
ICE index					0.56**	−0.35**
					(0.15)	(0.16)
Concentrated immigration	0.04	−0.05	0.05	−0.04	0.14**	−0.09**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
Residential stability	0.03	0.03	0.03	0.03	0.03	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Adults per child[†]	0.01	−0.03	0.01	0.02	0.14	−0.02
	(0.27)	(0.27)	(0.26)	(0.26)	(0.27)	(0.27)
Population density[††]	−0.04	0.08	−0.07	0.07	−0.04	0.04
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Collective efficacy		−0.48**	0.50**	−0.47**	0.66**	−0.52**
		(0.16)	(0.15)	(0.15)	(0.15)	(0.16)
Voluntary associations		0.13	0.14	0.13	0.13	0.12
		(0.08)	(0.07)	(0.07)	(0.08)	(0.08)
Organizations		0.05	0.04	0.04	0.05	0.05
		(0.06)	(0.05)	(0.05)	(0.06)	(0.06)
Kin/friendship ties		0.04	0.07	0.08	0.08	0.09
		(0.13)	(0.13)	(0.13)	(0.14)	(0.14)
Spatial proximity			0.22**	0.20**	0.33**	0.18**
			(0.06)	(0.07)	(0.06)	(0.05)
Prior homicide rate (1991–1993)				0.09**		0.24**
				(0.06)		(0.06)
Constant	2.00**	4.24**	3.78**	3.38**	4.23**	3.20**
	(0.06)	(0.75)	(0.74)	(0.79)	(0.74)	(0.79)
R^2	0.50	0.52	0.53	0.53	0.50	0.52

(Standard Errors in Parentheses)

[†]Adults per child multiplied by 100

[††]Population density multiplied by 10,000

$^{**}p < .01$; $^{*}p < .05$

Sources: 1990–1998 Chicago Police Data; 1995 PHDCN Survey; and 1990 Census.

effects of our set of social-process predictors means that the association is mediated or is spurious. What we can see, however, is that in this conservative test, the spatial lag effect remains robust for robbery.

Further Understanding the Spatial Dynamics of Violence

To interpret more fully the results of the spatial lag models, it is important to recall that in Equation (2), homicide is related to the value of each X variable in successively higher-order neighbors by a function of ρ, the coefficient for the spatial lag term. In Figure 8.3, we use the results from Model 4 in Tables 8.1 and 8.2 to demonstrate how

Table 8.3. Coefficients from the regression of 1995 logged robbery rate on neighborhood predictors.

	Maximum Likelihood	
Variables	(1)	(2)
LN Concentrated disadvantage	0.20**	0.03
	(0.05)	(0.04)
Concentrated immigration	0.00	0.03
	(0.04)	(0.03)
Residential stability	0.06**	0.02
	(0.02)	(0.01)
Adults per child†	0.11	-0.01
	(0.24)	(0.17)
Population Density††	−0.30**	−0.13**
	(0.07)	(0.05)
Collective efficacy	−0.29	0.14
	(0.15)	(0.11)
Voluntary assocations	0.03	0.02
	(0.07)	(0.05)
Organizations	0.02	−0.01
	(0.05)	(0.04)
Kin/friendship ties	−0.26**	−0.03
	(0.13)	(0.09)
Spatial proximity	0.76**	0.27**
	(0.03)	(0.04)
Prior logged robbery rate (1993)		0.68**
		(0.04)
Constant	2.74**	0.73
	(0.70)	(0.51)
R^2	0.75	0.91

(Standard Errors in Parentheses)

†Adults per child multiplied by 100

†† Population density multiplied by 10,000

$^{**}p < .01$; $^{*}p < .05$

this "spatial multiplier" process works with respect to two key covariates: concentrated disadvantage (which is logged) and collective efficacy.[19] The bars on the left side of the graph illustrate how the spatial multiplier process operates for concentrated disadvantage. The first set of bars in this series shows that, controlling for all other covariates in Model 4, a one-standard-deviation increase in the log of the disadvantage index *in the focal neighborhood* is associated with a 40 percent increase in the homicide rate in the focal neighborhood, according to the Police data, and a 24 percent increase according to the Vital Statistics.[20] The next set of bars reveals that all else being equal, a one-standard-deviation increase in the average level of concentrated disadvantage *in the first-order neighbors* of the focal neighborhood is associated with a 9 percent increase in the homicide rate in the focal neighborhood, according to the Police data, and a 4 percent increase according to Vital Statistics. The remaining bars show that the effects of disadvantage decrease exponentially with each succeeding level of contiguity. To gauge the cumulative effect, it is possible to add up all the bars in this series for each data set. This shows that a simultaneous one-standard-deviation increase in the log of the disadvantage index in the focal neighborhood, and in the first-, second-, and third-order neighbors, is associated with a 52 percent increase in homicide, according to Police data, and a 28 percent increase according to the Vital Statistics.

The right side of Figure 8.3 displays results for the same exercise conducted on collective efficacy. The coefficients for collective efficacy are more stable across the two data sets. A one-standard-deviation increase in the level of collective efficacy in the focal neighborhood is associated with a 12 percent reduction in the homicide rate, according to both the Police data and the Vital Statistics data. Cumulatively, a one-standard-deviation increase in collective efficacy in the focal neighborhood, and the first-, second-, and third-order neighbors is associated with a 15 percent reduction in the homicide rate of the focal neighborhood, according to the Police data, and a 14 percent drop according to the Vital Statistics.

Note that Figure 8.3 only displays the spatial effects associated with two independent variables, concentrated disadvantage and collective efficacy. A full decomposition of the spatial effect would include other variables in the model, in addition to the error term. Thus, the effects displayed in Figure 8.3 are only a fraction of the full spatial effect. What these results do show, however, is that the cumulative effects associated with both disadvantage and collective efficacy are substantively quite large, particularly when their spatial dynamics are taken into account.

Regimes of Racial Segregation

To this point our analysis has relied on an index of concentrated disadvantage that includes racial composition as one of its components. As we argued above, the high degree of racial segregation overlaid with poverty hinders our ability to disentangle the direct effects of neighborhood racial composition and neighborhood socioeconomic disadvantage in Chicago.[21] However, it is possible, and we would argue more meaningful, to examine whether the social and structural processes under study operate similarly across neighborhoods of differing racial composition. We address this issue by estimating spatial regime models (Anselin 1995a), which allow coefficients to vary across regimes defined by neighborhood racial composition while also controlling for spatial dependence.[22] To define these regimes, we divide Chicago's neighborhoods into two categories based on their 1990 racial composition: (1) less than 75 percent non-Hispanic black (henceforth referred to as "non-black" neighborhoods) and (2) 75 percent or more non-Hispanic black (henceforth referred to as "black" neighborhoods). There are 125 black neighborhoods, as defined by this typology, and they are on average 96.4 percent black, 2.5 percent white, and 2.8 percent Hispanic. There are 217 non-black neighborhoods, which on average are 54.3 percent white, 30.5 percent Hispanic, and 9.4 percent black.[23]

The results of the regime model are reported in Table 8.4. We use ICE as our inequality measure in these models, because the disadvantage index contains the percent black measure, which cannot be used both on the right-hand side of the regressions and in the definition of the regimes. Theoretically, we are interested in the propor-

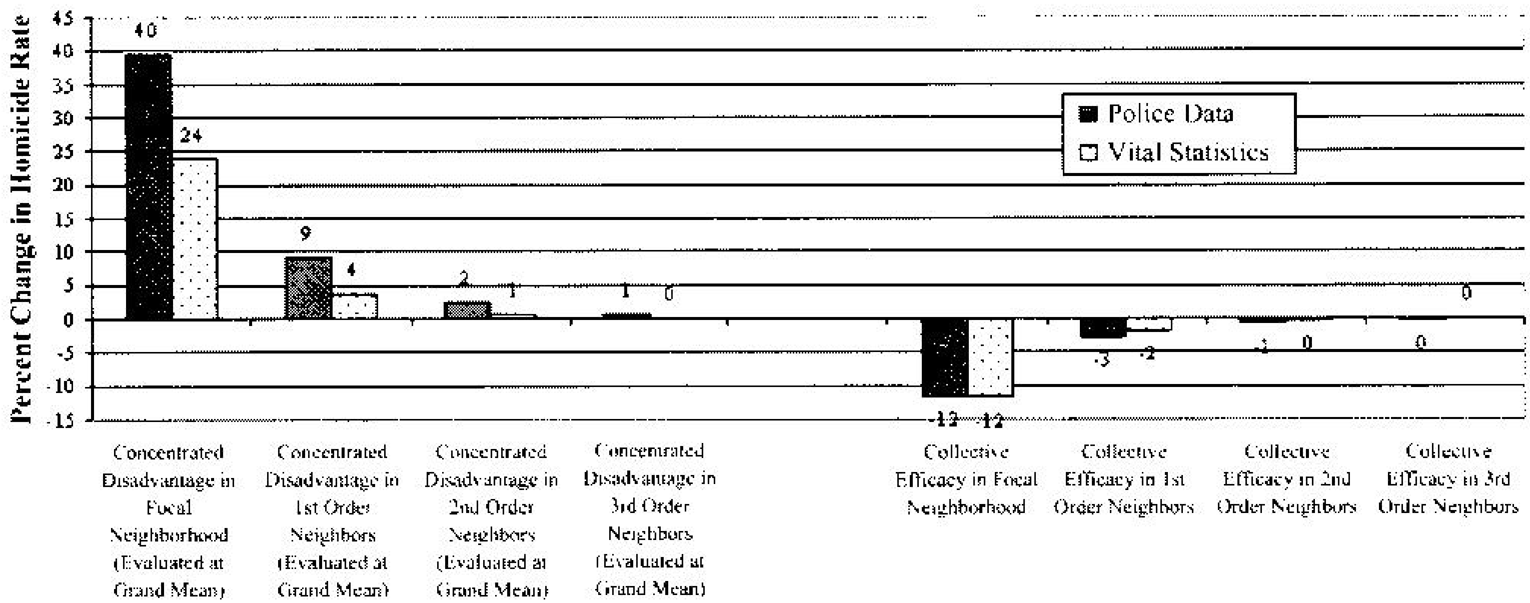

Figure 8.3. Percent change in homicide rate per standard deviation change in concentrated disadvantage and collective efficacy by spatial proximity to focal neighborhood.

Table 8.4. Coefficients from the regression of empirical Bayes Poisson homicide rates on neighborhood predictors by racial regimes.

	Incident-Based		*Victim-Based*	
	< 75% Black	≥ 75% Black	< 75% Black	≥ 75% Black
Variables	(1)	(2)	(3)	(4)
ICE index	1.20**	−0.87**	−0.67**	−0.02
	(0.28)	(0.35)	(0.23)	(0.29)
Concentrated immigration	−0.05	0.34	0.02	−0.69
	(0.07)	(0.48)	(0.06)	(0.39)
Residential stability	0.00	0.03	0.00	0.00
	(0.03)	(0.05)	(0.02)	(0.04)
Adults per child†	0.03	0.73	0.10	1.52
	(0.34)	(2.54)	(0.28)	(2.09)
Population density††	0.26	−0.24	0.05	−0.13
	(0.10)	(0.18)	(0.08)	(0.15)
Collective efficacy	−0.56*	−0.61*	−0.18	0.98**
	(0.25)	(0.29)	(0.21)	(0.24)
Voluntary associations	0.19	0.08	0.14	0.27*
	(0.12)	(0.15)	(0.10)	(0.13)
Organizations	0.00	0.08	−0.03	0.17†
	(0.09)	(0.11)	(0.07)	(0.09)
Kin/friendship ties	−0.13	0.20	0.05	0.36
	(0.20)	(0.29)	(0.17)	(0.24)
Constant	5.12**	3.88**	2.82**	5.12**
	(1.08)	(1.53)	(0.89)	(1.26)
Spatial proximity	0.41**		0.24**	
	(0.05)		(0.06)	
R^2	0.71		0.54	

†Adults per child multiplied by 100

††Population density multiplied by 10,000

$^{**}p < .01$, $^{*}p < .05$

Sources: 1990–1998 Chicago Police Data; 1995 PHDCN Survey; and 1990 Census.

tional distribution of affluence and poverty within racial regimes. The first two columns display results using the incident-based homicide outcome—column 1 contains the coefficients for the non-black neighborhoods, and column 2 contains coefficients for the black neighborhoods. In general, the results do not differ very much across regimes in the incident-based homicide model.[24] The ICE index and collective efficacy have significant negative associations with the homicide incident rate in both non-black and black neighborhoods. The spatial effect, which is estimated jointly across non-black and black neighborhoods, is also significant and large. The main difference is that population density has a significant negative effect only in non-black neighborhoods.

Turning to the victim-based homicide measure (columns 3 and 4), the results yield more differences across the two regimes.[25] In the victim-based homicide model, the ICE index is significantly associated with homicide only in non-black neighborhoods, whereas the association between collective efficacy and homicide is significant only in black neighborhoods. Moreover, in black neighborhoods, the measures of voluntary associations and organizations are positively associated with homicide, whereas in non-black neighborhoods these associations are non-significant. Again, the spatial effect is significant. Although there is evidence of differing magnitudes of effect across black and non-black neighborhoods, the overall results for collective efficacy and spatial proximity are fairly robust taking both homicide outcomes into account.

Conclusion and Implications

Our results suggest that spatial embeddedness, internal structural characteristics, and social organizational processes are each important for understanding neighborhood-level variations in rates of violence. Spatial proximity to violence, collective efficacy, and alternative measures of neighborhood inequality—indices of concentrated disadvantage and concentrated extremes—emerged as the most consistent predictors of variations in homicide across a wide range of tests and empirical specifications. Moreover, our analysis of racial "spatial regimes" suggested that structural characteristics and social processes have many similar effects on homicide rates in predominantly black, compared with non-black, neighborhoods. Although we did find some evidence of differences in coefficients across regimes— and it is noteworthy that the effect of collective efficacy is strongest in black neighborhoods—overall, the results suggest that a fairly stable causal process is operating in all parts of the city. Put differently, the evidence is more favorable than not to the idea that the fundamental causes of neighborhood violence are similar across race (see also Krivo and Peterson 2000; Sampson and Wilson 1995).

A major theme of our analysis is that homicide is a spatially dependent process, and that our estimates of spatial effects are relatively large in magnitude. Indeed the spatial effects were larger than standard structural covariates and an array of neighborhood social processes. The tendency of past research has been to focus on internal neighborhood factors, but they are clearly not enough to understand homicide. Local actions and population composition make a difference, to be sure, but they are severely constrained by the spatial context of adjacent neighborhoods. Our results suggest that political economy theorists are right in insisting on models that incorporate citywide dynamics (Logan and Molotch 1987). Hope (1995, 24) makes a similar point from the criminological perspective, suggesting that many intervention efforts have failed because they did not adequately address the pressures towards crime in the community that derive from forces external to the community in the wider social structure. Although very different in research style and method, the recent ethnographic work of Pattillo-McCoy (1999) also parallels our findings and discovery of the salience of spatial vulnerability, especially for black middle-class neighborhoods (Figure 8.1).

The puzzle that remains is to further disentangle spatial processes into constituent parts. At this juncture we are unable to pinpoint the relative contributions of exposure and diffusion, an agenda we are hopeful that criminological researchers and methodologists will have an interest in tackling. We believe that better longitudinal data on crime and social processes will provide a particular boon to disentangling temporal and cross-sectional diffusion. In the meantime, it seems clear that spatial proximity cannot be ignored in theories of violence.

Acknowledgment This paper selectively condenses previously published work; see especially Morenoff et al. 2001. We acknowledge the American Society of Criminology, publishers of the journal *Criminology*.

Notes

1. By neighborhood, the survey protocol stated: " . . . we mean the area around where you live and around your house. It may include places you shop, religious or public institutions, or a local business district. It is the general area around your house where you might perform routine tasks, such as shopping, going to the park, or visiting with neighbors."
2. Distinct from individual-level reliability (e.g., Cronbach's alpha), neighborhood reliability is defined as: $\sum\left[\tau_{00}/(\tau_{00}+\sigma^2/n_j)\right]/J$, which measures the precision of the estimate, averaged across the set of J neighborhoods, as a function of (1) the sample size (n) in each of the j neighborhoods and (2) the proportion of the total variance that is between-groups (τ_{00}) relative to the amount that is within-groups (σ^2). A magnitude of greater than .80 suggests that we are able to reliably tap parameter variance in collective efficacy at the neighborhood level. For further discussion of tools for assessing ecological context see Raudenbush and Sampson (1999).
3. We thank Richard Block for providing the police count data for 1996–1998. Homicide data from 1991–1993 were downloaded from the Chicago Homicide Data Set at the ICPSR data archive (www.icpsr.umich.edu). Homicide data from both time periods come from police counts, also compiled by Richard Block, that were geocoded based on the address where the incident occurred. The homicide counts for each neighborhood cluster include cases of non-negligent manslaughter but exclude deaths from injuries inflicted by law-enforcing agents.
4. We did not have access to vital statistics data for 1997 or 1998, so our two measures of homicide do not cover exactly the same period. Homicides in the vital statistics are coded as causes of death due to injuries inflicted by another person with intent to injure or kill, by any means. As with the police statistics, these homicide data include non-negligent manslaughter but exclude injuries inflicted by the police or other law-enforcing agents (NCHS 2000).
5. A long history of research on homicide has shown that victims tend to be killed in or very near to their neighborhoods of residence. For homicide, then, the victimization rate also serves as a proxy for homicide incidence, an assumption validated by the high correlation between vital statistics and the police-recorded incidence of homicide events. The correlation between the homicide rate calculated from vital statistics from 1996 data and that calculated from the police statistics for 1996–1998 is .71. The correlation between homicide rates calculated on the two data sets for 1991–1993 is .86.
6. An alternative approach to addressing the endogeneity of collective efficacy would be to examine simultaneous equation models, but in this procedure the choice of instrumental variables is often very difficult to justify (see discussion in Bellair 2000), and the existing literature has been harshly criticized as untenable (Fisher and Nagin 1978). The problem is that the exclusionary restrictions cannot be validated with the data at hand. We prefer to address endogeneity through a control for prior homicide on two grounds—no identifying restrictions are necessary, and it is a conservative test. The latter is true because the very high stability in homicide rates over time results in little residual variation left in the homicide rate to explain with other covariates. Also, prior levels of social process, for which we have no measures, may have influenced prior levels of crime and thus, may be mediated in their effect. However, *if* a significant association between social process and homicide maintains

after partialling the effect of prior homicide, endogeneity is an implausible inference in our panel model, since the homicide outcome is measured at a later time than the predictors; crime cannot influence the past.

7. The approximate posterior mode η_i^* for neighborhood i is a weighted average of that neighborhood's log homicide rate, estimated using only the data from that neighborhood, and the overall mode of the homicide rates estimated from the data generated by all of the neighborhoods. The weights accorded each component are proportional to their precisions. The more data collected in neighborhood i, the more precise will be the estimate based on the data from that neighborhood, and the more weight it will be accorded in composing η_i^*. The more concentrated the neighborhood rates around the overall mode, the more that overall mode will be weighted. Such approximate posterior modes are routinely produced as output from widely used statistical software for multilevel analysis (c.f., Raudenbush and Bryk 2002). The shrinkage of neighborhood-specific estimates toward an overall mode is not ideal, because it ignores prior information about how neighborhoods differ in their homicide rates. In principle, this leads to somewhat conservative estimates of the effects of neighborhood-level covariates. To assess the extent of bias, we replicated our results using standard regression analyses with the neighborhood-based rates as outcomes. Results were very similar. We chose the approach using posterior modes, because it extends better to spatial modeling. The standard approach using the neighborhood-based rates as outcomes does not extend well to the incorporation of spatial effects, because the extreme skewness of the neighborhood-specific rates contradicts the assumptions of the spatial regression procedures. Using the posterior modes solves this problem and produces stable and interpretable spatial results.
8. Spatial dependence may also be treated as a "nuisance," in the form of a spatial error model (Anselin 1988). The spatial lag model was chosen because it conforms to our theoretical approach that specifies spatial dependence as a substantive phenomenon rather than as a nuisance (see also Tolnay, Deane, and Beck 1996). Moreover, the spatial lag models generally outperformed the corresponding spatial error models in a variety of diagnostic tests.
9. Before computing the spatial lag term, we standardized the weights matrix by dividing each element in a given row by the corresponding row sum (see Anselin 1995a). Defined formally as $w_{ij}/\sum_j w_{ij}$, row standardization constrains the range of the parameter space in such a way that the resulting coefficient is no longer dependent on the scale of the distance employed in the weights matrix. The spatial lag parameter can be interpreted as the estimated effect of a one-unit change in the scale of the original variable from which it was created.
10. This model is often referred to as the simultaneous spatial autoregressive model, because the presence of the spatial lag is similar to the inclusion of endogenous explanatory variables in systems of simultaneous equations. All estimates of the spatial proximity models were derived using the program "SpaceStat" (Anselin 1995a).
11. Because ρ is multiplied by the β coefficient for each X variable in Equation (2), and $0 \leq \rho \leq 1$, it is possible to think of ρ as the rate at which the effects of each X variable are "discounted" in contiguous neighbors. Thus, if $\rho = .50$, then the effects of the average level of X in the first-order neighbors (Wx) will be half as strong as they are in the focal neighborhood. In the second-order neighbors, the effect will be reduced by one-quarter the size of $\beta(.50^2 = .25)$, and so on for each successive order of contiguity.
12. A color version of the map is displayed at the website http://www.csiss.org/best-practices.
13. It is possible to apply a test of statistical significance for the values of this typology, developed by Anselin (1995b). This test of local spatial association at each location i is referred to as the local Moran statistic, defined as $I_i = (z_i/m_2)\sum_j w_{ij}z_j$ with $m_2 = \sum_i z_i^2$, where the observations z_i and z_j are standardized values of y_i and y_j expressed as deviations from the mean (Anselin 1995a and 1995b). Under a conditional randomization approach, the

value of z_i at location i is held fixed, and the remaining values of z_j over all other neighborhoods in the city are randomly permuted in an iterative fashion. With each permutation, a new value of the quantity $\sum_j w_{ij} z_j$ is computed, and the statistic is recalculated. This permutation operationalizes the null hypothesis of complete spatial randomness. A test for pseudo significance is then constructed by comparing the original value of I_i to the empirical distribution that results from the permutation process (Anselin 1995b). We could not convey the information about statistical significance of the Moran typology for collective efficacy with the limited shading scheme of a black and white map—such a map entails an eight-fold categorization, which is better displayed in color. However, the symbols on the map representing homicide hot spots (stars) and cold spots (crosses) are based on only the statistically significant "high-high" and "low-low" values of the local Moran statistic for homicide. We have posted a more detailed color map at http://www.csiss.org/best-practices that also displays the significant spatial clustering of collective efficacy.

14. This graph does not take into account statistical significance of Moran's I, because there are very few neighborhoods that are in either the low-high or high-low categories and have statistically significant values of Moran's I (only 6 in low-high and 11 in high-low). These cell sizes are too small to generate reliable estimates of mean homicide rates.
15. Before taking its natural log, we added a constant (1.5) to the disadvantage scale to eliminate negative values.
16. The negative association between population density and homicide might go against conventional wisdom that it should be positive. The expectation of a positive association is probably more applicable to the city level (i.e., more densely populated cities may indeed have higher homicide rates), but it is less applicable to the neighborhood level, because many of the most devastated and poor areas *within* cities of the North and Midwest are those that became "depopulated" during the social dislocations of the 1970s and 1980s (Wilson 1987).
17. These prior homicide rates are also based on the over-dispersed Poisson distribution, using the same methodology described above.
18. Again, prior homicide is strongly correlated with the logged disadvantage index (.90). Consequently, as was the case in Table 8.1, we cannot reliably disentangle the independent effects of prior homicide and disadvantage on homicide in 1996.
19. In order to obtain the percentage change in the homicide rate per standard deviation change in the corresponding independent variable, we exponentiate the product of each regression coefficient and the standard deviation of the respective covariate.
20. Because the relationship between concentrated disadvantage and the homicide rate is nonlinear, the effect of a one-standard deviation increase in disadvantage depends on where in the distribution of disadvantage that change is evaluated. Figure 8.3 displays the difference in the homicide rate associated with moving from one-half of a standard deviation below the mean of disadvantage to one-half of a standard deviation above the mean on disadvantage.
21. We did attempt to re-estimate the models in Tables 8.1 and 8.2 by recalculating the disadvantage index without percent black, and instead, entering percent black as a separate covariate. Our major substantive results remained intact with this alternative specification. However, the Variance Inflation Figures increased dramatically—to over 5 in some cases for the percent black variable—indicating severe problems with multicolinearity. Nevertheless, the pattern of results for the other factors in the model was similar, especially for spatial proximity.
22. The spatial regime model is a switching regression model, in which the coefficients and constant term take on different values depending on the regime, and the coefficients of each regime are jointly estimated. The model also includes a spatial lag term that does not vary across regimes, meaning that the spatial process is assumed to be uniform across the entire city.

23. Although we specify only two regimes, we recognize that the "non-black" category encompasses a heterogeneous grouping of neighborhoods that may be predominantly white, predominantly Hispanic, or mixed. It is possible to expand the regime specification to more than two regimes, but further disaggregation of the non-black regime would result in very small sample sizes—there are only 69 neighborhood clusters that were over 75 percent white in 1990 and only 21 that were over 75 percent Hispanic. We thus present the more parsimonious two-regime specification and leave for future research the question of what explains differences across these two regimes. Our main interest here is the replicability of results in all black areas.
24. Both the overall Chow test for the structural stability of the regression model across the two regimes and the coefficient-specific Chow tests for stability across regimes reveal that there are no significant differences across regimes. This suggests that for incident-based homicide, the regression models for black and non-black neighborhoods are not significantly different.
25. In this model, the Chow test for the structural stability of the regression model across regimes indicates significant differences in the patterns of association across black and non-black neighborhoods. Coefficient-specific Chow tests indicate that the collective efficacy coefficient varies across regimes ($p = .01$), although the Chow tests for ICE ($p = .08$), concentrated immigration ($p = .09$), and organizations ($p = .08$) are all marginally significant.

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