NEIGHBORHOOD INEQUALITY, COLLECTIVE EFFICACY, AND THE SPATIAL DYNAMICS OF URBAN VIOLENCE*

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Highlighting resource inequality, social processes, and spatial interdependence, this study combines structural characteristics from the 1990 census with a survey of 8,872 Chicago residents in 1995 to predict homicide variations in 1996–1998 across 343 neighborhoods. Spatial proximity to homicide is strongly related to increased homicide rates, adjusting for internal neighborhood characteristics and prior homicide. Concentrated disadvantage and low collective efficacy—defined as the linkage of social control and cohesion—also independently predict increased homicide. Local organizations, voluntary associations, and friend/kinship networks appear to be important only insofar as they promote the collective efficacy of residents in achieving social control and cohesion. Spatial dynamics coupled with neighborhood inequalities in social and economic capacity are therefore consequential for explaining urban violence.

Over the course of the past century, criminological research in the ecological tradition has continually discovered the concentration of interpersonal violence in certain neighborhoods, especially those characterized by

poverty, the racial segregation of minority groups, and single-parent families.[1] Still, fundamental questions remain about what it is that communities "supply" (or fail to supply) that may explain the link between these structural features of neighborhood environments and the 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 appear to 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. By contrast, modern neighborhoods are often less distinctly defined with permeable borders. Social networks in this setting are more likely to traverse traditional ecological boundaries, implying that social processes are not neatly contained in geographic enclaves.

In short, despite marshalling impressive evidence that neighborhoods matter even in the modern city, criminologists by and large continue to rely on the classic urban-village metaphor to explain why. This paper builds on recent criminological research to integrate key dimensions of neighborhood-level structure, process, and spatial embeddedness that may help to explain the puzzle of crime's ecological concentration. In particular, we incorporate local institutional processes related to voluntary associations and local organizations, along with extra-local processes related to the spatial dynamics of violent crime. We integrate these dimensions of the urban landscape with a theoretical framework highlighting the role of social control and cohesion—even if not rooted in strong personal ties—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.

SOCIAL DISORGANIZATION THEORY
AND BEYOND

Our approach draws its motivation from an intellectual tradition that seeks to explain variation in rates of crime and violence. In their classic work, Shaw and McKay (1942) argued that low economic status, ethnic

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1. Space limitations preclude a literature review of structural covariates and violence. For summaries, see Land et al. (1990), Peterson and Krivo (1993), and Sampson and Lauritsen (1994).

heterogeneity, and residential instability led to community disorganization, which in turn accounted for delinquent subcultures and ultimately high rates of delinquency. It was not until the 1970s and 1980s, however, that social disorganization was defined explicitly as the inability of a community structure to realize the common values of its residents and to maintain effective social controls (Bursik, 1988; Kornhauser, 1978; Sampson and Groves, 1989). This theoretical definition of social disorganization has been formulated in systemic terms—that is, the local community is viewed as a complex system of friendship, kinship, acquaintanceship networks, and associational ties rooted in family life and ongoing socialization processes (Bursik and Grasmick, 1993a; Kasarda and Janowitz, 1974).

More recently, the intellectual tradition of community-level research has been revitalized by the increasingly popular idea of "social capital." Although there are conflicting definitions, social capital is typically conceptualized as embodied in the social ties among persons and positions (Coleman, 1990:304). Putnam defines social capital as "features of social organization, such as networks, norms, and trust, that facilitate coordination and cooperation for mutual benefit" (1993:36). Whatever the specific formulation, the sources of social capital stem not from the attributes of individuals but from the structure of social organization. The connection of systemic social disorganization and social capital theory has been articulated by Bursik (1999): Neighborhoods bereft of social capital (e.g., interlocking social networks) are less able to realize common values and maintain the informal social controls that foster safety.

The intuitive appeal of social capital notwithstanding, there are reasons to problematize the process by which strong social ties translate into low crime rates. First, in some neighborhood contexts, strong ties may impede efforts to establish social control. Wilson (1996), for example, has argued that many poor neighborhoods where residents are tightly interconnected through network ties do not produce collective resources such as the social control of disorderly behavior. His research suggests that disadvantaged urban neighborhoods are places where dense webs of social ties among neighbors may impede social organization: "[I]t appears that what many impoverished and dangerous neighborhoods have in common is a relatively high degree of social integration (high levels of local neighboring while being relatively isolated from contacts in broader mainstream society) and low levels of informal social control (feelings that they have little control over their immediate environment, including the environment's negative influences on their children)" (pp. 63–64). In her study of a black middle-class community in Chicago ("Groveland"), Pattillo-McCoy (1999) also acknowledges the limits of tight-knit social bonds in facilitating social control. She argues that although dense local ties promote social integration, they also foster the growth of networks that impede efforts to rid the

neighborhood of drug- and gang-related crime: "Because Groveland is very stable, thick kin, neighborly, and friendship ties are the norm. These networks positively affect both the informal and formal supervision of youth. . . . But at the same time that dense social ties are good, they also have negative repercussions. . .for organized criminal enterprises" (p. 70).

A second reason that it is problematic to assume a simple connection between strong social ties and low crime rates is that in many urban communities, shared expectations for social control are maintained in the absence of thick ties among neighbors (Sampson et al., 1999). Strong ties among neighbors are no longer the norm in many urban communities because friends and social support networks are decreasingly organized in a parochial, local fashion (Fischer, 1982; Wellman, 1979). Moreover, as Granovetter (1973) argued in his seminal essay, "weak ties"—i.e., less intimate connections between people based on more infrequent social interaction—may be critical for establishing social resources, such as job referrals, because they integrate the community by bringing together otherwise disconnected subgroups. Bellair (1997) extended this logic to the study of community crime by demonstrating that weak ties among neighbors, as manifested by less frequent patterns of social interaction, are predictive of lower crime rates. Research on dense social ties thus reveals somewhat of a paradox for crime theory. Many urbanites interact with their neighbors on a limited basis and thus appear to generate very little social capital. Moreover, urbanites whose strong ties are tightly restricted geographically may actually produce an environment that discourages collective responses to local problems.

To address these changes in urban reality, Sampson et al. (1997, 1999) proposed a focus on mechanisms that facilitate social control without requiring strong ties or associations. As Warren (1975) noted, the common belief that neighborhoods have declined in importance as social units "is predicated on the assumption that neighborhood is exclusively a primary group and therefore should possess the 'face-to-face,' intimate, affective relations which characterize all primary groups" (p. 50). Rejecting this outmoded assumption about the function of local communities, Sampson et al. (1997) highlighted the combination of a working trust and shared willingness of residents to intervene in social control. This linkage of trust and cohesion with shared expectations for control was defined as neighborhood "collective efficacy." Just as self-efficacy is situated rather than global (one has self-efficacy relative to a particular task), a neighborhood's efficacy exists relative to specific tasks such as maintaining public order.

Viewed through this theoretical lens, collective efficacy is a task-specific construct that highlights shared expectations and mutual engagement by residents in local social control (Sampson et al., 1999). Moving from a focus on private ties to social efficacy signifies an emphasis on shared

beliefs in neighbors' conjoint capability for action to achieve an intended effect and, hence, an active sense of engagement on the part of residents. As Bandura (1997) argues, the meaning of efficacy is captured in expectations about the exercise of control, elevating the "agentic" aspect of social life over a perspective centered on the accumulation of stocks of resources. This conception is consistent with the redefinition of social capital by Portes and Sensenbrenner as "expectations for action within a collectivity" (1993:1323).

Distinguishing between the resource potential represented by personal ties, on the one hand, and the shared expectations among neighbors for engagement in social control represented by collective efficacy, on the other, may help clarify the systemic model. In particular, social networks foster the conditions under which collective efficacy may flourish, but they are not sufficient for the exercise of control (see also Bursik, 1999). Thus, collective efficacy may be seen as a logical extension of systemically based social disorganization and social capital theory. The difference is mainly one of emphasis: Although we recognize and incorporate below the relevance of systemic networks for neighborhood social organization, we argue that collective capacity for social action, even if rooted in weak personal ties, may constitute the more proximate social mechanism for understanding between-neighborhood variation in crime rates.

RESEARCH STRATEGY AND NEW DIRECTIONS

In this paper, we strive to make both substantive and methodological contributions to neighborhood-level research on violence. Our integrated framework builds on the insights derived from social disorganization, social capital, and collective efficacy theory, coupled with a "routine activities" emphasis on the explanation of crime events. 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 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 event rate of homicide victimization. Applying this framework, we highlight two neglected dimensions of neighborhood context: (1) spatial dynamics arising from neighborhood interdependence, and (2) social-institutional processes.

SPATIAL DYNAMICS

Contrary to the common assumption in ecological criminology of analytic independence, we argue that neighborhoods are interdependent 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 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 sociodeomographic 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; Curtis, 1974; 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 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 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 paper, 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 identified by Mayer and Jencks (1989) with regard to informal and institutional social processes. Neighborhood-level social processes are not easy to study, of course, because the sociodemographic characteristics drawn from census data and other government statistics typically do not provide information on the collective properties of administrative units. Building on some of the pioneering efforts at direct measurement of social control (e.g., Hackler et al., 1974; Macoby, 1958) a growing number of studies have thus turned to original survey-based approaches to assess neighborhood-level social ties and associations. For example, Taylor et al. (1984:316) constructed block-level measures of the proportion of respondents in 63 Baltimore neighborhoods who belonged to an organization to which coresidents also belonged, and the proportion of respondents who felt responsible for what happened in the area surrounding their home. Both measures were significantly and negatively related to rates of violence, exclusive of other ecological factors (p. 320). A similar pattern emerged in Simcha-Fagan and Schwartz's (1986) study of 553 residents of 12 neighborhoods in New York City during the mid-1980s. They found a significant negative relationship between the rate of self-reported delinquency and the rates of organizational participation by local residents (p. 683).

Drawing on data collected from more than 300 communities in Great

Britain in 1982 and 1984, Sampson and Groves (1989) found that the density of local friendship networks was associated with lower robbery rates, whereas the level of organizational participation by residents was linked to lower rates of robbery and stranger violence (p. 789). The prevalence of unsupervised teenage peer-groups in a community had the largest associations with rates of robbery and violence by strangers. Variations in these dimensions of community social organization were shown to mediate, in part, the effects of community socioeconomic status, residential mobility, ethnic heterogeneity, and family disruption. In a similar study from the United States, Elliott et al. (1996) examined survey data from Chicago and Denver. A measure of "informal control" was negatively related to adolescent problem behavior in both sites, and like the British results, informal control mediated the prior effects of neighborhood structural disadvantage. Residentially unstable and poor neighborhoods displayed less social control, and they in turn suffered higher delinquency rates.

A number of studies have used survey data from 5,302 Seattle residents nested within 100 census tracts (Miethe and Meier, 1994) to investigate the connection between social processes and crime. Warner and Rountree (1997) found a significant negative association between assault rates and the proportion of respondents in white neighborhoods who engaged in neighboring activities with one another—including borrowing tools or food, having lunch or dinner, or helping each other with problems. In a subsequent study, Rountree and Warner (1999) examined the gendered nature of neighboring and found that the proportion of females engaging in neighboring activities was behind the association with lower rates of violent crime. Bellair (2000) approached the same data with a somewhat different perspective on social processes. He assumed that neighboring activities affect crime rates only indirectly, by increasing the likelihood that neighbors will engage in informal surveillance of one another's property. These causal paths were consistent with the results he obtained from a structural equation model.

Recently, Sampson et al. (1997) undertook a survey of 8,782 residents of 343 Chicago neighborhoods in 1995. Combining scales tapping mutual trust/cohesion and shared expectations for social control, they found that a summary measure of "collective efficacy" was associated with lower rates of violence, controlling for concentrated disadvantage, residential stability, immigrant concentration, and a set of individual-level characteristics (e.g., age, sex, SES, race/ethnicity, home ownership). Concentrated disadvantage and residential instability were also linked to lower collective efficacy, and the association of disadvantage and stability with violence was significantly reduced when collective efficacy was controlled. These patterns are consistent with the inference that neighborhood structural characteristics

influence violence in part through the construct of neighborhood collective efficacy.[2]

In short, most neighborhood studies to date 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 noted 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 (Hunter, 1985). The institutional component of social capital is the resource stock of neighborhood organizations and their linkages with other organizations. Similar to the idea of "bridging" social capital, Bursik and Grasmick (1993a) also highlight the importance of public control, defined as the capacity of community organizations to obtain extralocal 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. Only a few studies have examined voluntary associations (e.g., Simcha-Fagan and Schwartz, 1986; Taylor and Gottfredson, 1984), and almost none a community's organizational base (for an exception, see Peterson et al., 2000). In addition to incorporating the spatial dynamics of interpersonal violence, structural characteristics, and 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 as reported by residents.

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

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2. Homicides that result from domestic disputes or spousal abuse may seem to be unrelated to the social processes related to collective efficacy. However, as Browning (2001) demonstrates, women in collectively efficacious neighborhoods are more likely to disclose incidents of abuse and assault to their neighbors, protecting themselves from being victimized by further violence. Collective efficacy is also related to lower homicide rates among intimate partners. Thus, the span of collective efficacy appears to extend beyond street-level or public encounters (Sampson et al., 1997:918) to the case of partner violence "inside the home."

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, 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.[3] 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%.

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.[4]

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3. 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."

4. Distinct from individual-level reliability (e.g., Cronbach's alpha), neighborhood reliability is defined as Σ [$\tau_{00}/(\tau_{00} + \sigma^2/n_j)$] / J, which measures the precision of the estimate, averaged across the set of J neighborhoods, as a function of (1) the sample

In addition to the cohesion and control scales that define collective effi-cacy, 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 a community newspaper, block group or tenant association, crime pre-vention program, alcohol/drug treatment program, mental health center, or family health service. *Voluntary associations* taps the "social capital" involvement of residents in (1) local religious organizations; (2) neighbor-hood 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 (each coded 0, 1-2, 3-5, 6-9, 10 or more) that respondents reported 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 volun-tary 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 disadvan-tage* represents economic disadvantage in racially segregated urban neigh-borhoods. 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 female-headed families with children, and percentage of residents who are black. These variables are highly interrelated and load on a single factor using

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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 collec-tive efficacy at the neighborhood level. For further discussion of tools for assessing ecological context, see Raudenbush and Sampson (1999).

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 to 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, no white neighborhoods in Chicago 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 may 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 an equal share of poor and affluent families live 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% 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 our 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 principle data source comes from reports of homicide incidents to the Chicago Police Department. These data consist of aggregate homicide counts that have been geocoded 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.[5] 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

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5. 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 (http://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 includes cases of non-negligent manslaughter but excludes deaths that result from injuries inflicted by the police or other law-enforcing agents. There is one difference between the homicide data from the two time periods. In the latter period (1996–1998), the homicide count for each neighborhood cluster is based on the number of "incidents" that occurred there, where each incident may contain one

person-based measure of homicide victimization in 1996 derived from vital statistics rather than from police records.[6] 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.[7] 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 may 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 1991–1993. 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

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or more victims. This contrasts with the 1991–1993 homicide data, in which the neighborhood count is based on the number of victims that were murdered in each neighborhood in a given year. The two sets of measures are very highly correlated, however, and multiple-victim incidents are rare.

6. 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 time 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 was the case with the police statistics, these homicide data include non-negligent manslaughter but exclude injuries inflicted by the police or other law-enforcing agents (National Center for Health Statistics, 2000).

7. 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. This assumption is 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 (which we use in the analysis as independent variables) is .86.

predictors. This procedure also gives us some purchase on controlling for prior sources of crime not captured in our measured variables.[8]

STATISTICAL MODELS

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 overdispersed 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 autocorrelated. More specifically, using a hierarchical generalized linear model approach (McCullagh and Nelder, 1989; Raudenbush et al., 2000), 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 overdispersed Poisson distribution.

The advantage of this approach is threefold. First, it sensibly incorporates the skewed nature of the homicide outcome, which has many values of zero, while 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

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8. 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 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 because the homicide outcome is measured at a later time than the predictors; crime cannot influence the past.

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 overdispersed 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_i^* 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.[9] Next, we imported these posterior modes into software dedicated to estimating regression models with spatial dependence (Space-Stat). 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 $\Sigma_i w_{ij} y_i$ is the weighted average of homicide in neighboring locations.[10] The weights matrix is expressed as first-order contiguity, which defines neighbors as those NCs that share a common

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9. 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 (cf. Raudenbush et al., 2000). 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.

10. 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

border (referred to as the rook criterion).[11] 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

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

where y is an $N \times 1$ vector of observations on the dependent variable; Wy is an $N \times 1$ vector composed of elements $\Sigma_i w_{ij} y_i$, the spatial lags for the dependent variable; ρ is the spatial autoregressive coefficient; X is an $N \times K$ matrix of exogenous explanatory variables with an associated $K \times 1$ vector of regression coefficients β; and ε is an $N \times 1$ vector of normally distributed random error terms, with means 0 and constant (homoscedastic) variances.[12]

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, whereas 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

to our theoretical approach that specifies spatial dependence as a substantive phenomenon rather than as a nuisance (see also Tolnay et al., 1996). Moreover, the spatial lag models generally outperformed the corresponding spatial error models in a variety of diagnostic tests.

11. 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 $w_{ij}/\Sigma_j\ w_{ij}$, 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.

12. 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).

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:

$$y = X\beta + \rho WX\beta + \rho^2 W^2 X\beta + ... + \rho^m W^m X\beta + \varepsilon + \rho W\varepsilon + \rho^2 W^2\varepsilon + ... + \rho^m W^m \varepsilon, \tag{2}$$

where $m \to \infty$. 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.[13] 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 may 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

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13. Because ρ is multiplied by the β coefficient for each X variable in Equation (2), and $0 \le \rho \le 1$, 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 $\rho = .50$, 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 β ($.50^2 = .25$), and so on for each successive order of contiguity.

past research, homicide events are not randomly distributed with respect to geography. In fact, supplementary tabulations reveal that 70% of all homicides in Chicago between 1996 and 1998 occurred in only 32% 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 process 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, whereas 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 fourfold 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 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. 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.[14] Second, the symbols on the map represent values of the spatial typology of EB homicide rates, constructed from the

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14. 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 $I_i = (z_i / m_2)\Sigma_j w_{ij} z_j$ with $m_2 = \Sigma_i z_i^2$, 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, 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 $\Sigma_j w_{ij} z_j$ 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 eightfold 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"

Figure 1 Spatial Typology

Spatial Typology of EB Homicide Rate
⊕ Low-Low
★ High-High
Spatial Typology of Collective Efficacy
Low-Low
Low-High
High-Low
High-High

3   0   3   6 Miles
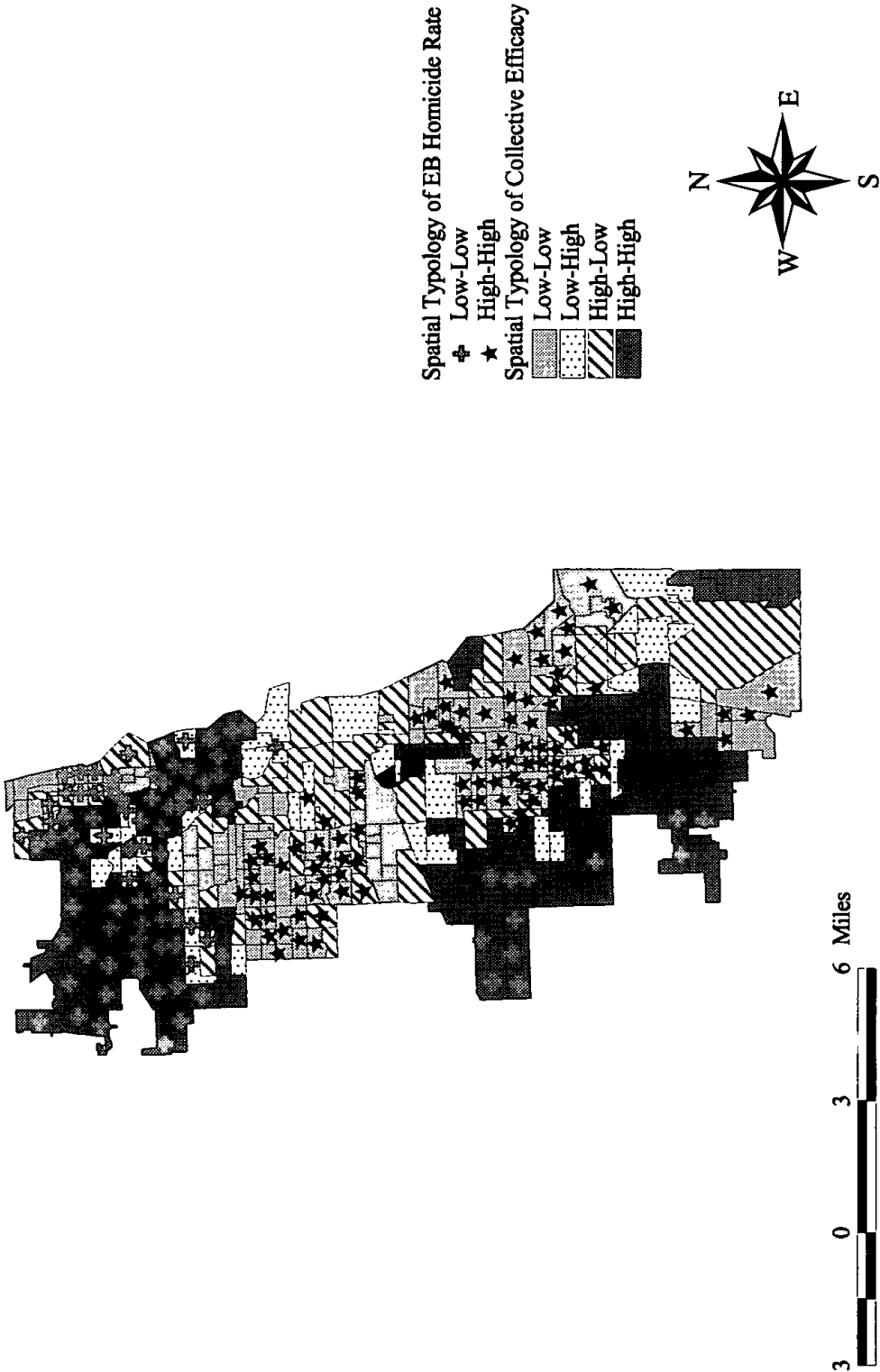
1996–1998 police data: Black stars indicate significant high-high values (i.e., homicide "hot spots"), and gray crosses indicate significant low-low values (i.e., homicide "cold spots").

We draw two general conclusions from Figure 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%) 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 the low levels of collective efficacy. Of the 103 homicide hot spots, 77 (or 75%) 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 in which the two typologies are at variance with one another. For example, 14 of the 93 homicide cold spots (15%) appear in neighborhoods with low levels of collective efficacy that are surrounded by high levels. Moreover, 15 of 103 homicide hot spots (15%) are in neighborhoods that have high levels of collective efficacy but are surrounded by neighborhoods with low levels. Neighborhoods where the level 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 2, which graphs the mean homicide rate for the four categories of the collective efficacy spatial typology.[15] Figure 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 level of collective efficacy. In other

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and "low-low" values of the local Moran statistic for homicide. Moreover, we have posted a color map on our website, http://phdcn.harvard.edu/res_pubs/maproom/index.html, which displays information regarding statistical significance for the clustering of collective efficacy using the local Moran statistic.

15. This graph does not take into account statistical significance of Moran's I, because very few neighborhoods 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.

Figure 2 Mean Homicide Rate by Level and Spatial Proximity to Collective Efficacy
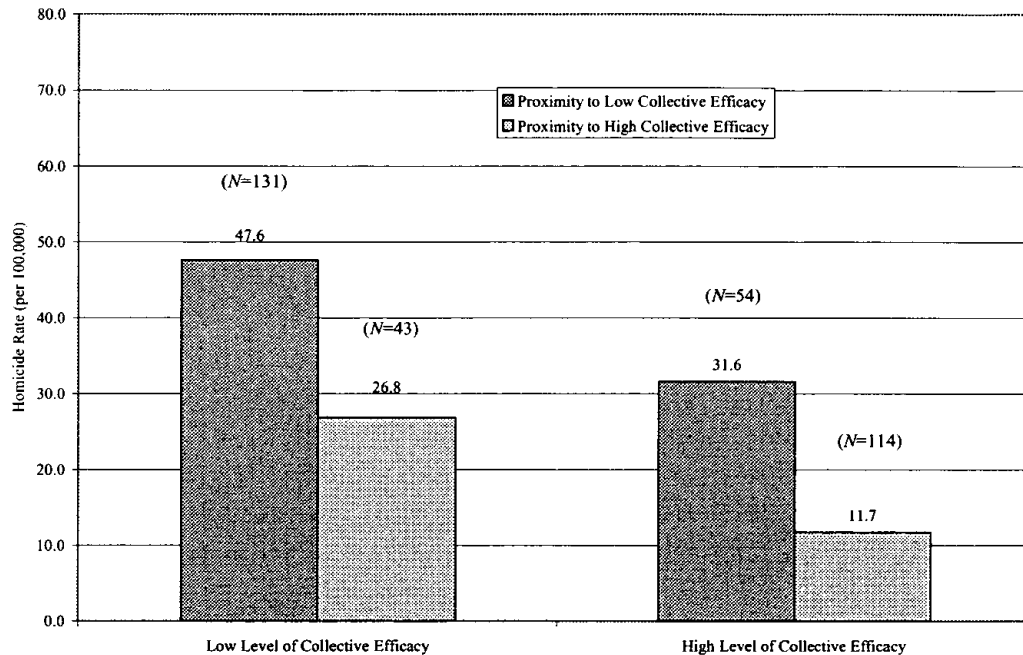
words, knowing the local level of social organization is not enough, a proposition we now test further in a multivariate spatial analysis of homicide rates with additional covariates.

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. The Appendix includes a correlation matrix for all of the independent variables included in subsequent regression models along with a table displaying their means and standard deviations. Table 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.[16] The results show that all of the coefficients in this model are significant, with the exception

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16. Before taking its natural log, we added a constant (1.5) to the disadvantage scale to eliminate negative values.

Table 1. Coefficients from the Regression of Incident-Based 1996–1998 Empirical Bayes Poisson Homicide Rate on Neighborhood Predictors: 1990–1998 Chicago Police Data; 1995 PHDCN Survey; and 1990 Census (Standard Errors in Parentheses)

Variables	OLS		Maximum Likelihood			
	(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[a]	0.01	−0.06	0.02	−0.12	−0.07	−0.16
	(0.33)	(0.33)	(0.30)	(0.30)	(0.32)	(0.31)
Population Density[b]	−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

[a]Adults per child multiplied by 100.
[b]Population density multiplied by 10,000.
*$p < .05$**; $p < .01$.

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.[17] 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

17. The negative association between population density and homicide may 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

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%), population density (by 20%), and collective efficacy (by 16.5%). 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 in 1995 and 1996–1998 homicide rates is really a reflection of the downward spiral of neighborhoods caused by prior violence.[18] The control for prior homicide reduces the magnitude of the collective efficacy coefficient (by 13%), but it still maintains significance. The control for prior homicide reduces the disadvantage coefficient more substantially (by 33%), 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 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

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). Some areas on the West Side of Chicago, for example, resemble virtual ghost towns yet continue to have high rates of violent crime. We examined this relationship more closely by mapping the concentrations of both density and homicide. The maps revealed that the association between high neighborhood density and low homicide rates appears to be strongest in affluent neighborhoods on the city's North Side, where there are many high-rise apartment buildings. To be sure, there are also neighborhoods with high density and high homicide rates—such as those with high-rise public housing—but it is more generally the case that the neighborhoods with the highest homicide rates (e.g., on the West and South Sides) have relatively low levels of population density. This finding dovetails with results from prior longitudinal research in Chicago on the association between neighborhood population loss—which tends to result in lower levels of population density—and higher homicide rates (Morenoff and Sampson, 1997). Our results also suggest that the density effect does not appear to operate through collective efficacy, because density is strongly negatively related to collective efficacy, as shown below in Table 4 .

   18. These prior homicide rates are also based on the overdispersed Poisson distribution, using the same methodology described above.

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.[19] The larger message appears to be that concentrated inequality in socioeconomic resources is directly related to homicide.

To assess robustness, Table 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 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 to 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,[20] 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 two 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 across all models in both Tables 1 and 2. These results obtain even after controlling for prior

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19. The effect of concentrated immigration becomes significant with the substitution of the ICE measure for the logged disadvantage scale. This change across model specifications is due in part to the fact that concentrated immigration is more highly correlated with the logged disadvantage scale (-.33) than it is with ICE (-.03), as shown in the Appendix.

20. Again, prior homicide is strongly correlated with the logged disadvantage index (.90), as shown in the Appendix. Consequently, as was the case in Table 1, we cannot easily disentangle the independent effects of prior homicide and disadvantage on homicide in 1996.

Table 2. Coefficients from the Regression of Victim-Based 1996 Empirical Bayes Poisson Homicide Rate on Neighborhood Predictors: 1990–1996 Vital Statistics Data; 1995 PHDCN Survey; and 1990 Census (Standard Errors in Parentheses)

Variables	OLS		Maximum Likelihood			
	(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[a]	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[b]	–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

[a]Adults per child multiplied by 100.
[b]Population density multiplied by 10,000.
*$p < .05$**; $p < .01$.

homicide rates. Strong spatial effects are also evident in both data sets, which again 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.

FURTHER UNDERSTANDING THE SPATIAL DYNAMICS OF HOMICIDE

To interpret the results of the spatial lag models in Tables 2 and 3, 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 3, we use the results from model 4 in Tables 1 and 2 to demonstrate how this "spatial multiplier" process works with respect to two key covariates: concentrated disadvantage (which is logged) and collective efficacy.[21] 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 show 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% increase in the homicide rate in the focal neighborhood according to the Police data and a 24% increase according to the Vital Statistics.[22] 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% increase in the homicide rate in the focal neighborhood according to the Police data and a 4% 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 all of the bars in this series for each data set. This shows that a simultaneous one standard 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% increase in homicide according to Police data and a 28% increase according to the Vital Statistics.

The right side of Figure 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

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21. 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.

22. 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 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 of disadvantage.

Figure 3 Percent Change in Homicide Rate per Standard Deviation Change in Concentrated Disadvantage and Collective Efficacy by Spatial Proximity to Focal Neighborhood
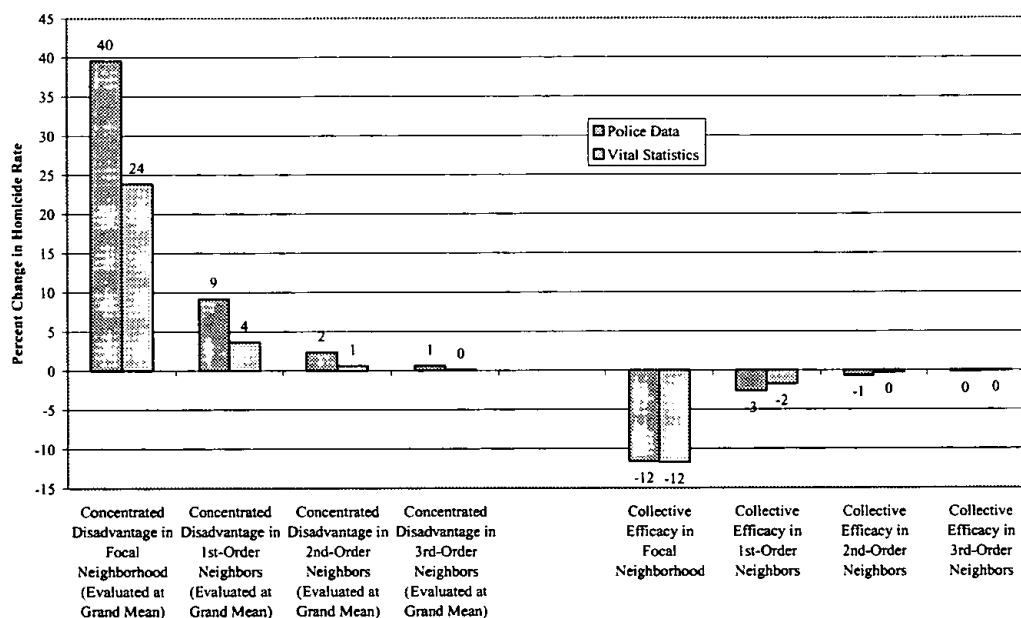
the level of collective efficacy in the focal neighborhood is associated with a 12% reduction in the homicide rate according to both the Police data and the Vital Statistics data. Cumulatively, a one standard deviation increase in collective efficacy in the focal neighborhood, and the first-, second-, and third-order neighbors, is associated with a 15% reduction in the homicide rate of the focal neighborhood according to the Police data, and a 14% drop according to the Vital Statistics.

Note that Figure 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 3 are only a fraction of the full spatial effect. What these results show, however, is that the cumulative effects associated with both disadvantage and collective efficacy are substantively 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.[23] 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 controlling for spatial dependence.[24] To define these regimes, we divide Chicago's neighborhoods into two categories based on their 1990 racial composition: (1) less than 75% non-Hispanic black (henceforth referred to as "non-black" neighborhoods) and (2) 75% 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% black, 2.5% white, and 2.8% Hispanic. There are 217 non-black neighborhoods, which on average are 54.3% white, 30.5% Hispanic, and 9.4% black.[25]

The results of the regime model are reported in Table 3. 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 proportional distribution of affluence and poverty within racial regimes. The first two columns display results using the incident-based homicide outcome—column 1 contains

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23. We did attempt to reestimate the models in Tables 1 and 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 (results available upon request), especially for spatial proximity and collective efficacy.

24. 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.

25. 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% white in 1990 and only 21 that were over 75% 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.

Table 3. Coefficients from the Regression of Empirical Bayes Poisson Homicide Rates on Neighborhood Predictors by Racial Regimes: 1990–1998 Chicago Police Data; 1990–1996 Vital Statistics Data; 1995 PHDCN Survey; and 1990 Census (Standard Errors in Parentheses)

Variables	Incident-Based		Victim-Based	
	<75% Black	>=75% Black	<75% Black	>=75% Black
	(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[a]	0.03	0.73	0.10	–1.52
	(0.34)	(2.54)	(0.28)	(2.09)
Population Density[b]	–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	

[a] Adults per child multiplied by 100.
[b] Population density multiplied by 10,000.
*$p < .05$; **$p < .01$.

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.[26] 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

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26. 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.

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.[27] 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 nonsignificant.[28] 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.

DISENTANGLING NEIGHBORHOOD SYSTEMIC PROCESSES

Although the regression results affirm that collective efficacy in achieving social control is an important factor for understanding variation in neighborhood homicide rates, they are less sanguine about the role of social ties. Both Tables 1 and 2 show that there is no independent association between social ties and neighborhood homicide rates after controlling for collective efficacy. These findings offer insight on the social disorganization tradition of recent neighborhood research, much of which focuses on the role of social ties. To bring these findings into sharper relief, and possible reconciliation, we constructed a social-process typology that classifies neighborhoods based on whether they fall above or below the median score on the indices of social ties and collective efficacy, yielding

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27. In this model, the Chow test for the structural stability of the regression model across regimes indicates that there are significant differences in the patterns of association across black and non-black neighborhoods. Coefficient-specific Chow tests indicate that the collective efficacy effect is the only one that significantly 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.

28. These findings are somewhat counterintuitive because they suggest that black neighborhoods with more organizational infrastructure have higher homicide rates. One interpretation is that the presence of organizations and voluntary associations in black neighborhoods could be in part a response to high levels of crime, or perhaps the greater salience of crime. However, these associations remain when controlling for prior levels of homicide. We believe that these findings should be further investigated in future research that includes better measures of neighborhood organizations (see below).

the following four categories: low ties—low efficacy; low ties—high efficacy; high ties—low efficacy; high ties—high efficacy.

We map this typology in Figure 4 and overlay on it symbols indicating the spatial clustering of low and high homicide rates (as was done in Figure 1). From the standpoint of the systemic perspective, we expect homicide rates to be lowest in neighborhoods that possess high levels of both social ties and collective efficacy. Indeed, 41 of the 93 homicide "cold" spots (44%) displayed on this map are located in areas that are high in both ties and efficacy (filled in dark gray). However, 31 of the cold spots (36%) are located in neighborhoods that are low in ties but high in collective efficacy (filled in diagonal stripes). Most of the neighborhoods where low homicide rates are clustered despite the absence of strong social ties are on the north side of the city. The traditional perspective on social disorganization predicts that homicide "hot" spots should be found predominantly in neighborhoods that are low in both ties and efficacy. Instead, the map shows that hot spots are divided almost evenly between neighborhoods that are low in both ties and efficacy (40 out of 103) and those that are high in ties and low in efficacy (38 out of 103). Dense networks do not appear to be necessary or sufficient in explaining homicide. These findings do not necessarily contradict the systemic perspective, however. Integrating the collective efficacy and systemic model, we would suggest that social ties create the capacity for informal social control, but it is the act of exercising control that is related to crime rather than the existence of social networks per se (Bursik, 1999).

To investigate this idea further, we examine the role of social ties as a predictor of collective efficacy by estimating the spatial regression models presented in Table 4. The results show that the social ties index is significantly positively associated with collective efficacy when it is introduced in models 2–5. Moreover, the institutional variables are also important correlates of collective efficacy in Table 4, even though they did not have independent associations with homicide in Tables 1 and 2. These results hold up after controlling for structural covariates, spatial autocorrelation, prior homicide rates, and after substituting the ICE index for the disadvantage index (compare columns 1–3 with 4–5).[29] Overall, these findings

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29. The spatial autocorrelation term for collective efficacy becomes nonsignificant after the social interactional and institutional process variables are added in models 2 and 3. One interpretation of this finding is that the spatial dependence term is significant in model 1 because it captures the effects of social ties and interactions that cut across neighborhood boundaries, along with similarities across neighborhoods on unobserved social and institutional process variables. When these processes are directly measured in model 2, they reduce the spatial dependence term to nonsignificance. However, spatial proximity remains significant for collective efficacy in the ICE models (columns 4 and 5), so this interpretation is contingent on the specification of inequality.

Figure 4 Spatial Typology

Spatial Typology of EB Homicide Rate
✦ Low-Low
★ High-High

Typology of Collective Efficacy and Social Ties
Low CE - Low Ties
Low CE - High Ties
High CE - Low Ties
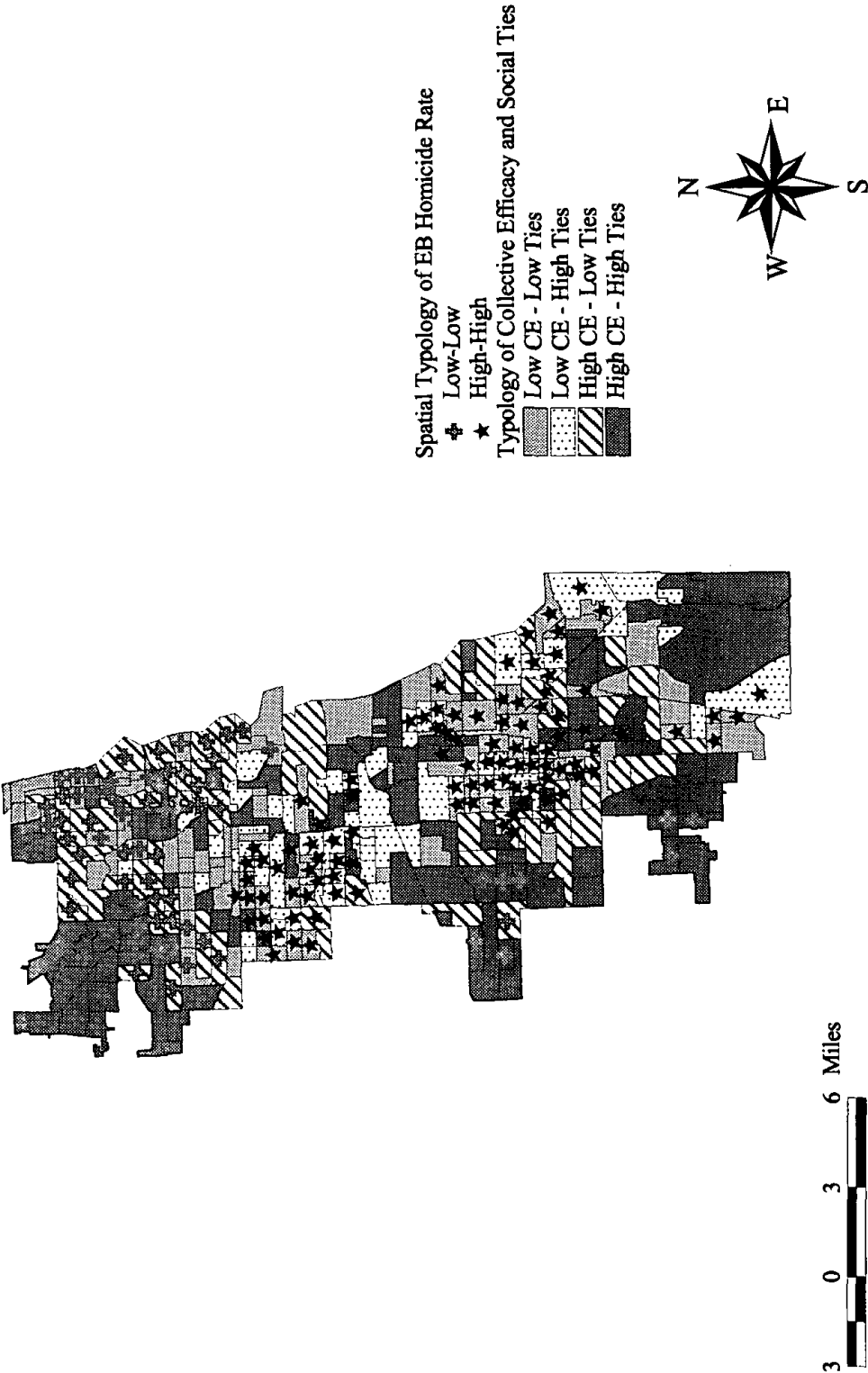High CE - High Ties

3   0   3   6 Miles

Table 4. Maximum Likelihood Coefficients from the Spatial-Lag Regression of Collective Efficacy (1995) on Neighborhood Predictors: 1995 PHDCN Survey and 1990 Census

Variables	(1)	(2)	(3)	(4)	(5)
LN Concentrated Disadvantage	−0.27**	−0.25**	−0.20**		
	(0.03)	(0.02)	(0.03)		
ICE Index				0.47**	0.34**
				(0.04)	(0.05)
Concentrated Immigration	−0.06**	−0.06**	−0.06**	−0.01	−0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Residential Stability	0.02**	0.01	0.01	−0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adults per Child[a]	−0.16	−0.11	−0.09	−0.12	−0.13
	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)
Population Density[b]	−0.11**	−0.08**	−0.09**	−0.09**	−0.09**
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Voluntary Associations		0.09**	0.09**	0.07**	0.07**
		(0.03)	(0.03)	(0.03)	(0.03)
Organizations		0.06**	0.06**	0.05**	0.05**
		(0.02)	(0.02)	(0.02)	(0.02)
Kin/friendship ties		0.28**	0.28**	0.33**	0.33**
		(0.04)	(0.04)	(0.04)	(0.04)
Spatial Proximity	0.15**	0.09	0.08	0.21**	0.13**
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
Prior Homicide Rate (1991–1993)			−0.04*		−0.06**
			(0.02)		(0.01)
Constant	3.46**	3.06**	3.23**	2.34**	2.85**
	(0.25)	(0.27)	(0.28)	(0.26)	(0.28)
R^2	0.63	0.72	0.72	0.72	0.73

[a]Adults per child multiplied by 100.
[b]Population density multiplied by 10,000.
$*p < .05$; $**p < .01$.

clarify a point that has been left ambiguous in much previous research on the systemic model: Social ties and institutional processes appear to operate indirectly on homicide rates by fostering collective efficacy. Although using somewhat different measures and terminology, Bellair (2000) also reaches a similar conclusion, suggesting a general process.

CONCLUSION AND IMPLICATIONS

Our results suggest that spatial embeddedness, internal structural characteristics, and social organizational processes are each important for

Further understanding of the spatial dynamics of collective efficacy is beyond the scope of this paper, but it is an issue that we believe bears emphasis.

understanding neighborhood-level variations in rates of violence. In particular, 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. The final and major test of these four predictors, where two independently measured indicators of homicide (police records and coroner's report) are analyzed in conjunction with a three-year average rate of prior homicide controlled (model 4 in Tables 1 and 2), bears out this conclusion. Interestingly, extreme inequality in resources—whether measured by "underclass" disadvantage or the concentration of income at both the upper and lower tails of the distribution (ICE)—exhibits unmediated effects on violence despite the control for prior homicide. The estimated direct effects of inequality and collective efficacy suggests that structure and process at the neighborhood level may work more independently than prior neighborhood theory has allowed (e.g., Sampson et al., 1997).

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).

Against the backdrop of these patterns, we believe four points should be emphasized, each of which carries implications for future research. First, a great deal remains to be learned about the relationship between social ties and crime. Future research may better understand the indirect relationship between social ties and crime by investigating the conditions under which strong social ties foster trust and social control.[30] In his review of community crime prevention interventions, Hope (1995:66–69) suggests that the communitarian approach, which relies on dense networks among residents to build communal solidarity, is not the only strategy for achieving social control. An alternative approach that is more common in the suburbs, which Hope calls "moral minimalism," achieves social control through weak ties among neighbors by emphasizing privacy over communalism and denying strangers access to the community and its resources. The achievement of social control in neighborhoods that lack a social

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30. We thank an anonymous reviewer for raising this point.

infrastructure of strong ties among neighbors presents a challenge to systemic theory that should be taken up in future research, both quantitative and ethnographic.

The second 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 the 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 city-wide 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 toward 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 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. In the meantime, spatial proximity cannot be ignored in theories of violence.

A third theme that emerges is the potential importance of further refining our understanding of "structural covariates" that have traditionally been linked to the poverty paradigm. Concentrated poverty is without any doubt a risk factor for the concentration of homicide. But at the other end of the distribution, the 1980s and 1990s have seen the quiet but increasing separation of educated and affluent residents from the middle class. This "upper" inequality or stratification of place has resulted in an increasing concentration of affluence (Massey, 1996, 2001), which in turn has yielded important consequences for the distribution of homicide. Our analysis introduced a new measure tapping such inequality of affluence relative to poverty, with results suggesting that it does matter for the explanation of violence. We controlled for organizations, voluntary associations, social control, and local ties, none of which accounted for the strong and consistent effect of the index of concentrated extremes. It may well be that the protective factor of relative affluence is linked to socialization or guardianship processes that are untapped in current data. Also, perhaps because of the investment potential in affluent areas, homicide does not lead to the

same cycle of decline that seems to be obtained in disadvantaged neighborhoods. We hope that future investigators probe the phenomenon of concentrated affluence in more depth, especially its interaction with racial segregation.

Fourth, one of our goals was to integrate the institutional and informal aspects of social process, following recent developments in systemic social disorganization, social capital, and collective efficacy theory. Somewhat to our surprise, however, the set of institutional processes was not that strong in predicting homicide. Organizations and voluntary associations turned out to be relatively unimportant, suggesting that perhaps criminological theory has overstated the benefits to be derived from local forms of institutional organization. Another finding is that cohesion coupled with social control seems to be the more proximate correlate of lower homicide relative to dense social ties. Further specifying the systemic model of disorganization (Bursik, 1999; Bursik and Grasmick, 1993a), the theory of collective efficacy suggests that social ties are important for crime control insofar as they lead to the activation of social control and mutual engagement among residents (Sampson et al., 1997). Our analysis, along with other recent research (Bellair, 2000), supports this mediated view.

In conclusion, we should emphasize that perhaps the biggest limitation of the present analysis concerns our measures of organizations and institutions. Drawn from survey (self) reports, we are limited to residents' perceptions of the organizations in the areas. Residents may be mistaken, of course, suggesting that independent data are needed on the number and type of organizations, along with their geographical jurisdictions (cf. Peterson et al., 2000). But probably more germane, it is not clear that the number of organizations is the key factor in social organization. Applying the logic we used for ties and efficacy, it may be that the density of organizations is important only insofar as it generates effective action on the part of the organizations that do exist. One can imagine a community with a large number of dispirited and isolated institutions, perhaps even in conflict with one another. This is hardly a recipe for social organization, suggesting that dense institutional ties are not sufficient. We therefore hope that future research is able to make advances in two ways—better objective measures of institutional density (e.g., Peterson et al., 2000) and direct measures of the organizational networks and processes of decision making that are at the heart of making institutions collectively efficacious.

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Appendix. Descriptive Statistics for Independent Variables

I. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1. LN Concentrated Disadvantage	1											
2. ICE Index	-0.86*	1										
3. Concentrated Immigration	-0.33*	-0.03	1									
4. Residential Stability	-0.20*	0.36*	-0.34*	1								
5. Adults per Child	-0.46*	0.52*	-0.07	-0.17*	1							
6. Population Density	0.09	-0.20*	0.34*	-0.59*	0.19*	1						
7. Collective Efficacy	-0.64*	0.70*	-0.12*	0.50*	0.20*	-0.43*	1					
8. Voluntary Associations	-0.45*	0.53*	-0.09	0.50*	0.07	-0.33*	0.61*	1				
9. Organizations	-0.06	0.14	-0.23*	-0.07	0.17*	0.00	0.25*	0.14*	1			
10. Kin/friendship ties	-0.05	-0.01	0.05	0.33*	-0.20*	-0.30*	0.39*	0.33*	0.20*	1		
11. Prior Homicide Rate (1991–93) Incident	0.90*	-0.75*	-0.32*	-0.17*	-0.37*	0.05	-0.60*	-0.39*	-0.07	-0.05	1	
12. Prior Homicide Rate (1991–93) Victim	0.90*	-0.71*	-0.38*	-0.08	-0.44*	-0.00	-0.56*	-0.35*	-0.08	-0.07	0.88*	1

*p < .05.

II. Means and Standard Deviations

	Mean	S.D.
LN Concentrated Disadvantage	0.22	(0.62)
ICE Index	0.02	(0.30)
Concentrated Immigration	0.00	(0.92)
Residential Stability	0.00	(1.79)
Adults per Child	11.75	(11.48)
Population Density	7028.44	(4100.83)
Collective Efficacy	3.89	(0.26)
Voluntary Associations	-3.24	(0.39)
Organizations	-0.27	(0.46)
Kin/friendship ties	3.14	(0.21)
Prior Homicide Rate (1991–93) Incident-based	3.14	(0.96)
Prior Homicide Rate (1991–93) Victim-based	3.27	(0.83)