the north central Pacific, the estimated residence time of ^{210}Pb at mid-depths is 200 to 400 years, decreasing to 80 to 100 years toward the Pacific margins [Y. Nozaki, K. K. Turekian, K. von Damm, *Earth Planet. Sci. Lett.* **49**, 393 (1980); H. Craig, S. Krishnaswami, B. L. K. Somayajulu, *ibid.* **17**, 295 (1973)]. Given the observed differences in the Pb isotopic composition of Mn crusts and nodules from different ocean basins (*18*), the residence time must be less than the ~10^3-year mixing time of the oceans [W. S. Broecker and T.-H. Peng, *Tracers in the Sea* (Eldigio Press, Columbia Univ., Palisades, NY, 1982)] but in the central Pacific may be sufficiently long to mix and integrate differing inputs from incoming water masses and the basin margins. Studies of ^{210}Pb indicate residence times in the upper ocean of ~10 years [R. M. Sherrell, E. A. Boyle, B. Hamelin, *J. Geophys. Res.* **97**, 11257 (1992)], which are much shorter than the residence time in deep water. The most important mechanism for Pb transport to the deep sea is scavenging by particulates, particularly organic particulates [A. R. Flegal and C. C. Patterson, *Earth Planet. Sci. Lett.* **64**, 19 (1983)], which may have varied considerably in the geologic past because of changes in biologic productivity.
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Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy

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It is hypothesized that collective efficacy, defined as social cohesion among neighbors combined with their willingness to intervene on behalf of the common good, is linked to reduced violence. This hypothesis was tested on a 1995 survey of 8782 residents of 343 neighborhoods in Chicago, Illinois. Multilevel analyses showed that a measure of collective efficacy yields a high between-neighborhood reliability and is negatively associated with variations in violence, when individual-level characteristics, measurement error, and prior violence are controlled. Associations of concentrated disadvantage and residential instability with violence are largely mediated by collective efficacy.

For most of this century, social scientists have observed marked variations in rates of criminal violence across neighborhoods of U.S. cities. Violence has been associated with the low socioeconomic status (SES) and residential instability of neighborhoods. Although the geographical concentration of violence and its connection with neighborhood composition are well established, the question remains: why? What is it, for example, about the concentration of poverty that accounts for its association with rates of violence? What are the social processes that might explain or mediate this relation (*1–3*)? In this article, we report results from a study designed to address these questions about crime and communities.

Our basic premise is that social and organizational characteristics of neighborhoods explain variations in crime rates that are not solely attributable to the aggregated demographic characteristics of individuals. We propose that the differential ability of neighborhoods to realize the common values of residents and maintain effective social controls is a major source of neighborhood variation in violence (*4, 5*). Although social control is often a response to deviant behavior, it should not be equated with formal regulation or forced conformity by institutions such as the police and courts. Rather, social control refers generally to the capacity of a group to regulate its members according to desired principles—to realize collective, as opposed to forced, goals (*6*). One central goal is the desire of community residents to live in safe and orderly environments that are free of predatory crime, especially interpersonal violence.

In contrast to formally or externally induced actions (for example, a police crackdown), we focus on the effectiveness of informal mechanisms by which residents themselves achieve public order. Examples of informal social control include the monitoring of spontaneous play groups among children, a willingness to intervene to prevent acts such as truancy and street-corner "hanging" by teenage peer groups, and the confrontation of persons who are exploiting or disturbing public space (*5, 7*). Even among adults, violence regularly arises in public disputes, in the context of illegal markets (for example, prostitution and drugs), and in the company of peers (*8*). The capacity of residents to control group-level processes and visible signs of social disorder is thus a key mechanism influencing opportunities for interpersonal crime in a neighborhood.

Informal social control also generalizes to broader issues of import to the well-being of neighborhoods. In particular, the differential ability of communities to extract resources and respond to cuts in public services (such as police patrols, fire stations, garbage collection, and housing code enforcement) looms large when we consider

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the known link between public signs of disorder (such as vacant housing, burned-out buildings, vandalism, and litter) and more serious crime (*9*).

Thus conceived, neighborhoods differentially activate informal social control. It is for this reason that we see an analogy between individual efficacy and neighborhood efficacy: both are activated processes that seek to achieve an intended effect. At the neighborhood level, however, the willingness of local residents to intervene for the common good depends in large part on conditions of mutual trust and solidarity among neighbors (*10*). Indeed, one is unlikely to intervene in a neighborhood context in which the rules are unclear and people mistrust or fear one another. It follows that socially cohesive neighborhoods will prove the most fertile contexts for the realization of informal social control. In sum, it is the linkage of mutual trust and the willingness to intervene for the common good that defines the neighborhood context of collective efficacy. Just as individuals vary in their capacity for efficacious action, so too do neighborhoods vary in their capacity to achieve common goals. And just as individual self-efficacy is situated rather than global (one has self-efficacy relative to a particular task or type of task) (*11*), in this paper we view neighborhood efficacy as existing relative to the tasks of supervising children and maintaining public order. It follows that the collective efficacy of residents is a critical means by which urban neighborhoods inhibit the occurrence of personal violence, without regard to the demographic composition of the population.

What Influences Collective Efficacy?

As with individual efficacy, collective efficacy does not exist in a vacuum. It is embedded in structural contexts and a wider political economy that stratifies places of residence by key social characteristics (*12*). Consider the destabilizing potential of rapid population change on neighborhood social organization. A high rate of residential mobility, especially in areas of decreasing population, fosters institutional disruption and weakened social controls over collective life. A major reason is that the formation of social ties takes time. Financial investment also provides homeowners with a vested interest in supporting the commonweal of neighborhood life. We thus hypothesize that residential tenure and homeownership promote collective efforts to maintain social control (*13*).

Consider next patterns of resource distribution and racial segregation in the United States. Recent decades have witnessed an increasing geographical concentration of lower income residents, especially minority groups and female-headed families. This neighborhood concentration stems in part from macroeconomic changes related to the deindustrialization of central cities, along with the out-migration of middle-class residents (*14*). In addition, the greater the race and class segregation in a metropolitan area, the smaller the number of neighborhoods absorbing economic shocks and the more severe the resulting concentration of poverty will be (*15*). Economic stratification by race and place thus fuels the neighborhood concentration of cumulative forms of disadvantage, intensifying the social isolation of lower income, minority, and single-parent residents from key resources supporting collective social control (*1, 16*).

Perhaps more salient is the influence of racial and economic exclusion on perceived powerlessness. Social science research has demonstrated, at the individual level, the direct role of SES in promoting a sense of control, efficacy, and even biological health itself (*17*). An analogous process may work at the community level. The alienation, exploitation, and dependency wrought by resource deprivation act as a centrifugal force that stymies collective efficacy. Even if personal ties are strong in areas of concentrated disadvantage, they may be weakly tethered to collective actions.

We therefore test the hypothesis that concentrated disadvantage decreases and residential stability increases collective efficacy. In turn, we assess whether collective efficacy explains the association of neighborhood disadvantage and residential instability with rates of interpersonal violence. It is our hypothesis that collective efficacy mediates a substantial portion of the effects of neighborhood stratification.

Research Design

This article examines data from the Project on Human Development in Chicago Neighborhoods (PHDCN). Applying a spatial definition of neighborhood—a collection of people and institutions occupying a subsection of a larger community—we combined 847 census tracts in the city of Chicago to create 343 "neighborhood clusters" (NCs). The overriding consideration in formation of NCs was that they should be as ecologically meaningful as possible, composed of geographically contiguous census tracts, and internally homogeneous on key census indicators. We settled on an ecological unit of about 8000 people, which is smaller than the 77 established community areas in Chicago (the average size is almost 40,000 people) but large enough to approximate local neighborhoods. Geographic boundaries (for example, railroad tracks, parks, and freeways) and knowledge of Chicago's neighborhoods guided this process (*18*).

The extensive racial, ethnic, and social-class diversity of Chicago's population was a major criterion in its selection as a research site. At present, whites, blacks, and Latinos each represent about a third of the city's population. Table 1 classifies the 343 NCs according to race or ethnicity and a trichotomized measure of SES from the 1990 census (*19*). Although there are no low-SES white neighborhoods and no high-SES Latino neighborhoods, there are black neighborhoods in all three cells of SES, and many heterogeneous neighborhoods vary in SES. Table 1 at once thus confirms the racial and ethnic segregation and yet rejects the common stereotype that minority neighborhoods in the United States are homogeneous.

To gain a complete picture of the city's neighborhoods, 8782 Chicago residents representing all 343 NCs were interviewed in their homes as part of the community survey (CS). The CS was designed to yield a representative sample of households within each NC, with sample sizes large enough to create reliable NC measures (*20*). Henceforth, we refer to NCs as "neighborhoods," keeping in mind that other operational definitions might have been used.

Measures

"Informal social control" was represented by a five-item Likert-type scale. Residents were asked about the likelihood ("Would you say it is very likely, likely, neither likely nor unlikely, unlikely, or very unlikely?") that their neighbors could be counted on to intervene in various ways if (i) children were skipping school and hanging out on a street corner, (ii) children were spray-painting graffiti on a local building, (iii) children were showing disrespect to an adult, (iv) a

Table 1. Racial and ethnic composition by SES strata: Distribution of 343 Chicago NCs in the PHDCN design.

Race or ethnicity	SES Low	SES Medium	SES High
≥75% black	77	37	11
≥75% white	0	5	69
≥75% Latino	12	9	0
≥20% Latino and ≥20% white	6	40	12
≥20% Latino and ≥20% black	9	4	0
≥20% black and ≥20% white	2	4	11
NCs not classified above	8	15	12
Total	114	114	115

fight broke out in front of their house, and (v) the fire station closest to their home was threatened with budget cuts. "Social cohesion and trust" were also represented by five conceptually related items. Respondents were asked how strongly they agreed (on a five-point scale) 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," and "people in this neighborhood do not share the same values" (the last two statements were reverse coded).

Responses to the five-point Likert scales were aggregated to the neighborhood level as initial measures. Social cohesion and informal social control were closely associated across neighborhoods ($r = 0.80$, $P < 0.001$), which suggests that the two measures were tapping aspects of the same latent construct. Because we also expected that the willingness and intention to intervene on behalf of the neighborhood would be enhanced under conditions of mutual trust and cohesion, we combined the two scales into a summary measure labeled collective efficacy (*21*).

The measurement of violence was achieved in three ways. First, respondents were asked how often each of the following had occurred in the neighborhood during the past 6 months: (i) a fight in which a weapon was used, (ii) a violent argument between neighbors, (iii) a gang fight, (iv) a sexual assault or rape, and (v) a robbery or mugging. The scale construction for perceived neighborhood violence mirrored that for social control and cohesion. Second, to assess personal victimization, each respondent was asked "While you have lived in this neighborhood, has anyone ever used violence, such as in a mugging, fight, or sexual assault, against you or any member of your household anywhere in your neighborhood?" (*22*). Third, we tested both survey measures against independently recorded incidents of homicide aggregated to the NC level (*23*). Homicide is one of the most reliably measured crimes by the police and does not suffer the reporting limitations associated with other violent crimes, such as assault and rape.

Ten variables were constructed from the 1990 decennial census of the population to reflect neighborhood differences in poverty, race and ethnicity, immigration, the labor market, age composition, family structure, homeownership, and residential stability (see Table 2). The census was independent of the PHDCN CS; moreover, the census data were collected 5 years earlier, which permitted temporal sequencing. To assess whether a smaller number of linear combinations of census characteristics describe the structure of the 343 Chicago neighborhoods, we conducted a factor analysis (*24*).

Consistent with theories and research on U.S. cities, the poverty-related variables given in Table 2 are highly associated and load on the same factor. With an eigenvalue greater than 5, the first factor is dominated by high loadings (>0.85) for poverty, receipt of public assistance, unemployment, female headed-families, and density of children, followed by, to a lesser extent, percentage of black residents. Hence, the predominant interpretation revolves around concentrated disadvantage—African Americans, children, and single-parent families are differentially found in neighborhoods with high concentrations of poverty (*25*). To represent this dimension parsimoniously, we calculated a factor regression score that weighted each variable by its factor loading.

The second dimension captures areas of the city undergoing immigration, especially from Mexico. The two variables that define this dimension are the percentage of Latinos (approximately 70% of Latinos in Chicago are of Mexican descent) and the percentage of foreign-born persons. Similar to the procedures for concentrated disadvantage, a weighted factor score was created to reflect immigrant concentration. Because it describes neighborhoods of ethnic and linguistic heterogeneity, there is reason to believe that immigrant concentration may impede the capacity of residents to realize common values and to achieve informal social controls, which in turn explains an increased risk of violence (*1–5, 7*).

The third factor score is dominated by two variables with high (>0.75) loadings: the percentage of persons living in the same house as 5 years earlier and the percentage of owner-occupied homes. The clear emergence of a residential stability factor is consistent with much past research (*13*).

Table 2. Oblique rotated factor pattern (Loadings ≥ 0.60) in 343 Chicago neighborhoods. (Data are from the 1990 census.)

Variable	Factor loading
Concentrated disadvantage	
Below poverty line	0.93
On public assistance	0.94
Female-headed families	0.93
Unemployed	0.86
Less than age 18	0.94
Black	0.60
Immigrant concentration	
Latino	0.88
Foreign-born	0.70
Residential stability	
Same house as in 1985	0.77
Owner-occupied house	0.86

Analytic Models

The internal consistency of a person measure will depend on the intercorrelation among items and the number of items in a scale. The internal consistency of a neighborhood measure will depend in part on these factors, but it will hinge more on the degree of intersubjective agreement among informants in their ratings of the neighborhood in which they share membership and on the sample size of informants per neighborhood (*26*). To study reliability, we therefore formulated a hierarchical statistical model representing item variation within persons, person variation within neighborhoods, and variation between neighborhoods. Complicating the analysis is the problem of missing data: inevitably, some persons will fail to respond to some questions in an interview. We present our hierarchical model as a series of nested models, one for each level in the hierarchy (*27*).

Level 1 model. Within each person, Y_{ijk}, the ith response of person j in neighborhood k, depends on the person's latent perception of collective efficacy plus error:

$$Y_{ijk} = \pi_{jk} + \sum_{p=1}^{9} \alpha_p D_{pijk} + e_{ijk} \qquad (1)$$

Here D_{pijk} is an indicator variable taking on a value of unity if response i is to item p in the 10-item scale intended to measure collective efficacy and zero if response i is to some other item. Thus, α_p represents the "difficulty" of item p, and π_{jk} is the "true score" for person jk and is adjusted for the difficulty level of the items to which that person responded (*28*). The errors of measurement, e_{ijk}, are assumed to be independent and homoscedastic (that is, to have equal standard deviations).

Level 2 model. Across informants within neighborhoods, the latent true scores vary randomly around the neighborhood mean:

$$\pi_{jk} = \eta_k + r_{jk}, \quad r_{jk} \sim N(0,\tau_\pi) \qquad (2)$$

Here η_k is the neighborhood mean collective efficacy, and random effects r_{jk} associated with each person are independently, normally distributed with variance τ_π, that is, the "within-neighborhood variance."

Level 3 model. Across neighborhoods, each neighborhood's mean collective efficacy η_k varies randomly about a grand mean:

$$\eta_k = \gamma + u_k, \quad u_k \sim N(0,\tau_\eta) \qquad (3)$$

where γ is the grand mean collective efficacy, u_k is a normally distributed random effect associated with neighborhood k, and τ_η is the between-neighborhood variance. According to this setup, the object of measurement is η_k. The degree of intersubjective agreement among raters is the intraneighborhood correlation, $\rho = \tau_\eta/(\tau_\eta + \tau_\pi)$. The reliability of measurement of η_k depends primarily on ρ and on the sample size per neighborhood. The entire three-level model is estimated simultaneously via maximum likelihood (*26*).

The results showed that 21% of the variation in perceptions of collective efficacy lies between the 343 neighborhoods (*29*). The reliability with which neighborhoods can be distinguished on collective efficacy ranges between 0.80 for neighborhoods with a sample size of 20 raters to 0.91 for neighborhoods with a sample size of 50 raters.

Controlling response biases. Suppose, however, that informant responses to the collective efficacy questions vary systematically within neighborhoods as a function of demographic background (such as age, gender, SES, and ethnicity), as well as homeownership, marital status, and so on. Then variation across neighborhoods in the composition of the sample of respondents along these lines could masquerade as variation in collective efficacy. To control for such possible biases, we expanded the level 2 model (Eq. 2) by incorporating 11 characteristics of respondents as covariates. Equation 2 becomes

$$\pi_{jk} = \eta_k + \sum_{q=1}^{11} \delta_q X_{qjk} + r_{jk}, \quad r_{jk} \sim N(0,\tau_\pi) \tag{4}$$

where X_{qjk} is the value of covariate q associated with respondent j in neighborhood k and δ_q is the partial effect of that covariate on the expected response of that informant on the collective efficacy items. Thus, η_k is now the level of efficacy for neighborhood k after adjustment for the composition of the informant sample with respect to 11 characteristics: gender (1 = female, 0 = male), marital status (composed of separate indicators for married, separated or divorced, and single), homeownership, ethnicity and race (composed of indicators for Latinos and blacks), mobility (number of moves in past 5 years), years in neighborhood, age, and a composite measure of SES (the first principal component of education, income, and occupational prestige).

Association Between Neighborhood Social Composition and Collective Efficacy

The theory described above led us to expect that neighborhood concentrated disadvantage (con. dis.) and immigrant concentration (imm. con.) would be negatively linked to neighborhood collective efficacy and residential stability would be positively related to collective efficacy, net of the contributions of the 11 covariates defined in the previous paragraph. To test this hypothesis, we expanded the level 3 model (Eq. 3) to

$$\begin{aligned}\eta_k &= \gamma_0 + \gamma_1(\text{con. dis.})_k + \gamma_2(\text{stability})_k \\ &\quad + \gamma_3(\text{imm. con.})_k \\ &\quad + u_k, \quad u_k \sim N(0,\tau_\eta)\end{aligned} \tag{5}$$

where γ_0 is the model intercept and γ_1, γ_2, and γ_3 are partial regression coefficients.

We found some effects of personal background (Table 3): High SES, homeownership, and age were associated with elevated levels of collective efficacy, whereas high mobility was negatively associated with collective efficacy. Gender, ethnicity, and years in neighborhood were not associated with collective efficacy.

At the neighborhood level, when these personal background effects were controlled, concentrated disadvantage and immigrant concentration were significantly negatively associated with collective efficacy, whereas residential stability was significantly positively associated with collective efficacy (for metric coefficients and *t* ratios, see Table 3). The standardized regression coefficients were −0.58 for concentrated disadvantage, −0.13 for immigrant concentration, and 0.25 for residential stability, explaining over 70% of the variability across the 343 NCs.

Collective Efficacy as a Mediator of Social Composition

Past research has consistently reported links between neighborhood social composition and crime. We assessed the relation of social composition to neighborhood levels of violence, violent victimization, and homicide rates, and asked whether collective efficacy partially mediated these relations.

Perceived violence. Using a model that paralleled that for collective efficacy (Eqs. 1, 4, and 5), we found that reports of neighborhood violence depended to some degree on personal background. Higher levels of violence were reported by those who were separated or divorced (as compared with those who were single or married), by whites and blacks (as opposed to Latinos), by younger respondents, and by those with longer tenure in their current neighborhood. Gender, homeownership, mobility, and SES were not significantly associated with responses within neighborhoods. When these personal background characteristics were controlled, the concentrations of disadvantage (t = 13.30) and immigrants (t = 2.44) were positively associated with the level of violence (see Table 4, model 1). The corresponding standardized regression coefficients are 0.75 and 0.11. Also, as hypothesized, residential stability was negatively associated with the level of violence (t = −6.95), corresponding to a standardized regression coefficient of −0.28. The model accounted for 70.5% of the variation in violence between neighborhoods.

Next, collective efficacy was added as a predictor in the level 3 model (Table 4,

Table 3. Correlates of collective efficacy.

Variable	Coefficient	SE	t ratio
Intercept	3.523	0.013	263.20
Person-level predictors			
Female	−0.012	0.015	−0.76
Married	−0.005	0.021	−0.25
Separated or divorced	−0.045	0.026	−1.72
Single	−0.026	0.024	−1.05
Homeowner	0.122	0.020	6.04
Latino	0.042	0.028	1.52
Black	−0.029	0.030	−0.98
Mobility	−0.025	0.007	−3.71
Age	2.09×10^{-3}	0.60×10^{-3}	3.47
Years in neighborhood	0.64×10^{-3}	0.82×10^{-3}	0.78
SES	3.53×10^{-2}	0.76×10^{-2}	4.64
Neighborhood-level predictors			
Concentrated disadvantage	−0.172	0.016	−10.74
Immigrant concentration	−0.037	0.014	−2.66
Residential stability	0.074	0.130	5.61
Variance components			
Within neighborhoods	0.320		
Between neighborhoods	0.026		
Percent of variance explained			
Within neighborhoods	3.2		
Between neighborhoods	70.3		

model 2). The analysis built in a correction for errors of measurement in this predictor (*30*). We found collective efficacy to be negatively related to violence ($t = -5.95$), net of all other effects, and to correspond to a standardized coefficient of −0.45. Hence, after social composition was controlled, collective efficacy was strongly negatively associated with violence. Moreover, the coefficients for social composition were substantially smaller than they had been without a control for collective efficacy. The coefficient for concentrated disadvantage, although still statistically significant, was 0.171 (as compared with 0.277). The difference between these coefficients (0.277 − 0.171 = 0.106) was significant ($t = 5.30$). Similarly, the coefficients for immigrant concentration and for residential stability were also significantly reduced: The coefficient for immigrant concentration, originally 0.041, was now 0.018, a difference of 0.023 ($t = 2.42$); the coefficient for residential stability, which had been −0.102, was now −0.056, a difference of −0.046 ($t = -4.18$). The immigrant concentration coefficient was no longer statistically different from zero. As hypothesized, then, collective efficacy appeared to partially mediate widely cited relations between neighborhood social composition and violence. The model accounted for more than 75% of the variation between neighborhoods in levels of violence.

Violent victimization. Violent victimization was assessed by a single binary item ($Y_{jk} = 1$ if victimized by violence in the neighborhood and $Y_{jk} = 0$ if not). The latent outcome was the logarithmic odds of victimization π_{jk}. The structural model for predicting π_{jk} had the same form as before (Eqs. 4 and 5) (*31*). Social composition, as hypothesized, predicted criminal victimization, with positive coefficients for concentrated disadvantage and immigrant concentration and a negative coefficient for residential stability (Table 4, model 1). The relative odds of victimization associated with a 2-SD elevation in the predictor were 1.67, 1.33, and 0.750, respectively. These estimates controlled for background characteristics associated with the risk of victimization. When added to the model, collective efficacy was negatively associated with victimization (Table 4, model 2). A 2-SD elevation in collective efficacy was associated with a relative odds ratio of about 0.70, which indicated a reduction of 30% in the odds of victimization. Moreover, after collective efficacy was controlled, the coefficients associated with concentrated disadvantage and residential stability diminished to nonsignificance, and the coefficient for immigrant concentration was also reduced.

Homicide. To assess the sensitivity of the findings when the measure of crime was completely independent of the survey, we examined 1995 homicide counts (Y_k is the number of homicides in neighborhood k in 1995). A natural model for the expected number of homicides in neighborhood k is $E(Y_k) = N_k\lambda_k$, where λ_k is the homicide rate per 100,000 people in neighborhood k and N_k is the population size of neighborhood k as given by the 1990 census (in hundreds of thousands). Defining $\eta_k = \log(\lambda_k)$, we then formulated a regression model for η_k of the type in Eq. 5. This is effectively a Poisson regression model with a logarithmic link with extra-Poisson variation represented by between-neighborhood random effects (*32*).

Although concentrated disadvantage was strongly positively related to homicide, immigrant concentration was unrelated to homicide, and residential stability was weakly positively related to homicide (Table 4, model 1). However, when social composition was controlled, collective efficacy was negatively related to homicide (Table 4, model 2). A 2-SD elevation in collective efficacy was associated with a 39.7% reduction in the expected homicide rate. Moreover, when collective efficacy was controlled, the coefficient for concentrated disadvantage was substantially diminished, which indicates that collective efficacy can be viewed as partially mediating the association between concentrated disadvantage and homicide (*33*).

Control for prior homicide. Results so far were mainly cross-sectional, which raised the question of the possible confounding effect of prior crime. For example, residents in neighborhoods with high levels of violence might be afraid to engage in acts of social control (*9*). We therefore reestimated all models controlling for prior homicide: the 3-year average homicide rate in 1988, 1989, and 1990. Prior homicide was negatively related ($P < 0.01$) to collective efficacy in 1995 ($r = -0.55$) and positively related ($P < 0.01$) to all three measures of violence in 1995, including a direct association ($t = 5.64$) with homicide (Table 5). However, even after prior homicide was controlled, the coefficient for collective efficacy remained statistically significant and substantially negative in all three models.

Further Tests

Although the results have been consistent, there are still potential threats to the validity of our analysis. One question pertains to discriminant validity: how do we know that it is collective efficacy at work rather than some other correlated social process (*34*)? To assess competing and analytically distinct factors suggested by prior theory (*4*, *5*), we examined the measure of collective efficacy alongside three other scales derived from the CS of the PHDCN: neighborhood services, friendship and kinship ties, and organizational participation (*35*). On the basis of the results in Tables 3 to 5 and also to achieve parsimony, we constructed a violent crime scale at the neighborhood level that summed standardized indicators of the three major outcomes: perceived violence,

Table 4. Neighborhood correlates of perceived neighborhood violence, violent victimization, and 1995 homicide events.

Variable	Model 1: social composition			Model 2: social composition and collective efficacy		
	Coefficient	SE	t	Coefficient	SE	t
*Perceived neighborhood violence**						
Concentrated disadvantage	0.277	0.021	13.30	0.171	0.024	7.24
Immigrant concentration	0.041	0.017	2.44	0.018	0.016	1.12
Residential stability	−0.102	0.015	−6.95	−0.056	0.016	−3.49
Collective efficacy				−0.618	0.104	−5.95
Violent victimization†						
Concentrated disadvantage	0.258	0.045	5.71	0.085	0.054	1.58
Immigrant concentration	0.141	0.046	3.06	0.098	0.044	2.20
Residential stability	−0.143	0.050	−2.84	−0.031	0.051	−0.60
Collective efficacy				−1.190	0.240	−4.96
1995 homicide events‡						
Concentrated disadvantage	0.727	0.049	14.91	0.491	0.064	7.65
Immigrant concentration	−0.022	0.051	−0.43	−0.073	0.050	−1.45
Residential stability	0.093	0.042	2.18	0.208	0.046	4.52
Collective efficacy				−1.471	0.261	−5.64

*Estimates of neighborhood-level coefficients control for gender, marital status, homeownership, ethnicity, mobility, age, years in neighborhood, and SES of those interviewed. Model 1 accounts for 70.5% of the variation between neighborhoods in perceived violence, whereas model 2 accounts for 77.8% of the variation. †Neighborhood-level coefficients are adjusted for the same person-level covariates listed in the first footnote. Model 1 accounts for 12.3% of the variation between neighborhoods in violent victimization, whereas model 2 accounts for 44.4%. ‡Model 1 accounts for 56.1% of the variation between neighborhoods in homicide rates, whereas model 2 accounts for 61.7% of the variation.

violent victimization, and homicide rate.

Consistent with expectations, collective efficacy was significantly ($p < 0.01$) and positively related to friendship and kinship ties ($r = 0.49$), organizational participation ($r = 0.45$), and neighborhood services ($r = 0.21$). Nonetheless, when we controlled for these correlated factors in a multivariate regression, along with prior homicide, concentrated disadvantage, immigrant concentration, and residential stability, by far the largest predictor of the violent crime rate was collective efficacy (standardized coefficient = −0.53, $t = -8.59$). Collective efficacy thus retained discriminant validity when compared with theoretically relevant, competing social processes. Moreover, these results suggested that dense personal ties, organizations, and local services by themselves are not sufficient; reductions in violence appear to be more directly attributable to informal social control and cohesion among residents (*36*).

A second threat stems from the association of racial composition with concentrated disadvantage as shown in Table 2. Our interpretation was that African Americans, largely because of housing discrimination, are differentially exposed to neighborhood conditions of extreme poverty (*15*). Nonetheless, a counterhypothesis is that the percentage of black residents and not disadvantage accounts for lower levels of collective efficacy and, consequently, higher violence. Our second set of tests therefore replicated the key models within the 125 NCs where the population was more than 75% black (see the first row of Table 1), effectively removing race as a potential confound. Concentrated poverty and residential stability each had significant associations with collective efficacy in these predominantly black areas ($t = -5.60$ and $t = 2.50$, respectively). Collective efficacy continued to explain variations in violence across black NCs, mediating the prior effect of concentrated disadvantage. Even when prior homicide, neighborhood services, friendship and kinship ties, and organizational participation were controlled, the only significant predictor of the violent crime scale in black NCs was collective efficacy ($t = -4.80$). These tests suggested that concentrated disadvantage more than race per se is the driving structural force at play.

Discussion and Implications

The results imply that collective efficacy is an important construct that can be measured reliably at the neighborhood level by means of survey research strategies. In the past, sample surveys have primarily considered individual-level relations. However, surveys that merge a cluster sample design with questions tapping collective properties lend themselves to the additional consideration of neighborhood phenomena.

Together, three dimensions of neighborhood stratification—concentrated disadvantage, immigration concentration, and residential stability—explained 70% of the neighborhood variation in collective efficacy. Collective efficacy in turn mediated a substantial portion of the association of residential stability and disadvantage with multiple measures of violence, which is consistent with a major theme in neighborhood theories of social organization (*1–5*). After adjustment for measurement error, individual differences in neighborhood composition, prior violence, and other potentially confounding social processes, the combined measure of informal social control and cohesion and trust remained a robust predictor of lower rates of violence.

There are, however, several limitations of the present study. Despite the use of decennial census data and prior crime as lagged predictors, the basic analysis was cross-sectional in design; causal effects were not proven. Indicators of informal control and social cohesion were not observed directly but rather inferred from informant reports. Beyond the scope of the present study, other dimensions of neighborhood efficacy (such as political ties) may be important, too. Our analysis was limited also to one city and did not go beyond its official boundaries into a wider region.

Finally, the image of local residents working collectively to solve their own problems is not the whole picture. As shown, what happens within neighborhoods is in part shaped by socioeconomic and housing factors linked to the wider political economy. In addition to encouraging communities to mobilize against violence through "self-help" strategies of informal social control, perhaps reinforced by partnerships with agencies of formal social control (community policing), strategies to address the social and ecological changes that beset many inner-city communities need to be considered. Recognizing that collective efficacy matters does not imply that inequalities at the neighborhood level can be neglected.

Table 5. Predictors of neighborhood level violence, victimization, and homicide in 1995, with prior homicide controlled. For violence and victimization as outcomes, the coefficients reported in this table were adjusted for 11 person-level covariates (see Table 3), but the latter coefficients are omitted for simplicity of presentation.

Variable	Violence as outcome			Victimization as outcome			Homicide in 1995 as outcome		
	Coefficient	SE	*t*	Coefficient	SE	*t*	Coefficient	SE	*t*
Intercept	3.772	0.379	9.95	−2.015	0.042	−49.24	3.071	0.050	62.01
Concentrated disadvantage	0.157	0.025	6.38	0.073	0.060	1.22	0.175	0.072	2.42
Immigrant concentration	0.020	0.016	1.25	0.098	0.045	2.20	−0.034	0.044	−0.77
Residential stability	−0.054	0.016	−3.39	−0.029	0.052	−0.56	0.229	0.043	5.38
Collective efficacy	−0.594	0.108	−5.53	−1.176	0.251	−4.69	−1.107	0.272	−4.07
Prior homicide	0.018	0.014	1.27	0.017	0.049	0.34	0.397	0.070	5.64
Variance									
Between-neighborhood variance	0.030			0.091			0.207		
Percent of variance explained between neighborhoods	78.0			43.8			73.0		

REFERENCES AND NOTES

1. For a recent review of research on violence covering much of the 20th century, including a discussion of the many barriers to direct examination of the mechanisms explaining neighborhood-level variations, see R. J. Sampson and J. Lauritsen, in *Understanding and Preventing Violence: Social Influences*, vol. 3, A. J. Reiss Jr. and J. Roth, Eds. (National Academy Press, Washington, DC, 1994), pp. 1–114.
2. J. F. Short Jr., *Poverty, Ethnicity, and Violent Crime* (Westview, Boulder, CO, 1997).
3. For a general assessment of the difficulties facing neighborhood-level research on social outcomes, see S. E. Mayer and C. Jencks, *Science* **243**, 1441 (1989).
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6. M. Janowitz, *ibid.* **81**, 82 (1975).
7. E. Maccoby, J. Johnson, R. Church, *J. Social Issues* **14**, 38 (1958); R. Taylor, S. Gottfredson, S. Brower, *J. Res. Crime Delinquency* **21**, 303 (1983); J. Hacker, K. Ho, C. Ross, *Social Problems* **21**, 328 (1974). A key finding from past research is that many delinquent gangs emerge from unsupervised spontaneous peer groups [F. Thrasher, *The Gang: A Study of 1,313 Gangs in Chicago* (Univ. of Chicago Press, Chicago, IL, 1963); C. Shaw and H. McKay, *Juvenile Delin-*

quency and Urban Areas (Univ. of Chicago Press, Chicago, IL, 1969), pp. 176–185; J. F. Short Jr. and F. Strodtbeck, *Group Process and Gang Delinquency* (Univ. of Chicago Press, Chicago, IL, 1965)].

8. For example, about half of all homicides occur among nonfamily members with a preexisting relationship: friends, neighbors, casual acquaintances, associates in illegal activities, or members of a rival gang. Illegal markets are especially high-risk settings for robbery, assault, and homicide victimization, whether by an associate or a stranger [A. J. Reiss Jr. and J. Roth, Eds. *Understanding and Preventing Violence* (National Academy Press, Washington, DC, 1993), pp. 18, 79; A. J. Reiss Jr., in *Criminal Careers and "Career Criminals*," A. Blumstein, J. Cohen, J. Roth, C. Visher, Eds. (National Academy Press, Washington, DC, 1986), pp. 121–160].
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10. J. Coleman, *Foundations of Social Theory* (Harvard Univ. Press, Cambridge, MA, 1990); R. Putnam, *Making Democracy Work* (Princeton Univ. Press, Princeton, NJ, 1993).
11. A. Bandura, *Social Foundations of Thought and Action: A Social Cognitive Theory* (Prentice-Hall, Englewood Cliffs, NJ, 1986).
12. See, generally, J. Logan and H. Molotch, *Urban Fortunes: The Political Economy of Place* (Univ. of California Press, Berkeley, CA, 1987).
13. See also J. Kasarda and M. Janowitz, *Am. Sociol. Rev.* **39**, 328 (1974); R. Sampson, *ibid.* **53**, 766 (1988).
14. W. J. Wilson, *The Truly Disadvantaged* (Univ. of Chicago Press, Chicago, IL, 1987).
15. D. Massey and N. Denton, *American Apartheid: Segregation and the Making of the Underclass* (Harvard Univ. Press, Cambridge, MA, 1993); D. Massey, *Am. J. Sociol.* **96**, 329 (1990).
16. J. Brooks-Gunn, G. Duncan, P. Kato, N. Sealand, *Am. J. Sociol.* **99**, 353 (1993); F. F. Furstenberg Jr., T. D. Cook, J. Eccles, G. H. Elder, A. Sameroff, *Urban Families and Adolescent Success* (Univ. of Chicago Press, Chicago, IL, in press), chap. 7. Research has shown a strong link between the concentration of female-headed families and rates of violence [see (*1*)].
17. D. Williams and C. Collins, *Annu. Rev. Sociol.* **21**, 349 (1995).
18. Cluster analyses of census data also helped to guide the construction of internally homogeneous NCs with respect to racial and ethnic mix, SES, housing density, and family organization. Random-effect analyses of variance produced intracluster correlation coefficients to assess the degree to which this goal had been achieved; analyses (*37*) revealed that the clustering was successful in producing relative homogeneity within NCs.
19. For purposes of selecting a longitudinal cohort sample, SES was defined with the use of a scale from the 1990 census that included NC-level indicators of poverty, public assistance, income, and education (*37*). Race and ethnicity were also measured with the use of the 1990 census, which defined race in five broad categories: "white," "black," "American Indian, Eskimo, or Aleut," "Asian or Pacific Islander," and "other." We use the census labels of white and black to refer to persons of European American and African American background, respectively. We use the term "Latino" to denote anyone of Latin American descent as determined from the separate census category of "Hispanic origin." "Hispanic" is more properly used to describe persons of Spanish descent (i.e., from Spain), although the terms are commonly used interchangeably.
20. The sampling design of the CS was complex. For purposes of a longitudinal study (*37*), residents in 80 of the 343 NCs were oversampled. Within these 80 NCs, a simple random sample of census blocks was selected and a systematic random sample of dwelling units within those blocks was selected. Within each dwelling unit, all persons over 18 were listed, and a respondent was sampled at random with the aim of obtaining a sample of 50 households within each NC. In each of the remaining NCs (n = 263), nine census blocks were selected with probability proportional to population size, three dwelling units were selected at random within each block, and an adult respondent was randomly selected from a list of all adults in the dwelling unit. The aim was to obtain a sample of 20 in these 263 NCs. Despite these differences in sampling design, the selected dwelling units constituted a representative and approximately self-weighting sample of dwelling units within every NC (n = 343). ABT Associates (Cambridge, MA) carried out the data collection with the cooperation of research staff at PHDCN, achieving a final response rate of 75%.
21. "Don't know" responses were recoded to the middle category of "neither likely nor unlikely" (informal social control) or "neither agree nor disagree" (social cohesion). Most respondents answered all 10 items included in the combined measure; for those respondents, the scale score was the average of the responses. However, anyone responding to at least one item provided data for the analysis; a person-specific standard error of measurement was calculated on the basis of a simple linear item-response model that took into account the number and difficulty of the items to which each resident responded. The analyses reported here were based on the 7729 cases having sufficient data for all models estimated.
22. Respondents were also asked whether the incident occurred during the 6 months before the interview; about 40% replied affirmatively. Because violence is a rare outcome, we use the total violent victimization measure in the main analysis. However, in additional analyses, we examined a summary of the prevalence of personal and household victimizations (ranging from 0 to four) restricted to this 6-month window. This test yielded results very similar to those based on the binary measure of total violence.
23. The original data measured the address location of all homicide incidents known to the Chicago police (regardless of arrests) during the months of the community survey.
24. The alpha-scoring method was chosen because we are analyzing the universe of NCs in Chicago and are interested in maximizing the reliability of measures [H. F. Kaiser and J. Caffry, *Psychometrika* **30**, 1 (1965)]. We also estimated an oblique factor rotation, allowing the extracted dimensions to covary. A principal components analysis with varimax rotation nonetheless yielded substantively identical results.
25. For a methodological procedure and empirical result that are similar but that used all U.S. cities as units of analysis, see K. Land, P. McCall, L. Cohen, *Am. J. Sociol.* **95**, 922 (1990).
26. S. W. Raudenbush, B. Rowan, S. J. Kang, *J. Educ. Stat.* **16**, 295 (1991).
27. D. V. Lindley and A. F. M. Smith, *R. Stat. Soc. J. Ser. B Methodol.* **34**, 1 (1972).
28. Although the vast majority of respondents answered all items in the collective efficacy scale, the measurement model makes full use of the data provided by those whose responses were incomplete. There is one less indicator, D_{pijk}, than the number of items to identify the intercept π_{jk}.
29. This degree of intersubjective agreement is similar to that found in a recent national survey of teachers that assessed organizational climate in U.S. high schools [B. Rowan, S. Raudenbush, S. Kang, *Am. J. Educ.* **99**, 238 (1991)].
30. The analysis of collective efficacy and violence as outcomes uses a three-level model in which the level 1 model describes the sources of measurement error for each of these outcomes. The level 2 and level 3 models together describe the joint distribution of the "true scores" within and between neighborhoods. Given the joint distribution of these outcomes, it is then possible to describe the conditional distribution of violence given "true" collective efficacy and all other predictors, thus automatically adjusting for any errors of measurement of collective efficacy. See S. Raudenbush and R. J. Sampson (paper presented at the conference "Alternative Models for Educational Data," National Institute of Statistical Sciences, Research Triangle Park, NC, 16 October 1996) for the necessary derivations. This work is an extension of that of C. Clogg, E. Petkova, and A. Haritou [*Am. J. Sociol.* **100**, 1261 (1995)] and P. Allison (*ibid*., p. 1294). Note that census blocks were not included as a "level" in the analysis. Thus, person-level and block-level variance are confounded. However, this confounding has no effect on standard errors reported in this manuscript. If explanatory variables had been measured at the level of the census block, it would have been important to represent blocks as an additional level in the model.
31. The resulting model is a logistic regression model with random effects of neighborhoods. This model was estimated first with penalized quasi-likelihood as described by N. E. Breslow and D. G. Clayton [*J. Am. Stat. Assoc.* **88**, 9 (1993)]. The doubly iterative algorithm used is described by S. W. Raudenbush ["Posterior modal estimation for hierarchical generalized linear models with applications to dichotomous and count data" (Longitudinal and Multilevel Methods Project, Michigan State Univ., East Lansing, MI, 1993)]. Then, using those results to model the marginal covariation of the errors, we estimated a population-average model with robust standard errors [S. Zeger, K. Liang, P. Albert, *Biometrics* **44**, 1049 (1988)]. Results were similar. The results based on the population-average model with robust standard errors are reported here.
32. The analysis paralleled that of criminal victimization, except that a Poisson sampling model and logarithmic link were used in this case. Again, the reported results are based on a population-average model with robust standard errors.
33. Although the zero-order correlation of residential stability with homicide was insignificant, the partial coefficient in Table 4 is significantly positive. Recall from Table 3 that stability is positively linked to collective efficacy. But higher stability without the expected greater collective efficacy is not a positive neighborhood quality according to the homicide data. See (*14*).
34. T. Cook, S. Shagle, S. Degirmencioglu, in *Neighborhood Poverty: Context and Consequences for Children*, vol. 2, J. Brooks-Gunn, G. Duncan, J. L. Aber, Eds. (Russell Sage Foundation, New York, in press).
35. "Neighborhood services" is a nine-item scale of local activities and programs (for example, the presence of a block group, a tenant association, a crime prevention program, and a family health service) combined with a six-item inventory of services for youth (a neighborhood youth center, recreational programs, after-school programs, mentoring and counseling services, mental health services, and a crisis intervention program). "Friendship and kinship ties" is a scale that measures the number of friends and relatives that respondents report are living in the neighborhood. "Organizational participation" measures actual involvement by residents in (i) local religious organizations; (ii) neighborhood watch programs; (iii) block group, tenant association, or community council; (iv) business or civic groups; (v) ethnic or nationality clubs; and (vi) local political organizations.
36. Similar results were obtained when we controlled for a measure of social interaction (the extent to which neighbors had parties together, watched each other's homes, visited in each others' homes, exchanged favors, and asked advice about personal matters) that was positively associated with collective efficacy. Again the direct effect of collective efficacy remained, suggesting that social interaction, like friendship and kinship ties, is linked to reduced violence through its association with increased levels of collective efficacy.
37. R. J. Sampson, S. W. Raudenbush, F. Earls, data not shown.
38. Major funding for this project came from the John D. and Catherine T. MacArthur Foundation and the National Institute of Justice. We thank L. Eisenberg and anonymous reviewers for helpful comments; S. Buka and A. J. Reiss Jr. for important contributions to the research design; and R. Block, C. Coldren, and J. Morenoff for their assistance in obtaining, cleaning, geo-coding, and aggregating homicide incident data to the NC level. M. Yosef and D. Jeglum-Bartusch assisted in the analysis.

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